Biometrics Identification Based on Visual Hand Movements Using Wavelet Transform

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Abstract. This work presents a novel technique of biometric identification based on the temporal history templates (THTs) of visual hand movements. The technique uses view-based approach for representation of hand movements, and uses a cumulative image-difference technique where the time between the sequences of images is implicitly captured in the representation of action. The low level representation of the action collapses the temporal structure of the motion from the video sequences of the hand movements while removing any static content from the video sequences to generate temporal history templates (THTs) of the hand movement. THTs of different individuals present distinctive 2-D motion patterns, where each pixel describes the function of temporal history of motion in that sequence. This THT are further sub-divided into four sub- images an average and three detailed images using multi resolution wavelet transforms. The approximate wavelet sub-image is considered as the feature for recognition. The recognition criterion is established using KNN nearest neighbor technique using Mahalanobis distance. The accuracy of accepting an enrolled subject (AAES %) and accuracy of rejecting an imposter (ARI %) are the indicators of identification performance of the technique. The experimental results from 5-different individual indicate that the THT based technique achieves high identification rate when subject specific movements are assigned to the subjects during enrolment.

1 Introduction

Biometrics-based authentication using computer vision technologies is emerging as a reliable method that can overcome some of the limitations of the traditional automatic personal identification technologies. Any human physiological or behavioural trait can serve as a biometric characteristic as long as it is universal, distinctive, sufficiently invariant with respect to matching criterion, and these characteristic should be physically measurable [1]. All traditional biometrics measures have certain limitations associated to them e.g. DNA can't be used in certain applications due to issues of contamination, sensitivity, cumberness and privacy; ear shape as a biometrics measure has a problem of non unique features; facial biometrics have got problems with aging, face disguise and variable imaging conditions; hand and finger geometry has limited applications, although fingerprints are very unique but they also have the problem of fake fingers, storage and imaging conditions problems; iris biometrics is difficult non intrusive and requires co-operation from the individual during enrolment

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and identification; and speech biometrics has the limitation of mechanical due to microphone and dependence on subjects' health etc[1]. Fingerprints, facial features, DNA, and retinal features are known to be the most common biometrics based on the physiological features. There are a number of publications describing methods using these features as the biometric characteristics. Other known biometrics such as key-stroke and gait analysis based on the behaviour of the individual [1]. However, not all-behavioural biometrics has been examined extensively The Hand is a dexterous part of the human body and is unique to the gesturer, but the use of hand gesture as a biometric has been given little treatment so far [2]. The hand gesture has been extensively used for developing Human Computer Interaction (HCI) applications and many other applications. This work is about a new biometrics method based on the temporal history templates (THTs) generated from the hand movements (gestures). The Spatio-temporal templates of hand movements are proposed as the behavioural biometric because they are unique to the hand, which performs the gesture, and are very distinctive to the gesturer [2]. Spatio Temporal templates of Hand gesture as a biometrics has the advantage of non-intrusiveness, are distinctive, unique and can't be forged easily.

2 Related Work

There are two main approaches in the literature about the automatic gait recognition [3]. The first method is based on the model based gait recognition, where a mathematical model describes the subject's movement and the second method applies the statistical description to the set of images. Statistical methods detect the temporal changes in gait by using optical flow techniques [4] [5].A statistical approach to the automatic gait recognition work, which is very similar to this technique has claimed very promising results[6]. Encouraging results on a small database of four subjects have also been reported for a technique that describes motion using velocity moments[7]. In the related work of identifying people by the use of behavioural biometrics gait distinguished people from their walking by extraction of video sequences from their walking patterns [8][9]. Little and Boyd used frequency and phase features from optical flow information to recognize people from their gait [6].

This work is based on the motion based template research. The motivation of this work comes from the real-time interactive applications developed by Davis and Bobick [10] [11] [12] [13] [14] [15] where they presented a real-time computer vision approach for representing and recognizing common human movements from low-resolution image sequences for its successful development of an application named as "Virtual Aerobic Instructor" [14] . This work is similar to the work done by Bobick and Davis to develop a Virtual Aerobic Instructor for aerobics exercises and Kids Room an interactive room where children can play with the monster in an interactive environment[14].

3 Identification Technique

The philosophy behind the approach for person identification is based on the spatio-temporal templates of hand movements for enrolment and identification.

3.1 Temporal History Template

This research is to test the efficacy of THT based method for identification on the basis of the Temporal History Templates (THTs) of hand movements. The representation of temporal history template (THT) is based on a view-based approach of hand movement representation, where movement is defined as the motion of the hand over time. The technique is based on collapsing the hand motion over time to generate a static image from the image sequence. This resulting static image can represent the whole sequence of hand movement. This single static image also gives all the properties (shape, direction, where & how) the motion is taking place in the image sequence. This technique is very suitable for short duration, non-repetitive, medium velocity movements making very much suitable for real-time biometric application [16].

3.1.1 Motion Image Estimation

For this work a simple temporal difference of frame technique (DOF) has been adopted [13]. The approach of temporal differencing makes use of pixel-wise difference between two or three consecutive frames in an image sequence to extract moving regions [13]. The DOF technique subtracts the pixel intensities from each subsequent frame in the image sequence, thereby removing static elements in the images. Based on research reported in literature, it can be stated that actions and messages can be recognized by description of the appearance of motion [16] [17] [18] [19] [20] [21] without reference to underlying static images, or a full geometric reconstruction of the moving hand [19]. It can also be argued that the static images produced using Temporal History Template based on the Difference of Frames (DOF) can represent features of temporally localized motion for identification [15] [16] [20] [21] [22].

This process can be represented mathematically as follows

Let $I(x, y, n)$ be an image sequence

&

let $D(x, y, n) = |I(x, y,n) - I(x, y,n-1)|$

Where $I(x, y, n)$ is the intensity of each pixel at location x, y in the n_{th} frame and $D(x, y, n)$, is the difference of consecutive frames representing regions of motion.

B (x, y, n) is the binarisation of image difference over a threshold of Γ

$$B(x, y, n) = \begin{cases} 1 & \text{if } D(x, y, n) > \Gamma \\ 0 & \text{otherwise} \end{cases}$$

To represent where and when motion occurred in the image, we form a Temporal-History Template (THT). The temporal history of the movement in THT is inserted into the data by multiplication of the intensity of each frame with a linear ramp representing time. H_N, pixel intensity is a function of the temporal history of Motion at that point. The result is a scalar-valued image where more recently moving pixels are brighter.

Then THT $(H_N(x, y))$ is:

$$==\text{Max}\left\{ \bigcup_{n=1}^{N-1} B(x,y,n)*n \right.$$

where N represents the duration of the time window used to capture the motion. In THT more recent movements of hand actions are brighter than the older positions represented with the darker values[15] [16] [20] [21] [22]. The delimiters for the start and stop of the movement are added automatically in the sequence. Feature Extraction and a Feature Recognition Platform using Multiresolution Wavelet Transform

3.1.2 Wavelet

The applications of wavelets extend in several areas such as signal processing, temporal series analysis, meteorology, image filtering and compression, and pattern recognition. This technique is based on the use of wavelets as basis functions for representing other functions. These functions have a finite support in time and frequency domain. Multi-resolution analysis is achieved by using the mother wavelet, and a family of wavelets generated by translations and dilations of it. A wide function can examine a large region of the signal and resolve the low frequency details accurately, while, a short basis function can examine a small region of the signal to resolve the time details accurately [23] [24].If $\Psi(x)$ represents the mother wavelet, the scaling is accomplished by multiplying 'x' by some scaling factor, if scaling factor is power of 2,yielding $\Psi(2^m x)$, where 'm' is integer, we get the cascaded 'octave band pass filter' structure. The wavelet function Ψ is translated along the time axis in order to cover an entire signal. This translation is accomplished by considering all the integral shifts of Ψ,

$$\Psi(2^m x-n) n \in Z$$

Thus putting all together gives a wavelet decomposition of signal,

$$\Psi_{mn}(x)=2^{m/2}\Psi(2^m x-n)$$

c_{mn} are the transform coefficients. These coefficients are computed by the wavelet transform, which is the inner product of the signal $f(x)$ with the basis functions $\Psi_{mn}(x)$. For classification there is no need for computing inverse transform, since there is no need to reconstruct the original signal. In computer vision, it is difficult to analyse the information content of the image directly from the grey-level intensity of the image pixels [24] . The approximate coefficients of the Wavelet transforms of the images can provide denoising and scale and rotation invariance [25].

This is because the low frequency components spread in the time domain can be treated as global property while the high frequency concentrated in time domain can be discarded. The multi-resolution capability of wavelets also provides the capability to examine the signal at various scales and provides for reduced data. This paper reports the use of wavelet coefficients of the THT for extracting the required features for classifying the THT.

3.1.3 Discrete Wavelet Transform

The classical DWT suffers a drawback, that it is unable to restore the translation invariance properties of the image. The idea is to restore translational invariance properties of the image by defining a slightly different, DWT, called the Stationary Wavelet Transform, SWT. In classical DWT the computational step is that each decomposition of the original image generates four sub images. In the following level, the approximated image, which is the low pass sub image, is, decomposed. Iterative decomposition of the approximated images forms a pyramidal wavelet transform. In the pyramidal wavelet transform, the filtered versions of each sub image are down sampled by a factor of two: this is also called as dyadic transform. The SWT algorithm is very simple and is close to the DWT. More precisely, for level 1, the DWT for a given image can be obtained by convolving the signal with the pair of low pass filter (H) and a high pass filter (G) and then down sampling by 2 along both rows and columns. SWT is similar to DWT and can be obtained by convolving the image with pair of low pass filter (H) and a high pass filter (G) but without down sampling along rows and columns [26]. In these experiments SWT (Figure 1) has been used resulting in the decomposed image being of the same size after decomposition ensuring the translational invariance.

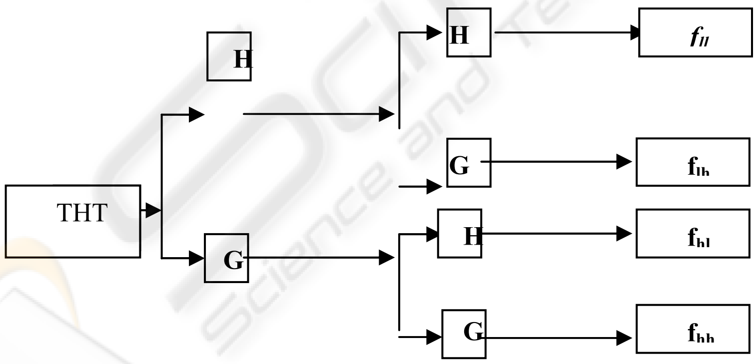


Figure 1: Two-Dimensional Stationary Wavelet Transform of THT

- f_{ll} sub-image: Both horizontal and vertical directions have low frequencies.
- f_{lh} sub-image: The horizontal direction has low frequencies and the vertical one has high frequencies.
- f_{hl} sub-image: The horizontal direction has high frequencies and the vertical one has low frequencies.
- f_{hh} sub-image: Both horizontal and vertical directions have high frequencies.

The wavelet used in these experiments is ‘db1’ and is implemented following the multiresolution scheme [24]. As the THT contains gray level data integrated over time the analysis on the multiresolution level will give good classification results. The two-dimensional (2-D) SWT of a gray scale image correspond to multi-resolution approximation expressions [23]. This work reports the use of 2-D SWT to propose a pattern recognition solution for hand identification. Wavelet transforms using ‘db1’ are the simplest to implement, computationally the least demanding, provide high spatial localization and are orthonormal [23]. For these reasons, this paper reports the choice of ‘db1’wavelet transform to extract local intensity distribution information from THT. Two-dimensional SWT is applied which results in four sub images of THT, namely as average image (f_{ll}), and three detail images (f_{lh}, f_{hl}, f_{hh}). The average image (f_{ll}) is concatenated to make a single column vector representing a persons biometric model the remaining three detail images (f_{lh}, f_{hl}, f_{hh}) are discarded.

3.2 Identification Technique

3.2.1 Mahalanobis Distance

The Mahalanobis distance is a very useful way of determining the "similarity" of a set of values from an "unknown” sample to a set of values measured from a collection of "known" samples. It is computed by the equation below:

$$r^2 \equiv (\mathbf{f} - \mathbf{k}_x)' \ \mathbf{C}^{-1} (\mathbf{f} - \mathbf{k}_x)$$

where r is the Mahalanobis distance from the feature vector **f** to the mean vector $\mathbf{k}_x$, and **C** is the covariance matrix for **f**.

Let $\mathbf{k}_1$, $\mathbf{k}_2$... $\mathbf{k}_n$ be the means (templates) for the n-classes, and C_1, C_2, ..., C_n are the corresponding covariance matrices. Feature vector **f** is classified by measuring the Mahalanobis distance from **f** to each of the means, and assigning **f** to the class for which the Mahalanobis distance is minimum.

3.3 Identification and Recognition Performance

The main goal of this research is to test the identification based on the hand movements of individuals, so accuracy is considered as the criterion for performance analysis. Identification requires the subject being identified to lay claim to that identity, so that the method may decide on either accepting the enrolled subject or rejecting the subject. As with any security system, given that the subject is, or is not, a true instance of the enrolled subject, there are four possible outcomes of the errors [1] .The accuracy of any biometric method is generally judged by four error rates.

- Acceptance of Authentic Enrolled Subject (AA) or Genuine Accept Rate (GAR)
- Acceptance of Imposter Subject (IA) or False Accept Rate (FAR)
- Rejection of Authentic Subject (RA) or False Reject Rate (FRR)
- Rejection of Imposter Subject (RI) or Genuine Imposter Rejection (GRR)

The biometric system accuracy requirements depend greatly on the application. In forensic applications, such as criminal identification, FRR rate (and not FAR) is the critical design issue, because we do not want to miss a criminal even at the risk of manually examining a large number of potentially incorrect matches that the biometric system identifies. In some cases the FAR might be one of the most important factors in a highly secure access-control application, where the primary objective is prevent impostors (e.g., at airports). Many civilian applications require the performance requirements to lie between these two limits of both FAR and FRR. In high-risk applications such as bank ATM card verification, for example, a false match would mean the loss of several hundred dollars, while a high FAR might lead to the loss of a valued customer. As our main goal is to test the THT based method for its identification accuracy for authentication. The first and the fourth identification rates are the main goals to test the efficacy of the method. So AAES (%) and ARI (%) are computed.

AAES (%)

= 100 X Total no of times correctly identifying an enrolled subject/ Total no of enrolled subject attempts

ARI (%)=100 X Total no of correctly rejecting an imposter/ Total no of imposter attempts.

4 Method

The method of person identification is logically divided into two separate modules: an enrolment (or training) module and a recognition (or testing) module. In first step the experimentation for enrolment and recognition is carried out and the video sequences of hand movements from the different individuals are captured and stored. From the video sequences of different individuals THTs are computed and stored. Both the enrolment and the recognition module make use of a feature extraction sub-module, which converts the THTs into set of features (f_{II} images of THT), which are very distinctive to the hand, which performs the movement. The enrolment module is responsible for enrolling new individuals in the system database. During the enrolment phase, the individual supplies a number of samples of his/her hand movements. A model of the individual is built based on the features extracted from the instances of the hand movements. During the recognition phase, the individual supplies test sample of his/her hand movement, and a measure of similarity is computed between the features of the test hand movement with the available model to establish the identity of the individual, using KNN nearest neighbor approach using Mahalanobis Distance. The efficacy of the technique is determined by computing the Accuracy of Accepting an Enrolled Subject AAES (%) and Accuracy of Rejecting the Imposter (ARI%).

4.1 Experimental Settings

For testing the efficacy of the method and to test the performance of identification AAES (%) and ARI (%) has to be computed. To compute the AAES (%) and ARI (%) experiments have to be conducted. The experiments were conducted to check whether the THT based method is subject dependent or gesture dependent method.

4.1.1 Experiments for Subject Dependency

To check the method with respect to the subject, each subject is assigned "moving all fingers clockwise" common hand movement (common to all subjects). Each subject repeated the movement for 50 times. There were total (5X 50=250 video sequences of common movements) from 5 different individuals. The THTs of each video sequence was computed and features computed using (f_{il}) *images of THT*. During the training of the K-NN classifier the first 20 samples of the subject's reference samples and (4X30=120) of imposter samples from the 4 different subjects were used to set the person's biometric model by setting the mahalanobis thresholds, while the last 30 samples of (f_{il}) *images of THT* per subject were used for testing to compute AAES (%). Testing the other 30 samples of other 4 subjects was used as the imposter samples to compute the ARI (%). The subject who's (f_{il}) *images* of the THT representation are within this threshold is correctly identified as the genuine subject otherwise the impostor. For each subject the classifier is trained on recognising that subject's 20 reference samples, whilst at the same time recognising that the other 4 subjects (4X30=120) are not from the same subject. To facilitate this the desired output of the mahalanobis classifier for the target subject was set to '1',whilst the desired output for the other 4 impostors is set to '0'.This process is repeated for each subject acting as a target and the other 4 subjects as the impostors. For checking the efficacy of the approach Accuracy of Accepting an Enrolled Subject (AAES %) and ARI (Accuracy of Rejecting an Imposter %) is calculated and tabulated.

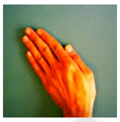
First Frame	Intermediate Frame	End Frame	THT
			
All Subjects With Common Hand Movement "All Finger Moving Clockwise"			

Figure 2: Hand Movement Assigned to all Subjects "All Finger Moving Clockwise"

4.1.2 Experiments for Gesture Dependency

To test the method with respect to the subject, each subject is assigned different subject specific movement as described in Figure 2. Each subject repeated the movement for 50 times. There were total (5X 50=250 video sequences of subject specific movements) from 5 different individuals. The THTs of each video sequence was computed and features computed using (f_{il}) *images of THT*. During the enrolment process each subject is assigned with a unique identifier. The identifier is assigned according to the subject specific movement e.g., the subject assigned the movement left has the unique identifier of "LEFT". The subject who's (f_{il}) *images* of the THT representation are within this threshold is correctly identified as the genuine subject otherwise impostor. The testing is repeated as explained in 4.1.1. For checking the efficacy of the approach Accuracy of Accepting an Enrolled Subject AAES (%) and Accuracy of Rejecting an Imposter ARI (%) is calculated and tabulated.

5 Results and discussion

Table 1-4 describes the results of achieved AAES% and ARI % by the use of subject specific hand movements and common hand movements, over a 5-subject population. The test results indicate that the THT based person identification is movement dependent. The row indicates the average accuracies corresponding to different subjects. The test results indicate that the THT based method is dependent to the subject specific movement. The good identification results are attributed to the ***(f_{IJ})*** *images of THT* as features and its better discriminating ability for identification. The use of ***(f_{IJ})*** *images of THT* has the advantage of computationally less expensive. Test result indicates that the THT based method is gesture dependent method.

Table 1

AAES (%) WITH SUBJECT SPECIFIC MOVEMENTS						
SUBJECT IDENTIFIER	MTTF	RIGHT	FIST	HOLD	AFPR	AVERAGE
MTTF	93	0	0	0	0	93 %
RIGHT	0	90	0	0	0	90 %
FIST	0	0	94	0	0	94%
HOLD	0	0	0	95	0	95 %
AFPR	0	0	0	0	96	96 %

Table 2

ARI (%) WITH SUBJECT SPECIFIC MOVEMENTS						
SUBJECT IDENTIFIER	MTTF	RIGHT	FIST	HOLD	AFPR	AVERAGE
MTTF		89.00	90.00	95.00	96.00	92.50 %
RIGHT	89.00		92.00	93.00	92.00	92.33 %
FIST	90.00	86.00		85.00	90.50	87.17 %
HOLD	96.00	87.00	86.00		94.00	89.00 %
AFPR	90.00	95.00	96.00	92.00		94.33 %

Table 3

AAES (%) WITH COMMON MOVEMENTS						
SUBJECT IDENTIFIER	MTTF	RIGHT	FIST	HOLD	AFPR	AVERAGE
MTTF	62	0	0	0	0	62 %
RIGHT	0	66	0	0	0	66 %
FIST	0	0	59	0	0	59 %
HOLD	0	0	0	58	0	58 %
AFPR	0	0	0	0	69	69 %

Table 4

ARI (%) WITH COMMON MOVEMENTS						
SUBJECT IDENTIFIER	MTTF	RIGHT	FIST	HOLD	AFPR	Aver-age
MTTF		58	52	54	62	56.5 %
RIGHT	51		51	52	50	51 %%
FIST	62	51		56	54	53.66 %
HOLD	56	59	52		58	56.33 %
AFPR	50	65	55	63		61 %

6 Conclusion

This paper has researched a new method of person identification by the use of hand movements as a new biometric measurement. The low level representation of the action collapses the temporal structure of the motion from the video sequences of the hand movements while removing any static content from the video sequences to generate temporal history templates THTs of the hand movement. THTs of different individuals present distinctive 2-D motion patterns where each pixel describes the function of temporal history of motion in that sequence. The scale, translation and rotation invariant features have been used for discrimination of the THT for identification. On the basis of the experimental results it can be concluded that the THT based method can be used for biometric identification with proper caution and methodology. On the basis of the preliminary experimental results it can be concluded that: The THT based method can be successfully used for identification when subject uses subject specific movements. The next step is to test the accuracy on large database and its sensitivity analysis.

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