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AUTHENTICATED HANDSIGN RECOGONITION FOR HUMAN COMPUTER INTERACTION

S.Sharaenya[#1] and C.S.Manikandababu[*2]

[#]Student, ECE, Sri Ramakrishna Engineering College, Coimbatore ,India

[*] Assistant Professor (SI.Grade), ECE, Ramakrishna Engineering College, Coimbatore, India

***Abstract*— Hand sign recognition is garnering attention in the recent years due to its diverse applications. It aids Human Computer Interaction (HCI) which transforms the way the machines are operated. Providing reliable machine authentication in HCI is crucial to allow secure access to the data. The main aim of the project is to identify the authorized user by knuckle pattern identification, which is discriminative. The features of the knuckle pattern will be extracted accurately by using the SURF algorithm. The hand sign of the authorized user will be then captured to perform the analogous action. The contour of the hand sign is extracted from the image on preprocessing and compared with the hand signs stored in a database. An efficient matching algorithm will be employed to find the closest sign related to the input posture.**

***Index Terms*—Hand Gesture, Human Computer Interaction, Image Processing, Object Detection.**

I. INTRODUCTION

Hand Recognition of sign languages is one of the major concerns for the international deaf community. However, contrary to popular belief, sign language is not universal. Wherever communities of deaf people exist, sign languages develop, but as with spoken languages, these vary from region to region. There is no unique way in which such a recognition can be formalized. Every country has its own interpretation. They are not based on the spoken language in the country of origin. In fact their complex spatial grammars are markedly different. Sign language recognition is a multidisciplinary research area involving pattern recognition, computer vision, natural language processing and psychology. Sign language recognition is a comprehensive problem because of the complexity of the visual analysis of hand gestures and the highly structured nature of sign languages. A functioning sign language recognition system can provide an opportunity for a mute person to communicate with non-signing people without the need for an interpreter. It can be used to generate speech or text making the mute more independent. Unfortunately, there has not been any system with these capabilities so far. All researches till date have been limited to small scale systems capable of recognizing only a minimal subset of a

full sign language. The most complicated part of dynamic hand gesture recognition is the sign language recognition as both local and global motions of the hand preserve necessary information in addition to temporal information. In order to recognize even the simplest hand gesture, the hand must be detected in the image. Once the hand is detected, a complete hand gesture recognition system must be able to extract the hand shape, the hand motion and the spatial position of the hand. Moreover, the hand movement for a particular sign follows some temporal properties.

Hand gestures are a type of communication that is multifaceted in a number of ways. Hand gestures provide an attractive alternative to the cumbersome interface devices used for human-computer interaction (HCI). Thus, integrating the use of hands in HCI would be of great benefit to users. Smart environments have recently become popular to improve our quality of life. Gesture recognition capabilities implemented in embedded systems are very beneficial in such environments to provide various apparatuses with efficient HCI. Real time processing is an essential feature to use hand signs for HCI. Since real time recognition incurs very high computational costs, a powerful full-specification PC is necessary to implement recognition systems as software. However, such systems are very large physically, and consume large amount of power, which is not suitable for embedded systems. Improvements in field programmable gate arrays (FPGAs) have driven a huge increase in their use in space, weight, and power constrained embedded computing systems. The implementation of FPGAs has raised the possibility of achieving portable systems that can recognize hand gestures without bulky PCs while decreasing the response time due to their computing power. Hand gestures are generally either hand postures or dynamic hand gestures. Hand postures are static hand poses without any movements. However, hand gestures are defined as dynamic movements, which are a sequence of hand postures. This paper focuses on hand posture recognition, and proposes a new real-time system of hand sign recognition that integrates all processing tasks that includes an image capture circuit with an on-board camera. Human Computer Interaction (HCI) is a sophisticated way of interaction between humans and computers by making computers more amendable to the user's need.

HCI provides a great advantage to people with disabilities by visually recognizing the actions performed by them. It is necessary to provide authenticated HCI because it is very important to prevent identity theft. Authentication of a person by means of biometrics is more desirable. Among the various biometric characteristics, the texture pattern in Finger-Knuckle Print (FKP) is more unique and can serve as a distinctive biometric identifier. It has contact-less image acquisition and ensures better security of the system. This provides an effortless and secure access to the data. Hand sign recognition using webcam provides more functionality than common input devices in the computer. The hand sign database is created according to the demands of the user. The action performed by the user is made to be recognized by the system. The hand sign recognition is done by comparing the image stored in the database and the current input sign. Finally according to the user requirements, the corresponding action takes place in the system. Finger knuckle print (FKP), has been proposed for personal authentication with very interesting results. One of the advantages of FKP verification lies in its user friendliness in data collection. However, the user flexibility in positioning fingers also leads to a certain degree of pose variations in the collected query FKP images. The widely used Gabor filtering based competitive coding scheme is sensitive to such variations, resulting in many false rejections. We propose to alleviate this problem by reconstructing the query sample with a dictionary learned from the template samples in the gallery set. The reconstructed FKP image can reduce much the enlarged matching distance caused by finger pose variations; however, both the intra-class and inter-class distances will be reduced. We then propose a score level adaptive binary fusion rule to adaptively fuse the matching distances before and after reconstruction, aiming to reduce the false rejections without increasing much the false acceptances. Experimental results on the benchmark PolyU FKP database show that the proposed method significantly improves the FKP verification accuracy.

II. REVIEW OF KNUCKLE BASED HAND SIGN ALGORITHM

The system that transformed preprocessed data of the detected hand into a fuzzy hand-posture feature model by using fuzzy neural networks and based on this model, the actual hand posture were determined by applying fuzzy inference. The fuzzy features like distance between the finger tips, bendiness of each finger, angle between finger joint and plane of palm of given hand were calculated. The correct identification rate is in average above 96% with a limitation of the need of using a homogenous background. The limitation of this method is that it uses fixed input resolution and not implemented in real time performance [1]. Detecting and tracking of bare hands in cluttered background. For every frame captured from a webcam, the hand was detected, then key points were extracted for every small image that contains the detected hand gesture and fed into the cluster model to map them into a bag-of-words vector, which was then fed into the multiclass SVM training classifier to recognize the hand gesture. The system achieved satisfactory real-time performance regardless of the frame resolution size as well as high classification accuracy of 96.23%. The important factors that affected the accuracy of the system are the quality of the webcam in the training and testing stages, the number of training images and choosing number of clusters to build the cluster model. The system can be made suitable for different input resolution pixel sizes[10]. SOM-Hebb classifier, which employed both neuron culling and perturbed training data. They have also proposed a novel video processing architecture. A whole recognition algorithm was implemented in hardware using an FPGA connected to an on-board CMOS camera. This system was designed to recognize 24 ASL hand signs, and its accuracy was tested by simulations and experiments. The proposed hand sign recognition system could carry out recognition at a speed of 60 fps and 60 recognitions per second with a recognition accuracy of 97.1%[7]. The flexibility in positioning of fingers lead to a certain degree of pose variations in the collected query FKP images. Gabor filtering based on competitive coding scheme is sensitive to such variations and resulted in many false rejections. To alleviate this problem, the query samples were reconstructed with a dictionary consisting of samples in the gallery set. The reconstructed FKP image could reduce the matching distance caused by finger pose variations. However, both the intra-class and inter-class distances will be reduced. To enhance the FKP matching process, a reconstruction based matching scheme was proposed to reduce the enlarged matching distance. Adaptive binary fusion(ABF) rule was proposed to make the final decision by fusing the matching scores before and after reconstruction. The ABF ensured a good reduction of false rejections without increasing much the false acceptances, which lead to much lower equal error rates than state-of-the-art methods. One of the advantages of FKP verification lies in its user friendliness in data collection. This proposed method significantly improves the FKP verification accuracy. However, it has a high algorithmic complexity[3]. SIFT hardware accelerator which is the fastest so far used to implement SIFT algorithm. It has two hardware components, one for key point identification, and the other for feature descriptor generation. The key point identification part has three stages: 1) Gaussian filtering and DoG image computation; 2) key-point detection; and 3) gradient magnitude and orientation computation. The stage 1 was designed for building the Gaussian-filtered images and difference-of-Gaussian images, these images are used as inputs of stage 2 and stage 3. Stage 2 received DoG images to identify the key points with stability checking. The stage 3 was used to compute the gradient magnitude and orientation of each pixel in the Gaussian images. The feature descriptor generation part received the locations (including x and y coordinates) of the key points from stage 2 and the related gradient histograms from stage 3. The processing time of the key point identification was only 3.4ms for one video graphics array (VGA) image. One of the major contributions made in this paper is an architecture that used rotating SRAM banks for Segment Buffer Supporting Sliding Window Operation. The accuracy can be determined by comparing the results produced by the SIFT accelerator to that obtained from a SIFT software. It has a few disadvantages. It requires a large internal memory and complex hardware logic. It also has a high computational complexity[5]. The system consisted of two modules: hand gesture detection module and hand gesture recognition module. The detection module could accurately locate the hand regions with a blue rectangle. This is mainly based on Viola-Jones method. In the recognition module, the Hu invariant moments feature vectors of the detected hand gesture were extracted and a Support Vector Machines (SVMs) classifier was trained for final recognition[9]. Adaptive skin colour detection and motion detection were combined to generate hand location hypotheses. Histograms of oriented gradients (HOG) were used to describe hand regions. Extracted HOG features were projected into low dimensional subspace using PCA-LDA. In the subspace, a nearest neighbor classifier was applied to recognize gestures. Experimental results showed that the proposed method gained detection rate up to 91% and it could process in real-time. Its disadvantage is that highly sensitive to illumination, not reliable and Expensive computation in order to achieve scale invariance [6]. The concept of object-based video abstraction was used for segmenting the frames into video object planes (VOPs), as used in MPEG-4, where hand is considered as a video object (VO). The redundant frames of the gesture video sequence were discarded and the key hand poses (key video object plane (VOP) were used in MPEG-4 domain) for summarization and recognition. The palm and finger motions were represented in terms of 'shape change' of the hand. The global hand motion were represented in terms of motion trajectory in 2D space. The proposed gesture representation could handle different gestures consisting of different number of states. The key frame based gesture representation was the summarization of the gesture with finite number of gesture states. In case of global hand motion, trajectory estimated from the corresponding VOPs bared spatial information regarding the hand positions in the gesture sequence, which was utilized successfully in the gesture classification stage. However, the results obtained by VOP extraction based on edge change detection suffered from boundary inaccuracy. Change detection methods did not support moving background. As the number of objects in the image increased, boundary inaccuracy increases in case of change detection methods. Douglas Chai et al (2002) have described a fast, reliable, and effective algorithm that exploits the spatial distribution characteristics of human skin color. The face location was identified by performing region segmentation with the use of a skin color map. The color analysis and the different color space models were studied. The three colour space models that were studied are RGD,HSV and YCbCr. These are some, but certainly not all, of the color space models available in image processing. YCrCb color space was effective as the chrominance information can be used for modeling human skin in this color space and will avoid the extra computation required in conversion. HSV color space was compatible with human color perception, and the hue and saturation components reported to be sufficient for discriminating color information for modeling skin color. However, this color space was not suitable for video coding. A normalized RGB color space was employed to minimize the dependence on the luminance values. Therefore, it is important to choose the appropriate color space for modeling human skin color. The factors that need to be considered are application and effectiveness. The intended purpose of the face segmentation will usually determine which color space to use and at the same time, it is essential that an effective and robust skin color model can be derived from the given color space[4]. The identification and verification are done by passwords, pin number, etc., which is easily cracked by others. Biometrics is a powerful and unique tool based on the anatomical and behavioral characteristics of the human beings in order to prove their authentication. This paper proposes a novel recognition methodology of biometrics named as Finger Knuckle print (FKP). Hence this paper has focused on the extraction of features of Finger knuckle print using Scale Invariant Feature Transform (SIFT), and the key points are derived from FKP are clustered using K-Means Algorithm. The centroid of K-Means is stored in the database which is compared with the query FKP K-Means centroid value to prove the recognition and authentication. The comparison is based on the XOR operation. Hence this paper provides a novel recognition method to provide authentication. Results are performed on the PolyU FKP database to check the proposed FKP recognition method. Biometrics is defined as the measure of human body characteristics such as fingerprint, eye, retina, voice pattern, Iris and Hand measurement. It is a powerful and unique tool based on the anatomic and behavioral characteristics of the human beings. Most anatomical characteristics used for security application are fingerprint, Iris, face and palm print .Apart from anatomical characteristics, behavioral characters like voice, signature, and gait moments are also used to recognize the user. Most biometric systems that are presently used in real time applications, typically uses a single biometric characteristic to authenticate a user. So authentication leads major part in the secured way of communication. Currently, passwords and smartcards are used as the authentication tool for verifying the authorized user. However, passwords are easily cracked by dictionary attacks, as well as the smart cards are stoles by anybody, and then we cannot check who the authorized user is. So the biometrics is an only remedy for the problems. This paper discusses about the new biometric identifier named as finger knuckle print. Many researchers are going on this new emerging biometric because, which is an also unique characteristic like fingerprint, Iris, etc in order to prove the genuine user. The Finger Knuckle print recognition system contains data acquisition, ROI extraction, feature extraction, coding, and matching process. The features of FKP are extracted using the Gabor filtering with the cropped region of interest. The Gabor filter features are matched for recognize the user. The average values of global and local orientation features of finger back surface or FKP was analyzed and matched with Fourier transform and Gabor filter respectively. An Image of Finger Knuckle Print Zhang, et.al proposed the score level fusion with FKP was performed with the phase congruency, local feature and local phase features novel approach to extract the Invariant Features as key points used for object recognition. Using Hough transform the local information of FKP was accessed using Scale Invariant Feature Transform (SIFT) and Speed up Robust Features (SURF) algorithm is used to get the key points using the scaling and invariant features which were matched to rove the user authentication Ajay et.al, proposed a new method of triangulation, which is used to authenticate the hand vein images of finger knuckle surface of all fingers[8].

III. PROPOSED ALGORITHM

In the proposed system, the authentication of the person is done by capturing the knuckle print by using the webcam and matching it with the pattern stored in the database. Further usage of the computer by the person is allowed only if both the pattern matches. Hand signs are captured by the webcam and are processed to perform corresponding action. We broadly classify our project into two modules. They are: Knuckle print authentication, Hand sign recognition. The overall block of the knuckle print authentication and hand sign recognition is shown in the Figure 3.1.

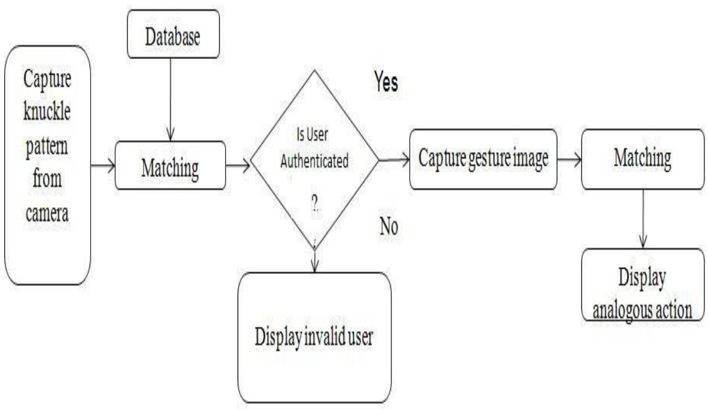


Fig 3.1 Knuckle Print Authentication and Hand sign Recognition

The knuckle pattern is captured by using the web camera. The features of captured knuckle pattern are extracted and compared with the pre-loaded image in the database. If the captured knuckle pattern does not matched with any image in the database, it will display invalid user and further access of the system will be denied. If the captured knuckle pattern is matched with any one of the image in the database, it will show that the user is authenticated and it allows to user to communicate with the system by using hand signs. In the hand sign recognition system, the hand posture is captured by using the web camera. The features of the hand sign image will be extracted and is matched with the pre-loaded signs in the database. The analogous action will be performed depending on the user input. The texture pattern in the finger-knuckle print (FKP) is highly unique and thus can serve as a distinctive biometric identifier. The use of FKP to recognize subjects is first exploited in where FKP is represented by a curvature based shape index. FKP is transformed using the Fourier transform. The band-limited phase only correlation (BLPOC) is employed to determine the similarity between two FKP images. Gabor filter based competitive code (CompCode) has been used to extract local features. Two FKP images are matched with the help of these local features from a FKP. Features extracted from FKP with the help of principal component analysis (PCA), independent component analysis (ICA) and linear discriminant analysis (LDA) are used for matching. However, these subspace analysis methods generally fail to extract the distinctive line and junction features from the FKP images. Features such as orientation and magnitude information (ImCompCode & MagCode) extracted by Gabor filter have been considered for comparing two FKP images. Global and local features and their combination are used to represent FKP images for recognition. The Fourier coefficients of the image have been taken as the global features while orientation information from the Gabor filters are considered as local features. Weighted sum rule is used to fuse the local and the global matching scores. Local features induced by the phase congruency (PC) model have been used. The orientation and phase information are used in addition with phase congruency (PC). Score level fusion is used to fuse these features to improve the KP recognition accuracy. However, to the best of authors' knowledge, there does not exist any technique to index the features of FKP images to minimize the search space. The problem of FKP based identification system is to find the top t best matches for a given query from the database of FKP images. One traditional way to find the top t best matches of the query image is to search all FKP images in the database. The process of retrieving these images from the database is found to be computationally expensive. For a large database, there is a need to design an efficient indexing technique to reduce the cost of searching because an indexing technique performs better than ustering and classification techniques. Following are the characteristics that are to be taken into consideration while indexing features of FKP images.

_ Number of features extracted from an image is not fixed.
_ Number of extracted features is generally large.
_ Number of features of two images of the same subject obtained at two different instant of time may not be the same.
_ There may be partial occlusion in the image.
_ A query image may be rotated and translated with respect to the corresponding image in the database.

It is expected that any indexing technique should be support all the above issues efficiently. Geometric hashing is an indexing technique which is found to be the most suitable for indexing the features of FKP images as it can handle efficiently the issues like: (i) it can index the variable number of features having high dimensionality (generally >500 features per image), (ii) it can index features of all images in the database in a single hash table efficiently, (iii) for any new image, extracted features can be added into the hash table without modifying the existing hash table, and (iv) it can handle rotation and partial occlusion. However, it involves high memory and computational cost as there exists redundant insertion of each feature into the hash table to handle rotation and occlusion. In this paper, the geometric hashing is boosted in such a way that it insert features exactly once which reduces both memory and computational cost significantly without compromising the recognition accuracy. It can also handle the problem of rotation and partial occlusion efficiently. In this knuckle print authentication, the knuckle pattern is captured using camera. Then the captured image undergoes following sections.

i. Image Pre-processing

a. Image Resize

The captured image is converted into a standard size image (256x256**)**. It is necessary to resize the image because all the cameras do not have the same resolution.

b. Grayscale Conversion

Grayscale images are black-and-white images. In photography, a grayscale digital image is an image in which the value of each pixel is a single sample, that is, it carries only intensity information.

c. Median Filtering

Median filter is often used to remove noise and it is a nonlinear digital filtering technique. Noise reduction is a typical pre-processing step to improve the results of later processing (for example, edge detection on an image). Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise.

d. Histogram Equalization

This method usually increases the contrast of many images, especially when the data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower contrast to gain a higher contrast. The following steps are performed to obtain Histogram equalization: The frequency of each pixel value is obtained in matrix form. The probability of each frequency is calculated.

The probability of each pixel value occurrence = frequency of pixel value/no of pixels

Cumulative histogram of pixel 1=a
Cumulative histogram of pixel 2=a+frequency of pixel 2=b
Cumulative histogram of pixel 3=b+frequency of pixel 3=c
The Cumulative distribution probability (*cdf*) of each pixel is found by using,

cdf of pixel 1=a/no. of pixels

Calculate the final value of each pixel by multiplying cdf with (no. of bins)cdf of pixel 1.

ii. Feature Extraction

The features of the pre-processed image are extracted using Scale-Invariant Feature Transform (SIFT) algorithm. SIFT is an algorithm in computer vision to detect and describe local features in images. The SIFT key points of objects are extracted from reference images and stored in database. An object is recognized in a new image by individually comparing each feature from new image to this database and finding the matching features. From full set of matches, subset of key points that agree on the object and its features are identified in new image to filter out good matches. SIFT image features provide a set of features of an object that are not affected by many of the complications experienced in other methods, such as object scaling and rotation. Scale Invariant Feature Transform (SIFT) Four major steps in SIFT are scale space extrema, key-point localization, orientation assignment and key-point descriptor. The main idea behind the detection of scale space extrema is to identify stable features from texture that remain invariant to change in scale and viewpoint. This technique has been implemented efficiently by using a difference of Gaussian (DOG) function to identify potential key-points. DOG images are used to detect key-points with the help of local maxima and minima across different scales. Each pixel in DOG image is compared with eight neighbors in the same scale and nine neighbors in the neighboring scales. The pixel is selected as a candidate key-point if it is either local maxima or a local minima. Orientation is assigned to each key-point to achieve invariance to image rotation. To determine key-point orientation, a gradient orientation histogram is computed in the neighborhood of key-point. The feature descriptor is computed as a set of orientation histograms on pixel neighborhoods. Each histogram contains eight bins while each descriptor contains an array of four histograms around the key-point. This generates SIFT feature descriptor ~D of length 128.

a.Scale-space peak selection

Difference-of-Gaussian (DoG) function is used to identify potential interest points that are invariant to scale and orientation. DoG is mainly used to detect edges in the image.

$$DoG = G_{\sigma 1} - G_{\sigma 2} = \frac{1}{\sqrt{2\Pi}}\left(\frac{1}{\sigma 2} e^{-(x^2+y^2)/2\sigma_1^2} - \frac{1}{\sigma 2} e^{-(x^2+y^2)/2\sigma_2^2}\right)$$

(3.1)

Each sample point is compared with the eight closest neighbours in image location and nine neighbours in the scale above and below. This is done to detect the locations of all local maxima and minima i.e. peaks of,

$$DoG * I(x,y,\sigma) \qquad \textbf{(3.2)}$$

DOG images are used to detect key-points with the help of local maxima and minima across different scales**.**

b. Key-point localization

The points that have low contrast or that are poorly localized along the edges are eliminated because they are sensitive to noise. Key-points are selected based on measures of their stability.

c. Orientation Assignment

Assigning a consistent orientation to each key-point based on local image properties, the key-point descriptor can be represented relative to this orientation and therefore achieve invariance to image rotation. For each image sample, *Lx,y*, the gradient magnitude, *m*, and orientation, *θ*, is pre-computed using pixel differences:

$$\mathbf{m = q(-Lx+1,y - Lx-1,y)^2 + (Lx,y+1 - Lx,y-1)^2}$$
(3.3)

$$\mathbf{\theta = tan\ 1((Lx,y+1 - Lx,y-1)/(Lx+1,y - Lx-1,y))}$$
(3.4)

d. The local image descriptor

A key-point descriptor is created by first computing the gradient magnitude and orientation at each image sample point, these points are then weighted by a Gaussian window. These samples are then accumulated into orientation histograms. This allows for wider local position shifts. While allowing for an object to be recognized in a larger image, SIFT image features also allow for objects in multiple images of the same location, taken from different positions within the environment, to be recognized. SIFT features are also very resilient to the effects of "noise" in the image.

iii.Matching

The features of captured knuckle pattern are compared with the pre-loaded image in the database. If the captured knuckle pattern is not matched with any image in the database, it will be displayed as invalid user. If the captured knuckle pattern is matched, it shows that the user is authenticated and it moves to second module of this system i.e., Hand sign recognition system.

a. Gesture Image Identification

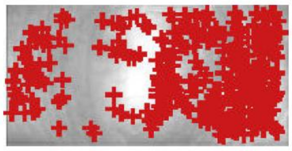
Gesture image identification is tested with knuckle identification and the algorithm is applied to get a finite robustness in extracting the image quality and verification and the algorithm used here is SURF and one of the finite algorithm for the improvement of image quality and better then SIFT algorithm.

b. Surf Algorithm

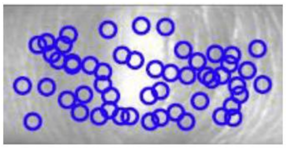
SURF (Speeded Up Robust Features) like SIFT, the SURF approach describes a key point detector and descriptor. It makes use of Hessian matrix for the detection of key-point. For a pixel P(x,y) of an image I, the Hessian matrix H(P,σ) at scale r can be defined as follows

$$H(P,\sigma)=\begin{bmatrix} L_{xx}(P,\sigma)L_{xy}(P,\sigma) \\ L_{yx}(P,\sigma)L_{yy}(P,\sigma) \end{bmatrix} \qquad \textbf{(3.5)}$$

L (*P*,σ)*L* (*P*,σ) *xx xy L* (*P*,σ)*L* (*P*,σ) *yx yy* are the convolution of the Gaussian second order derivatives with the image I at pixel P. Keypoints are found by using a so called Fast-Hessian Detector that bases on an approximation of the Hessian matrix for a given image point. The responses to Haar wavelets are used for orientation assignment, before the keypoint descriptor is formed from the wavelet responses in a certain surrounding of the keypoint. The descriptor vector has a length of 64 floating point numbers but can be extended to a length of 128. As this did not significantly improve the results in our experiments but rather increased the computational costs, all results refer to the standard descriptor length of 64.



3.2 (a) SIFT Features



3.2 (b) SURF Features

To speed up the computation, second order Gaussian derivatives in Hessian matrix are approximated using box filters. To detect key-points at different scales, scale space representation of the image is obtained by convolving it with the box filters. The scale space is analyzed by up-scaling the filter size. A non-maximum suppression in a 3x3x3 neighborhood is implemented to localize the key-points over scale. A rectangular window around each detected key-point is used to compute its descriptor which is termed as key-point descriptor. The window is splitted into 4x4 sub-regions. For each sub-region, Haar wavelet responses are extracted.

IV. RESULTS AND DISCUSSIONS

a. Introduction

The CRR values of the knuckle image of 256x256 were evaluated using the MATLAB software by implementing image resize technique. From the values, we proved that the proposed SURF algorithm has a better quality in identifying the knuckle image for a better security authentication.

b. Pre-Processing Result

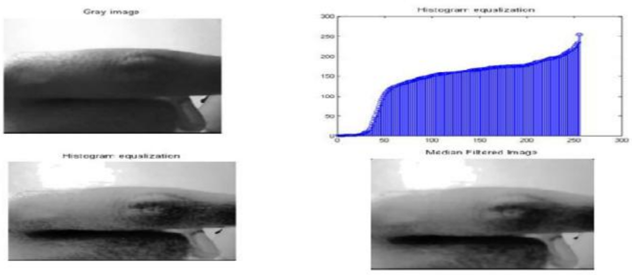


Fig 4.1 Pre-processing Result using MATLAB

Fig 4.1 shows the pre-processing which including gray image, histogram equalization and median filtering method for a clear visible output, given input is converted into gray scale image & histogram equalization is calculated followed by Median filtering technique.

c. Database Creation Result

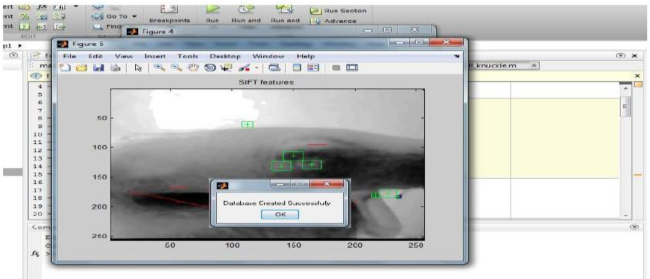


Fig 4.2 Database creation Result using MATLAB

Fig 4.2 shows the database creation the given image is stored inside the database and it is later compared with the given input image from the web camera which is attached with the system

Fig 4.3 shows the detected output after the input image compared with the database, the given input image is stored with the user name and when the input image is compared it will show the user name is detected.

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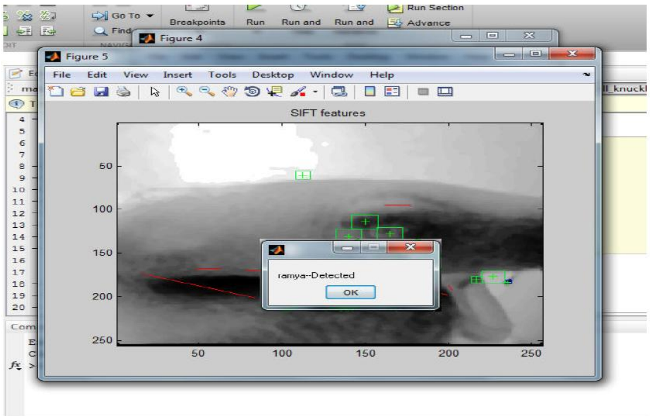

Fig 4.3 Valid user result using MATLAB

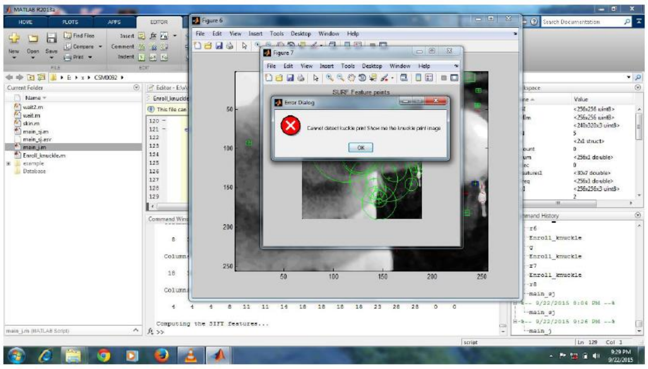

Fig 4.4 Invalid user result using MATLAB

Fig 4.4 Shows when there is any change in the direction of knuckle the input image will not be matched with the data base and we will get an error report “cannot detect the knuckle print show me the knuckle print image”.

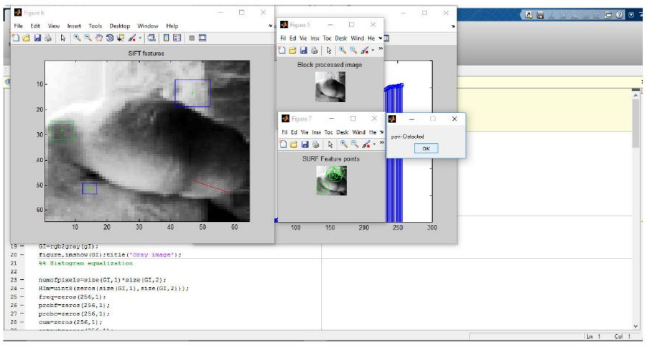

Fig 4.5 SURF and SIFT Features

Fig 4.5 shows SURF and SIFT algorithm , when the input image is preprocessed and when the detection is verified ,proposed SURF and SIFT algorithm is applied and compared to prove that SURF algorithm is the fast and efficient algorithm.

V. Conclusion

A novel SIFT algorithm is compared with the new algorithm that requires many stage of preprocessing. We obtained that all considered approximate transforms perform very close to the ideal SURF. However, the proposed transform possess a computational complexity and is faster than all other approximations under consideration. In terms of security identification, knuckle authentication is a challenging process in terms of Image quality improvement. Hence the new proposed transform is the best algorithm for the knuckle identification in terms of image selection and also in terms of Image Quality metrics such as CRR and Hit rate. The CRR values obtained are Optimum threshold values for SIFT and SURF feature extractors to achieve maximum CRR of 96.36% and 99.69% respectively are found to be 0.2 and 0.09 with the sampling step of 4. Future work includes the implementation of Hand sign technique in VLSI hardware kit and also to approximate versions for various hand sign to provide a better authentication prototype.

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