ZKG INTERNATIONAL

ISSN: 2366-1313

MULTIMODAL BIOMETRIC SYSTEMS FOR AADHAR

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ABSTRACT

Aadhar Biometrics is a science of identifying humans from their physiological and behavioural characteristics. The current era is driven by technology and now it is possible to have compact biometric scanners of various types and the computers that can handle enormous data and calculations required for biometric authentications are now available at affordable cost. Besides this current world is facing threats from terrorism and it has become a global concern to implement strict security and surveillance measures. The biometric systems have become good option for access control, human identification, and authorization because of their advantages over conventional security systems.

Keywords: Aadhar, Biometric, Multimodal

1. INTROUDCTION

Signature verification is an important research area in the field of authentication of a person as well as documents in e-commerce and banking. We can generally distinguish between two different categories of signature verification systems: online, for which the signature signal is captured during the writing process, thus making the dynamic information available, and offline for which the signature is captured once the writing process is over and thus, only a static image is available. In case of static systems morphological characteristics of signatures are used for forgery detection. In case of dynamic system, the speed, pressure, acceleration based dynamic features make it possible to identify the signing style. This makes

ISSN: 2366-1313

dynamic system more secure. Forgeries are possible in real life, and they are difficult to identify in case of static systems.

Use biometrics date back over a thousand years. In East Asia, potters placed their fingerprints on their wares as an early form of brand identity. In Egypt's Nile Valley, traders were formally identified based on physical characteristics such as height, eye colour, and complexion. This information helped identify trusted traders whom merchants had successfully transacted business in the past. The Old Testament also provides early (if not perfect) examples of voice recognition and biometric spoofing. Biometrics as a commercial, modern technology has been around since the early 1970‟s, when the first commercially available device was brought to market. One of the first commercial applications was used in 1972 when a Wall Street company, Shearson Hamil, installed Identimat, a finger-measurement device that served as a time keeping and monitoring application. Since this 1972 deployment, biometrics has improved tremendously in ease of use and diversity of applications. The advancement of biometrics has been driven by the increased computing power at lower costs, better algorithms, and cheaper storage mechanisms available today [1].

2. PROBLEM STATEMENT

In this paper various biometric traits are studied in detail. The topic for research is "Aadhar Biometric Authentication Systems", it consists of unimodal as well as multimodal Aadhar biometric systems. First unimodal biometrics implementations are focused and then the multimodal systems using fusion techniques are implemented. Biometrics such as fingerprints, palmprints, finger-knuckle print, face, iris, online signatures, keystroke dynamics & their multimodal implementations are explored. Focus of research is to use image processing techniques for biometric identification, as many biometric traits like fingerprints, palmprints, face, iris etc. are represented by images. We have developed algorithms based on image and signal processing for pre-processing, feature extraction and matching of various Aadhar biometric traits. Image processing techniques based on spatial as well as frequency domain image enhancement, wavelets, transforms & vector quantization are used. Improvement in the results by fusion of unimodal biometrics is discussed. The Aadhar biometric traits tend to vary with ageing; technique to improve performance of biometric system using multimodal approach is presented in this work.

3. Multimodal Biometrics for Aadhar

We have discussed biometric systems based on only one biometric trait or methodology of identification i.e., they rely on the evidence of a single source of information for authentication; such systems are called as unimodal biometric systems. For any unimodal system 100% accuracy is not possible and besides this they suffer from problems such as noise in sensed data, intra-class variations, inter-class similarities, non-universality & spoof attacks. Another thing is that as the enrolled population increases the feature vector space becomes crowded and it becomes difficult to classify these vectors correctly. Some of the limitations imposed by unimodal biometric systems can be overcome by including multiple sources of information for establishing identity [12]. Such systems, known as multimodal biometric systems, are expected to be more reliable due to the presence of multiple & (fairly) independent pieces of evidence [13]. Their decisions are combined through fusion techniques implementing "AND" or "OR" rule, allowing user to be verified using either any one or both the modalities.

Definition of Multimodal Biometrics for Aadhar

Multimodal biometrics refers to the use of a combination of two or more biometric modalities in a verification / identification system. Identification based on multiple biometrics represents an emerging trend. The most compelling reason to combine different modalities is to improve the recognition rate. This can be done when biometric features of different biometrics are statistically independent. The International Committee for Information Technology Standards (INCITS) Technical Committee M1, Biometrics, and researchers have described methods for performing

ISSN: 2366-1313

multi-biometric fusion [4], [5]. In general, the use of the terms multimodal or multi-biometric indicates the presence and use of more than one biometric aspect (modality, sensor, instance and/or algorithm) in some form of combined use for making a specific biometric verification/identification decision [2]. A multimodal system can combine any number of independent biometrics and overcome some of the limitations presented by using just one biometric as your verification tool. For instance, it is estimated that 5% of the population does not have legible fingerprints, a voice could be altered by a cold and face recognition systems are susceptible to changes in ambient light and the pose of the subject. A multimodal system, which combines the conclusions made by several unrelated biometrics indicators, can overcome many of these restrictions. Multimodal systems are generally much more vital to fraudulent technologies because it is more difficult to forge multiple biometric characteristics than to forge a single biometric characteristic [1], [3].

Categories of Multimodal Biometric Systems

To further the understanding of the distinction among the multibiometric categories [11], [10] they are briefly summarized in the following: Multimodal biometric systems take input from single or multiple sensors measuring two or more different modalities of biometric characteristics. For example, a system combining face and iris characteristics for biometric recognition would be considered a “multimodal” system regardless of whether face and iris images were captured by different or same imaging devices. It is not required that the various measures be mathematically combined in anyway. For example, a system with fingerprint and face recognition would be considered “multimodal” even if the “OR” rule was being applied, allowing users to be verified using either of the modalities. Multi-algorithmic biometric systems take a single sample from a single sensor and process that sample with two or more different algorithms. The technique could be applied to any modality. Algorithms can be designed to optimize performance under different circumstances. Multi-instance biometric systems use one sensor (or possibly multiple sensors) to

ISSN: 2366-1313

capture samples of two or more different instances of the same biometric characteristics. For example, systems capturing images from multiple fingers are multi-instance rather than multimodal. Multi-sensorial biometric systems sample the same instance of a biometric trait with two or more distinctly different sensors. Processing of the multiple samples can be done with one algorithm or some combination of multiple algorithms. For example, a face recognition application could use both a visible light camera and an infrared camera coupled with specific frequency (or several frequencies) of infrared illumination.

In multimodal biometrics we use more than one biometric modality hence we have more than one decision channels. We need to design a mechanism that can combine the classification results from each biometric channel; this is called as biometric fusion. Multimodal biometric fusion combines measurements from different biometric traits to enhance the strengths and diminish the weaknesses of the individual measurements. Fusion at matching score, rank and decision levels have been extensively studied in the literature. Multimodal Biometrics with various levels of fusion such as sensor level, feature level, matching score level and decision level are possible. Multimodal biometric system can implement any of these fusion strategies or combination of them to improve the performance of the system. In this paper we have mainly implemented feature level & score level fusion.

4. Fingerprint Recognition of Aadhar

The captured fingerprint needs pre-processing & mainly pre-processing steps include fingerprint filtering, orientation estimation, core point detection, segmentation etc. For the pre-processing three algorithms are presented in the thesis. They are as follows

Orientation Field Estimation: Optimized Neighborhood Averaging (ONA) algorithm for estimating the orientation field of the fingerprint. This orientation field is used for directional fingerprint filtering and core point detection. The proposed algorithm has

ISSN: 2366-1313

better estimation of the orientation field as compared to Orientation Estimation using Squared Gradients only.

Core Point Detection: The correlation-based fingerprint recognition systems require a consistent registration point for fingerprint feature extraction. This is high curvature point or core point present on the fingerprint. A core point detection mechanism using multiple features such as coherence of gray scale gradient, Poincare index, angular coherence & orientation field mask is presented here. This technique has given 98% accuracy for fingerprint having clear core points with average execution time of 520ms, this method performs better as compared Poincare index-based method.

Fingerprint Segmentation: Automatic segmentation of fingerprint using Gabor Magnitude. This novel algorithm is using Gabor magnitude map for separation of fingerprint from the background. Otsu's automatic thresholding is used for automation; no manual setting of threshold is required. This algorithm gives 94% segmentation accuracy. This algorithm is fast and needs no manual intervention as compared to existing mean & variance-based method, gradient direction-based approach & modified gradient-based approach.

These algorithms are used for segmentation of fingerprints and ROI extraction. This ROI is then used for extraction of feature vectors. Kekre's wavelets are used for multiresolution analysis of the fingerprints and extraction of texture feature through wavelet energy. Overall accuracy (CCR) of 84.40% is achieved by this technique. Testing is done in both the authorization as well as recognition mode; i.e. 1:1 matching & 1: N matching is performed. In another approach fingerprint matching using partitioned complex Walsh plane in transform domain is implemented. The intermediate Walsh transform is used for Cal & Sal function plot in complex plane, the mean and density-based feature vectors are used for extraction of texture information. This approach is further extended for Hartley, DCT, Kekre's Transform & Kekre's Wavelets. In this case the Even & Odd functions are used for plotting in

ISSN: 2366-1313

complex plane. The matching is performed using the core point ROI as well as full finger. The accuracy of core point ROI based matching is higher. However, there is not a very wide variation in the performance of different transforms, it ranges from 86.2% CCR for Walsh to 79.2% CCR for DCT. Walsh transform based feature vector gives best results, closely followed Hartley & Kekre's Wavelets. This is shown in Fig 1.

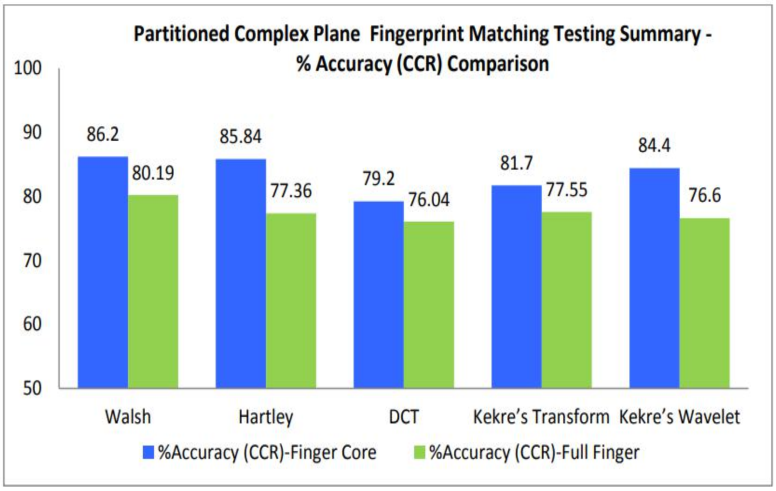

Fig. 1. Performance Comparison for Accuracy (CCR) of All the Transforms Discussed Above for Generation of Partitioned Complex Plane in Transform Domain

Palmprint Recognition

Palmprint images are rich in texture and the palmprint based biometric systems are also multi-step processing systems. Methods for palmprint preprocessing including Region of Interest (ROI) localization and extraction, intensity normalization are presented in this thesis. Kekre's wavelets are used for extracting texture information from the palmprints. The selected ROI is subjected for multilevel decomposition using Kekre's Wavelets as well as normalized Haar wavelets. The feature vector in the form of wavelet energy is extracted. For matching Euclidian distance as well as Relative Energy Entropy (REE) are used as distance metrics. Different variants of feature vectors are tested based on these metrics and normalization modes. Euclidian distance-based classification of palmprint feature vectors gives higher performance. Fusion of these feature vectors is also performed using score normalization. Overall accuracy of the palmprint recognition is 89.17% in case of Kekre's wavelets and for Haar wavelets the accuracy is 85.43%. This is shown in Fig. 2. For the given database and test scenario kekre's wavelets perform better than Haar wavelets. As Kekre's wavelet matrix has only integer values as compared to the real numbers in case normalized Haar Wavelets, Kekre's wavelets are faster.

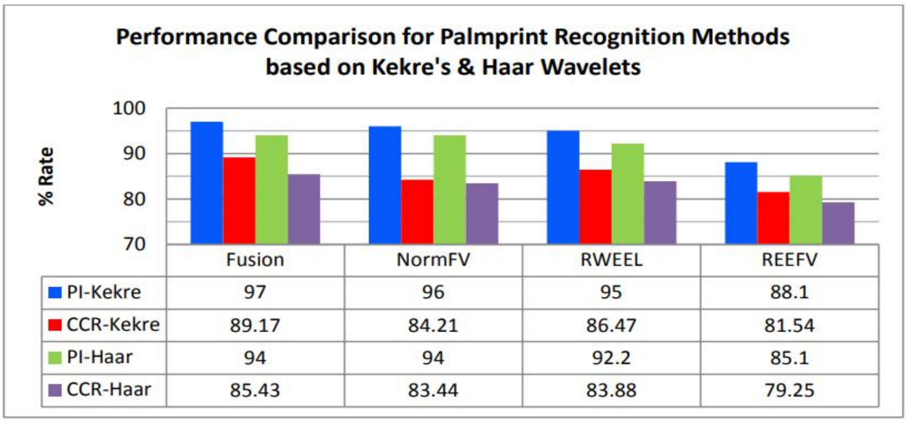

Fig. 2. Comparison of Different Palmprint Recognition Methods Implemented

Walsh transform is used to generate complex Walsh plane, by intermediate transform of palmprint ROI. This plane is used to generate feature vector. Fusion of Row & Column Transform mean and Density with DC and Sequency coefficient gives 90% PI.

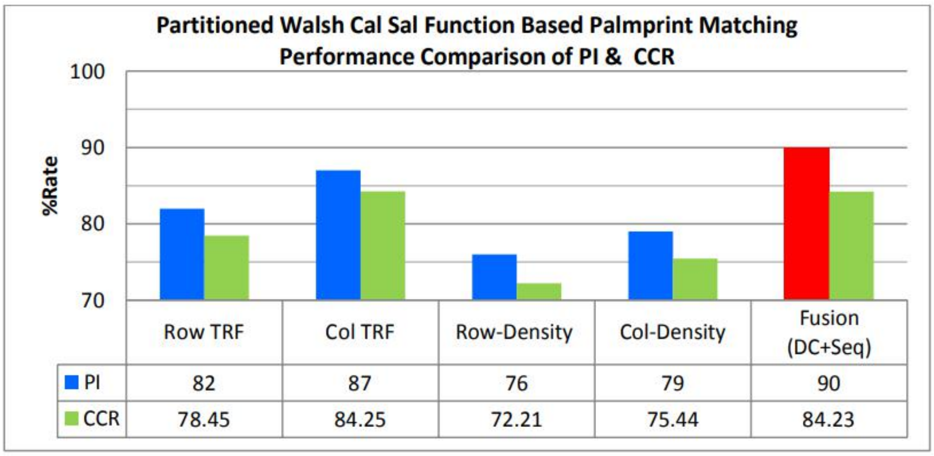

Fig. 3. Performance Comparison for Feature Vector Variants of Partitioned Walsh Cal-Sal Function Palmprint Matching

ISSN: 2366-1313

The individual Row & column transform mean-based feature vectors have 82% and 87% PI as shown in Fig. 7.3, this shows that due to fusion of feature vector with DC & Sequency component the performance has improved. The correct classification ratio (CCR) for the matching tests is 84.23%.

Iris Recognition

Iris recognition is performed using feature vectors extracted by vector quantization, transform coefficients of Row & Column mean based feature vector, Kekre's wavelets and partitioned complex plane in transform domain of Walsh, Hartley, DCT, Kekre's Transform & Kekre's Wavelets.

Table 1: Performance Improvement in Total Accuracy (CCR) Achieved due to Iris Pre-processing & Normalization

Algorithm	Total Accuracy (With Normalization)	Total Accuracy (Without Normalization)	Improvement (%)
DCT	85.29	64.21	33
DCT-RM	89.21	74.96	19
DCT-CM	88.55	68.55	29
WHT	89.80	66.10	36
WHT-RM	92.40	75.78	22
WHT-CM	93.00	72.65	28
LBG	86.70	81.25	07
KMCG	92.12	87.10	06
KFCG	95.18	89.10	07

Effect of normalization of iris on the recognition accuracy is also explored in this thesis. Normalization includes segmentation of iris (iris localization) & unwrapping of iris. This process removes unwanted background from iris image. Table 1 shows the performance comparison for iris recognition based on full 2D DCT/ WHT Row & Column mean of DCT & WHT coefficients (DCT/WHT RM & CM) and the vector quantization using LBG, KMCG and KFCG. KFCG based feature vector gives highest accuracy of 95.18% with normalization. Here the accuracy for combined left & Right iris is given; this is an example of multi-instance iris recognition. The normalization process gives performance improvement of up to 36% for full 2D WHT based feature vector-based iris recognition and minimum of 6% for KMCG based systems. Vector Quantization based methods have better performance than the transform-based methods.

Multimodal Biometrics

Multimodal, multi-algorithmic & multi-instance biometric systems based on some of the above-mentioned biometric traits are discussed here. Fusion of face and iris is done through a novel fusion mechanism. Unimodal face recognition system is fused with a multi-instance iris recognition system. Decision level as well as feature level fusion is implemented. The results are shown in Fig. 7.9, the face and iris feature fusion give highest accuracy of 98% as compared to the accuracy of individual systems. This fusion mechanism is termed as hybrid multimodal fusion. Besides these face & keystroke dynamics multimodal, multialgorithm fingerprint recognition, multi-instance & multi algorithmic iris recognition systems are explored. The results clearly indicate that the combination of the biometric traits through different level of feature & decision fusions increases accuracy of the recognition. The final accuracy also depends on the selection of feature vector, enrolment & training samples and performance of individual biometric traits.

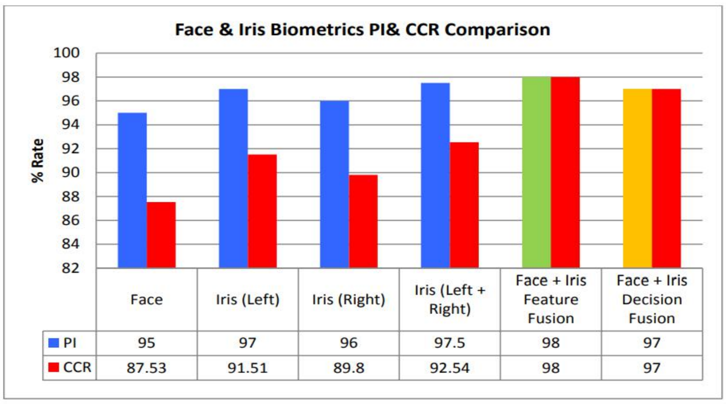

Fig 4. PI & CCR comparison for Final Hybrid Multimodal System with Face & Iris Recognition Systems

ISSN: 2366-1313

In another variation face & keystroke dynamics based multimodal biometric system is implemented. This is an example of physiological & behavioral biometric fusion. Final CCR is 88 % for decision fusion & 90% for feature fusion as compared to 87.53% CCR of face recognition system and 75% CCR of keystroke dynamics-based biometrics. Multi-algorithmic fingerprint recognition & multi-instance iris recognition systems have also been explored here. It is found that this mode of fusion also improved the performance of the final system as compared to individual traits performance.

CONCLUSION

This paper is focused on multimodal biometric systems, their types and the performance improvement achieved. The definition and types of multimodal biometric systems, different feature fusion mechanisms are elaborated. Different multimodal combinations are discussed here. Face & iris based multimodal system are discussed. This system is implemented by combining a unimodal face recognition system and a combination of multi-algorithmic & multi-instance biometric system; this system is called as hybrid multimodal system. Though the system is complex the achieved CCR is 98% (face-87.53% & iris- 97.5%). The fusion of face & iris is an example of fusion of two physiological biometric traits. In section 6.4, face & dynamic keystroke information based biometric systems are combined to implement multimodal biometric system. This is an example of physiological & behavioral biometric fusion. The results clearly show the improvement in the performance, the CCR of final multimodal system is 90% is greater than the individual biometric systems (face-87.53%, keystroke75%). Both the feature fusion and decision fusion of feature vector is implemented in the face & keystroke dynamics fusion.

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