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Identification of Person by fusion and using Scale Invariant Feature Transform

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Abstract

Traditionally, passwords and ID cards have been used to restrict access to secure systems. However, security can be easily breached in these systems when a password is divulged to an unauthorized user or a card is stolen by an impostor. By using biometrics it is possible to establish an identity based on "who you are,"Current biometric systems make use of fingerprints, hand geometry, iris, retina, face, facial thermograms, signature, gait, palm print and voiceprint to establish a person's identity.

We present multimodal face and fingerprint biometric verification system to improve the performance. We presented fusion of face and fingerprint to provide better accuracy. Simulation results shows that proposed multimodal recognition system is very efficient to reduce the false rejection rate. Here we can take two images, decomposition of images is carried out by using DWT i.e. Discrete Wavelet Transform, after decomposition , fusion of decomposition is carried out which produces a fused image. Then SIFT (Scale Invariant Feature Transform), features are extracted from the fused image that are stored in database. After extracting SIFT features matching are performed.

1. Introduction

In recent years, biometric-based authentication systems have been widely used in many applications which require reliable verification/identification scheme.

Several biometric authentication traits are offering 'up-to the-mark' and negotiable performance in respect of recognizing and identifying users. However, none of the biometrics is giving cent percent accuracy. Multibiometric systems [1] remove some of the drawbacks of the uni-modal biometric systems by acquiring multiple sources of information together in an augmented group, which has richer detail. Utilization of these biometric systems depends on more than one physiological or behavioural characteristic for enrollment and verification/ identification [2]. Multi-resolution approach in wavelet is well suited to manage the different image resolutions. Many research works have studied on multi-resolution representation of signals and have established that multi-resolution information for a number of image processing applications including the image fusion. Wavelet coefficients coming from different images can be appropriately combined to obtain new coefficients, so that the information in source images is collected appropriately. The discrete wavelet transform (DWT) allows the image decomposition in different kinds of coefficients preserving the image information. A wavelet-based image fusion method is therefore required to identify the most important information in the input images and to transfer it into the fused image.

A multisensor multimodal biometric system fuses information at low level or sensor level of processing is expected to produce more accurate results than the systems that integrate information at a later stages, namely, feature level, matching score level, because of the availability of more richer and relevant information.

2. Brief literature review

The research on multimodal started, and different multimodal biometrics has been developed with combination of various traits, that is, face and finger print, face and iris, iris and finger print etc. The most commonly used biometrics is face, that is, either as a single trait or combined with other trait as multimodal biometrics. Face combined with other biometrics at different level of fusion [9], that is, feature, score and decision (Ross and Jain, 2003). Muhammad Imran Razzak, Rubiyah Yusof and Marzuki Khalid presented multimodal face and finger veins biometric authentication [8]. Andreas Uhl and Peter Wild presented multimodal personal verification system using hand images by combining hand geometry and palm image. Directional convolution masks are used to extract the palm futures from normalized palm image, whereas, finger length and width is extracted for hand geometry palm and finally, different level of fusion is performed [6].

David G. Lowe presented a method for extracting distinctive invariant features from images that can be used to perform reliable matching between different views of an object or scene [3]. Fingerprint verification was done by applying Scale invariant feature transform which shows better results than minutiae points and ridge patterns [5]. For face authentication to determine the real potential and applicability of the Scale invariant feature transform method, different matching schemes are proposed and tested using the BANCA database and protocol, showing better result [14].

2. Wavelet Decomposition for Images

This process basically takes two images of face and finger after taking images wavelet decomposition is performed on both images followed by a fusion of decomposition of two images which produces fused image of low resolution. It has the capability to provide good localization for both frequencies and space domains. The wavelet based image fusion would be applied to two dimensional multispectral face and fingerprint at each level.

Figure1.Face.jpg
Figure2.Fingerprint.jpg

Figure 3.Fused Image

3. Scale invariant feature transform

The scale invariant feature transform, called SIFT [3] descriptor, has been proposed by and proved to be invariant to image rotation, scaling, translation, partly illumination changes. Following are the major stages of computation used to generate the set of image features

3.1. Scale space extrema detection

The first stage of keypoint detection is to identify locations and scales that can be repeatably assigned under differing views of the same object. Detecting locations that are invariant to scale change of the image can be accomplished by searching for stable features across all possible scales, using a continuous function of scale known as scale space. It is implemented efficiently by using a difference-of-Gaussian function to identify potential interest points that are invariant to scale and orientation. To efficiently detect stable keypoint locations in scale space, we have proposed using scale-space extrema in the difference-of-Gaussian function convolved with the image, $D(x, y, \sigma)$, which can be computed from the difference of two nearby scales separated by a constant multiplicative factor k.

3.2. Keypoint localization

In order to detect the local maxima and minima of $D(x, y, \sigma)$, each sample point is compared to its eight neighbors in the current image and nine neighbors in the scale above and below. It is selected only if it is larger than all of these neighbors or smaller than all of them. The cost of this check is reasonably low due to the fact that most sample points will be eliminated following the first few checks. Once a keypoint candidate has been found by comparing a pixel to its neighbors, the next step is to perform a detailed fit to the nearby data for location, scale, and ratio of principal curvatures. This information allows points to be rejected that have low contrast or are poorly localized along an edge. At each candidate location, a detailed model is fit to determine location and scale. Keypoints are selected based on measures of their stability.

3.3. Orientation assignment

By assigning a consistent orientation to each keypoint based on local image properties, the keypoint descriptor can be represented relative to this orientation and therefore achieve invariance to image rotation. The scale of the keypoint is used to select the Gaussian smoothed image, L, with the closest scale, so that all computations are performed in a scale-invariant manner. For each image sample, $L(x, y)$, at this scale, the gradient magnitude, $m(x, y)$, and orientation, $\theta(x, y)$, is precomputed using pixel differences:

$$m(x,y) = \sqrt{(L(x+1,y) - L(x-1,y))^2 + (L(x,y+1) - L(x,y-1))^2}$$

$$\theta(x,y) = \tan^{-1}((L(x,y+1) - L(x,y-1))/(L(x+1,y) - L(x-1,y)))$$

An orientation histogram is formed from the gradient orientations of sample points within a region around the keypoint. Peaks in the orientation histogram correspond to dominant directions of local gradients. The highest peak in the histogram is detected, and

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then any other local peak that is within 80% of the highest peak is used to also create a keypoint with that orientation. one or more orientations are assigned to each keypoint location based on local image gradient directions. All future operations are performed on image data that has been transformed relative to the assigned orientation, scale, and location for each feature, thereby providing invariance to these transformations.

3.4. Keypoint descriptor:

The local image gradients are measured at the selected scale in the region around each keypoint. These are transformed into a representation that allows for significant levels of local shape distortion and change in illumination. This approach has been named the Scale Invariant Feature Transform (SIFT), as it transforms image data into scale invariant coordinates relative to local features. An important aspect of this approach is that it generates large numbers of features that densely cover the image over the full range of scales and locations.

In this paper only the keypoint descriptor information is taken from image but before this fused image is normalized by histogram equalization, after invariant SIFT features are extracted from the fused image. For image matching and recognition, SIFT features are first extracted from a set of reference images and stored in a database.

A new image is matched by individually comparing each feature from the new image to this previous database and finding candidate matching features based on their feature vectors. The keypoint descriptors are highly distinctive, which allows a single feature to find its correct match with good probability in a large database of features. However, in a cluttered image, many features from the background will not have any correct match in the database, giving rise to many false matches in addition to the correct ones. The correct matches can be filtered from the full set of matches by identifying subsets of Keypoints that agree on the object and its location, scale, and orientation in the new image. SIFT features extracted on the fused image is shown below.

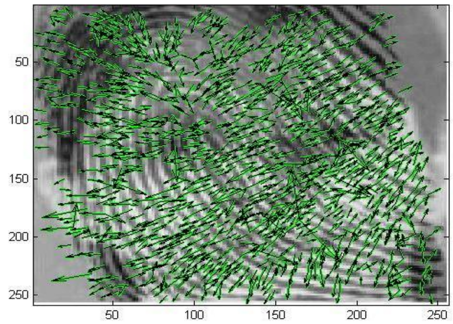


Figure 4. SIFT Features extracted from the

Fused Image

4. Steps of matching

1. Match (image1, image2). This function reads two images, finds their SIFT [4] [5] [6] features, and displays lines connecting the matched Keypoints. A match is accepted only if its distance is less than dist Ratio times the distance to the second closest match. It returns the number of matches displayed.

2. Find SIFT (Scale Invariant Fourier Transform) Keypoints for each image. For finding the SIFT Keypoints specify what are its locations and descriptors.

3. It is easier to compute Euclidean distances between two images

4. Assume some distance ratio for example suppose distance ratio=.4 it means that it only keep matches in which the ratio is less than distance Ratio.

5. Now for each descriptor in the first image, select its match to second image.

6. Then create a new image showing the two images side by side.

7. Lastly a figure is shown with lines joining the accepted matches.

5. Simulation and result

To test the performance of our system apply above steps in our previous image from which SIFT features are extracted. Now suppose that these extracted feature points are stored in the database, if a person comes he repeat same steps which are described above. After applying these steps to our image, matching image looks like this.

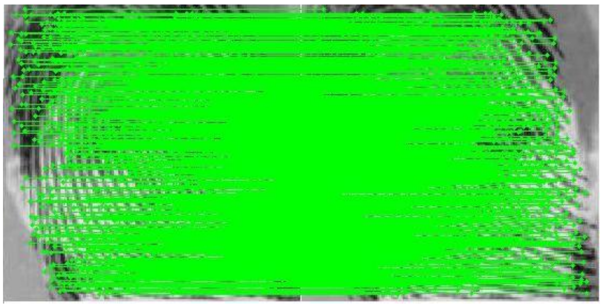
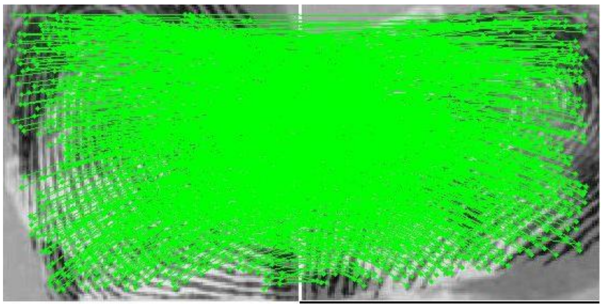


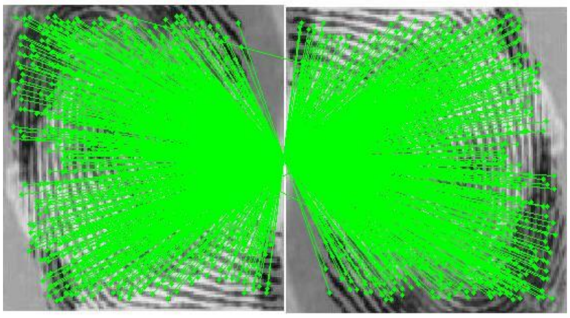
Figure 5. Matching

These are the all matching points of a person indicating that a person is authentic. So same procedure repeats for every person, for every person its Keypoints are extracted after extracting Keypoints it is stored in the database and for matching, same procedure follows.

If image is rotated by 90 degree then also it shows above 95% of matching as shown below.



If image is rotated by 180 degree then also it shows above 95% of matching as shown below.



If image is rotated by 270 degree then also it shows above 95% of matching as shown below.

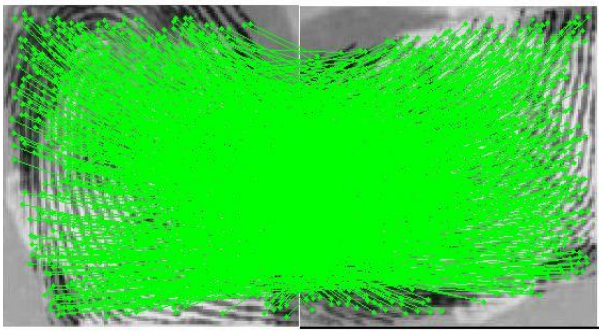


Table 1:

For various image transformations applied to a sample of 20 images, this table gives the percent of keys that are found at matching locations and scales (Match %)

Image transformation	**Match %**
A. Rotate by 90 degrees	96
B. Rotate by 180 degrees	98
C. Rotate by 270 degrees	98.61

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FUTURE WORK

We will takedatabase of 50 persons. The face and fingerprint database are collected for individuals by taking the image of 256x256 and resolution is set to 72 dpi. For the sake of the experiment cropped face has been taken which covers face only and for the fingerprint cropped fingerprint has been taken which covers ridges and lines. Decomposition is done by DWT. After decomposition image fusion is done by weighted averaging method ,after obtaining the fused images of face and fingerprint, fused image is preprocessed by histogram equalization for normalization. For facial and fingerprint image matching, SIFT feature comparison will be done based on Euclidean distance of feature vectors for the recognition of human identity.

How to use *window based verification (WBV) scheme* For image fusion into our system is the subject of our future research.

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