International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

An Objective Evaluation of Harris Corner and FAST Feature Extraction Techniques for 3D Reconstruction of Face in Forensic Investigation

Sincy John*[1], Ajit Danti[2]

Submitted: 09/05/2023 **Revised**: 19/07/2023 **Accepted**: 06/08/2023

Abstract: 3d reconstructed face images are the volumetric data from two dimensions, it can provide geometric information, which is very helpful for different application like facial recognition, forensic analysis, animation. Reconstructed face images can provide better visualization, than a two dimensional image can provide. For a proper 3d reconstruction one of primary step is feature extraction. The objective of this study is to conduct a comprehensive evaluation of two prominent traditional feature extraction techniques, namely Harris Corner and FAST (Features from Accelerated Segment Test), for the purpose of 3D reconstruction of face images in forensic analysis. In this research paper feature extraction was carried out using the Harris corner detection and FAST Feature technique. 3D reconstruction is completed using the retrieved features. In this study a comparative analysis was conducted assessing the aspect ratio, depth resolution. The results of the assessment provide valuable insights into the strengths and limitations of both techniques, aiding researchers and practitioners in selecting the most suitable method for 3D face image reconstruction applications.

Keywords: *3D reconstruction, Features from accelerated segment test, Harris corner detection*

1. Introduction

The face holds significant importance in the human body. The face is crucial for communication, sensory perception, social interaction, personal identity, health indications, and aesthetics. Its multifaceted functions make it an integral part of human existence, enabling us to interact with others, understand the world, and express our-selves effectively. Reconstructing the face is a complex task due to its numerous intricate features, limited data and viewpoints, imaging constraints, computational demands, each individual has unique facial characteristics and variations. The face is a non-rigid object that can undergo deformations due to facial expressions and muscle movements. Researchers and developers in the field of face reconstruction continually strive to improve techniques and algorithms to overcome these challenges and achieve more accurate and realistic reconstructions.

3D face reconstruction plays a valuable role in forensic analysis by providing ac-curate and detailed facial representations that can aid in investigations and identification. 3D face reconstruction can assist in identifying individuals involved in criminal activities. By reconstructing the face from low-quality images, forensic experts can generate a visual representation that can be compared to databases, missing person's records, or other sources to identify potential matches.

The reconstruction of face images typically involves a multi-step process that in-corporates various techniques and algorithms. The process begins with acquiring relevant data. The acquired data often undergoes preprocessing to enhance its quality and suitability for reconstruction. This may involve image filtering, noise reduction, alignment, or calibration to correct distortions or inconsistencies in the data. The next step involves extracting key facial features from the acquired data. Common facial features include the eyes, nose, mouth, eyebrows, and other distinguishable land-marks. Feature extraction algorithms, such as edge detection, template matching, or machine learning-based approaches, are applied to identify and localize these features accurately.

Feature extraction is essential in 3D face reconstruction as it provides the foundational information for shape modelling, texture mapping, expression capture, bio-metric identification, forensic analysis, and computational efficiency. Accurate and robust feature extraction techniques contribute to achieving realistic and detailed reconstructions of the human face. These techniques aim to identify and extract relevant facial key points that can be used to estimate the 3D geometry of the face. Numerous feature extraction methods have been proposed in the literature, each with its own strengths and limitations. Among these methods, Harris Corner and FAST (Features from Accelerated Segment Test) have emerged as popular choices due to their effectiveness and efficiency.

This paper deals with the study of feature extraction

[1] *Department of Computer Science and Engineering, Christ University, Bengaluru, India*
[2] *Department of Computer Science and Engineering, Christ University, Bengaluru, India*
* *Corresponding Author Email: sincyjohn2@gmail.com*

techniques using Harris corner detection algorithm and features from accelerated segment test (FAST). The main aspect of this study is to provide the overview of existing techniques so that it helps to develop improved algorithm which helps in forensic department for identifying low quality images. Researching traditional feature extraction methods like Harris corner and FAST is still important because they offer interpretability, computational efficiency, robustness to noise, and can be complementary to deep learning approaches. They provide valuable insights, well-established techniques, and alternative solutions for various applications, especially in cases with limited training data or resource constraints. Each technique's benefit and drawback are explained. The comparison is based on objective assessment and execution time is also performed.

2. Related Works

Face recognition and 3D reconstruction are two closely related fields that have received considerable attention in computer vision and biometrics research. In this literature review, we will explore the advancements and key contributions in Harris corner and fast corner feature in other domains.

Murtopo et al. [1] proposes a method for signature verification that uses the Harris corner detector to extract features from signatures and the K-nearest neighbour (KNN) algorithm to classify signatures as genuine or forged. Harris corner detector is a robust corner detection algorithm that is relatively insensitive to noise and illumination changes. This makes it a good choice for extracting features from signatures, which are often affected by these factors.

Authors proposes a feature extraction algorithm for irregular small celestial bodies (ISCBs) in weak light environments. The algorithm uses the Harris corner detector to extract features from ISCB images [2]. The paper evaluates the proposed algorithm on a dataset of ISCB images. The results showed that the proposed algorithm was able to extract features from ISCB images that were not visible to the naked eye. The paper also investigated the effect of the parameters of the Harris corner detector on the performance of the proposed algorithm. The results showed that the optimal parameters for the Harris corner detector depended on the image quality.

The paper proposes a method for detecting vibration in HUD images using the Harris corner detector [3]. It first uses an improved Canny edge detector to extract edges from the HUD image, then uses the Harris corner detector to extract corners from the edges. Authors uses a threshold to filter out weak corners, then uses a voting scheme to match corners between images. Finally uses the matched corners to estimate the vibration of the HUD image.

In this paper Rezvan Pakdel and John Herbert discusses the use of the Harris corner detector in a cloud-based framework for object recognition [4]. The Harris corner detection algorithm relies on the autocorrelation of either image intensity values or image gradient values. By analysing the local variations in these values, the algorithm identifies corners within the leaf image. This method is analysed with different values of sigma, threshold, and radius. This suggests that the performance and characteristics of the Harris corner detector are examined by varying these parameters to assess its effectiveness in capturing relevant corner information.

Paper presents a method for clustering half profile face images based on feature points. The method uses the Harris corner detector, BRISK, SURF, SIFT and FSIFT to detect feature points in half profile face images. The feature points are then used to calculate a feature vector for each image. The feature vectors are then clustered using agglomerative hierarchical clustering [5].

This paper provides a comprehensive overview of map-merging methods for simultaneous localization and mapping (SLAM) applications [6]. The paper discusses the different types of map-merging methods, including feature-based methods, probability-based methods, and optimization-based methods. FAST corner detection is a valuable tool for SLAM applications. It is fast, efficient, and robust to noise and illumination changes. However, it is not scale-invariant or rotation-invariant, so it is important to be aware of these limitations when using FAST corner detection in SLAM applications.

The paper proposes a method for gesture recognition on mobile terminals based on an improved FAST corner detection algorithm [7]. The proposed method first uses background subtraction and multicolour space to detect the hand in the image. Then, an improved FAST corner detection algorithm is used to detect the fingertips. The feature points are then screened by non-maximum suppression. Finally, gesture recognition is realized by matching feature points.

Authors put forward a practical methodology for facial emotion recognition from videos [8]. It highlights the use of various techniques, such as optical flow, face detection, corner detection, feature extraction, feature selection, and classification, to achieve high accuracy in emotion classification. The suggested process entails a number of phases. To begin with, motion in the input movies is detected using an optical flow approach based on the Lucas-Kanade (LK) algorithm. The next step is pre-processing, which comprises grayscale conversion and face detection using the Viola-Jones method on the discovered LK frames. On the grayscale frames, the FAST corner detection method is used to identify facial landmark points. The Neighbor-hood Difference Features (NDF) are used in the subsequent stage to extract features. To choose the best collection of features from the mined features, the Modified Plant Genetics-Inspired Evolutionary Optimization (MPGEO) algorithm is utilized. The Deep Attention-based Bidirectional LSTM with Equilibrium Optimizer (DABLEO) classifier for emotion classification is then given the chosen features.

This paper [9] addresses issues with the FAST algorithm commonly used for corner detection in video streams. The problems identified are image edge missing and corner redundancy. The paper proposes a solution called the constant filling method to fill the target image, followed by judging the pixel points of a 90-degree Bresenham circle. This reduces the number of discrete contrast points for Bresenham circles in the FAST algorithm by a quarter. Finally, SAD non-maximum suppression is used to obtain corner points in the video stream.

This paper discusses a proposed FAST-Harris fusion corner detection algorithm to improve the shortcomings of the Harris algorithm, such as low detection accuracy and positioning accuracy [10]. The algorithm establishes a corner detection fusion model with several steps. First, the target image is padded, and then the FAST algorithm is applied with a reduced number of contrast points (25%) to quickly capture candidate corners. Next, the candidate corners are screened individually using the Harris algorithm with the Scharr operator to achieve accurate detection. Finally, the real corners are obtained using SAD for non-maximum suppression.

By considering above literature, we found some research gaps:

• Limited exploration on traditional feature extraction technique for 3d face reconstruction for forensic analysis

• With minimal dataset traditional feature extraction technique show better performance when compared to machine learning methods.

• Hybrid and FAST techniques are used in domains other than facial reconstruction are showing better results.

3. Traditional Feature Extraction Technique

Traditional image feature extraction techniques in computer vision includes Harris corner detection, Shi-Tomasi Corner Detector, Scale-Invariant Feature Transform (SIFT) [15], Speeded-Up Robust Features (SURF) [18], Features from Accelerated Segment Test (FAST), Binary Robust Independent Elementary Features (BRIEF), Oriented FAST and Rotated BRIEF (ORB). The performance of each method depends on the type and complexity of 2d image in terms of lighting, side poses, low resolution images etc. The objective of this survey is to have more comprehensive work on Harris corner detection and fast feature technique for 3d face reconstruction.

3.1. Harris Corner Detection

The Harris corner detector is a corner detection algorithm that is commonly used in computer vision algorithms to extract corners and infer features of an image. It was first introduced by Chris Harris and Mike Stephens in 1988 upon the improvement of Moravec's corner detector [12]. The Harris corner detector works by calculating the response of a window around each pixel in an image [13]. The response is a measure of how much the intensity of the image changes when the window is shifted in different directions. If the response is high, then the pixel is likely to be a corner.

The Harris corner detector is based on the following equation 1:

$$R = \det(G) - n(trace(G))^2 \tag{1}$$

where:

R is the response of the corner detector

G is the structure tensor of the image

n is a parameter that controls the tradeoff between detecting corners and detecting edges

The structure tensor is a matrix that measures the second-order derivatives of the image intensity. It is calculated by convolving the image with two Sobel filters, one in the x-direction and one in the y-direction. The determinant of the structure tensor measures the extent to which the intensity of the image changes in different directions. The trace of the structure tensor measures the overall intensity change in the image. The Harris corner detector is a popular corner detection algorithm because it is relatively simple to implement and it is robust to noise and illumination changes. However, it can be sensitive to scale changes.

3.2. FAST Feature Extraction

Features from accelerated segment test (FAST), a corner detection algorithm introduced by Ed-ward Rosten and Tom Drummond in 2006, is used to identify interest points in an image. [11]. An interest point is a pixel which has a well-defined position and can be robustly detected. The FAST algorithm is particularly well-suited for real-time applications because it is very computationally efficient.

The FAST algorithm works by first dividing the image into a grid of cells. Each cell contains 16 pixels, and the algorithm tests each cell to see if it contains a corner. The algorithm tests a cell for a corner by checking if a set of 9 contiguous pixels in the cell are all brighter or darker than the intensity of the central pixel in the cell. If this condition is met, then the cell is classified as a corner. The FAST algorithm is very efficient because it only tests a small number of pixels in each cell. This makes it much faster than other corner detection algorithms, such as the Harris corner detector. However, the FAST algorithm is not as accurate as the Harris corner detector, and it may miss some corners.

4. Proposed Methodology

Proposed methodology by using traditional methods for feature extraction for 3D reconstruction of face images involve, first a Haar cascade filter is used to detect the face in the image. Then preprocessing, this step is to pre-process the face images. This involve resizing the images to a common size, converting them to grayscale, and normalizing the brightness and contrast. Then the feature extraction technique is used to extract the features to form the features with depth details to reconstruct the 3d from 2d image. Feature extraction technique is done by Harris corner detection and Fast corner detection.

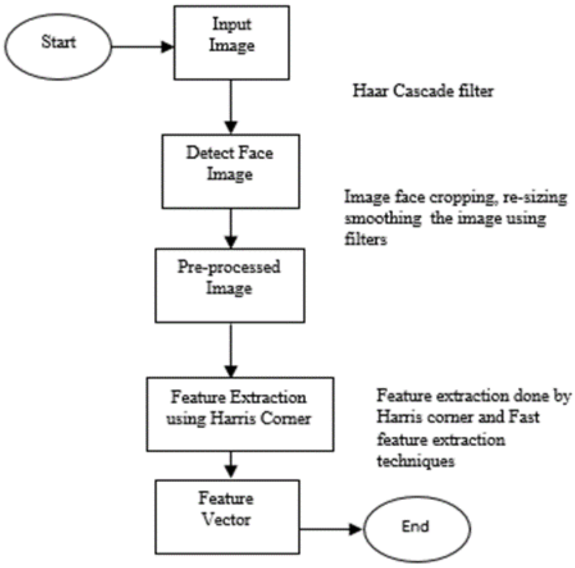

Fig. 1. Flow Chart of Feature Extraction

Feature extraction in face images using Harris corner detection is a technique for identifying and isolating the key features in a face image. These features can then be used to represent the image in a more compact and efficient way. The Harris corner detector is a technique for detecting corners in images. Corners are points in an image where the intensity changes rapidly in two or more directions. These points are often used as features for image recognition and 3D reconstruction.

Algorithm for Harris Corner Detection features

Input: I_m.: The input image.

Output: The extracted features

Step 1: Loading the input image I_m.

Step 2: Resizing the image using Haar cascade object detector I_m.

Step 3: Convert the image to grey scale, I_g

Step 4: Apply median filter to smoothen the image, S_m.

Step 5: Calculate the Sobel derivatives of the image.

Step 6: Calculate the structure tensor.

Step 7: Apply the Harris corner detector to extract the features by equation 1.

features = cv2. Harris(S_m).

Step 8: Stop

The FAST feature detector is a technique for detecting features in images that are both fast and accurate. FAST features are typically small, bright spots in an image. These points are often used as features for image recognition and 3D reconstruction.

Algorithm for FAST feature Extraction

Input: I_m: The input image

Output: The extracted features

Step 1: Convert the image to grayscale.

Step 2: Apply a threshold to the image to identify the bright spots.

Step 3: Apply the FAST feature detector to the image to identify the features.

Step 4: Return the extracted features.

Step 5: Stop.

The input image is converted to grayscale. This is because the FAST feature detector only works on grayscale images. A threshold is applied to the image to identify the bright spots. This is done by comparing each pixel in the image to the threshold value. If the pixel value is greater than the threshold value, then the pixel is considered to be a bright spot. The FAST feature detector is applied to the image to identify the features. The FAST feature detector works by examining a small neighborhood around each pixel in the image. If the neighborhood meets certain criteria, then the pixel is considered to be a feature. The extracted features are returned. The extracted features are a list of points in the image that have been identified as features.

5. Performance Measurements

Performance of the 3D reconstructed images using the feature extraction techniques was evaluated quantitatively and qualitatively. Quantitatively done by using mean, median, standard deviation, aspect ratio and depth resolution

5.1. Mean, Median, Standard Deviation

Analyzing the mean, median, and standard deviation of vertices in a 3D image can provide useful information about the shape and distribution of the object represented by the image. The mean can give an idea of the central tendency of the vertex coordinates in the 3D space. This can help in understanding the overall size and shape of the object. The mathematical expression for Mean is represented by M given in equation 2. Where x is the sum of observations and n is total number of total number of observation:

$$M = \frac{\sum x}{n} \tag{2}$$

The median can give a more robust estimate of the central tendency, as it is less sensitive to outliers than the mean. This can be particularly useful if the object has a few vertices that are significantly different from the others, as it can help to identify these points and their impact on the overall shape. M_0 represents the median for odd case and M_e represents the median for even case given in equation 3. Where n is the total number of observations

$$M_o = \frac{(n+1)}{2} \tag{3}$$

$$M_e = \frac{\left(\frac{n}{2}\right)^{th} + \left(\frac{n}{2}+1\right)^{th}}{2}$$

The standard deviation can provide information about the spread of the vertex coordinates around the mean. A larger standard deviation indicates a greater variation in the vertex positions and may suggest a more complex shape. Conversely, a smaller standard deviation suggests a more regular and uniform shape. S represent the standard deviation given in equation 4. Where x is the observations, M is the mean and n is the total number of observations.

$$S = \sqrt{\frac{\sum (x-M)^2}{n}} \tag{4}$$

5.2. Aspect Ratio

Aspect ratio in 3D images refers to the proportional relationship between the width, height, and depth of an object or scene being represented in 3D space. It is the ratio of the longest dimension to the shortest dimension. In 3D imaging, aspect ratio is important because it affects the perception of depth and spatial relationships within the image. If the aspect ratio is not properly calibrated or distorted, it can result in visual distortion and inaccurate interpretation of the image. For example, if the aspect ratio is compressed or stretched in one direction, it can result in objects appearing wider or narrower than they actually are, which can affect the accuracy of measurements and analysis. A represent the aspect ratio given by equation 5. Where w is the width and h is the height.

$$A = \frac{w}{h} \tag{5}$$

5.3. Depth Resolution

Depth resolution in 3D images refers to the ability of the imaging system to distinguish between objects or features that are at different depths or distances from the camera. It is a measure of the smallest distance that can be reliably detected between two objects at different depths. Depth resolution is affected by several factors, including the resolution of the camera sensor, the quality of the optics, and the depth range of the imaging system. In general, a higher resolution camera sensor and better optics can result in a higher depth resolution. The depth range of the imaging system can also affect the depth resolution, as a larger depth range may result in lower resolution at longer distances. Depth resolution is an important consideration in many applications of 3D imaging, such as object recognition, robotics, and autonomous vehicles. High depth resolution is particularly important in applications where

objects are located at varying distances from the camera and need to be accurately identified and tracked.

6. Experimental Analysis

An Intel Core i5 3.0 GHz processor with 8 GB of RAM and a 64-bit operating system were used to carry out this study. Python libraries including NumPy, Pandas, Matplotlib, Seaborn, sci-kit-learn, and PyTorch are some of the tools used in this study. Version 3.7.4 of the Anaconda Navigator IDE used these tools.

In conclusion, this study describes the creation and operation of a system that uses machine learning to extract features from 2D images. For experimental analysis

AFLW2000-3D dataset is used. It includes 2000 facial photos with 68-point 3D facial landmark annotations [19]. The head positions represented by the photos in the collection are varied and include frontal view and profile view. Since these models need to be able to precisely recognize landmarks in a variety of positions, the dataset presents a challenge for 3D facial landmark identification models. The images are pre-processed and implemented both feature extraction techniques to the same data set to examine and compare the effectiveness of both methods for a more reliable and effective 3D face reconstruction. The vertices in a 3D image's mean, median, and standard deviation, aspect ratio, and depth resolution were all examined to determine the effectiveness and applicability of these techniques.

Table 1 and table 2 describes the mean, median, standard deviation, aspect ratio and depth resolution of the 3d reconstructed images using the two feature extraction techniques that is Harris corner feature extraction and Fast feature extraction technique.

Table 1. Mean, Median, standard deviation, aspect ratio and depth resolution 3 sample images using Harris corner detection

Input Images	*Mean*	*Median*	*Standard Deviation*	*Aspect Ratio*	*Depth Resolution*
Sample Image 1	24.59	11.41	23.88	1.85	0.726
Sample Image 2	37.53	28.14	27.47	1.47	0.773
Sample Image 3	22.58	9.2	25.08	1.55	0.548

Table 2. Mean, Median, standard deviation, aspect ratio and depth resolution 3 sample images using Fast Corner Feature Detection

Input Images	*Mean*	*Median*	*Standard Deviation*	*Aspect Ratio*	*Depth Resolution*
Sample Image 1	21.01	10.36	19.75	2.21	0.725
Sample Image 2	35.94	29.32	25.88	1.48	0.726
Sample Image 3	20.58	3.67	25.08	1.58	0.544

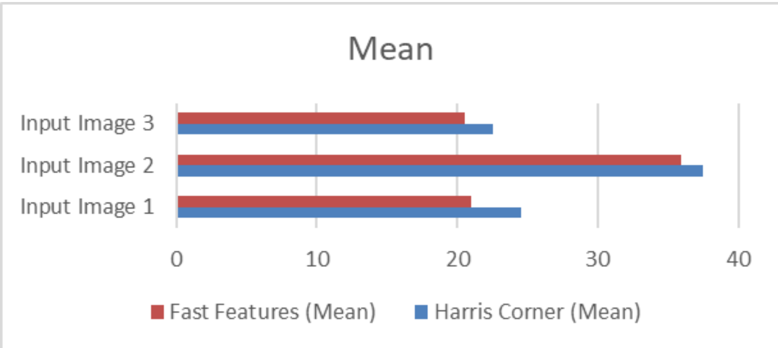

Fig. 2. Graph showing Mean of 3 different input using fast corner detection and Harris corner detection

The mean of a set of data is the average value of the data, and the standard deviation is a measure of how spread out the data is. If the mean is high, then the features are likely to be spread out, while a low mean indicates that they are more clustered together. This can be used to get an idea of how sensitive the feature extraction algorithm is to noise. Based on the experimental analysis, 3d reconstructed using the extracted feature using fast features have low mean value. In this case, the mean of the Harris corner vertices is 24.59, 37.53, 22.58 for three input images while the mean of the fast features vertices is 21.01, 35.94, 20.58. This means that the Harris corner vertices are, on average, located further away from the origin than the fast features vertices. Figure 2 represent the graph showing the mean of three different input images of the 3d representation using fast corner detection and Harris corner detection.

The median of the 3d reconstructed by extracted features can be used to get a more robust estimate of the central tendency than the mean, as it is less sensitive to outliers. Outliers are data points that are significantly different from the others. For example, if a feature extraction algorithm is sensitive to noise, then it may be more likely to extract outliers. The median can be used to get a more accurate estimate of the central tendency of the features, even if there are outliers present. Figure 3 represent the graph showing the median of three different input images of the 3d representation using fast corner detection and Harris corner detection.

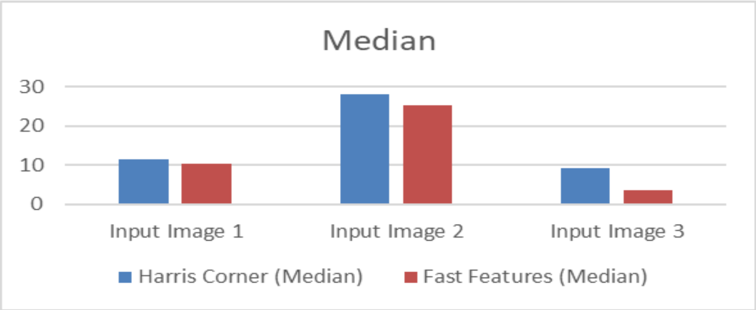

Fig. 3. Graph showing Median of 3 different input using fast corner detection and Harris corner detection

The standard deviation of the 3D reconstructed images by extracted features can be used to get an idea of the spread of the features around the mean. A larger standard deviation indicates that the features are more spread out, while a smaller standard deviation indicates that they are more clustered together. This can be used to get an idea of how sensitive the feature extraction algorithm is to noise. The standard deviation of the Harris corner vertices is 23.88, 27.47, 25.08, while the standard deviation of the fast features vertices is 19.75, 25.88,25.08. This means that the Harris corner vertices are more spread out than the fast features vertices. Figure 4 represent the graph showing the standard deviation of three different input images of the 3d representation using fast corner detection and Harris corner detection.

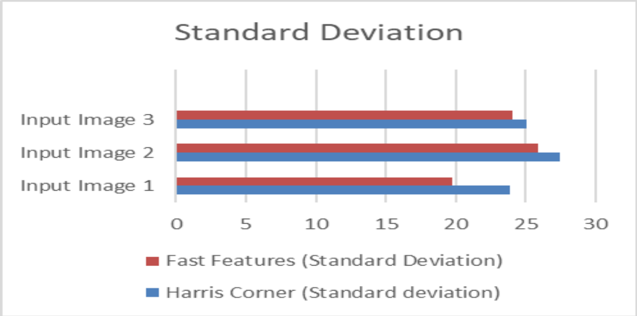

Fig. 4. Graph showing Standard Deviation of 3 different input using fast corner detection and Harris corner detection

Aspect ratio of the 3D reconstructed images is higher in FAST corner detection and lower in Harris corner detection, it implies that FAST is more likely to detect corner features that are elongated or have a higher width-to-height ratio, while Harris is more likely to detect corner features that are more square or have a lower width-to-height ratio. The aspect ratio of features refers to the proportion between the width and height of the detected corners. A higher aspect ratio indicates that the corners are more elongated, resembling lines or edges, while a lower aspect ratio suggests that the corners are more square or closer to a circular shape. Figure 5 depicts the graph showing the aspect ratio of three different input images.

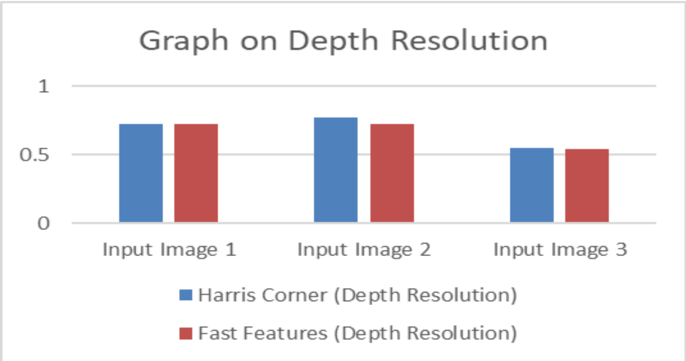

Fig. 5. Graph showing Aspect Ratio of 3 different input using fast corner detection and Harris corner detection

Depth resolution in the context of 3D face reconstruction refers to the accuracy and precision with which the depth or distance information of the 3D facial surface is estimated from the input data. A higher depth resolution indicates a more accurate and detailed representation of the 3D facial geometry, while a lower depth resolution implies a less precise reconstruction. The values of depth resolution obtained for 3 input images using Harris corner detection are 0.725, 0.726, and 0.548. The values of depth resolution obtained for 3 input images using Fast corner detection are 0.726, 0.773, and 0.544.

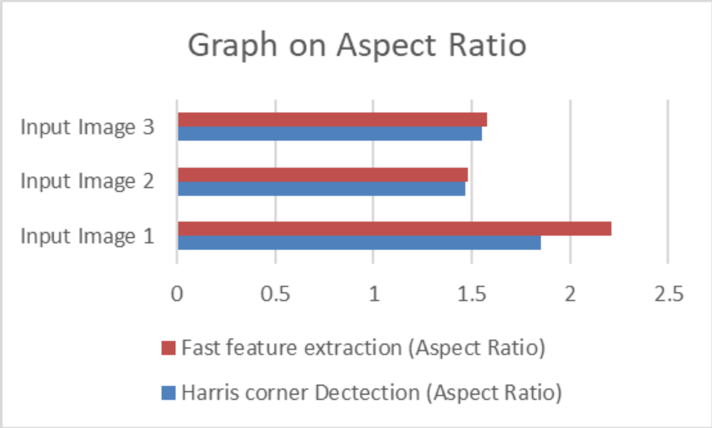

Fig. 6. Graph showing Depth Resolution of 3 different input using fast corner detection and Harris corner detection

Figure 6 represents the depth resolution using fast corner and Harris corner detection using three different images. The values of depth resolution for both Harris corner detection and Fast corner detection are similar. This suggests that both methods are effective at detecting corners in images. However, the values of depth resolution for Fast corner detection are slightly higher than the values of depth resolution for Harris corner detection. This suggests that Fast corner detection may be slightly more accurate than Harris corner detection.

Qualitative analysis was done using the extracted features, 3d reconstruction was done using Harris corner detection and FAST feature extraction. Figure 7 represent the 3d reconstruction using the Harris corner detection for sample input images 1 and 2. Figure 8 represent the 3D reconstruction using the FAST feature extraction technique for sample input images 1,2 and 3.

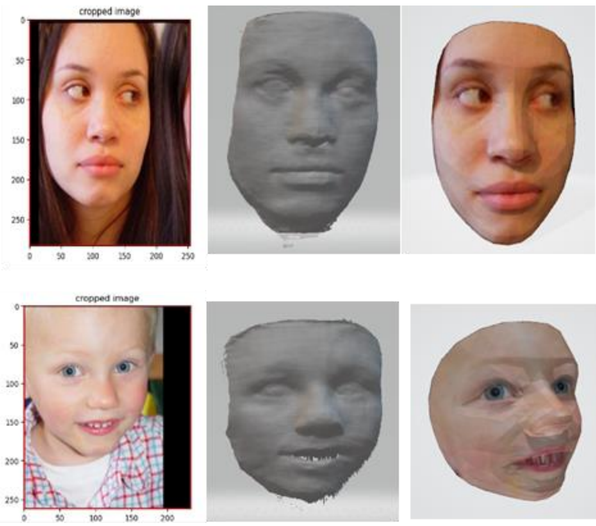

Fig. 7. 3d reconstruction using Harris corner detection features for sample input image 1 and 2

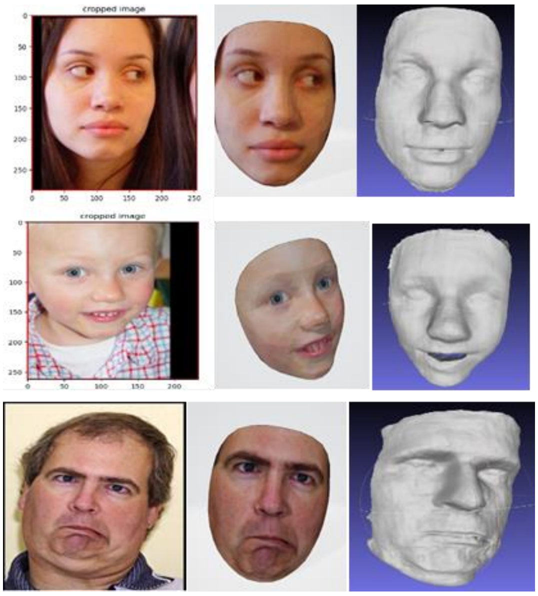

Fig. 8. 3d reconstruction using Fast corner features for sample input image 1,2 and 3.

Table 3 depicts the L1 Loss calculated for the reconstructed images using Harris corner detection and Fast feature extraction. In the 3d reconstruction using FAST features have low L1 loss given by the equation 6 where G_o is the generated output and R_o is the real output.

$$L1\ Loss = \sum_{i=1}^{n} |G_o - R_o| \tag{6}$$

Table 3. L1 Loss for the reconstructed 2 sample images using Harris corner detection and FAST corner detection

Input Images	***L1 loss for reconstructed Image for Harris Corner***	***L1 loss for reconstructed Image for Fast Features***
Input Image 1	0.2725	0.1432
Input Image 2	0.2281	0.1127

The L1 loss is a measure of the difference between two images. A lower L1 loss indicates that the two images are more similar. In the table 3, the L1 loss for the reconstructed image of Input Image 1 using the Harris Corner detector is 0.2725, while the L1 loss for the reconstructed image of Input Image 1 using the Fast Features detector is 0.1432. This means that the reconstructed image of Input Image 1 using the Fast Features is more similar to the original image than the reconstructed image using the Harris corner detection. Similarly, the L1 loss for the reconstructed image of Input Image 2 using the Harris Corner detector is 0.2281, while the L1 loss for the reconstructed image of Input Image 2 using the Fast Features detector is 0.1127. This means that the reconstructed image of Input Image 2 using the Fast Features detector is also more similar to the original image than the reconstructed image using the Harris Corner detector. Figure 9 depicts the graph showing L1 Loss the two different sample images.

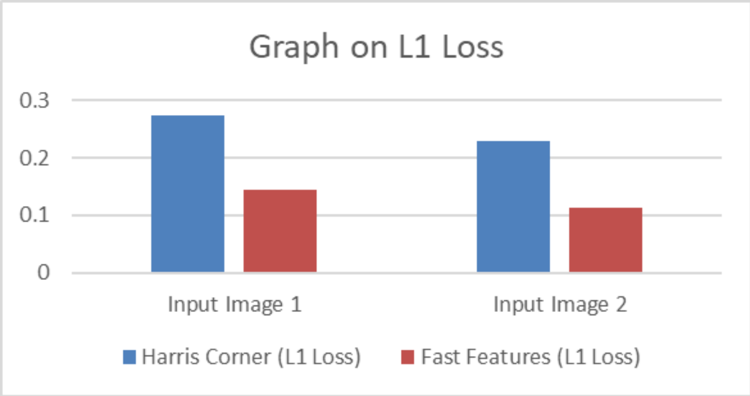

Fig. 9. Graph showing L1 Loss of 2 different input using fast corner detection and Harris corner detection

7. Conclusion

This paper was concentrated on feature extraction techniques like Harris corner detection and fast corner features for 3d face reconstruction. Performance was evaluated based on mean, median, standard deviation, aspect ratio and depth resolution. In the context of 3D face reconstruction, feature extraction plays a crucial role in identifying key points or corners on the face that can be used to reconstruct the 3D shape accurately. From the experimental study it was found that fast corner features perform better when it comes to 3d reconstruction. The depth resolution and aspect ratio was higher for fast corner detection. A higher aspect ratio suggests more elongated or line-like features, while a lower aspect ratio indicates more square or circular features. Evaluating the depth resolution can provide insights into the quality and fidelity of the reconstructed 3D face shape.

Acknowledgements

This study received no financing help from public, private, or nonprofit organizations. Our Sincere acknowledgment goes to faculty members of the Department of computer science engineering at Christ University.

Author contributions

Sincy John: Background work, conceptualization, methodology, dataset collection, implementation, result analysis and comparison, preparing and editing draft, visualization, Software **Ajit Danti:** Supervision, Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] Murtopo, A.A., Priyatna, B. and Mayasari, R., 2022. Signature Verification Using The K-Nearest Neighbor (KNN) Algorithm and Using the Harris Corner Detector Feature Extraction Method. Buana Information Technology and Computer Sciences (BIT and CS), 3(2), pp.35-40.

[2] Cao, M. and Gao, Y., 2023. Feature extraction algorithm of an irregular small celestial body in a weak light environment. PeerJ Computer Science, 9, p.e1198.

[3] Ma, R.G., Cao, T. and Wang, W.X., 2014. HUD image vibration detection on improved edge detection and corner extraction. International Journal of Signal Processing, Image Processing and Pattern Recognition, 7(1), pp.393-404.

[4] Pakdel, R. and Herbert, J., 2015, May. A cloud-based data analysis framework for object recognition. In International Conference on Cloud Computing and Services Science (Vol. 2, pp. 79-86). SCITEPRESS.

[5] Sarwas, G., Skoneczny, S. (2019). Half Profile Face Image Clustering Based on Feature Points. In: Choraś, M., Choraś, R. (eds) Image Processing and Communications Challenges 10. IP&C 2018. Advances in Intelligent Systems and Computing, vol 892. Springer, Cham. https://doi.org/10.1007/978-3-030-03658-4_17.

[6] Yu, Shuien, Chunyun Fu, Amirali K. Gostar, and Minghui Hu. "A review on map-merging methods for typical map types in multiple-ground-robot SLAM solutions." Sensors 20, no. 23 (2020): 6988.

[7] Jian, Chengfeng, Xiaoyu Xiang, and Meiyu Zhang. "Mobile terminal gesture recognition based on improved FAST corner detection." IET Image Processing 13, no. 6 (2019): 991-997.

[8] Vedantham, R., Reddy, E.S. Facial emotion recognition on video using deep attention based bidirectional LSTM with equilibrium optimizer. Multimed Tools Appl (2023). https://doi.org/10.1007/s11042-023-14491-1

[9] Y. Wang, J. Wang, H. Lv, Y. Li and Z. Yang, "Optimization of Corner Detection Algorithm for Video Stream Based on FAST," 2021 International

Conference on Electronic Information Engineering and Computer Science (EIECS), Changchun, China, 2021, pp. 479-483, doi: 10.1109/EIECS53707.2021.9587940.

[10] Wang, Yifan, Yang Li, Jiaqi Wang, Haofeng Lv, and Zeli Yang. "A Target Corner Detection Algorithm Based on the Fusion of FAST and Harris." Mathematical Problems in Engineering 2022 (2022).

[11] Viswanathan, D.G., 2009, May. Features from accelerated segment test (fast). In Proceedings of the 10th workshop on image analysis for multimedia interactive services, London, UK (pp. 6-8).

[12] Chris Harris and Mike Stephens (1988). "A Combined Corner and Edge Detector". Alvey Vision Conference. Vol. 15.

[13] Dey, Nilanjan; et al. (2012). "A Comparative Study between Moravec and Harris Corner Detection of Noisy Images Using Adaptive Wavelet Thresholding Technique". arXiv:1209.1558.

[14] M. Trajković and M. Hedley. “FAST corner detection”. Image and Vision Computing, Vol. 16, PP. 75–87, 1998.

[15] Edward Rosten and Tom Drummond, “Machine learning for high speed corner detection”. In 9th European Conference on Computer Vision, vol. 1,pp.430–443,2006.

[16] Biadgie, Y., Sohn, K.A.: ‘Speed-up feature detector using adaptive acceleratedsegment test’, IETE Tech. Rev., 2016, 33, (5), pp. 492–504.

[17] Malik, Jyoti, Ratna Dahiya, and G. Sainarayanan. "Harris operator corner detection using sliding window method." International Journal of Computer Applications 22, no. 1 (2011): 28-37.

[18] Anitha, J.J. and Deepa, S.M., 2014. Tracking and recognition of objects using SURF descriptor and Harris corner detection. International Journal of Current Engineering and Technology, 4(2), pp.775-778.

[19] Zhu, Z. Lei, X. Liu, H. Shi, and S. Z. Li. Face alignment across large poses: A 3d solution. In CVPR, 2016.

[20] Gooda, S. K. ., Chinthamu, N. ., Selvan, S. T. ., Rajakumareswaran, V. ., & Paramasivam, G. B. . (2023). Automatic Detection of Road Cracks using EfficientNet with Residual U-Net-based Segmentation and YOLOv5-based Detection. International Journal on Recent and Innovation Trends in Computing and Communication, 11(4s), 84–91. https://doi.org/10.17762/ijritcc.v11i4s.6310

[21] Morzelona, R. (2021). Human Visual System Quality Assessment in The Images Using the IQA Model Integrated with Automated Machine Learning Model . Machine Learning Applications in Engineering Education and Management, 1(1), 13–18. Retrieved from http://yashikajournals.com/index.php/mlaeem/article/view/5