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Privacy Preserving using Primary Biometrics and Softbiometrics

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Abstract : In many applications, unimodal biometric systems often face significant limitations due to sensitivity to noise, intra class variability, data quality, pressure, dirt, dryness and other factors. Multimodal biometric authentication systems aim to fuse two or more physical or behavioral traits to provide optimal Genuine Acceptance Rate (GAR) Vs Imposter Acceptance Rate (IAR) curve i.e. Receiver‘s Operating Characteristic (ROC). Soft biometrics can be used to improve the performance of traditional biometrics. The equipment used for softbiometric is low in cost and methods are easy to understand. The aim of this paper is to examine whether easily measurable characteristics such as weight, gender etc with the finger geometry and knuckle print can improve the verification process in biometrics. Each biometric trait produces a varied range of scores i.e. heterogeneous scores. Various scores normalization techniques have been developed for fusion of such scores. Whereas this paper presents a technique for producing compatible scores (homogeneous). Decision level AND rule can be used to show the improvement of the combined scheme. This approach is useful for low security requirements. Also use of softbiometrics such as body weight with primary can reduce the Total Error Rate.

Keywords: Biometrics verification, fusion, multimodal, softbiometrics, knuckle print.

I. INTRODUCTION

A Unimodal Biometric Authentication System (UBAS) is usually more cost-efficient than a multimodal biometric system. However, it may not always be applicable in a given domain because of the limitations and problems like skin dryness, disease, data quality, pressure, dirt, oil and high IAR. In a multimodal system (MBAS) that uses different biometric traits, fusion can be done at three different levels of information, (a) Feature extraction level, (b) Matching Score (c) Decision [1]. Our proposed system is based on Matching Score level fusion.

Feature matching or input projection on template generates a score range which varies for different biometric traits. Scores are usually the number of features matched. There are two major challenges in the fusion, first is the heterogeneous nature of scores generated by different biometric traits and second is the overlapping score distribution of genuine and imposter. So, to fuse two or more traits, score normalization (numerical scaling) is performed to overcome the limitation of incompatibility of scores [2, 3]. We suggest using soft biometrics, i.e. easily measurable personal characteristics as additional evidence in biometric recognition, i.e. they are not unique and permanent throughout the lifetime of an individual, but still they have discriminating power, they are stable from the application point of view (e.g. in daily use), they are easily collectable and unobtrusive. Of course, soft biometrics alone is not suitable for applications where high or medium-level security is needed. Soft biometrics can be used to strengthen the verification or identification. In certain applications the strength of soft biometrics may be found exactly in their weakness since they are not unique, they do not pose the threat of identity theft and they may be felt less obtrusive than traditional biometrics. Additional benefit can be gained with soft biometrics, if they can be used for other purposes than identity recognition.

The aim is to examine the performance of biometrics in verification type application when softbiometrics characterstics are used with the finger geometry and knuckle print.

The paper is organized as follows. Related research is presented in Section 2, modalities used and the collection of the database are described in Section 3,4,5. The proposed architecture is given in section 6. The results are given in Section 7 .Conclusions is presented in Section 8. In last section references are given.

II. RELATED WORK

Previous work in multimodal biometric system design shows that they may be either be based on single input and multiple algorithm or multiple samples and single algorithm or they may utilize two or more different modalities, it has been empirically proven in that multimodal biometrics can improve the performance but these improvement can come at a cost [5]. A number of studies showing the advantages of multimodal biometrics have appeared in the literature. Dass and Nandakumar [2] used hyperbolic tangent (tanh) for normalization and weighted geometric average for fusion of voice and face biometrics. They also proposed a hierarchical combination scheme for a multimodal identification system. Prabhakar et al. [3] have experimented with several fusion techniques for face and voice biometrics, including sum, product, minimum, median, and maximum rules and they have found that the sum rule outperformed others. Nandakumar et al. [4] note that the sum rule is not significantly affected by the probability estimation errors and this explains its superiority.

Ross and Jain [5] proposed an identification system based on face and fingerprint, where fingerprint matching is applied after pruning the database via face matching. Yagar and Amin et al. [6] considered several fusion strategies, such as support vector machines, tree classifiers, and multilayer perceptrons, for face and voice biometrics. The Bayes classifier is found to be the best method. Yagar et al. [7] combined face, fingerprint, and hand geometry biometrics with sum, decision tree, and linear discriminant-based methods. The authors report that the sum rule outperforms others. It should be noted that the number of samples per subject in the databases used by researchers affects the complexity of the appropriate fusion systems. More samples may allow utilizing complex knowledge-based (e.g., perceptron) techniques. Hand-based biometrics has attracted lots of attention and personal identification by using palm print, hand geometry, 3D finger geometry, and hand vein have been proposed in the literature Maltoni et al [8] represented palm print with orthogonal line ordinal features which achieved significantly high accuracy with low computational cost; Zhang & Yuan [9] developed a prototype latent-to-full palm print matching algorithm which can recognize partial and latent palm prints in full palm prints database with recognition rates of 78.7% and 69% by using minutiae features, the method requires high quality palm images with a resolution of at least 400 dpi. Kumar et al. [10] extracted texture feature, global texture energy and interesting points from the palm and then matched in a hierarchical fashion, which achieved adequate performance, while the correlation of different features from the same palm is not considered yet. Heikki et al. [11] presented a projective-invariant representation for hand features to create robust Projective Permutation Invariant (PPI) hand geometry biometrics technology which is peg-free, noncontact, and nonintrusive. Above mentioned methods execute identity authentication on unimodal manner.

III. FINGER GEOMETRY

Hand-based biometrics has attracted lots of attention and personal identification. Here we will use finger geometry at our first level. After scanning of hand, preprocessing is done as shown in figure 1. All the fingers are processed. Then we consider only the index finger to avoid the storage size otherwise template size will be very large and requires a lot of storage space.

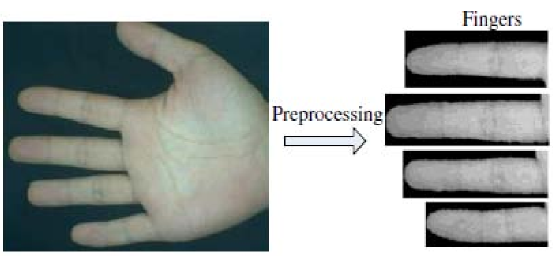

Figure 1. Preprocessing of finger.

After the preprocessing of finger image, the shape feature are extracted. If a finger shape feature dimension is an even integer N, then the finger can be divided into N/2 parts along length direction.

Figure 2: Finger shape vector

The areas of each part over and below the horizontal axis are calculated and then normalized to generate the finger shape vector as shown in figure 2.

IV. KNUCKLE PRINT

These prints refers to the flexion shrinks in the inner skin of knuckles. These prints has mainly two features : the location of the lines and the patterns of each line.

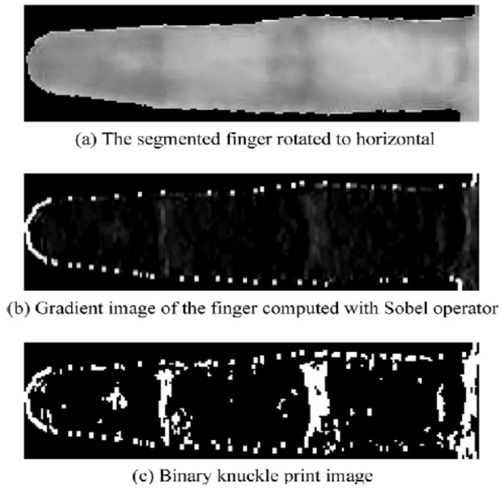

Figure 3 : Detected Knuckle prints and their binarization

In this paper, we analysis the pattern of the front surface of the index finger knuckle. The lines on front knuckle surface are nearly vertical. Thus the gradient along the length direction will reflect the knuckle print location trait while the vertical projection of the gradient projection vector is enough for coarse level match. The concept of detection of knuckle segmented finger rotated to horizontal in 3(a) . In figure 3(b) prints and their binarization is shown in figure 3 The gradient image is calculated with the help of Sober operator. Then the binarization of the detected knuckle print is done as shown in figure 3(c).

V. SOFT BIOMETRIC AND THEIR EXTRACTION

Soft biometrics traits are those characteristics that provide some information about the individual, but lack the distinctiveness and permanence to sufficiently differentiate ant two individuals. These traits can be either discrete or continuous traits like gender, eye color etc. are discrete and weight, height etc. are continuous in nature. To utilize soft biometrics, there must be a mechanism to automatically extract these features from the user during the recognition phase. As the user interacts with the primary biometric system, the system should be able to automatically measure the soft biometric characteristics like height, age and gender without any interaction with the user. This can be achieved using a special system of sensors. For example, a bundle of infra-red beams could be used to measure the height. A camera could be used for obtaining the facial image of the user, from which information like age, gender, and ethnicity could be derived. These observed soft biometrics information could then be used to supplement the identity information provided by the user's primary biometric identifier. Extensive studies have been made to identify the gender, ethnicity, and pose of the users from their facial images. Shah et al. [13] proposed a mixture of experts consisting of ensembles of radial basis functions for the classification of gender, ethnic origin, and pose of human faces. Their gender classifier classified users as either male or female with an average accuracy rate of 96%. Age determination is a more difficult problem due to the very limited physiological or behavioral changes in the human body as the person grows from one age group to another. There are currently no reliable biometric indicators for age determination.

VI. PROPOSED ARCHITECTURE

A guided search strategy is essential to reduce the computational burden and to avoid the blind search for the best fit between the template patterns and the sample pattern. We propose here to consider finger geometry, knuckle print, soft biometrics and adopt different classification methods in a hierarchical manner to facilitate a coarse-to-fine hand metric matching for personal identification. Figure 4 illustrates the general structure of our system. The geometrical feature of one finger is considered a Level-1 feature, the knuckle print of the same finger as Level-2 feature, and final level feature is softbiometric. The features in the hierarchical feature database are retrieved and compared with input features, in a multilevel fashion.

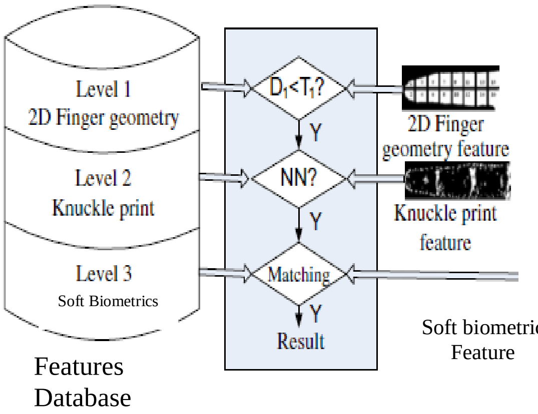

Figure 4 Proposed Hierarchical matching architectures

The proposed architecture runs in serial mode [12]. First the finger shape vectors are matched. If they matched then knuckle print features are matched. At the last level softbiometric features can be matched to verify the person. Softbiometric may be height, gender or any other feature as per the requirement. Let x be the feature vector corresponding to the primary biometric. Without loss of generality, let us assume that the output of the primary biometric system is of the form $P(\omega_i \mid \mathbf{x})$, $i = 1, 2, \ldots, n$, where $P(\omega_i \mid \mathbf{x})$ is the probability that the test user is ω_i given the feature vector **x**. If the output of the primary biometric system is a matching score, it is converted into posteriori probability using an appropriate transformation. For the secondary biometric system, we can consider $P(\omega_i \mid \mathbf{x})$ as the prior probability of the test user being user ω_i Let $\mathbf{y} = [y_1, y_2, \ldots, y_k, y_{k+1}, \ldots y_m]$ be the soft biometric feature vector, where y_1 through y_k are continuous variables and y_{k+1} through y_m are discrete variables. The updated probability of user ω_i, given the primary biometric feature vector **x** and the soft biometric feature vector **y**, i.e., $P(\omega_i \mid \mathbf{x}, \mathbf{y})$ can be calculated using the Bayes rule as

$$P(\omega_i|\mathbf{x},\ \mathbf{y}) = \frac{p(\mathbf{y}|\omega_i)\ P(\omega_i|\mathbf{x})}{\sum_{i=1}^{n} p(\mathbf{y}|\omega_i)\ P(\omega_i|\mathbf{x})}. \qquad (1)$$

If we assume that the soft biometric variables are independent, equation (1) can be rewritten as

$$P(\omega_i|\mathbf{x},\,\mathbf{y}) = \frac{p(y_1|\omega_i)\cdots p(y_k|\omega_i)\ P(y_{k+1}|\omega_i)\cdots P(y_m|\omega_i)\ P(\omega_i|\mathbf{x})}{\sum_{i=1}^{n} p(y_1|\omega_i)\cdots p(y_k|\omega_i)\ P(y_{k+1}|\omega_i)\cdots P(y_m|\omega_i)\ P(\omega_i|\mathbf{x})}. \qquad (2)$$

In equation (2), $p(y_j \mid \omega_i)$; $j = 1, 2, \ldots, k$ represents the conditional probability of the continuous variable y_j given user ω_i. This can be evaluated from the conditional density of the variable j for user ω_i. On the other hand, discrete probabilities $p(y_j \mid \omega_i)$; $j = k+1, k+2, \ldots, m$ represents the probability that user ω_i is assigned to the class y_j. This is a measure of the accuracy of the classification module in assigning user ω_i to one of the distinct classes based on biometric indicator y_j. In order to simplify the problem, let us assume that the classification module performs equally well on all the users and therefore the accuracy of the module is independent of the user.

VII. EXPERIMENTS AND RESULTS

Our experiments demonstrate the benefits of utilizing softbiometrics with finger geometry and knuckle print. In our hand image database, 1500 images from 150 different hands are collected. Out of ten images from each hand, one image is selected for enrollment and the remaining nine were used for testing. For verification purpose softbiometrics is also used at level III.

Table-1 Time Consumption for each procedure

Operation	Preprocessing	Feature extraction	Level-1 matching	Level-2 matching	Level-3 matching
Time (ms)	720	151	1.5	1.3	520

As shown in table -1 the time consumption for preprocessing as well as for each level matching is given. We know that softbiometric are not permanent but due to these False Acceptance Ratio is decreased. The verification accuracies of three levels and fusion system can be shown by Receiver Operating Characteristics Curve.
AND fusion rule perform fusion on decision level which means that at the first step the hard decision (accept or reject) is made by individual expert depending on the threshold set for each modality. Different ratio between FAR and FRR can be achieved by varying thresholds of each single modality. The receiver operating characteristics curve shows the ROC for each modalities and their fusion. The results are better for the fusion than each individual modality.

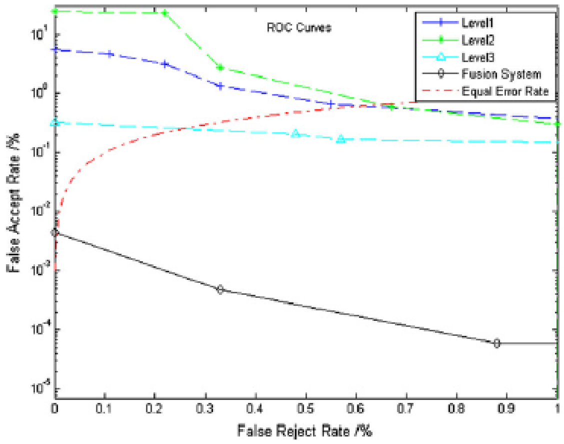

Figure 5: The ROC curves for three levels and fusion systems

VIII. CONCLUSION

Multimodal biometrics system removes several problems present in the unimodal systems. By integrating multiple cues including softbiometrics, these systems can improve the performance of traditional biometric system. We have formulated a mathematical framework based on the Bayesian decision theory for integrating the soft biometric information with the finger geometry and knuckle print. Methods to incorporate time varying soft biometric information such as age and weight into the soft biometric framework will be studied. The method presented in this paper can be used to enhance the performance of existing hand geometry based systems without compromising on the transaction time since all the biometrics (finger geometry, knuckle print and softbiometric) are acquired simultaneously. The foreseen applications of soft biometrics are in strengthening the performance of traditional biometrics by fusion. The main classes of deployment would involve decreasing the probability of false acceptance or false rejection in medium and low security applications. The main advantages of using soft biometrics to strengthen traditional biometrics are improved performance and more difficult circumvention.

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