Depth estimation in handheld augmented reality: a review

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ABSTRACT

Depth estimation involves capturing the depth information of a scene in the form of depth data. This depth information can be applied in computer vision tasks to enhance perception and comprehension. In handheld augmented reality (AR), depth estimation refers to the capability of a handheld device to estimate the depth or distance of objects in the real world based on input from its camera feed. Currently, there is a lack of work that reviews on this topic. Thus, this paper reviews and discusses the technologies regarding depth estimation on handheld devices and their applications in relation to AR. We employ partially the systematic review procedure to allow more specific focus for our, broken into three main focuses. First, we discuss the methods to obtain depth data on handheld devices. Next, we discuss on the existing frameworks that enable depth estimation for handheld AR. Then, we compile and discuss the applications of depth estimation for handheld AR based on the reviewed papers. Finally, we discuss the novelties and limitations of the current research to determine the gaps in this field of research.

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1. INTRODUCTION

Depth estimation is the task of inferring and extracting a scene's depth data. This depth estimation data can be utilized for perception and understanding of various computer vision applications such as autonomous driving and robotics navigation [1]. While previous research has used depth cameras such as the Microsoft Kinect and Intel RealSense [2], [3], the emergence of increasingly powerful handheld devices has changed the research landscape. Depth estimation using handheld devices can provide a more accessible alternative compared to the traditional setups [1]. The widespread use of handheld or mobile devices in recent years has significantly changed how people engage with technology [4]. Smartphones and tablets are already common in daily lives. Some of these devices are also equipped with high end specifications. This has opened the door to a broader research opportunities and challenges, one of them being in the area of depth estimation in handheld augmented reality (AR). AR is a technology superimposes digital content onto real-world environment through specific displays [5]. A variety of technological tools are used, including multimedia applications, 3D modelling, tracking and registration in real-time, intelligent interaction, and sensing [6]. AR has seen usage in various industries such as robotics [7] and education [8]. The ability to enhance the surrounding with valuable information using AR can give significant boost to these fields [9]-[11].

Depth estimation in the context of handheld AR refers to the ability of a handheld device to estimate the depth or distance of objects in the real world from a camera feed. This technology is essential for creating realistic and interactive AR experiences on handheld devices, particularly for handling occlusions and collision detection [12]. However, while the fusion of handheld devices and depth estimation shows ubiquitous potential, there are still several difficulties in successfully integrating depth estimation on handheld devices since they have limited processing resources and are power-constrained. Because of this, the algorithms used for depth estimation must be carefully chosen to strike a compromise between accuracy and efficiency. Depth estimation techniques can help to generate accurate representations of spatial relations. For example, semantic geo-registration improves the global pose estimation of AR systems through detailed depth maps derived from video frames, which are important when it comes to aligning virtual objects with their real-world counterparts [13].

Additionally, the use of RGB-D cameras enables the collection of depth maps that make virtual interactions more realistic by incorporating lighting conditions and occlusions of objects into consideration [14]. This ability is useful in applications where precise perception of depth is required, such as in educational tools and surgical navigation systems [15]. The challenges for depth perception for handheld devices is significant due to their smaller screens and as touch is only 2D it makes it difficult for the mobile devices to select an object that is far away or hidden from sight. Raycasting and shadow displays have been suggested as means of assisting users in the accurate selection of virtual objects thus improving the usability of handheld AR systems [16].

Based on our literature search, there has been no work that reviews and discusses the emerging technologies regarding depth estimation on handheld devices. Thus, our goal for this review is to discover the current state-of-the-art and challenges regarding this field thus our main contribution is providing insights into the previous works that have been done to estimate depth for use in handheld AR. In this review, we discuss the general applications of depth estimation in AR and the technologies to implement depth estimation in handheld devices. We also discuss on the general pipeline and flow of depth estimation as well as the current existing libraries that can provide depth estimation for handheld AR. The remaining sections of the paper are organized as follows: section 2 discusses the review methodology. Section 3 discusses the overview of depth estimation in handheld AR and depth data acquisition methods in handheld AR. Section 4 describes the existing handheld AR frameworks that are able to perform depth estimation. Section 5 discusses the applications of depth estimation in AR. Then, we discuss the novelties and limitations of the reviewed papers in section 6 and conclude the paper in section 7.

2. REVIEW METHOD

For our review, the methodology partially follows the procedure of a systematic literature review, in which we define the research questions (RQ) to guide on the focus of the review [17]. By using this procedure, we are able to constrain our review to a more specific focus. The RQ are as outlined in Table 1. RQ1 pertains to the methods for depth data acquisition in handheld AR, RQ1 pertains to the existing frameworks that allow depth estimation in handheld AR, and RQ3 pertains to the applications for depth estimation in handheld AR.

Table 1. Research questions

RQ code	Description
RQ1	What are the methods for depth data acquisition in handheld AR?
RQ2	What are the existing frameworks that allow depth estimation in handheld AR?
RQ3	What are the applications for depth estimation in handheld AR?

Paper selection was conducted by searching the major indexing databases. The databases that we chose include SCOPUS, WoS, and ACM Digital Library. We used the following keyword combination when performing our search:

("depth" OR "depth estimation") AND ("handheld" OR "mobile" OR "smartphone" OR "tablet") AND "augmented reality"

These keywords can provide a comprehensive result for our search as it includes the usual terms that are used in everyday life. Our paper selection is based on certain criteria, including limited to the five-year period from 2018 to 2023, papers published in journal and conference proceedings and written in English. From the search results, a total of 580 articles were returned that matched our criteria. After screening the titles and abstracts, we selected 26 papers for the review.

Once we have identified the selected papers for review, we analyze each paper and compiled them in a table. In this table, we classify the contents by following the outlined RQ, namely the depth data acquisition, the frameworks used, and which area it is applied. We also make note of the strengths and weaknesses of each paper in the table. Thus, from this table we were able to systematically review the papers that follow our focus based on the RQ.

3. DEPTH ESTIMATION IN HANDHELD AR

In this section, we discuss on the overview of depth estimation in AR to visualize the general look on the topic, down to our focus on handheld AR. This allows us to establish the direction of this review. The depth data acquisition methods for handheld AR are also discussed in this section. This satisfies our first research question (RQ1).

3.1. Overview of depth estimation in AR

For this review, we focus on handheld devices. Figure 1 shows an overview of the topic of depth estimation in AR, in which we narrow down our focus. We start with AR displays as it is one of the fundamentals of AR. Then, under handheld display we classify the focus of our review based on the RQ which is depth data acquisition methods, existing frameworks that allow depth estimation in handheld AR, and the applications for depth estimation in handheld AR. There are multiple ways to view AR applications, including head-mounted displays (HMD), handheld devices, or projection-based, also known as spatial augmented reality (SAR) [18]. HMDs are devices that a person wears on the head and used to overlay virtual and real environments in the user's view [19]. Handhelds are miniature computer devices that a user can grasp by hands. Smartphones, personal digital assistants (PDA), and tablets are commonly used as handheld AR displays [20]. SAR employs video projectors, optical components, holograms, and various tracking technologies to project visual information directly onto tangible objects. This variant in design compared to the more traditional means for visualisation allows the viewer to become better integrated with the task at hand, and less concerned with the viewing medium [21].

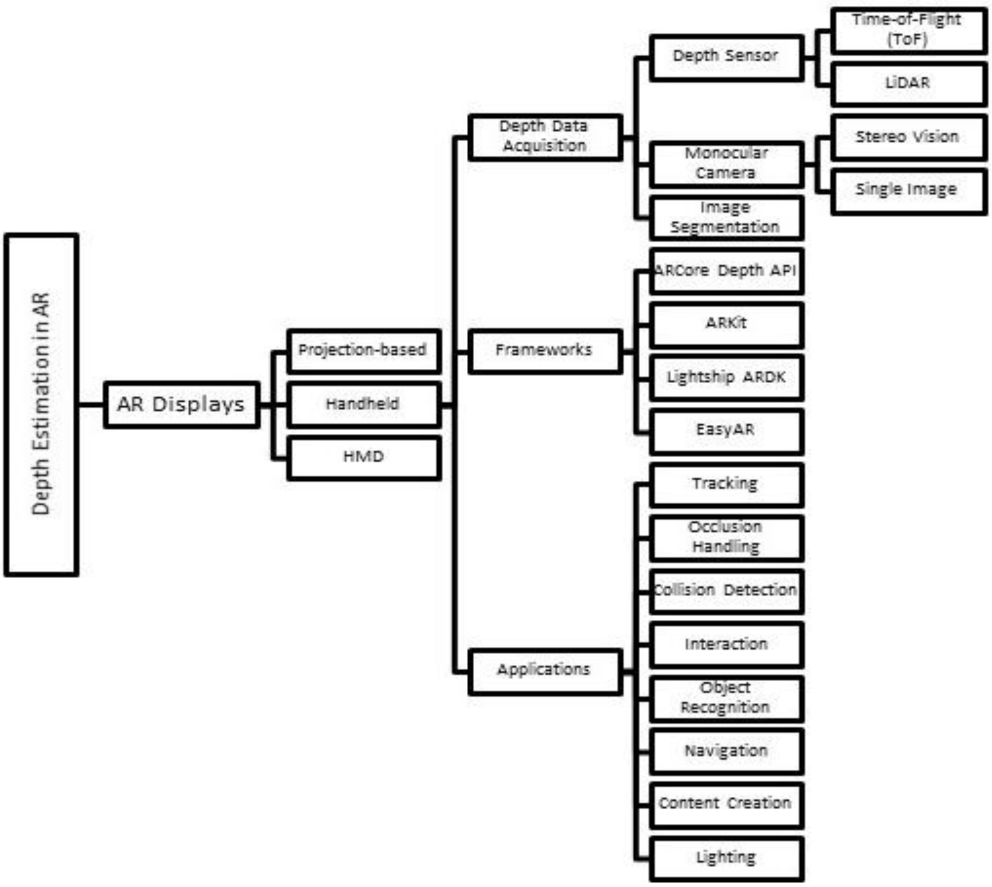

Figure 1. Depth estimation in handheld AR

The goal of depth estimation is to acquire the distance measurement of the objects in the image to the camera. The measurement obtained is typically stored as depth map or depth data. On handheld AR, the data can be used for various applications, including AR. While we are focusing on handheld devices, it is worth noting that some methods are interoperable between multiple platforms, such as in [22] whereby they conduct their test on a desktop and on a smartphone. However, it is clear that there is a difference in performance because of the limitation of the smartphone. Thus, our review highlights the methods to overcome the limitations and discusses the future directions in this research field.

3.2. Depth data acquisition in handheld AR

This section discusses the technologies and methods that have been used for acquiring depth data for use in handheld AR. From our readings, we can classify the technologies as depth sensor, monocular depth estimation (stereo and single image), and scene segmentation. The explanation for each technology is discussed further below.

3.2.1. Depth sensor

Depth sensors are specialized cameras that can estimate depths. In literature, there are multiple research that have utilized depth sensors in context of depth estimation on handheld AR, which can be classified as using time of flight (ToF) and light detection and ranging (LiDAR). The depth sensors are compared in Table 2, in which we compare the sensing mechanism, the strengths and limitations of ToF and LiDAR.

Table 2. Depth sensors comparison

	ToF	LiDAR
Sensing mechanism	Measures the time taken for a light to travel to an object and back to determine distance [23]	Utilizes laser-pulse time-of-flight data to measure distances and back-scatter intensities [24]
Strengths	– registered depth and intensity data at a high frame rate, compact design, low weight and reduced power consumption [25] – can operate under low or complex ambient light conditions [26]	– ability to create accurate high-resolution models [27] – allows for accurate depth perception, potentially overcoming current limitations in depth perception [28]
Limitations	– resolution of depth maps captured by ToF cameras is limited compared to HD color cameras, affecting their direct usability in 3D reconstruction [29] – measurement accuracy is degraded by multi-path interference [30]	– inefficient power consumption [31] – detailed data acquisition, especially in scenarios requiring precise measurements at longer distances [32]

There are some works that have been done that utilize depth sensor on handheld devices. Used hand pose estimation from depth data obtained from a depth sensor (Intel RealSense D435) attached to smartphone (Huawei P20) [33]. LiDAR on iPad Pro 2020 to obtain depth data [34]. ToF on a Google Tango device [35]-[37]. However, the Tango project was discontinued by Google and succeeded with ARCore [38]. ToF on high-end smartphones that have ToF camera embedded [12], [39]. ToF is the common depth sensor found on high end Android devices, meanwhile LiDAR is currently only available on iOS devices [40].

3.2.2. Monocular depth estimation

A. Stereo vision

In general, stereo vision involves stereo matching technique, which is using two or more cameras placed at known positions to capture the same scene simultaneously. This is to determine whether two pixels of distinct images correspond to the same point in the real scene. By comparing the disparities (horizontal shifts) between corresponding pixels in the images, the depth map is estimated and refined the matched pixels based on the principles of triangulation [41]. Objects that are closer to the cameras will have larger disparities. In stereo vision, images are captured from two slightly offset cameras. This offset allows the system to calculate depth information by comparing the disparity between corresponding points in the two images. In context of monocular camera, the triangulation is performed based on tracking and identifying two keyframes before performing the stereo matching to obtain the sparse depth and densifying the sparse depth. Valentin *et al.* [42] proposed a pipeline of depth from motion for monocular depth estimation on handheld that utilizes stereo matching as part of the pipeline. Their work is now integrated in the Google ARCore framework, as Depth API [43]. This API has been used in other works such as DepthLab [44] in which they utilized Depth API to create a set of depth interaction library to facilitate AR developers in using the depth data in the API.

Multi-view stereo (MVS) performs stereo matching with more than two cameras, which in case of monocular camera, more than two keyframes. The main goal is to improve the accuracy compared to stereo vision and reduce the presence of holes in the estimated depth map. Yang *et al.* [2] proposed using the MVS method estimate monocular depth. Their method incorporates a deep neural network model to refine the generated depth map and reduce the noise from the tracking process. They also include incremental mesh generation in their method to perform 3D reconstruction from the depth map generated.

B. Single image

Deep learning models, such as convolutional neural networks (CNNs), can be trained on depth data to estimate depth from a single image. Single-image depth estimation is the task of predicting the depth or distance information for each pixel in a 2D image, using only a single image as input. It is a long-standing problem in computer vision and has only been able to be adequately tackled with the advent of deep learning [45]. As with the limitation of handheld devices, most solutions require client-server system, but some works have been able to achieve real-time results running on the device only. This is a big leap in progress since it minimizes privacy and latency issues [45].

Most of the solutions proposed performs knowledge distillation, a process of transferring knowledge from larger models to a more compact one [1]. This allows the models running on the complex hardware to be implemented on some handheld devices. Another optimization process is through neural architecture search (NAS), which is a technique for automating the modelling of neural networks. Methods for NAS can be categorized according to the search space which defines the type of neural network that can be designed and optimized, search strategy which defines the approach used to explore the search space and performance estimation strategy which is evaluating the performance of a possible neural network from its design without constructing and training the model [46].

As it is the norm for deep learning solutions, datasets play an important role for training the models. The common datasets that are used in literature for handheld single image is NYU Depth V2, Middlebury 2014, MegaDepth, and KITTI dataset. NYU Depth V2 is composed of video sequences from a variety of indoor scenes as recorded from the Microsoft Kinect [47]. It features 1,449 labeled pairs of aligned RGB and depth images [48]. The Middlebury 2014 dataset [49] contains 33 images. They are all indoor scenes with varying difficulties including repetitive structures, occlusions, wiry objects and untextured areas [50]. MegaDepth [51] one of the largest monocular depth estimation dataset consisting of 130,000 samples. However, Benavides pointed out that most images have large portions of invalid pixels that are masked out [48]. Furthermore, all photos collected from the internet thus the quality of the color images is inconsistent. Other common issues include motion blur, noise, and lack of detail [48]. The KITTI dataset [52] contains 93,000 samples acquired via LiDAR sensor corresponding to 56 scenes.

In Figure 2 the PhoneDepth dataset was proposed to overcome the current limitations of the current datasets which include low quality of images from method of collecting the images, specific domains such as autonomous driving, and small number of samples [48]. The datasets contain 6,035 images of which 1,202 are outdoor scenes and 4,833 are indoor scenes. Figure 2(a) shows the setup of PhoneDepth dataset capture connected to the PC while Figure 2(b) shows a close up of the setup. The images are obtained from two handheld devices and a professional ZED depth camera as the ground truth. The phones have resolution of 4096×3072 and 2686×2016, while the depth camera has a resolution of 1280×720.

(a)

(b)

Figure 2. PhoneDepth dataset capture setup [48] (a) setup of PhoneDepth dataset capture connected to the PC and (b) shows a close up of the setup

C. Image segmentation

Image segmentation allows objects in a scene to be represented in a way that is understandable to the computer for further analysis, with depth being one of them. Image segmentation method is more suitable to use in outdoor scenarios as it can overcome the distance limitation of most depth sensors which is around 5-20 m [53]. In literature, few have done image segmentation-based depth estimation in context of handheld AR, and all of them use client-server architecture. The image frames are captured via handheld device while the segmentation task is offloaded to a high-end computer server. The segmentation task segregates the objects in the image in layers. These layers can be used as masks for use in AR applications such as occlusions or photo composition [54], [55].

4. EXISTING FRAMEWORKS FOR DEPTH ESTIMATION IN HANDHELD AR

Implementing depth estimation in handheld AR involves selecting suitable methods or libraries to estimate depth from the device's camera feed. There are some frameworks that can be used for depth estimation in handheld AR. In this section we discuss in brief for each of the available frameworks.

- ARCore Depth API: ARCore, developed by Google, is an AR framework that equips developers with essential technologies and APIs to create high-quality AR applications for handheld devices. This framework can be deployed on Android and iOS devices. The depth estimation API within ARCore utilizes a single camera and employs the Depth from Motion (DfM) algorithm [42]. In addition, it can also obtain depth data from ToF when available.
- ARKit: ARKit is an AR framework developed by Apple specifically for their own devices such as iPhone or iPad. The framework features advanced depth sensing features on supported Apple devices that have LiDAR sensor embedded [56]. It enables instant AR object placement without the need for scanning feature points and it also supports occlusion handling of people.
- Lightship ARDK: the developers of Pokemon GO, Niantic, launched the Lightship ARDK framework for developing AR applications for handheld devices [57]. The framework supports depth estimation through a depth estimation model based on MVS [58]. Earlier version of the framework is standalone, however recently the developers released version 3.0, which integrates the framework with the Unity AR Foundation framework. This allows developers to enhance AR Foundation feature sets with theirs, including depth estimation.
- EasyAR: EasyAR is an AR framework developed by VisionStar Information Technologies [59]. This framework is able to be deployed on Android and iOS devices. The depth estimation method is undisclosed, but it is assumed that the method is based on single image monocular depth estimation, based on the documentation which mentioned that it is based on RGB input [60]. The depth data generated by the framework can be used for spatial mapping and occlusion handling.

5. APPLICATIONS OF DEPTH ESTIMATION IN HANDHELD AR

This section explores the applications of depth estimation in handheld AR. We have classified the applications that were discovered in our review as tracking, occlusion handling, 3D reconstruction, collision detection, interaction, object recognition, improved lighting, navigation, and content creation. We discuss the related research in each of the applications.

5.1. Tracking

Depth data allows AR applications to understand the depth and spatial relationships of objects in the user's environment. This enables more accurate placement and scaling of virtual objects, making them appear as if they exist in the real world [39]. Depth estimation helps with tracking the position and movement of the device in real-time, which is crucial for maintaining the alignment of virtual objects with the physical world. Tracking with depth data also allows markerless overlaying of objects. Used depth data to obtain geometric property of real object and use as correspondence for pose estimation between target and model [36]. Their method replaces the use of fiducial markers as they mentioned that markers are not efficient in implementing in complex industrial environments because difficulty of installing markers in precise position. Tracking object velocity is also a useful application of depth data. Obtained depth data using the LiDAR sensor in iPad Pro 2020 to track the velocity of robot joints [34].

5.2. Occlusion handling

AR apps can utilize depth information to detect physical objects in the scene and ensure that virtual objects appear behind or in front of them, providing a more convincing and immersive experience. A typical AR system without depth understanding usually just superimposes the virtual object on the real scene, regardless of whether it is behind or in front of objects [61]. Thus, occlusion handling is an important aspect to increase the realism of AR [62]. This ensures that the user can feel that the object is seamlessly augmented in the scene.

5.3. 3D reconstruction

AR has been used to facilitate the process of 3D reconstruction, particularly during the object scanning. Thisse *et al.* [63] proposed an enhanced pipeline for 3D reconstruction using a mobile device for data acquisition and performing reconstruction on a remote server. The method optimized the user experience during scanning by incorporating an AR object into the scene. This object guides the user during data acquisition and aids in selecting the keyframes necessary to produce a high-quality model [64].

5.4. Collision detection

Real time generation of scene mesh and use as the collider for real objects. Tian *et al.* [12] used voxels to represent the scene mesh. Using this method does not generate a detailed geometrical representation, but they argued that detailed geometry is not necessary for collision detection if there is no need for accurate response. Piyavichayanon *et al.* [64] used Depth API to obtain the depth data and used mesh generation algorithm to reconstruct the scene mesh. They used this mesh for collision detection during telemanipulation of AR environment. DepthLab [44] also utilize the Depth API for collision detection on ARCore-based applications.

5.5. Interaction

Depth data can be used to detect hand gestures and pose estimation. Depth data from depth sensor to perform pose estimation of a hand [33]. The system generates 3D skeleton and uses the hand post estimation from the depth data to simulate the hand gestures. Client-server system to transmit depth data from Leap Motion, a hand gesture tracking depth sensor to a handheld device for target selection on occluded and distant objects. They used photon unity networking (PUN), a networking library that uses transfer control protocol (TCP) [65] for the data transmission. Single image estimation method to perform the pose estimation [66].

5.6. Object recognition

Depth information can assist in recognizing and tracking objects in the scene, which is valuable for applications like virtual try-ons in retail or identifying landmarks in tourism. Single image estimation to detect objects and send audio feedback to a visually impaired person [67]. Wadhwa *et al.* [68] proposed human detection for creating shallow depth-of-field using a single camera on smartphone. The method is currently integrated in camera app on Google smartphones, known as portrait mode. Human detection to measure distance between humans for monitoring social distancing [69]. Used depth from Depth API to detect foods for estimating the calorie intake of a meal [70].

5.7. Improved lighting

Depth data can help to estimate the lighting condition of the environment, thus improving the AR realism by responding to changes in lighting conditions. Environment map from depth to estimate lighting [35]. The system was able to achieve real time performance, which allows the simulation of lighting effects when the virtual object is being moved such as shadows.

5.8. Navigation

AR navigation apps can leverage depth estimation for more accuracy and precision in providing turn-by-turn guidance, avoiding object, and presenting contextually relevant information overlays. Attached a handheld device with ARCore Depth API enabled to a robot for the pathfinding [71]. The method allows the implementation of robot pathfinding and placement with spatial awareness without using depth sensors.

5.9. Content creation

AR content creators can use depth estimation to align virtual elements with the real world, simplifying the process of designing AR experiences. Avinash and Sharma [72] proposed a a deep learning-based solution for face reconstruction that predicts the depth maps of the face, both forward and backward facing. The solution is also able to estimate the depth of the occluded part of the face. With this method, it has potential to accelerate the creation of 3D avatars for use in various applications such as virtual meetings or metaverse. Tsunezaki *et al.* [73] proposed a 3D reconstruction system that is able to reproduce the material appearance such as glossiness or reflectance. Facebook researchers presented a photo manipulation method that converts a 2D photo into depth enabled 3D photo [74]. Proposed a system that segments the background of a scene and replace with a virtual background [75].

6. DISCUSSIONS

This section discusses the novelties and limitations of the reviewed papers. Most of the reviewed works are able to provide of real-time solutions, which is important for AR applications. There are also works that have been implemented in real world products such as portrait mode in Google smartphones, ARCore Depth API and Facebook's 3D photography feature. These innovations highlight the practical applications of depth perception in enhancing user experiences. Furthermore, there is also work that can enable support for power users, as demonstrated in [39]. Extending the workspace virtually on small device such as the smartphone allow more data to be displayed without connecting to larger displays.

In AR, occlusion handling and collision detection emerge as critical aspects, ensuring that rendered objects follow the rules of sight and physics respectively. Depth understanding plays a pivotal role in enabling effective occlusion handling and collision detection within AR scenes, enhancing immersion and realism. Some works have enabled occlusion handling and collision detection on handheld AR. Additionally, efforts have been directed towards facilitating AR development through tools like the DepthLab library. This resource enables developers to harness depth data from platforms like the ARCore Depth API, helping with tasks such as occlusion handling, collision detection, and lighting manipulation. Depth estimation can also potentially enhance object detection tasks. By leveraging depth information, algorithms can more accurately discern the spatial characteristics of objects, improving the efficacy of detection systems across various domains.

There are common issues found in the current research. Notably the computational limitations and training datasets for machine learning based solutions. Depth data can also be ambiguous in certain surface textures such as reflective, shiny or transparent. There are also works that implement client-server solutions, which introduces latency issues. A consistent and fast network connection is required for this type of solution to work efficiently. Depth sensors have been appearing on handheld devices, however it is still a costly solution that is only available on high end devices. In the event that it is more commonly available on mid-range devices in the future, it is predicted that more research will be focusing on this device.

Based on our findings, depth estimation in handheld AR has been improved significantly with the arrival of state-of-the-art frameworks and libraries. Notably, Depth API and ARDK allows depth estimation using only the RGB camera on device, with the option of using ToF when available. This will allow more developers to leverage the technology as it will be accessible to massive amount of users. Thus, it can be predicted that the applications of depth estimation in handheld AR that was discussed will be reach a broader audience. Such implications will also increase motivations for future research to improve this field further. This study has highlighted the possible research directions based on the current achievements and limitations. However, since we have constrained our focus based on the RQ, it is possible that we have overlooked some papers that may further highlight the future directions on the research. We also did not fully explore on each of the frameworks described. A more in-depth comparison of each frameworks could be explored in the future.

7. CONCLUSION

In this paper, we reviewed several papers regarding depth estimation on handheld AR. The papers selected are ranged from 2018 to 2023. From the review, we provide an overview of depth estimation in AR and narrow down to handheld AR in terms of depth data acquisition methods, which can be classified as depth sensor, monocular depth estimation and image segmentation. Monocular depth estimation approach can be further classified as stereo vision and single image.

In this review we also discuss on the existing frameworks that allow depth estimation on handheld devices for use in AR. Furthermore, the applications of depth estimation in handheld AR were also classified and discussed based on the reviewed papers. Finally, we discussed on the novelties and limitations of the current research to identify the research direction that can be pursued in this field of research. The challenges that still offer room for improvement include computational complexity, overcoming ambiguous depth data due to certain surface textures and latency issues. Recommendation for research direction is to improve the depth acquisition method, as it plays a major role in the resulting depth estimation.

Our review underscores the significance of depth estimation in handheld AR and emphasizes the ongoing need for research in this field. We lay down the foundation for paving the way to future research. It is our hope that our review will be a valuable resource for researchers and practitioners improving depth estimation in handheld AR. We encourage further research and innovation in this exciting and rapidly developing area.

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