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Human Identification Based on SIFT Features of Hand Image

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Abstract: The use of hand features for human identification is a reliable and convenient method that has a greater influence than other biometric techniques because of its simplicity and dependability. In this study, we suggested a technique for identifying individuals using all the features of a hand image which differs from the previous methods of identifying individuals depending on either the features of the palmprint only or the features of the fingerprint only. Therefore, the paper aims to build an efficient system to identify individuals depending on the features of the hand image using Scale Invariant Feature Transform (SIFT) features. Our proposed system comprises three main stages. The first stage includes removing the background and unimportant objects and extracting the hand area from the captured image. The SIFT feature is then applied to extract the robust features from the hand area. Finally, the matching stage depends on the maximum matching points of the SIFT points between the test and training image. The outcomes demonstrate the correct recognition rate (CRR), accuracy, and recall are 99.65%, 99.32%, and 98.62%, respectively. Thus, the effectiveness and efficiency of the suggested approach have been proven.

Keywords: Biometrics, SIFT, CRR, Hand Identification, Segmentation.

1. INTRODUCTION

Currently, there is significant research on the biometrics recognition system, which includes several biometrics characteristics including (biological and behavioral) [1], [2]. Technologies that measure and analyze biological aspects of the human body for user authentication are known as biometrics. The two modes of the biometric authentication system are enrollment and recognition. The sensor is used to gather biometric data, which is then put in a database together with the individual's identity for use in the enrolment mode. In the identification mode, the sensor once more provides the biometric data, which is then utilized to identify the user by matching it to previously recorded information [3]. Traditional methods of authentication like passwords, PINs, tokens, and smart cards are no longer applicable for use with techniques that demand a very high-security level. The biometrics system replaces traditional approaches by using human biological features or behavioral attributes that serve to identify a person and have the advantage of being difficult to copy, steal, and forge. Hand recognition is one of the early biometric techniques for automatic human identification [4], [5]. Palmprints are a unique biometric feature because of their characteristics, including good efficiency, maximum speed, ease of use, and relatively inexpensive. Palmprint recognition has gained a lot of care over the past decade [6], [7]. A small patch of the palm's texture is defined as a palmprint that contains more data that is helpful for personal authentication systems. Additionally, it has a distinctive feature (individuality indicates that no two persons have the same features), which is also known as permanency because it won't change throughout one's lifetime [8], [9]. Today, various research mechanisms have been improved to obtain and merge hand and palm print features at the same time, greatly improving their performance [10], [11]. The hand's geometry such as the veins in the palm, the texture of the palm and fingers, the fingerprint, and many more details are all contained in a hand image. The fundamental benefit of a biometric-based identification is that it is non-transferable, meaning the owner must go through the identification and authentication process themselves rather than giving it to someone else [12], [13]. The process of identifying individuals using hand features may face many problems because the hand image taken for the person does not only contain the hand area but also contains the background and some unimportant information, and this affects the extraction of the robust features from the hand area, so we need to extract only the hand area and delete the rest of the unnecessary data. Thus, we can extract the features using SIFT features and then perform the matching based on the maximum number of matching points. This paper seeks to construct a practical technique for extracting hand area and identifying individuals using SIFT features. The rest of the article is organized as follows: the related work is dedicated in section 2. The structure of the proposed hand identification system is illustrated in section 3. Section 4 contains the results and discussion. Section 5 of this article presents its conclusions.

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2. RELATED WORK

Several studies on palmprint recognition have been conducted in recent years. Poonia et al. [14] presented a palmprint template that is non-invertible and maintains the geometric data of the minute points. The template cannot be used to determine the palmprint orientation because information about the minutiae direction and placement is not provided. The suggested template is resistant to the reconstruction process as well as rotation and scaling. And finally, for template matching, an effective computational method called Delaunay triangulation-based internal angle matching is employed. According to the test results, the recognition rate and error rate are equal to 95.4% and 0.37%, respectively. Ahmad et al. [15] proposed an approach that is focused on numerous features that are derived from a single template. To attain precision and high performance, this work combines hand and palm print features. Hand features, palm length, palm width, and palm ratio are interesting features of the suggested system. The characteristics of the hands are measured in terms of their length, width, and length of fingers. An integrated feature vector is created using these features. The suggested system only extracts features that are resistant to slight changes in hand position. A composite feature vector made up of the 20 features that were retrieved is generated by establishing bounding boxes for each object in each image. Comparing the combined feature vector to saved templates allows one to determine the average of the combined feature vector. The test results show the achieved accuracy is 95.5%. Mustafa et al. [16] presented a new harmony search-based palm print identification approach by calculating the Gaussian distribution. Preprocessing, the initial stage in this technique involves segmenting the palmprint's region of interest (ROI) based on its geometrical shapes. Following processing of the ROI area, which serves as input for the algorithm of harmony search to extract features from palm print images using a variety of parameters. Gaussian distribution is applied to compute the distance between elements of region palm print images. According to the test results, the recognition rate achieved is 92.60%. Gayathri et al. [17] presented a palm print-based identification methodology that extracts several features from the palm print using the Gabor wavelet entropy, fuses those features at the feature level using the Dempster- Shafer theory, and classifies the results using the nearest neighbor method. The wavelet transform can be used to group features with the same vector together. With the use of wavelets, another aspect of the image can be retrieved. Wavelet entropy can be utilized to extract properties like contrast, correlation, energy, and homogeneity. At the feature level, the features are combined. This is followed by palmprint matching using the nearest neighbor classifier. The test results achieve accuracy rate of 98.6%. Alzoubiady et al. [18] proposed an automated palmprint biometric technique. Three steps make up the implementation process. The first step involves pre-processing algorithms based on image requirements and clipping to create a more appropriate image for palm prints. Then feature is extracted using a contourlet-based approach to get a decent correlation and a KL transform to get foreign values that lessen the input. Finally, the backpropagation neural network is used for classification and authenticates data. The test results achieve accuracy rate of 96%. Yuan et al. [19] proposed an approach that is focused on recognizing people based on hand images. First, the image is preprocessed using the CLAHE method, then images are normalized. Second, a large dataset was used to design and train a convolutional neural network structure. Using hand images as the network's input, various depth features, including the fusion layer feature, were extracted. Finally, SVM classifiers were used to obtain classification outcomes. To use various SVM classifiers, a fusion approach has been used. The test results achieve accuracy rate of 90.51%.

3. PROPOSED HAND IDENTIFICATION SYSTEM

The layout of the proposed hand identification system and its main stages are discussed in detail in this section. Figure 1 demonstrates the proposed system's three main stages, including preprocessing stage, feature extraction stage, and matching stage, as described below.

A. Preprocessing Stage

This stage represents the first stage of the proposed system to preserve the image quality, which aims to extract the hand image. Furthermore, the hand image quality affects the feature extraction and matching stages. In this stage, several tasks have been conducted to improve image quality. These tasks are explained in the steps below.

1) Color Hand Image Loading

The input RGB-colored hand image format is loaded in the JPEG format (i.e., .jpg), in which the value of each pixel is represented by three bytes, as shown in Figure 2 (a).

2) Convert to Grayscale Image

This step aims to convert the color hand image to a grayscale image, in which the value of each pixel is represented by one byte instead of three bytes because it carries only the intensity information, as shown in Figure 2 (b).

3) Hand Image Segmentation

This step seeks to partition the grayscale image into two significant partitions (i.e., hand image area (its pixels denoted by 1) and background (its pixels denoted by 0)). It is accomplished by the thresholding operation that works on converting an image into a binary image by selecting a proper threshold value to separate image pixels into multiple regions, this process is done based on setting pixels to white (or 1) if the gray value exceeds or equals the threshold value thus representing the hand; or set to black (0) if smaller thus representing the background. In this paper, the appropriate threshold of the database is equal to 70 as shown in Figure 3, where (a) explains the grayscale image while (b) illustrates the segmented binary image.

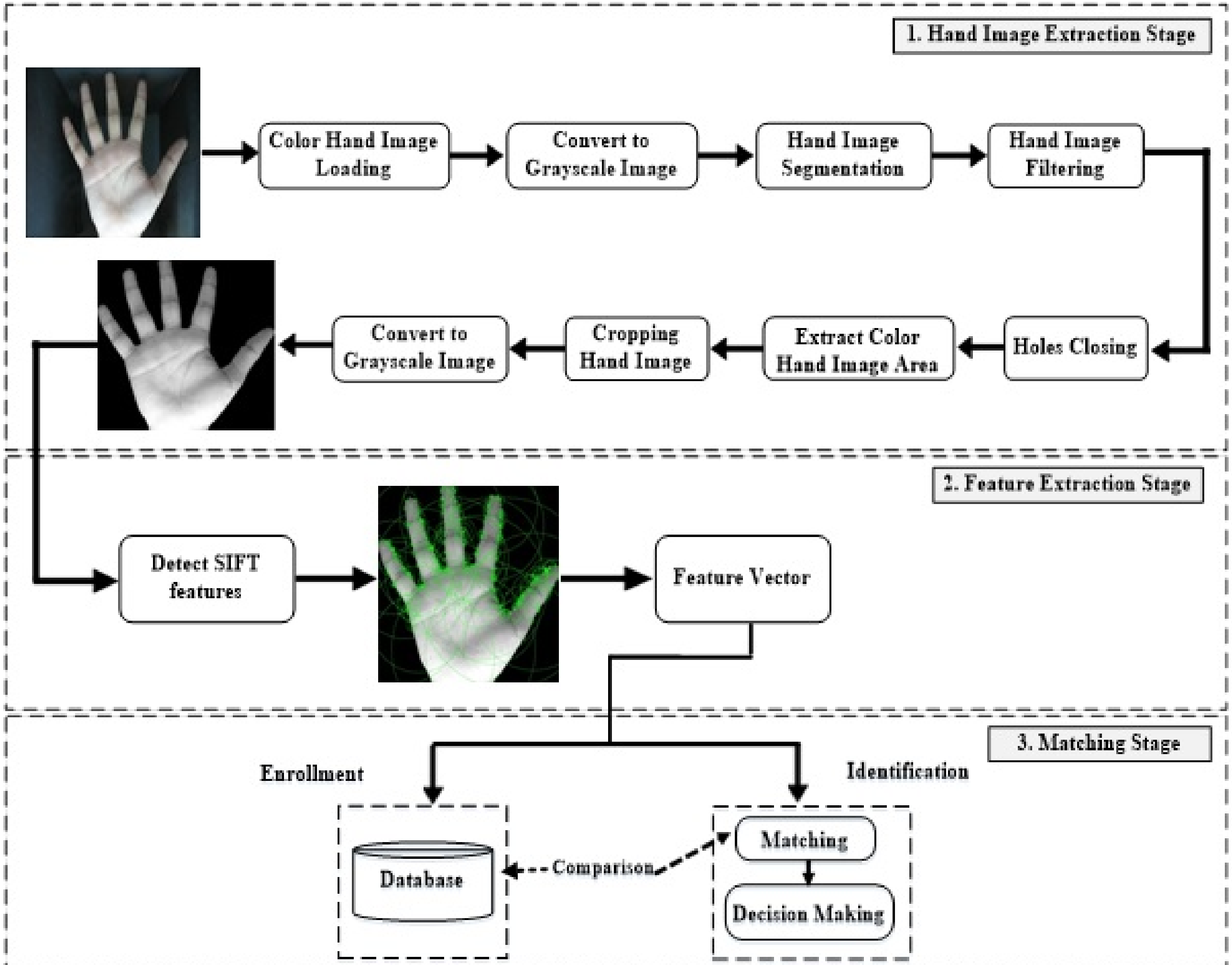

Figure 1. The proposed system layout of hand recognition system

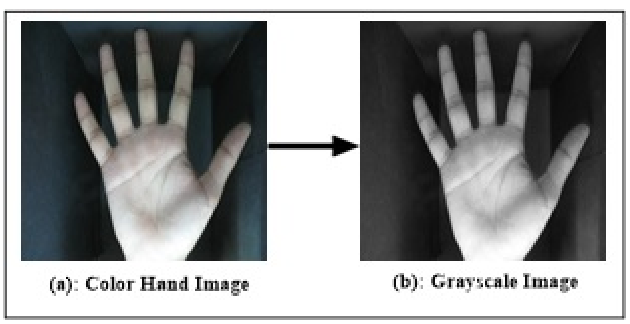

Figure 2. Convert color to grayscale image

4) Hand Image Filtering

The obtained binary image contains the white hand area and the black background area. It also includes some unimportant objects beside the hand area where the red circle represents these objects as shown in Figure 4 (a), which must be removed. This process is done by determining the connected objects in the image based on the size of these objects and filtering it by selecting the largest object which represents the hand area that is extracted, but, other objects that have less area are considered unimportant and therefore deleted, as illustrated in Figure 4 (b).

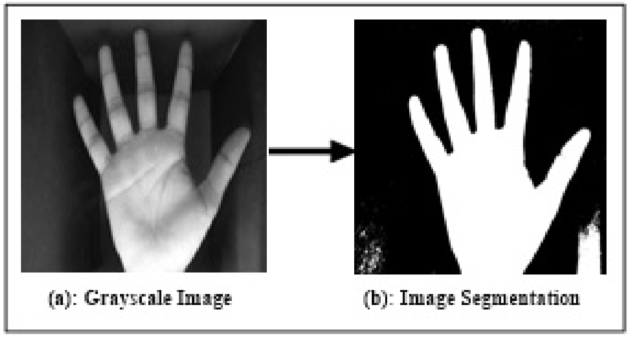

Figure 3. Image segmentation

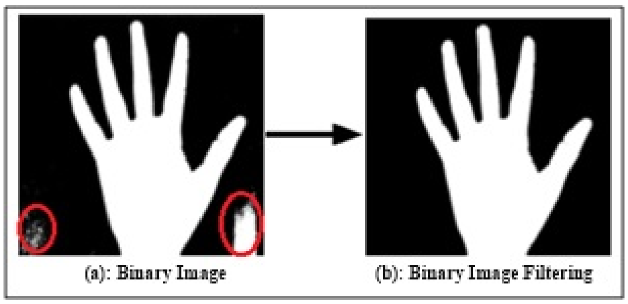

Figure 4. Binary image filtering

5) *Holes Closing*

The binary hand image resulting from the filtration process contains some holes that need to be closed, thus, the problem is that the area is mostly (but not entirely) closed, thus we need to close all holes. To solve these problems morphological closing operation is performed on the binary image, using the structuring element. A dilation followed by erosion is the morphological close operation, and both operations use the same structuring element. Figure 5 (a) shows the hand image that contains the holes so that the holes are surrounded by red circles, and also shows the binary mask of the hand image after closing the holes in Figure 5 (b).

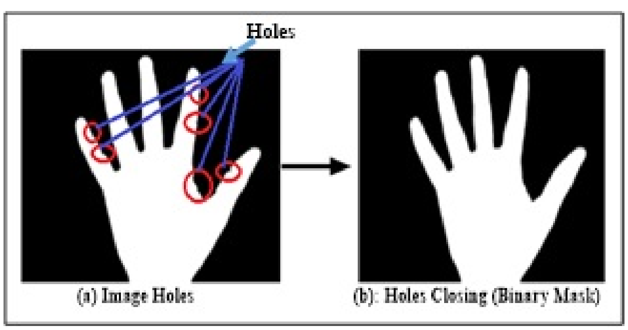

Figure 5. Binary mask of the hand image

6) *Extract Color Hand Image Area*

This step aims to extract the colored hand image and delete the background. This process is done by multiplying the binary mask that was acquired in the previous step in the original image as illustrated in Figure 6 (a), where the color values of the original image are multiplied by the color value of the binary mask. If the color value is multiplied by the white color, the color value is obtained, while when it is multiplied by the black color, the background is obtained, and thus we get the color hand image and the black background, as shown in Figure 6 (b).

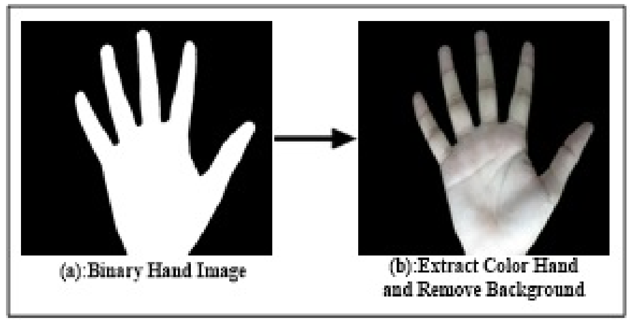

Figure 6. Extract color hand image area

7) *Cropping Hand Image*

The obtained hand image contains the hand area and it is surrounded by a black area that is not important and does not contain features. Therefore, we will make scanning of the area from all sides and remove this area as illustrated in Figure 7 (a), where the red arrows represent this area that we need to remove, while (b) represents the image resulting after the cropping process.

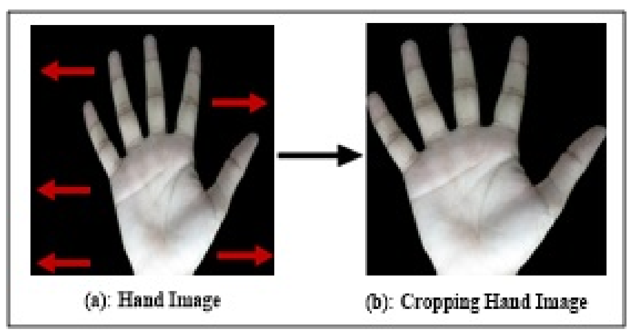

Figure 7. Cropping hand image

8) *Convert to Grayscale Image*

This step aims to convert a color image to a grayscale image to decrease the amount of data that must be processed, which can make the feature extraction process faster and more efficient. This is because grayscale images have only one channel (intensity) instead of three channels (red, green, and blue) in a full-color image as illustrated in Figure 8 (b).

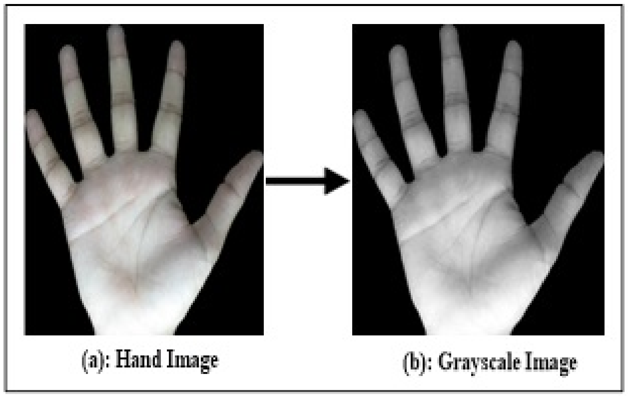

Figure 8. Convert to grayscale image

B. Feature Extraction Stage

This stage seeks to extract distinctive features from the hand area to achieve better results in the matching stage. In this paper, the Scale Invariant Feature Transform (SIFT) is an approach for identifying and extracting local feature descriptors that are largely resistant to variations in lighting, noise in the image, rotation, scaling, and slight modifications in vision. The SIFT algorithm is mainly divided into four main steps [20], [21]. A more detailed description of SIFT can be found in the original paper by Lowe [22].

1) Scale-Space Extrema Detection

During the initial stage of computing, all scales and image locations are searched. It is executed by using a difference-of-Gaussian function to identify prospective interest points that are independent of scale and orientation [23], [24].

2) Keypoint Localization

To identify the location and scale at each prospective location, a detailed model is fitted. Key points are chosen based on indicators of stability [23], [24].

3) Orientation Assignment

According to the local image gradient orientations, each key point location gets one or more orientations. All subsequent processes are carried out on image data that has been transformed to account for each feature's assigned orientation, scale, and location. This ensures that the transformations are invariant [23], [24].

4) Keypoint Descriptors

According to the local image gradient orientations, each key point location gets one or more orientations. All subsequent processes are carried out on image data that has been transformed to account for each feature's assigned orientation, scale, and location. This ensures that the transformations are invariant [23], [24].

SIFT was designed to work with grayscale images, and it has been found to be more robust and accurate when applied to grayscale images. This is because SIFT relies on the intensity variations within an image to detect features, and these variations are more pronounced in grayscale images compared to full-color images. Figure 9 . demonstrates the implementation of SIFT features on the selected image from the database.

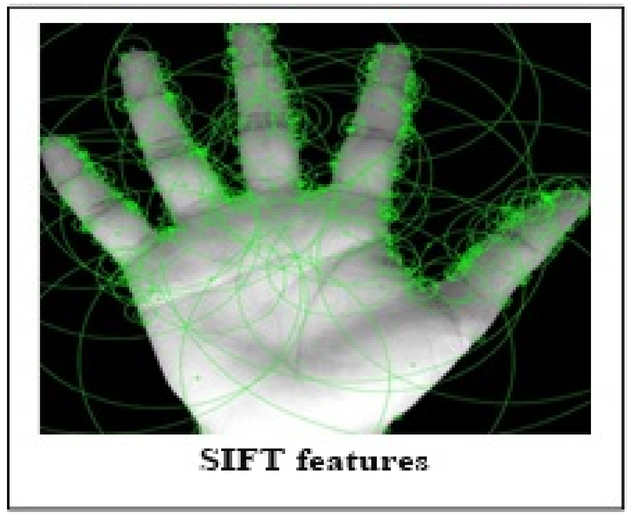

Figure 9. Feature extraction

C. Matching Stage

After The final stage in the suggested method is matching, which refers to the process of comparing an input pattern with a set of stored patterns or templates to discover the best match. This is typically done in order to classify the input pattern or to identify it as a particular object or entity. The similarity measure is calculated by comparing the SIFT points of the test image with the SIFT points of all the training images saved in the database based on finding the largest number of match SIFT points between the test image and the training images when the training image contains the largest number of matching points, which means that the test image belongs to this class. Figure 10 shows the SIFT feature of a test image that has been matched with itself, while Figure 11 shows the SIFT feature of the test image that has been matched with the training image from the same class, but Figure 12 shows the SIFT feature of the test image that has been matched with the training image from the various class.

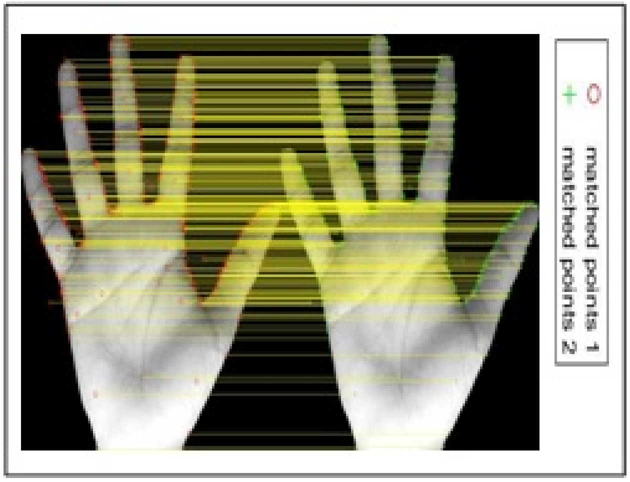

Figure 10. Matching test image with itself

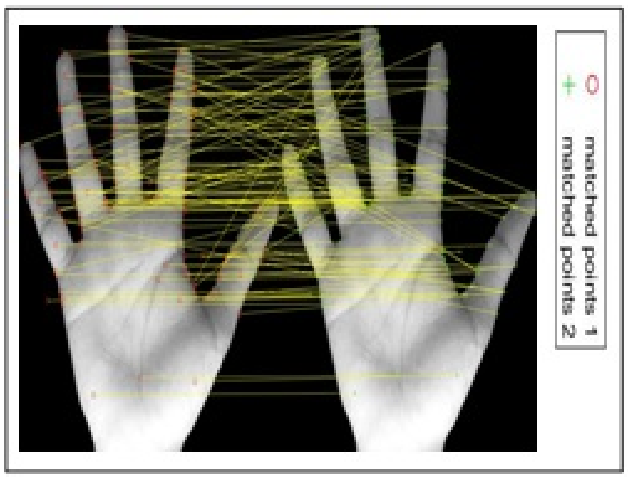

Figure 11. Matching test image with same class

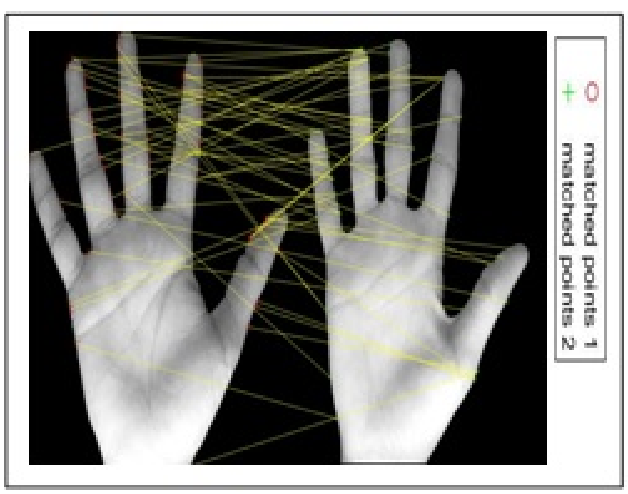

Figure 12. Matching test image with various class

4. RESULTS AND DISCUSSION

This section focuses on evaluating the performance of the suggested hand recognition system using one database publicly available. The database is called IIT Delhi Touchless Palmprint Database (Version 1.0) and was updated in December 2013, the updated version of the database now has original color images (instead of grayscale images available earlier). This updated version of the database still has images from 230 users, these images are all in the bitmap (*.bmp) format. Six images from each user of the left and right hand. This database is available in [25]. Figure 13 shows sample images of one user selected randomly from this database where each user has six images for each left and right hand as H_L_1, H_L_2, H_L_3, H_L_4, H_L_5, H_L_6, H_R_1, H_R_2, H_R_3, H_R_4, H_R_5, H_R_6, respectively.

Correct recognition rate (CRR), accuracy, and recall are three metrics used to evaluate the proposed system's effectiveness and accuracy.

A. *Correct Recognition Rate (CRR)*

Measures the ratio of correctly identified samples to all tested samples, as equation 1 [26].

$$CRR = \frac{Numberofcorrectidentifiedimages}{Totalnumberoftestimages} \times 100\% \quad (1)$$

B. *Accuracy*

Is defined as the proportion of correct estimates as equation 2 [27].

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

C. *Recall*

Calculates the proportion of detected ground truth annotations, as equation 3 [28].

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

Thus, the main difference between CRR and accuracy is that the CRR only takes into account the number of correctly classified samples, while accuracy considers both true and false classifications. Therefore, accuracy may be a more comprehensive metric for evaluating model performance, particularly when dealing with imbalanced datasets where the classes have different proportions. However, CRR can be a useful metric when the cost of false positives and false negatives is equal, and the classes are balanced.

The experiments are carried out by splitting the database into two groups; testing, and training, where each class contains six samples, chosen 80% for training and 20%

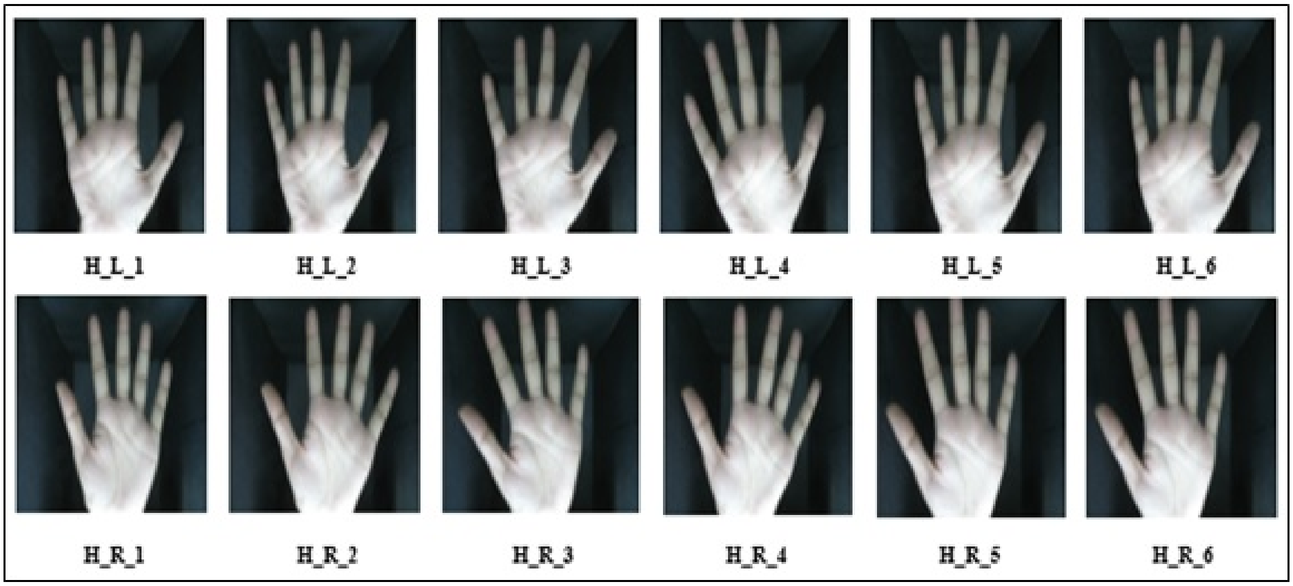

Figure 13. Six samples for one user from database for each left and right hand

for testing for each left and right-hand image. The process of identifying individuals is done by passing the test image and training image to all the stages of the proposed system which includes extracting the hand area from the captured image then, SIFT features are extracted from the hand area, and these features points are used in the matching process which is based on the maximum matching points. The experimental findings demonstrate that the CRR, accuracy, and recall are 99.65%, 99.32%, and 98.62%, respectively as shown in Figure 14.

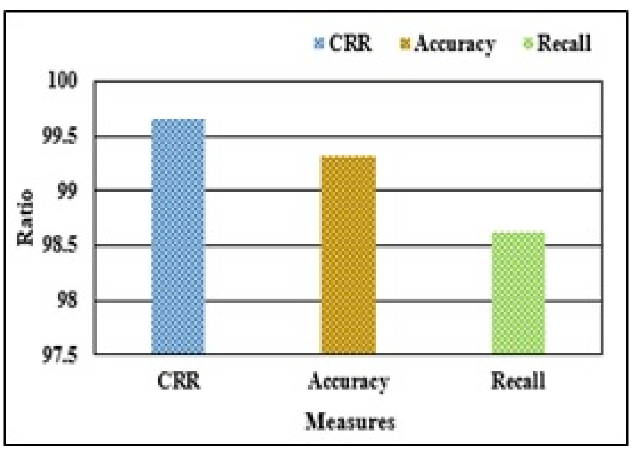

Figure 14. The results of CRR, accuracy, and recall

There are several advantages of using SIFT features for hand image identification:

1) Scale invariance

SIFT features are scale-invariant, which means they can be detected at different scales. This makes them suitable for hand image identification, where hands can be of various sizes.

2) Rotation invariance

SIFT features are also rotation-invariant, meaning they can be detected even if the hand is rotated in the image.

3) Robustness

SIFT features are robust to noise and changes in lighting conditions, which is important for hand image identification tasks.

4) Distinctiveness

SIFT features are highly distinctive, meaning they can accurately describe the unique features of a hand, such as the shape of the fingers and the position of the joints.

Table I compares our suggested strategy with other previously published studies and demonstrates that it yields superior outcomes from other previous tests. The results in Table I showed the suggested approach provides a greater CRR, accuracy, and recall than other earlier studies. Thus, the effectiveness of our suggested system has been proven.

TABLE I. Compare our proposed with previous experiments

Reference	CRR%	Accuracy%	Recall%
[14]	95.4%	-	-
[15]	-	95.5%	-
[16]	92.60%	-	-
[17]	-	98.6%	-
[18]	-	96%	-
[19]	-	90.51%	-
Our Proposed	99.65%	99.32%	98.62%

5. CONCLUSION

In this section, a new method is suggested to identify individuals by using their hand image features. This paper seeks to extract hand area from the acquisition image, and SIFT features are extracted from this area then the matching process is done based on the maximum SIFT points matching. To evaluate the effectiveness of the suggested system, one database has been utilized and is publically available in [25]. The test results showed the highest CRR, accuracy, and recall are 99.65%, 99.32%, and 98.62%, respectively.

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