A Review of Multibiometric System with Fusion Strategies and Weighting Factor

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***Abstract*—Biometric is a technology for verification or identification of individuals by employing a person's physiological and behavioural traits. Although these systems are more secured compared the traditional methods such as key, smart card or password, they also undergo with many limitations such as noise in sensed data, intra-class variations and spoof attacks. One of the solutions to these problems is by implementing multibiometric systems where in these systems, many sources of biometric information are used. This paper presents a review of multibiometric systems including its taxonomy, the fusion level schemes and toward the implementation of fixed and adaptive weighting fusion schemes so as to sustain the effectiveness of executing the multibiometric systems in real application.**

Keywords- b*iometric, multibiometric, level of fusions, fixed weighting, adaptive weighting***.**

I. INTRODUCTION

In the modern world, there is a high demand to authenticate and identify individuals automatically. Hence, the development of technology such as personal identification number (PIN), smartcard or passwords have been introduced. However, those technologies are inadequate since they are disclosable and transferable. For example, PIN and smart card can be duplicated, misplaced, stolen or lost, long password can be hard to remember by client and short password can be guessed easily by the imposter [1,2].

In order to overcome these problems, biometric-based authentication and identification methods are introduced in late 90s. By applying biometric systems, it is possible to identify the person, or to validate a claimed identity. Hence, the biometric systems have become an active research since these systems can be implemented as security protection systems (e.g., access control), criminal investigations, logical access points (e.g. computer login) and surveillance applications (e.g., face recognition in public spaces).

A biometric system is essentially a pattern-recognition system that recognizes a person based on a feature vector derived from a specific physiological or behavioural characteristic the person possessed for authentication or identification purposes [3]. It differs from classical user authentication system which is based on something that one has (e.g., identification card, key) and/or something that one knows (e.g., password, PIN). Hence, a number of physiological and behavioural traits can be utilized in the biometric systems such as fingerprint, iris, face, hand geometry, palm print, finger vain structure, gait, voice, signature. Depending on the context of applications, biometric systems may operate in two modes i.e. verification or identification [4,5]. Biometric verification is the task of authenticating the test biometric sample with its corresponding pattern or model according to the claim given by user. Whereas, biometric identification is the task of associating a test biometric sample with one of number of patterns or models that are available from a set of known or registered individuals [6].

Most biometric systems deployed in real-world applications are unimodal. These systems suffer with problems such as noise in sensed data, non-universality, upper bound on identification accuracy and spoof attacks [7]. In order to overcome the problem, Hong et al. [8] examined the possible performance improvement of biometric systems by using multiple biometrics. This paper showed that by integrating with other multiple biometric sources, the performance was indeed improved. Such systems, known as multibiometric systems can improve the matching accuracy of biometric systems and deterring spoof attacks [2].

Mutibiometric systems can also improve other limitations faced by biometric systems. For example, the multibiometric system can address the non-universality problem encountered by biometric systems. If a person cannot be enrolled in the fingerprint system, this person can aid the problem using other biometric traits such as voice, face or iris. The multibiometric systems can also reduce the effect of noise data. If the quality biometric sample obtained from one sources is not sufficient, the other samples can provide sufficient information to enable decision-making. Another advantage of multibiometric over single biometric systems is that, they are more resistant to spoof attacks since it is difficult to simultaneously spoof multiple biometric sources. The multibiometric systems are able to incorporate a challenge-response mechanism during biometric acquisition by acquiring a subset of the trait in some random order [9].

However, the multibiometric systems also have major drawbacks compared with single biometric systems. For example, the cost for the implementation of multibiometric systems is more expensive since these systems require many sensors. Furthermore, such a system may also increase the user inconvenience and required the user to interact with more than one sensor. For example, in a multibiometric system, both fingerprint and iris images of a person are required. Therefore, a user not only needs to touch the fingerprint scanner, but also needs to work together with an iris imaging system. Such activity gives impact on the raising of computation, memory and storage. Moreover, this also increases the operating time during enrollment and verification process [9].

In order to describe the current scenario of multibiometric systems, this review paper is organized as the following. Section II describes the taxonomy of multibiometric systems which explained the different roles of multibiometric systems in term of multi-sensor, multi-algorithm, multi-instance, multi-sample and multimodal systems. Section III provides detailed explanation for the level of fusion techniques that used in the combination phase for the fusion of different sources of biometric information. Finally, a review toward to the implemention of fixed and adaptive weighting fusion schemes is then discussed in the Section IV.

II. Taxonomy Of Multibiometric System

Based on the nature of the sources of biometric information, a multibiometric system can be classified into five categories which are multi-sensor, multi-algorithm, multi-sample, multi-instance and multi-modal systems. The scenario of multibiometric systems is depicted as in Fig.1.

Multi-sensor systems: Multi-sensor systems employ multiple sensors to capture single biometric trait of an individual. The example of this system is reported in [10] where multiple 2D cameras are used to capture the image of subject. Subsequently, in [11], an infrared sensor and visible-light sensor are applied to acquire the information of a person’s face while in Rowe and Nixon [12] and Pan et al. [13], a multi spectral camera has been employed to acquire images of iris, face or finger. The application of multi-sensors in the researches is able to enhance the recognition ability of the biometric systems. For instance, the infrared and visible-light images of person’s face can present different types of information which can enhance the matching accuracy based on the nature of illumination due to ambient lighting.

Multi-algorithm systems: multi-algorithm systems combine the output of multiple methods such as feature extraction or/and classification algorithms for the same biometrics data [7]. In other words, the supplementary information by more than one algorithm helps to improve the performance. So, utilization of new sensor is not required thus it is cost effective. However, this system has a drawback due to many feature extraction and matching modules can cause complexity of system computation. Example of this system can be found in Lu et al. [14] where three different feature extraction schemes which are Principle Discriminate Analysis (PCA), Independent Component Analysis (ICA) and Linear Discriminate Analysis (LDA) have been combined to improve a face recognition system. Another researcher has also combined multiple algorithms such as Iterative Closet Point (ICP), PCA and LDA to perform 3D face recognition [15]. In Imran et al. [16], three subspace algorithms such as PCA, Fisher Linear Discriminant (FLD) and ICA are applied for palm print and face separately in order to determine the best algorithm performance. The result shows that the ICA algorithm performs well for both individual modalities.

Multi-sample systems: multi-sample systems use multiple samples derived from the same biometrics acquired by a single sensor. The same algorithm processes each of the samples and the individual results are fused to obtain an overall recognition results. The advantage of using multiple samples is to avoid poor performance due to the slack properties of sample if only one sample is used. This system has been studied in Chang et al. [17] for face recognition where 2D face image has been applied as a baseline in order to compare the performance of multi-sample 2D + 3D face in speech recognition. Another research has proposed multi-sample approach to UMACE filter classifier by combining scores from several samples from lipreading features and spectrographic features [18].

Multi-instance systems: In this system, the biometric information has been extracted from the multiple instances of the same body trait. For example, the left and right index finger and iris of an individual is proposed in Jang et al. [19] and Prabhakar and Jain [20], respectively.

Multi-modal systems: multi-modal systems use the evidence of multiple biometric traits to extract the biometric information of an individual. These different biometric traits can come from a variety of modalities [9]. The multi-modal system is reliable due to the presence of multiple independent biometrics. However, the drawback of this system is due to the substantial cost because of the requirement of many sensors. The example of this system has been reported by Brunelli and Falagivna [21] where a person identification system using face and speech is presented. This research showed that by combining three biometrics i.e. frontal face, face profile and voice using sum rule combination scheme, the system performance has been improved [22]. Another combination such as fingerprint, face and finger vein has been presented in Hong et al. [8] while Ramli et al. [23], and Lip and Ramli [24] used the speech signal as a biometric trait to the biometric verification system and lipreading image as a second modality to assist the performance of the single modal system in the multibiometric systems.

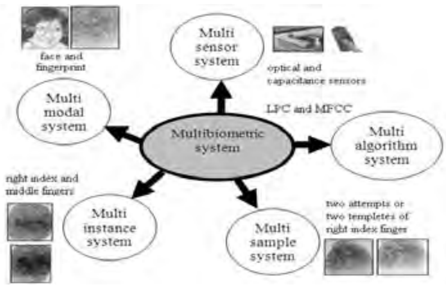

Figure 1. Scenarios in a multibiometric system

III. Level of Fusion

The important issue to designing multibiometric system is to determine the sources of information and combination strategies. Depending on the type of information to be fused, the fusion scheme can be classified into different levels. According to Sanderson and Paliwal [25], the level of fusion can be classified into two categories, fusion before matching (pre classification) and fusion after matching (post classification) as shown in Fig. 2.

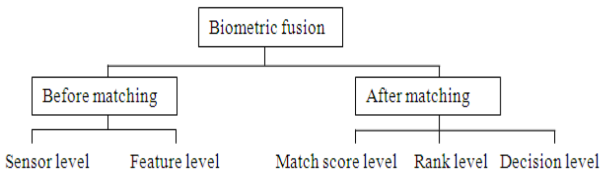

Figure 2. Level of fusion

For fusion before matching, the integration of information from multibiometric sources in this scheme includes fusion at the sensor level and fusion at the feature level. Meanwhile, fusion after matching can be divided into two categories which are fusion at the match score level and fusion at the decision level.

A. Fusion Before Matching

- Sensor Level Fusion

In this level, the raw data from the sensor are combined together as shown in Fig. 3. However, the source of information is expected to be contaminated by noise such as non-uniform illumination, background clutter and other [26]. Sensor level fusion can be performed in two conditions i.e. data of the same biometric trait is obtained using multiple sensors; or data from multiple snapshot of the same biometric traits using a single sensor [27, 28].

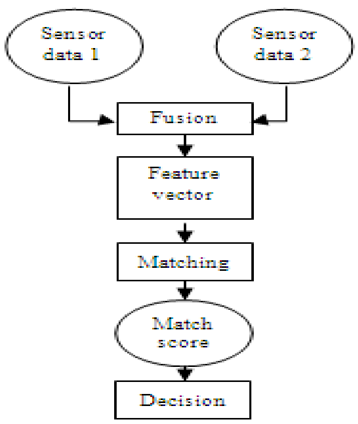

Figure 3. Sensor level fusion process flow

- Feature level fusion

In feature level fusion, different feature vectors extracted from multiple biometric sources are combined together into a single feature vector as depicted in Fig. 4. This process undergoes two stages which are feature normalization and feature selection. The feature normalization is used to modify the location and scale of feature values via a transformation function and this modification can be done by using appropriate normalization schemes [2]. For instance, the min-max technique and median scheming have been used for hand and face [9] and the mean score from the speech signal and lipreading images scores have been employed in the feature level fusion [24]. Another research has implemented Scale Invariant Feature Transform (SIFT) to obtain features from the normalized fingerprint and ear [29]. Consequently, feature selection is executed to reduce the dimensionality of a new feature vector in order to improve the matching performance of the feature vector by accepting more authentic as true accept. There are several feature selection algorithms have been applied in the literature for instances Sequential Forward Selection (SFS), Sequential Backward Selection (SBS) and Partition About Medoids [30]. The advantage of the feature level fusion is the detection of correlated feature values generated by different biometric algorithms, and, in the process, identifying a salient set of features that can improve recognition accuracy [2]. However, in practice, fusion at this level is hard to accomplish due to the following reasons i.e. the feature sets to be joined might be incompatible and the relationship between the joint feature set of different biometric sources may not be linear [31]. Moreover, concatenating two feature vectors yield a new feature vector which gives larger dimensionality compared to the original once thus leads to the dimensionality problem. Large feature variance affects the system accuracy and also increases the processing time. Hence, only few researchers have focused on the feature level scheme compared to the other levels of fusions such as score level and decision level.

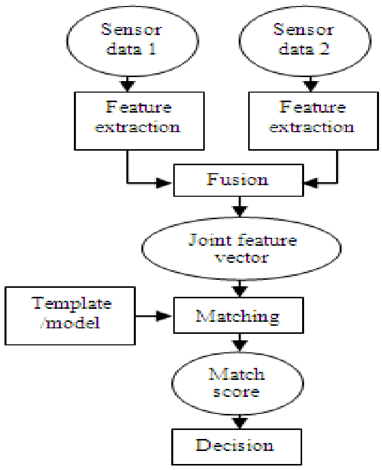

Figure 4. Feature level fusion process flo

B. Fusion After Matching

- Score level fusion

In score level fusion, the match outputs from multiple biometrics are combined together to improve the matching performance in order to verify or identify individual as shown in Fig. 5 [32]. The fusion of this level is the most popular approach in the biometric literature due to its simple process of score collection and it is also practical to be applied in multibiometric system. Moreover, the matching scores contain sufficient information to make authentic and imposter case distinguishable [6]. However, there are some factors that can affect the combination process hence degrades the biometric performance. For example, the matching scores generated by the individual matchers may not be homogenous due to be in the different scale/range or in different probability distribution. In order to overcome this limitation, three fusion schemes have been introduced i.e. density-based schemes; transformation-based scheme; and classifier-based scheme [7]. The density-based scheme is based on score distribution estimation and has been applied in well-known density estimation models such as Naive Bayesian and Gaussian Mixture Model (GMM) [33]. This scheme usually achieves optimal performance at any desired operation point and estimate the score density function accurately. However, this scheme requires a large number of training samples in order to perfectly approximate the density functions. Moreover, it requires more time and effort for the operational setting compared to the other schemes. On the other hand, the transformation-based scheme is commonly applied for the score normalization process. This process is essential to change the location and scale parameters of the underlying match score distributions in order to ensure compatibility between multiple score variables [7]. This scheme can be applied using various techniques such as sum rule, product rule, min rule and max rule techniques [34]. In the classifier-based scheme, the scores from multiple matchers are treated as a feature vector and a classifier is constructed to discriminate authentic and imposter score [33]. From the literatures, various types of classifiers such as SVM, neural network and *multi-layer perceptron (*MLP) [34] have been implemented to classify the match vector in this scheme. However, this scheme has some drawbacks such as unbalanced training set and misclassification problems.

- Decision level fusion

Fusion at the decision level is executed after a match decision has been made by the individual biometric source as depicted in Fig. 6. So far, there are many different methods have been applied to join the distinct decision into a final decision such as "AND" and "OR" rules [24], majority voting, weighted majority voting, Bayesian decision fusion, Dempster-Shafer theory of evidence and behaviour knowledge space [7]. On the other hands, Ramli et al., [35] implemented the proposed decision fusion by using the spectrographic and cepstrumgraphic as features extraction and UMACE filters as classifiers in the system to reduce the error due to the variation of data.

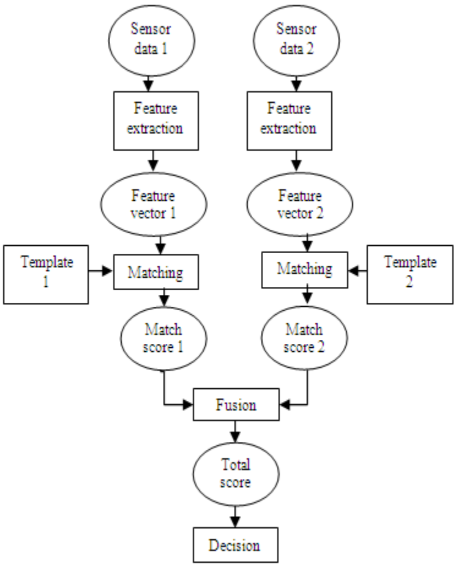

Figure 5. Score level fusion process flow

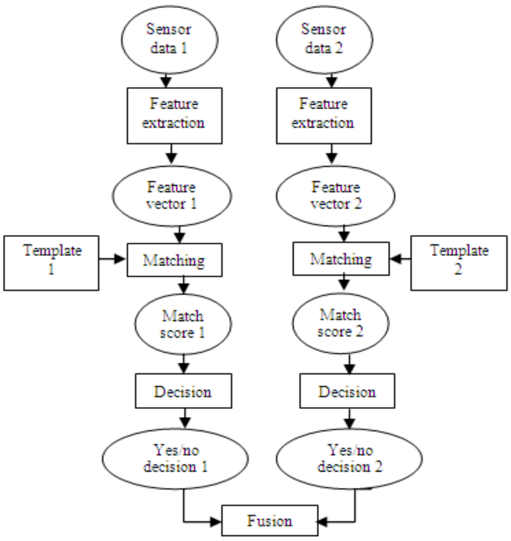

Figure 6. Decision level fusion process flow

IV. FIXED AND ADAPTIVE WEIGHTING IN BIOMETRIC

Multibiometric systems are found to be useful and exhibit robust performance over the single biometric systems. However, in uncontrolled conditions, the reliability of the multibiometric systems drops severely. As the results, the systems are poorly executed in uncertain condition. Therefore, it is imperative to assign different weighting in fusion scheme to each biometric trait in order to vary the importance of matching scores of each biometric trait since the optimum weight can maximize the performance of multibiometric system.

In general, multibiometric systems can be divided into two categories of weighting scheme which are fixed and adaptive weighting. In the fixed weighting, the fusion weight is fixed for each training data set. Otherwise, retraining the optimum weight is needed. Research of fixed weighting fusion has been done as reported in Parviz and Moin [34]. This study presented fusion of score produced independently by speaker recognition system and face recognition system using weighted merged score. The result shows that the identification of 51% was achieved for the speech only system and 92% for the face system. Subsequently, performance of the integration system using the optimal weight is observed up to 95%. In another study was done in Brunelli and Falavigna [35], the weighting product is applied to fuse two voice features i.e. static and dynamic and three face features i.e. eye, noise and mouth. This research used tan-estimators for score normalization and weighted geometric average was used for score combination. The results showed the correct identification percentage of the integrated system is 98% which represents a significant improvement compared to 88% and 91% rates provided by the single systems i.e. speaker and face based system respectively. The EER performance of face recognition, voice recognition and the integrated face and voice recognition are obtained as 3%, 3.4% and 1.5% from this experiment respectively. Imran et al. [16] has presented the score level fusion of palm and face modalities using weighted sum rule for different algorithms (PCA, FLD and ICA). The results showed that the performance of fusion of face and palm with ICA, FLC and PCA are 75.52%, 73.69% and 66.60%, respectively. In additional, Ramli et al., [36] used the weighting factor for combination of audio and visual scores and the min-max normalization technique in fusion scheme to determine the performances of speech based biometric systems at different levels of signal to noise ratio i.e. clean, 30dB, 20dB and 10dB. The results show the EER performance of the integration system in clean, 30dB, 20dB and 10dB SNRs are observed as 0.0019%, 0.0084%, 0.9356% and 5.0160%, respectively compared to the EER performances of 1.1599%, 2.5113%, 19.3423% and 39.8649% for audio only system.

The second approach of weighting in fusion scheme is an adaptive weighting where the fusion weight is adaptable according to the current system condition. Two methods which are reliability estimation and reliability information can be applied in an adaptive weighting. The reliability estimation is performed either relying on the statistic-based measure or directly based on the quality of signal. Two methods have been proposed for the statistics based reliability measure i.e. entropy of posteriori probabilities and dispersion of posteriori probabilities. In the quality of signal, the weight for fusion scheme is adapted corresponding to the quality of the current input signal instead of using the optimum weight estimated from the available training set. On the other hand, the reliability information can be obtained by the shape of posteriori probabilities [37].

Study on the adaptive weighting can be found in Gurban and Thiran [38] where the audio visual phonetic classification accuracy using GMM entropy has been studied and 54.44% accuracy has been achieved. In another research, the entropy of a posteriori probabilities using MLP states has been applied [17]. The reliability information can be obtained by the shape of a posteriori probabilities distribution of HMM states and the results showed that the audio visual speech recognition performance at 10dB SNR using inverse entropy and negative entropy are obtained as 93.35% and 94.30%, respectively. According to Soltane et al. [39], GMM based Expectation Maximization (EM) estimated algorithm for score level data fusion based on face and speech modalities is proposed. The database obtained from eNTERFACE 2005 contained 30 subjects was used for the experiments. The result shows that EER performance for face and voice are 44.94% and 2.690% respectively. In order to reduce the EER performance for face mode, the combination of face-voice with different weighting has been applied. The result shows that combination of face-voice is able to reduce the percentage of EER to 8.73%. Kisku et al. [29] presents a robust feature level fusion technique of fingerprint and ear. In this paper, the reliability of each fused matching score has been increased by applying adaptive Doddington's user- weighting scheme. The proposed adaptive weighting scheme is to decrease the effect of imposter users rapidly. In this scheme, the adaptive weights has been computed by using tan hyperbolic weight for each matcher by assigning weights to individual matching scores. The identification rate for the proposed system are obtained as 98.71% while that for fingerprint and ear biometrics are found as 95.02% and 93.63%, respectively.

The comparison of fixed weighting and adaptive weighting can also be found in Lau et al. [40]. This paper presents a multibiometric verification system that combines speaker, fingerprint and face biometrics and fusion has been done in score level using GMM entropy. Their respective equal EER are 4.3%, 5.1% and the range of 5.1% to 11.5% for matched conditions in facial image capture. Fusion by majority voting gave a relative improvement of 48% over speaker verification. In another experiment, a fixed weight is assigned to each biometric trait. The weights are varied within the [0,1] range in steps of 0.1 to find values that gave the best performance. There is an improvement of 52% additional relative improvement of 52%, which corresponds to EER range of (0.50% and 0.84%). The weighting for each biometric has then been adjusted by using the fuzzy logic framework in order to account the external conditions that affect verification, such as finger position, facial geometry and lightning conditions. The result shows fuzzy logic fusion generated a further improvement of 19% which corresponds to an EER range of 0.31% to 0.81%.

V. CONCLUSION

Multibiometric systems are expected to alleviate many limitations of biometric systems by combining the evidence obtained from different sources using an effective fusion scheme. In this paper, the sources of biometric information were presented. The description regarding the level of fusions was also presented in this paper. From the study, it reveals that, performance of multibiometric systems can be further improved if an appropriate fusion strategy is used especially for the system which executed in uncontrolled environment. Hence, a different weighting in fusion is applied to maximize the performance of multibiometric system. Based on the review, the most promising recent research that can be implemented is fusion at the score level involving adaptive weighting. This approach have great potential to get rid the uncertain problem such as noise in sensed data, non-universality, upper bound on identification accuracy and spoof attacks.

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