

Methods and Tools for the Quantification and Improvement of Measurement Uncertainty in Light Field Measurement for Projection Systems

Dissertation (monograph) approved by the Doctoral Committee of
Hamburg University of Technology
in pursuit of the academic degree of

Doktor-Ingenieur (Dr.-Ing.)

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from
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2026

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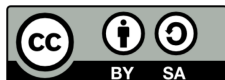
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Date of oral examination

25.06.2026

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DOI:

<https://doi.org/10.15480/882.17771>

Foreword

This dissertation is the result of years devoted to a deceptively simple yet technically demanding question: how can the quality of a virtual image in three-dimensional space be rigorously characterized when a conventional camera captures only intensity and not the directional information that defines the image itself? At the Institute for Mechatronics in Mechanics at Hamburg University of Technology, this question gave shape to the work presented here. During this time, I had the opportunity to automate a six-degree-of-freedom goniophotometer test bench, develop the Intersecting-Planes Concept for efficient light-field reconstruction, and validate the overall approach on a real automotive head-up display.

Like a reconstruction built from many projections, a doctorate emerges through experiments, setbacks, long nights, and moments of insight. This journey has challenged me intellectually and personally, while also teaching me patience, independence, and perseverance.

This work would not have been possible without the guidance, trust, and support of many people. My deepest gratitude goes to my supervisor, Prof. Dr.-Ing. Thorsten Alexander Kern, for his confidence in my work, for the scientific freedom he granted me, and for challenging me at the most critical points of this research. I would also like to sincerely thank Prof. Dr.-Ing. Alexander Penn, for kindly serving as the second examiner of this dissertation, and Prof. Dr. rer. nat. Ralf God, Chair of the examination committee, for his valuable feedback and support in bringing this thesis to completion.

My sincere thanks also go to my colleagues at the Institute for the stimulating technical discussions, the shared coffee breaks, and the sense of belonging they created at TUHH. I am equally grateful to the students with whom I had the pleasure to work; their contributions and commitment enriched this research in many ways.

Finally, I would like to thank my family: my parents, Jaipal Reddy and Swaroopa; my sibling, Santhosh Reddy; my wife, Mounika; and my children, Maansi Reddy and Aarya Ridvik Reddy. Your patience, encouragement, and belief in me sustained me, especially during the times when measurements did not converge, and the path forward seemed uncertain. Thank you!

Sravan Shelam

Abstract

Projection-type optical systems, such as Head-Up Displays (HUDs), Virtual Reality (VR), and Augmented Reality (AR), provide immersive experiences in virtual worlds or ergonomically present supplementary information in real-world contexts. These systems play a crucial role in modifying the light emitted by imagers to generate virtual images in front of the user, greatly enhancing user engagement and interaction. In VR and AR applications, the immersive quality and usability of the system depend critically on the fidelity and stability of these virtual images.

Central to these experiences is the concept of a virtual image, an image plane created in a space without physical representation. A virtual image typically arises when projection systems modify and direct light to form the perception of an object or scene at a specific location in space. However, a significant challenge in such optical systems is image distortion, which occurs as light passes through complex optical paths.

A wide range of optical technologies including holograms, Fresnel lenses, traditional lenses, and mirror optics are employed to construct these systems. As images propagate through these elements, distortions can cause elements of the virtual image to be projected at varying distances. This results in visual inconsistencies that can disrupt the immersive experience. While the human visual system can often compensate for these distortions unconsciously, evidence shows that persistent image distortion may lead to discomfort, motion sickness, and headaches. These effects hinder long-term ergonomic usage and holistic user experience.

Image distortion in these systems is inherently three-dimensional due to the complex arrangement of optical components. This 3D distortion is a major challenge for optical design, impacting device quality and user satisfaction, especially for AR applications. Accurately measuring and characterizing these distortions requires advanced methods. To address this, a light field measurement system has been developed, with the ability to reconstruct images and analyze spatial and angular light information far beyond the limits of human perception.

This thesis addresses the sources and impacts of three-dimensional distortion in projection-type optical systems. It presents a comprehensive measurement methodology for evaluating image quality. By tackling these challenges and optimizing projection systems, this work contributes to improved user experience and long-term usability in next-generation immersive display technologies.

Summary

This thesis delves into the development of an innovative 6 DoF (Degrees of Freedom) goniometer setup, specifically engineered to measure three-dimensional distortions with precision surpassing the human eye's resolution. The primary innovation of this setup lies in its ability to capture and analyze these distortions in a way that has not been previously explored, necessitating significant developmental work. The project's comprehensive scope extends to compiling a comprehensive catalogue of light fields from projection systems. This effort is pivotal for virtualizing devices, thereby facilitating a retrospective comparison of various devices based on emerging standards in perceptual sciences.

Our approach computes light field vectors for every pixel in a given field of angular range, which are processed by an image reconstruction algorithm known as the Inverse Radon transform. This methodology reconstructs the source's light radiation characteristics and geometry at a distance, which gives a better understanding of how light behaves in three-dimensional space. Moreover, by analyzing contrast features extending into multiple image planes, the project demonstrates its validation and enhanced ability to understand the complex interplay between image plane placement and contrast measurements. Analyzing visual perception is essential to understanding how images are interpreted and how they look under different viewing conditions.

The modified Radon transformation type advanced application in this context allows the reconstruction of vector fields and a detailed analysis of the scattering function of the plane. The ideal result of the project is a complete digital twin of the apparatus, which can be used in design simulations. That digital twin would act like it was visible from any position in the angular range of the defined area, thus allowing engineers and designers a potent tool for visualizing and tweaking optical systems before physical prototyping. It streamlines the design process while greatly boosting the accuracy and speed of creating optical devices, setting the stage for more efficient and user-friendly projection systems in the future.

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Symbol directory

Symbol	Description	Unit
$\vec{p}_{int}$	Intersection point plane - vector	mm
A_i	Voxel adress in dimension i	–
$\vec{b}_p$	base vector of plane	mm
$\vec{b}_r$	base vector of a light ray	mm
d_{cross}	Distance traversed within one voxel	mm
d_{max}	Maximum distance within one voxel	mm
$f(x,y)$	2D Image	–
$f(x,y,z)$	3D Image	–
f	Focal length of a camera lens	mm
I_{rw}	Weighted light ray intensity	–
I_r	Light ray intensity	–
$\vec{n}_p$	normal vector of plane	–
P_i	Position of voxel	mm
s_i	Voxel size in dimension i	mm
θ	Angle of emergence from a camera lens	rad
$\vec{v}_r$	directional light vector	–
y	Position of a pixel on sensor	mm

List of Abbreviations

2D	2 Dimensional
3D	3 Dimensional
ADAS	Advanced Driver Assistance Systems
AR	Augmented Reality
AWGN	Additive White Gaussian Noise
CPU	Central Processing Unit
CTF	Contrast Transfer Function
df	Degrees of freedom
DLP	Digital Light Processing
DOF	Depth of Field
EFL	Effective Focal Length
ESP	Enhanced System Performance
FOV	Field of View
FPN	Fixed Pattern Noise
GPU	Graphic Processing Unit
GUI	Graphical User Interface
HMI	Human-Machine Interface
HUD	Head-up Display
IPC	Intersecting Planes Concept
LCD	Liquid Crystal Display
LCOS	Liquid Crystal on Silicon
LMK	Luminance Measuring Camera
LSF	Line Spread Function
MNC	Multi-Neighbor Concept
MTF	Modulation Transfer Function
MVS	Multi-View Stereo
NED	Near Eye Displays
OLED	Organic Light-Emitting Diode
PGU	Picture Generation Unit

PSF	Point Spread Function
PSNR	Peak Signal Noise Ratio
RMSE	Root Mean Square Error
SfM	Structure from Motion
SSIM	Structural Similarity Index
VES	Vision Enhancement System
VID	Virtual Image Distance
Voxel	Volume pixel
VR	Virtual Reality

1 Introduction

The rapid advancement of immersive technologies, such as Virtual Reality (VR) and Augmented Reality (AR), has revolutionized various industries, including automotive and entertainment. These technologies enhance user experience and safety and introduce new challenges in visual display quality and user comfort. Accurate measurement of projection systems ensures optimal performance and user safety. However, the current methods, such as traditional cameras that capture only light intensity, are not sufficient. They result in limited depth information and do not provide detailed insights into light intensity and direction, which are crucial for advanced techniques like digital refocusing and depth reconstruction. This gap in measurement techniques is a pressing issue, especially when evaluating projection systems in VR, AR and Head-Up Displays (HUDs) under diverse conditions. Specialized measurement techniques are urgently needed to address these challenges and ensure high-performance standards. This thesis focuses on developing and refining these crucial measurement technologies for projection systems used in immersive applications. By addressing current limitations and exploring advanced methods, the research aims to enhance the accuracy and quality of these technologies.

1.1 Motivation

The increasing demand for immersive and lifelike technologies, such as virtual reality (VR) and augmented reality (AR), has significantly emphasized the paramount importance of ensuring human safety. This is not just a matter of comfort, but a crucial aspect of protecting the eyes and the overall visual system. Exposure to intense light, harmful wavelengths, or particles can cause damage and impair vision. Prolonged exposure to specific visual stimuli, such as bright lights or flickering screens, can lead to visual fatigue, discomfort, and, in some cases, headaches. The eyes are strained due to inappropriate lighting conditions, such as glare or inadequate illumination, which is a common concern [1][2]. Implementing a proper lighting design is crucial to foster a safer and more comfortable visual experience.

In environments heavily reliant on technology, ensuring the safety of visual displays is paramount. This involves avoiding features that could cause distractions or discomfort and addressing potential safety hazards associated with visual interfaces. As technologies continue to advance, they are becoming increasingly immersive and integrated into our daily lives. This rapid development can potentially revolutionize numerous industries, including the automotive industry. One notable application of AR technology is the implementation of head-up displays (HUDs) in vehicles. By overlaying virtual information on the driver's field of view, HUDs can improve road safety by providing essential real-time data without requiring the driver to shift their focus away from the road [3][4]. For example, HUDs can display navigation instructions, speed limits, collision warnings, and other crucial information directly in the driver's line of sight. This augmented reality experience ensures that drivers have access to vital information while keeping their attention on the road ahead. In addition, VR technology significantly benefits the automotive industry, particularly in product development. Engineers can utilize virtual reality environments to create virtual prototypes and simulate various scenarios, allowing more efficient and cost-effective testing processes. Virtual reality enables engineers to virtually experience and evaluate designs, make necessary adjustments, and identify potential problems before physical prototypes are built. This not only accelerates the product development cycle but also helps to improve overall design quality and performance. By integrating VR and AR technologies into automotive applications, manufacturers can improve safety, user experience, and innovation in the industry. As these technologies continue to evolve, we can expect further advances that will shape the future of transportation and revolutionize how we interact with vehicles.

Accurate measurements of these devices are crucial in ensuring the quality of the visual experience perceived by the user. However, conventional cameras can only capture the amount of light that reaches a single pixel, resulting in a two-dimensional representation with brightness and color values. In contrast, light field cameras offer a more advanced measurement capability by capturing the amount of light and the direction or angle from which it emerges. This results in a vector light field that provides information about the light distribution in every direction and at every point in space. Light field technology can be utilized in various imaging techniques, including digital refocusing, viewpoint switching, increased depth of field, and scene depth reconstruction [5][6]. However, it is essential to note that every projection system these technologies use significantly influences the light field. A reflective or transmissive screen is typically employed to convert the power of the light field into a visible image. Head-up displays (HUDs) use a projection system to create a virtual image on a screen, as shown in Figure 1.1. Given these projection systems' unique characteristics and requirements,

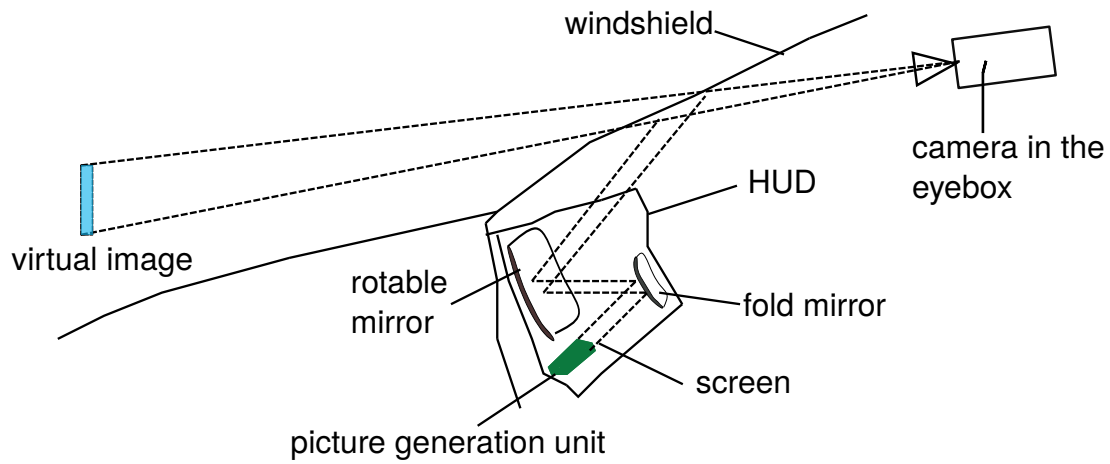


Figure 1.1: *Head-up Display Optical Path Diagram: illustrating the journey of light from the PGU through mirrors to form a virtual image for the driver*

traditional measurement methods have been adapted and tailored to evaluate the performance of HUDs and similar immersive technologies. These specialized measurement techniques are used to assess parameters such as two-dimensional image quality, brightness, resolution, color accuracy, and overall fidelity of the virtual image.

The primary objective of this thesis is to develop and refine measurement technology for projection systems, specifically targeting virtual reality (VR), augmented reality (AR), and head-up displays (HUDs). Precise evaluation of projection systems is essential for their effectiveness and success in various applications. To achieve this, precise measurement techniques are required to assess parameters such as distances, angles, and other physical characteristics. This report aims to highlight the challenges associated with accurately measuring projection systems. With technological advancements, new and improved measurement techniques offer enhanced capabilities and accuracy. In particular, techniques such as light fields, light field cameras, and automated goniophotometers have proven effective in accurately measuring image parameters and tracking the image profile of projection systems [7]. By exploring and implementing these advanced measurement techniques, this research aims to contribute to developing more reliable and precise measurement technology for projection systems. Identifying and addressing the challenges inherent in current measurement methods will help

overcome limitations and ensure the accuracy and quality of projection systems. Ultimately, the insights gained from this work will pave the way for advancements in projection system design, optimization, and performance evaluation, thus driving the advancement of VR, AR, and HUD technologies.

1.2 Problem Statement

Near-eye displays (NEDs) and head-up displays (HUDs) technology have become increasingly popular in recent years, because of their ability to provide users with important information without requiring them to look away from the road. However, there are significant challenges in accurately measuring the luminance, contrast, homogeneity, and clarity of projected information under different ambient conditions, such as night view, virtual image positions, or focal distance on an infinite viewing plane. Accurate measurement is essential to ensure that the information transmitted to drivers is reliable and easily interpretable.

The testing of projection systems requires a combination of photometric and dimensional data to achieve the necessary optical quality. Both photometric and dimensional measurements are equally important in measuring distance, location, and virtual image size to evaluate them. Photometric measurements include luminance and chromaticity measurements, while dimensional measurements include depth of focus (DOF), field of view (FOV), and virtual image size [8][9]. The accuracy of these measurements is critical to ensuring the projection of the virtual image concerning the observer's eye. However, measuring these parameters accurately can be challenging due to varying ambient lighting conditions and image distortion, aberration, and ghosting measured by the point deviation reflected from a target virtual image. Without standardized measurement methods, it isn't easy to objectively assess the performance of different HUD systems.

Current image quality measurements of NEDs and HUDs face several challenges that affect their accuracy and reliability [10][11][12]. Some of the significant problems of current image quality measurements of HUDs include:

1. Lack of standardized measurement methods: The absence of standardized measurement methods makes it difficult to compare and evaluate the performance of different HUD systems objectively. Normated measurement methods are needed to ensure accurate, reliable, and reproducible measurements.

2. Inability to measure all parameters: Current methods can only accurately measure some of the projection devices' photometric and dimensional parameters. However, measuring other parameters such as contrast, homogeneity, and clarity can be challenging due to the varying ambient lighting conditions and image distortion, aberration, and ghosting.
3. Limited accuracy in different ambient lighting conditions: The accuracy of current image quality measurements of NEDs and HUDs is limited under various ambient lighting conditions, such as night view, virtual image positions, or focal distance on an infinite viewing plane. These conditions can affect the accuracy of the photometric and dimensional measurements, leading to unreliable results.
4. Limited depth of field (DOF) measurement: DOF measurement is essential in evaluating the legibility of immersive displays and virtual images. However, current measurement methods can only measure DOF accurately in a limited range, which affects their reliability.
5. Inadequate field of view (FOV) measurement: FOV measurement is critical in evaluating the effectiveness of HUDs in conveying information to drivers.
6. Expensive and time-consuming measurement methods: Current image quality measurement methods for immersive displays are often costly and time consuming, making it challenging to evaluate the performance of different projection systems in a timely and cost-effective manner.

Addressing these challenges is critical to improving the accuracy and reliability of HUD image quality measurements. Standardized measurement methods that can measure all parameters accurately under different ambient lighting conditions, including wider DOF and FOV measurements, would improve the evaluation of the performance of HUDs. Furthermore, more cost-effective and less time-consuming measurement methods could reduce evaluation costs and facilitate the adoption of HUD technology. The primary focus is analyzing lighting systems, particularly those integrated into projection systems for human-machine interfaces such as head-up displays, virtual reality, and augmented reality systems. This analysis involves assessing and quantifying the performance data derived from light field measurements of these products.

Although all these challenges exist, the need for a better method to quantify projection systems is imminent. At the same time, light can be considered as a vector field. While imaging technology such as medical imaging, photogrammetry, structured light imaging, and holography methods exist to quantify vector fields, their application to the quantification of projection system quality is limited. However,

they provide the potential to create a complete characterization of the light vectors. Moreover, incorporating vector-field imaging principles into projection system design may enable real-time feedback loops during manufacturing or operational stages. Such implementations allow on-the-fly corrections of distortions, aberrations, or color inaccuracies by actively monitoring and adjusting the output vector field. As a result, the development of standardized methodologies for light-vector quantification in projection systems could revolutionize fields such as cinema, augmented reality (AR), and virtual reality (VR), where the quality of the visual experience depends on precise control of light properties. All of this leads to the following main hypotheses of this thesis.

1. A 2D image plane within a 3D space can be effectively identified by analyzing the contrast information that is distributed among voxels, where this contrast acts as the origin of light. This method leverages the inherent differences in light intensity to pinpoint and define the plane's boundaries and orientation within the spatial context.
2. If a projection-type system can generate variable test patterns, then a contrast measurement methodology utilizing these patterns will yield a more accurate characterization of 3D distortions than traditional methods, specifically in volumetric contrast reconstruction and spatial integrity.
3. When measurements are conducted through observations from multiple directions, an optimal number of images required to maximize the quality of volumetric contrast reconstruction.
4. By measuring contrast variations at multiple positions within an image volume, it is possible to reconstruct the spatial location of the virtual image plane. This hypothesis postulates that the contrast gradients in the volume serve as key indicators for estimating the precise positioning of the virtual image.

1.3 Organization

The thesis is organized as follows.

- Chapter 2 introduces the relevant literature that is closely connected to the research in this thesis in the area of projection systems, virtual images, head-up displays, light field technology, and image reconstruction overview.

- Chapter 3 presents a detailed introduction to the hardware components of the measurement test set-up. This includes an overview of positioning stages, positioning kinematics, and the luminance measurement camera, which are essential for the precise and accurate execution of the tests.
- Chapter 4 presents the software development process for creating a light field, which includes image acquisition, base vectors, and light vectors. This chapter delves into the techniques employed for light field reconstruction, including the radon transform, line weighting effect, and parallel computation. The software design and implementation aspect highlights the key methodologies used to generate and reconstruct the light field.
- Chapter 5 outlines a comprehensive analysis of contrast measurement in the reconstructed light field volume data, which are generated using various test patterns such as line pairs, checkerboards, and dot patterns. The chapter delves into understanding contrast in visual systems through these test patterns, while also examining the influence of different coordinate systems (spherical and Cartesian) and the number of images used in the reconstruction process. This exploration provides critical insight into how these factors affect the accuracy and quality of the reconstructed images.
- Chapter 6 focuses on evaluating the contrast characteristics of the reconstructed light field under various test scenarios and patterns. This analysis offers valuable insights into the quality and fidelity of the reconstructed data, highlighting its effectiveness in capturing and reproducing contrast information from the test patterns. The thesis concludes by validating the projected or displayed test images, both virtual and in reality, using devices such as HUD's.
- Finally, Chapter 7 provides a comprehensive conclusion and outlines potential directions for future research.

2 Prior Knowledge

This chapter lays the foundation for understanding the subsequent sections of this dissertation by covering crucial concepts such as projection systems, light field technology, and image reconstruction. The chapter provides an overview of each topic, including theoretical and practical aspects. In addition, it discusses how these concepts are applied in the context of the research questions in this dissertation. A comprehensive grasp of these subjects is imperative to elucidate the research findings later in the dissertation fully. Additionally, it examines the process of reconstructing 3D structures from multiple images, employing techniques like Structure from Motion (SfM) and Multi-View Stereo (MVS). These methods are vital for accurate image reconstruction and play a critical role in applications requiring precise spatial representation.

2.1 Projection systems

Projection systems play a crucial role across various domains, ranging from entertainment to industrial applications. Using advanced technologies such as DLP (Digital Light Processing), LCOS (Liquid Crystal on Silicon), LCD (Liquid Crystal Display), and organic light-emitting diode, these systems project images onto surfaces for diverse purposes, including multimedia presentations, medical imaging, automotive displays, and simulation environments. The effectiveness of projection systems depends on factors such as the quality of the imaging elements, projection distance, viewing angle, ambient lighting conditions, and characteristics of the projection surface [13]. Optimal performance requires carefully considering and calibrating these variables to ensure clear, vibrant, and accurately rendered visuals. Moving from the realm of projection systems to the fundamentals of optics, this thesis delves into the classification of images and the distinction between real and virtual representations.

2.1.1 Virtual images

In optics, images can be classified into real and virtual. While the actual intersection of light rays forms real images, virtual images are formed by the apparent intersection of light rays. This means that virtual images cannot be projected onto a screen and can only be seen through the eye of an observer. In this chapter, we will explore virtual images in more detail. A virtual image appears to be in a different location from where the light rays that produce it actually originated. In other words, virtual images are formed by the apparent intersection of light rays that do not actually converge at the location of the image. These images are always erect, while real images are inverted in some scenarios. The virtual image is shown in Figure 2.1.

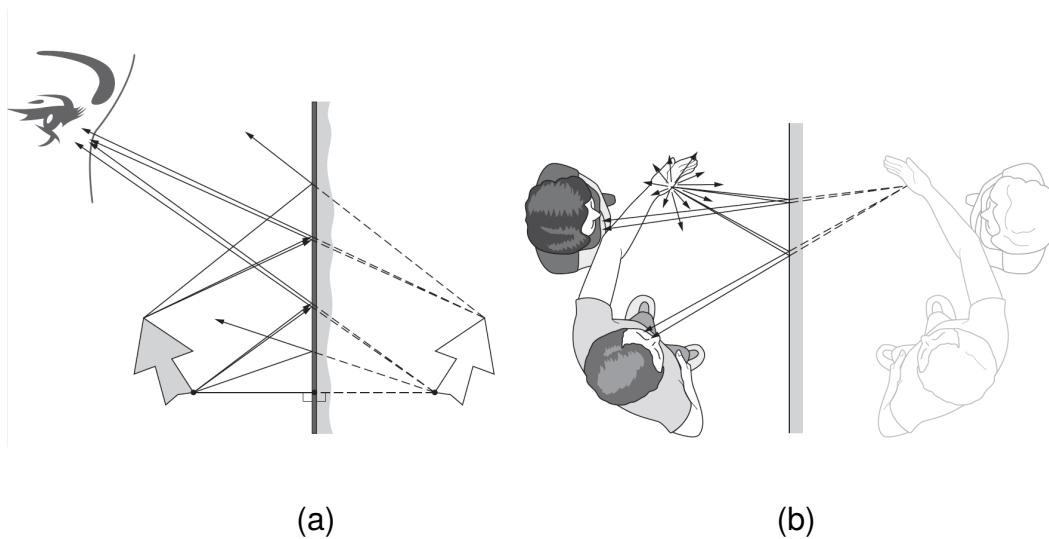


Figure 2.1: *Images of an extended object in a planar mirror (a); Images in a planar mirror (b) [14]*

Virtual images have several unique characteristics, including being always upright. They cannot be projected onto a screen since they do not exist at the location where they appear to be, and they can only be seen through the observer's eye. Virtual images have a variety of practical applications in optics, such as the design of optical instruments like microscopes, telescopes, and cameras. For example, in a microscope, the objective lens produces a real image of the object being viewed, which is then magnified by the eyepiece to produce a virtual image seen by the observer. Virtual images are also widely used in virtual reality technology, where computer-generated images are projected onto a headset or screen to create the illusion of a three-dimensional world. In this case, the optics create virtual images at an apparent distance to the eye. The screens are just in front of the eyes, but the optics let them appear as if they are at an infinite distance [15]. As we navigate

the intricacies of virtual images and their practical applications in optics, we must recognize how these concepts intersect with modern technological innovations such as virtual reality (VR) and augmented reality (AR).

2.1.2 AR/VR devices

Nowadays, VR and AR are widely recognized technologies. As technology and software advance, VR and AR have found extensive applications in various fields, such as health services, hospitality, education, tourism, culture, military, construction design, engineering, gaming, entertainment, and more. It is not uncommon for people to get confused between VR and AR. Virtual reality (VR) enables users to watch and interact with a virtual environment through a VR device. All the images displayed in VR are computer-generated and, therefore, "counterfeit". However, Augmented Reality (AR) generates virtual objects that appear in the real environment when viewed through a mobile phone, tablet, or AR glasses. AR creates a semi-real and false image, combining real and virtual [16].



Figure 2.2: Comparison of the physical design and form factor of two leading headsets in extended reality: Microsoft HoloLens, an augmented reality (AR) headset (a), and Oculus Go, a virtual reality (VR) headset (b) [17][18]

Figure 2.2 highlights the contrasting designs of AR and VR headsets. This comparison is relevant to the discussion because it underscores the functional differences between AR and VR technologies, which are increasingly intersecting with optics and imaging. The Microsoft HoloLens emphasizes transparent lenses for overlaying digital information onto the real-world view, showcasing its AR capabilities. Meanwhile, the Oculus Go features an opaque display designed to immerse users entirely in a virtual environment, illustrating VR technology. This comparison helps us understand how these technologies use optics and imaging to create different user experiences. Figure 2.3 shows the operational outputs of two popular headsets. The Microsoft HoloLens image illustrates how virtual elements like

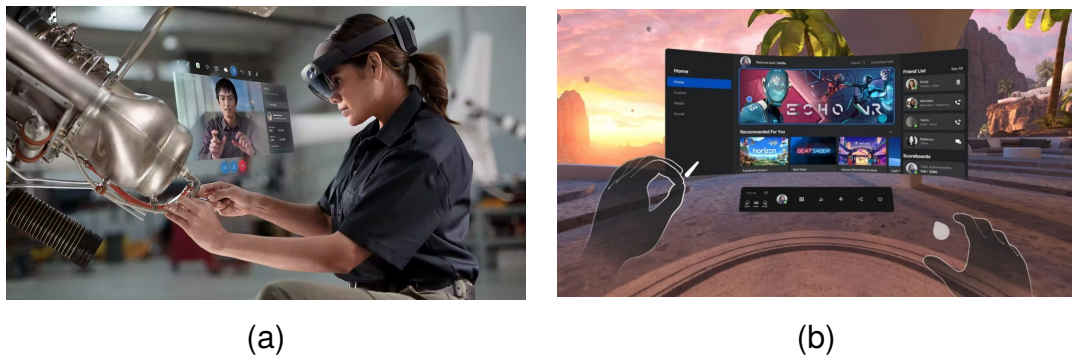


Figure 2.3: Visual demonstration of the user interface and application environment provided by Microsoft HoloLens for augmented reality (AR) experiences (a), compared with the immersive 3D graphics and simulated environment presented by Oculus Quest 2 for virtual reality (VR) experiences (b) [19][20]

holographic interfaces are projected seamlessly into a real-world context, supporting hands-free navigation and interaction. On the other hand, the Oculus Quest 2 image represents an entirely virtual world that envelops the user, highlighting high-definition 3D visuals optimized for gaming, training, or entertainment purposes.

Table 2.1 outlines the core technical specifications of the Microsoft HoloLens 2, such as its resolution, processing power, and sensors. These specifications highlight the device's advanced capabilities, such as improved hand tracking, wider FOV for better immersion, and lightweight design adjustments for user comfort during extended use. This detailed overview underscores why the HoloLens 2 is a leading AR headset in industrial and enterprise applications.

The near-eye display (NED), consisting of a light engine (such as a miniature projector) and a waveguide/combiner, projects virtual images seamlessly overlaid with the real-world environment and directed into the user's eye, as shown in Figure 2.4. The light engine is the source of augmented images or light rays, producing virtual content that is collimated and guided towards the waveguide/combiner. The waveguide is a flat optical component that propagates light using total internal reflection (TIR). Light rays, often color-coded (e.g., red, green, and blue), are injected into the waveguide at specific angles and reflect multiple times within it. To ensure accurate alignment, output couplers, such as diffractive gratings or reflective coatings, redirect the light rays from the waveguide at precise angles. This allows the projected virtual image to align seamlessly with the user's real-world view, creating an immersive augmented reality (AR) experience. AR headsets often

Display	Optics	See-through holographic lenses (waveguides)
	Resolution	2k 3:2 light engines
	Holographic density	>2.5k radiants (light points per radian)
	Eye-based rendering	Display optimization for 3D eye position
Sensors	Head tracking	4 visible light camera
	Eye tracking	2 IR cameras
	Depth	1-MP time-of-flight (ToF) depth sensor
	IMU	Accelerometer, gyroscope, magnetometer
	Camera	8-MP stills, 1080p30 video

Table 2.1: Detailed technical specifications of the Microsoft HoloLens 2 headset, focusing on its hardware capabilities and ergonomic improvements tailored for augmented reality applications [21]

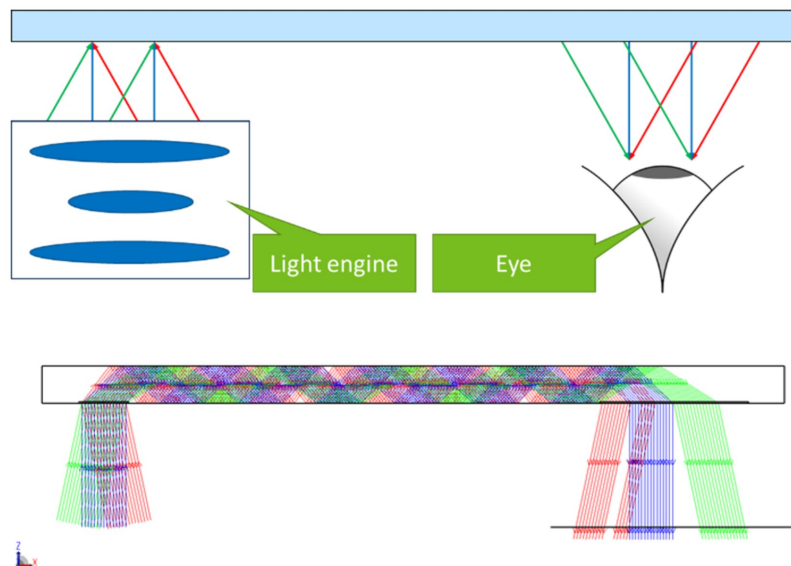


Figure 2.4: AR Optical System: Ray Tracing Simulation in Zemax OpticStudio [22]

incorporate multiple visible (VIS) and near-infrared (NIR) cameras for environment sensing, including object or marker detection. These cameras enhance spatial awareness and facilitate interaction with virtual content, further integrating the artificial image with the physical world.

To better understand the technological foundation underpinning these immersive experiences, it is essential to consider the core technical specifications and sensor

capabilities of the Apple Vision Pro as shown in Figure 2.5 and Table 2.2. It represents a significant advancement in immersive display technology, ushering in a new era of spatial computing. By seamlessly integrating real and virtual environments, it provides users with highly interactive and intuitive experiences that respond naturally to movement and intention. The system leverages state-of-the-art sensor fusion, real-time spatial mapping, and intelligent user interface design to deliver both augmented reality (AR) and virtual reality (VR) applications. The Vision Pro's sophisticated optics and biometric security via iris-based authentication showcase its cutting-edge integration of hardware and software for next-generation immersive applications [23][24].



Figure 2.5: *Apple Vision Pro headset (top) and a user interacting with an immersive digital workspace using projected virtual displays (bottom) [23]*

While devices such as the Apple Vision Pro exemplify the forefront of immersive spatial computing by blending the physical and digital worlds, a foundational element of these experiences lies in the display technologies that enable the seamless integration of virtual information into the field of view. Among these, the head-up display (HUD) stands out as a pioneering approach for presenting critical data within the user's natural line of sight.

Display	Dual micro-OLED 23 million pixels total
Resolution (per eye)	3660x3200 pixels
Pixel pitch	7.5 microns
Cameras and Sensors	2 high-res main cameras 6 world-facing tracking cameras 4 eye-tracking cameras TrueDepth camera LiDAR scanner 4 inertial measurement units (IMUs) flicker and ambient light sensors
Biometric Au- thentication	Iris-based Optic ID

Table 2.2: *Apple Vision Pro technical specifications [25]*

2.1.3 Head-up display

A Head-up display (HUD) is an advanced transparent display system mounted within a vehicle's dashboard. It provides drivers with a seamless view of crucial information about the vehicle, such as speed, navigation, and fuel capacity. This information is projected directly onto the windshield in the driver's line of sight, allowing them to maintain their focus on driving. Designed for ease of use, HUDs are optimized to ensure that the information appears on the same visual plane as the exterior environment. This means drivers do not need to refocus their eyes when looking between the projections on the screen and the road ahead, as shown in Figure 2.6. With the ability to display essential information directly in the driver's line of sight, HUDs are a vital safety feature in modern vehicles, reassuring drivers and passengers. They allow drivers to keep their eyes on the road while still having access to essential information about the vehicle's performance.

Figure 2.7 shows the ray tracing optical system of the Head-Up Display in a car, demonstrating the main elements that are key to projecting a virtual image into the driver's line of sight. The system starts with an LCD (Picture generation unit); it generates the source image that has to be shown. It directs the light from the display to a flat mirror, guiding it to a freeform mirror. They create reflectively perfect freeform mirrors to correct optical aberrations and collimate the image properly. The collimated light is then reflected off the windshield, which serves as a combiner. This makes the virtual image appear hovering at a specific depth in front of the driver's sights (the 'virtual image' position). The way the system is designed, the image is augmented reality overlays, perceptible in the eyebox, denoting the limits

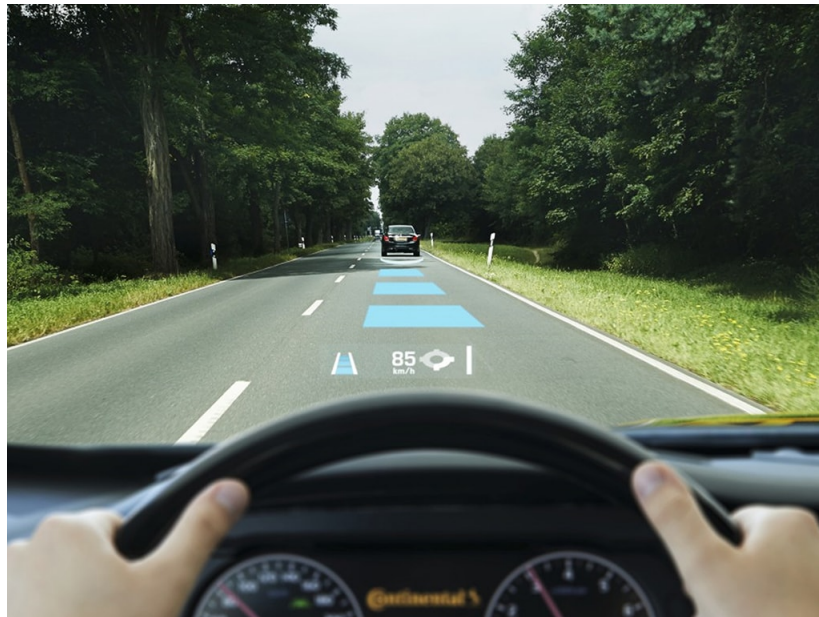


Figure 2.6: *HUD projection in automotive systems displaying navigation and speed information, demonstrating real-time augmented reality integration to enhance driver experience and safety by overlaying critical data directly onto the driver's field of view [26]*

of places that the driver's eyes can see the projected image with clarity. The virtual image is positioned at a comfortable distance for viewing to avoid eye strain and permit immediate shifts of focus between the road and the display, as can be seen in Figure 2.8.

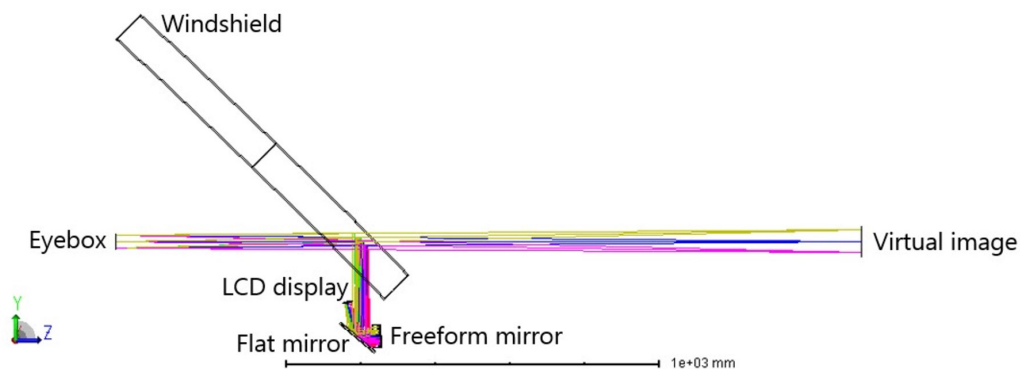


Figure 2.7: *HUD Optical System: Ray Tracing Simulation in Zemax OpticStudio [27]*

In automotive technology, HUD systems have become vital, improving driver safety and convenience. HUDs revolutionize how drivers interact with vehicle data by projecting essential information onto the windshield within the driver's line of sight. However, to ensure optimal usability and effectiveness, human-centered design

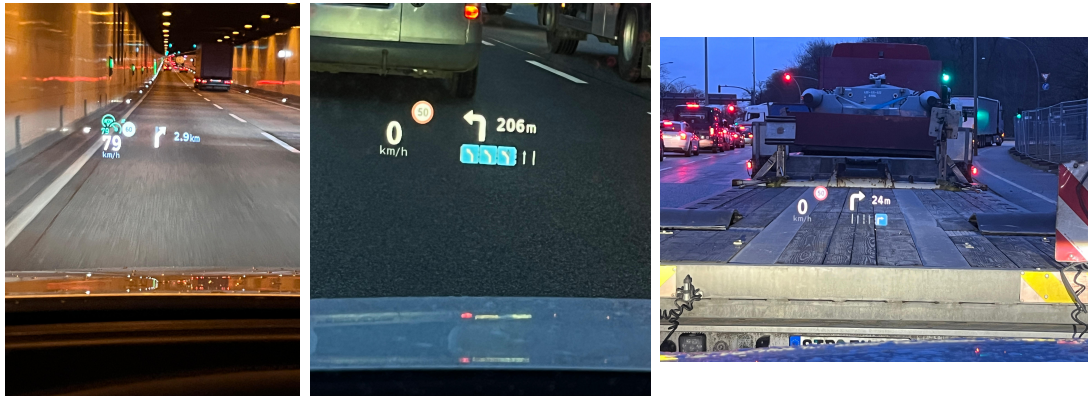


Figure 2.8: *Smart car HUD images illustrating advanced driver assistance systems (ADAS) features like speed and navigation in various traffic conditions*

considerations must guide the development of HUD technology [28][29][30]. Factors such as illumination, size, placement, and considerations for information presentation and visual ergonomics are central to creating HUDs that seamlessly integrate into the driving experience while prioritizing safety.

- **Illumination and reflectance:**

HUDs interact with various illumination sources to produce unwanted reflections, adversely affecting driver contrast sensitivity and peripheral target detection. The brightness of HUD images may also inhibit the eye's dark adaptation at night, impairing low-luminance object detection. These aberrant images can cause distractions and confusion, impairing driving performance and inducing accidents.

- **Size and placement:**

Automotive head-up displays (HUDs) require continuous viewing. They may force drivers to adopt static or awkward positions for prolonged periods, potentially leading to distraction and impairment of the visual system. The HUD image can be superimposed upon the road to avoid the detrimental effects of a background scene, but this requires drivers to shift their attention between the display and the road ahead. Additionally, some objects may appear to pass through the HUD image and appear on the near side, which can be disruptive.

- **Binocular disparity and diplopia:**

Excessive binocular disparity and discomfort may occur if the HUD image is not correctly collimated with the outside world, especially when objects in the traffic environment are at varying distances. Misalignment between the HUD and the outside image is disconcerting and can affect cognitive workload and driver performance, particularly at night or in fog. Some degree of misalignment is inevitable.

- **Information clutter:**

Automotive HUD designers face the challenge of displaying much information without causing visual clutter, which can compete or even conflict with critical environmental cues. This issue is particularly important for Vision Enhancement System (VES) operation during night view or in fog. The monochrome infrared image produced by VES may divert attention from areas of interest outside the HUD window and require drivers to reinterpret information content. The safety implications of obscured critical information in the environment must also be considered.

- **Background scene complexity:**

The legibility of a Head-Up Display (HUD) in a car can be compromised due to the complex and dynamic surroundings in which the driver operates. The implementation of a HUD can result in a deterioration of information legibility, especially when superimposed on visually complex driving environments. This reduced legibility can increase the risk of accidents.

- **Focus and accommodation:**

Visually accommodating from a distant object to a near point is essential in registering sharply focused images. This involves lens and pupil accommodation, as well as convergence. If a display configuration requires the driver to switch their focal point from near (display screen) to far (exterior landscape), their performance could be diminished.

- **Color and contrast:**

Correct color and contrast values are essential for HUD displays to ensure usability and safety in all operating conditions. The human eye is more sensitive to contrast than absolute luminance, allowing accurate perception over various lighting conditions. Successive contrast, the effect on perception in a dynamic situation when shifting focus between objects or views, can cause reduced perception. HUD systems typically use green light to display symbology, as the human eye is most sensitive to this wavelength.

The practical design and implementation of automotive HUD systems are paramount for ensuring driver safety and usability. Key considerations such as illumination and reflectance management, optimal size and placement, mitigation of binocular disparity and diplopia, avoidance of information clutter, adaptation to background scene complexity, maintenance of focus and accommodation, and meticulous attention to color and contrast are essential. Addressing these factors enhances the legibility and usability of HUD displays, minimizes distractions, reduces cognitive workload, and promotes safer driving experiences across various environmental conditions and driving scenarios.

2.2 Light field technology

From the design principles to advancements in imaging technology, light field photography represents a significant leap forward in capturing and processing visual data. The theoretical basis for light field photography was introduced by G. Lippmann in 1908. To map the direction of light, he proposed a multi-lens photo plate (lens array) [31]. The term "Light Field" was first introduced in a scientific publication by Andrey Gershun in 1936, where he discussed the radiometric properties of light in three-dimensional space. Higher-dimensional light field data has enabled significant progress in light field imaging technology, offering new capabilities in computer vision such as depth sensing, post-capture refocusing, etc. [32] Compared to traditional 2-D photography, the advancement in light field imaging technology has led to a better understanding of computer vision problems by enabling the capture of more comprehensive data about a scene. In 1992, Edward Adelson et al. published their work on the first single-lens plenoptic camera; this camera featured a lens array placed at the sensor plane, which allowed it to gather light in a sub-region of the aperture, unlike ordinary cameras that gather light across the full area of the lens aperture [33].

Marc Levoy et al. proposed a simplified mathematical 4-D light field notation in 1996. The aim was to reduce the total light field data set's size and simplify the reconstruction of the radiance function. The notation represents the light field as a function of both position and direction in 4-D space as shown in Figure 2.9, decreasing the complexity in light field reconstruction and making it more manageable [34].

In 2002, Jason Yang and his colleagues developed a "Real-Time Distributed Light Field Camera" that allows multiple viewers to navigate a dynamically changing light field. This camera is composed of 64 commodity video cameras arranged in an 8 x 8 array and connected to off-the-shelf computers [35]. The innovative camera system can capture and process a large amount of light field data in real-time, allowing live light field images to be generated. This technology has applications in a variety of fields, including virtual reality, robotics, and medical imaging. This camera system represents a significant advancement in light field imaging technology, as it can capture and process a high volume of data.

In 2005, Ren Ng revolutionized light field imaging by developing the first handheld camera that combined software refocus with the physical capabilities of a light field camera. Digital refocusing is a critical component of light field imaging, and Ng's work opened up new possibilities for post-capture refocusing and depth sensing [37]. By capturing multiple views of a scene, the camera could extract depth

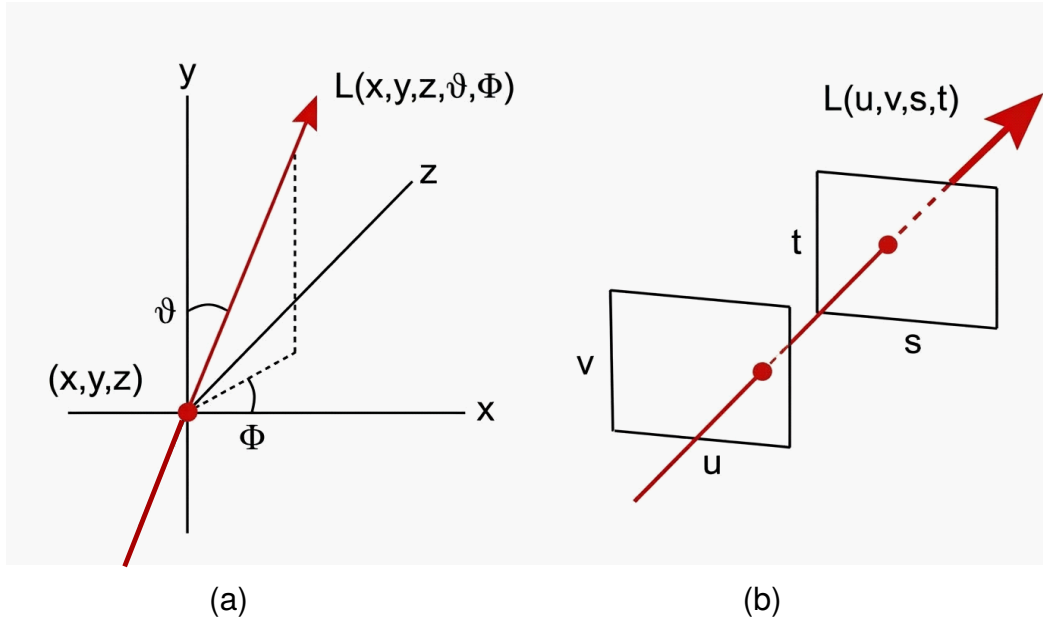


Figure 2.9: 5D light field representation (a); 4D light field representation (b) [36]

information and create images with different focal points, providing greater flexibility in image processing. Ng's innovation in light field technology paved the way for further advancements and has led to exciting new applications in areas such as virtual and augmented reality. In 2010, Raytrix announced the first commercial plenoptic camera, which was followed by the introduction of Lytro's first consumer light field camera in 2012.

2.3 Light field camera

The light field, in the context of imaging technology, captures both spatial and directional information of light, enabling effortless reconstruction of images with varying focus depths, rendering of images from multiple viewing angles, and even synthesis of images at novel positions. Light fields can be recorded using either a camera array or a light-field camera. Stanford University developed multi-camera light-field capture systems using a camera array, as depicted in Figure 2.10a. This approach captures high-resolution images from various viewing perspectives, with each image corresponding to a 2D slice of the 4D light field. By capturing enough 2D slices, the complete 4D light field can be reconstructed. The resulting light-field data can be conveniently used to render images at different focus depths and from novel perspectives.



Figure 2.10: Stanford camera array (a) [38]; Lytro light field camera (b) [39]; Raytrix light field camera (c) [40]

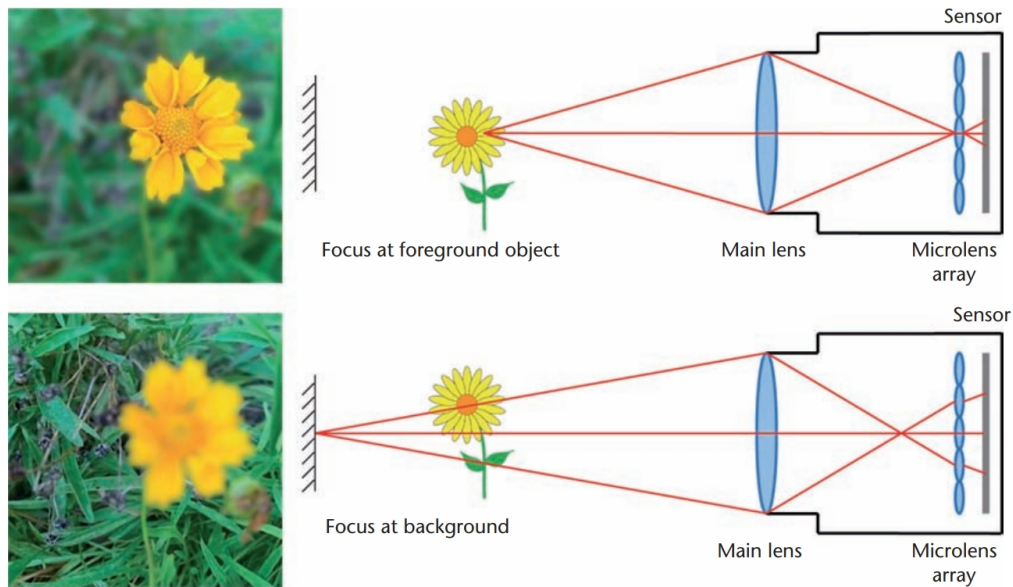


Figure 2.11: Microlens array refocusing effects on the foreground (a); background object (b) [41]

The other method of capturing a light field is to use a light-field camera based on a microlens array, such as the Lytro camera in Figure 2.10b or the alternative design of Raytrix (shown in Figure 2.10c), where the microlenses have different focal lengths. In a single-lens-based light field camera, as shown in Figure 2.11, each microlens covers several pixels and captures directional information about the light. The 4D light field can be obtained by combining the entire microlens image [41].

The light-field camera can refocus on any depth plane by rearranging the pixels on the sensor, as it records both position and angle information from the light field. The camera uses Levoy's two-plane light-field parameterization to render images at different focus depths according to the geometric relationships [42][43]. By calculating the coordinates of the points at which the light path intersects with the primary lens and the sensor for each 3D point in the scene, the final refocused image can be obtained by integrating the corresponding light ray from the light field. This virtual refocus plane can be at an arbitrary depth, enabling a specific depth of field to be achieved within any plane.

While light-field cameras revolutionize how we capture and manipulate light rays within a scene, they ultimately capture and process light information in a 2D sensor grid. However, the quest to represent the world in its proper three-dimensional form goes beyond capturing light. This is because the human visual system can perceive depth and distance in ways that traditional cameras cannot. Many real-world applications, such as autonomous vehicles and virtual reality, require a complete understanding of 3D space. Accurate 3D representation requires capturing not only the geometry of objects, but also their interaction with light, including phase, polarization, and spectral information, to achieve a more holistic understanding of the scene. This yearning for depth information pushes us towards the realm of 3D image reconstruction, a technology that strives to build upon the captured light data and unlock the hidden three-dimensionality embedded within it.

2.4 3D image reconstruction overview

Throughout history, humans have been depicting three-dimensional information in two-dimensional forms, such as the visual representation of hunters and animals. From ancient cave paintings to modern canvases and film rolls, the practice of converting 3D image information into 2D has remained essentially unchanged. This historical context not only connects us to the evolution of these technologies but also highlights the enduring human quest to represent the world in its proper three-dimensional form. The limitation is that surfaces like cave walls and canvases can only store information in two dimensions. Consequently, mentally reconstructing the original 3D object from 2D data has been left to the human brain, which has served its purpose for a long time. However, in today's era, although the dimensional limitations of image capturing persist, the applications have evolved. Images are no longer solely intended for human visual consumption but are also processed by machines and algorithms. With the assistance of computers, data can be stored

and analyzed in more than two dimensions. However, capturing data in three dimensions requires the development of algorithms that mimic the subconscious abilities of the human brain -generating 3D information by combining two or more 2D images.

Three-dimensional (3D) reconstruction techniques have revolutionized both medical imaging and visual computing fields, albeit with distinct focuses and methodologies. These techniques hold immense potential, primarily revolving around converting medical imaging data, such as MRI, CT, or ultrasound scans, into detailed representations of anatomical structures within the human body. The primary aim is to assist healthcare professionals in diagnosis, treatment planning, and medical education. Techniques such as volume rendering, surface rendering, and segmentation are commonly employed to visualize internal organs, identify abnormalities, and simulate surgical procedures [44][45]. In contrast, visual 3D reconstruction encompasses various applications, including computer vision, robotics, augmented reality, virtual reality, and 3D modelling. This field involves reconstructing three-dimensional scenes or objects from visual data captured by cameras or depth sensors. Photogrammetry, stereo vision, structure-from-motion (SfM) and point-cloud processing are utilized to create accurate 3D models of real-world environments or objects. The potential of these technologies is vast, offering new possibilities and advancements in a wide range of fields.

Image reconstruction, a technique used to visually represent objects or scenes from acquired data through imaging systems, has a rich history dating back to the mid-19th century. Its early applications were evident in fields such as astronomy and medicine, where it proved invaluable in extracting images from noise and blur. Over time, image reconstruction techniques have been widely adopted in various industries, including automotive and aerospace. In recent years, advances in automotive technology have underscored the significant benefits of image reconstruction in terms of user convenience and safety. Across industries, image reconstruction finds utility in analyzing volumes with diverse structures, particularly when observation is limited to external radiation. In astronomy, the need to extract images buried in noise led to early developments in image reconstruction techniques. Similarly, in medicine, the advent of computed tomography in the 1960s by William H. Oldendorf marked a milestone in the field, allowing the analysis of the human body through radiation [46]. Despite these early successes, the challenge of reconstructing volumes through digital computing persisted, underscoring the ongoing need for innovation in image reconstruction methodologies.

3D image reconstruction is creating a three-dimensional representation of an object or scene from a set of two-dimensional images. It is achieved using image reconstruction techniques, such as the inverse Radon transformation or back

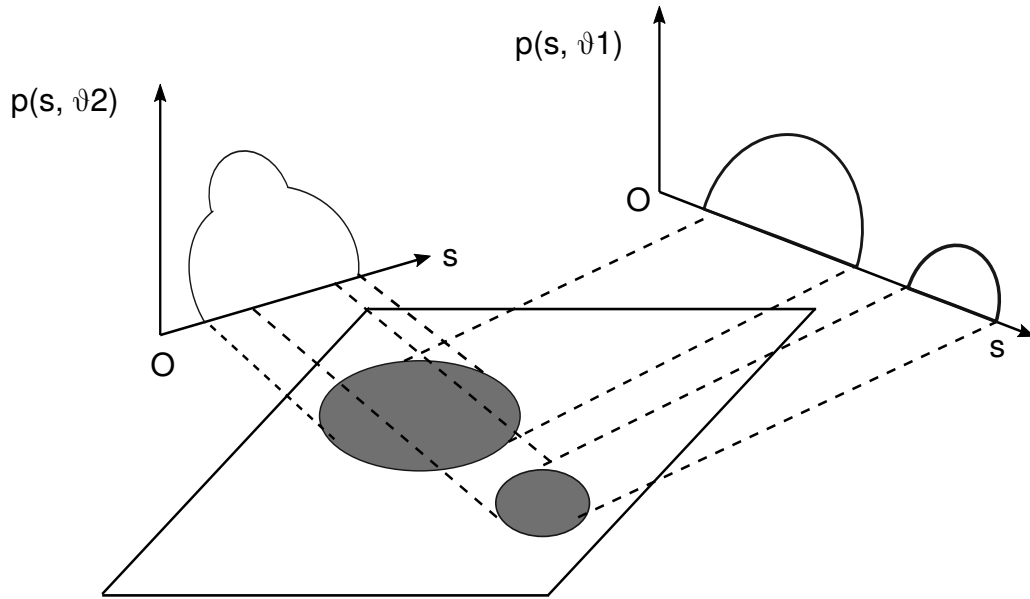


Figure 2.12: Projection $p(s, \vartheta)$ and its dependence on orientation: a visual representation of how object features are mapped to different planes based on angular variations [47]

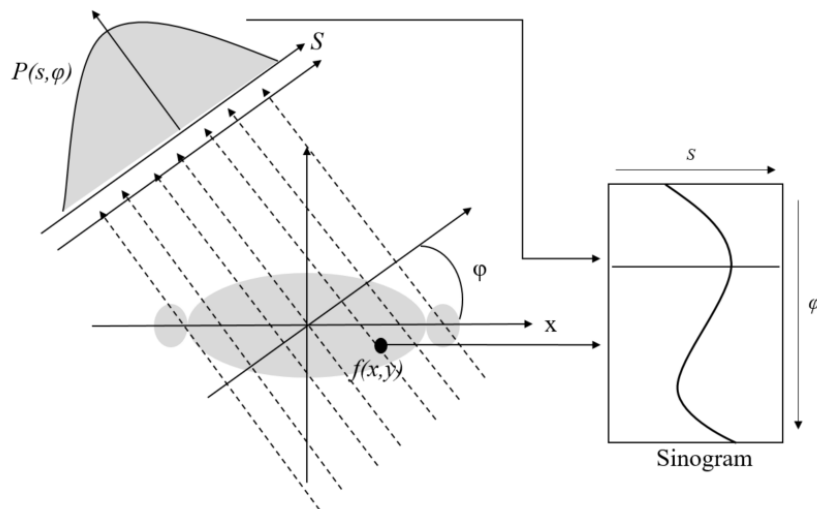


Figure 2.13: Projection $p(s, \vartheta)$ in the s - ϑ -coordinate system: Visualization of the Radon Transform and its representation as a sinogram, which shows the relationship between projections at varying angles (ϑ) and distances (s) for tomographic reconstruction [47]

projection. Projection $p(s, \theta)$ is a line integral, and the angle is θ dependent, as shown in Figure 2.12. We can observe the trajectory of a sine wave if we project the point source projection data set $p(s, \theta)$ in the s - θ coordinate system, as in Figure 2.13. Because of this observation, the projection data set is referred to as a sinogram. Line integrals measured by detectors on a rotating coordinate system were fed through an inverse Radon transformation into numerically accumulated damping information in space. These algorithms aim to extract depth, shape, and spatial information from 2D image data, thereby reconstructing the original 3D object. By leveraging computational power, these algorithms can analyze multiple perspectives or incorporate additional sensor data to represent the underlying 3D structure accurately. This advancement opens up new possibilities for various fields, including computer vision, medical imaging, virtual reality, robotics, and more.

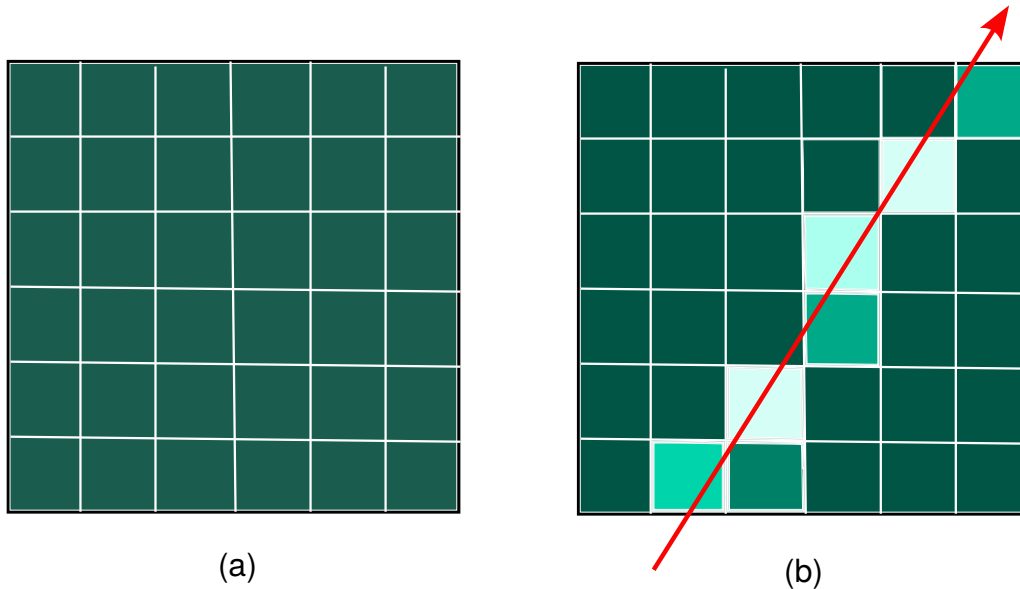


Figure 2.14: Pixel grid before light intensity addition (a); and after adding light intensity with a specific direction (b)

The challenges of analyzing three-dimensional distortions in projection systems are similar to those in other fields that rely on imaging. In both cases, it is necessary to calculate the three-dimensional origin of light from an outside observer's position. However, the significant difference is that in projection systems, the light source is part of the object being tested, and the observation angle from the eye box is relatively small. To overcome this, measuring the light field with high precision is necessary, enabling the recording of the three-dimensional shape, and the two-dimensional emission characteristic of the object under test.

3 Test Setup

The test setup chapter provides information on the components for constructing a Goniophotometer to capture light fields. This involves exploring components such as motors, axes, hexagon arm, monitor, and HUD. Understanding the role of each of these components is essential to building a functional Goniophotometer. By the end of this chapter, a comprehensive understanding of the hardware required to capture light fields using a Goniophotometer setup will be available.

To advance and enhance technologies like heads-up displays (HUDs) and virtual reality (VR) headsets, it is crucial to research the image quality perceived by users. This research requires accurate measurements, particularly in the field of optics. The optics laboratory at the Institute for Mechatronics in Mechanical Engineering recognizes the importance of measuring these devices' image quality. It has constructed a goniophotometer, a specialized instrument for precise measurements. Analysis of lighting systems with a focus on projection systems for the human-machine interface (heads-up displays, virtual and augmented reality systems). By obtaining accurate image quality measurements, researchers can gain valuable insights into the performance and limitations of these devices. This knowledge will inform the design and optimization of future HUDs, VR headsets, and related technologies, leading to improved user experiences and increased adoption of these immersive technologies in various domains, including gaming, entertainment, training, and industrial applications.

3.1 Data acquisition

The bespoke Goniophotometer testing apparatus, illustrated in Figure 3.1, is a state-of-the-art tool used in the laboratory setup described in this thesis. It features a high-end luminance measuring camera (LMK) that can capture images from various positions. The experimental setup can achieve 6 degrees of freedom for the goniophotometer by utilizing three rotational and translational stages, all equipped with stepper motors and motion controllers. The translational and rotational axes have an outstanding resolution of 0.03 mm and 0.012 arc-minute, respectively,

ensuring the measurements' precision and accuracy. The X-axis stepper motor is fitted with an integrated brake to prevent the goniophotometer from falling due to its weight under gravitational force, enhancing the safety and stability of the setup.

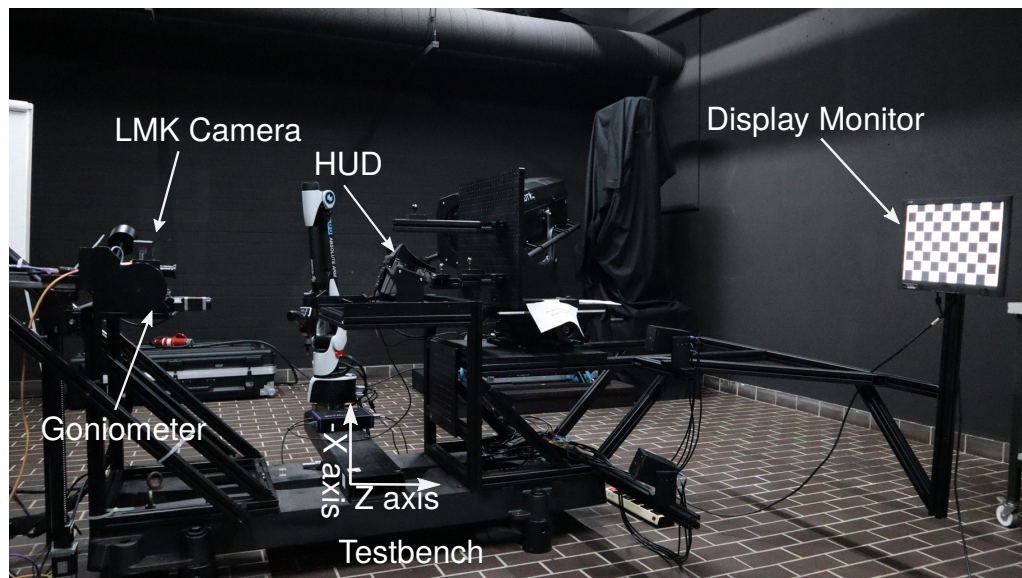


Figure 3.1: *High precision Goniophotometer test stand at Hamburg University of Technology*

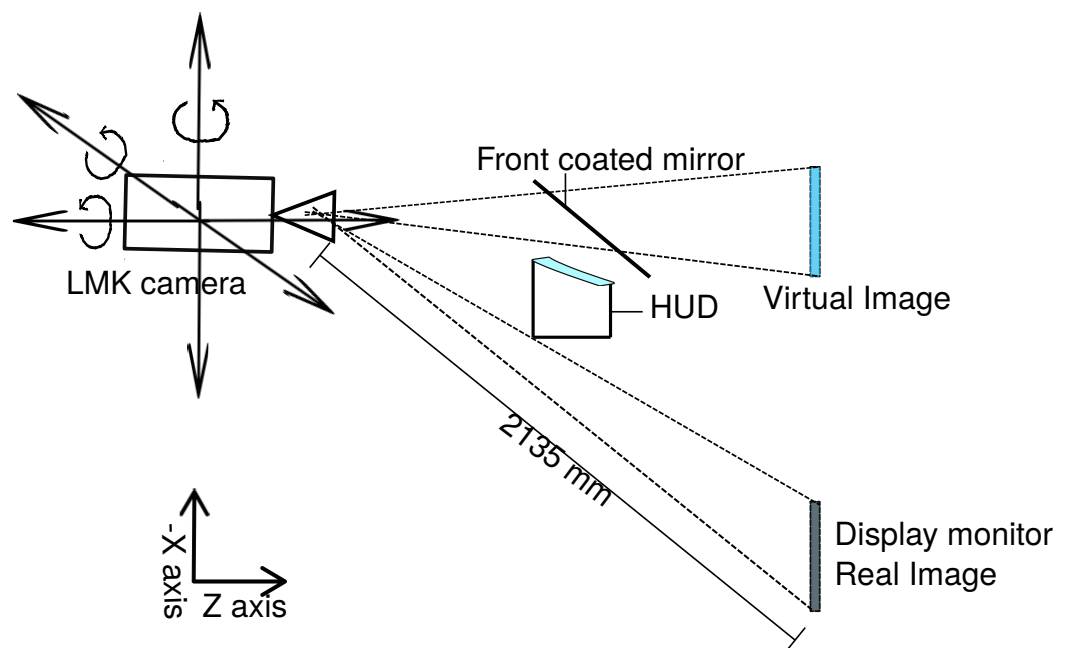


Figure 3.2: *Goniophotometer optical path diagram*



Figure 3.3: Optical bench configuration for Head-Up Display (HUD) testing

The current HUD in the laboratory is fixed, as shown in Figure 3.2 and 3.3. The virtual image is projected on the front-coated glass plate, which temporarily acts like a windshield. While the current HUD is fixed, future iterations may incorporate adjustable features to enable greater customization and flexibility.

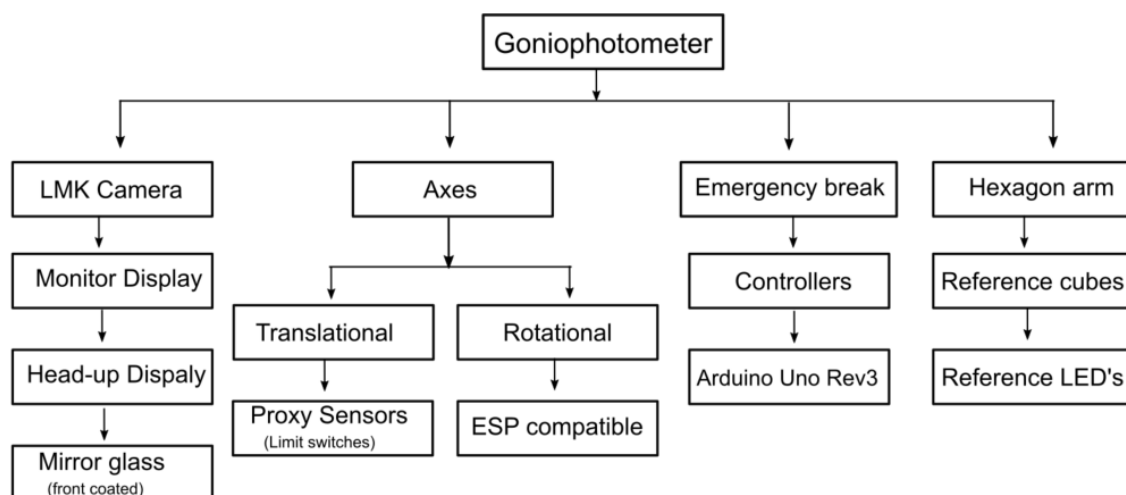


Figure 3.4: Goniophotometer test setup block diagram

3.2 Positioning Stages and Kinematics

The six axes of the Goniophotometer test setup are managed using Newport single-axis motion controllers (model SMC100PP), which are highly efficient, user-friendly, and capable of controlling both DC servo and stepper motors. These controllers can be daisy-chained for up to 31 axes, supporting even complex configurations. Newport's proprietary ESP (Enhanced System Performance) software further streamlines the setup process for rotational stages by enabling the automatic uploading of stage-specific operating parameters, ensuring proper configuration [48] [49]. Unfortunately, ESP compatibility is not available for translational stages, necessitating the manual configuration of the motion controllers.

To address this limitation, an optional solution involves saving motor parameters to the Arduino Uno Rev3. While this requires manual configuration initially, once set, these parameters can be stored on the Arduino for consistent application across multiple experiments. Despite the additional effort, the combination of Newport's motion controllers and the Arduino Uno Rev3 has proven to be a highly reliable and effective system for managing rotational and translational stages in the Goniophotometer test setup. This setup ensures accurate and dependable measurements critical to the experimental workflow.

Axis	Stage	Minimum Incremen- tal Mo- tion[mm]	Positioning Repeata- bility [mm]	Ball Screw Lead [mm]	Travel Range [mm]
X	THK SKR2006A	0.03	± 0.005	6	140.9
Y	THK SKR3306A	0.03	± 0.005	6	505
Z	THK SKR3306A	0.03	± 0.005	6	505

Table 3.1: *Linear motion stages relevant technical specifications [50]*

Axis	2-Phase Motor	Stepping	Minimum Incremental Motion[deg]	Standing Error [deg]
X	SANYO DENKI103H5210-4541		1.8	± 0.09
Y	SANYO DENKI103H5205-4240		1.8	± 0.09
Z	SANYO DENKI103H7126-0710.B		1.8	± 0.054

Table 3.2: Linear motion stepper motors relevant technical specifications [51]

Axis	Stage	Minimum Incremental Motion[deg]	Bidirectional Repeatability [deg]	Travel Range [mm]
X-Rotation	MKSURS100BPP	0.0002	± 0.006	360*
Y-Rotation	MKSBGS80PP	0.0002	± 0.0015	90
Z-Rotation	MKSURS50CPP	0.0005	± 0.005	360*

Table 3.3: Rotation motion stages relevant technical specifications [52][53]

* In practice, the rotation was constrained due to the mechanical setup



Figure 3.5: Stage of a transnational's axis [50]

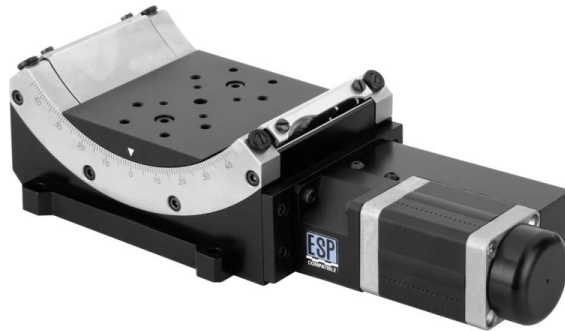


Figure 3.6: *Stage of Y-axis rotation [52]*



Figure 3.7: *Stage of Z-axis rotation [53]*

3.3 Luminance measuring camera

A special-purpose camera called a luminance measurement camera (LMK), as shown in Figure 3.8, is used to calculate various parameters of light sources. The LMK 6 color features an internal filter wheel with six high-quality glass filters. Four filters are designed for color measurements according to the CIE 1931 standard colorimetric observer, enabling the accurate measurement of both luminance and color data. The remaining slots on the filter wheel can be customized with special filters. This camera can capture three types of images: greyscale, colour, and luminance. The following parameters can be measured using these images: luminance distributions $L(x,y)$, color and chromaticity distributions. By using these measurements, the following lighting-engineering parameters can also be calculated: Illuminance distribution $E(x,y)$, Luminous intensity distribution $I(x,y)$. The LMK camera has been provided with Lmk LabSoft software and an ActiveX interface that allows it to capture and process different images in real-time. In addition, the software provides three extra capturing methods for creating the following image references:

- Singlepic: It captures a single image with a fixed exposure time
- Multipic: It captures multiple images with the same exposure time and then superimposes them to create a final image. This method helps reduce noise and increase the signal-to-noise ratio in the image.
- HighDyn: This capturing method is different from the other two methods as it adjusts the exposure time dynamically based on the scene's brightness. This method captures multiple images with different exposure times and then combines them to create a final image with a high dynamic range, meaning it can capture both bright and dark areas of the scene in detail.

These options give the user greater control over the image-capturing process, allowing them to achieve the desired results for their specific application.

The experimental setup is operated in a temperature-stabilized dark room designed to maintain consistent environmental conditions crucial for precise measurements. Temperature stabilization minimizes thermal fluctuations that could adversely affect the positioning system's performance, ensuring reliable and repeatable results. Additionally, the dark room is meticulously engineered to eliminate unwanted stray light, which can introduce noise and compromise the accuracy of the measurements. Combining temperature control with controlled lighting conditions provides an optimized environment for high-precision experiments, effectively reducing external interferences and enhancing measurement quality.



Figure 3.8: *Luminance measuring camera (LMK 6 color)*

Paramter	Value
Imaging Sensor	2464 × 2056 Pixel Sony-CMOS [IMX 250 (2/3"); 12 Bit digital]
Measuring quantity	Luminance: L (cd/m ²), Chromaticity coordinates for supported color spaces: RGB, XYZ, Luv, Lab
Measuring range	Integration/exposure time from 100 μs to 15 s. 1 ms ≈ max. 10,000 cd/m ² , 3 s ≈ max. 3.3 cd/m ²

Table 3.4: *Technical details of LMK6 Camera [54]*

3.4 Positioning error analysis

The current goniophotometer test bench setup has five degrees of freedom; when we move the camera into different orientations, it's extremely important to have a precise movement position given as input. To exercise and measure the actual position of the camera compared to the recorded or indicated position of the test bench, we are using the hexagon arm to measure the positioning error. Positioning errors can occur due to various factors, such as errors in the measurement process or the system itself. The recorded deviations are used to create a correction matrix that can be applied to the measured positions of the camera during the goniophotometer tests. By applying this correction matrix, we can reduce positioning errors and improve the accuracy of the measurements. In some cases, positioning errors can be corrected through the use of advanced algorithms or by applying corrections based on known reference points.

To quantitatively assess the positional error of the imaging system, an algorithm was implemented to robustly detect the four corner points and the centroid of each camera-captured target. A series of images was acquired at distinct spatial positions and multiple orientations. As depicted in Figure 3.9, the green rays correspond to the calculated centroid positions of 12 image captures. Closer examination of Figure 3.9 (zoomed-in view) reveals that these centroid trajectories do not converge to a common intersection point, even though the nominal target distance was identical for all camera positions. Instead, the intersection points exhibit systematic deviation across each row of camera locations, reflecting residual alignment or calibration inaccuracies. At the reference distance of 2150 mm, the maximum observed deviation of centroid intersection points is approximately 10 mm in the horizontal (y-axis) and 15 mm in the vertical (x-axis) directions, respectively.

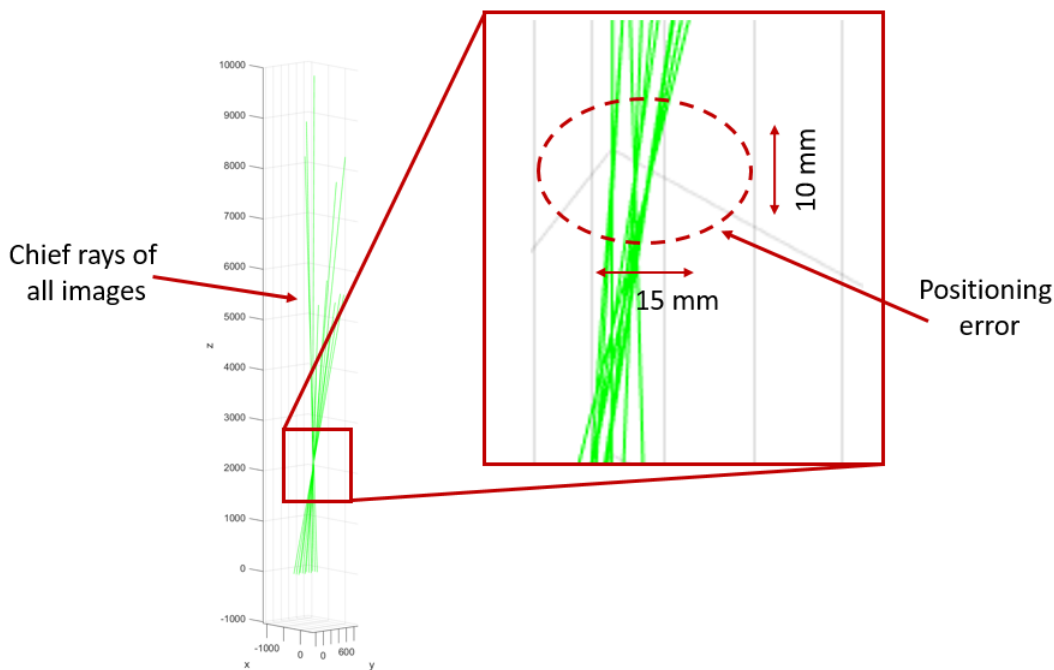


Figure 3.9: *Demonstration of positional error through ray-tracing from image corners and centers*

The deeper position error analysis conducted by Mr. Wadke in his project work titled "Positional error analysis of linear stages of goniophotometer using intrinsic parameters of LMK6-5 camera." He used different calibration patterns (Checkerboard, Asymmetric Circles, and ChAruCo) to calibrate the camera and analyze the positional accuracy of the linear stages based on the calibrated camera parameters. The calibrated camera was then used to measure the positional errors of the linear stages by comparing the actual positions with the positions estimated using the

3 Test Setup

camera. The positional error analysis includes measurements along the X, Y, and Z axes with displacement steps of 0.5 mm and 5 mm. The results provide insights into the accuracy and repeatability of the linear stages in the goniophotometer.

Stage (Axis)	Data points	Average error (mm)	Average error (%)
X	19	0.081759	16.35
Y	18	0.047164	9.43
Z	19	0.001132	0.226

Table 3.5: Positional accuracy for linear stages with 0.5 mm displacement [55]

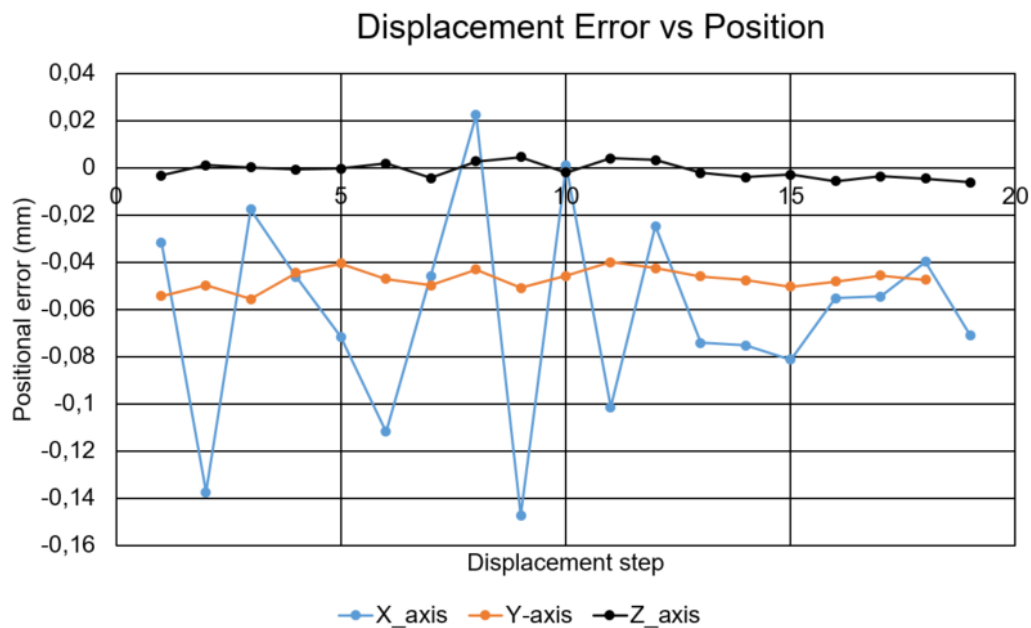


Figure 3.10: Displacement error dependence on reference positions (0.5 mm Step)

Stage (Axis)	Data points	Average error (mm)	Average error (%)
X	19	0.5996	11.99
Y	18	0.5025	10.05
Z	19	0.0210	0.42

Table 3.6: Positional accuracy for linear stages with 5 mm displacement [55]

The average error is the mean of individual measurement errors across all data points for the given axis, while the average error percentage expresses this value relative to the step size 0.5 mm and 5 mm, respectively.

This study systematically quantified the positional errors occurring along the X, Y, and Z axes of linear stages using subpixel reprojection techniques. The results revealed that the X-axis was the most susceptible to error, exhibiting the highest

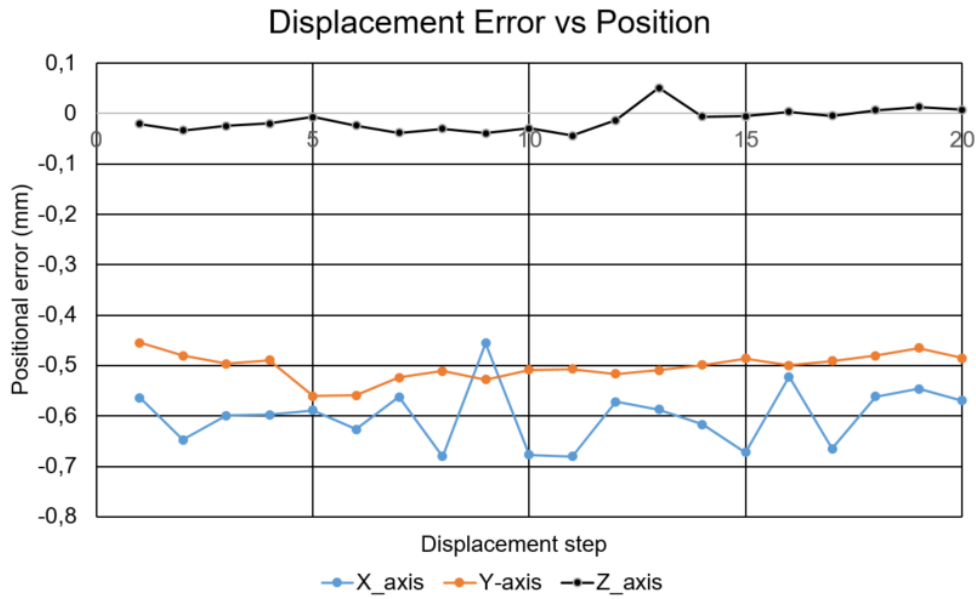


Figure 3.11: *Displacement error dependence on reference positions (5 mm Step)*

average positional deviations due to its limited rigidity and greater vulnerability to vibrations. The Y-axis, while demonstrating commendable repeatability, consistently undershot expected positions and manifested average error rates higher than those of the Z-axis. In contrast, the Z-axis achieved superior accuracy and repeatability, with errors remaining below 1% for both displacement steps, although localized errors were observed at select positions.

Despite these insights, the scope of the study was constrained by several factors. The measurements were conducted over a limited travel range, and the displacement steps were not minimized to fully exploit the hardware's 0.03 mm resolution, potentially overlooking finer error details. Furthermore, the absence of validation against an external ground truth limits the certainty with which the true accuracy of the measurement methodology can be assessed.

4 Software Design and Implementation

In this chapter, readers will gain a comprehensive understanding of the entire image acquisition process, light field data creation, and light field image reconstruction. The details of image acquisition using a Goniophotometer test setup will be delved into. Specifically, the process of capturing images with a camera in different orientations to acquire data about the light field will be explored. The creation of light field data from these camera-captured images involves capturing multiple images of a scene from different viewpoints to obtain a dense set of data about the light rays traveling through the scene. This light field data can then be reconstructed into a 3D representation of the scene using various techniques, which will also be covered in this chapter. By the end of this chapter, readers will have a comprehensive understanding of the entire image acquisition process, light field data creation, and light field image reconstruction.

4.1 Light field Creation

The advent of light field technology has revolutionized the field of computational photography, offering new dimensions in image capture and post-processing. This chapter presents a novel approach for creating light field data from conventional camera-captured images. The method presented in this thesis leverages advanced algorithms to synthesize light field representations by interpolating and extrapolating information from multiple 2D images captured from varying viewpoints. The proposed technique involves the integration of image registration, depth estimation, and viewpoint synthesis to construct a comprehensive light field dataset. This data will establish a database containing spatial and angular information about light vectors, allowing for a thorough understanding of the variable focal image plane of the virtual image. This approach enhances the spatial and angular resolution of the captured scene and facilitates sophisticated post-capture manipulations such as refocusing, depth mapping, and 3D reconstruction.

4.1.1 Intrinsic and Extrinsic Parameters

Calibration of extrinsic and intrinsic parameters is crucial in computer vision. It ensures that the images captured by a camera can be accurately mapped to the real world. Understanding these parameters allows for the accurate reconstruction of three-dimensional (3D) scenes, which is essential for various applications such as 3D modeling: Without calibration, the model would be warped and inaccurate [56][57]. Calibration helps translate 2D image points into accurate 3D locations. Robotic vision relies on precise measurements in the real world. Intrinsic and extrinsic calibration corrects for distortions caused by the camera's lens, allowing for accurate distance and size calculations. Augmented reality: AR overlays virtual objects in the real world. Calibration ensures that these virtual objects appear correctly positioned and scaled relative to real-world objects.

Imagine a camera that captures the 3D world and projects it onto a 2D image plane. This process involves two main transformations:

Extrinsic parameters: These describe the camera's pose (position and orientation) in the 3D world [58] [59]. Imagine moving the camera around a room – the extrinsic parameters change accordingly. A rotation matrix and a translation vector typically represent these.

Intrinsic properties: These describe the internal properties of the camera, such as the focal length, the principal point (center of distortion), and the distortion coefficients [60]. These are like the unique fingerprints of the camera's lens. A camera matrix usually represents them.

Calibrating intrinsic parameters involves determining the camera's internal properties by analyzing images of known calibration patterns. This calibration accurately measures distances, angles, and other geometric properties within the camera field of view [61]. Extrinsic parameter calibration involves determining the camera's position and orientation relative to the world coordinate system. This can be achieved by capturing images of a calibration target (checkerboard pattern) as shown in Figure 4.1 and 4.2, from different viewpoints and using mathematical algorithms to estimate the camera's pose. We can accurately relate the camera's image coordinates to real-world coordinates by calibrating intrinsic and extrinsic parameters.

Camera calibration is a critical process in computer vision, often performed using a 2D checkerboard pattern. This method relies on capturing images of a known and regularly structured checkerboard, the observed 2D pattern. This pattern offers several advantages. First, its known size and structure allow for precisely identifying specific points within the image. Second, a clever trick simplifies the calibration

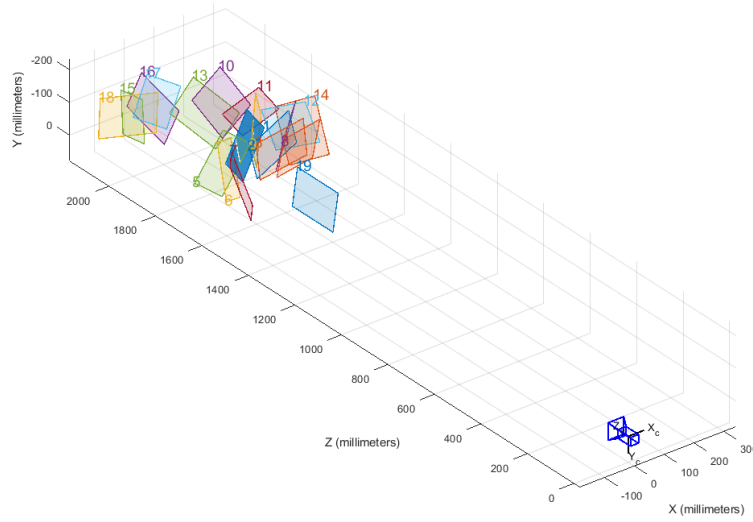


Figure 4.1: *Spatial distribution of calibration targets relative to the camera*

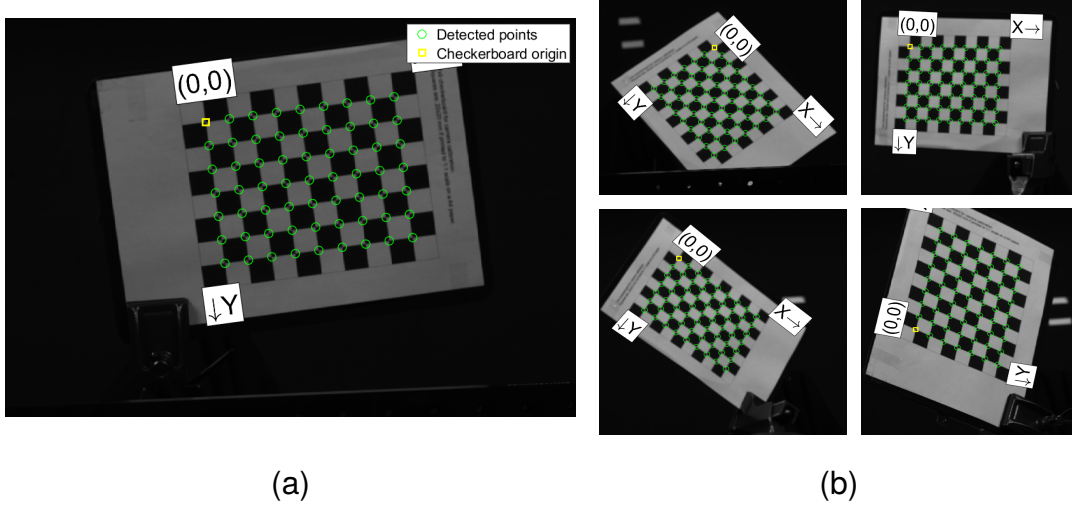


Figure 4.2: *Detection of checkerboard corner points*

process: we can set the world coordinate system in the corner of the checkerboard [62]. This simplifies the 3D representation as all points on the board lie in the X/Y plane, meaning that their Z coordinate is inherently zero. This eliminates the need to define complex 3D positions for each checkerboard corner, streamlining the calibration workflow.

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} c & cs & xH \\ 0 & c(1+m) & yH \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r11 & r12 & r13 & t1 \\ r21 & r22 & r23 & t2 \\ r31 & r32 & r33 & t3 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

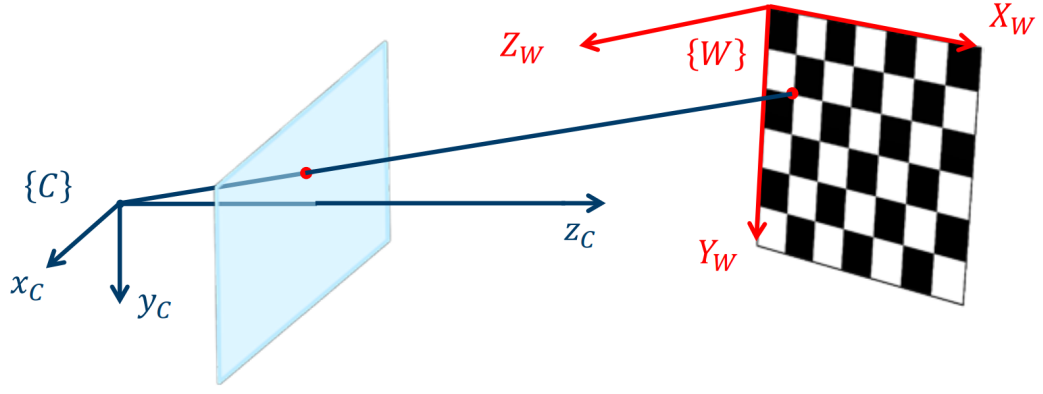


Figure 4.3: Relationship between camera and world coordinate systems using a checkerboard pattern for calibration

The Z coordinates of each point on the checkerboard are equal to zero, simplifying the calibration process. By setting Z to zero, we can effectively ignore depth, allowing us to delete the third column of the extrinsic parameter matrix. This reduction streamlines calculations and focuses the transformation on the 2D plane, enhancing the accuracy and efficiency of mapping the 2D checkerboard points to the camera's image plane.

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} c & cs & xH \\ 0 & c(1+m) & yH \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r11 & r12 & t1 \\ r21 & r22 & t2 \\ r31 & r32 & t3 \end{bmatrix} \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix}$$

When a single point on the checkerboard is observed, it generates a specific equation that relates the point's 3D world coordinates to its 2D pixel coordinates in the image as seen in Figure 4.3. The observed 2D point on the checkerboard corresponds to a unique equation that encapsulates the projection of that point from the 3D checkerboard plane to the 2D image plane, considering the camera's orientation, position, and internal characteristics.

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = K \begin{bmatrix} r1, r2, t \end{bmatrix} \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix}$$

Intrinsic matrix:

$$K_{int} = \begin{bmatrix} f/p_x & 0 & 0 \\ 0 & f/p_y & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Euler equations are fundamental in rigid body dynamics, describing rotational motion in 3D space. Developed by Leonhard Euler, these equations simplify complex rotations by breaking them into simpler rotations (yaw, pitch, and roll) using Euler angles as illustrated in Figure 4.4. This approach is crucial in fields like robotics, aerospace, and computer graphics, where rotation matrices derived from Euler angles allow for precise tracking and control of object orientation. Euler equations are vital for modeling, predicting, and controlling rotational systems in modern applications by relating angular velocities to a body's moment of inertia.

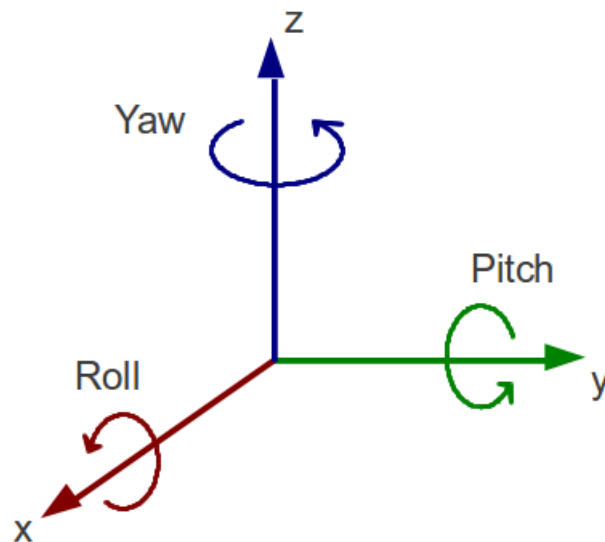


Figure 4.4: Representation of the yaw, pitch and roll angles

Determining extrinsic camera parameters involves establishing the camera's rotation and translation concerning the goniophotometer workspace. This is achieved by recording the camera's position in various orientations during image capturing. It is essential to determine the rotation angles for each axis accurately. When rotating around a specific axis, the coordinates of the other two axes will change while the axis of rotation remains constant. The rotation angles for these axes can be calculated using the following equations:

Rotation about X-axis

$$R_x = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \alpha & -\sin \alpha \\ 0 & \sin \alpha & \cos \alpha \end{bmatrix}$$

Rotation about Y-axis

$$R_y = \begin{bmatrix} \cos \beta & 0 & -\sin \beta \\ 0 & 1 & 0 \\ \sin \beta & 0 & \cos \beta \end{bmatrix}$$

Rotation about the Z-axis

$$R_z = \begin{bmatrix} \cos \gamma & -\sin \gamma & 0 \\ \sin \gamma & \cos \gamma & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

External camera parameters refer to camera settings and characteristics that are not intrinsic to the camera but vary concerning the world frame [63]. These parameters include the camera's position and orientation in the 3D space, also known as the extrinsic parameters. The extrinsic parameters determine the relationship between the camera and the world coordinate systems. We can effectively align the camera's viewpoint and perspective with the real-world scene by accurately estimating and calibrating these parameters.

Figure 4.5 depicts the transformation from world coordinates to camera coordinates, a key process in camera calibration. This transformation involves two key elements: the translation vector, denoted as 't,' represents the displacement of the world coordinate system about the camera coordinate system, and the rotation matrix, denoted as 'R,' which rotates the world coordinate system to align with the camera coordinate system. By combining the translation vector and rotation matrix, we can accurately map points or objects from the world frame to the camera frame, facilitating precise spatial analysis and visualization, which is crucial in camera calibration.

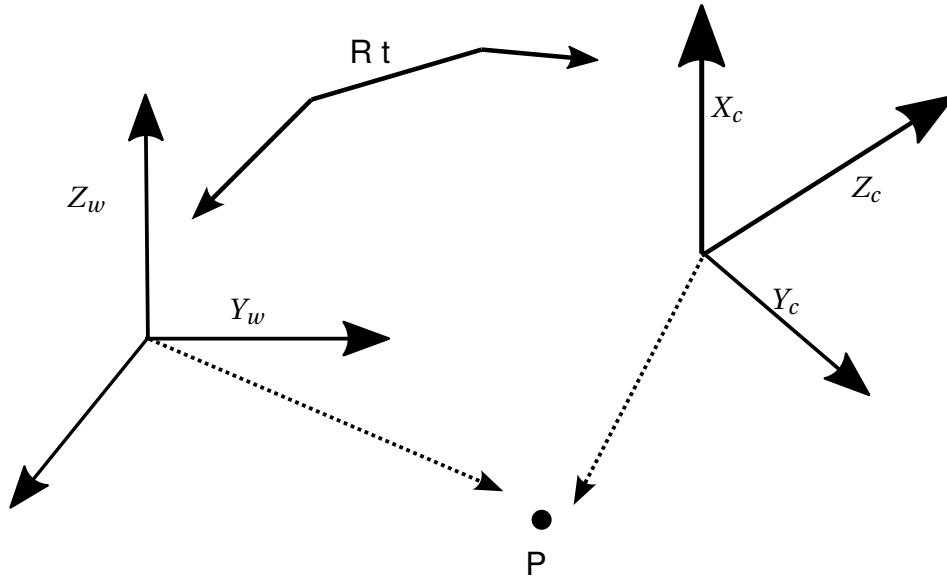


Figure 4.5: Conversion of world to camera coordinates

$$t = \begin{bmatrix} tx \\ ty \\ tz \end{bmatrix} \quad R = \begin{bmatrix} r11 & r12 & r13 \\ r21 & r22 & r23 \\ r31 & r32 & r33 \end{bmatrix}$$

The extrinsic matrix includes both rotation and translation:

$$\begin{bmatrix} R & t \end{bmatrix} \text{ or } \begin{bmatrix} r11 & r12 & r13 & tx \\ r21 & r22 & r23 & ty \\ r31 & r32 & r33 & tz \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Figure 4.6 provides an overview of the various coordinate systems involved. Transformation of world coordinates to camera coordinates is accomplished through the extrinsic matrix. This matrix encapsulates the rotation and translation parameters necessary to align the world coordinate system with the camera coordinate system. The extrinsic matrix establishes the spatial relationship between the world and the camera, enabling accurate positioning of objects within the camera's field of view.

$$\begin{bmatrix} Xc \\ Yc \\ Zc \\ 1 \end{bmatrix} = P \begin{bmatrix} r11 & r12 & r13 & tx \\ r21 & r22 & r23 & ty \\ r31 & r32 & r33 & tz \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} Xw \\ Yw \\ Zw \\ 1 \end{bmatrix}$$

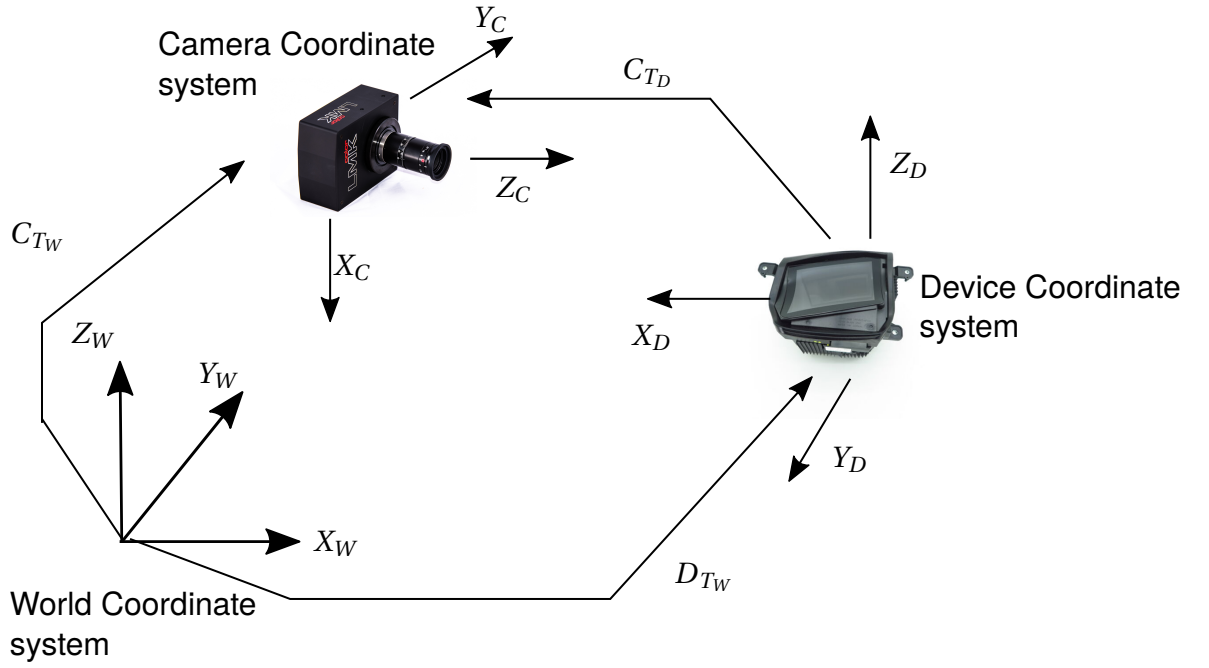
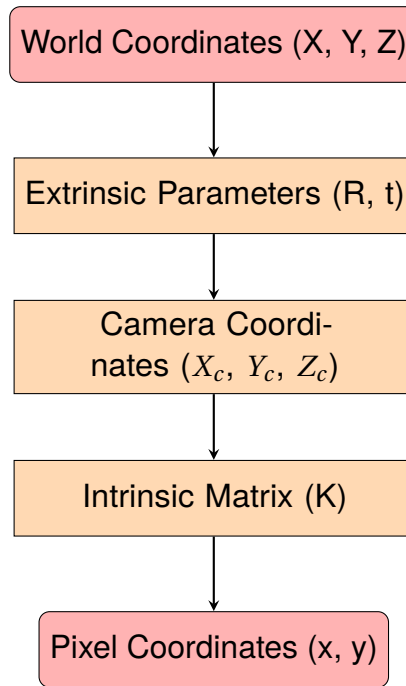


Figure 4.6: Overview of different coordinate systems

Where $P = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$

Once the camera coordinates are obtained, the crucial next step is their conversion into pixel coordinates. This conversion is made possible by the intrinsic matrix, is a key concept that facilitates the transformation from camera coordinates to image coordinates. The intrinsic matrix plays a pivotal role in mapping from world coordinates to pixel coordinates, enabling precise object localization in the captured image. This process is fundamental for further analysis and interpretation of the scene. The conversion from world coordinates to pixel coordinates can be expressed as follows:

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} f/p_x & 0 & 0 \\ 0 & f/p_y & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & tx \\ r_{21} & r_{22} & r_{23} & ty \\ r_{31} & r_{32} & r_{33} & tz \end{bmatrix} \begin{bmatrix} X_w \\ Y_w \\ Z_w \\ 1 \end{bmatrix}$$



With the defined intrinsic and extrinsic parameters, we can move beyond simple pixel localization and delve into the light information captured at each pixel. Understanding this mapping is crucial for static image analysis and advanced applications such as light field reconstruction, requiring a set of light field vectors.

4.1.2 Base vectors and Light vectors

Having established the mapping from world coordinates to pixel coordinates through the intrinsic matrix, we can now delve deeper into the light information captured at each pixel. Light field reconstruction requires generating a set of light field vectors from each captured image pixel. This process is typically done using an analytical approach that involves modeling the geometry and optics of the camera setup. Once the light field vectors are generated, they can be used to reconstruct the whole light field within a specified angular range based on the measurement data.

A fundamental approach has been used, (Figure 4.7) where different regions of the sensor store image information of the scene from various angles [64]. By implementing the geometric optics principle, multiple views of a scene are constructed using different regions of the aperture [65]. The camera-captured images will only provide 2D information about the target being captured; the x and y-pixel location of

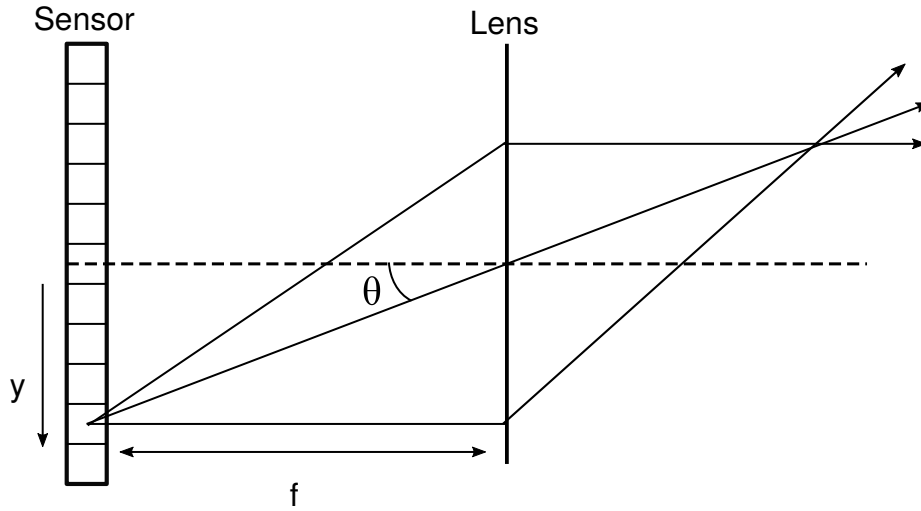


Figure 4.7: *Tracing of a principal ray for fixed projection*

the sensor has the intensity value and the direction of the light vector, as explained in equation 4.1.

$$\tan\theta = \frac{y}{f} \Rightarrow \theta = \arctan\left(\frac{y}{f}\right) \quad (4.1)$$

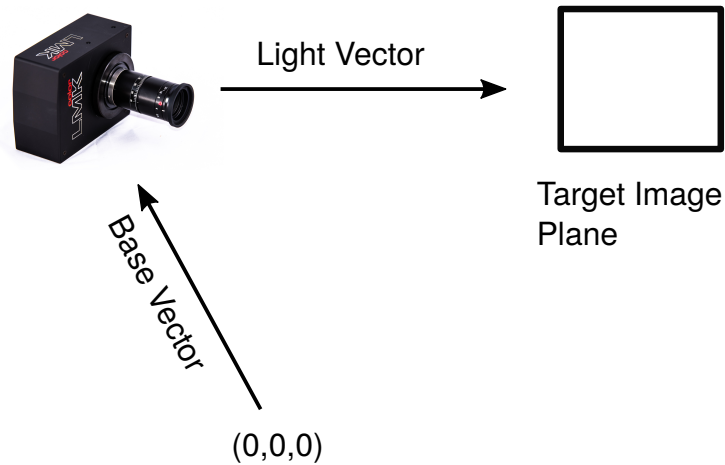


Figure 4.8: *Overview of Base Vector and Light Vector*

A light vector is a vector from the camera sensor to the target image, as shown in Figure 4.8. It is important to note that a base vector is a crucial component in the light vector generation process. Unlike a light vector, computed from the sensor to the target, a base vector represents the vector from the world coordinate origin of the Goniophotometer setup to the camera's current position. The base vector's orientation is a reference point for accurately computing the light vector's

direction. Without an accurate base vector, the reconstructed light field will not align correctly with the real-world scene, underscoring the necessity of this component for accurate results.

In order to reconstruct an original image from different perspectives, the images captured from various positions are used as input to the algorithm. For each pixel, a single light vector contains the light intensity and the computed direction from the sensor to the target object plane. These light vectors are then used to create light field data for each captured image. The light field data includes vectors of light information for all pixels in the image, allowing for the reconstruction of the original image from different viewpoints. Generating these light vectors is a critical step in the reconstruction process, as it directly affects the accuracy and quality of the final reconstructed image.

The number of light vectors generated for a specific image is determined by several factors, with the number of pictures captured being the most significant. More images result in more light vectors being generated, significantly improving the accuracy and quality of the reconstruction. The number of images captured has a direct impact on the quality of the reconstruction, making it a crucial factor to consider in the reconstruction process. The more images captured, the higher the quality of the reconstruction, highlighting the importance of this factor.

4.1.3 Optimal Image Sampling for Reconstruction

As previously mentioned, the number of captured images directly affects the number of light vectors generated, influencing the reconstruction quality. Let's delve deeper into this process by examining how images captured from different positions and orientations, as illustrated in Figure 4.9, are utilized as input for the light field creation algorithm. This algorithm generates vectors that store information about the amount of light and its calculated direction for each pixel in space across all captured images. The light field data comprises both the base vector, indicating the camera's position relative to the origin in the world coordinate system, and the light vector, created for each pixel of the sensor and includes intensity and direction information. With a camera objective of 50 mm, each pixel represents a field of view (FOV) of 0.237 arc min. A typical measurement involving 12 positions of a checkerboard results in 25 million rays that are used for reconstruction purposes. Figure 4.9 presents the visualization of the light field vectors. The origins of these vectors correspond to the actual camera positions measured in the world coordinate system. By visualizing the light field vectors, it is possible to gain insights into the spatial distribution and orientation of the captured light rays, providing a comprehensive representation of

the scene. This visualization allows a better understanding of the light field data and facilitates further analysis and reconstruction processes.

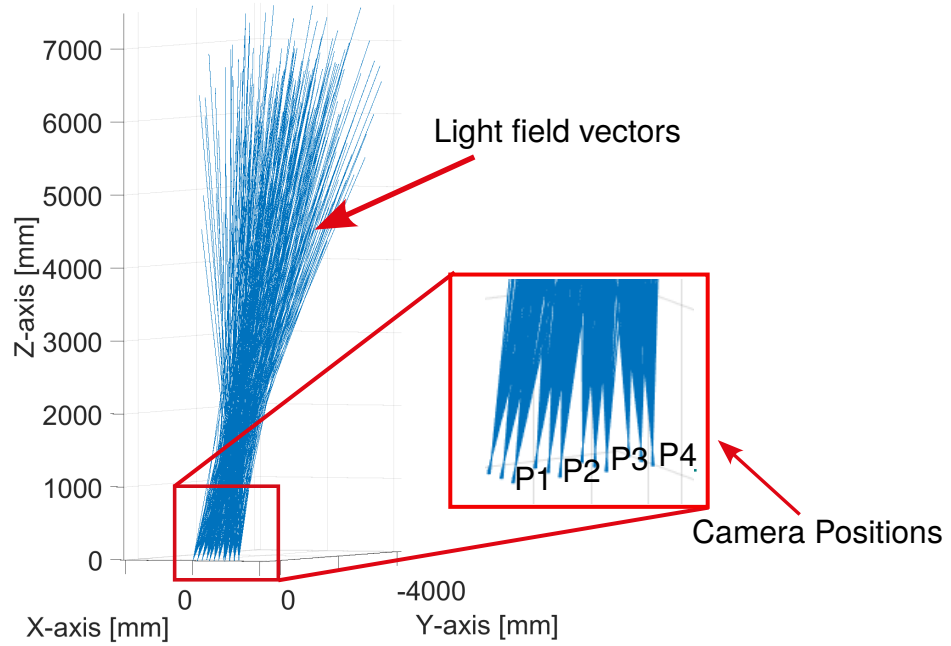


Figure 4.9: *Light field vectors generated for different camera positions*

4.2 Light field Reconstruction

As we conclude Section 4.1, focusing on creating light fields by exploring intrinsic and extrinsic parameters, base vectors, and optimal image sampling, we have established a comprehensive understanding of the foundational elements necessary for effective light field generation. This groundwork is crucial for the subsequent processes involved in light field reconstruction. With a solid understanding of light field creation, we can delve into the critical task of light field reconstruction in this section, where the captured data are transformed into a meaningful 3D representation.

In image reconstruction, the Radon transform is a fundamental mathematical tool widely used in image processing and medical imaging, particularly in computed tomography (CT). Introduced by Johann Radon in 1917, this integral transform enables the reconstruction of an object from its projections [66]. In essence, the Radon transform takes a function defined in two-dimensional space. It transforms it into a set of one-dimensional integrals, each representing the projection of the function along a specific angle.

The image shown in Figure 4.10 represents a square with a pixel value of 1 (white) against a background with a 0 (black) pixel value. We aim to calculate the Radon transform for this image over multiple angles. We will choose a set of angles (θ) between 0 and 180 degrees, typically excluding another 180 degrees to avoid redundancy. We simulate a line passing through the image at each angle θ , then calculate the pixel values along this line and store the sum in the corresponding position in the Radon transform result. This process is repeated for all the angles chosen. The resulting data structure, typically a 2D matrix, is called a sinogram. In the sinogram, one dimension represents the angle (θ), while the other dimension represents the distance (ρ) from the center of the image to the line. Each element in the sinogram stores the sum of pixel values encountered along a ray at a specific angle and distance. The sinogram will display brighter regions where the line intersects denser parts of the image (the square, in this case). By analyzing the sinogram, we can gain insight into the original image's structure based on how light intensity varies between different angles and distances [67][68]. This method allows for the reconstruction of the image from its projections, providing a powerful tool for understanding and interpreting the underlying spatial information.

1	0	1
0	1	0
1	0	1

Figure 4.10: *An example of a binary image matrix*

Figure 4.11 illustrates the tomographic reconstruction process and outcomes using the Shepp-Logan phantom. On the left is the original phantom image, often used as a standard model in computed tomography research. On the right are reconstructed images created through back projection using an increasing number of projections (1, 3, 7, 15, 31, and 63), demonstrating how the quality of the reconstructed image improves as the number of projections increases, artifacts are reduced, and clarity is enhanced. This progression highlights the importance of projection quantity in achieving accurate image reconstructions in tomography.

To reconstruct images from light field data, the light field itself needs to be processed. The volume in which the light vectors converge is determined based on location and size, as illustrated in Figure 4.9. Like pixels on a 2D image plane, the volume is

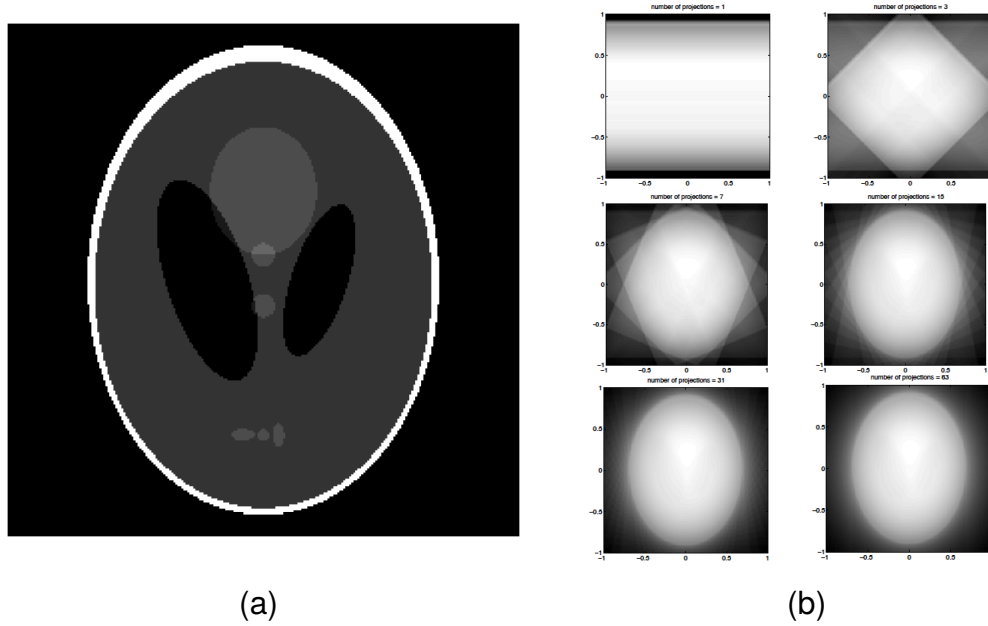


Figure 4.11: *Original Shepp-Logan Phantom (a); reconstructed image for (1,3,7,15,31,63) projections (b) [47]*

divided into small volumetric pixels known as "voxels". When a light vector intersects a voxel, the intensity value of that ray is accumulated within the voxel. Voxels with multiple intersecting rays exhibit higher intensity values, while untouched voxels remain at zero intensity. The 3D image volume can be sliced into 2D image planes to visualize the reconstructed results. Higher intensity values are represented as white pixels, while lower values are depicted as black. A series of images is obtained by slicing the volume at different depths; a series of images is obtained, enabling further analysis. Furthermore, the data can generate a 3D object, enhancing the understanding and utilization of the reconstructed light field.

4.2.1 Image Volume Dimensions

The creation of the volume, a crucial step in the light field image reconstruction process, is a process that demands full attention. Once the light field data is generated, the next step is to create a volume where most light rays converge or intersect, known as the convergence volume. This volume is crucial for the image reconstruction process as it determines the level of detail and accuracy in the reconstructed images. The resolution of the convergence volume is defined using a 3x1 vector, specifying the resolution in each dimension. For instance, if the voxel resolution is set as [1 1 10], the volume has a resolution of 1 unit in the x-direction, 1 unit in the y-direction, and 10 units in the z-direction. These values

significantly impact the final quality and spatial representation of the reconstructed images. A higher resolution, achieved by decreasing the size of the voxels, will result in a sharper and more detailed picture. However, this comes at the cost of increased computational resources and longer processing times.

The process of creating the volume involves three steps, which are as follows:

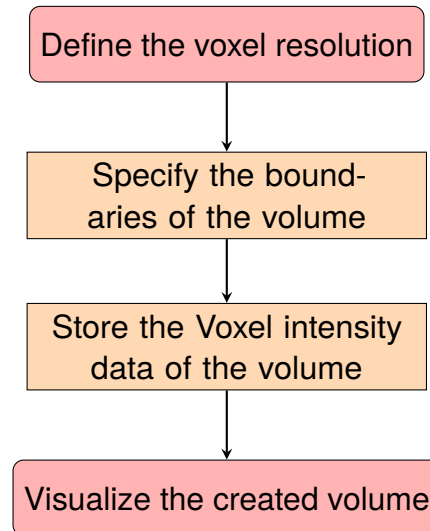


Figure 4.12: Flowchart for the steps of volume creation [69]

- **Step1: Boundaries**

To create the volume where light rays converge, a systematic process of determining the boundaries of the volume is followed. This involves examining the mesh grid of the light field data (as shown in Figure 4.9). The volume extends from a specific value in the x-axis direction (X_{min}) to a greater value (X_{max}) with a step size based on the previously defined resolution in the x-direction, resulting in the vector x . The same approach applies to the y and z axes: the volume extends from (Y_{min}) to (Y_{max}) and (Z_{min}) to (Z_{max}), respectively, with a step size based on the previously defined resolutions in the y and z directions, resulting in the vectors y and z . The vectors x , y , and z represent the dimensions of the volume.

- **Step 2: Voxel data storage**

After defining the boundaries of the whole volume, the volume is divided into a certain number of voxels, which are the 3D equivalent of pixels. The resolution vector components specify the dimensions of each voxel inside the whole volume. The relationship between the resolution and the resolution vector

components is depicted in Figure 4.13. The resolution vector determines the gridding of the entire volume into voxels. More voxels lead to higher resolution and vice versa.

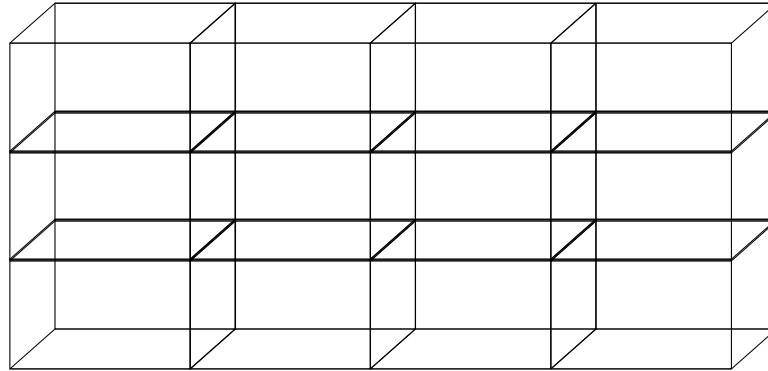


Figure 4.13: *Visualization of Voxels in a Volume*

- **Step 3: Visualization of the created volume**

Volume creation is a crucial step in the light field image reconstruction process. Figure 4.14 below illustrates an example of the volume created, represented by the red-marked cuboid around the area where most of the light rays converge. It is essential to ensure that all the light rays entering the volume from the bottom side will leave the volume from its upper side. This requirement is met by setting the upper boundary of the volume to allow all the light rays to pass through it while blocking out any stray rays. This ensures that the volume contains only the light rays needed for the image reconstruction and eliminates unwanted data. It is important to note that the size and shape of the volume created will affect the final image reconstruction. The volume should be large enough to encompass the targeted image and all the necessary light rays but not so large that it includes extraneous data.

4.2.2 Optimizing Volume Reconstruction Performance

The reconstruction speed is a crucial consideration when employing traditional radon transformation techniques. Identifying voxels that contain valuable information from the light vectors can be time-consuming. To overcome this challenge, the system developed in this thesis utilizes high-performance computing capabilities, specifically a 16-core system coupled with an NVIDIA Quadro RTX 5000 GPU. This powerful setup allows us first to generate a volume comprising voxels where most light vectors converge, as depicted in Figure 4.14, with the direction of the light

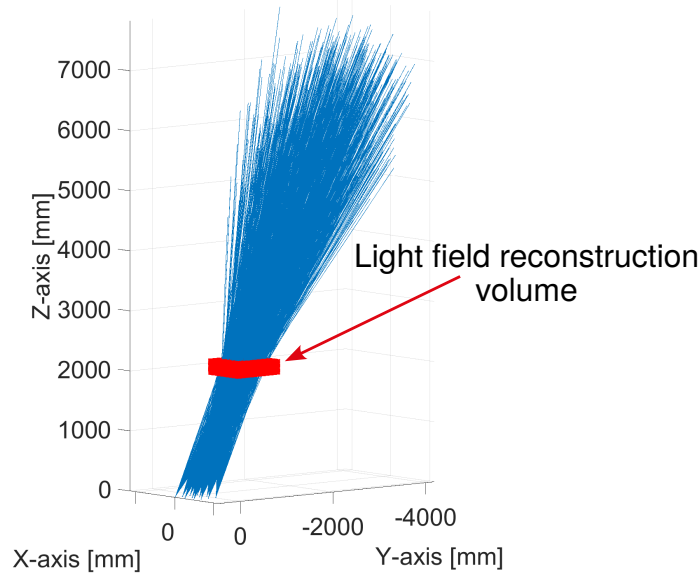


Figure 4.14: *Light data volume visualization*

vectors represented by lines. To optimize the reconstruction process, we introduce a cutoff distance parameter. If the distance between a voxel's coordinates and the associated light vector is less than the cutoff distance parameter, the intensities of the light vectors are accumulated within that voxel. This enables us to visualize the reconstruction. However, this method incurs a significant computational overhead due to the processing required for many voxels.

The volume reconstruction is implemented in this flow:

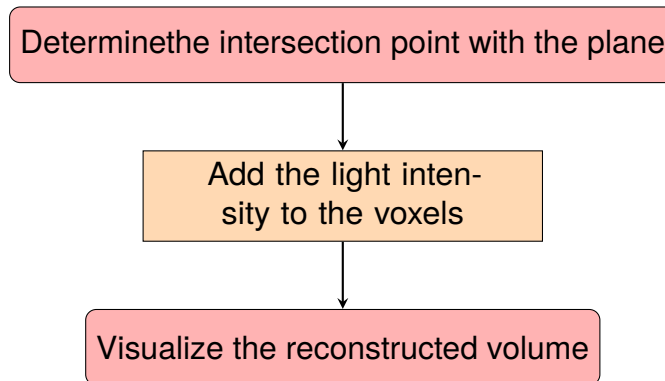


Figure 4.15: *Flowchart showing the steps of volume reconstruction*

In addition to traditional methods, we have also investigated the application of linear algebraic equations to determine the intersection points between light vectors and the image plane within the volume. This process of determining the intersection

points is a key part of the reconstruction process, and it demands full attention. By comparing these coordinates with the voxel coordinates, we can decide if a particular line intersects with the volume. Only the voxels intersected by the light vectors are considered, and their intensities are accumulated accordingly. To complete the Radon transformation process, an average intensity is calculated. The equations involved in this approach are as follows:

$$\begin{aligned} X &= X_1 + t(X_2 - X_1) \\ Y &= Y_1 + t(Y_2 - Y_1) \\ Z &= Z_1 + t(Z_2 - Z_1) \end{aligned} \quad (4.2)$$

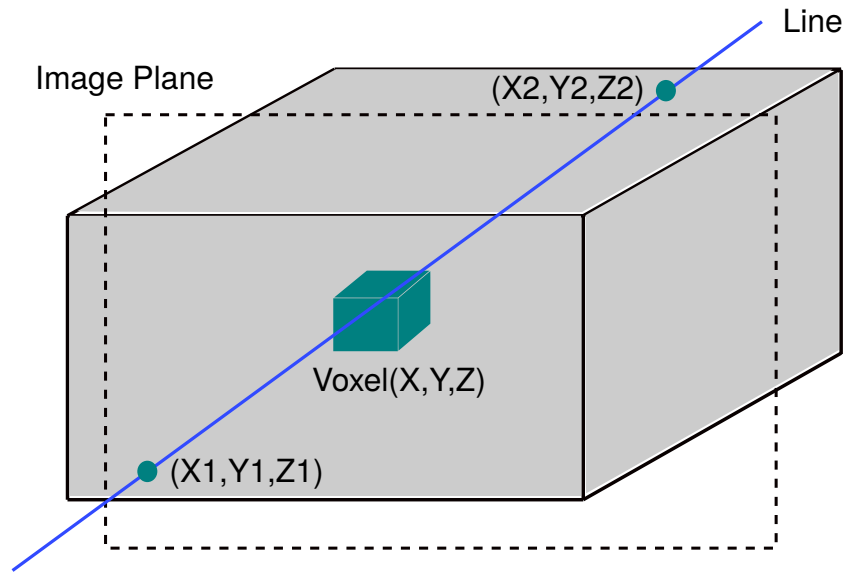


Figure 4.16: Intersection of a light vector and image plane (voxel)

In the alternative approach we have explored, the coordinates (X, Y, Z) represent the point of intersection with the image plane, while t is a constant value. The line is defined by the coordinates $(X_1, X_2, Y_1, Y_2, Z_1, Z_2)$, as depicted in Figure 4.16. By employing this method, we can substantially reduce the computational time needed for light field reconstruction. Using linear algebraic equations enables efficient identification and accumulation of voxel intensities, leading to a faster and streamlined reconstruction process. This approach offers improved computational efficiency without compromising the accuracy of the reconstruction results.

To enhance the visualization of the reconstructed results, we employ a slicing technique to extract 2D image planes from the generated 3D image volume. We obtain a series of 2D images that can be further analyzed by slicing the volume at different depths. During visualization, high-intensity values are rendered as white

pixels, while low values are depicted as black pixels. This color mapping scheme facilitates easy identification and interpretation of the reconstructed features and structures. The sliced images provide valuable insights into the reconstructed scene from various perspectives and depths. These images serve as a foundation for further analysis, including assessing the accuracy of the reconstruction, identifying specific details or patterns, and comparing the reconstructed data with the original input.

In volume reconstruction, two approaches—iterative methods and the intersecting plane concept (IPC)—are analyzed to determine the most effective solution. The simplified program flowchart (Figure 4.17) shows that the volume reconstruction operates in iterations. Each iteration focuses on the influence of one light ray within a single slice. A slice is defined by two planes in the xy-orientation (Figure 4.20). After completing this iterative process for all slices and light rays, a subroutine condenses the highly redundant point list into a new list format. The condensed list retains the same structure but contains only one entry per voxel. This optimized list is then saved and can be utilized to render images or perform further analysis.

4.2.3 Computational Resource Utilization

When working with volume reconstruction, it becomes evident that there are significant performance challenges. Although we did not conduct an in-depth runtime analysis, we deduced several key issues. While not exhaustive, the runtime data used for the pie chart (Figure 4.18) represents multiple test runs using different light field datasets. It is worth noting that these tests were performed on a shared workstation, so there might have been a slight influence from the activities of other users, although we made efforts to monitor and minimize this impact. Additionally, the precise impact of different parameters on computation time was not accurately quantified. Nevertheless, these tests provide a valuable overview of some of the performance issues encountered.

Figure 4.18 shows that the subroutine "CompareUpdated" accounts for a significant portion of the total runtime, surpassing 92% in this particular case. This percentage tends to increase as more data is processed, despite MATLAB's automatic utilization of multiple CPU cores. The primary purpose of this subroutine is to add intensity values from the points list to an array (Figure 4.17). For each light ray, there is a points list containing all the voxels intersected by the ray. Currently, the subroutine searches the entire array separately for each component of the points' coordinates to find the correct row in the 2D array. This approach is highly inefficient, considering that the row can be calculated directly using the known

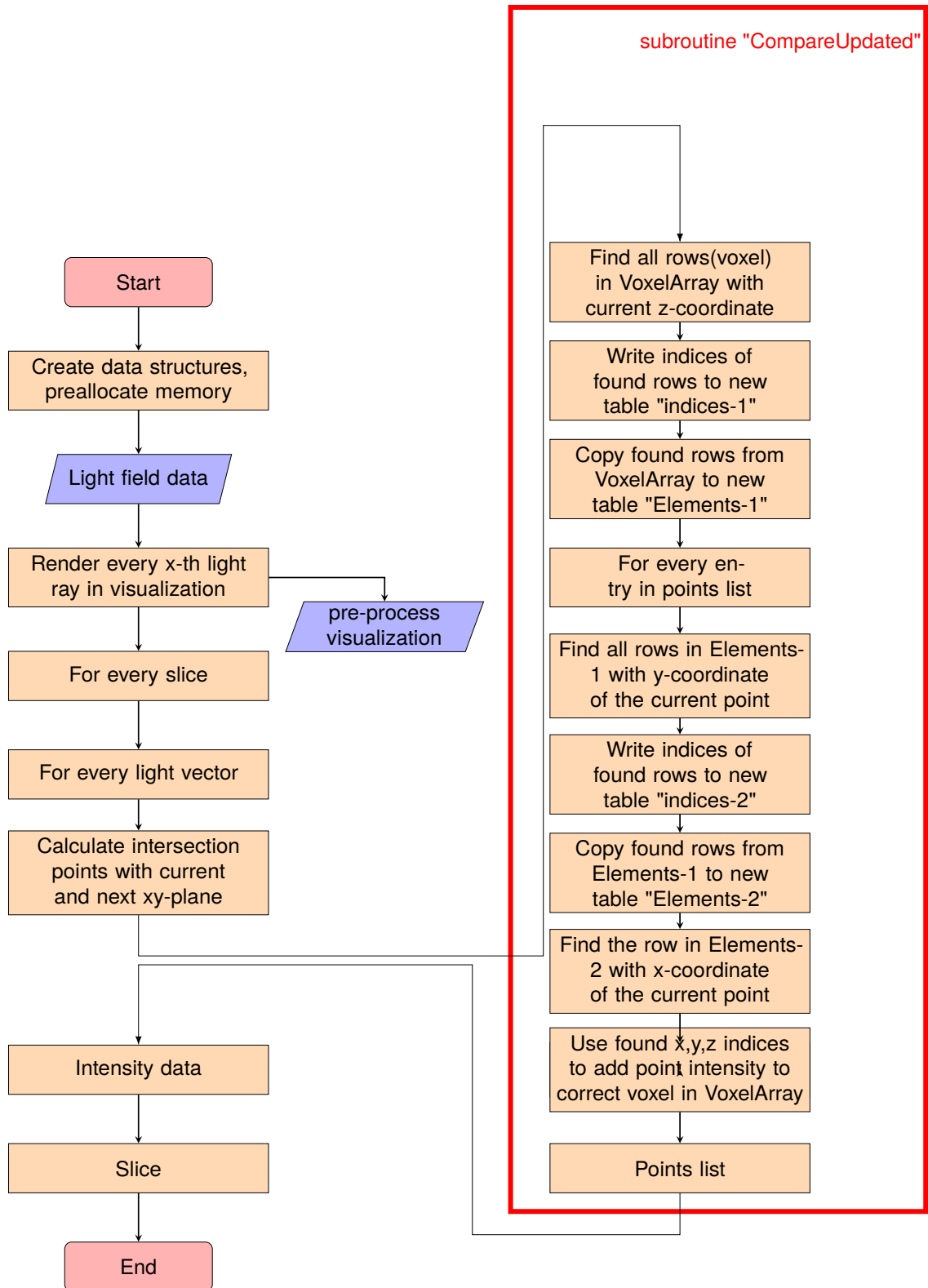


Figure 4.17: Flowchart of the Volume Reconstruction [70]

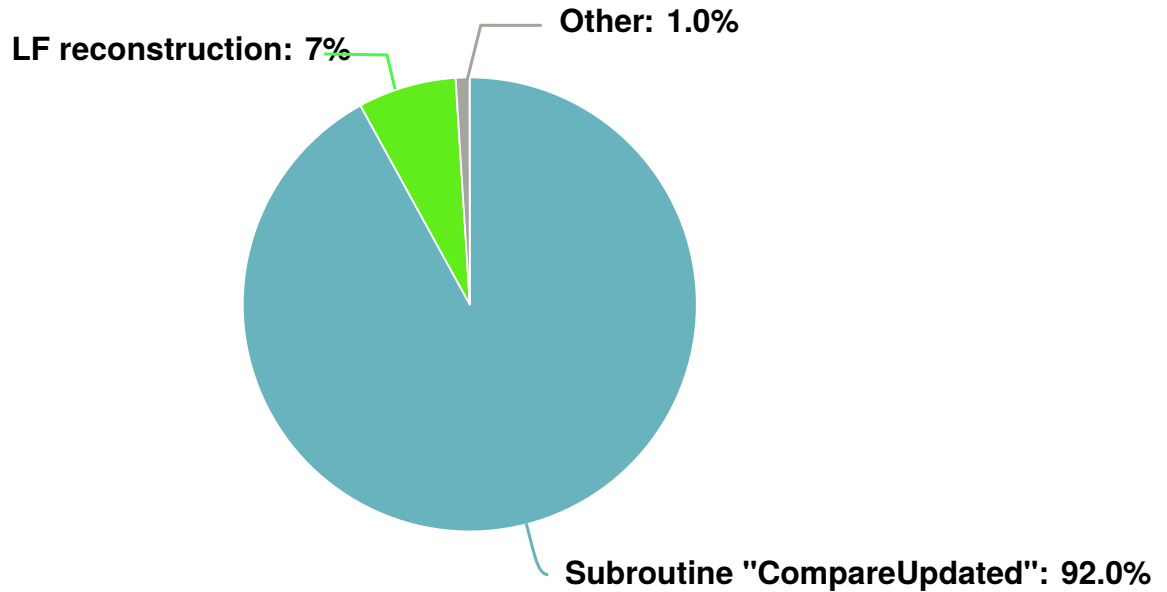


Figure 4.18: *Computation time of various subsections of the volume reconstruction, image volume same as in IPC runtime tests [70]*

voxel size and the overall image volume. Moreover, a 3D array could provide a more efficient way of addressing specific voxels.

4.2.4 IPC Working Principle

In the IPC (Intersecting Planes Concept) method, the borders of each voxel in the volume are defined as planes using base vectors and normal vectors. This vectorized approach allows us to efficiently calculate the intersection points between a light ray and the voxel borders using a single equation (eq. ??). By using this vectorized approach and equation (eq. ??), we can efficiently calculate the intersection points between the light rays and the voxel borders as detailed in Figure 4.20. This allows us to determine which voxels are traversed by the light rays and perform the necessary computations for light field reconstruction or visualization.

IPC is a powerful method for solving complex geometric problems by leveraging the intersection of multiple planes. It offers several advantages, including enhanced precision in volume reconstruction, efficient computation of intersections, and adaptability for diverse applications. The IPC's inherent flexibility makes it suitable for tasks requiring accurate geometric calculations, such as visualization of intersecting volumes or line intersections. Additionally, the algorithm supports optional features such as line weighting, visualization of rays and volumes, and runtime feedback to enhance its utility further.

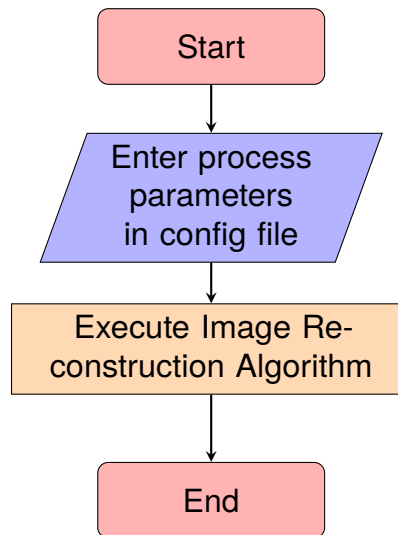


Figure 4.19: Flowchart of the config file

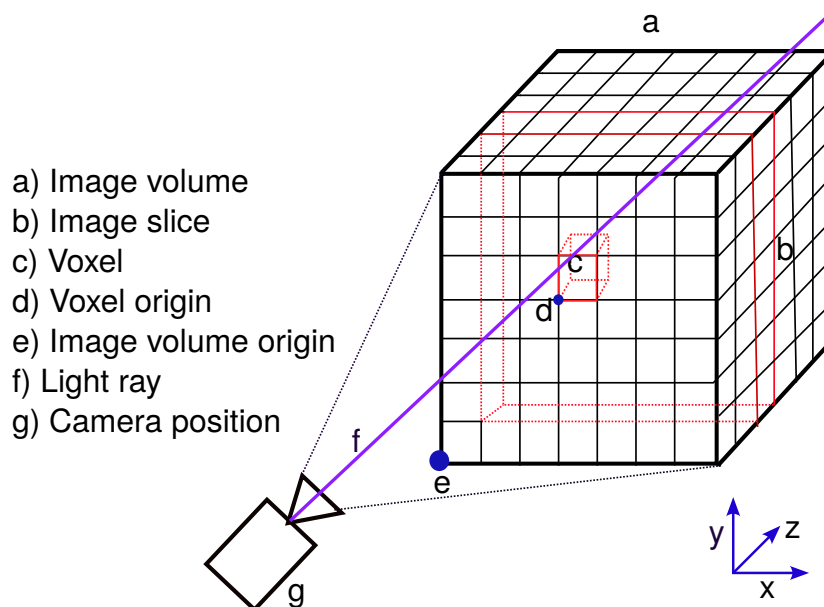


Figure 4.20: Graphical definitions of terms for volumetric imaging and ray tracing [70]

To complement the IPC's functionality and improve the efficiency of its implementation, a separate configuration file (Figure 4.19) was introduced. This config file serves as a centralized hub for managing all key parameters and paths. Users can easily input and modify variables; a brief description accompanies each parameter to facilitate understanding and customization. By invoking the IPC algorithm from within the config file, users can streamline their workflow, automate repetitive tasks,

and tailor the execution process to their specific needs. While the config file is not inherently part of the IPC, its inclusion simplifies the management of features such as runtime visualization and automated function calls.

In the context of Figure 4.21, it is evident that most data structures are created immediately after importing the light field data. Since the size of these arrays or potential size is known at this stage, it becomes crucial to pre-allocate sufficient memory to avoid repeated resizing. Frequent resizing of large arrays can severely impact performance.

For storing the intensity values of the voxels, a 3D matrix is used. However, when saving these values in a list, additional information beyond the intensity value itself needs to be stored, namely the location of the voxel. This adds three more values, increasing the size of the data. Moreover, searching for the intensity of a specific voxel becomes time-consuming when the entire list has to be searched. To address these concerns, a 3D array is utilized and can be thought of as a stack of multiple 2D arrays. Consequently, the address of a cell in a 3D array requires an additional value compared to a 2D array. In IPC, each voxel is assigned an address consisting of the A_x , A_y , and A_z components. These components indicate the voxel's position in the respective direction. For example, an address of $x=2$, $y=4$, and $z=3$ corresponds to the second voxel in the x direction, the fourth voxel in the y direction, and the third voxel in the z direction (see Figure 4.20). The voxel address directly corresponds to its position in the 3D array. This efficient addressing scheme facilitates rapid and redundancy-free storage and retrieval of intensity values.

$$(A_i - 1) \cdot s_i = P_i \quad (4.3)$$

Although for voxel sizes other than $1 \times 1 \times 1$ mm, the actual position P_{xyz} of a voxel cannot be used directly as the address, it can be calculated using Equation 4.3. It is important to note that due to restrictions imposed by MATLAB's parallel computing capabilities, the exclusive use of this 3D array was not feasible in all cases.

Eliminating redundancies is also crucial when saving the results to a file, as the maximum size that a '.mat' file can handle is limited to around two gigabytes [71]. This size limit can be quickly exceeded when combining a large image volume with small voxel sizes. Therefore, when working with high resolutions, selecting a smaller image volume is necessary not only for computational efficiency but also to reduce the file size.

The IPC's efficiency in processing a dataset is influenced by several parameters. The number of voxels and the amount of light field data are the most significant

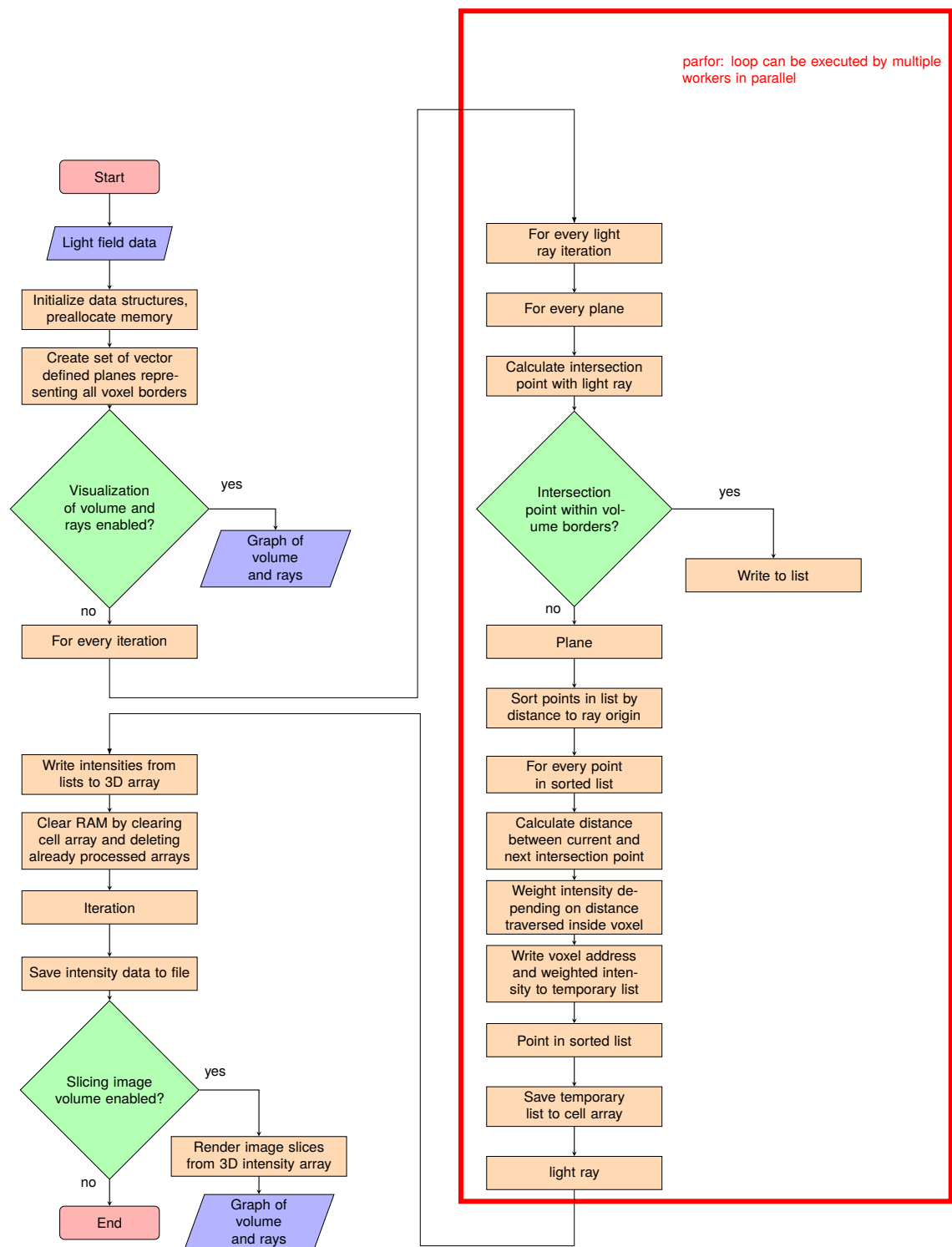


Figure 4.21: Flowchart of IPC [70]

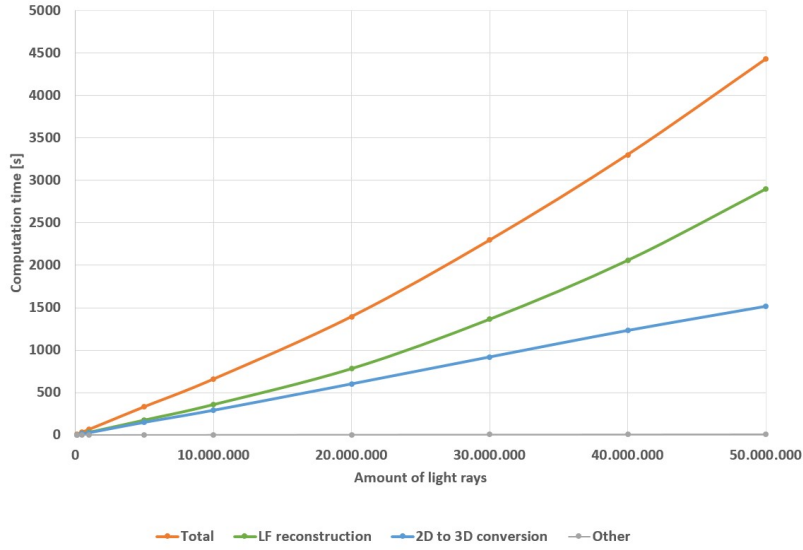


Figure 4.22: IPC runtime with light field data of different sizes [70]

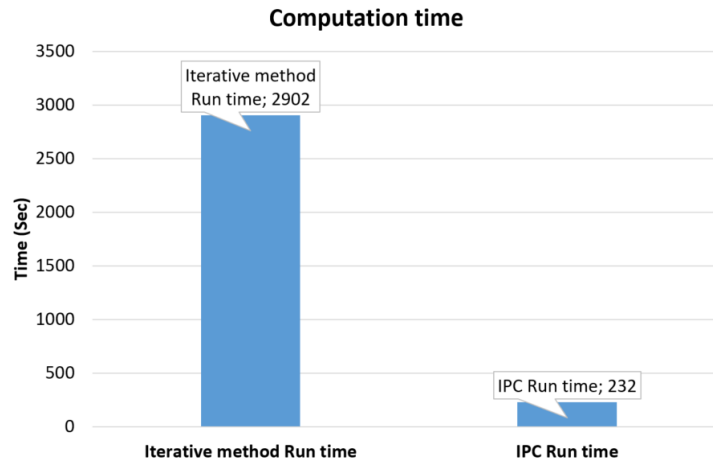


Figure 4.23: Comparison of computation time of both Iterative method and IPC [70]

factors, while data import, initialization, image rendering, and saving results to a file have a negligible impact on the total runtime. This efficient processing capability of the IPC is a testament to its design and implementation.

Figure 4.22 demonstrates that the number of individual light rays in a dataset influences the total computation time almost linearly. For smaller datasets with fewer rays, the computation time is evenly split, with approximately 50% attributed to the actual reconstruction process and 50% to the conversion from a cell array to a 3D array. However, as the number of light rays increases, the reconstruction process becomes dominant, accounting for approximately 75% of the total run time when processing 50 million rays.

Using the same data set and parameters as in Figure 4.18 and 4.23, the IPC demonstrates its speed and effectiveness by achieving a computation time of under 232 seconds. This is approximately 92% faster than the 2902 seconds required by the Iterative method to reconstruct the same images. This performance advantage becomes even more significant for larger image volumes, particularly those with more slices. While there may be very specific conditions where the performance gap narrows, no scenario has been identified in which the iterative method outperforms the IPC, at least on a 16-core processor.

4.2.5 Line Weighing Algorithm Effect

The core concept of the IPC revolves around representing the boundaries of voxels using planes defined by their respective normal vectors. To initiate the process of determining the path of each ray, two lists of vectors are generated. One list comprises base vectors $\vec{b}_p$ for all planes, while the other contains the corresponding normal vectors $\vec{n}_p$ (see Figure 4.24).

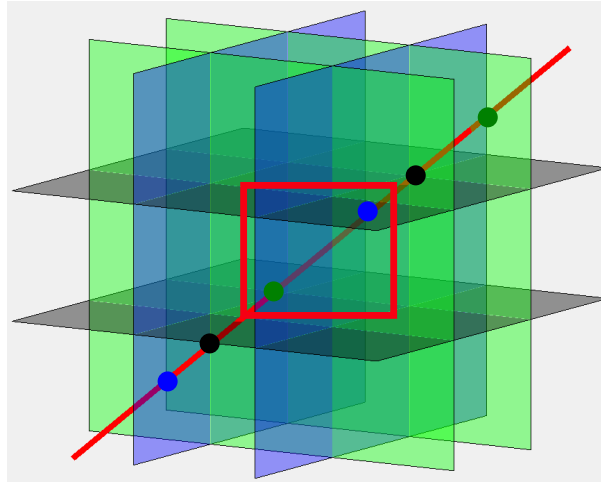


Figure 4.24: Graphic representation of a light ray (red) crossing voxel borders represented by planes [70]

The following steps are performed for each ray, leveraging multi-threading to compute multiple light rays in parallel (as discussed in Section 4.2.6). Initially, the intersection points $\vec{p}_{int}$ of the light ray, characterized by a base vector $\vec{b}_r$ and a direction vector $\vec{v}_r$, with all planes are calculated using Equation 4.4. This computation determines the points at which the ray intersects with the planes.

$$\vec{p}_{int} = \vec{b}_r + \frac{\vec{n}_p \cdot (\vec{b}_r - \vec{b}_p)}{-(\vec{n}_p \cdot \vec{v}_r)} \vec{v}_r \quad (4.4)$$

To ensure that only relevant intersection points are considered, any point lying outside of the image volume is disregarded in the calculations. Consequently, only intersection points inside the volume are stored in a list. Once all intersection points have been computed, the list is sorted based on their distance from the origin of the ray as shown in Figure 4.25. This sorting process employs the standard MATLAB quick sort algorithm. In the sorted list, each pair of consecutive points represents an entry and exit point into and out of a particular voxel. This pairing provides valuable information about the traversal path of the ray through the voxels in the volume.

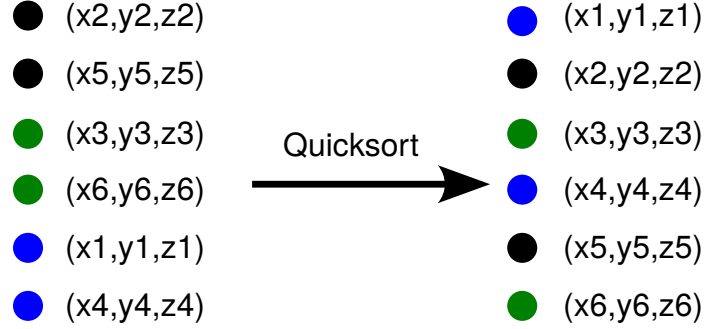


Figure 4.25: *Sorting of the intersection points with the planes*

Instead of directly adding the entire intensity of a light vector (I_r) to a voxel, a weighting factor between 0 and 1 is applied. This factor is calculated as the ratio of the length of the vector section that intersects the voxel (d_{cross}) to the distance from one corner of the voxel to the opposite corner (d_{max}), as shown in equation 4.5. The resulting weighted ray intensity (I_{rw}) is then added to the voxel.

$$I_{rw} = I_r \cdot \frac{d_{cross}}{d_{max}} \quad (4.5)$$

This weighting approach considers the portion of the light vector that traverses the voxel relative to its overall length. By considering the intersection length in proportion to the maximum distance across the voxel, a more accurate representation of the light's contribution to the voxel's intensity is achieved. This accounts for the varying lengths of the light vector that pass through different voxels along its path. Applying this weighting factor, the voxel's intensity is adjusted based on the relative portion of the light vector it covers. This allows for a more precise representation of how much light is effectively contributing to each voxel, taking into consideration the specific geometry of the intersected region. This approach is crucial for accurately capturing the light distribution and producing realistic reconstructions. The weighted ray intensity (I_{rw}) provides a more refined measure of the light's

impact on the voxel, ensuring that the intensity values are appropriately scaled and representative of the amount of light passing through each voxel.

Following sorting the intersection points, an iterative process commences, involving the calculation of distances between consecutive points. By comparing these distances to the maximum distance within a voxel, the intensity can be weighted as specified in Equation 4.5. The voxel address needs to be determined to assign the weighted intensity to the appropriate voxel. In some cases, at least one component of the voxel address cannot be directly derived from the intersection point coordinates. This intersection point must lie precisely between two voxels along at least one dimension. For these specific address components, the light vector direction is utilized to identify the correct voxel accurately.

While the IPC is designed to handle any light ray, there is a particular scenario where the calculation of rays is not yet accurate. This occurs when a light ray is perfectly parallel to a single axis and lies exactly within a plane along that axis. In such cases, the entire vector represents one continuous intersection point. However, this situation typically arises when the image volume is positioned directly in front of the camera, and the occurrence rate of these parallel rays is usually below 0.1%. When dealing with this special case, the intensity is assigned to one of the two voxels the ray traverses instead of splitting it equally between them. The resulting error from this approximation is minimal and unlikely to be noticeable. Additionally, specific instructions on handling these rays can be easily incorporated.

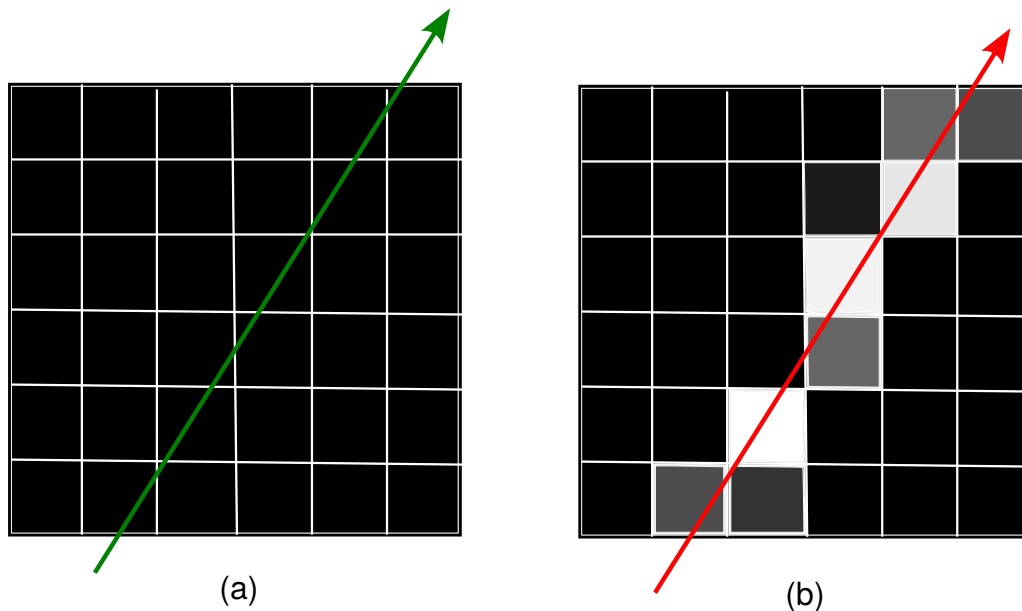


Figure 4.26: *Illustration of ray casting, showing the accumulation of intensity along a light vector before (a); and after it passes through a volume of voxels (b)*

4.2.6 Parallel Computing

MATLAB's parallel computing toolbox provides valuable functionality for optimizing the code execution in parallel on multiple CPU cores [72] [73]. MATLAB efficiently utilizes available computational resources by utilizing parallel for-loops and other parallel computing features. This allows for significant speed improvements, especially when dealing with computationally intensive tasks, such as ray tracing and voxel calculations. Parallel for loops distribute the workload across multiple cores, enabling simultaneous execution of independent iterations. This parallelization significantly reduces the overall computation time, as multiple iterations can be processed simultaneously. It effectively harnesses the power of multi-core processors, maximizing performance and improving the algorithm's efficiency.

Furthermore, the potential for a GPU-adapted version is an exciting prospect. Graphics Processing Units (GPUs) are highly parallel processors designed to handle large-scale parallel computations efficiently. They excel at tasks that can be parallelized, making them well-suited for accelerating computations involved in ray tracing and voxel calculations. Using the parallel computing toolbox and exploring the possibility of GPU adaptation, MATLAB provides a robust platform for improving the algorithm's performance [72][74]. It enables the utilization of parallel processing capabilities, whether through multi-core CPUs or GPUs, to achieve faster and more efficient computations. This allows for the processing of larger datasets and more complex simulations.

The calculations for individual light rays are independent, allowing them to be performed in parallel (Figure 4.21). Using multiple cores on a processor enables a significant reduction in computation time. However, achieving parallel execution requires sacrificing single-core performance. The challenge arises when writing the computed intensity values to the corresponding cells in the 3D array. MATLAB restricts access to shared array indices within a parfor-loop, preventing simultaneous writing to the same cell by multiple loop instances. As multiple light rays may hit the same voxel, the intensity of the voxel needs to be summed, requiring the addition of new intensity values from each light ray.

In a parallel computing scenario, the order of iterations is not guaranteed, which makes the direct addition of computed intensities to the voxel array within the parallel loop infeasible. A solution has been devised as a workaround, but it considerably slows down the algorithm when executed on a single core. However, even with just two cores, the performance slowdown is outweighed by the benefits of parallel execution. Identifying a better solution to this issue holds significant potential for further speed improvements in the algorithm, providing an optimistic outlook for the future of the project.

Instead of directly writing the intensity value of a voxel resulting from a light ray to the 3D array, it is stored in a temporary list along with the corresponding voxel address. This list is defined within the parfor-loop, allowing unrestricted access. Upon completion of the iteration, this temporary list is written to a cell array. Since each iteration only needs to write one element to the cell array, accessing it from within the parfor-loop is feasible using the loop index.

After all iterations of the parfor-loop are finished, a non-parallel loop iterates through the lists in the cell array and writes the intensities to the 3D array. Storing one list per ray introduces significant redundancies, resulting in high memory requirements. With many rays and a decent resolution, the RAM usage can quickly exceed 100 gigabytes. The parfor-loop can be divided into multiple parts to address this issue, allowing the values from the redundant cell array to be written to the non-redundant 3D array between iterations. By clearing the cell array and removing already computed light rays, RAM is freed up, enabling the process to repeat. The number of rays computed within each iteration can be adjusted manually, although excessively high values may cause program crashes. Lower values, on the other hand, only result in a slight decrease in performance without causing any significant issues.

5 From Pixels to Perception: Understanding Contrast in Visual Systems

This chapter explains the realm of projection systems is explained, focusing on a key performance metric: contrast measurement. Contrast measurement techniques vary depending on the specific application, and they play a crucial role in determining the projected images quality. Several test patterns are commonly used when evaluating the contrast performance of a Head-Up Display (HUD). These patterns are visual aids to assess the display's ability to produce clear and distinct images. Among the test patterns used, three notable examples include line pair, checkerboard, and dot patterns. Analysts can use these test patterns to comprehensively evaluate key aspects such as spatial resolution, contrast sensitivity, artifact detection, pixel-level performance, and overall display uniformity. This holistic approach ensures that the HUD delivers optimal performance, clarity, and reliability in real-world applications, where accurate and precise visual information is crucial for user safety and effectiveness. This analysis forms the foundation for applying these principles in novel 3D applications, as explored in this thesis. Finally, the chapter discusses the impact of different coordinate systems, Cartesian and spherical, on image reconstruction and contrast performance. The influence of the chosen coordinate system and the number of images used are analyzed to understand their effects on the accuracy and reliability of contrast measurements.

5.1 Introduction to Contrast Measurement

Contrast refers to the visual difference in the brightness, color, or grayscale levels between different elements within an image or on display. It is a measure of the distinguishability or separation between these elements, enabling viewers to perceive and interpret visual information effectively [75] [76] [77]. Contrast is commonly expressed as a ratio, percentage, or difference in luminance or color

values. Contrast plays a crucial role in shaping our visual perception. It helps us perceive shapes, edges, textures, and details in images or displays. High contrast enhances visual clarity and makes images or text easier to read and interpret, while low contrast can result in reduced visibility and legibility. Contrast is a significant component of image quality. It helps highlight specific elements and important details and differentiate between objects or regions of interest.

Contrast influences the user experience in various contexts. In displays like monitors, TVs, or mobile devices, optimal contrast ensures comfortable viewing, reduces eye strain and enhances user engagement. In applications of augmented reality (AR) or virtual reality (VR), contrast management contributes to immersive and realistic virtual experiences [78]. Adequate contrast levels are essential for people with visual impairments, color vision deficiencies, or other visual challenges, enabling them to perceive content effectively and participate equally in various activities.

The historical development and evolution of contrast measurement techniques have transitioned from subjective visual assessments to more objective and quantitative methods. It all started with visual inspection, where trained observers used their keen eyes to subjectively assess contrast in images and displays through human visual perception. With the advancement of technology, visual sensitometry was introduced. Sensitometers and densitometers measured the density of photographic film, offering a more objective assessment by analyzing differences in light transmission [79][80]. The development of objective metrics and algorithms introduced standardized measures such as the contrast ratio and modulation transfer function (MTF), ensuring more reliable and comparative evaluations. This progression has enabled a more accurate and standardized contrast assessment in various imaging and display systems.

In three-dimensional volumetric measurements, contrast remains undefined and lacks a standardized framework. This chapter seeks to bridge that gap by adapting traditional methods of contrast measurement, initially developed for two-dimensional imaging, to the context of 3D volumetric analysis. Extending these methodologies establishes a systematic approach for quantifying contrast within volumetric data.

5.2 Contrast Measurement Techniques

Visual performance is vital to the function of HUD systems, as with any display. Accurate system design and final inspection for quality control ensure that light and

colors are vivid enough to be discernible from surroundings in any lighting condition and that projections are aligned correctly and clearly for in-focus binocular viewing. To evaluate the contrast ratio of the display, different test patterns are shown on the monitor.

5.2.1 Line pair pattern

The line pair pattern is commonly used for contrast measurement because it allows us to accurately evaluate the display's ability to distinguish fine details and edges. The line pair pattern consists of alternating black and white lines with varying thicknesses and spacings [81] [82]. When displayed on a screen, these lines create high contrast between the black and white regions. The pattern tests the display's ability to render these high-contrast areas without blurring or blending the lines. By examining how well the display reproduces the fine details and edges of the line pairs, we can assess its ability to maintain sharpness and contrast. A display with high contrast capability will accurately render the alternating black and white lines as distinct entities, clearly delineating their boundaries.

Measurement of contrast performance using the line-pair pattern helps identify potential issues with the display, such as poor resolution, insufficient contrast ratio, or artifacts that may affect image quality. It provides a quantitative assessment of how well the display can reproduce fine details, a valuable metric for evaluating a display system's overall sharpness and clarity.

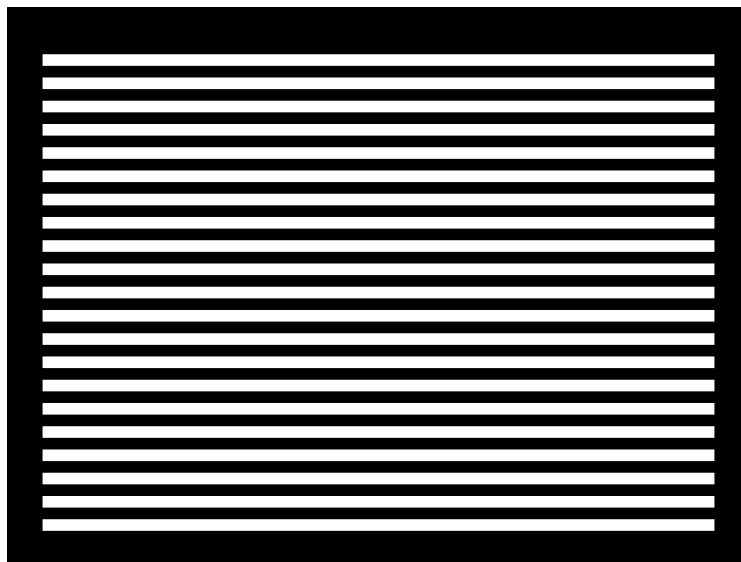


Figure 5.1: *Horizontal line pattern with alternating black and white stripes*

Using the line pair pattern for contrast measurement brings various technical advantages that contribute to its effectiveness [83][84]. These advantages include:

- **Sensitivity to Resolution:** The line pair pattern is sensitive to the display resolution. The ability to discern individual lines in the pattern directly relates to the display's spatial resolution. By observing the clarity and sharpness of the lines, we can gauge the display's resolution capabilities.
- **High Contrast Detection:** The line pair pattern, with its precision, creates distinct areas of high contrast between the black and white lines. This precision makes it an effective tool for evaluating the display's ability to render high-contrast regions accurately. It helps identify any blurring or blending of the lines, which could indicate loss of contrast or poor image quality, instilling confidence in its effectiveness..
- **Quantitative Measurement:** The line pair pattern, with its ability to provide quantitative contrast performance measurement, offers an objective and precise way to calculate various metrics such as contrast modulation and spatial frequency response. This objectivity and precision enable precise comparisons between different systems.
- **Standardized Testing:** The line pair pattern has become a standard test in the industry for contrast measurement. It offers a consistent and well-defined method for evaluating contrast performance across displays and systems. This standardization allows for reliable comparisons and benchmarking of displays, aiding in developing and improving display technologies.

Using the line pair pattern for contrast measurement lies in its sensitivity to resolution, high contrast detection, quantitative measurement capabilities, and standardized testing procedures. These factors contribute to its effectiveness as a tool for assessing and optimizing the contrast performance of display systems.

5.2.2 Checkerboard pattern

Using checkerboard patterns for contrast measurement provides several benefits in assessing the performance of a display. Checkerboard patterns consist of alternating black and white squares arranged in a grid-like fashion. When displayed on a screen, these patterns offer valuable insights into the display's ability to render contrasting colors and maintain optimal contrast ratios accurately. The checkerboard pattern effectively evaluates a display's contrast capabilities because it highlights the distinction between adjacent black and white squares [85]. We can assess the display's ability to preserve sharp transitions by examining the boundaries between

these squares. This pattern allows for detecting any artifacts, such as uneven contrast, which may adversely affect image quality. Furthermore, the regular grid structure of the checkerboard pattern aids in assessing the uniformity of contrast across the display. It enables us to identify variations in contrast performance across different screen regions, including potential brightness or contrast level discrepancies. Quantitative analysis of contrast performance using checkerboard patterns provides valuable metrics for comparing and benchmarking displays. By measuring contrast modulation and contrast ratios, we can objectively evaluate and rank the quality of displays for various applications, such as visual displays, monitors, or projectors.

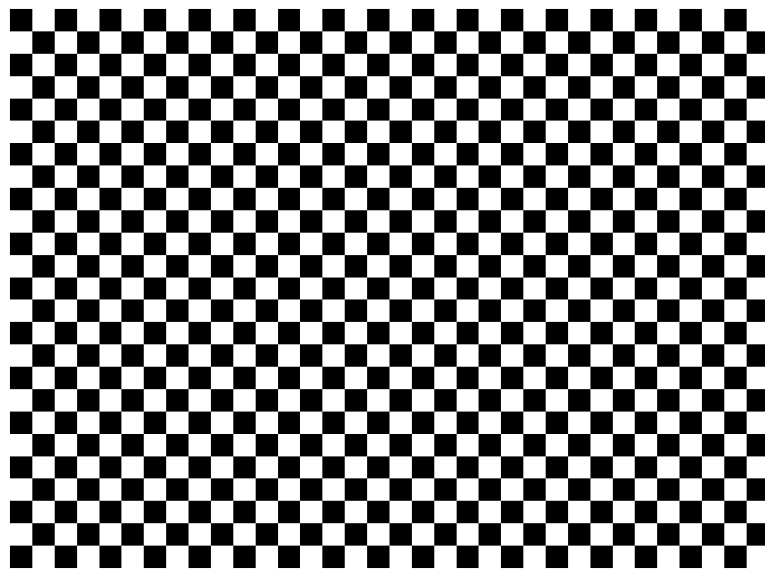


Figure 5.2: Visual representation of a 2D Checkerboard pattern with alternating black and white squares

Checkerboard patterns are used for contrast measurement for several reasons [86]:

- **Contrast Sensitivity:** The Checkerboard pattern is highly effective in evaluating a display's ability to render contrasting colors accurately. The alternating black and white squares create regions of high contrast, allowing for precise assessment of the display's contrast sensitivity.
- **Spatial Frequency Response:** The checkerboard pattern provides information about a display's spatial frequency response. By varying the size and spacing of the squares, it is possible to evaluate how well the display reproduces different spatial frequencies. This enables the identification of potential limitations or distortions in the display's ability to resolve fine details accurately [87].

- **Artifact Detection:** The Checkerboard pattern aids in detecting artifacts such as moiré patterns or pixelation. These artifacts may arise due to interaction between the display's resolution and the pattern's spatial frequency. By carefully examining the rendered pattern, it becomes possible to identify unwanted patterns or pixel irregularities that could impact image quality and contrast performance.

The checkerboard pattern is highly effective for contrast measurement because it can assess contrast sensitivity, analyze spatial frequency response, detect artifacts, enable quantitative analysis, and adhere to standardized testing procedures. These advantages make it an invaluable tool for evaluating and optimizing the contrast performance of display systems.

5.2.3 Dot pattern

Dot patterns are utilized in contrast measurement for several compelling reasons; these patterns comprise collections of dots with varying sizes and spacing. One key advantage of dot patterns is their ability to assess a display's capability to represent varying brightness and contrast levels. By analyzing how well the display renders dots of different sizes, it is possible to gauge its ability to reproduce subtle variations in luminance accurately. This enables the detection of potential issues, such as compression of brightness levels or a limited dynamic range, affecting the overall contrast and fidelity of the displayed images. In addition, dot patterns allow for examining a display's spatial resolution and pixel-level performance. Since the dots in the pattern are typically densely packed, they allow the evaluation of a display's ability to reproduce fine details and textures faithfully. This includes the display's capability to accurately render small, closely spaced dots without blurring or merging them, as this would result in a loss of contrast and clarity. In addition, dot patterns offer a visual representation of contrast at different spatial frequencies. Observing how well the dots are rendered across different regions of the pattern, any variations in contrast response across various frequencies can be identified. This helps in evaluating the display's ability to maintain consistency in contrast on different scales, crucial to accurately reproducing details in images with varying levels of complexity [88].

The use of dot patterns for contrast measurement has numerous advantages that enhance the assessment of display performance [89]. These advantages include:

- **Assessment of Pixel-Level Performance:** Dot patterns evaluate a display's performance at the pixel level. The densely packed dots in the pattern enable

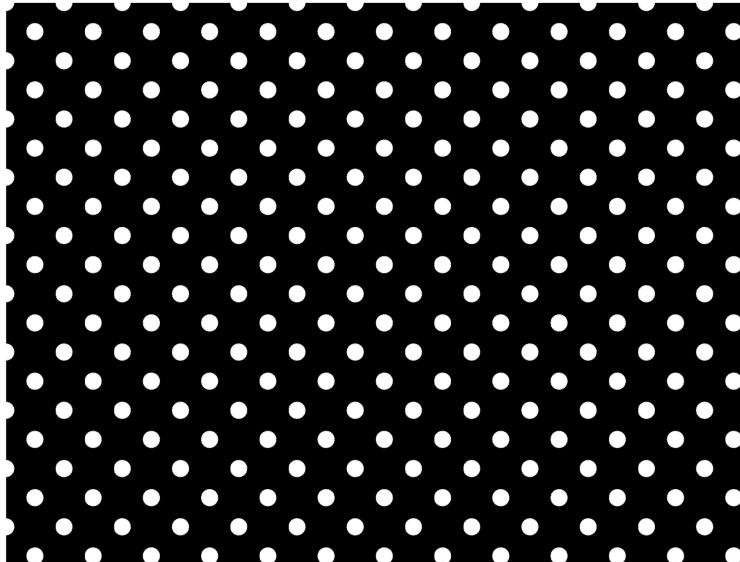


Figure 5.3: *Monochrome Dot pattern with white dots on a black background*

analysts to assess the display's ability to render fine details and textures. Observing the individual dots enables the detection of any blurring, merging, or distortion that may compromise contrast and image clarity at the pixel level.

- **Analysis of Contrast Response:** Dot patterns offer insight into the contrast response of a display at different spatial frequencies. By examining the distribution and visibility of dots at different sizes and spacings, it becomes possible to evaluate how well the display maintains contrast at various scales. This analysis helps identify discrepancies or irregularities in the contrast response, providing valuable information for optimizing the display's performance.
- **Detection of Compression and Dynamic Range Limitations:** Dot patterns allow for detecting issues related to brightness compression and a limited dynamic range. By analyzing the rendered dots and their transitions, analysts can identify any loss of contrast or fidelity caused by inadequate representation of varying brightness levels. This assessment is particularly important for displays that accurately reproduce a wide range of brightness levels in images or videos.

Dot patterns for contrast measurement lie in their ability to assess pixel-level performance, evaluate spatial resolution, analyze contrast response, and detect compression and dynamic range limitations. These advantages contribute to a comprehensive understanding of the contrast capabilities of a display, facilitating improvements in image quality.

Pattern	Pros	Cons
Line pair pattern	- High precision in measuring spatial resolution - Effective for detecting fine details - Helpful in determining modulation transfer function (MTF)	- Sensitive to alignment and orientation errors - Limited to linear structures
Checkerboard pattern	- Assesses contrast sensitivity effectively - Detects artifacts efficiently	- Less effective for high-frequency detail measurement - More complex to analyze
Dot pattern	- Helpful in detecting uniformity and consistency issues - Can be used for various object shapes - High sensitivity to low contrast details	- May not provide precise spatial frequency information

Table 5.1: *Performance Evaluation of Different Test Pattern Strategies*

Understanding contrast measurement techniques is essential for image analysis. In the next section, we will explore coordinate systems and how they play a role in image reconstruction.

5.3 Coordinate Systems and Image Reconstruction

The LMK camera is equipped with a manual focus adjustment mechanism, operated by a rotatable screw located on the lens. An initial measurement process was performed to achieve the highest level of image quality. During this measurement, the camera's orientation along the X, Y, and Z axes was fine-tuned using random values until the photographed object was accurately centered within the image sensor's frame. Subsequently, the focus ring was manually adjusted to achieve optimal image clarity and sharpness, ensuring that the resulting images met the highest quality standards.

5.3.1 Cartesian Coordinate System

In the initial phase, the images were captured using the Cartesian coordinate system. As illustrated in Figure 5.4, we designated point A as the starting point with optimized focus; moreover, it was located at a distance of $L = 2125$ mm from point B, represented by the monitor. Points E, G, and F were strategically marked to delineate the extremities of the Cartesian coordinate system. However, it is important to note that due to the constraints of the Cartesian coordinate system, maintaining a constant distance is not always feasible with the LMK camera. For each object, a series of 100 images was meticulously taken. Only the Z rotation underwent alteration when the camera moved between points A and E. In contrast, the Y rotation was the variable factor when transitioning from points A to G. This approach allowed for a comprehensive exploration of the camera's performance across different orientations within the Cartesian coordinate system.

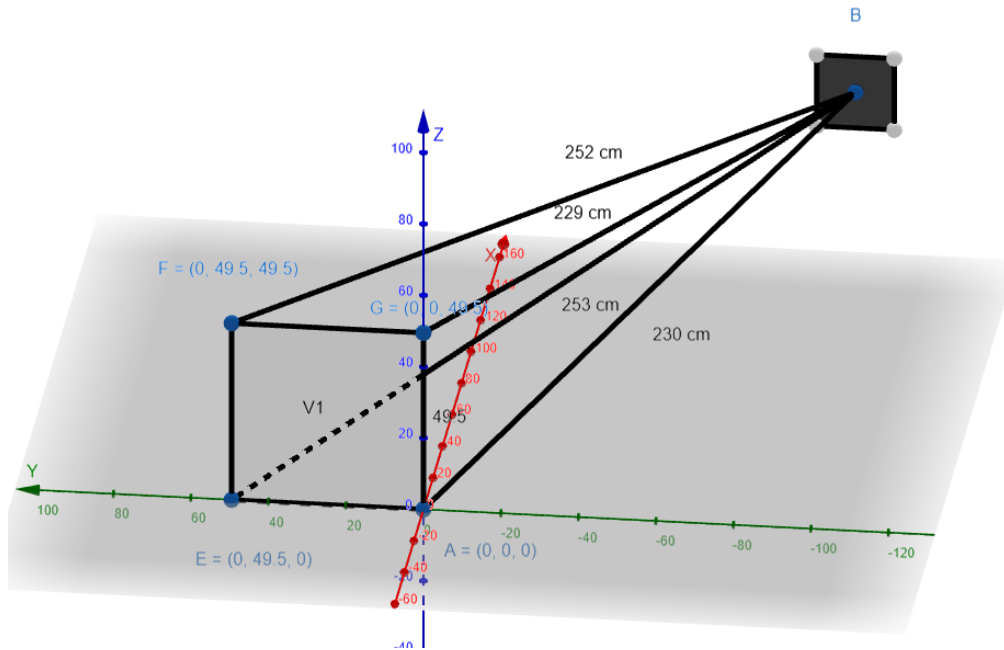


Figure 5.4: A 3D model of Cartesian coordinate system [90]

A comprehensive set of 100 images featuring a 40-pixel checkerboard pattern was meticulously captured within the framework of camera movements conducted within the Cartesian coordinate system. Figure 5.5, presented below, focuses explicitly on comparisons between points A, E, G, and F. Point A was carefully chosen as the starting point, where optimal focus was ensured. It should be noted that image quality exhibited fluctuations during camera movement by the Cartesian coordinate system. As depicted in Figure 5.5, the images captured by the camera revealed varying degrees of focus. In particular, the image at point A in Figure 5.4

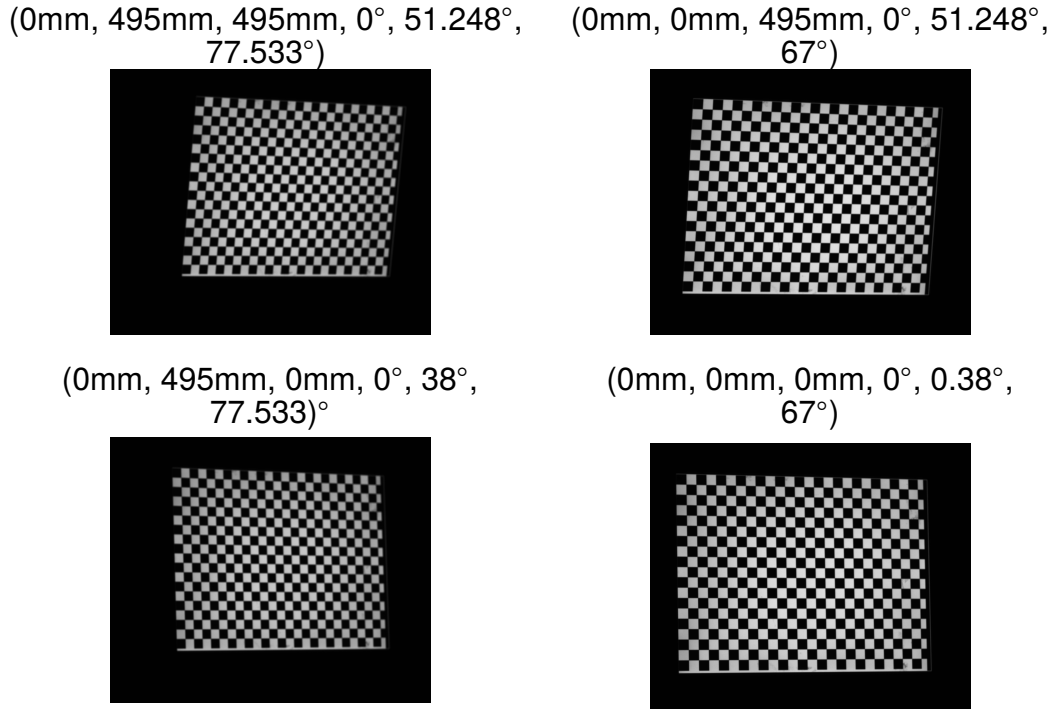


Figure 5.5: *The images of the Cartesian points of CB-40 Pixel (X-trans, Y-trans, Z-trans, X-rot, Y-rot, Z-rot)*

exhibits exceptional sharpness, while the images of the other points exhibit varying levels of blurriness in specific pixel regions. This discrepancy in image quality underscores the inherent limitations of the Cartesian coordinate system. To gain a deeper understanding of the impact of coordinate systems on the reconstruction process, the investigation now focuses on assessing the implications of employing the spherical coordinate system instead of the Cartesian system.

5.3.2 Spherical Coordinate System

The spherical coordinate system offers several advantages when capturing images of distant objects. Unlike the Cartesian system, it allows for a comprehensive view of the surroundings without requiring intricate rotations or frequent adjustments. This is particularly beneficial because capturing distant objects in the Cartesian system can introduce perspective distortion. One notable advantage is the reduction of perspective distortion. Spherical coordinates help minimize this distortion, enabling the capture of more accurate representations of distant objects [91]. The distance between the LMK camera and the display monitor remains constant in the spherical coordinate system, as illustrated in Figure 5.6. This stability in distance contributes to maintaining a consistent focus on distant objects as the camera moves. In

contrast, achieving and maintaining focus on a distant object within the Cartesian system while adjusting multiple axes simultaneously can be challenging. Spherical coordinates simplify this process and enhance the quality of images of distant objects.

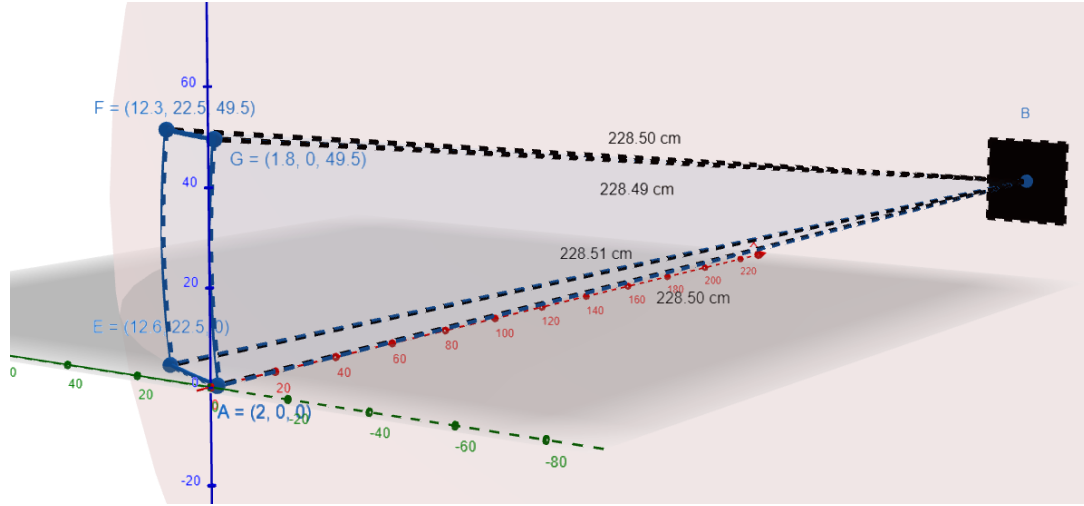
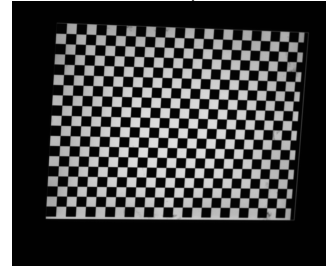
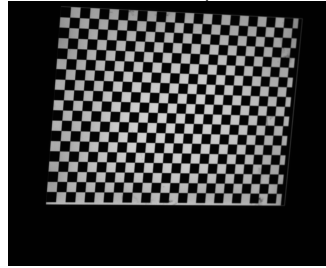


Figure 5.6: A 3D model of Spherical coordinate system [90]

(123.mm, 225mm, 495mm, 0°, 51.42°, (17.48mm, 0mm, 495mm, 0°, 51.42°, 77.27°)



(125.59mm, 225mm, 0mm, 0°, 38°, 73.28°)

(20mm, 0mm, 0mm, 0°, 0.38°, 67°)

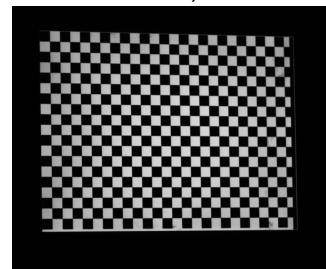
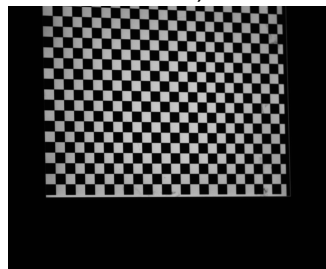


Figure 5.7: The images of the Spherical points of CB-40 Pixel (X-trans, Y-trans, Z-trans, X-rot, Y-rot, Z-rot)

As depicted in Figure 5.7, it is evident that all the camera-captured images exhibit a sharp focus when employing the spherical coordinate system. This highlights the

substantial impact of the choice of coordinate system on the quality of captured images. In this regard, the spherical coordinate system emerges as a superior option to the Cartesian coordinate system. Its distinct advantage lies in its capacity to more accurately capture the natural perspectives and distortions encountered by cameras. This results in images of higher quality, making it an advantageous choice for image reconstruction.

5.3.3 Influence of the coordinate system

In the comparative study of coordinate systems, namely the Cartesian and spherical coordinate systems, the impact of camera motion on the quality of reconstructed images is examined while comparisons between these coordinate systems are drawn. To conduct this assessment, we employed a checkerboard pattern, a commonly used calibration target in computer vision, containing 40 pixels. We chose this pattern for its ability to provide a high-contrast, easily detectable image for the camera to capture. We then proceeded to capture 50 images of this pattern using spherical coordinates, subsequently reconstructing them. In parallel, we captured another set of 50 images of the same object but with camera movements confined to Cartesian coordinates, and these images were also reconstructed.

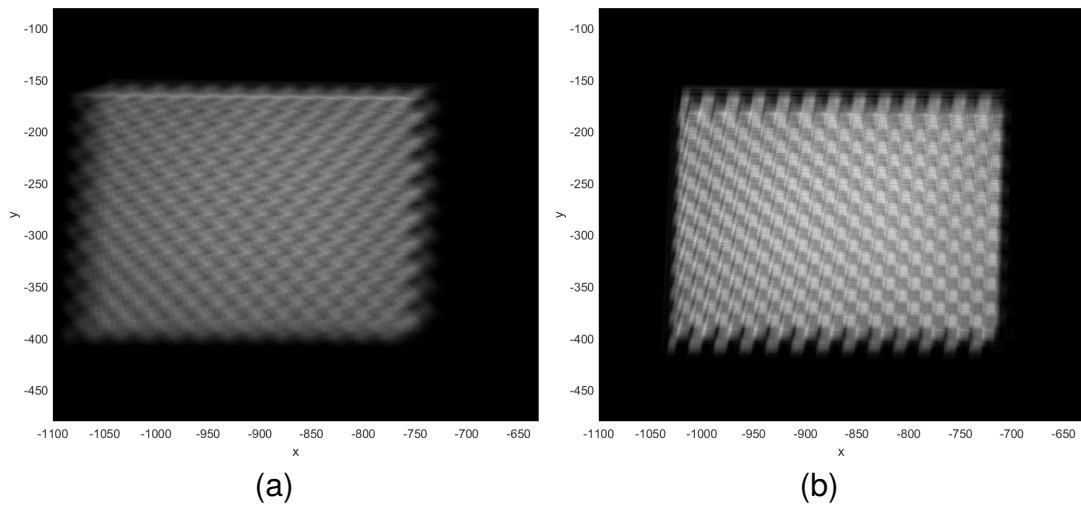


Figure 5.8: *Reconstructed checkerboard of 40 pixels in Cartesian (a); Spherical coordinates system (b)*

Figure 5.8 vividly illustrates the ramifications of camera motion on the quality of the reconstructed images when both spherical and Cartesian coordinate systems were utilized. It becomes abundantly clear that the choice of coordinate system exerts a significant influence over the resulting quality of the reconstructed images. The

image plane in Cartesian coordinates has contrast values, $\text{contrast1} = 0.19$ and $\text{contrast2} = 0.41$, whereas the spherical coordinate system has $\text{contrast1} = 0.51$ and $\text{contrast2} = 0.69$. This insight underscores the importance of selecting the appropriate coordinate system to achieve optimal image quality in various imaging scenarios.

5.3.4 Influence of the number of images

In the study, a distinctive pattern comprising vertical black and white lines with a pixel resolution of 16 was used. It served as a basis for comparing five distinct groups. In particular, all images were captured while the camera was in motion within spherical coordinates. The crux of the investigation lies in understanding the pivotal role that the number of images plays in image reconstruction quality. Figure 5.9 encapsulates this phenomenon, showcasing varying levels of image quality after reconstructing the same object across a different number of images. Specifically, the visual quality of the reconstructed images gradually increases from the group with 10 images to the group with 50 images. This underscored the profound influence that the quantity of images exerts on the quality of the reconstructed images, emphasizing the paramount importance of the number of images in the reconstruction process.

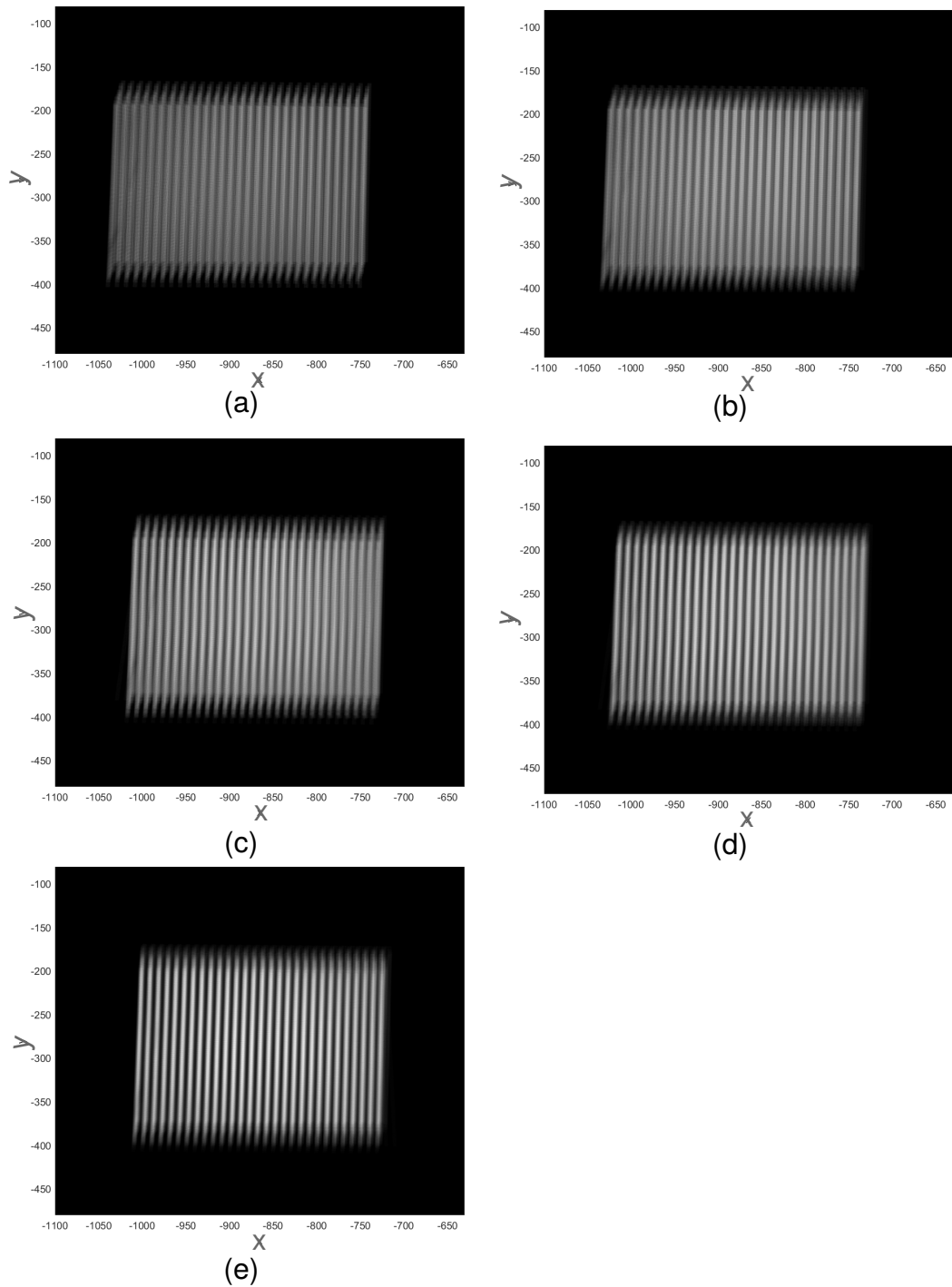


Figure 5.9: Image reconstruction of vertical line pair with 10 Images (a); 20 Images (b); 30 Images (c); 40 Images (d); 50 Images (e)

To go deeper into this phenomenon, we thoroughly analyzed the contrast plots shown in Figure 5.10, which allowed us to discern and quantify the direct impact of the number of reconstructed images on image quality. This analysis offers

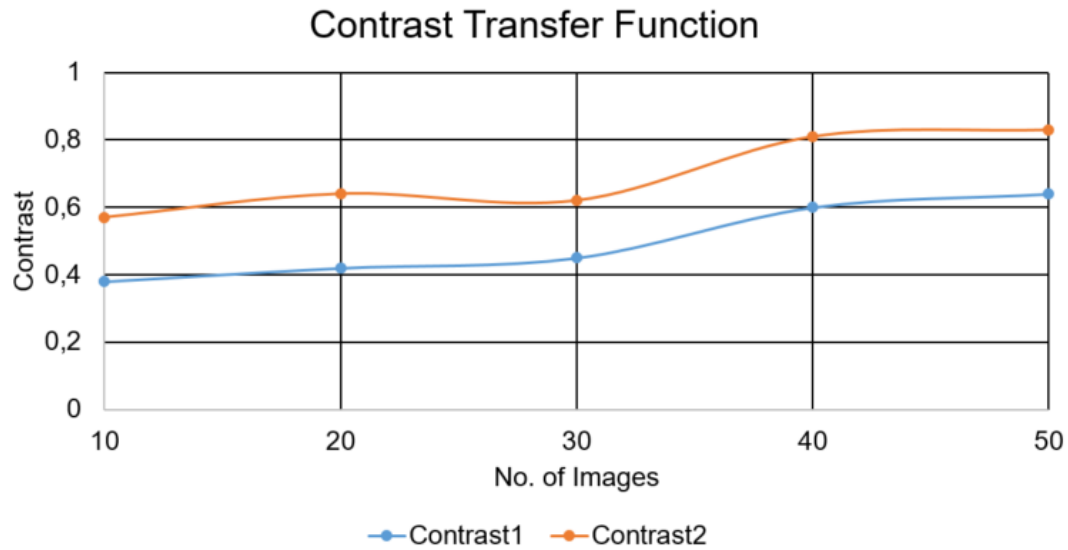


Figure 5.10: Contrast of vertical line pair with varying no. of images

insight into the relationship between image quantity and reconstruction quality, providing a foundation for making informed decisions in various imaging scenarios. Recognizing this dependency, 50 images were deemed an appropriate reference point for subsequent analysis.

6 Validating Contrast Measurement

The previous Chapter, From Pixels to Perception: Understanding Contrast in Visual Systems, introduced the importance and relevance of contrast measurements. The following chapter expands on the critical aspect of validating contrast measurement techniques. It begins by examining the use of real- and virtual-monitor images to assess contrast performance. Subsequently, it explores various methods for plane identification, including a comparative analysis of line-pair, checkerboard, and dot patterns. The methods for identifying planes within images are crucial for accurate contrast measurement. The chapter further discusses the application of these techniques to head-up displays.

6.1 Display Monitor Real Image

To evaluate the contrast performance of the experimental setup, tests were conducted using a simple test pattern displayed on the test setup monitor. The test pattern consisted of line pair patterns with different thicknesses, namely 32 pixels, 16 pixels, 8 pixels, 4 pixels, and 2 pixels. These patterns can be seen in Figures 6.1(a) and 6.2 (a), respectively. To begin the evaluation process, we created light field data by capturing images from multiple views using a camera. Subsequently, we reconstructed the light field images from the acquired data. As per the technical setup, the line pair pattern was aligned parallel to the camera sensor plane. Figure 6.3 presents the reconstructed light field image volume, showcasing both horizontal and vertical line pairs. The image volume was divided into 140 slices to identify the optimal image plane for further processing. We carefully analyzed these slices and determined the most suitable image plane. The ideal image slice, depicted in Figures 6.1(b) and 6.2(b), corresponds to each line pair pattern with varying thicknesses. This comprehensive evaluation utilizing the line pair patterns and light field image volume reconstruction analysis allows assessment of the contrast performance of the experimental setup. The findings obtained from this process will serve as a foundation for further analysis and interpretation of the experimental results.

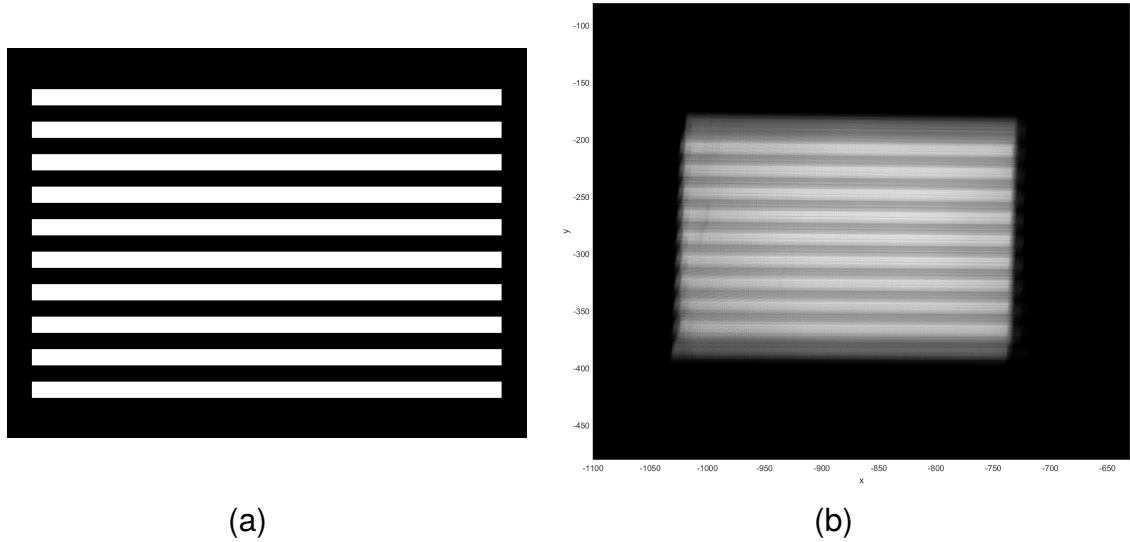


Figure 6.1: *Horizontal Line Pair Pattern 32 pixels original (a); Example of a reconstructed image slice at 2125 mm (b)*

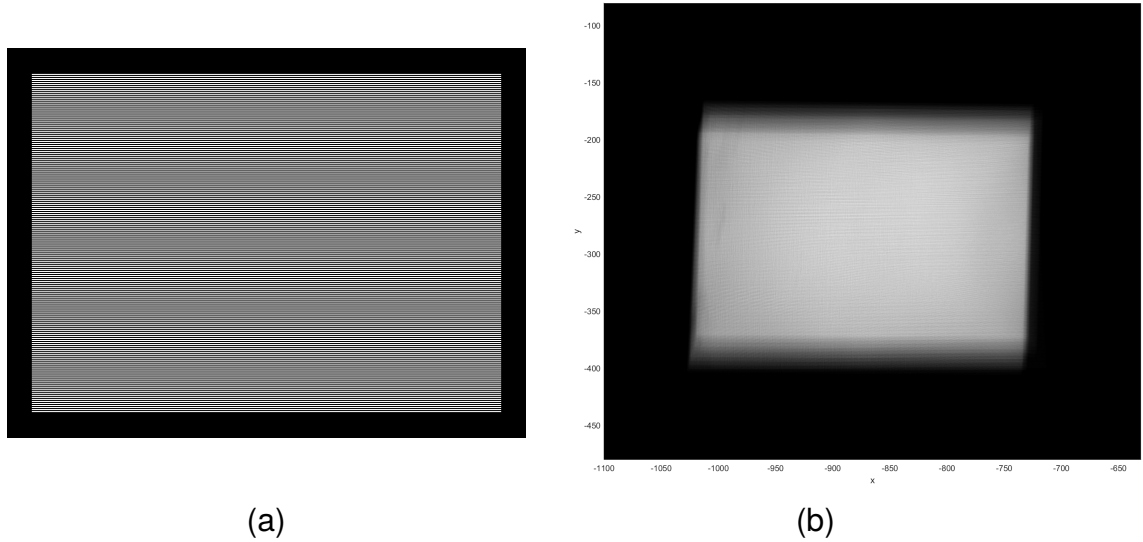


Figure 6.2: *Horizontal Line Pair Pattern 2 pixels original (a); Example of a reconstructed image slice at 2125 mm (b)*

In addition to the horizontal line pair test pattern discussed earlier, we also utilized a vertical line pair test pattern, as illustrated in Figures 6.4(a) and 6.5(a). This allowed us to measure both the horizontal and vertical contrast of the light field reconstructed images. We performed intensity measurements vertically from left to right to calculate the contrast in the horizontal line test pattern. Similarly, we performed intensity measurements horizontally from top to bottom for the vertical line test pattern. This process was repeated for all slices in the image volume. By incorporating both horizontal and vertical line pair test patterns, we

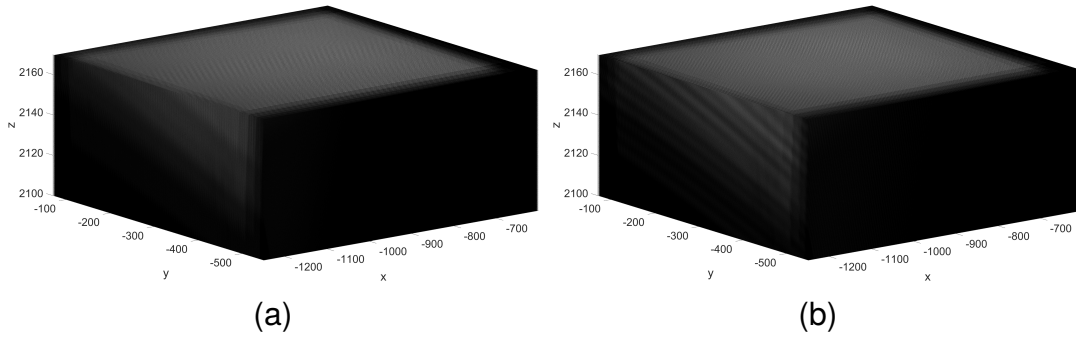


Figure 6.3: Light field reconstructed Line pair Horizontal volume (a); Vertical volume (b)

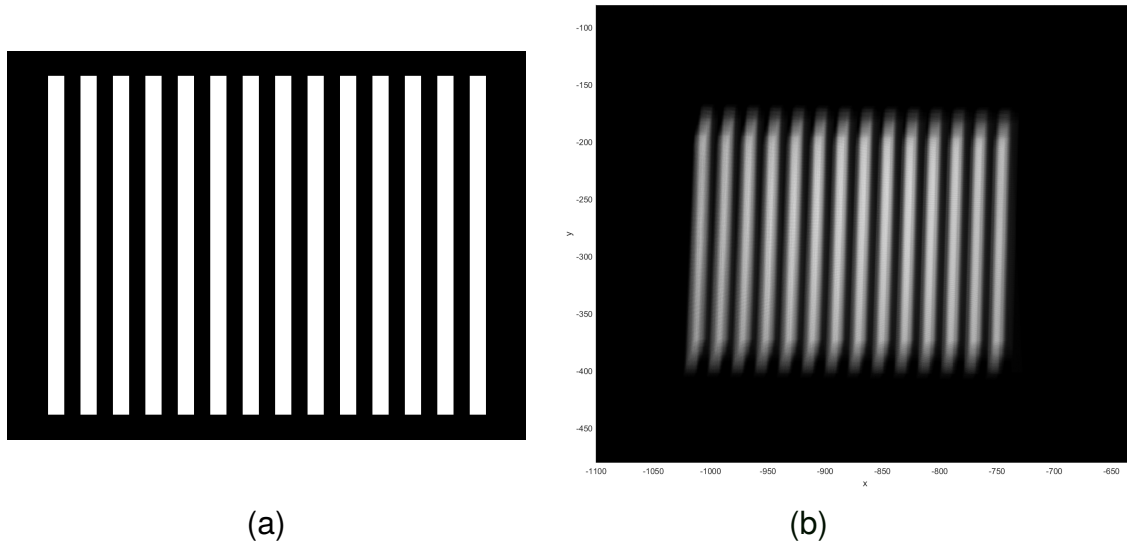


Figure 6.4: Vertical Line Pair Pattern 32 pixels original (a); Example of a reconstructed image slice at 2125 mm (b)

could comprehensively evaluate the contrast characteristics of the reconstructed light field images. The intensity calculations along different orientations provided valuable insights into the contrast performance in horizontal and vertical directions. These measurements contribute to the understanding of the overall quality and characteristics of the light field reconstruction process.

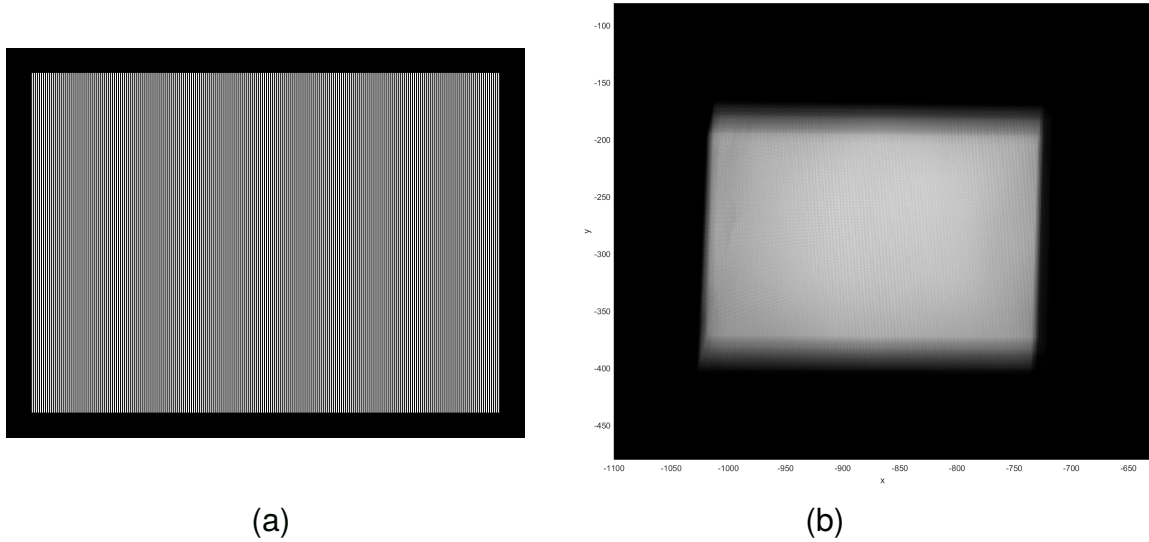


Figure 6.5: *Vertical Line Pair Pattern 2 pixels original (a); Example of a reconstructed image slice at 2125 mm (b)*

6.2 Measuring Contrast in Light Field Reconstructed Images

Prior to quantifying the contrast of the light field reconstructed images, it was important to assess the brightness variation within the images. Figure 6.6 visualizes the method being used to analyze the amplitude and frequency of the brightness variations. It became evident that the brightness exhibited varying amplitudes and frequencies, presenting a challenge in calculating simple contrast variations across the reconstructed image.

We introduced a fitting algorithm to address the challenge of brightness variations and develop a more comprehensive approach to contrast measurement. This algorithm, with its adaptability to changing amplitude and frequency characteristics, reassures us of the robustness of the research. We could use this fitting algorithm to judge the contrast more effectively, providing a more generalized contrast transfer function (CTF) approach than traditional contrast measurement techniques. Incorporating the fitting algorithm enabled us to capture the complex nature of brightness variations and extract meaningful contrast information. This approach allowed for a more accurate and robust assessment of contrast performance in the light field reconstructed images. The optimized curve fitting equation is shown in the following equation.

$$F = a \cdot \sin(2 \cdot \pi \cdot f \cdot x + \phi) + m \cdot x + c$$

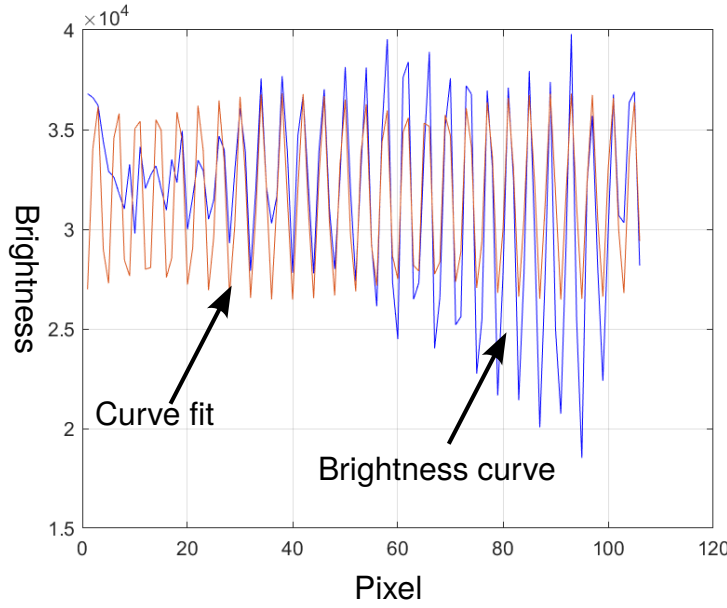


Figure 6.6: Example of a brightness variation across line pair pattern before curve fitting and after curve fitting

F = curve fit; a = amplitude; f = frequency; ϕ = phase; m = slope; c = offset

To ensure precise results, optimal starting points were established for the core parameters, explained in detail in the appendix 'Optimizing Curve Fitting for Brightness Analysis', which provides a comprehensive guide to the curve fitting process. Once the optimal curve fit, as depicted in Figure 6.6, was obtained for the brightness variation, we proceeded with the contrast calculation. In Figures 6.7 and 6.8, we introduced two contrast metrics, namely Contrast1 and Contrast2, defined as follows:

Contrast1: This metric was calculated by dividing the amplitude of the fitted curve by the offset. It provides a measure of the relative variation in brightness from the baseline level. Contrast1 quantifies the ratio of the amplitude of the fitted curve to the offset, allowing us to assess the magnitude of contrast about the baseline brightness.

$$\text{Contrast1} = \frac{\text{Amplitude}}{\text{Offset}} \quad (6.1)$$

Contrast2: In this metric, the contrast was calculated using the traditional approach of considering the maximum and minimum values of the brightness variation across the image slice. Contrast2 was obtained by dividing the difference between the maximum and minimum brightness values by their sum. It represents the relative

contrast based on the range of brightness variations observed within the image slice.

$$\text{Contrast2} = \frac{\text{Max} - \text{Min}}{\text{Max} + \text{Min}} \quad (6.2)$$

Contrast1 was calculated after applying the curve fitting process to the brightness variation of the reconstructed image slice from the volume. It allows us to evaluate the fitted curve's contrast performance. On the other hand, Contrast2 was determined using a traditional approach that directly considers the maximum and minimum brightness values within the image slice.

The display monitor affixed to the test bench was characterized by a resolution of 1024 x 768 pixels, with each pixel having a size of 0.32 mm. By carefully examining the contrast performance plots and conducting multiple measurements, including the most recent ones, along with the utilization of advanced light field image reconstruction techniques, we were able to determine the maximum spatial resolution attainable. The analysis showed that the maximum spatial resolution achievable was 2 pixels, with 50 images used in the process. This implies that the display system could effectively distinguish and represent details up to the size of 2 pixels. Furthermore, this resolution translates to an angular resolution of approximately 1.03 arc minutes at a typical analysis distance of 2125 mm from the camera; the human eye's angular resolution is in this range [92]. The remaining line pair thicknesses of 32, 16, 8, and 4 pixels correspond to 33.13, 16.56, 8.28, and 2.07 arc minutes. The measurement of spatial resolution provides crucial insight into the level of detail and clarity the display system can resolve. It allows us to understand the system's capability to accurately render fine details and discern subtle differences in the displayed content. The determined spatial and angular resolutions serve as essential parameters in evaluating the performance and quality of the display system.

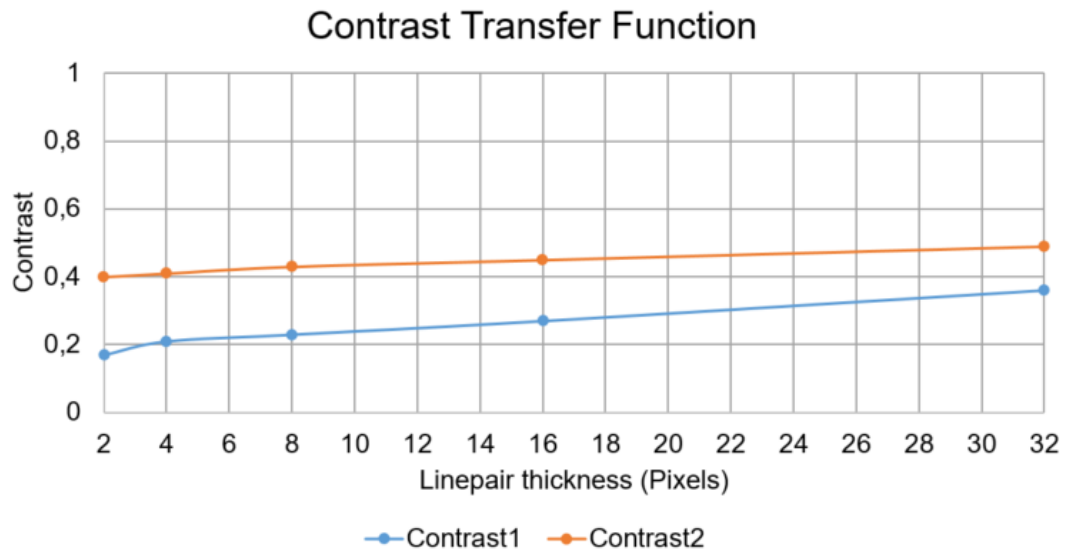


Figure 6.7: CTF of horizontal line pair pattern

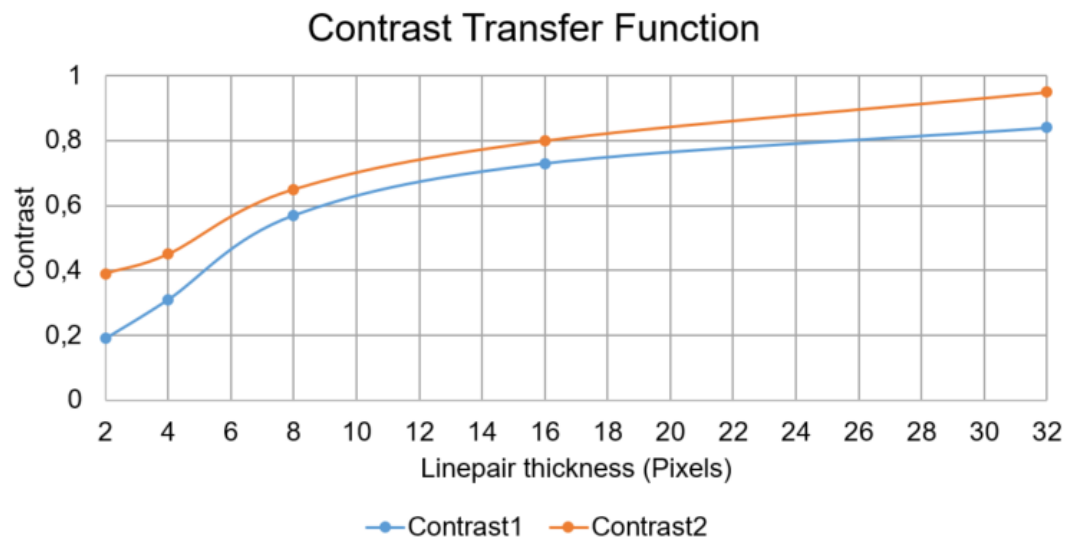


Figure 6.8: CTF of vertical line pair pattern

6.3 Methods for Plane Identification: A Comparative Analysis

With the matrix of contrast measurements now defined, we conducted a comprehensive analysis to explore the three-dimensional volume and identify the image plane. A thorough analysis, using various test patterns such as line pair, checkerboard, and dot patterns, was conducted to determine the image plane that offered the highest contrast based on performance.

6.3.1 Assessing Contrast Performance Using Line Pair Patterns

To facilitate the interpretation of the contrast data obtained from the various line pair patterns, we employed the "box plot" technique, which is known for its effectiveness in visualizing distribution and summary statistics [93]. The box plot provides key insights into the distribution of the sample data, showcasing important statistics such as the median, 25th and 75th percentiles, and potential outliers. Box plots representing the contrast values for the 4-pixel line pair pattern within the image reconstruction volume were generated by the analysis. Figures 6.9 and 6.10 depict the box plots corresponding to the image slices situated at a distance of 2100 mm to 2170 mm from the camera. These box plots offer a concise summary of the contrast distribution for each image slice. In each box plot, the top and bottom edges of the box represent the 75th and 25th percentiles, respectively, providing a visual representation of the range in which the majority of the contrast values fall. The red line within the box signifies the median, representing the central tendency of the contrast data for that particular image slice. We gained valuable insights into the distribution and variation of contrast values across the different image slices within the specified distance range by utilizing the box plot technique. This visualization technique facilitated a comprehensive understanding of the contrast performance for the 4-pixel line pair pattern and aided in identifying any potential outliers or trends within the data.

The box plot's horizontal axis is labeled "Image Volume Slice". The slices show a distance of 0.5 mm with an offset of 2100 mm. The range of values on the vertical axis, labeled "Contrast," extends from 0 to 1, denoting the contrast levels observed in the image slices. Additional visual aids were incorporated to understand the contrast distribution clearly. The "GlobalMax" indicates the maximum brightness value observed within each image slice. This metric is a reference

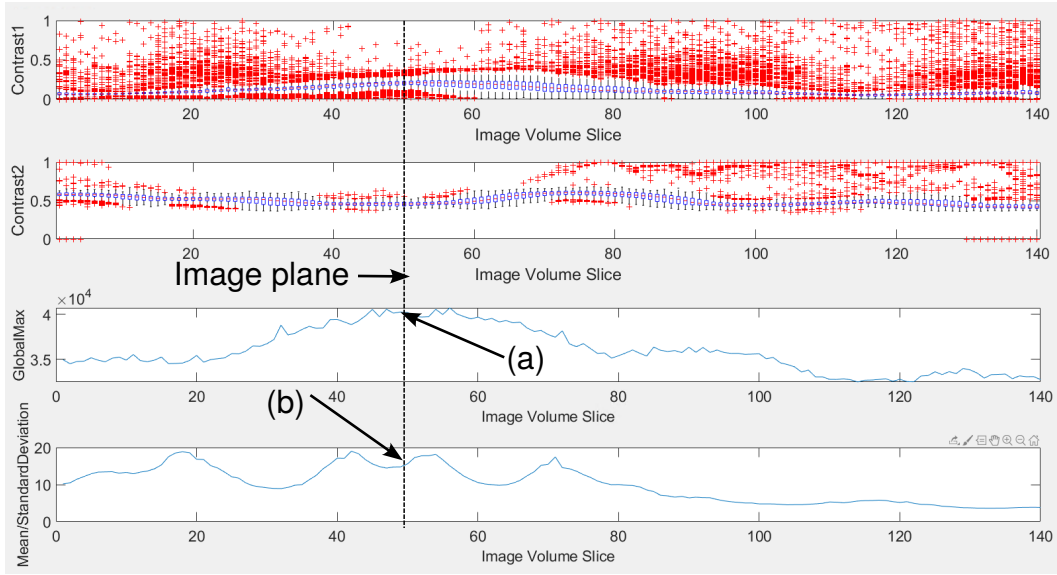


Figure 6.9: 4 Pixels line pattern contrast horizontal with Contrast, GlobalMax and Mean/StandardDeviation

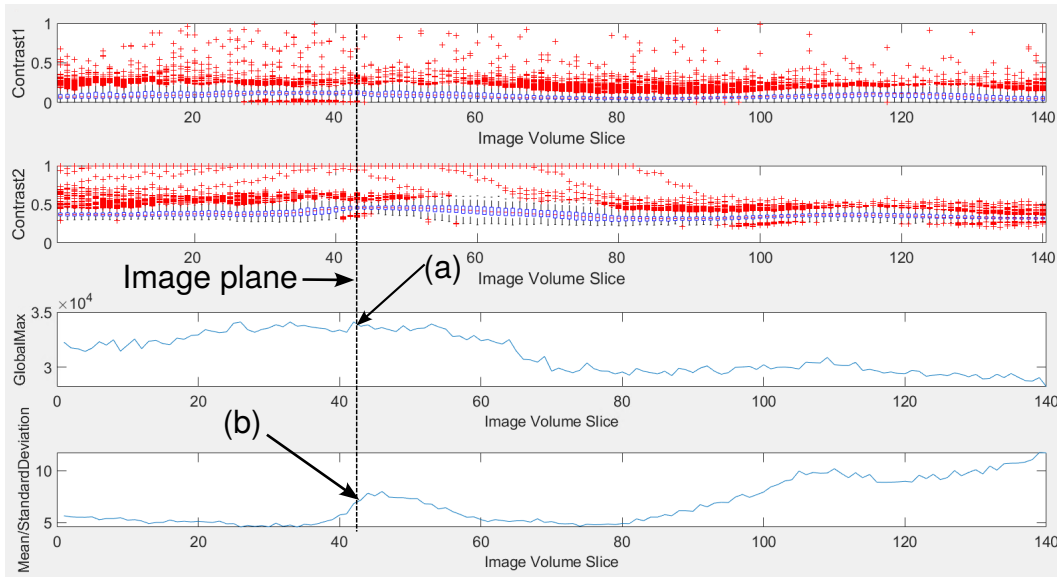


Figure 6.10: 4 Pixels line pattern contrast vertical with Contrast, GlobalMax and Mean/StandardDeviation

point for comparing the contrast performance across different slices. Moreover, the "Mean" and "Standard Deviation" provide further insights into the overall contrast characteristics. By analyzing these statistical measures, we can identify the image slice with the highest contrast across the entire image volume. This allows us to pinpoint the optimal image plane that exhibits exceptional contrast properties. In Figure 6.9 and Figure 6.10, a dotted line is plotted to indicate the image plane

with high contrast. Notably, two points labeled 'a' and 'b' are marked along the dotted line. These points correspond to the varying values observed in each plot, highlighting the specific contrast levels associated with different image slices.

6.3.2 Evaluating Contrast Performance with Checkerboard Patterns

Contrast performance measurements based on line pairs work well. However, they may show non-optimum results when applied to image planes in a non-orthogonal position to the analysis plane. Therefore, alternative methods were chosen, such as checkerboard patterns. The checkerboard pattern was used for contrast measurement. The measurements were conducted using two different setups: one with the display monitor parallel to the camera sensor plane and the other with the display monitor inclined at an angle to the camera sensor plane. This allowed us to evaluate the impact of the image plane orientation on the contrast performance. In the parallel setup (Figure 6.12), a checkerboard pattern consisting of square tiles with a resolution of 40x40 pixels was displayed on the monitor. Light field data was generated from the images captured by the LMK camera. This process was repeated in the inclined setup (Figure 6.14), where the image plane (the screen view) was inclined to the camera sensor plane. The checkerboard image volume was reconstructed using an appropriate algorithm from the acquired light field data. To measure the contrast, a pattern recognition algorithm was developed to detect the corners of the checkerboard on the image slices within the reconstructed volume (Figure 6.11). Once the corners were identified, a specific part of the checkerboard called a "tile" was selected for the contrast calculation. The tile comprises a pair of black and white squares. Similarly to the analysis performed on the line pair patterns, a contrast analysis was conducted on the checkerboard pattern, considering both horizontal and vertical lines. In Figure 6.11, the blue line represents the contrast value across the tile. This contrast value was determined by evaluating the intensity variation between the black and white squares. Combining the contrast measurements from both the horizontal and vertical lines, the analysis was extended to the next pair of squares in the pattern and subsequently across the entire reconstructed image, providing a comprehensive assessment of the contrast performance. This approach allowed us to evaluate the contrast characteristics of the checkerboard pattern under different image plane orientations. The analysis of contrast across the tile provided valuable insight into the contrast performance of the checkerboard pattern, enabling us to assess its suitability for contrast measurement in the experimental setup.

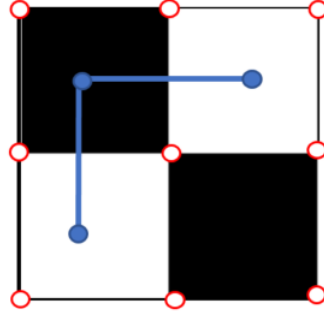


Figure 6.11: *Checkerboard corner detection*

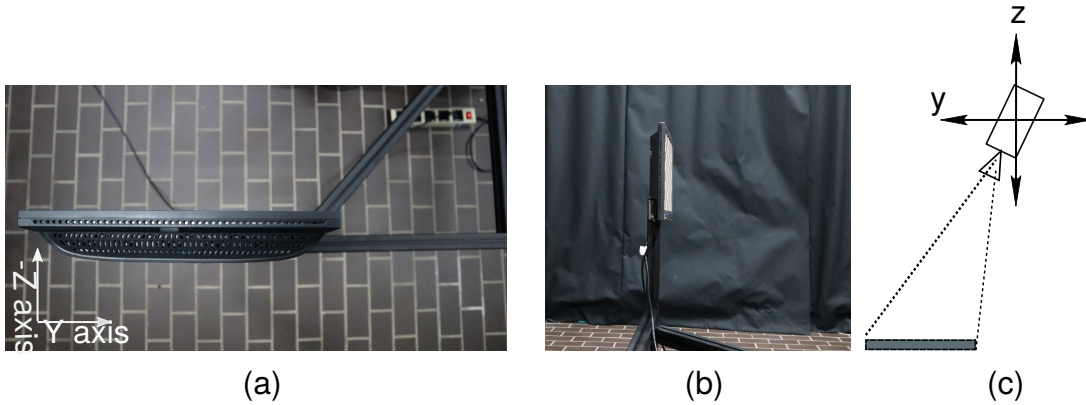


Figure 6.12: *Display monitor straight Top view (a); Side view (b); Path diagram (c)*

The reconstructed light field images are shown in Figures 6.13 and 6.15, offering valuable contrast maps that effectively distinguish the orientation of both straight and inclined display monitors. Through meticulous analysis of these plots, we can precisely determine the position of the display monitor in both parallel and inclined configurations. For instance, in Figure 6.13, the image plane of the straight display monitor is identified at a distance of 2150 mm. On the other hand, in Figure 6.15, the inclined display monitor exhibits one corner positioned at a distance of 2100 mm from the camera plane, while the other corner is at a distance of 2170 mm. It is worth noting that the surface fitting applied to the contrast data may reveal certain irregularities. Some data points deviate from the fitted surface. These outliers are highlighted with a dotted line box. A robust algorithm is necessary to accurately distinguish between the noise and original data points of the contrast to address this issue. This algorithm ensures the proper density of data points and maintains the continuity of the surface. We can obtain a more reliable representation of the contrast distribution by effectively identifying and eliminating noise. The contrast measurements obtained from the reconstructed light field images enable us to study the image plane of a target in greater detail. Furthermore, these measurements

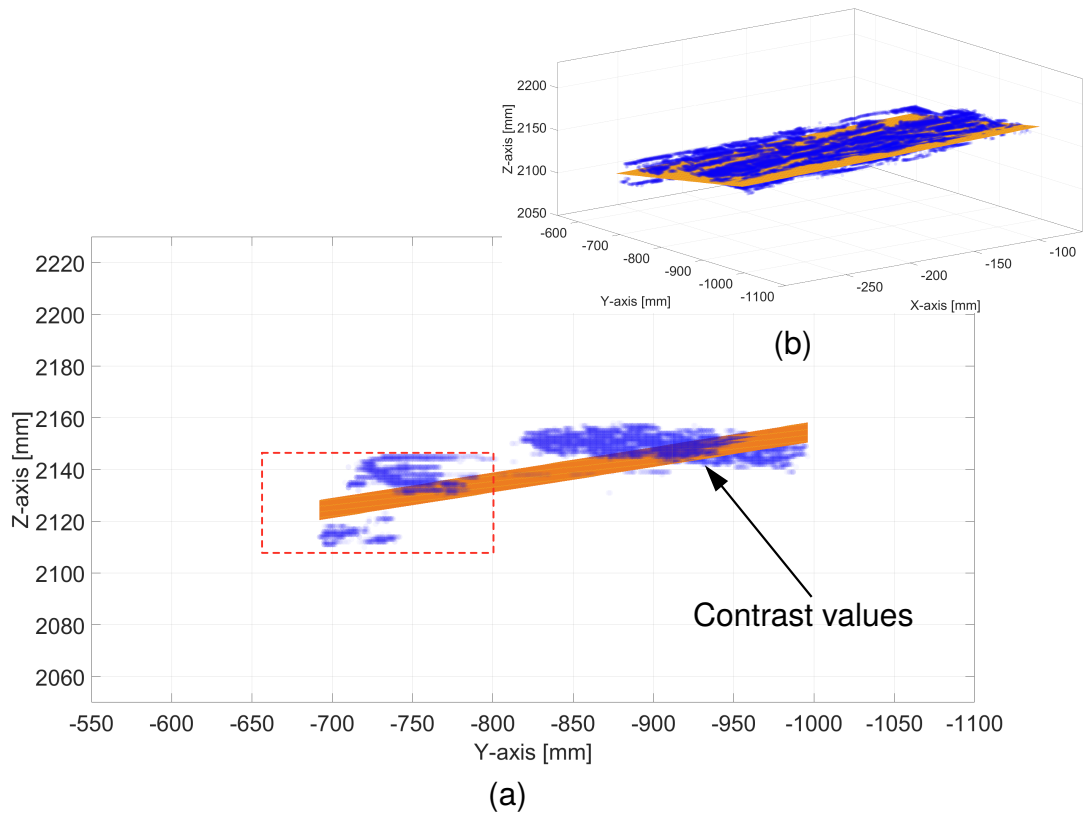


Figure 6.13: Display monitor straight surface fitting (a) YZ-plane view; (b) 3-Dimensional view

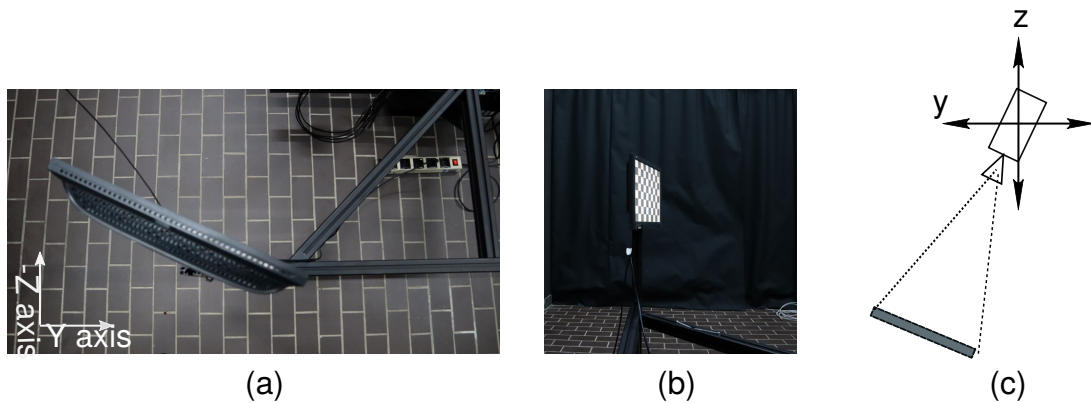


Figure 6.14: Display monitor inclined Top view (a); Side view (b); Path diagram (c)

facilitate discussions on topics such as the deviation of virtual images in augmented reality head-up displays from their actual positions. By and large, the contrast maps generated from the reconstructed light field images serve as a valuable tool for identifying and studying the position of display monitors in different orientations.

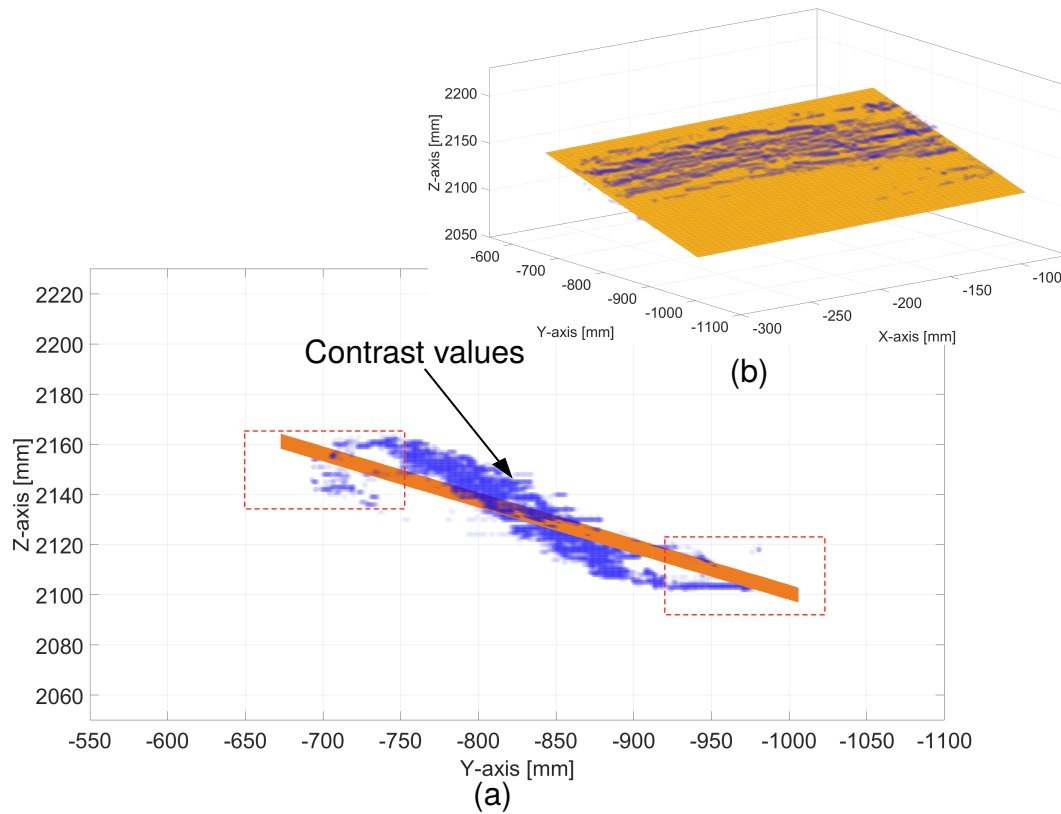


Figure 6.15: *Display monitor inclined surface fitting (a) YZ-plane view; (b) 3-Dimensional view*

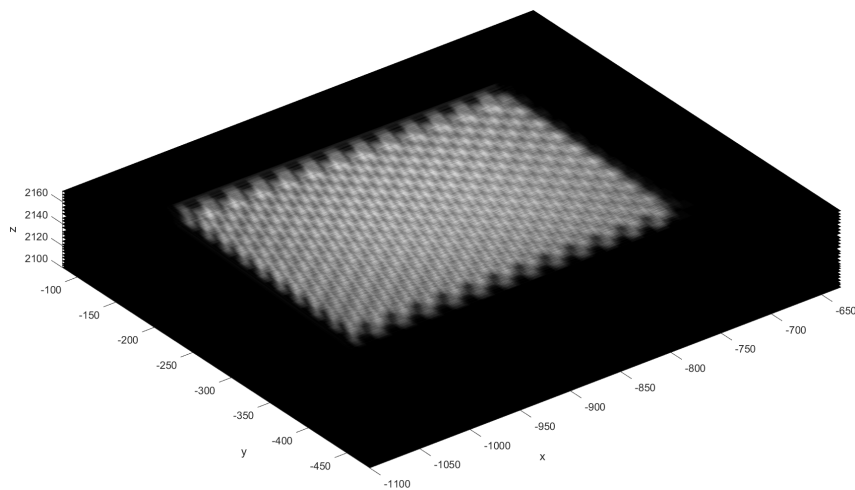


Figure 6.16: *Checkerboard pattern light field reconstructed image volume*

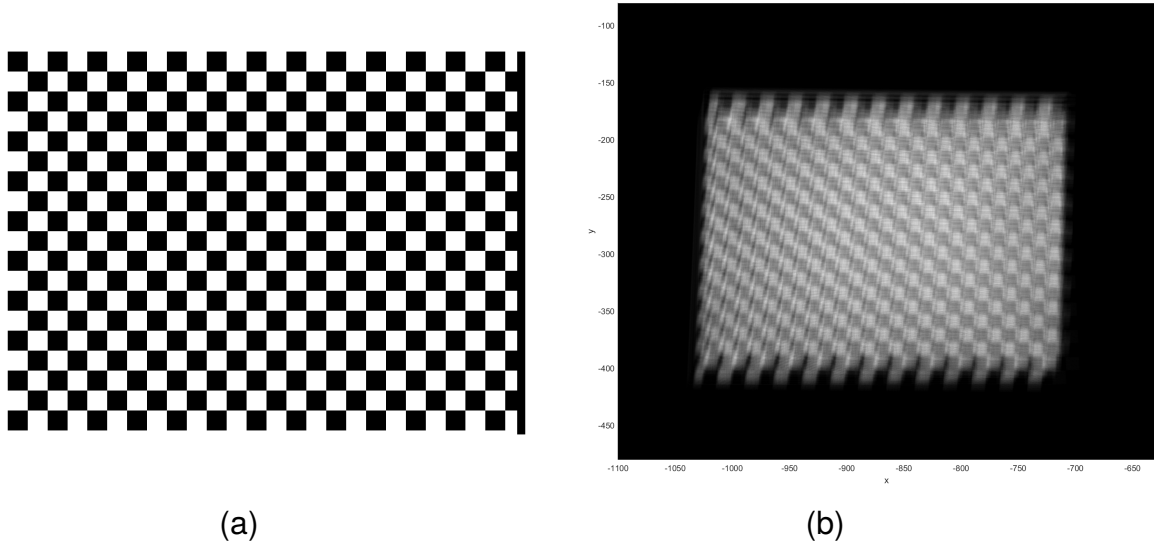


Figure 6.17: Checkerboard pattern with 40x40 pixels resolution (a); Example of a reconstructed image slice at 2125 mm (b)

6.3.3 Quantifying Distortion Using Dot Patterns

In the previous sections, we utilized real image test patterns, such as line pair patterns and checkerboard patterns displayed on the monitor to measure and identify three-dimensional distortion. Additionally, we employed real images of dot patterns to validate and determine the high-brightness image plane in the light field reconstruction volume data. The dot pattern was also inclined and straight to the camera plane, similar to the checkerboard pattern. The resulting surface-fitted image plane, derived from the intensity values of the dot pattern, resembles the display monitor's orientation, demonstrating its effectiveness for both checkerboard and dot pattern real images. Therefore, in the pattern recognition and 3D distorted image plane identification process, the checkerboard pattern was utilized and dot patterns were introduced for contrast measurement to better account for distortions and apply more robust algorithms. Dot patterns are commonly employed in image quality measurement techniques, such as optical distortion, where the dots undergo magnification or demagnification when moving diagonally from the center to the corner of the image [94]. The dot pattern holds significant importance in assessing image quality; a single high-magnification image is captured using a line-scan camera through a novel approach to dot placement analysis. This captured image is then subjected to meticulous analysis, employing the principles of rigid body rotation to precisely match the actual dot positions with a predefined template of expected positions. This method makes the evaluation of dot placement errors rapid and accurate. The dot pattern is a critical image quality indicator, enabling an efficient and reliable assessment in this innovative approach [95].

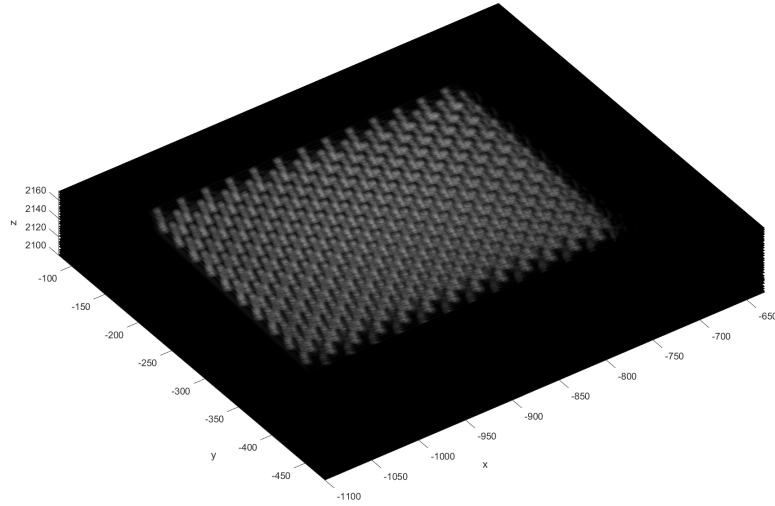


Figure 6.18: *Dot pattern light field reconstructed image volume*

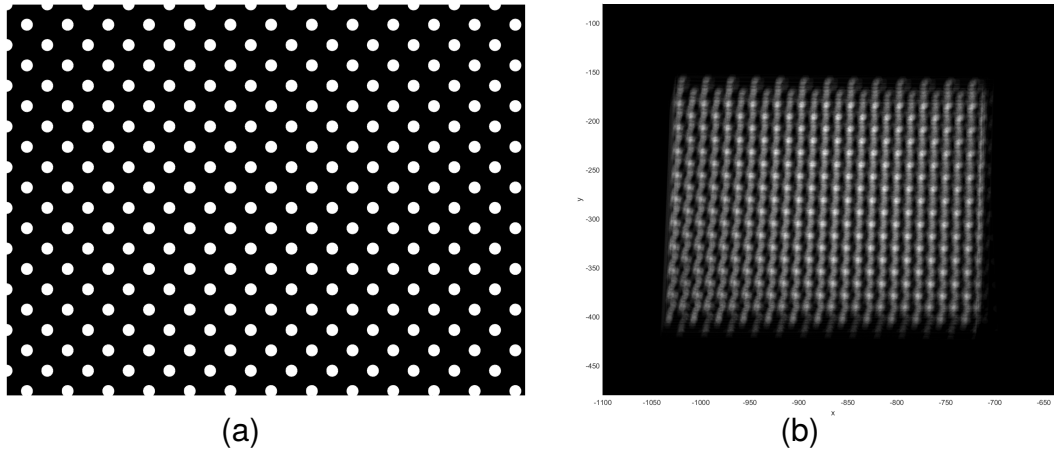


Figure 6.19: *Dot pattern with a radius 10 pixels resolution (a); Example of a reconstructed image slice at 2125 mm (b)*

To ensure a fair and equal comparison, we designed the dot pattern in a way that the white circle centers of the dot pattern align or correspond to the white square centers in the checkerboard pattern, as shown in Figure 6.19 (a). This alignment is crucial as it allows for a direct comparison between the two patterns, ensuring that any differences in the measurements are due to the patterns themselves and not their alignment.

6.4 Display Monitor Virtual Image

Incorporating contrast measurement and reconstructing the plane's position, the research further advanced to measure a virtual image. The primary objective was to discern and analyze the distorted shape in the virtual images produced by projection systems such as HUD, VR, and AR devices. This investigation is pivotal in understanding the limitations and potential improvements needed to enhance these immersive technologies' image quality and user experience. By detecting and analyzing the shape of distortion in virtual images, this approach not only aids in identifying potential aberrations but also paves the way for optimizing the performance of these advanced imaging technologies. This, in turn, holds the promise of more immersive and visually captivating experiences for users, instilling hope for future advancements in imaging technologies.

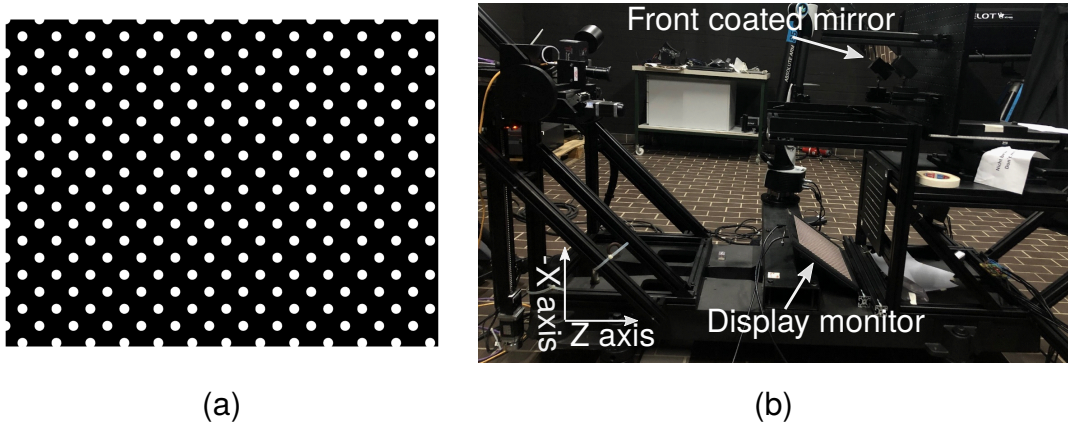


Figure 6.20: *Dot pattern (a); Experimental set-up with a dot pattern on display (b)*

In Figure 6.20 (b), a dot pattern was displayed as an image on a display monitor positioned at the base of a test bench, and, by reflection through the mirror, it appeared to the camera as a virtual image. The camera captured virtual images reflected from the front-coated mirror, and the resulting light field data were utilized to reconstruct a high-resolution light field image. The voxel size of the reconstructed light field volume is 0.2 mm along each axis [96]. Through analysis, we searched for the position of the highest intensity within the volume, and the results were satisfactory. As shown in Figure 6.20 (b), one edge of the monitor display is observed to be 120 mm closer and 29.24 degrees of rotation in the Y-axis to the front-coated glass mirror. When the surface fitting was applied to the light field volume reconstruction, as depicted in Figure 6.21, the resulting image exhibited a fitted image plane that closely resembled the orientation of the display monitor with an uncertainty of 0.19 degrees and 60 mm in displacement observed in Figure 6.20(b). This outcome confirms that the target image plane can also be

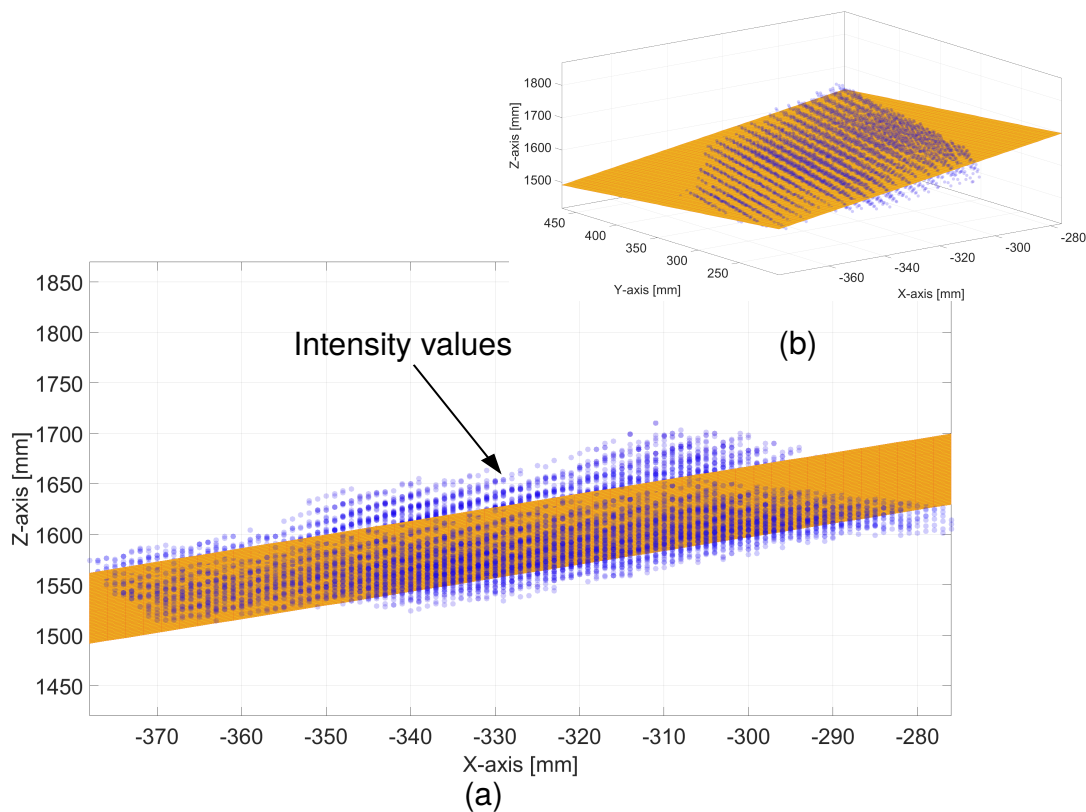


Figure 6.21: *Dot pattern virtual image surface fitting (a) XZ-plane view; (b) 3-Dimensional view*

identified in virtual images. This understanding enables better comprehension of how virtual images are perceived and displayed under various circumstances, ultimately enhancing comprehension of their impact on virtual image display.

6.5 Head-up Display

After conducting a comprehensive evaluation of real images displayed on the monitor using various test patterns, such as line pair, checkerboard, and dot pattern, the next step involved a thorough assessment of the performance of virtual images at a known virtual image distance (VID), as depicted in Figure 6.20. Following the successful completion of the virtual image evaluation, the focus now shifts to the Head-Up Display (HUD) performance assessment using the same test patterns employed earlier. The laboratory HUD, equipped with a picture generation unit (PGU) of 1.8" and a resolution of 480x240 pixels, has a VID in the range of 2 meters. The evaluation of HUD performance with these test patterns is crucial to

determining the quality and accuracy of the displayed information and to ensure an enhanced user experience with this advanced technology.

As shown in the experimental setup in Chapter 3: **Test Setup**, the HUD was arranged to project virtual images. This setup uses a front-coated plane mirror with dimensions 300x300 mm instead of a windshield. The choice of using a front-coated mirror is not arbitrary; it is a deliberate decision made to understand the 3D distortion of the HUD on a plane mirror before considering the actual curved windshield. The HUDs are designed to project virtual images only on the curved windshield instead of a plane glass plate. So, the virtual image projection on the front-coated plane mirror will have an image deviation, but this was a well-thought-out decision process before purchasing the mirror. This initial aim was to observe the 3D distortion of the HUD on the plane mirror, a crucial step in understanding the impact of different projection surfaces on the HUD's performance.

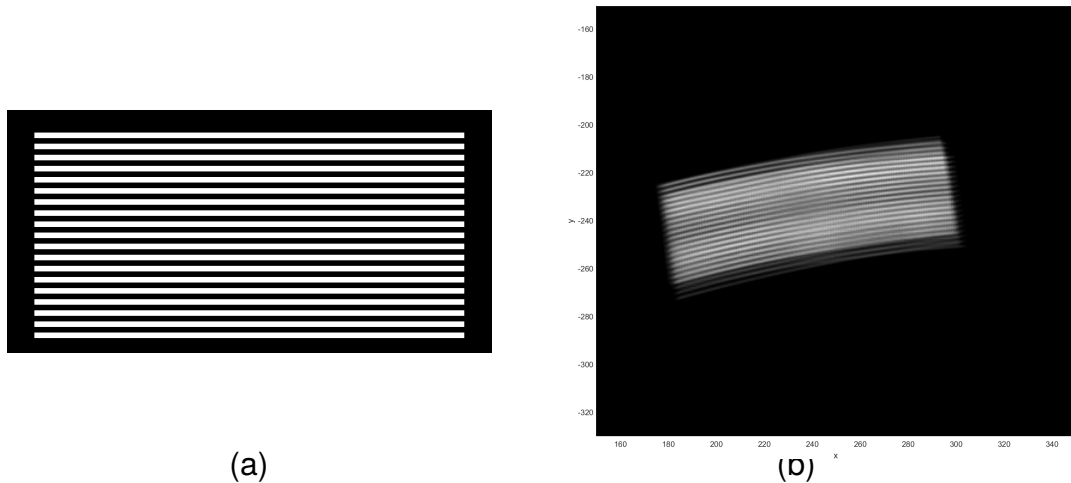


Figure 6.22: HUD Horizontal Line pair 16 pixels resolution - Test pattern (a); Example of a reconstructed image slice (b)

During the calibration of the HUD, the images were captured in a Cartesian coordinate system instead of a spherical coordinate system. In contrast, the projected virtual image of the HUD has a varying image plane. The horizontal and vertical line pair patterns with 16-pixel resolution, as shown in Figures 6.22 and 6.23, are projected from the HUD. The LMK camera was moved to different orientations within the eye-box scan limits to capture the virtual image. In the reconstructed light field images, different image slices of the image volume were shown to identify the sharp image plane. The image slices have a resolution of 0.5 x 0.5 pixels in the XY-plane and 0.5 pixels in the Z-plane, and we can observe that it is difficult to notice that one image slice of the volume has an image sharpness over the complete image in the XY-plane. In contrast, different regions of the image slices have the image sharpness. The horizontal line pair pattern has contrast values

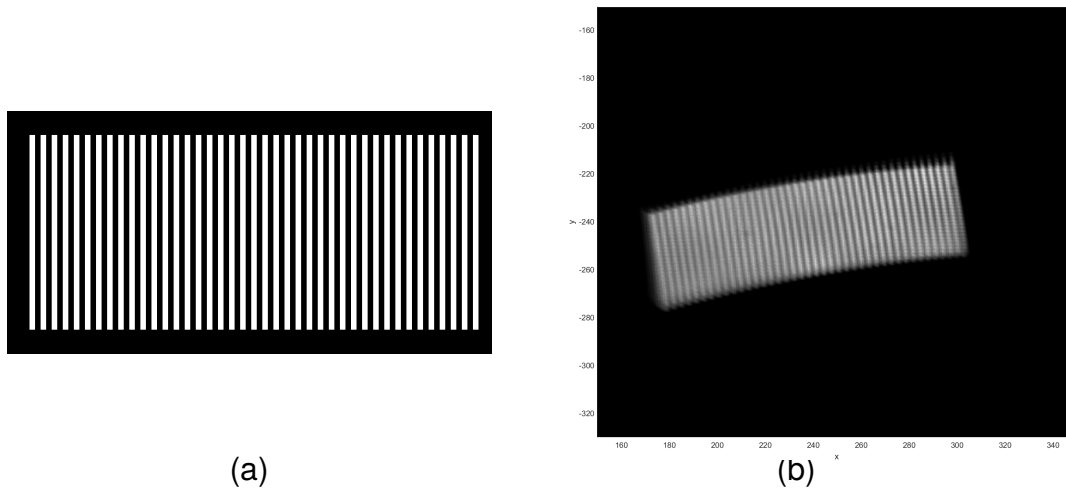


Figure 6.23: HUD Vertical Line pair 16 pixels resolution - Test pattern (a); Example of a reconstructed image slice (b)

like $\text{contrast1} = 0.21$ and $\text{contrast2} = 0.46$, while the vertical line pair pattern has contrast values like $\text{contrast1} = 0.25$ and $\text{contrast2} = 0.66$.

Head-up Display (HUD) systems commonly use checkerboard and dot patterns to assess image quality and distortion characteristics. These patterns are shown in Figures 6.24 and 6.26; they serve as test patterns that are projected onto the HUD display to evaluate its performance. The checkerboard pattern is used to assess the spatial resolution and distortion of the HUD display. When projected onto the HUD, any distortion or aberration in the display will be visible as irregularities in the squares. Analyzing the distortion in the checkerboard pattern areas where the display may need calibration or adjustment can be identified to achieve a uniform and accurate image rendering.

The dot pattern, a key element in the evaluation process, allows assessment of the HUD's contrast and brightness levels across the display. When projected onto the HUD, the dot pattern allows for a comprehensive assessment of the display's ability to reproduce different brightness levels. Any irregularities or non-uniformity in the brightness levels can be identified using the dot pattern, helping to ensure that the HUD produces clear and consistent images under different lighting conditions. By using these test patterns during the development and calibration of HUD systems, manufacturers can ensure that the displayed information is accurate, precise, and free from distortion, providing drivers with a safe and reliable augmented reality experience on the road.

From the light field reconstructed images in Figure 6.24 and 6.26, at first, we can observe that the images are distorted in the 2D-image plane; this was a foreseen result of a front-coated plane mirror being used to project a virtual image from

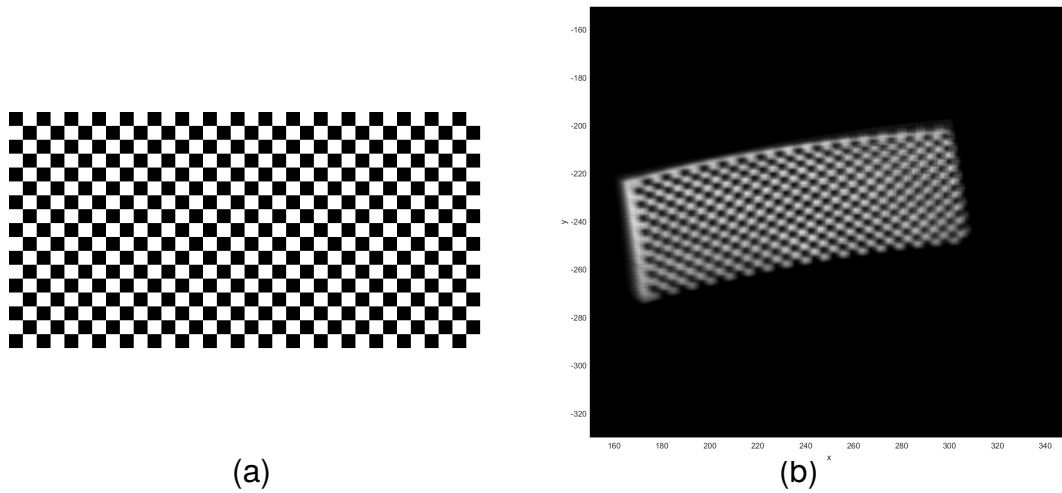


Figure 6.24: HUD Checkerboard 40 pixels resolution - Test pattern (a); Example of a reconstructed image slice (b)

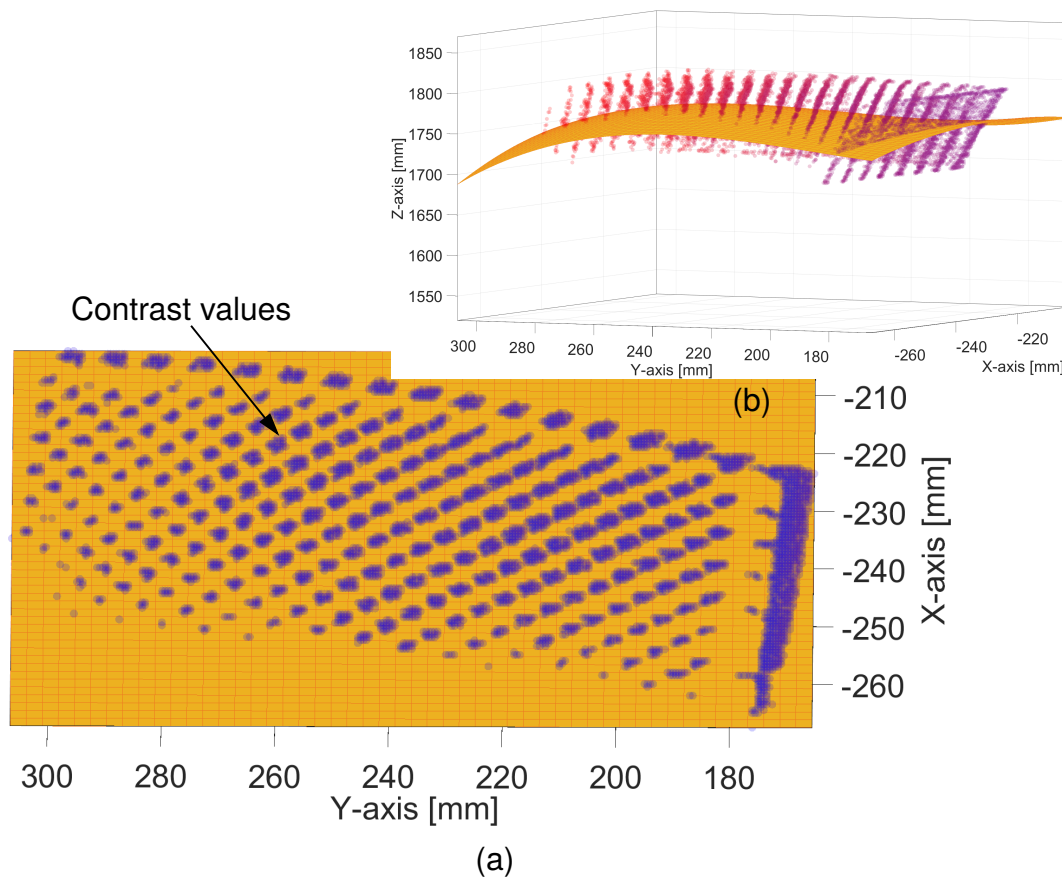


Figure 6.25: HUD projected checkerboard pattern surface fitting (a) XY-plane view; (b) 3-Dimensional view

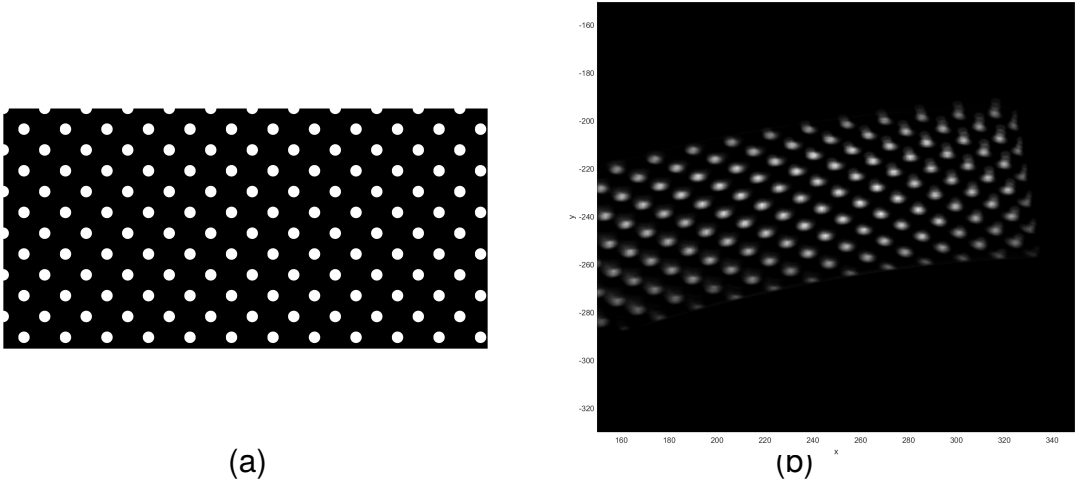


Figure 6.26: HUD Dot pattern radius 15 pixels resolution - Test pattern (a); Example of a reconstructed image slice (b)

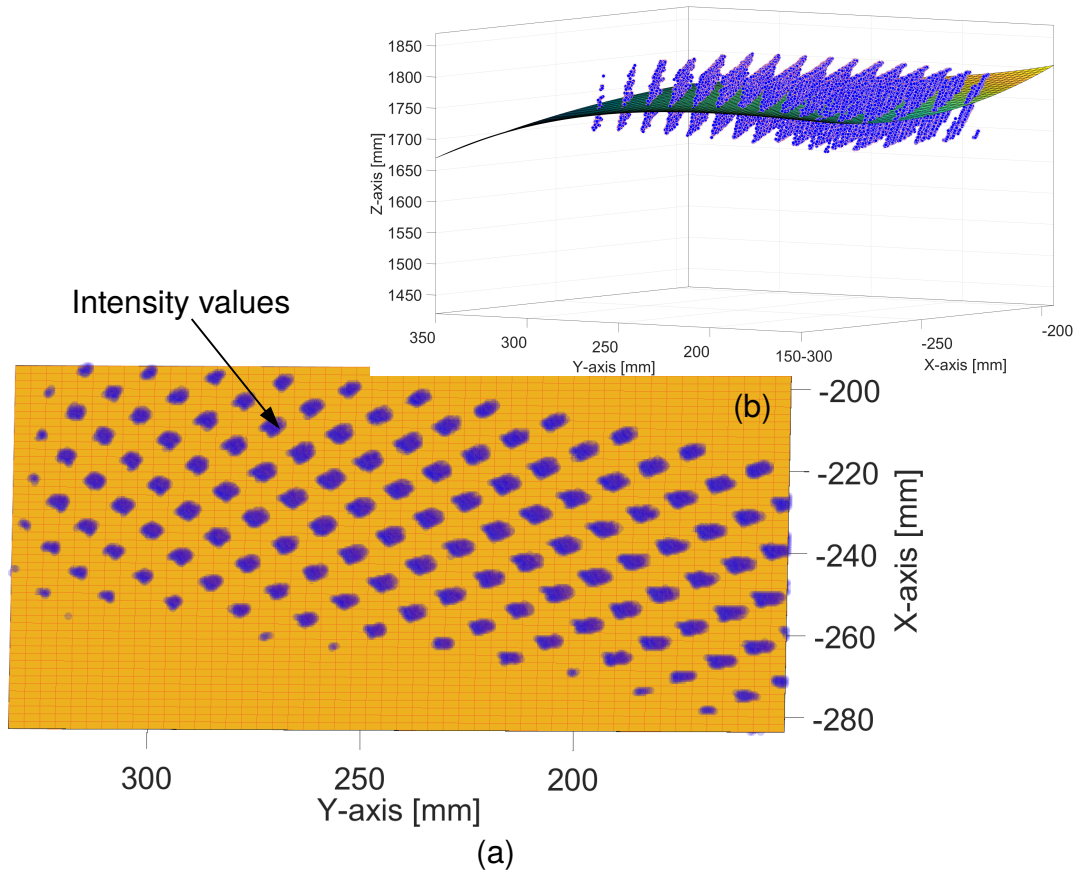


Figure 6.27: HUD projected dot pattern surface fitting (a) XY-plane view; (b) 3-Dimensional view

HUD instead of the curved windshield. The magnification on the reconstructed image slices changes when we move from the center of the image plane to the corner. HUD checkerboard has $\text{contrast1} = 0.31$ and $\text{contrast2} = 0.63$ from the reconstructed image plane.

Figures 6.25 and 6.27 present a 3D scatter plot illustrating the relationship between X, Y, and Z coordinates. X and Y define a curved trajectory within the plane, while Z increases from 1450 mm to 1850 mm along this trajectory. The fitted surface, a third-degree polynomial, closely aligns with the data points, demonstrating a robust fit and capturing the non-linear interactions between X and Y in determining Z. This visualization effectively elucidates the spatial relationships within the dataset. The virtual image plane exhibits curvature and a variable virtual image distance (VID). As a result, the left side of the image plane is farther from the XY plane than the right side, indicating that the virtual image projection of the HUD is non-linear with the provided light field data.

7 Conclusions and Outlook

Summary of System Design and Purpose: The goniophotometer test setup was designed to comprehensively characterize projection systems for human-machine interfaces (HMIs), with a particular focus on head-up displays (HUDs). The test system incorporates six degrees of freedom (6 DoF), enabling precise control over both translational movements (X_Trans, Y_Trans, Z_Trans) and rotational movements (X_Rot, Y_Rot, Z_Rot). This level of flexibility allows for accurate positioning and scanning within the eye box, ensuring a thorough and exhaustive evaluation of optical performance. A key component of the setup is an LMK camera, which captures grayscale, luminance, and color images across the entire field of view (FoV) of the HUD. The system performs a complete eye-box scan, simulating how a user perceives the virtual imagery under different viewing angles. The high-resolution movement capability of the test setup ensures measurements that closely match human visual resolution, allowing for precise characterization of display properties. The HUD under test was securely mounted on a test bench, projecting virtual images, while a display monitor was also integrated into the setup to serve as a reference for real-world images.

The entire setup was housed in a darkroom environment for measurement consistency and accuracy, minimizing both artificial and natural light interference. This controlled lighting condition significantly reduces stray light and scattering, which could otherwise impact measurement precision. To enhance repeatability and accuracy, a common reference point was established for the LMK camera before each measurement cycle. This was achieved using three sets of LED light sources mounted on the test setup; the camera was used for self-calibration and homing. By resetting to a consistent starting position, positional errors and measurement variability were minimized, leading to greater reliability and reproducibility of the results. The measurement process was fully automated, enabling the system to capture images from both the HUD and the reference display monitor without manual intervention. Automation significantly reduces human-induced errors, ensures consistency, and improves efficiency during large-scale data collection. An emergency brake mechanism was integrated into the setup for safety and system protection. This could be activated through a software-controlled button within the system interface or via a physical hardware emergency stop button, ensuring an

immediate response in case of unexpected issues or mechanical failures. Having established the physical setup and capabilities of the goniophotometer for precise HUD measurements, the next crucial step involves translating the captured images into meaningful light field data.

Camera Calibration and Light Field Construction: It is essential to determine the camera's orientation within the world coordinate system to generate light field vectors from camera-captured images. This requires accurate calibration of intrinsic and extrinsic camera parameters, defining the camera's internal characteristics (such as focal length and distortion) and its position and orientation relative to the global reference frame. A checkerboard test pattern was used to obtain these parameters, where images were captured at different orientations. The detection of checkerboard corners enabled precise computation of the camera's transformation matrix, ensuring accurate spatial alignment of the captured data. Once calibration was completed, light field data was constructed using base and light vectors. The base vector represents the position of the camera relative to the world coordinate system, serving as a reference for defining light propagation. The light vector, on the other hand, extends from the camera sensor to the displayed real image or projected virtual image, capturing both directional information and intensity values for each pixel. This dataset forms the foundation for light field reconstruction, as it encodes how light rays travel through space, facilitating three-dimensional scene interpretation. Understanding the process of constructing light field data using base and light vectors is crucial as it provides a deeper understanding of the data and its role in image reconstruction. After setting up a robust method for calibrating the camera and generating precise light field vectors, this foundational step paves the way for the subsequent reconstruction of images from the captured data.

With the aim of reconstructing images from the captured light field data, an image volume was generated using a specified voxel resolution. Optimizing the volume reconstruction process required efficient data handling techniques to minimize computation time while preserving image fidelity. A key enhancement involved identifying high-intensity or high-contrast values, allowing for targeted processing of critical image regions. Additionally, an intersecting plane concept was employed to manage computational resources efficiently. This concept involves dividing the image volume into intersecting planes, each of which can be processed independently, ensuring that the reconstruction process remains scalable for large datasets. The influence of the line weighting algorithm was analyzed to improve image reconstruction quality further. This technique refines how light rays contribute to the final reconstructed image by assigning varying levels of importance based on intensity and directional consistency. The algorithm adjustments allowed for more accurate alignment of light field vectors, reducing noise and enhancing the sharpness of the reconstructed virtual image.

In order to effectively identify a 2D image plane within a 3D space, contrast information distributed across voxels plays a crucial role, as contrast variations define the boundaries and orientation of the plane. The method utilized in this study leverages light intensity differences to pinpoint the spatial location of an image plane, where contrast serves as the origin of light. The system can extract key features that define the virtual image plane's position and orientation by analyzing how intensity values are distributed across a voxel grid. The first hypothesis is validated through the process of light field data construction and reconstruction. Since light vectors encode direction and intensity information for each pixel, a high-contrast area within the reconstructed volume corresponds to a dominant light-emitting surface; essentially, the image plane. By refining the voxel resolution and employing an intersecting plane concept, the reconstruction process prioritizes the highest contrast regions, thereby enhancing the accuracy of plane identification. This ensures the reconstructed virtual image maintains high fidelity, aligning precisely with its real-world counterpart. With the image volume successfully reconstructed from light field data, the focus shifts to evaluating the practical performance of the resulting projection systems.

Methods for Contrast Evaluation: The performance of the projection system's key metric contrast measurement was thoroughly evaluated to assess critical characteristics, including spatial resolution, contrast sensitivity, artifact detection, and display uniformity. These evaluations are essential for understanding the system's ability to render images accurately and consistently under varying conditions. A line pattern was employed to measure contrast, serving as an effective method to evaluate the display's capacity to distinguish contrast modulation and its response to spatial frequency. This approach allows for a detailed analysis of how well the system can differentiate between subtle gradations of light and dark; it is crucial for high-quality visual output in applications such as medical imaging, cinematic displays, or advanced simulations. Additionally, a checkerboard pattern, consisting of an alternating grid of black and white squares, proved to be a powerful tool for assessing the display's contrast performance. This pattern highlights the distinction between adjacent black and white squares, making it easier to identify the system's ability to maintain sharp boundaries and consistent contrast across the screen. By systematically identifying variations in contrast across different regions of the display, this method provides valuable quantitative and qualitative metrics for comparing and benchmarking the performance of different display technologies. Such comparisons are vital for optimizing system design and ensuring reliability across diverse use cases. Furthermore, dot patterns of varying sizes were utilized to evaluate display uniformity and detect low-contrast details with high sensitivity. These patterns revealed brightness and texture inconsistencies across the display, offering insights into potential manufacturing defects or operational limitations. This

illustrates the second hypothesis by demonstrating how a projection system's use of variable test patterns (lines, checkerboards, dots) enables a sophisticated contrast measurement approach. This approach provides detailed insights into the system's performance—such as distinguishing subtle contrast variations and maintaining spatial consistency—which could lead to a more accurate characterization of 3D distortions.

Influence of Coordinate Systems and Image Quantity: The investigation revealed critical factors influencing the quality of reconstructed images. Firstly, the choice of the coordinate system significantly impacts image quality. A comparative study demonstrated that spherical coordinates yielded superior contrast values to Cartesian coordinates under camera motion, highlighting the necessity of selecting an appropriate coordinate system for optimal results. Secondly, we established the profound influence of image quantity on reconstruction quality. As illustrated by the analysis of vertical line patterns captured with spherical coordinates, increasing the number of images from 10 to 50 resulted in a marked improvement in image quality. Contrast plot analysis further substantiated this direct correlation, underscoring the importance of image quantity in achieving high-fidelity reconstructions. Consequently, we determined that 50 images provided a reliable reference point for subsequent analyses. These findings collectively emphasize the crucial roles of coordinate system selection and image quantity in optimizing image reconstruction outcomes across various imaging applications. This demonstrates the validity of the third hypothesis by showing that capturing images from multiple directions enabled by spherical coordinates and camera motion benefits from increasing images, with 50 emerging as an adequate quantity for maximizing reconstruction quality.

A comprehensive approach to validating contrast measurement techniques was presented. The research began with an examination of real- and virtual-monitor images, followed by an exploration of various methods for plane identification, including a comparative analysis of line-pair, checkerboard, and dot patterns. These methods are critical for accurate contrast measurement, and their application to head-up displays was discussed. The study also evaluated the contrast performance of an experimental setup using line pair patterns with varying thicknesses, and the maximum spatial resolution was determined. A fitting algorithm was introduced to address the challenge of brightness variations in light field reconstructed images, leading to a more generalized contrast transfer function (CTF) approach. The research further advanced to measure a virtual image and discern and analyze the distorted shape present in virtual images produced by projection systems such as HUD devices. We have seen a spatial relationship between X, Y, and Z coordinates using a 3D scatter plot and fitted third-degree polynomial surface. This model demonstrates that the virtual image plane is curved with a variable virtual

image distance (VID), resulting in a non-linear virtual image projection of the HUD relative to the provided light field data. This aligns with the fourth hypothesis that by measuring contrast variations at multiple positions within an image volume, it is possible to reconstruct the spatial location of the virtual image plane, as contrast gradients in the volume serve as key indicators for estimating the precise positioning of the virtual image.

Identification of Systematic Errors and Proposed Solutions: The contrast results from the measurement system reveal significant shortcomings, including weak contrast performance and the presence of ghost-image artifacts, which compromise the quality and reliability of the imaging output. A detailed and rigorous analysis identified the root cause of the poor contrast, particularly the inadequate distinction between the boundaries of horizontal and vertical lines in the contrast images—as a systematic positioning error within the goniophotometer test setup. This error introduces inconsistencies that blur the sharp delineation necessary for accurate contrast evaluation, thereby affecting the system's ability to produce high-fidelity images. To investigate this issue, a preliminary and expedited approach referred to as a "quick and dirty" method was employed. This involved identifying the corners and centers of the images captured at various positions and orientations using the goniophotometer. We observed a critical finding by performing ray-tracing from the camera positions to these identified points: the rays did not converge at a single intersection point, even though the target distance remained constant across all camera positions. This divergence indicates a misalignment or positional inaccuracy in the test setup, directly contributing to the observed contrast degradation and ghost-image artifacts. To address this systematic positioning error, further in-depth study is required, incorporating advanced kinematics analysis to characterize the nature and magnitude of the error fully. This should include the development of both an error model and a compensation matrix to mitigate the systematic inaccuracies in the goniophotometer's positioning. Such a matrix would adjust for the positional deviations, ensuring that subsequent measurements are aligned correctly and consistently. The accuracy of the goniophotometer's home position is paramount, as it has cascading effects on the image capture process and subsequent image reconstruction. Even minor misalignment can propagate through the system, leading to compounded errors that degrade the quality of the final output. To ensure the reliability of the measurement system, extensive testing for repeatability and reproducibility must be conducted across multiple trials. These tests will help establish a strong correlation between repeated measurements, validating the consistency and accuracy of the results.

Outlook: Toward Realistic HUD Testing: In the current goniophotometer test setup, a backend reflective coated mirror is used to capture and perceive virtual images generated by the Head-Up Display (HUD). However, this configuration has

a notable limitation: the mirror's flat and parallel surfaces on both sides can lead to image ghosting, where faint duplicate images appear due to unintended reflections. In contrast, a real vehicle windshield, which serves as the projection surface in actual HUD applications, features a curved geometry that has been meticulously accounted for during the HUD's design phase to optimize image projection and clarity. To enhance the accuracy of virtual image reconstruction, we propose testing with an actual windshield instead of a plane-parallel mirror. This approach allows for a more realistic evaluation of HUD performance, enabling the study of contrast loss, image doubling, and optical distortions under real-world conditions.

Image reconstruction algorithms can be further optimized to enhance both computational efficiency and the ability to process large-scale datasets. One significant improvement involves parallelizing computations and transitioning from CPU-based processing to GPU acceleration. By leveraging GPU architecture, which excels at handling massively parallel tasks, reconstruction speed can be significantly improved, enabling real-time or near-real-time processing of high-resolution images. The image-capturing process is automated, ensuring consistent data collection with minimal human intervention. However, we believe that future developments could focus on fully automating the entire workflow, from calibrating the system and initiating home positioning to capturing images, generating light field data, reconstructing images, and processing contrast measurements. This end-to-end automation would not only streamline testing procedures, but also reduce measurement variability and enhance repeatability.

The light field approach incorporates a variable focus mechanism, allowing the gaze to seamlessly shift between the foreground and background. This capability provides a powerful tool for understanding and analyzing the depth of field in reconstructed images, offering nuanced insights into spatial relationships and visual clarity across different planes. Developing a comprehensive catalog of light fields derived from projection systems facilitates the virtualization of these devices, enabling a robust framework for comparing their performance against the latest standards in perceptual sciences. This catalog is a valuable resource, allowing for systematic evaluation and benchmarking of projection technologies based on depth resolution, contrast, and perceptual fidelity. Such comparisons are essential for advancing the design and optimization of imaging systems, ensuring they meet the evolving demands of users in fields like virtual reality, augmented reality, and high-fidelity display technologies. Furthermore, the creation of a complete digital twin of the device offers significant benefits for design simulations. This digital twin replicates the physical projection system with high fidelity, allowing engineers to visualize and assess its performance from any observation point within a specified angular range. This virtual representation enables detailed simulations that mimic real-world viewing conditions, providing a realistic preview of how the device will

perform under diverse scenarios. By integrating the digital twin into the design process, developers can identify potential improvements, refine system parameters, and reduce the need for costly physical prototypes. The use of a digital twin provides a robust and reliable platform for design simulations, offering reassurance about the effectiveness of the proposed solution.

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will stop if the current distance between the motor and the limit switch is less than 0.030625 mm. The repeatability of the switch is therefore equal to 0.030625 mm.

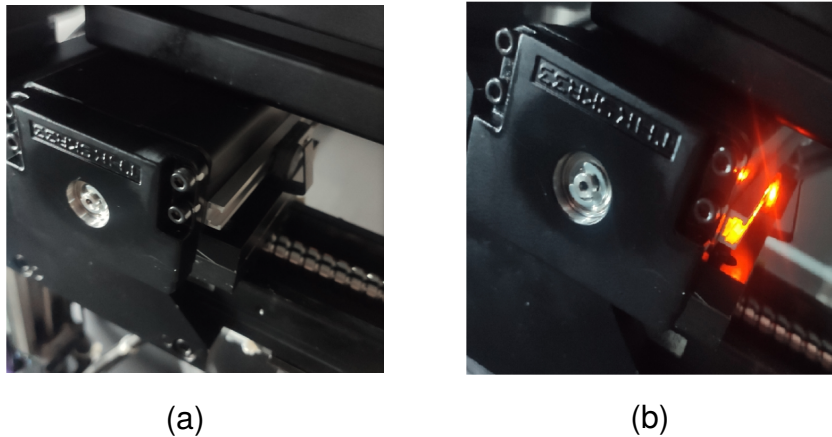


Figure A.2: Activated limit switch (a); note the lack of an LED shine (b)

A.1.1 Emergency break

The emergency brake system on the Z-axis or the vertical axis of the test bench is not just a feature, but a critical safety measure that plays a pivotal role in ensuring the safety of the installation. A software switch and a physical button can trigger the break. The brake is wired so that the axis is locked in position when no current passes through it, preventing any unwanted vertical movement. It is important to note that the brake is always applied when the system is turned off using the software switch. Before starting the test setup, the physical brake must first be released, followed by releasing the software brake to initiate measurements. This ensures the brake is only disengaged when the system is actively used, minimizing the risk of accidents or unintended movements. Furthermore, the emergency brake can also be helpful in cases where the system encounters unexpected problems or malfunctions during measurements. By quickly triggering the brake, the system can be stopped and any issues can be addressed before the measurement process resumes.

A.2 Calibration and referencing

The Hexagon Absolute Arm is a highly versatile and portable coordinate measuring device that plays a crucial role in the calibration and referencing process. It uses

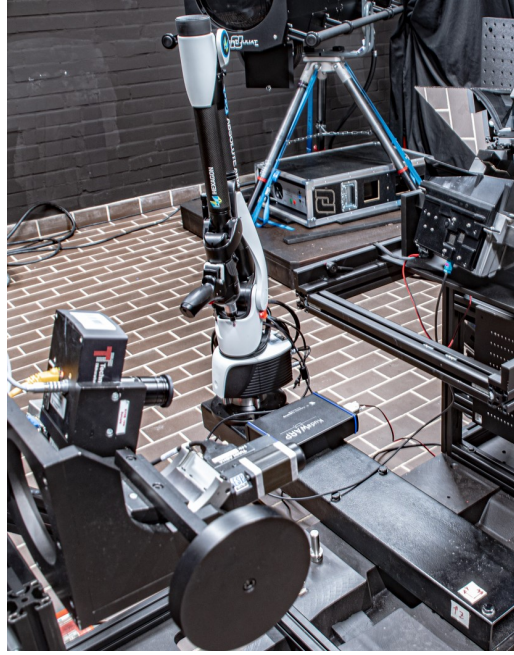


Figure A.3: Hexagon arm

Paramter	Value
Max. logitudinal error(E_{UNI})	0.029 mm
Max. probe deviation in size(P_{SIZE})	0.10 mm
max. probe deviation in position(L_{DIA})	0.038 mm
Max. prove deviation in shape(P_{FORM})	0.021 mm
Max. reach	2.48 meter
Scanning accuracy(RS5 SSA)	0.043 mm

Table A.1: Absolute Arm specifications [97]

a specialized probe to sense discrete points on the surface of physical objects and measure their geometry relative to the world coordinate system. This state-of-the-art measuring arm is an integral part of the testing equipment and is installed on the test bench, as shown in Figure A.3. The positioning of the arm is crucial to ensure that the probe tip can reach the maximum possible distance where the camera can move. The Hexagon Absolute Arm is a highly accurate measuring device that captures precise measurements of complex shapes and geometries. It is an ideal tool for various testing and measurement applications. Its portable and user-friendly design allows us to easily and efficiently measure and analyze the geometric properties of physical objects, making it an invaluable asset in the laboratory.

A.2.1 Reference cubes

To ensure robust, repeatable, and precise measurements in the laboratory, we have taken several steps to ensure the accuracy of the testing equipment. One of the key components in this process is the measurement cube attached to the camera, as shown in Figure A.4(a). Using the world coordinates as the origin, the measurements can start from a known reference point, which is essential to achieving accurate and reliable results. Furthermore, another reference cube has been fixed at the base of the test bench, as shown in Figure A.4(b), to provide an additional reference point for the measurements. These cubes, with their known and fixed positions, allow us to accurately measure the geometry of the camera and the test bench, ensuring the reliability of the measurements.

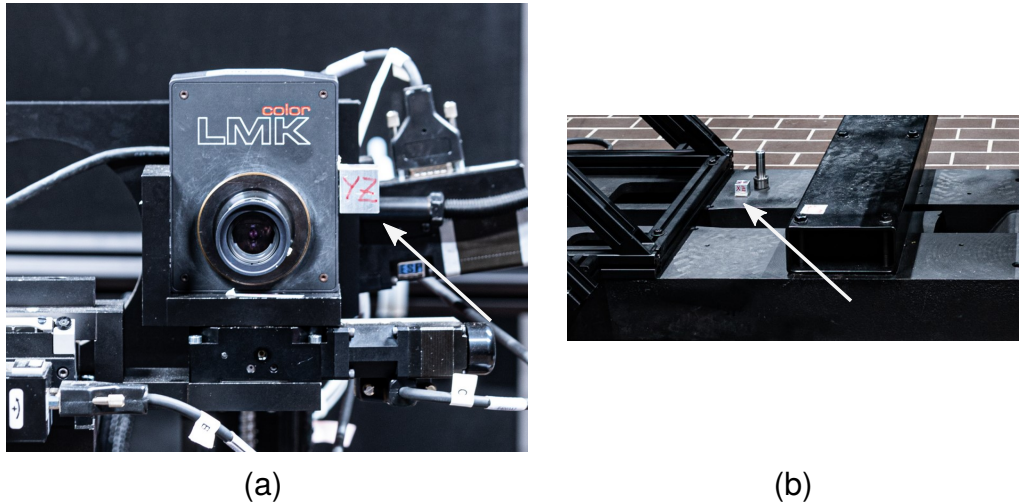


Figure A.4: Reference cube (a) Camera reference cube; (b) Test bench reference cube

The measurement cubes are marked with three planes, divided into XY, XZ, and YZ planes on both. These markings allow us to easily and accurately identify the planes and take precise measurements of each plane using the probe tip of the hexagonal absolute arm. By measuring the coordinate position of a minimum of three points on each cube plane, we can obtain the geometry of the cube plane. With this information, we can calculate the planes' intersection point (corner), which is essential for accurately measuring the geometry of physical objects. Using these precise and reliable measurement techniques, we can measure accurate positions and orientations of the camera. This allows us to analyze and evaluate the camera's systematic positioning error effectively.

A.2.2 LED's home position

However, one significant challenge in this measuring process is establishing a consistent optical home or start position for the measurements. This poses difficulties in ensuring consistent and reliable data collection. The laboratory has embarked on automating the measurement process to address this challenge. By automating the positioning of the devices and establishing a standardized home position, they aim to improve the accuracy and efficiency of their measurements. This automation will streamline the data collection, minimize human error, and enable more consistent and reliable measurements. Using proxy sensors or limit switches is a common practice to obtain an approximate origin position for new measurements. However, relying solely on these sensors may result in inconsistent origin positions and, thus, unreliable measurements. A robust optical home position system was implemented in the goniophotometer test bench setup to ensure a precise and repeatable origin position.

To achieve this, three sets of LED units were installed, two on the right side and one on the left side of the test bench, as shown in Figure A.5(a). Each set consists of three blue LED lights arranged in a triangular pattern with a red LED in the center, as illustrated in Figure A.5(b). By moving the LMK camera around in the world coordinate space, the LEDs can be detected, and their corresponding world coordinates can be determined. These coordinates can then be used to calculate the optical home position of the system, providing a reliable and precise source for perpetual measurements [98]. Moreover, using LED lights as reference points ensures that the origin position can be established independently of any external factors that may affect the position of the test bench or camera. Additionally, this setup allows for easy calibration and verification of the optical home position, ensuring accurate and consistent measurements.

A.2.3 Monitor display

To ensure accurate and reliable measurements of the HUD's projected virtual images, it is important to establish a baseline for the real images displayed on the monitor. So, before measuring the virtual images from the projection systems, we decided to measure the real images first, and for that, we installed a display monitor with a 4:3 aspect ratio as an extension to the existing test bench, as shown in Figure A.7. The display monitor provides a convenient and flexible way to display various test patterns, including line pair patterns, checkerboard patterns, and dot patterns displayed and captured with a camera at different orientations.



Figure A.5: Home position reference (a) Reference LEDs in three positions; (b) Reference LEDs

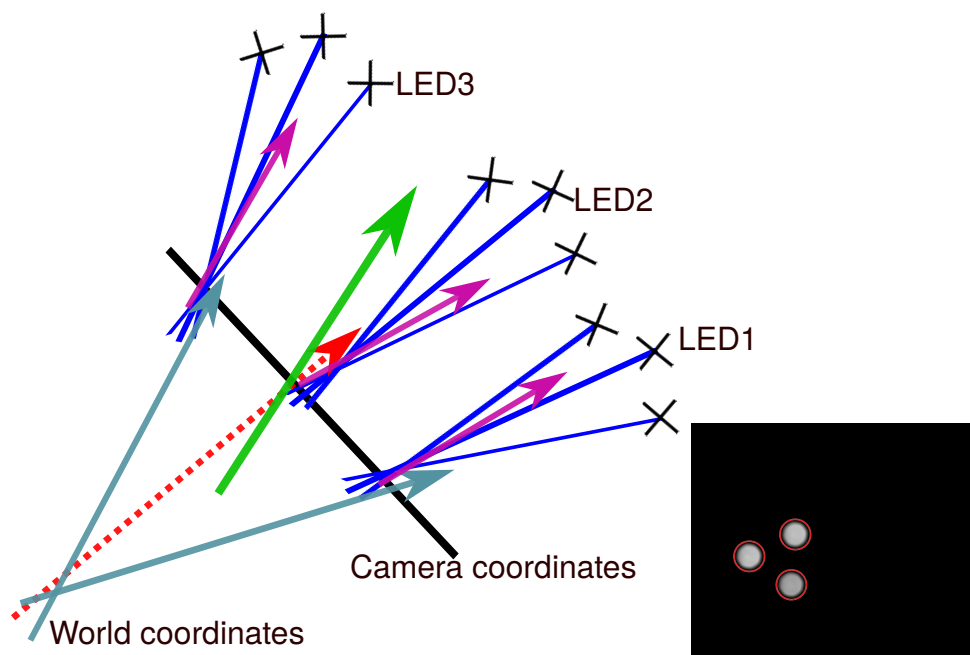


Figure A.6: Ray sketch of home position with reference LEDs



Figure A.7: 15-inch LCD with a resolution of 1024 x 768 pixels (XGA)

By analyzing the captured images, we can assess the performance of the camera and image processing algorithms.

The display monitor, with its ability to be adjusted in different positions, such as parallel and inclined to the camera plane, provides a flexible way to simulate different viewing angles and distances. This flexibility allows us to evaluate the performance of the HUD under various conditions, such as during different driving scenarios or for users with different heights and seating positions. Furthermore, using a display monitor as an extension to the test bench not only provides a valuable tool for calibrating and evaluating the performance of the HUD system but also demonstrates the adaptability of the testing conditions.

A.3 Image Acquisition

The test setup is initiated by releasing both the physical brake and the software limit; then, the camera finds the optical home position concerning the light sources of the LEDs. The images can be captured by moving the camera in two different approaches, manually and automatically, visually confirming camera positions. These positions are automated to capture different numbers of images, ensuring comprehensive data collection. Visually confirmed positions are derived from the test pattern projection devices (display monitor or HUD), real objects, or virtual

images. The measurements will take place without natural and artificial light to reduce the impact of external light.

The LMK camera, a key component of the measurement setup, has two objective lenses of 25 mm and 50 mm. This dual-lens system was chosen for its versatility, allowing us to capture images at varying distances with optimal clarity and precision. These lens objectives have a fixed focus, meaning the focal length is predetermined and cannot be adjusted during use. The sharp focus has been meticulously set before initiating the measurement process to ensure optimal clarity and precision in the captured images or data. This pre-focusing is crucial for maintaining consistency and accuracy throughout the measurement, as any alteration to the focus after the process begins could compromise the quality and reliability of the results. The test pattern images, like line pair, checkerboard, and dot pattern images, were displayed through the display monitor and HUD. The LMK camera will be moved in the world coordinate system to different positions to capture images, and the camera-captured images will be stored in a folder with the world coordinate positions.

A.3.1 Optimizing Curve Fitting for Brightness Analysis

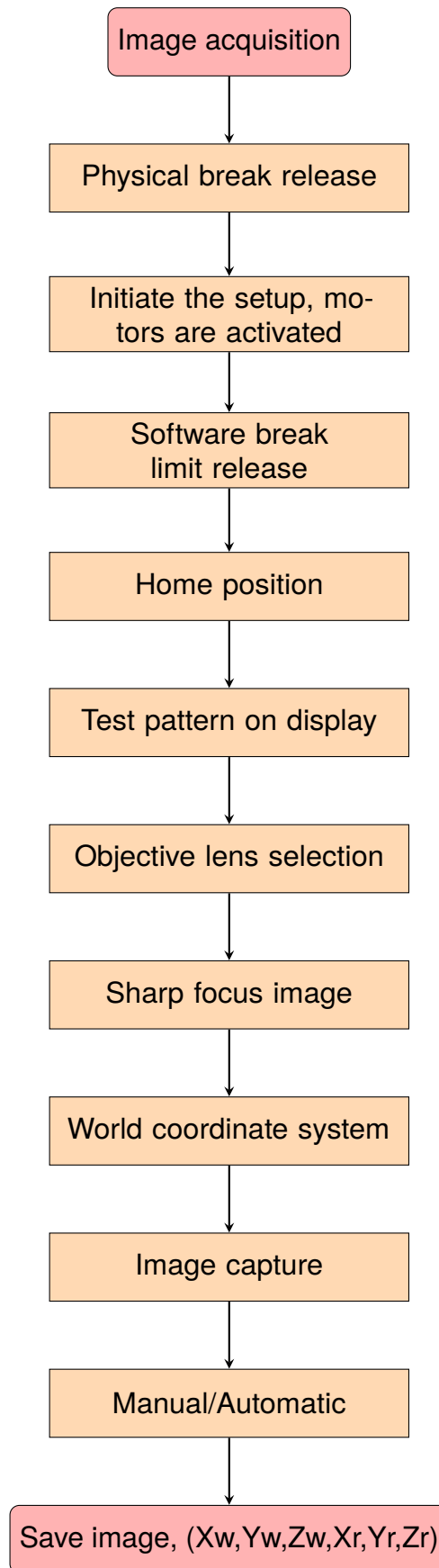
We employed a derivative-free method to enhance the optimization of the curve-fitting process. This approach effectively refined the fitting parameters without relying on derivative information. To initiate the fitting procedure, appropriate starting values were assigned to crucial parameters in the equation, including amplitude, frequency, phase, slope, and offset. The selection of these initial values was carried out in the following manner:

$$F = a \cdot \sin(2 \cdot \pi \cdot f \cdot x + \phi) + m \cdot x + c$$

$$a = 2 \cdot \sigma(b); f = FFT(b); c = \mu(b); \phi = 0; m = 0$$

$$b = \text{brightness}$$

- **Amplitude (a):** The initial value for the amplitude parameter was estimated based on an analysis of the observed brightness variations within the reconstructed images. Choosing a value that adequately represented the range of brightness fluctuations was crucial.
- **Frequency(f):** The frequency parameter's starting value was meticulously determined by analyzing the spatial frequency characteristics exhibited by the

**Figure A.8:** *Flowchart of the image acquisition*

brightness variations. Careful consideration was given to selecting a value that captured the dominant frequency components.

- **Phase(ϕ):** The phase parameter's initial value was set to align the fitted curve with the observed brightness variations. By appropriately selecting the phase value, we ensured the curve's alignment and coherence with the actual data.
- **Slope(m):** The slope parameter's starting value was established by considering the overall trend and gradient of the brightness variations. This value played a crucial role in determining the steepness or shallowness of the fitted curve.
- **Offset(c):** The offset parameter's initial value was determined by analyzing the reconstructed images' baseline or average brightness level. This value helped ensure that the fitted curve accurately captured the variations around the baseline.

By carefully selecting suitable starting values for these parameters, we aimed to initialize the curve-fitting process in a manner that closely approximated the observed brightness variations. This allowed for more effective and accurate optimization of the fitting algorithm, ultimately enabling a robust assessment of contrast variations in the light field reconstructed images.

A.4 Factors Affecting Contrast Measurement

When conducting contrast measurements, it is crucial to consider various factors that can significantly impact the results. Here's a discussion of some of the key factors that can influence contrast measurements:

1. **Ambient Lighting Conditions:** Ambient lighting conditions play a significant role in contrast measurement. The amount and type of ambient light can affect the perceived contrast of an image or display. Ambient bright lighting can increase the overall luminance level, potentially reducing the apparent contrast. On the other hand, dim or low-light environments can enhance perceived contrast. To ensure accurate measurements, it is essential to control and standardize ambient lighting conditions during contrast evaluation [99].

2. **Viewing Angle:** The viewing angle refers to the angle at which an observer views the image or the display. The contrast can vary with viewing angle due to factors like screen technology and the presence of polarizers. Some displays, such as LCDs, may exhibit changes in contrast as the viewing angle deviates from

the optimal viewing position. It is crucial to consider the intended viewing angle and align it with the measurement setup to obtain consistent and representative contrast measurements [100].

3. **Display Characteristics:** Different display characteristics can impact contrast measurements. Display technologies, like LCD, OLED, or projection systems, have inherent properties that affect contrast performance. Factors like black level, peak luminance, color gamut, and dynamic range influence a display's contrast capabilities. Additionally, display settings, such as brightness and gamma adjustments, can affect the perceived contrast. Understanding the specific characteristics of the display being measured is essential for accurate and meaningful contrast evaluations.

4. **Measurement Methodology and Instrumentation:** The methodology and instrumentation used for contrast measurement can also affect the results. Different measurement techniques, algorithms, or metrics may yield varying contrast values. It is important to follow standardized measurement procedures and use appropriate instruments calibrated and validated for contrast measurements. Consistency in measurement methodology ensures comparability and reliability of contrast data across different evaluations.

5. **Image Content and Test Patterns:** The content of the image or the test pattern used for the contrast measurement can influence perceived contrast. Some patterns or images may inherently possess higher contrast due to the arrangement or characteristics of their elements. Selecting appropriate standardized test patterns representing the intended application or industry standards is essential.

Considering these factors and controlling for their influences is essential to obtain accurate and meaningful contrast measurements. Researchers, designers, and quality control professionals can ensure reliable and consistent contrast evaluations in imaging and display systems by understanding and accounting for these variables.

A.5 The Evolution and Impact of Photogrammetry

Photogrammetry is a captivating fusion of art, science, and technology that enables the precise collection of information about physical objects and the environment. It produces highly detailed and accurate representations of the world by recording, measuring, and interpreting photographic images and electromagnetic radiation

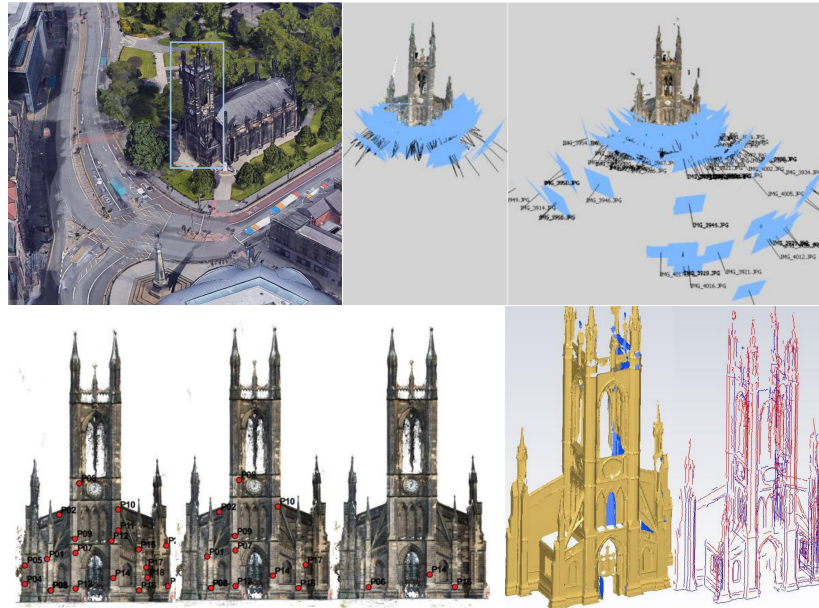


Figure A.9: 3D reconstruction of a church using photogrammetry [105]

patterns. It is a powerful tool for scientists, engineers, and researchers to study the natural and built environment, from tracking changes in land use to monitoring structural integrity [101][102]. Beyond its technical aspect, photogrammetry demands an eye for detail, an understanding of light and shadow principles, and an appreciation for image capture as an art form. It offers a unique perspective on the world, revealing hidden insights and unlocking discoveries. With rapid technological advancements and the growing demand for precise data, the future of photogrammetry holds exciting possibilities. Over the years, photogrammetry has evolved from an analogue-optical-mechanical process to a digital method based on computer algorithms and digital images. Digital photogrammetry, or softcopy photogrammetry, is widely used today for precise measurements of three-dimensional objects and terrain features using only two-dimensional photographs. It finds applications in surveying, architecture, geology, and underwater research [103] [104]. Advancements in technology and the quest for greater accuracy and efficiency have propelled photogrammetry into an essential tool across various fields. As technology advances, photogrammetry is poised to become even more precise, efficient, and versatile. Its capability to capture detailed measurements and create comprehensive maps and models of the environment is vital for understanding and managing the world around us, making photogrammetry an increasingly crucial aspect of endeavours.

A.5.1 Structure from Motion (SfM)

The 'Structure-from-Motion' method is rooted in the principles of stereoscopic photogrammetry, enabling the reconstruction of a three-dimensional structure from a sequence of overlapping and offset images [106]. Unlike conventional photogrammetry, SfM automatically determines the scene's geometry, camera positions, and orientation without the need for predefined targets with known 3D positions [107]. All variables are solved simultaneously through iterative bundle adjustment based on a database of automatically acquired features from overlapping images. Unlike traditional methods that rely on known camera positions or control points, SfM estimates scene geometry and camera positions by identifying matching features across multiple images. This approach ensures greater automation and flexibility in 3D reconstruction. The success of SfM relies on the superior image quality attained through meticulous consideration of sensors, settings, and acquisition designs. SfM automates the generation of 3D point cloud and texture models from 2D images by determining camera positions and spatial locations of features through computer vision algorithms. Evaluation of the camera position involves calculating the Euclidean distance between the reconstructed and ground-truth camera positions, producing the average distance and standard deviation metrics [108]. SfM is a powerful technique for efficient and accurate 3D reconstruction with broad applicability across various fields.

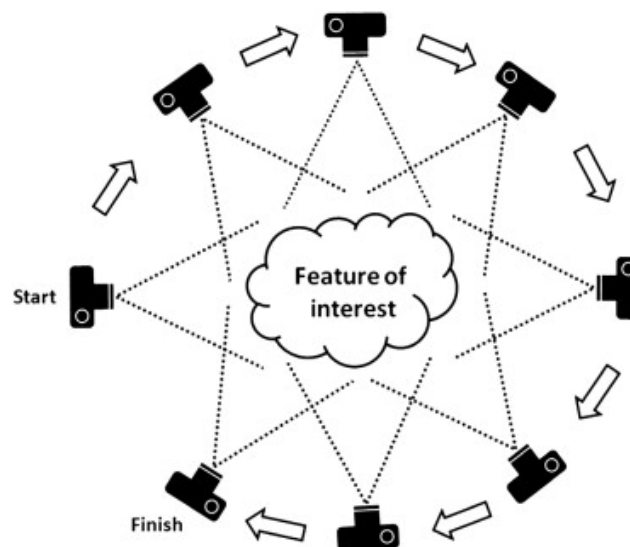


Figure A.10: *Structure-from-Motion (SfM) Instead of a single stereo pair requires the SfM technique, multiple overlapping photos as input for feature extraction and 3D reconstruction algorithms [106]*

A.5.2 Multi-View Stereo (MVS)

Creating accurate and dense 3D point clouds from a sequence of images is a fundamental task, and the multi-view stereo (MVS) approach has emerged as a powerful method for achieving this goal. Recent advancements have yielded a range of impressive algorithms, particularly adept at reconstructing textured objects and scene regions [109]. MVS, a key component of computer-aided photogrammetry, involves deriving 3D models from sets of 2D images captured from varying perspectives. The primary objective is to achieve the precise geometric reconstruction of the scene or object by detecting correspondences between images and calculating the positions of 3D points these images collectively capture. The MVS process begins by aligning images into a 3D coordinate system by estimating camera positions and orientations. Subsequently, correspondences are established by matching features, with algorithms such as triangulation used to link these features to 3D points [110][111]. These steps is creating a dense 3D model textured to present a realistic appearance. Such models find applications across diverse domains like computer graphics, robotics, virtual reality, and beyond.

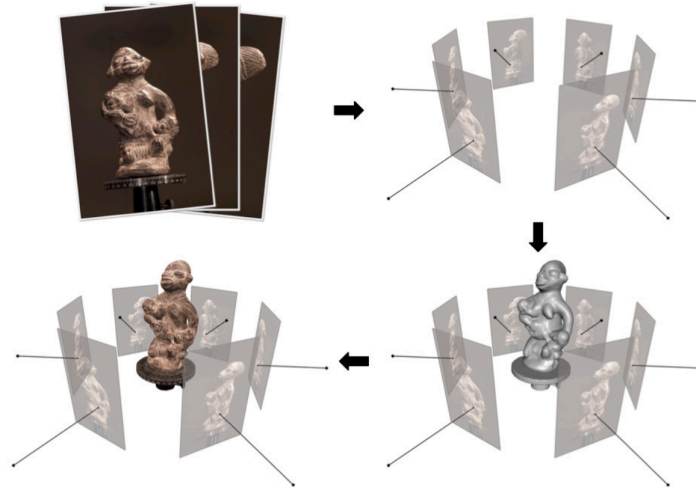


Figure A.11: Example of a multi-view stereo pipeline [111]

A.6 Real-world 3D Entities

In the experimental setup A.12, a fixed position (x,y,z) and a consistent orientation (ω_y, ω_z) were maintained for capturing all photos. The central focus was on the dynamic component, achieved by systematically rotating the object about its axis. This rotational movement was carried out over a complete 360° cycle, meticulously

capturing images at each incremental step. Notably, the object's rotation was exclusively confined to the z-axis.

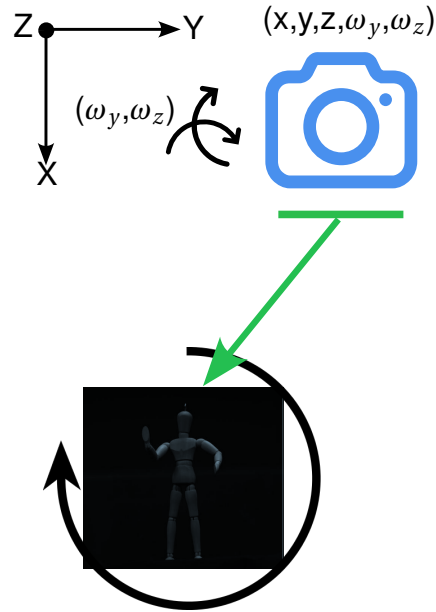


Figure A.12: Fixed camera with object turning over [112]

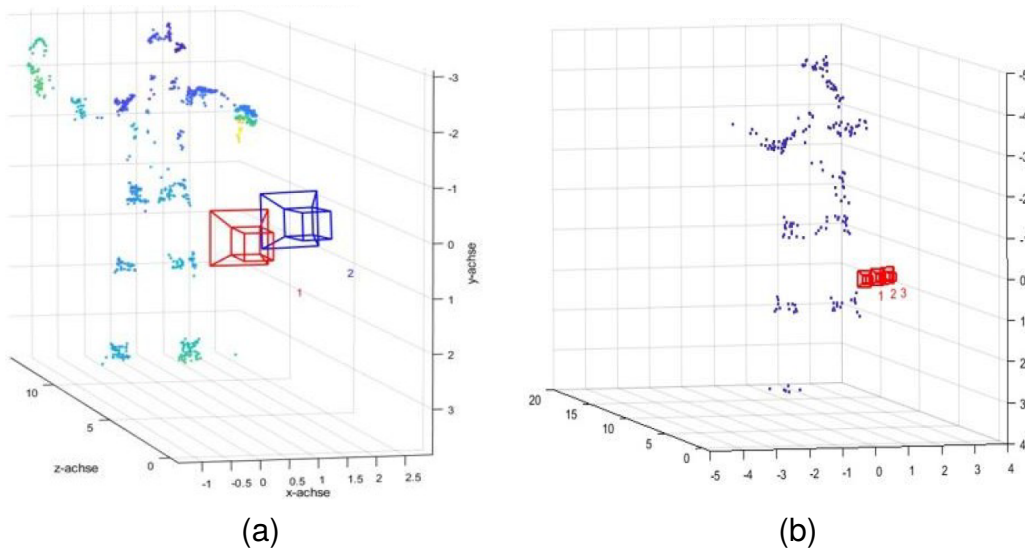


Figure A.13: 3D Structure from two views (a); multiple views with fixed camera (b) [112]

In another experiment, A.14, a shift in focus was introduced, whereby the object remained stationary while the camera exhibited movement. This adjustment led to a scenario where the camera could traverse in all spatial directions (x,y,z) and perform rotations about the y-axis and z-axis. It is important to note that rotations were carried out along the y-axis and z-axis. The rationale behind this choice is

that rotation around the x-axis wouldn't contribute significantly to determining the object's dimensions, as this aspect could be accurately derived from the images themselves. Each photograph was taken from specific coordinates (x_i, y_i, z_i) and precise angles $(\omega_{yi}, \omega_{zi})$, a visual depiction of which can be found in Figure A.14.

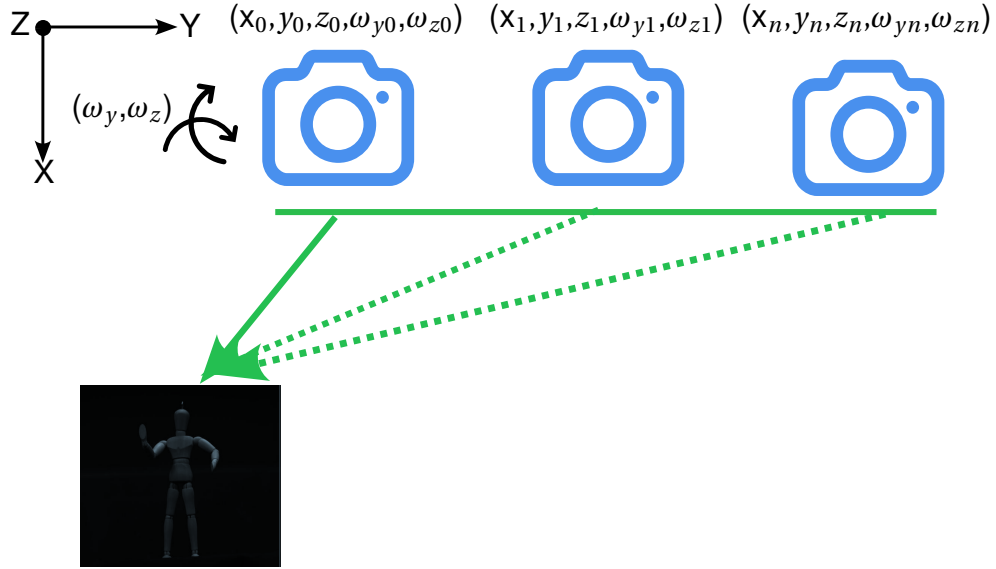


Figure A.14: Fixed object with moving camera [112]

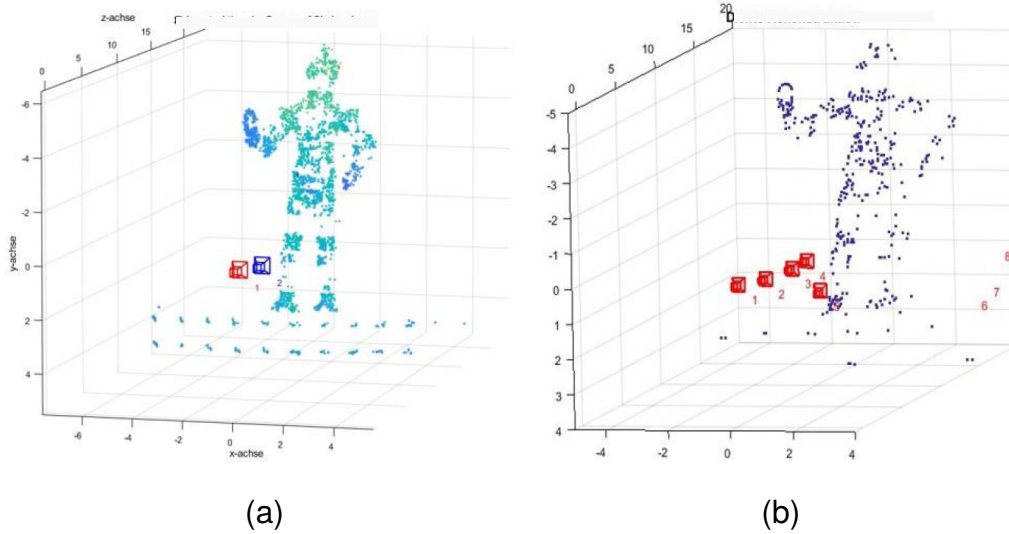


Figure A.15: 3D Structure from two views (a); multiple views with moving camera (b) [112]

As anticipated, the 'Fixed object with moving camera' approach yields superior results, attributed to the inherent functionality of the algorithms. This outcome aligns with expectations, considering the foundational principles of the applied algorithms. As elucidated in the sub-division, the Structure from Motion (SfM) technique hinges on accurate knowledge of camera positions to construct a comprehensive 3D

representation. Notably, the Multi-View Stereo (MVS) experiment adhered to this premise, facilitating the algorithm's ability to precisely determine camera positions and assemble a more accurate 3D model. This disparity prompts an inquiry into the consistent effectiveness of the 3D structure from two views in Figure A.15(a). An explanation can be sought for the mechanisms of each algorithm. The initial '3D structure from two views' algorithm identifies robust points and establishes the essential matrix, subsequently leveraging this information to determine camera positions. This sequential approach ensures that sufficient data is acquired before proceeding to subsequent steps.

On the other hand, '3D structure from multiple views' initially identifies camera positions, followed by the definition of the strongest corners. In cases where camera positions are nearby, this approach may fall short of detecting an adequate number of points for accurate reconstruction. The key to the consistently superior results of the '3D structure from two views' lies in its strategic data accumulation process, guaranteeing a more reliable foundation for subsequent calculations. It exhibited highly favourable results; however, it is constrained by a notable limitation: its applicability is confined to scenarios involving only two views. On the contrary, '3D structure from multiple views' presents a distinct advantage. This approach can construct a 3D model encompassing a multitude of views, offering a more comprehensive representation. Furthermore, it should be noted that '3D structure from multiple views' in Figure A.15(b) outperforms particularly when dealing with a moving camera, augmenting its capability to yield superior outcomes compared with the '3D structure from multiple views' fixed camera in Figure A.13(b).

Objective evaluation of 3D reconstruction can be conducted using the following methods:

1. Validate Point Density and Continuity: Before concluding the 3D model, ensure that the points are distributed densely and continuously throughout the reconstructed object. This step is crucial for accurate representation and subsequent analysis.

2. Evaluate Error Metrics: To quantify the accuracy of your 3D model, it is advisable to utilize appropriate error metrics. The Root Mean Square Error (RMSE) metric can provide insights into the differences between the reconstructed model and the ground truth. Evaluating error metrics allows you to assess your reconstruction's fidelity and identify potential areas for improvement.

B Appendix

The MATLAB scripts and data used in this work are available at:
<https://github.com/shelam/Creation-of-LightField-data>
(accessed July 29, 2025)