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A HYBRID APPROACH FOR LANDMARK DETECTION OF 3D FACES FOR FORENSIC INVESTIGATION

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ABSTRACT

Facial landmark detection is a key technology in many forensic applications, such as facial identification and facial reconstruction. However, the accuracy of facial landmark detection is often limited in 3D face images due to the challenges of occlusion, illumination, and pose variations. This paper proposes a hybrid approach for landmark detection of 3D faces for forensic investigation. A hybrid method of edge contour detection and Harris corner detection is proposed for feature extraction in face images for forensic investigation. Edge contour detection is used to detect the boundaries of the face, while Harris corner detection is used to detect the corners. The advantage of using a hybrid method of edge contour detection and Harris corner detection for feature extraction in face images is that it can capture both global and local features of the face. Edge contour detection can capture global features, such as the overall shape and outline of the face, while Harris corner detection can capture local features, such as the corners of the mouth, nose and eyes which are vital for facial reconstruction. Experimental results show that the proposed method outperforms existing landmark detection algorithms in terms of time complexity and minimum loss.

Keywords: *Facial Reconstruction, Edge Contouring Detection, Harris Corner Detection, Hybrid Method, Landmark detection.*

1. INTRODUCTION

Facial reconstruction techniques play a crucial role in computer vision by enabling accurate representation and interpretation of human faces. They have diverse applications ranging from face recognition, virtual reality, animation, forensics, law enforcement, robotics and medical applications, and are essential for various real-world scenarios where accurate facial representation is critical [1-3]. Future usage of facial reconstruction is anticipated to rise with technological improvement. One of the key challenges in this area is the ability to extract robust and discriminative features from facial images that are robust to variations in lighting, pose, and expression. To an extent, this problem can be solved by pre-processing the images before extracting features and extracting features that are resilient to variations in image quality.

Feature extraction is the crux step in the process of face image detection and recognition. It is crucial for obtaining the images' most pertinent and discriminative information. These information includes shape, texture of the skin, shape of the eyes, nose, mouth. These extracted features are further used for facial recognition, 3D face reconstruction and facial detection. Feature extraction assists in acquiring the best feature from huge data sets by choosing and combining variables into features.

Facial reconstruction is a crucial task in the field of forensics, archaeology, and medical science. Landmark detection plays a critical role in facial reconstruction, as it helps in identifying key features of the face, such as the nose, mouth and eyes. Traditional landmark detection methods rely on manual annotation, which is time-consuming and prone to errors. In recent years, deep learning-based methods [4,5] have shown great success in

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landmark detection. However, they require large amounts of annotated data to train accurate models. To overcome the limitations of traditional and deep learning-based methods, a hybrid approach that combines the strengths of both approaches can be used. A hybrid approach for landmark detection can improve the accuracy and efficiency of facial reconstruction, making it a relevant topic for exploration in the field of computer vision and forensics.

This paper proposes a hybrid approach by using Edge contour detection for most prominent features and Harris corner detection for minute details which result in efficient landmark detection. Contours are recovered using edge contour detection and Corners are identified using the R score from Harris corner detection.

The main contribution of this paper as follows

- It is necessary to detect the facial image and to pre-processes the image before the feature extraction to increase the efficiency. First the face in the image is detected using the Haar cascade object detector.
- Then the different filters like Gaussian, mean and median filter were applied to normalize the image. From this median filter gave the optimal result compared to the other two filter based on psnr value.
- We present the hybrid algorithm for extracting the facial features from the face images for face reconstruction, the hybrid method includes the Edge contour detection, Harris corner detection.
- The performance evaluation was based on the error, which is the difference between the predicted value and the actual value, by comparing the key points detection with the ground truth points and anticipated output points, the experimental findings demonstrate that the suggested method has a low loss graph.

2. RELATED WORK

Hybrid approach involves combining multiple methods either it is used for facial reconstruction systems or it can be used to extract features from the face image. In order to improve performance on face recognition tasks, a hybrid technique aims to combine the best aspects of various approaches. Very less studies are done on hybrid approach, the following papers from [3,6-9] uses combination of methods. Authors of [3] uses Hidden Models of Markov (HMM) and Local Binary Pattern (LBP) hybrid approach for facial recognition. HMM considers images as variable sequence of time and then decomposes into blocks. LBP used for feature extraction, probability score is calculated. The recognition is based on the maximum probability score. Two major drawbacks of the system, the system can misclassify non-face images as faces. This is because the HMM is trained on a dataset of face images, and it may not be able to distinguish between faces and other objects that have similar features. The system can misclassify images that contain multiple faces as a single face. In 2017 [6] authors extracted the local features by double coding local binary pattern and global features in face images by using Gabor filter bank. The disadvantage of the work is that, the system is sensitive to changes in illumination, pose, and expression.

Dual-tree M-band wavelet transform is used for extracting features in which facial expression decomposed into different level, energy and entropy are extracted as features and Gaussian mixture model used as classifier for recognition [7]. The drawbacks of the method are that, the method is sensitive to changes in illumination and pose. This means that the method may not be able to accurately recognize facial expressions in images that are taken in different lighting conditions or with different facial poses.

Authors uses Principle Component Analysis to extract global features and Local binary pattern for extracting the local features and then artificial neural network is used for face recognition [8]. The method might be costly to compute, which is a potential drawback. The MLP neural network requires a large amount of computation in addition to the computationally demanding PCA and LBP feature extraction procedures. This might render the suggested approach unsuitable for real-time applications. In [9] hybrid feature extraction method is used for brain tumor classification in which Normalized GIST descriptor with PCA for extracting the brain features. The paper proposes a hybrid feature extraction method that combines the advantages of two existing methods: principal component analysis (PCA) and normalized gray-level intensity features (NGIST). PCA is a dimensionality reduction technique that can be used to extract the most important features from a dataset. NGIST is a texture feature extraction method that can be used to capture the spatial distribution of intensity values in an image.

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Harris corner detection is a well know feature extraction techniques it is been used in different domains for extracting the corner details [10]. The authors of the paper introduce a novel image feature extraction algorithm that takes inspiration from the SIFT descriptor and Harris corner detection algorithm. The paper provides a comprehensive analysis of the Harris corner detector. The authors present a detailed study of the algorithm and propose several improvements that can be made to the detector. The paper also evaluates the repeatability rate of the detector and shows that it is relatively robust to transformations. In the proposed algorithm, the image is pre-processed by being screened twice, followed by Harris corner detection to identify corner positions, which are then refined to sub-pixel level using an iterative algorithm. A 104-dimensional feature vector is produced when the feature point data is represented using a rotation invariant fast extraction (RIFD) descriptor. The proposed algorithm has the ability to quickly and efficiently detect image features, making it suitable for image matching and other image processing applications [11]. The experimental results show that the proposed algorithm can quickly and accurately extract stable features in images. It has great application prospects in many image matching systems.

Few challenging problems in this area are alignment of the eye, different poses and eye movements. This paper specifically focuses on the Harris corner detection algorithm as an approach for detecting corners of the eyes for eye extraction. Features are extracted from the preprocessed images using Harris corner detection method and then compared with a database containing features for further analysis [12]. The paper does not discuss the computational complexity of the proposed method. It is possible that the algorithm may be too computationally expensive for some applications.
Harris corner detection algorithm is used for feature extraction in X-ray images to identify bone fracture along with Houhg line detection [13]. The paper proposes a method for bone fracture detection and classification using X-ray images. The method combines image processing techniques, such as Canny and Sobel edge detection, with machine learning techniques, such as linear discriminant analysis (LDA).
Authors use Harris corner detection algorithm to detect the center point of oysters as these are detected as corners and binary threshold segmentation done to separate the corners, when two or more corners are adjacent in the beach background [14]. The method first establishes a mathematical model for multiline detection based on the linear distribution of maricultures. Then, it uses a minimum cosine distance sum as the judgment basis in the clustering algorithm to detect the centerline of marine breeding. Finally, the clearance volume is estimated using a three-point estimation scheme. Disadvantage of the method is that The method is not able to automatically identify fallen oyster stones. Fallen oyster stones with obvious edge contours were eliminated by visual inspection in this study, but a polygon geometry detection approach could be used in the future to automatically identify these stones.

In this paper in order to identify small irregular celestial bodies hybrid feature extraction is done using brief feature descriptor for extracting fast feature points and Harris corner detection method to select the feature points [15]. The method first uses bilateral filtering and improved histogram equalization to improve the brightness and clarity of the images. Then, it uses the ORB feature point detection algorithm to extract feature points from the enhanced images. Finally, it uses the Hamming distance screening method to remove mismatched feature point pairs. Limitation is that the method is computationally expensive.

Most of current research work based on artificial intelligence approaches The potential disadvantages of using CNNs for landmark detection include the need for large datasets, significant computational power (often requiring a GPU), limited robustness to occlusions and low-resolution images, and sensitivity to changes in pose. while CNNs have shown excellent performance in landmark detection tasks, they may not be the best choice for all applications.

There has been relatively little research on hybrid-based approaches for feature extraction in face images. While some research has been done on hybrid-based approaches for feature extraction in face images, it has not received as much attention as other approaches such as deep learning-based methods. One reason for this is that deep learning has shown excellent performance on benchmark datasets and has become the dominant approach in recent years. However, hybrid-based approaches have several potential advantages, including improved robustness to variations in lighting, pose, and expression, and the ability to leverage complementary information from different feature

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extraction techniques. Future research in this area could explore more advanced hybrid-based approaches, combining both traditional feature extraction methods and deep learning-based methods, to further improve the performance of facial recognition systems.

Harris corner detection is a well-established method for detecting corners in images that has been used in computer vision for several decades. Recent research has continued to use this technique in various applications, including image registration, object recognition, and tracking. For example, Harris corner detection has been used in recent research to improve the accuracy of registration between different medical images, and in combination with machine learning-based approaches to achieve state-of-the-art performance in object detection tasks.

The following research gaps were discovered by taking into account the aforementioned literature:

- Most current research on landmark detection is based on deep learning approaches, which have some potential disadvantages, such as the need for large datasets, significant computational power, and limited robustness to occlusions and low-resolution images.
- There has been relatively little research on hybrid-based approaches for feature extraction in face images, which have several potential advantages over deep learning-only approaches, such as improved robustness to variations in lighting, pose, and expression, and the ability to leverage complementary information from different feature extraction techniques.

3. PROPOSED METHODOLOGY

Feature extraction in face images undergoes a 2 step process, first the images are pre-processed and in the next step, the feature extraction is done through a hybrid method. Input image is first converted to grey format. The Haar Cascade Object Detector is used to crop the face image and then Mean Filter is applied. After that feature extraction is done by a hybrid method in which features extracted from Contour Detection and the Harris Corner Detector are combined. Figure 1 show the block diagram of the proposed methodology.

The results of both contour detection and Harris corner detection methods are combined in the proposed hybrid method. The contours and Harris corners are extracted from the image and used as input features for the facial recognition algorithm. This approach can help to improve the performance of the recognition algorithm by providing it with more information about the facial features. Contour detection and Harris corner detection are two different techniques used in image processing.

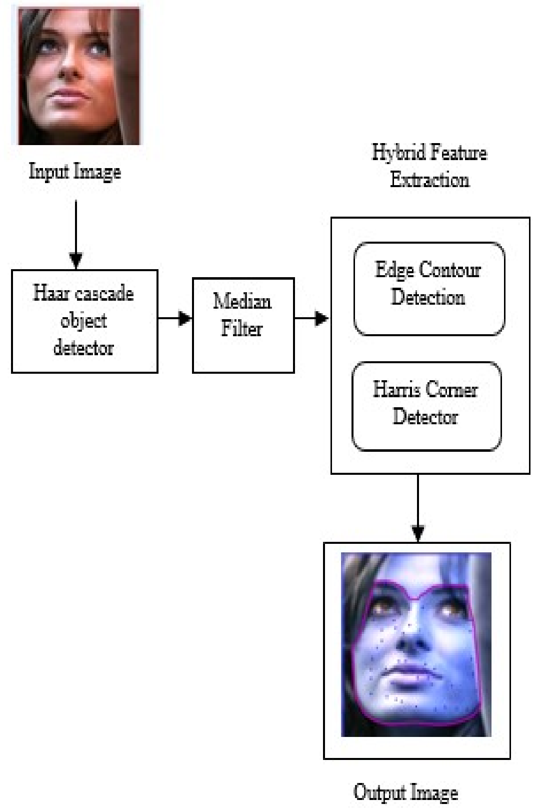

Figure 1: Proposed architecture for Landmark Detection for facial reconstruction

To identify the boundaries of objects in an image, contour detection is utilized, while Harris corner detection is used to detect points of interest or corners in an image. These two techniques can be combined by first using contour detection to identify the overall shape of an object, and then applying Harris corner detection to identify specific points of interest within that object. Applications like object recognition or tracking can benefit from this, where both the overall shape and specific points of interest are important for identifying an object.

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3.1 Haar Cascade Object Detector

In this, face is detected and cropped using a Haar cascade object detector. It is a type of object detection algorithm that is based on the concept of Haar-like features [16]. The Haar cascade object detector searches the image for pixel value patterns resembling those in human faces. In particular, it searches for patterns in images of bright and dark areas that are grouped in a way that is typical of a face, such as the existence of, a nose, eyes, a chin and mouth. The method accomplishes this by employing a number of classifiers, each of which searches the image for a particular collection of features. These characteristics are known as Haar features and are typically rectangular in shape. In order to find areas of the image that are likely to include a face, the Haar cascade object detector runs each of these classifiers to every conceivable position in the image, at various sizes and orientations. The method determines that a face has been detected in a particular area of the image if sufficient classifiers find a pattern that resembles a face there.

3.2 De-noising Using Median Filter

One common method to decrease the impact of noise in an image is to denoise a face image using a median filter. The median filter can be utilized to reduce noise while keeping the image's edges and details intact. To denoise a face image using a median filter, first the face image is loaded and the window size of median filter is defined This window size will determine the number of neighboring pixels that are used to calculate the median value for each pixel. A typical window size for a face image is between 3x3 and 7x7 pixels. Apply the median filter to the face image. The median filter determines the median value of the adjacent pixels within the window size for each pixel in the picture. The output pixel value is then set to this median value. If f(i,j) is a noisy image, one can derive the filtered image g(x,y) by,

$$g(x, y) = M_d\{f(i, j)\}, for\ (i, j)\ in\ w(i, j) \qquad (1)$$

Where g(x, y) is the filtered output pixel at position (x, y), M_d is the median , f(i, j) is the input pixel at position (i, j), and w(x, y) is the window of neighboring pixels centered at (x, y). The median function returns the median value of all the pixel values in the window w(x, y). Median filters can be used to reduce noise and improve the quality of the images before extracting features. One of the advantages of using median filters is that they are computationally efficient and easy to implement. They can also be used to reduce the effects of lighting and pose variations by smoothing out the image.

3.3 Hybrid Feature Extraction Method

A hybrid feature extraction method for faces is a fusion of various feature extraction methods with the goal of enhancing facial recognition performance by supplying more robust and discriminative characteristics. The idea behind a hybrid method is to combine the strengths of different feature extraction methods is to improve the robustness and discriminative power of the extracted features. Using a hybrid method can also help to address the challenges of extracting features from facial images with varying lighting, pose, and expression

In this proposed method a hybrid method could combine the robustness of contour detection to changes in lighting, pose, and expression with the robustness of the Harris corner detector to variations in the image quality. Edge contour detection can be more robust to changes in lighting and pose, while Harris corner detection can be more robust to changes in expression and occlusion. Additionally, by combining the two methods can improve the accuracy and robustness of facial recognition systems by providing more diverse and discriminative features. This can help to overcome the limitations of using either method alone, which may not be sufficient to capture all relevant facial features.

This can enhance the performance of facial recognition by providing a more robust and discriminative set of features. The proposed method uses the edge contour detector to detect the contours of the face, and then the Harris corner detector is applied to the contours to extract the features.

The algorithm for the hybrid method proposed

Algorithm for feature extraction using hybrid approach

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Input: AFLW2000 3D database
Output: Combined Features
Step 1: Start
Step 2: Loading the input image.
Step 3: Resizing the image using Haar cascade object detector
Step 4: Image is converted to grey scale
Step 5: Apply median filter to smoothen the image
Step 6: Apply the Edge Contour detector to the smoothened image to detect the contours of the face
Step 7: Apply the Harris corner detector to the contours to extract the features
Step 8: Stop

3.3.1 Edge contour detection

By connecting all continuous spots with the same colour or intensity, one can determine the borders of an image by using contour detection. With edge-based methods, the differential property describes how well a contour representation fits to boundary points. Active contours, or snakes, detect and extract the contours of facial features. Active contour can be used to identify edges in a face image by detecting and tracking the facial features that define the boundaries of the face. The technique involves deforming a curve or contour to minimize an energy function that represents the total cost of the contour's deformation. The energy function is high at the edges and low in the regions away from the edges. In particular, snakes can be used to detect the facial landmarks, since the object of interest is face and it will detect edges of face excluding the other details, which are specific points on the face that are important for feature extraction. Once the snake landmarks are detected, they can be used to normalize the face image, align multiple face images for comparison, or extract feature descriptors such as the distances between the landmarks. The active contour is represented by n(s) = (x(s), y(s)) [17], the energy function is expressed as

$$E^*_{snake} = \int_{snake}^{*} E_{snake}\big(n(s)\big)d(s) = \int_0^1 \Big(E_{int}\big(n(s)\big) + E_{img}\big(n(s)\big) + E_{con}\big(n(s)\big)\Big)\,ds \tag{2}$$

where E_{int} reflects the internal energy of the curve E_{img} generates the image forces and E_{con} generates the external constraint forces [17-18]. The external energy, whose value reflects how closely the curve resembles the actual contour, can be created by combining E_{img} and E_{con}. The curve is evolved until it reaches the object's boundary by reducing the energy function.

3.3.2 Harris corner detector

This is a computer vision algorithm used to detect corners in an image [19]. It is a popular algorithm used for feature detection in image processing. It works by analyzing the variations in intensity of small image patches, and identifying points where these variations in intensity are significant in multiple directions. The Harris corner detector can be used to recognize important facial features including the eyes, nose, and mouth in the context of face detection. These features are typically characterized by sharp changes in intensity or texture, which make them stand out from the surrounding facial region.

It uses a technique called "cornerness" to determine which pixels in an image are likely to be corners. Often used in applications such as object tracking, image registration, and panorama stitching. It is based on the hypothesis that corners in an image typically exhibit a high degree of intensity variation in all directions. It is based on the idea that corners in an image have a high degree of "interest" or "distinctiveness" compared to other regions of the image. The Harris corner detector uses a combination of the intensity gradient and the eigenvalues of the second-moment to detect corners. The corners of an image are significant elements and are frequently mentioned as interest points because they are resistant to illumination translation, and rotation.

The sum of squares of the intensity differences of the corresponding pixels in these two windows is used to compute the intensity variation for a specific shift [20]. The average change function E(u,v), where u,v are the x,y coordinates of each pixel in our 3 x 3 window and I is the intensity value of the pixel, is the sum of all the sum squared differences (SSD). All of the pixels in the image's features have high E(u,v) values, as determined by some threshold.

$$E(u,v) = \sum_{x,y} w(x,y)[I(x+u,y+v) - I(x,y)]^2 \tag{3}$$

E(u,v) function is maximized by applying Taylor Expansion [21] to the above equation.

$$E(u,v) \approx [u,v](\sum \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix})\begin{bmatrix} u \\ v \end{bmatrix} \quad (4)$$

Where I_y and I_x are image derivatives in y and x directions and summed-matrix J is given by:

$$J = \sum w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \quad (5)$$

Equation is rewritten as follows [21-22]:

$$E(u,v) \approx [u \quad v] J \begin{bmatrix} u \\ v \end{bmatrix} \quad (6)$$

To identify whether a window is a corner or not, a score, R, is computed for each window using the equation below:

$$R = \det(J) - k(trace(J))^2 \quad (7)$$

Where
det(J)= $\lambda_1 \lambda_2$, trace (J)= $\lambda_1 + \lambda_2$
λ_1 and λ_2 are the Eigen values of M. Thus, whether a region is an edge, a corner, or flat surface is determined by the magnitudes of these eigenvalues. The R value determines whether a region is flat, edge or corner [23,24,25]. If R is less than zero, pixel is edge and if it is greater than zero, pixel is corner.

In figure 2, the R value is peak at 1.4 when the pixels were between 20000 to 30000 suggests that the image contains a high number of corners with strong intensity variations. This is because the Harris corner detector uses the eigenvalues of the structure tensor to measure the corner strength, and a large eigenvalue indicates a strong corner. The fact that the peak R value occurs at 1.4, which is the maximum value for the Harris corner detector, suggests that these corners are very strong.

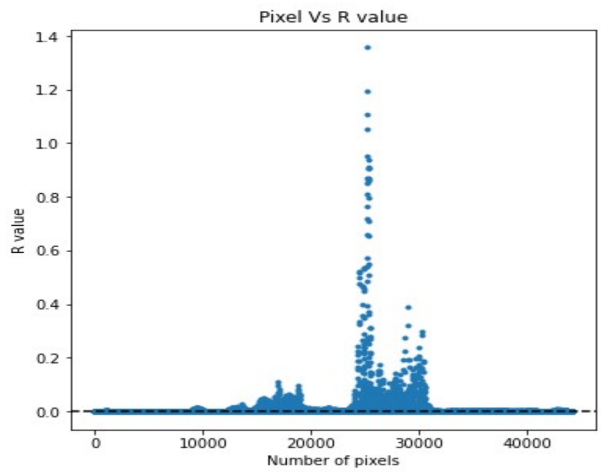

Figure 2: Graph for R value and pixel

The fact that these corners are located in the range of 20000 to 30000 pixels suggests that they are located in the center of the image. The intensity of pixels in the center of the image are usually high compared to its edges. As a result, the Harris corner detector is more likely to detect corners in the center of the image.

4. RESULT AND DISCUSSION

The hybrid feature extraction approach is performed on AFLW2000-3D dataset [2] in which the dataset contains 2000 images. Figure 3 depicts the images from the database. Python programming is used for implementation. To evaluate the performance of the proposed method, conducted a series of experiments on a dataset of facial images. Extracted features from the images using the proposed hybrid method, and then evaluated the performance using a state- of-the-art facial recognition algorithm

Figure 3: Sample Input Images

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Face detection using the Haar cascade object detector: The Haar cascade is a face detection method based on machine learning. By applying the Haar cascade object detector, the algorithm can identify and locate the faces present in the image, it is trained to recognize specific patterns or features that are characteristic of faces, such as the arrangement of eyes, nose, and mouth. Face cropped images using haar cascade classifier. figure 4 represent the cropped images.

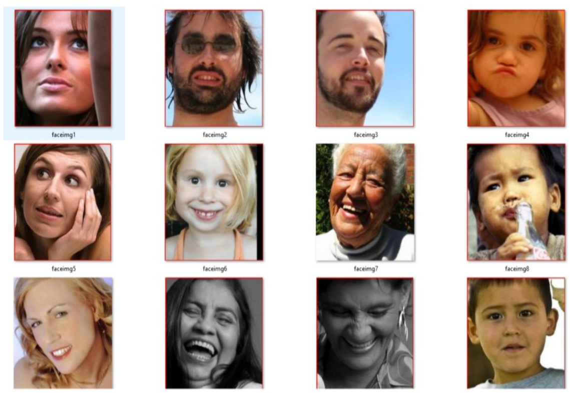

Figure 4: Cropped using haar cascade filter

Then the image is converted to grey scale and applied different filters to normalize the image: Normalization is a process that aims to enhance the quality or improve the visual appearance of an image. In this step, three types of filters are used: mean, Gaussian and median filter.

Mean filter: It is a simple filter that changes each pixel's value to the average of its surrounding pixels. This filter is frequently used to blur the image or reduce noise.

Median filter: A non-linear filter called the median substitutes each pixel's value with the median value of the pixels around it. While preserving the image's boundaries and fine features, it is effective at reducing noise.

Gaussian filter: The Gaussian filter is a linear filter that applies a weighted average to the pixels in the neighborhood. It is commonly used for blurring or smoothing the image.

Comparing the filters based on PSNR value: PSNR stands for Peak Signal-to-Noise Ratio [26] and is a measure of the quality of an image after being processed or compressed. It compares the real image with the processed image and estimates the ratio of the signal's maximum achievable power to the noise's power. In this context, the PSNR value is used as a metric to evaluate the performance of the different filters. Table 1 represents the filters and the PSNR(db).

Table 1: The Filters and PSNR Value.

Filters	PSNR (db.)
Mean Filter	30.592
Gaussian Filter	28.207
Median Filter	27.958

According to the statement, the PSNR values of the images processed with the mean filter, Gaussian filter, and median filter were compared. Among these filters, the median filter gave the optimal result based on the PSNR value. This shows that, in terms of minimizing noise and retaining visual integrity, the median filter preserved image quality better than the mean and Gaussian filters. The histogram image of the mean, Gaussian and median filters are plotted figure 5,6,7 depicts the same.

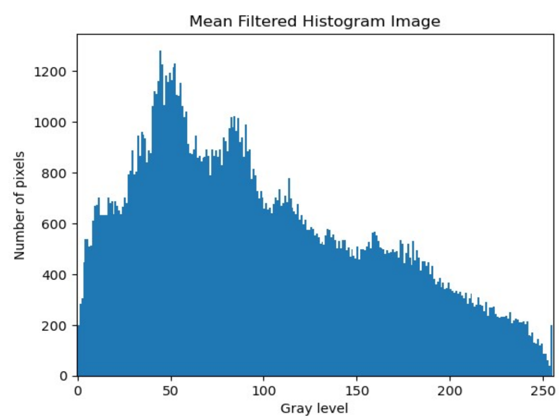

Figure 5: Histogram image of Mean filtered image

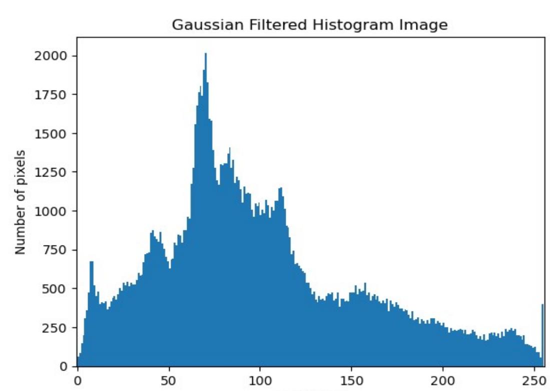

Figure 6: Histogram image of Gaussian filtered image

Figure 7 shows the histogram image of median filtered image depicts that the image has a

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relatively consistent range of intensities without distinct tonal variations or dominant brightness values.

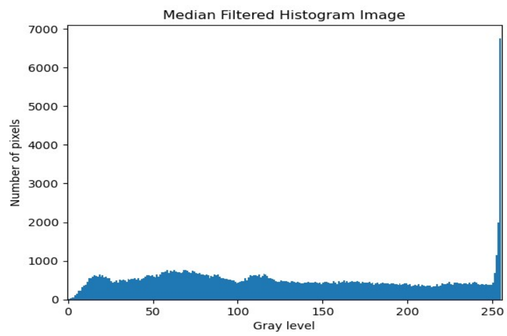

Figure 7: Histogram image of Median filtered image

A median filter is used to denoise the image after it has been converted to grey scale. Figure 8 shows the pre-processed images.

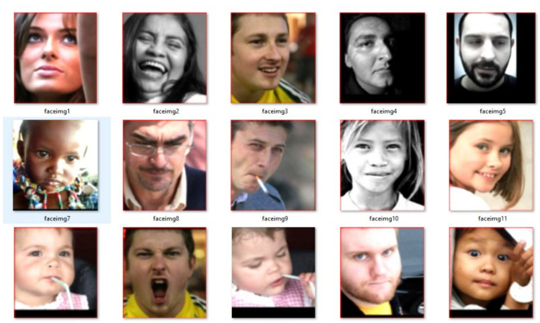

Figure 8: Output of Median filter

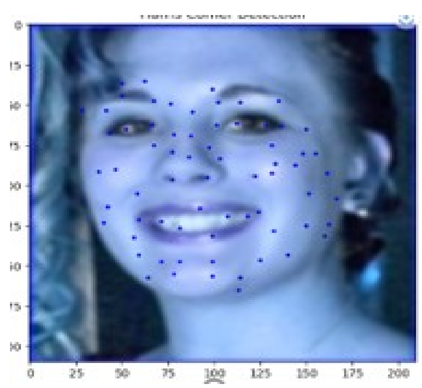

Figure 9: Landmark detection using hybrid model

Figure 9 represents the combined features after applying the hybrid method, the features are confined to the face itself after applying the edge contour detection.

The loss function is calculated by taking the difference of predicted output represented by P_out and real output represented R_out. The L1 loss of the proposed method is 3.364. Figure 10 depicts the loss graph plotted for loss and number of epochs.

$$L1\ Loss = \sum_{i=1}^{n} |P_{out} - R_{out}| \tag{8}$$

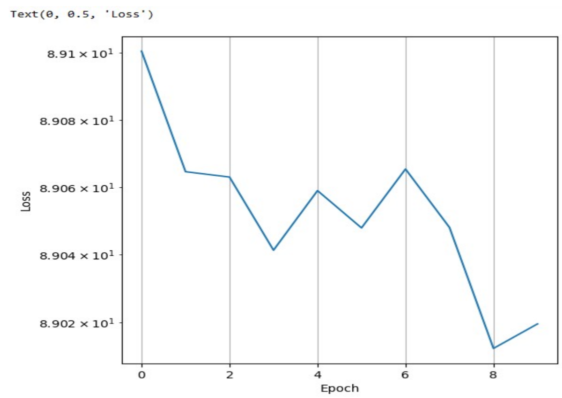

Figure 10: Loss graph plotted against epochs

Experimental analysis with different hybrid combination of methods, sift [29] and surf [30] was done using the AFLW2000-3D database. In [29] and [30] sift and surf methods are used for extracted features for 3d face reconstruction and facial recognition. The table 2 shows that the proposed method (Edge Contour, Harris Corner Detection) has the lowest L1 loss of 3.364, followed by Edge Contour, Moravec Corner Detection [27] with a loss of 10.35, and Edge Contour, Kitchen Rosenfeld Corner Detector [28] with a loss of 11.43. L1 loss for sift [29] was 8.25 and for surf [30] it was 7.11. The execution time of the proposed method is also the lowest, at 13 minutes 2 seconds. The lower L1 loss of the proposed method suggests that it is able to detect corners more accurately than the other two methods. This is perhaps because the Harris corner detector outperforms the Moravec, Kitchen Rosenfeld corner detectors, sift and surf in terms of robust to noise and variations in illumination. The lower execution time of the proposed method suggests that it is more efficient than the other two methods. The Harris corner detector has a simpler algorithm than the Moravec and Kitchen Rosenfeld corner detectors [27,28], which is probably the cause of this. Overall, the findings of the experimental analysis point to the proposed method (Edge Contour, Harris Corner Detection) as being

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more precise and effective than the other two methods taken into consideration.

Table 2: The Methods, L1 Loss and Execution Time.

Feature Extraction Methods	L1 Loss	Execution Time
Edge Contour and Harris corner detection (Proposed Method)	3.364	13min 2 sec
Edge Contour and Moravec corner detection	10.35	45 min 37sec
Edge Contour and Kitchen rosenfeld Corner Detector	11.43	20 min 41 sec
SIFT [29]	8.25	17 min 4sec
SURF [30]	7.11	15min 27sec

Figure 11 represents graph plotted between different method and L1 loss, in which the proposed method as minimal loss of 3.364 compared to the other two hybrid methods. Graph is plotted between different methods and execution time, in this the suggested method takes less execution time compared to other two methods depicted in figure 12.

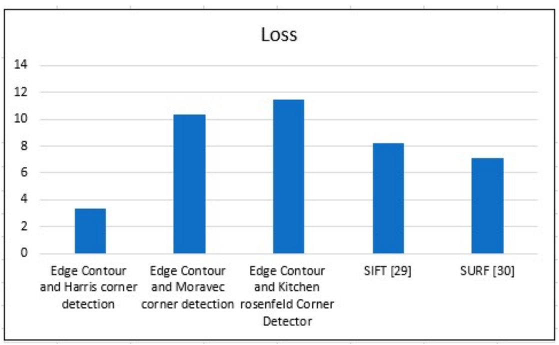

Figure 11: Loss graph plotted different Hybrid Method

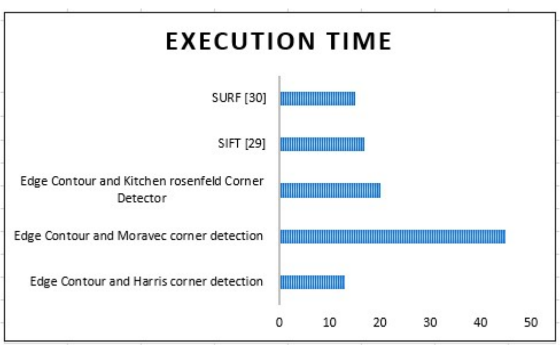

Figure 12: Execution Time plotted different Hybrid Method

The landmark map which is obtained after the hybrid feature extraction method is shown in figure 13. when the landmarks are confined to the face region, it ensures that the 3d face reconstruction process focuses specifically on the facial structure. this targeted approach improves the accuracy and reliability of the reconstruction, resulting in a more realistic and faithful representation of the face in three dimensions.

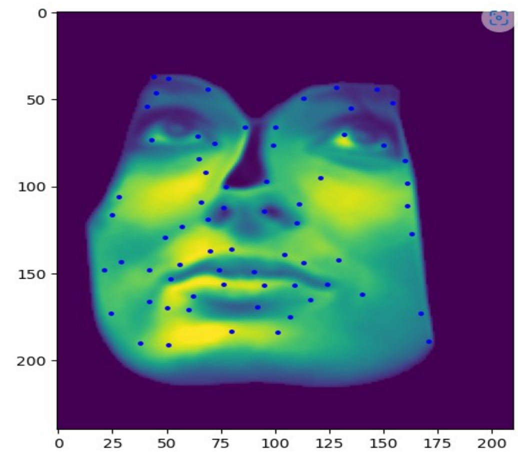

Figure 12: Landmark Map using the proposed method

5. CONCLUSION

Proposed a hybrid method for feature extraction in face images. The method combines the strengths of two different methods, edge contour detection and Harris corner detection, to improve the robustness and accuracy of feature extraction. The proposed method was able to achieve the lowest L1 loss and the shortest execution time among the other methods. This suggests that the proposed method is able to detect corners more accurately and efficiently than the other methods.

This hybrid approach is a useful option for face recognition systems where the photos are captured under various circumstances. For precise face identification, it is necessary to be able to extract features from images that are unaffected by changes in lighting, position, and expressions. In such challenging scenarios, the suggested strategy increases the efficacy of facial recognition systems. In future work, the proposed method can be further improved by using a more sophisticated approach to select the most salient corners.

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