FACULTY OF SCIENCE AND TECHNOLOGY

MASTER'S THESIS

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Abstract

Integration of 3D model production from a single 2D RGB picture using machine learning into mainstream human 3D modelling requires significant evaluation data with an appropriate reference value relative to structured light approach scanning. The purpose of this work is to bridge the gap between the structured light technique and the machine learning algorithm generation method through a comparative analysis based on qualitative criteria such as accuracy and efficiency. The subsequent research was undertaken in two parts. Phase 1 centered on the experimental setup of the data collecting approach utilizing several scanning techniques on the sample model in a controlled setting, whereas phase 2 focuses on the analysis of the subsequent data to determine functional equivalency. The most significant finding of the comparison study is the practicality of the PIFuHD machine learning algorithm with respect to the Artec EVA scanner in terms of efficiency and equivalent precision. Despite the advancements in Machine learning algorithm for generative 3D modeling, major improvements are necessary to achieve functional parity with the structured light scanning approach in terms of accuracy.

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To my wonderful family and friends, whose support has always inspired me:

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Chapter 1 Introduction

Utilizing 3D modeling has proved useful for furthering research, increasing design processes, and improving educational outcomes [1]. Traditional anthropometric measures do not depict the three-dimensional shape of the human body, and with the advent of CAD software and 3D scanning technologies, 3D human modeling has become a need for engineering product design [2]. However, structured light approach 3D scanning technologies, despite their significance, are not accessible to the general public or researchers due to their expense and demand for specialist technicians. In addition, they demand the continual presence of 3D models that require specialized training to maintain a still position and zero motion conditions, which is taxing for the models. The particular models may not have the time or stamina to be present in a controlled environment, which is required for 3D scanning utilizing the structured light approach employed by the Artec EVA Scanner.

This challenge has led to the development of machine learning scanning technology, which has led to a novel method of capturing 3D data of human models that does not require any further equipment than a computer on which to execute the application. This new developing approach of 3D scanning employs open-source deep learning algorithms, making it possible for customers to receive 3D model data for their desired model from a single RGB photograph. This makes the acquisition of a 3D model economical, user-friendly, and extremely efficient in terms of speed and mobility. But for the seamless integration of this technology to work in the current 3D modelling industry, a comparative reference value is required that can enable body data "consumers" to comprehend these 3D body digitalization technologies and make well-informed selections when selecting the most appropriate solution for their specific company requirements.

The objective of the work described in this paper was to investigate a qualitative and comparative evaluation of the Structured light technique and the machine learning scanning method for anthropometric data, utilizing standard sample, data collecting processes, and analytic procedures. Although similar studies on the compatibility and dependability of different scanning methods have been conducted in the past, this study is unique in that it compares data collected from the newly established deep learning algorithms Learned Vertex Descent and PIFuHD to structured light methods such as the Artec EVA scanner utilizing similar procedures for data collection and analysis.

The research objective will establish the following results:

- Comparative examination of the precision and effectiveness of the 3D structured light scanning and Machine Learning scanning technologies
- Comprehensive and impartial evaluation of the functional equivalency of machine learning scanning vs structured light 3D scanning in the human 3D modelling sector

1.1 Objective

This thesis will examine the basic concepts, data gathering methodologies, and processing workflows of structured light and machine learning-based 3D scanning approaches. By exposing the technical complexities of each technique, we want to clarify their basic distinctions and parallels.

Evaluation of Accuracy and Precision: The accuracy and precision of the reconstructed models is a crucial component of 3D scanning. The qualitative performance measures of both strategies will be evaluated. This study will assist discover situations when one strategy performs better than the other.

Data Complexity and Processing Efficiency Various applications require differing degrees of data complexity. We will study the scalability and efficiency of each technique in terms of data amount, complexity, and processing resources needed. This knowledge will be essential for selecting the best appropriate strategy in real-world situations.

Application and Use Situations: To highlight the real-world consequences of our findings, this thesis will examine and explain particular use cases in which each technique shines or suffers difficulties. In doing so, we want to provide light on the domain-specific applicability of the structured light approach and machine learning-based 3D scanning techniques.

1.2 Scope and Limitations:

This investigation will compare the structured light approach with 3D scanning techniques based on machine learning. Existing 3D scanning techniques, such as laser-based and photogrammetry-based technologies, will be omitted from this study to keep a focused scope. In addition, the scope of the study will be restricted to commercially accessible and open-source implementations of the chosen methodologies.

1.3 Organization of the Thesis:

The thesis will be structured into several chapters, each addressing specific aspects of the comparative analysis. The organization will be as follows:

1. Introduction: Provides an overview of the research problem, objectives, scope, and limitations.
2. Literature Review: Surveys the existing body of literature on 3D scanning, structured light method, and machine learning-based approaches, and highlights the gaps and contributions of this thesis.
3. Methodology: Describes the research methodology, experimental setup, and data collection procedures for evaluating the two 3D scanning techniques.
4. Comparative Analysis: Presents the results of the qualitative assessment, comparing the structured light method and machine learning-based approach in terms of accuracy, efficiency, and applicability.
5. Discussion: Analyzes the findings, interprets the results, and discusses the implications of the comparative analysis.
6. Conclusion: Summarizes the research outcomes, reiterates the key findings, and proposes future research directions.

By conducting a thorough comparative analysis of the structured light method and machine learning-based 3D scanning techniques, this thesis endeavors to contribute to the advancement of 3D scanning technologies and inform decision-making processes for their practical implementation in various industries and research domains.

Chapter 2 Related Work

2.1 Human 3D Modelling

3D human modelling is the state-of-the-art modern-day anthropometric assessment method that allows us to recover the 3D geometry and appearance of human body in a digital format from various scanning and modeling techniques using several sources like light, pictures, movies, or depth data [1]. These digital formats may include Proprietary 3D file formats, such as AutoCAD's DWG files or Blender's BLEND files, which are used specifically for their respective optimized programs. Neutral digital file formats include STL, OBJ, 3MF, etc., which are cross-platform, so they can be used to create a file in one program and transmit it to someone using a different program, and they will be able to open and edit the file. The data format of these digital 3D files consists of four primary features, which are the model's geometry, its surface texture, scene details, and its animation [2].

Using these digital formats gives us the opportunity to make a virtual digitalized representation of the real physical human body, which can be used in broad range and field of applications. Ergonomic analysis utilizing a digital human model created by ergonomic human modeling tools such as 3DSSPP has been introduced to facilitate a more rapid and cost-effective design process [3-5]. In virtual reality simulations, the majority of virtual objects are represented by three-dimensional models, which consist of a collection of triangles with common edges and vertices [6]. Integration of human factors in any system of simulation-based engineering requires involvement of the 3D human model data solely for demographic purpose. Human-Centered Design in Aviation is a collaborative effort between pilots and human factors engineers in aircraft development and operation. Pilots bring vital operating environment knowledge and are the primary demographic for designing product solutions [7]. Anthropometry and biomechanics studies is one of the major field of science which requires accurate 3D human model for design purpose as they are used for risk assessment and safety evaluations of assistive technologies for rehabilitation purpose of patient specific product [8].

Some of the core challenges that human 3D modelling faces are accuracy and efficiency of the entire process. Human body shape estimation from natural images is extremely difficult due to variables such as the diversity of human bodies, clothing, and points of view [9]. The structured light method is frequently employed in human 3D modeling, but it presents its own unique challenges. An obstacle is the precision of the 3D reconstruction, particularly when dealing with small or complex objects. In the case of machine learning image based algorithm, the shallow depth of field affects image-based 3D reconstruction and can result in a 3D model with a lower resolution [10]. In 3D human shape estimation, estimating the full 3D shape of a person from a single RGB image remains an open problem. Model-based approaches can generate accurate meshes of bare, undergarmented human bodies, but they are incapable of estimating details and non-modeled elements such as hair or clothing [11]. In terms of speed and efficiency, structured light method requires more time to capture the image, and demands unwavering presence of the model itself, which can be exhausting for the model too. While single RGB image-based 3D modelling software can process the construction of 3D model without the constant presence of the model, it requires the estimation of 3D position from 2D position. Optimization of a 3D human model's projection to 2D predictions can also be computationally costly and ambiguous [12].

2.1.1 Human 3D modelling for Sports Engineering

In recent years, the application of 3D human modeling in sports engineering design has received considerable interest. This method has several benefits in terms of shape and form preservation, adaptability, repeatability, and high culture throughput [13]. In addition, 3D human modeling based on imaging technology has been utilized to collect and evaluate the real-time motions of athletes. Researchers may create sports analysis systems that give real-time feedback and insights into an athlete's performance by recording the movements of players using 3D imaging technology. This data may be utilized to identify improvement areas, optimize training regimens, and avoid injuries[14].

One such noteworthy illustration is the Aerodynamic investigation of tucked positions in alpine skiing [15]. In this study, experiments were done in a wind tunnel utilizing 3D scans of male and female athletes for this investigation. The effect of arm configurations in various postures, such as low-tucked, high-tucked, and flying postures, was investigated. Consistent patterns were identified between tests and simulations of computational fluid dynamics, emphasizing the significance of arm posture in aerodynamics. In this study, the 3D model of the sample skiers obtained through 3D modelling technology played a vital role in the digital assessment of the performance of index in a competitive sport such as alpine skiing.

2.2 3D Scanning using Structured Light Method (STL)

The structured light method is a 3D scanning approach that use the optical triangulation concept to gather 3D data and build 3D representations of objects or surfaces. This approach entails projecting structured grating fringes onto a subject or object and recording the deformation of the pattern using cameras or sensors. As the fringes travel through the subject, they are converted into measurement fringes, and the distance between each pattern point may be measured to provide a 3D morphological representation [16].

The structured light method is a widely utilized technique for 3D human body scanning. The process involves projecting a known light pattern onto the body's surface and capturing the pattern's deformation of the human body surface with cameras. This technique permits the collection of anthropometric data, such as surface, volume, and cross-sectional measurements [17]. Using the collected depth information, a 3D representation of the item surface is reconstructed. This may be accomplished by triangulating the depth measurements from several perspectives to derive the 3D coordinates of each surface point [18]. The generated 3D model may be viewed and examined for a variety of purposes.

Numerous industries, including forensic medicine, breast surgery, historical clothing, and anthropometry, have developed a significant interest in three-dimensional (3D) scanning using structured light.. Structured light scanning mitigates the drawbacks of conventional documentation methods and gives more accurate 3D findings. The Pico Scan 3D scanner, which was developed expressly for structured light scanning, is capable of recreating hairy, moist, and dark-skinned areas that are difficult to capture using photogrammetry or laser scanning. The validity of 3D measurements based on structured light scanning has been demonstrated, and more research is underway to scan open wounds with depth data[19]. Structured light 3D scanning has been investigated as a method for making 3D models of displayed clothes in the subject of historical clothing. While photogrammetry and 3D modeling tools have been widely utilized, structured light scanning offers a novel technology with potential accuracy and methodological advantages [20].

2.2.1 Artec EVA 3D Scanner

The portable Artec EVA scanner is a structured light scanning equipment for 3D surface scanning. It is simple to use, collects both geometry and texture data, and has been effectively used in a variety of human applications. The scanner is useful for collecting comprehensive 3D models of the human body and other items due to its user-friendliness, precision, and ability to accommodate subject movement [21, 22]. The method of 3D scanning with the Artec EVA scanner entails collecting the object's or body part's form and surface characteristics. The operator swings the portable scanner around the subject to obtain numerous perspectives. The scanner projects structured light patterns onto the surface, and its cameras or sensors capture the deformation of the patterns. Using software such as Artec Studio, the collected data is then processed to create a 3D model of the human part [23].

2.3 Machine Learning Scanning Technology:

As a 3D scanning technology, machine learning algorithms utilize machine learning techniques to evaluate and understand 3D data received from diverse sources, such as RGB photos, 3D scans, medical images, and point clouds, and produces a 3D model based on that information using its working principle.

The operating principles of machine learning algorithms as a 3D scanning technology involve numerous fundamental characteristics. Initially, the algorithms use enormous 3D data sets to discover patterns and correlations within the data. This procedure, called as training, includes providing labeled samples of 3D models and their respective properties or attributes to the algorithms [24]. The algorithms then evaluate the data using statistical approaches and uncover patterns that may be utilized to make predictions or produce new 3D models. Second, the algorithms leverage a variety of feature extraction and representation strategies. In the context of 3D scanning, these approaches entail extracting pertinent characteristics from 3D data, such as form, texture, or geometric qualities [25]. The machine learning algorithms then learn to correlate these traits with certain groups or categories of 3D objects. In addition, the algorithms may leverage various machine learning models, including deep learning models, to manage the complexity and high dimensionality of 3D data. Due to their capability to develop hierarchical representations of the input, deep learning models, such as convolutional neural networks (CNNs), are very good at evaluating and interpreting 3D data [26]. These models are composed of numerous layers of linked nodes that learn to extract increasingly abstract properties from incoming data. In addition, algorithms may be trained using various optimization approaches, such as gradient descent, to iteratively alter model parameters and reduce the discrepancy between expected and actual outputs [27]. This process, known as model optimization or training, enables algorithms to enhance their performance over time and provide more accurate predictions or more realistic 3D models.

In 3D human modeling, one use of machine learning techniques is the development of realistic 3D clothed human body models. The methods use parametric models for 3D bodies and clothing to capture body form and position, which are fundamental elements of 3D human modeling [19]. Traditional models are often learnt from minimally-clothed 3D scans and have difficulty generalizing to the complexity of clad humans in popular photos and movies. To overcome this issue, researchers have built generative 3D mesh models that can learn the deformation of clothes using 3D scans of various positions and types of clothing. Effectively expanding the depiction of the human body model to include clothes, these models may create garment samples for various body forms and positions [19].

2.3.1 Learned Vertex Descent

Learned Vertex Descent (LVD) is an unique optimization approach in which a network use local image or volumetric data to anticipate repeatedly per-vertex paths toward an ideal body/hand surface. It blends gradient descent optimization with deep neural networks for precise and efficient posture estimation. The suggested method is immediately transferable to diverse jobs with little network modifications, and it can accommodate a greater variety of body forms than prior state-of-the-art methods [28].

In contrast to prior methods that directly regress the parameters of a low-dimensional statistical body model (e.g., SMPL) from input photos, this method is trained in an ensemble of per vertex neural fields networks [28]. On the basis of neural characteristics collected from the present vertex projection, the network predicts, in a distributed fashion, the vertex fall direction towards the ground truth. At inference, this network, named LVD, is utilized within a gradient-descent optimization pipeline until convergence, which often happens in a fraction of a second even when all vertices are initialized as a single point. A comprehensive examination reveals that the method is capable of capturing the underlying body of clothed humans with vastly varied body forms, representing a major advance over the current state of the art [28].

LVD combines the benefits of traditional optimization with learning-based techniques. LVD captures out-of-mean structures substantially more precisely than all past work. Unlike optimization techniques, it does not suffer from local minima, and it converges in only six rounds. The superior performance is attributable to the distributed per-vertex predictions and the error feedback loop – the current vertex estimate is iteratively validated against the image evidence, a feature present in all optimization schemes but absent in learning-based methods for human shape estimation [28].

2.3.2 PIFuHD: Multi-Level Pixel-Aligned Implicit Function for High-Resolution 3D Human Digitization

PIFuHD is an end-to-end, multi-level framework that infers the 3D geometry of clothed people at an unprecedentedly high 1k picture resolution in a pixel-aligned manner, preserving the original inputs' features without post-processing. This method is distinct from coarse-to-fine methods in that no explicit geometric representation is mandated at coarse levels. Instead, implicitly encoded geometrical context is conveyed to higher levels without prematurely establishing explicit geometrical determinations [29].

This technique was originally presented in Pixel-Aligned Implicit Function (PIFu) encoding [30]. The pixel-aligned structure of the representation enables the smooth, principled fusion of the learnt holistic embedding via coarse reasoning with the picture characteristics learned from the high resolution input. Each level integrates increasingly more information than the previous level, with the final geometry determination done only at the highest level. For a comprehensive reconstruction, the system must retrieve the unseen backside from a single picture. As with poor resolution input, missing information that cannot be predicted from visible data will produce in predictions that are too smooth and blurry. Conditioning the multi-level pixel-aligned form inference with the inferred back-side surface normal eliminates ambiguity and considerably enhances the perceived quality of the reconstructions, resulting in a more constant degree of detail between the viewable and occluded portions [29].

2.4 Comparative Analysis Approach

Since its creation in the 1980s, the 3D imaging business has expanded rapidly. There are currently several types of 3D surface imaging systems, each employing unique hardware, software, computer vision algorithms, and landmarks, resulting in varying measurement locations and degrees of precision and accuracy. While manufacturers and independent studies have evaluated the systemic and random errors of specific 3D surface imaging systems, factors such as population samples, landmarking, measurement definitions, data cleaning processes, and analysis methods impede the ability to make informed comparisons between systems and manually collected data [1].

The objective of the comparative analysis method is to examine the efficacy of 3D scanning technology and machine learning scanning technology in 3D human modeling. This approach has two goals: first, to propose a methodology to assess the accuracy and efficiency of different body measurement extraction methods (e.g., body scanners, machine learning algorithm) using consistent criteria, and second, to collect data and conduct the corresponding analyses for the first instance of the proposed methodology [1]. The accuracy of a 3D model relates to how closely it resembles the genuine human anthropometry. Considerations for efficiency include processing time and computational demands. Complexity of human traits, data quality, scanner setup, algorithm design, and processing resources may all impact the comparison.

In the previous studies, using a comparative analysis methodology, the performance and precision of multiple 3D scanning methods for human 3D modeling were examined. A research aims to assess the quality and precision of surface models and landmark data derived from contemporary clinical CT scanning, 3D structured light scanning, photogrammetry, and the MicroScribe digitizer. In a topographical analysis, the study evaluated 13 distinct photogrammetric software applications and compared surface models created by different approaches for four articulated human thighs[31]. The accuracy and quality of surface models vary depending on the scanning technology and reconstruction software utilized, as demonstrated by the study's findings. Compared to the MicroScribe digitizer, the 3D structured light scanning and photogrammetry techniques generated surface models with more precision and detail. However, the clinical CT scanning approach produced the most accurate and comprehensive surface models of the studied procedures. The study also highlighted the need of selecting suitable software tools for photogrammetry to achieve accurate and trustworthy findings[31].

Chapter 3 Methodology

3.1 General Research Design

The design of the study was observational with repeated measurements, and it was done in two phases during which a series of 3D Scanned images were obtained from participants using three scanning techniques.

In the first step, an experimental apparatus was developed to acquire 3D scans of two different people in different interval standing in a controlled lighting setting. The structured light approach was utilized directly in a controlled setting to acquire 3D data for further data processing. In order to remove outlier variables while comparing the different scanning approaches, high-resolution photos of the sample models were captured using the exact same setup for machine learning scanning. The experience of the user and the models are documented for further analysis.

In step 2, the scanned 3D data are postprocessed in their respective algorithm software, and the final 3D photos are analyzed in conjunction with the user's and model's documented experiences. After analyzing both the 3D data and the recorded experience data, a final side-by-side comparison is performed.

3.2 Experimental Setup

3.2.1 Sample Selection

There was a total of 2 participants in the trial. The recruitment of the test sample model 1 was co-ordinated by the author through personal connection. Test sample model 2 data is a previously collected data from the study “Aerodynamic investigation of tucked positions in alpine skiing” by Knut Erik Teigen Gilijarhus [15]. All participants were volunteers who gave informed agreement for their data to be used in the study.

Figure 1: Test Input Sample 1

Figure 2: Test Input Sample 2

3.2.2 Artec EVA Scanner Data Collection

Using the Artec EVA scanner, we performed a series of procedures to acquire data. First, the scanning environment was provided optimal lighting condition using 4 different light panel in 4 different directions. Next, the scanner was correctly configured and calibrated. This required connecting the scanner to a computer and installing the required software. We installed the Artec Studio 15. The program offered an intuitive interface for managing the scanner and collecting scans.

After setting up the scanner, we commenced data collection with test sample 1. The user carried in his back pocket a portable battery attached to the scanner. The scanner was held in one hand while the laptop computer was held in the other. The representative model stood in the centre of the regulated, lit atmosphere. As soon as the scanner began scanning, it produced a structured pattern of light onto the model being scanned. The scanner's cameras, which are positioned at various angles, caught the light patterns. During the process of data gathering, the scanner was moved around the model to obtain scans from various angles. This enabled us to obtain a more accurate and comprehensive depiction of the scanned model. The scanner was also utilized to acquire texture data, which was incorporated to the 3D model as visual details. The scanner then applies sophisticated algorithms to the collected light patterns to recreate a 3D representation of the scanned object in the computer.

The 3D representation was postprocessed in the Artec Studio 15 software in the laptop computer and a stereolithographic file (stl.) was created in the computer from which the required 3D model and the mesh data were collected for analysis.

3.2.3 Learned Vertex Descent Data Collection

The learned Vertex Descent python code was available on Github. We cloned the repository from the github and uploaded it sandbox which is a platform for running the code. While running code, the input image of sample 1 and 2 was uploaded. After the runtime of the code was finished, the a stereolithographic file (stl.) of both sample 1 and 2 were obtained which was later used in the analysis.

3.2.4 PIFuHD Data Collection

In order to start data collection using the PIFuHD, we obtained the RGB image of test sample 1 and 2 in their respective optimally lighted set up. To run the input in high resolution, a computing unit of high computational resources is required which was unavailable in our domain. But the issue was quickly resolved using Google Colab.

Google Colab is a well-known platform for doing Python-based deep learning tasks. It offers a Jupyter Notebook environment and significant hardware resources, such as the Nvidia K80 GPU with 12 GB of RAM and 4.1 TFLOPS capability [32]. The PIFuHD demo code was available on google colab using which we ran the input image of both sample 1 and 2. In neural rendering, a neural network and a differentiable renderer are employed to create a 3D model from a single RGB picture using PIFuHD. After running the code, the obj. file of the sample 1 and 2 was available in the pifuhd result directory which was later used for analysis.

3.3 Comparative Analysis Setup

3.3.1 Qualitative Assessment

When picking a 3D imaging method using digital technologies, the 3D digital object that depicts the body surface of the subject is a crucial factor [1].

To visually assess the accuracy of the 3D Models provided by each of the scanning methods, the rendered image of the front, back, side and top view of both sample 1 and sample 2 were set in a side-by-side comparison. All models utilize the same axis convention. The camera orientation varies based on the view: the front camera faces negative Z, the rear camera faces positive Z, the leftside camera faces negative X, and the rightside camera faces positive X.

To measure the density and level of detail of the model, 3D mesh triangles and vertices are also visually assessed.

3.3.2 Comparative Assessment

After data collection, the data of both the qualitative visual assessment of sample 1 and 2, and the documented experience of the data collection are run through some comparative assessment. The criteria for the comparative assessments are accuracy of the 3D images obtained from the model to the original input, and the efficiency of the data collection process.

The accuracy quality of a 3D mesh model can be assessed in terms of fidelity, element quality, and mesh complexity. Fidelity is the degree to which the mesh model accurately replicates the model. This characteristic was assessed by observing the pose estimation, the geometric detail and the surface texture of the 3D model. Element quality refers to the geometric qualities of the triangles or elements that make up the mesh. The mesh model's element quality is determined by analyzing geometric-based indicators such as aspect ratio and edge length [33]. Mesh complexity is proportional to the mesh's density and amount of detail. A denser mesh often comprises more triangles and vertices, resulting in a more accurate depiction of the model being represented. The mesh triangle and vertices are both observed and counted for the accuracy assessment of the models derived from both sample 1 and 2 for all three scanning techniques.

The efficiency of the data gathering process was evaluated based on the scanning techniques' speed, usability, portability, and computing load requirements. Speed influences how long it takes for the complete procedure to follow up on sample 1 and 2 and generate the final 3D model output. In order to determine the practicability of the three scanning approaches, the user-friendliness or difficulty level of the entire data gathering procedure for both the user and the model is evaluated. Portability is a crucial notion in terms of efficiency, since it directly influences the speed and usability of data collecting. Last but not least, the computational load demand is evaluated, since it will define the hardware requirements essential for the experiment to even begin.

Chapter 4 Experimental Results and Comparative Analysis

4.1 Qualitative Assessment

Visual assessment of the 3D pictures generated by digital scanning techniques illustrates the scanning performance with 3D images, including image fidelity, quality, artifacts, and accuracy. Table 1 and Table 2 showcases the 3D images of the outcome of 3D Scans on test input sample 1 using Artec EVA Scanner, Learned Vertex Descent and PIFuHD from different comparable angle. Here based on the data collection section, we are using a live specimen as test input data for on hand real time output.

Figure 3: Test Input Sample 1

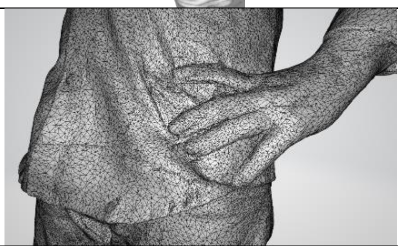
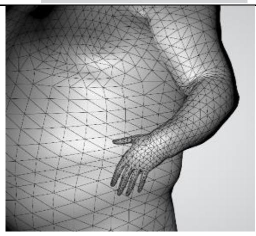
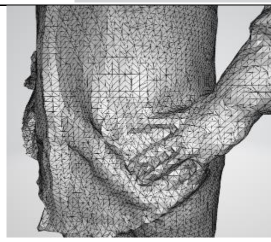
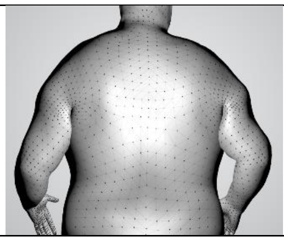
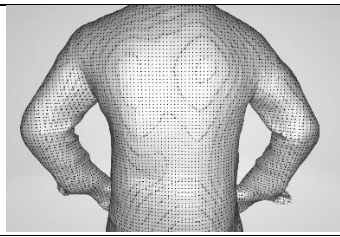
Sample1	Artec EVA Scanner	LVD	PIFuHD
Side View			
3D Mesh Triangle View			
3D Mesh Vertices View			

Table 1 : Qualitative Assessment of 3D images of the 3D Scanning of Sample 1 using Artec Eva 3D Scanner (STL). Learned Vertex Descent and PIFuHD : Side View, 3D Mesh Triangle View and 3D Mesh Vertices View

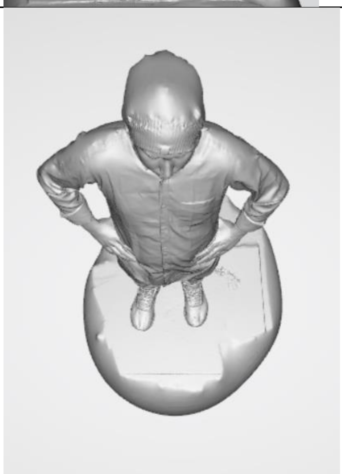
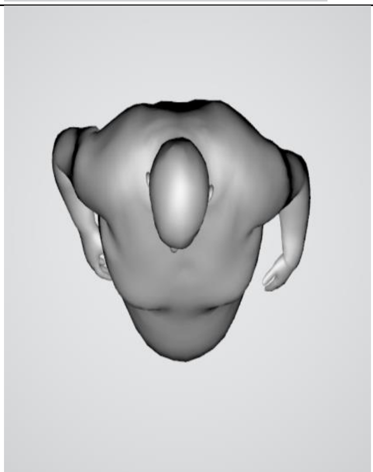
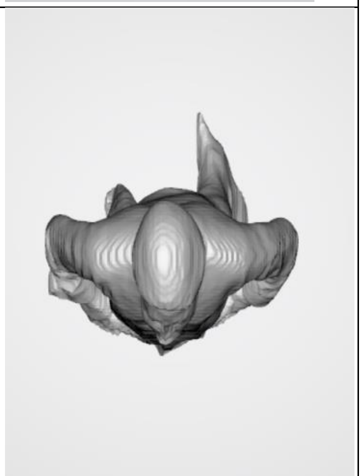
Sample 1	Artec EVA Scanner	LVD	PIFuHD
Front View			
Back View			
Top View			

Table 2: Qualitative Assessment of 3D images of the 3D Scanning of Sample 1 using Artec Eva 3D Scanner (STL). Learned Vertex Descent and PIFuHD : Front , Back and top View

Table 3 and Table 4 represents the 3D images of the final outcome of 3D Scans on test input sample 2 using Artec EVA Scanner, Learned Vertex Descent and PIFuHD from different comparable angle. Here based on the data collection section, we are using a predetermined test input directly from the Knut Erik research article as test input data for output in the purpose of sports engineering.

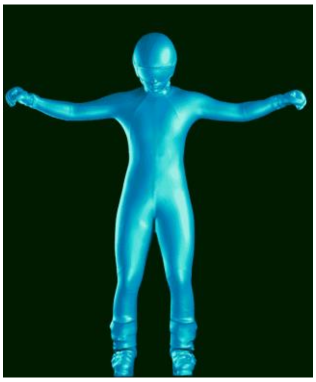


Figure 4: Test Input Sample 2

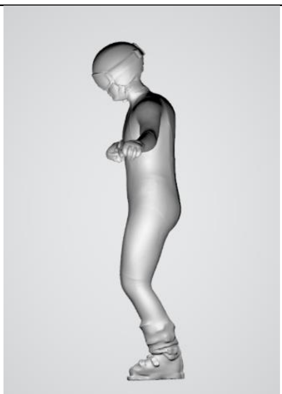
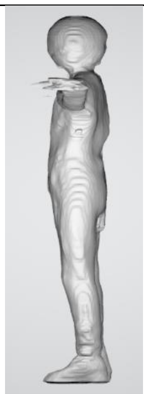
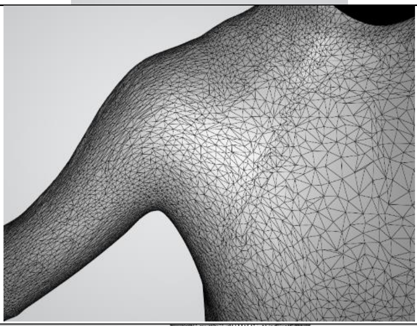
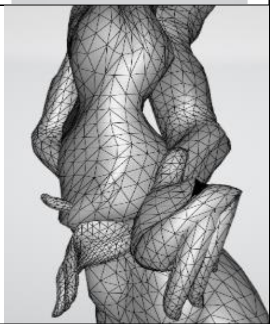
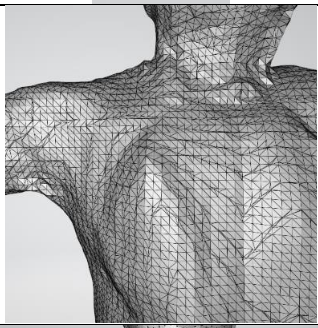
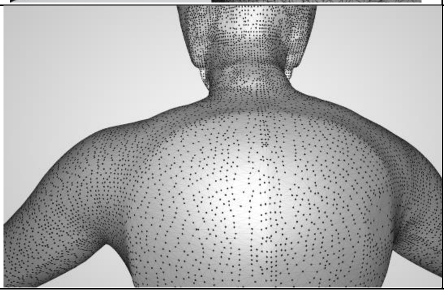
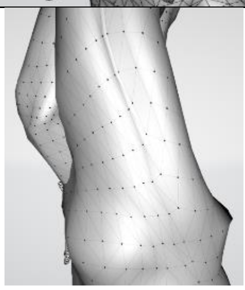
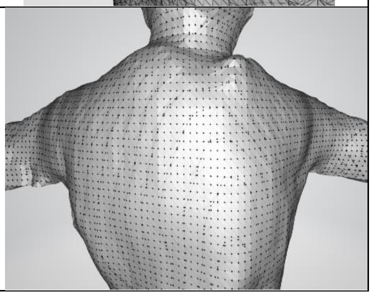
Sample 2	Artec EVA Scanner	LVD	PIFuHD
Side View			
3D Mesh Triangl e view			
3D Mesh Vertex View			

Table 3 : Qualitative Assessment of 3D images of the 3D Scanning of Sample 2 using Artec Eva 3D Scanner (STL). Learned Vertex Descent and PIFuHD: Side View, 3D Mesh Triangle View and 3D Mesh Vertices View

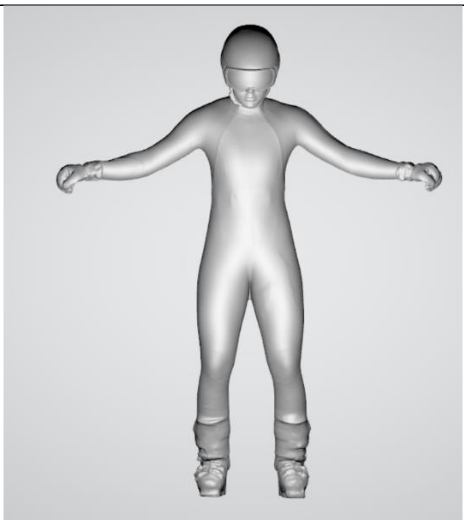
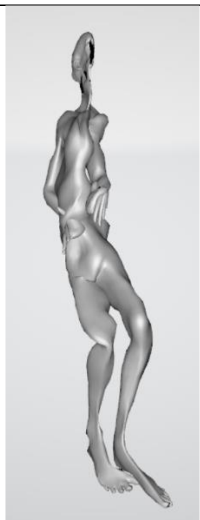
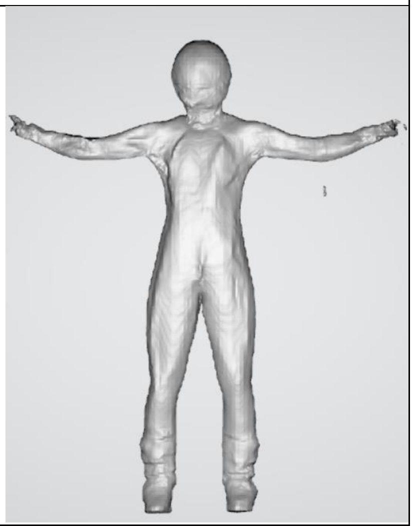
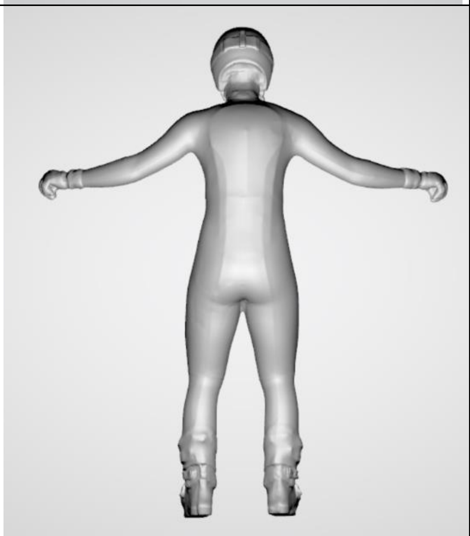
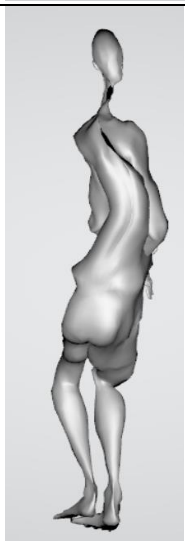
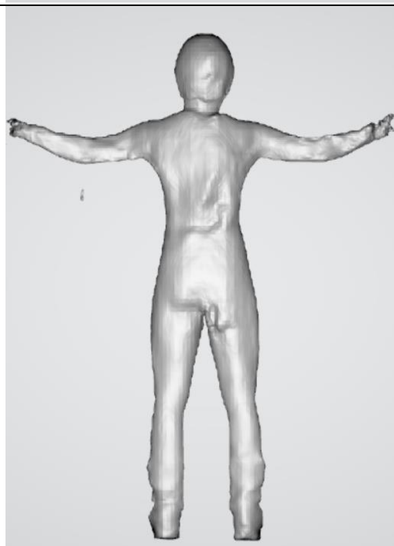
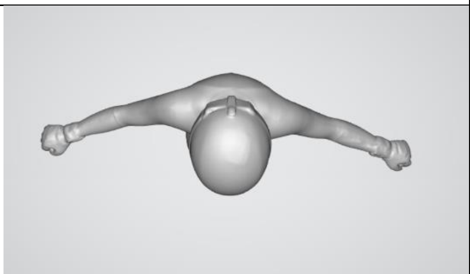
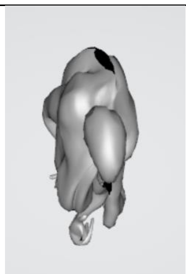
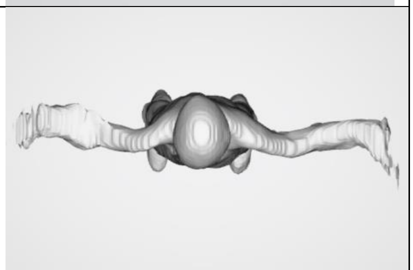
Sample 1	Artec EVA Scanner	LVD	PIFuHD
Front View			
Back View			
Top View			

Table 4 : Qualitative Assessment of 3D images of the 3D Scanning of Sample 2 using Artec Eva 3D Scanner (STL). Learned Vertex Descent and PIFuHD : Front , Back and top View

4.2 Comparative Assessment:

4.2.1 Accuracy Comparison

4.2.1.1 Comparison of the accuracy achieved by Structured Light Method (STL)

- **Fidelity:** If we make a side by side comparison between Test Sample Input 1 and 2 , and Artec EVA Scanner section of Table 1, Table 2, Table 3 and table 4, it can be derived from visual assessment that , in terms of pose estimation, geometric details and surface texture, Artec EVA Scanner managed to capture high fidelity 3D model of both test input sample 1 and 2 retaining the original geometry of the model.
- **Element Quality:** If we take a closer look at the 3D mesh triangle view section of the Artec EVA Scanner from table 1 and 3 of input sample 1 and 2 respectively, we can see low aspect ratio of the elements suggesting a more uniform or symmetrical part that is of higher quality. The edge length of the elements are close to uniformity which also emphasizes better quality
- **Mesh Complexity: :** The mesh count of EVA scans of sample 1 and 2 in terms of triangles are 500000 and 211182 respectively. The mesh count of EVA scans of sample 1 and 2 in terms of vertices are 248866 and 105,593. These numbers are higher number of mesh triangles and vertices representing denser and high level of detail complexity.

4.2.1.2 Comparison of the accuracy achieved by Learned Vertex Descent (LVD)

- **Fidelity:** We make a side-by-side comparison between Test Sample Input 1 and 2, and LVD section of Table 1, Table 2, Table 3 and Table 4. It can be derived from visual assessment that, in terms of pose estimation, LVD retains the pose of sample 1 but completely loses for sample 2. In terms of geometric details and surface texture, LVD fails to retain both of them, both in sample 1 and sample 2. This determines the fidelity capture of LVD is very low for both input samples.
- **Element Quality:** If we observe the 3D mesh triangle view section of the LVD from table 1 and table 3 of input sample 1 and 2 respectively, we can see that the triangle elements have high aspect ratio. We can also see that in both cases, the edge lengths uniformity gets distorted drastically in different places. This confirms low element quality in both sample 1 and 2.
- **Mesh Complexity:** The mesh count LVD scans of sample 1 and 2 in terms of triangles are 13776 and 13780 respectively. The mesh count EVA scans of sample 1 and 2 in terms of vertices are 6890 and 6900 respectively. These are very low number of mesh triangles and vertices representing thin and low level of detail complexity.

4.2.1.3 Comparison of the accuracy achieved by PIFuHD

- **Fidelity:** We account a side-by-side comparison between Test Sample Input 1 and 2, and PIFuHD section of Table 1, Table 2, Table 3 and Table 4. By visual assessment, in terms of both pose estimation and geometric details, PIFuHD retains them both in sample 1 and sample 2. In terms of surface texture, PIFuHD losses details both in sample 1 and sample 2.
- **Element Quality:** When we observe the 3D mesh triangle view section of the PIFuHD from table 1 and table 3 of input sample 1 and 2 respectively, the find the aspect ratio to be low. But in both cases, we see some deformation in edge lengths losing the quality of the elements. A medium quality of element of the triangles can be assessed from this observation for both samples.

- **Mesh Complexity:** The mesh count PIFuHD scans of sample 1 and 2 in terms of triangles are 112088 and 110324 respectively. The mesh count EVA scans of sample 1 and 2 in terms of vertices are 336264 and 330972 respectively. By this observation we can say that a high number of mesh triangles and vertices are found. This showcases dense and high level of detail complexity in both samples.

4.2.1.4 Comparative assessment of the Accuracy of three techniques

By using the comparative accuracy assessment formula from our earlier study of data analysis, we showcase a comparison of characteristics of sample 1 and 2 3D images in terms of fidelity, element quality and mesh quality for all the above cases of 3D scanning method. Table 5 represents a side-by-side comparison of them.

Accuracy	**Artec EVA**		**LVD**		**PIFuHD**	
Samples	1	2	1	2	1	2
Fidelity	High	High	Low	Lowest	Medium	Medium
Element Quality	High	High	Low	Low	Medium	Medium
Mesh Complexity	High	High	Low	Low	High	High

Table 5: Comparative Accuracy Assessment of 3D images of the 3D Scanning of Sample 1 and 2 using Artec Eva 3D Scanner (STL). Learned Vertex Descent and PIFuHD : Fidelity, Element Quality and Mesh Quality

4.2.2 Efficiency Assessment

4.2.2.1 Comparison of the Efficiency achieved by Structured Light Method (STL)

- **Speed:** The scanning speed of the Artec EVA scanner depends on the dexterity of the operator. In our sample one test scenario, it took around 60 minutes to scan the entire body. It took us 10 minutes to post-process the final obj. file format in the Artec Studio application. This took us a total of 70 minutes time from scanning to getting the final output of the 3D model of sample one.
- **Ease of Use:** Artec EVA scanner requires the co-operation of both the user and the model simultaneously at the same time. This demands the unwavering physical presence of the test sample model in a still motion while the user takes the scanner in his hand and moves around the model to take the scan. The user needs to hold the computer connected in his hand while skilfully move around the model to take scanner making it difficult to use. The model also cannot move while the scan is being taken making it exhausting for the model as well.
- **Portability:** While the Artec EVA is limited in portability when connected with an AC current setup, it can be possible to move with it by optional battery pack to offer full portability [34].
- **Computational load requirements:** The software, Artec Studio 15 for the Artec EVA requires min. 12 GB of RAM for Artec Eva (SD mode) and NVIDIA graphics card with at least 2GB of VRAM. Highly recommended for best computation speeds is an NVIDIA card with a CUDA computing capacity of at least 6.1 and 8+ GB of VRAM [34].

4.2.2.2 Comparison of the Efficiency achieved by Learned Vertex Descent (LVD)

- **Speed:** The scanning speed of the LVD depends on the computational time required to process the sample input image. It took us 5mins to run all the program code involved in the algorithm present in google collab.

- **Ease of Use:** The usability of LVD is highly convenient as it only requires the picture of the test subject and not the presence of the subject. As a result, just by acquiring the single RGB picture of the test subject, and putting it as a input while running the algorithm, any person can acquire a 3D model of the model.
- **Portability:** The program fully runs on a programmed algorithm. The portability depends on what kind of computer is run with it. For a desktop computer, typically with high specifications requirement, the portability is limited. However, with a laptop computer, the program becomes fully portable.
- **Computational load requirements:** While the specification of the computation load requirements is not explicitly specified based on the source of the algorithm, our program run on a specification of 16GB of RAM with NVIDIA graphics card with 4GB of VRAM.

4.2.2.3 Comparison of the Efficiency achieved by PIFuHD

- **Speed:** Similar to the LVD, the scanning speed of PIFuHD depends on the computational time required to process the sample input image. But the computational time also depends on the picture resolution of RGB image. In our case, we are limited to using 256-pixel version of the image which took approximately 10 minutes to run all the program code involved in the algorithm present in google collab.
- **Ease of Use:** The ease of usage is comparable to LVD. In our situation, it was feasible to operate the computer on any computer utilizing the Google Collaborate platform, which was really efficient and user-friendly. This also did not require the presence of the model itself, other than a sample input image of the model, making it incredibly simple to utilize.
- **Portability:** The software operates entirely on a predefined algorithm. The portability is dependent on the type of computer used. The mobility of a desktop computer with high-specification requirements is often limited. With a laptop computer, though, the software becomes completely portable. Using the Google Collaborator platform, however, the software becomes even more platform-agnostic, since it can be accessed from any Internet-connected computer in the globe.
- **Computational load requirements:** The processing demands of PIFuHD are anticipated to necessitate substantial computational resources for implicit function reconstruction, differentiable rendering, and optimization. Specific hardware requirements and execution time may vary based on the selected implementation and data collection. The minimum VRAM computational requirements to run on computer is 12GB of VRAM.

4.2.2.4 Comparative assessment of the Efficiency of three techniques

By using the comparative efficiency assessment formula from our earlier study of data analysis, we showcase a comparison of efficiency of 3D scanning our test input sample 1 in terms of speed, ease of use, portability and computational load requirement for all the above cases of 3D scanning method. Table 6 represents a side-by-side comparison of them.

Accuracy	**Artec EVA**		**LVD**		**PIFuHD**	
Samples	1	2	1	2	1	2
Fidelity	High	High	Low	Lowest	Medium	Medium
Element Quality	High	High	Low	Low	Medium	Medium
Mesh Complexity	High	High	Low	Low	High	High

Table 6: Comparative Efficiency Assessment of the 3D Scanning of Sample 1 using Artec Eva 3D Scanner (STL). Learned Vertex Descent and PIFuHD: Speed, Ease of Use, Portability and Computational Load Requirements

Chapter 5 Discussion

5.1 Evaluation of Accuracy and Efficiency

In terms of 3D human modeling, the objective of this study was to acquire a comparative evaluation of the accuracy and efficacy of machine learning scanning in comparison to structured light scanning. While it was expected that, among the three scenarios, the scanned images of the sample model obtained from the Artec EVA scanner maintained the highest level of similarity in terms of pose estimation, geometric properties, and surface texture details, the deep learning algorithm PIFuHD demonstrated significantly better performance than the learned vertex descent algorithm in terms of fidelity, element quality, and mesh complexity. While PIFuHD struggled with texture detail, it exhibited mesh complexity for both Sample 1 and Sample 2 comparable to that of Artec EVA. In terms of efficiency, the Artec EVA required the greatest time and a high level of expertise to operate. Another challenging criterion for the sample models was the necessity of continual model presence while getting scanned by the Artec EVA. In contrast, both PIFuHD and LVD were simple to operate and took minimal time. PIFuHD also had the most mobility of all the technologies, which was an intriguing outcome. The ability to conduct the algorithm scanner anywhere in the globe with access to the internet and a computer and without requiring the presence of the model was a very realizable accomplishment.

5.2 Functional Equivalency of Application and Use Situations

A second purpose of the study was to conduct a thorough and unbiased evaluation of the functional equivalence of machine learning scanning vs structured light 3D scanning in the human 3D modeling industry. Structured light technique scanning and machine learning scanning both have their own benefits and drawbacks. The purpose of the procedures may only be selected according to the needs of the body model customer. Therefore, a real functional equivalence cannot be achieved. For instance, if we consider our earlier example of 3D human modeling for sports engineering in alpine skiing, computational fluid dynamics will demand the maximum level of model accuracy to obtain the ground truth performance index value [35]. This is only possible with the use of structured light technology, such as the Artec EVA scanner. In contrast to machine learning scanning, efficiency is compromised in order to attain this objective. Alternatively, if the body model consumer cannot afford the time and money necessary for the scanning of the 3D model and just requires a 3D model near enough to the sample, machine learning algorithm scanning is better. This relates to our earlier example of scanning a human model in order to create garment samples for various body shapes and apparel styles [18].

5.3 Limitation of the Study

In both instances of the aim, the result and interpretation of the study were limited by significant restrictions. First, a shortage of processing resources made high-resolution machine learning scanning impractical. PIFuHD demands inputs of high resolution and large computational processing capacity in order to provide more accurate results, which skews the real performance of PIFuHD's output value. Second, the absence of a consistent way of data collection and data analysis for various 3D scanning technologies makes it very challenging to achieve functional equivalence criteria for comparison analysis. Due to a lack of time and resources, insufficient sample data were collected to confirm the study's repeatability. Due to a lack of time and resources, other developing machine learning scanning techniques were not evaluated as part of this study as well.

Chapter 6 Conclusion

In our comparison study, the structured light scanning, and machine learning scanning methods were evaluated and compared based on the precision of the 3D scanned model and the efficacy of the 3D scanning process for data collecting. According to the research findings, the precision of the structured light approach is unmatched compared to that of the machine learning scanning method. Images scanned using the Artec EVA scanner feature the highest fidelity, element quality, and mesh complexity, resulting in the highest quality 3D model output. During the machine learning scanning, PIFuHD's fidelity and element quality were modest, but its mesh complexity was high. The LVD has the lowest values for fidelity, element quality, and mesh complexity, making it the least accurate 3D scanning method in terms of precision.In terms of efficiency, LVD was the simplest and quickest to use, while also being highly portable and requiring minimal computing effort. PIFuHD yielded the same outcome in terms of usability, but it was the most portable and required the most processing power. While Artec EVA needed the least amount of computing load, it required the longest time and was the most complex to use. The Artec EVA has the lowest portability among all scanning methods.

In the human 3D modeling sector, the functional equivalency of machine learning scanning vs structured light 3D scanning is still disputed and ambiguous, according to the research. In our evaluation, the accuracy and efficiency of the structured light approach and machine learning scanning were inconsistent, rendering the functional equivalency subjective dependent on the body model consumer's intended use.

Future research will aim to promote the adoption of improved methods, parameters, and criteria for evaluating the repeatability and compatibility of measuring methods, as well as the introduction of superior methods for establishing reference values and benchmarks when extracting comparative assessment data. In order to reach functional equivalence standards in the 3D modelling industry, more emerging state-of-the-art machine learning scanning methods will be considered as part of those comparative assessments with a larger sample size and higher computation load resources for more accurate comparison of the Human 3D modeling.

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