Review on Fusion Algorithms for Multimodal Authentication System

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Abstract - **Technological revolution in this world is spreading so far that it has replaced knowledge based and token based recognition systems with biometric systems. These systems accurately recognise/authenticate an individual to access his confidential data/accounts. When multiple traits are fused together, it results into highly accurate multimodal systems. This system improvise rate of recognizing an individual. Multiple biometric traits cannot be cloned simultaneously and hence it is highly secured system. The match scores of different persons are sufficient enough to recognise them and differentiate them from each other. The match scores do not require higher storage capacity as well as higher computational complexity. Hence, match score fusion is highly preferable to recognize an individual. This paper therefore reviews algorithms for fusion at match score level with various state of arts namely linear weighted sum rule (LWSR), product rule, majority voting rule, Support vector machine (SVM), Bayesian fusion, fuzzy rule method, etc. The improved performance of fused system is observed from its Receiver Operating Characteristic (ROC) curve. It has been observed that for these methods, TER of a fused system decreases and the GAR of fused system increases i.e. recognition performance of fused system is better as compared to unimodal systems. LWSR is a linear hard decision rule based method. In almost all practical applications nonlinearity exists in scores of different models. So classification based systems are used for fusion. The recognition performance of RBF based QP SVM system is higher as compared to other kernel based systems i.e. GAR of RBF fused system increases and is better as compared to other kernel based QP SVM systems. Classification based methods like SVMs result into higher amount of recognition rate of almost as compared to rule based methods like LWSR.**

Keywords - **multibiometric systems; rule based methods; classification based methods;LWSR; SVM**

I. INTRODUCTION

Security has become an important aspect for each and every individual in this technological revolutionary world. As the technology grows humans are getting more and more insecure for their personal confidential belongings.

Nowadays, ATM pins are stolen and money in bank accounts is being stolen through internet. Thus there is a need of developing such systems whose password is a possession of the physical or behavioral part of a person's own body. Hence the motivation for this research is to develop a security system that comprises of multiple biometric traits as a password for the system [1 2 3].

Biometric traits are the unique distinctive measurable descriptors for every individual [1]. Any recognition system requires unique descriptors being presented by the individuals at the time of accessing any confidential data. There are mainly three types of descriptors viz. (1) token based descriptors as for example passport, driving licence, voter card, etc. (2) knowledge based descriptors as for example password, personal identification number (PIN), etc. and (3) biometrics based descriptors as for example face, fingerprint, iris, etc. In a token based as well as knowledge based systems identities can easily be spoofed by an intruder. Biometric traits are unique possessions of every individual so they cannot be easily spoofed by an intruder. Hence, biometric based descriptors are widely replacing other two descriptors because of their uniqueness, distinctiveness and secured characteristics. Biometrics that are feasible for authentication systems are fingerprints, face, vein patterns, iris, retina, ear, gait, hand geometry, voice, keystroke patterns and signature[1 2 3]. A particular person consists of N number of biometrics within itself. So which biometric trait must be chosen for a particular system should be chosen poses a serious question to think about. So authors in [4] have defined seven criteria for the selection of a biometric trait. The comparison of several biometric traits based upon these factors is given in table I. In table I, 1 stands for good characteristic, 3 stands for bad characteristic and 2 stands for neither a good nor a bad characteristic. In this table, a=universality, b=uniqueness, c=Permanence, d=Measurability, e=Performance, f=Acceptability and g=Circumvention. From table I, it is clear that one needs to always have trade off in these characteristic so as to have a particular biometric. As can be seen from table I, biometrics can be relied upon are face, fingerprint and iris.

Table I. Comparison of biometric traits [4]

Criteria / Biometrics	A	B	C	D	E	F	G
Face	1	3	2	1	3	1	1
Fingerprint	2	1	1	2	1	2	2
Hand geometry	2	2	2	1	2	2	2
Iris	1	1	1	2	1	3	3
Retina	1	1	2	3	1	3	3

Voice	2	3	3	2	3	1	1

Any biometric system generates two types of scores in matching phase viz. a genuine score and an impostor score. A genuine matching score is generated when two feature vectors corresponding to the same individual are compared, and an impostor matching score is generated when feature vectors from two different individuals are compared [4]. Matching stage generates either a distance score or a similarity score. For a biometric system, similarity score if calculated must be high for the genuine person and distance score must be low for genuine person and vice versa. After the matching phase different threshold points are taken and depending upon the score values, different metrics are calculated so as to evaluate the performance of a biometric system. The evaluation about the performance of a biometric system is done from metrics such as False Acceptance Rate (FAR), False Rejection Rate (FRR), Genuine Acceptance Rate (GAR), Equal Error rate (EER), Total Error Rate (TER) and Receiver Operating Characteristic (ROC) curve as descripted below [4]. **False Acceptance rate (FAR):** FAR is the measure of extent of falsely accepted individuals by a system [4]. **False Rejection Rate (FRR)**: FRR is the measure of extent of falsely rejected individuals by a system [4]. **Genuine Acceptance Rate (GAR):** It is an alternative metric for FRR used to measure performance of a system.

GAR=1-FRR

Receiver operating characteristic (ROC): ROC plot is a visual characterization of the trade-off between the FAR and the FRR. In a ROC plot when the value for threshold increases corresponding FAR increases and FRR decreases. So a system must be chosen such that both the error values are optimal which will be obtained at EER. Thus, in developing a biometric system mostly EER value is taken where FAR=FRR and corresponding value of t_h is chosen as optimal value. The ROC plot can also be visualised as a plot of FAR vs. GAR, with varying threshold values. From this plot, the system that yields the highest GAR corresponding to the lowest FAR is accurate one. Thus there is always a trade off between selection of FAR and FRR/GAR for a particular biometric system. **Equal Error Rate (EER):** The rate at which both accept and reject errors are equal is known as EER. The value of the EER is obtained from the ROC curve. The EER compares the accuracy of system with different ROC curves. In general, the system with the lowest EER is most accurate.

The whole research work comprises of 4 sections. Section I comprises of introduction about biometric systems. Section II consists of literature review about different levels of fusion. Section III reviews about various rule based techniques and classification based techniques used for fusion at match score level discussed in detail. Section IV concludes that Linear Weighted Sum Rule (LWSR) and Support Vector Machine (SVM) are the most efficient fusion techniques.

II. FUSING MULTIMODAL SYSTEM

Most of the biometric systems employed till date are unimodal in nature but the use of a single biometric for security applications is inefficient in nature. So in order to develop an efficient biometric system multiple sources of information should be used [4 5]. A multimodal biometric system is more reliable due to the presence of multiple independent traits of individuals. Multimodal biometric system overcomes the problem of non-universality, noise in sensed data and spoofing [4 5]. A multi-modal biometric system relies on the evidences presented by multiple sources of biometric information. Multimodal system offers a substantial improvement in the matching accuracy of a biometric system depending upon the information being combined and the fusion methodology adopted [4]. The number of traits to be used in a specific multibiometric application is decided by various factors such as the cost of deployment, enrollment time, expected error rate, etc [4 5].

In order to develop a multimodal system, several unimodal systems need to be fused. Fusion in biometric is very important task which needs to be carried out with utmost care else the multimodal system so constructed will result in degradation of its performance. There are generally three levels of fusion namely feature level, match score level and decision level defined based on the type of information needed to be fused [4, 5]. The amount of information available for fusion reduces drastically once the matcher has been invoked. Classification of different levels of fusion is shown in figure 1.

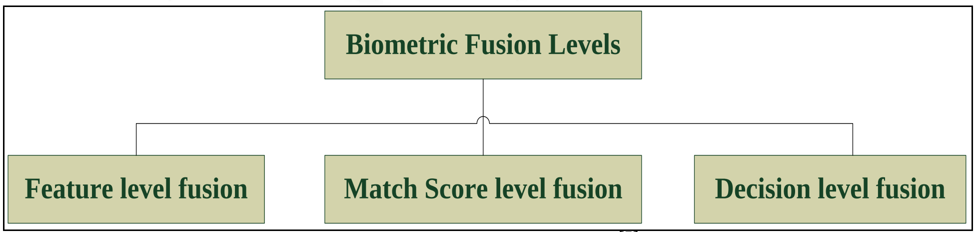

Figure 1 Levels of Fusion [5]

1. Feature-level fusion:

The data obtained from each sensor is used to compute a feature vector. As the features extracted from one biometric trait are independent of those extracted from the other, it is reasonable to concatenate the two vectors into a single new vector [5]. The new feature vector now has a higher dimensionality and represents a person's identity in a different hyperspace.

2. Score-level fusion:

Each system provides a matching score indicating the proximity of the feature vector with the template vector. In score-level fusion the match scores output by multiple biometric matchers are combined to generate a new match score that can be subsequently used by the verification/identification modules for an identity decision as shown in figure 3. These techniques attempt to minimize/maximize the FRR/GAR for a given FAR [1-5].

3. Decision-level fusion:

Each sensor can capture multiple biometric data and the resulting feature vectors individually classified into the two classes - accept or reject. A majority vote scheme, such can be used to make the final decision.

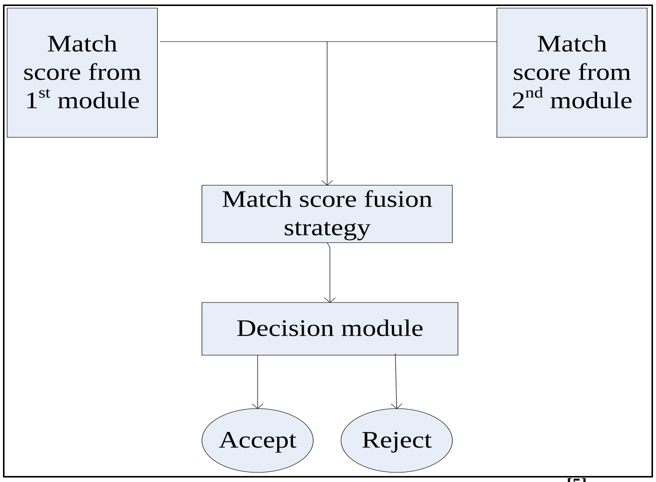

Figure 2 Fusion at the Matching score level [5]

Feature level fusion schemes typically require the development of new matching techniques thereby introducing additional challenges. Fusion at the feature extraction level results in large dimension, redundant and incompatible feature templates. Fusion at the decision level is considered to be the vague due to the lack of information content. Thus the fusion at match score level is carried out which contains sufficient amount of information to distinguish an individual. The feature template of an individual model is of a larger size. After fusing the feature templates of different models, the computation of matching scores and decision making results in higher computational requirements. Also, the feature templates may not be compatible with each other. The match score is a single numeric representation of an individual's identity. Thus the decision making of such a system when fused at match score level requires comparatively less computation as compared to fusion at the feature level. There are two types of match scores genuine and an impostor score. A genuine score is computed when a feature template of an individual is matched with its own database stored template. An impostor score is computed when a feature template of an individual is matched with the templates of all other users stored in the database. Fusion at the match score level includes fusion of matching scores of individual models which are homogeneous or can be made homogeneous using normalization methods [5, 7-9]. Thus, it is the most popular technique used because of its simplicity and easy availability of the scores and contains sufficient information to recognise an individual.

III. Algorithms for Match Score Level Fusion

Match scores are easily generated and hence this level of fusion is widely used due to its simplicity, less storage requirements and lower computational complexity. Match score level fusion is carried out using [5, 8, 9] two broad categories of methods i.e. (a) rule based fusion and (b) classification based fusion as shown in figure 3.

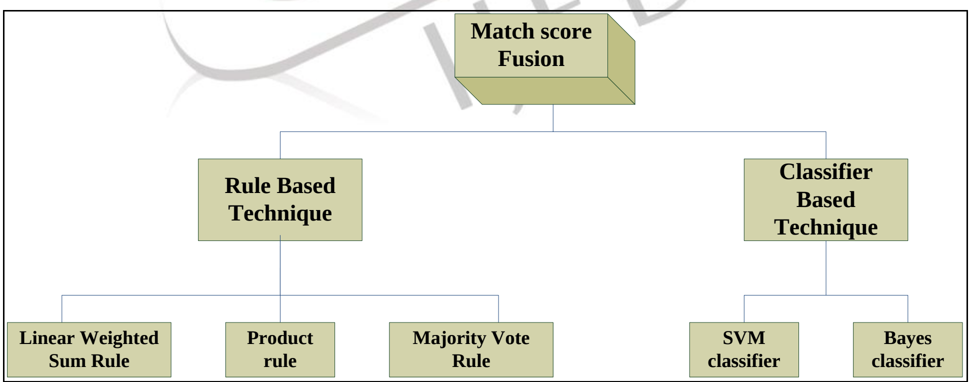

Figure 3 Methods at the Match score level [8]

Rule based fusion consists of several methods such as sum rule, product rule, weighted sum rule, min rule, max rule, t-norms, fuzzy rules, etc. Classification based fusion consists of methods such as Support Vector Machine (SVM), Bayesian classifier, neural networks, C 4.5 decision tree, Linear Discriminant Analysis (LDA), etc. Match score level fusion involves integration of matching scores from several unimodal biometric systems. Algorithms\techniques for fusion at match score level for multimodal system involve rule based fusion and classification based fusion techniques. Integration of scores from several unimodal systems is carried out by defining a fixed rule on the scores in rule based fusion technique. This rule based fusion involves methods such as sum rule, product rule, linear weighted sum rule (LWSR), min rule, max rule, fuzzy rules, majority voting rule, etc. Normalisation techniques are used on scores from individual biometric models before applying rule based fusion technique. Normalisation scales the score set and transforms them to common domain for compatibility of individual biometric models.

There are several score normalisation techniques available viz. min-max method, decimal scaling, z-score method, tanh method, double sigmoid method and MAD Median rule. Min-max normalisation is the simplest algorithm that only involves finding the minimum and maximum scores generated by a specific biometrics matcher [8]. To use Z-score normalisation, the score distribution's mean μ and standard deviation σ must be found in advance. Such prior knowledge can only be estimated from a training set and it is sensitive to outlier [8]. Tanh normalisation is also sensitive to outlier [8]. Median and Median Absolute Deviation (Median and MAD), which uses the median of the biometrics score distribution is less affected by outliers than the Z-score and Tanh method [8]. However the risk of this normalisation is that once the normalised score is a Gaussian distribution, it cannot be normalised effectively. Double Sigmoid normalisation requires careful tuning of the t, r_1 and r_2 to choose the region with linear mapping characteristic [8]. Here t is the reference point, r_1 and r_2 denote the left and right edges of the linear mapping region. The scores outside this linear mapping region are transformed non-linearly to increase the separation of genuine user and impostor score distributions [8]. All normalisation methods have been compared based upon their original distribution retaining property, how much sensitive they are to outliers and whether they map the scores to a common range or not. Summary about the comparison of all these methods is given in table II. In this table II, Y stands for yes and N stands for no.

Table II Comparison of normalisation methods [8]

No normalisation methods	Properties	Distribution Retaining Property	Sensitivity property	Common range mapping property
Min max		Y	Y	Y
Z score		N	Y	N
Tanh		N	N	Y
Median and MAD		N	N	N
Double sigmoid		N	N	Y

The developer of the multimodal biometric system always has to trade off in these three properties in order to choose a particular normalisation technique for mapping of scores. From table II, it is clear that min max method is the only method which retains its original distribution before and after the normalisation. Also, for effective fusion mapping of scores from different modalities to a common domain is necessary. The property of mapping to common range is satisfied only by Min-max, tanh and double sigmoid method. But tanh and double sigmoid methods do not retain their original distributions after normalisation. Hence, even though the min-max normalisation is sensitive to outliers but it still retains the original distribution of scores and also maps the scores from different models to a common range.
After normalisation of scores is completed, the unimodal systems now become compatible with each other and hence they can be integrated or fused at this level. Several rule based techniques are applied to these scores.

Sum rule:
Sum rule combines the biometric scores corresponding to a particular individual by applying sum rule on the scores that come for fusion. Mathematical representation for the sum rule is given in equation 1.

$$S_f^{'} = S_1^{'} + S_2^{'}$$

Where, S_f' is the fused score and S_1' and S_2' are the normalised scores of 1st and 2nd biometric models respectively.
Sum rule is very simple and computationally efficient. All biometric models are given equal importance i.e. all biometric traits to be fused are considered to be of equal importance.

Product rule:
Product rule combines biometric scores corresponding to a particular individual by applying product rule on the scores that come for fusion. Mathematical representation for the product rule is given in equation 2.

$$S_f^{'} = S_1^{'} * S_2^{'}$$

Where, S_f' is the fused score and S_1' and S_2' are the normalised scores of 1st and 2nd biometric models respectively. Product rule is very simple and computationally efficient. When multiple representations of a single biometric are available for fusion then product rule performs better than sum rule.

Min rule:
Min rule combines biometric scores corresponding to a particular individual by selecting minimum of the scores that come for fusion. Mathematical representation for the min rule is given in equation 6.

$$S_f^{'} = \min(S_1^{'}, S_2^{'})$$

Where, S_f' is the fused score and S_1' and S_2' are the normalised scores of 1st and 2nd biometric models respectively. Min rule is very simple and computationally efficient. This rule forces the score of only one biometric model to be used for fusion. Thus it is not a robust technique to be used for efficient fusion.

Max rule:
Max rule combines biometric scores corresponding to a particular individual by selecting maximum of the scores that come for fusion. Mathematical representation for the min rule is given in equation 4.

$$S_f^{'} = \max(S_1^{'}, S_2^{'})$$

Where, S_f' is the fused score and S_1' and S_2' are the normalised scores of 1st and 2nd biometric models respectively. Max rule is very simple and computationally efficient. This rule also forces the score of only one biometric to be used for fusion. Thus it is not a robust technique to be used for efficient fusion.

Linear Weighted Sum Rule (LWSR):

There are two types of biometric systems one is a weaker biometric system and other is a stronger biometric system. A biometric model with lesser amount of EER is said to be a stronger biometric as compared to other biometric model. In almost all practical fusion applications that involve fusion of two or more biometric models, all of these models have different EER values. In [5] all the models were assigned equal weights. But in real time applications the biometric models need to be weighted according to their EER values. A stronger biometric model must be assigned higher weight as compared to weaker biometric model.

Thus several weight assignment strategies are proposed in literature for effective fusion in a multimodal system [8].

Equal Error Rate Weighting Strategy:

Each biometrics Equal Error Rate, EER, is used to weight their contributions [8]. Biometrics with higher EER is assigned with lower weight.

D-Prime Weighting Strategy:

Each biometrics genuine and impostor scores separation, d' is used to weight their contributions [8]. Biometrics with higher d' *is* assigned with higher weight.

FAR/FRR Weighting Strategy:

False Acceptance Rate (FAR) and False Rejection Rate (FRR) values are threshold dependent, therefore a training section is required for different operating point to find these parameters [8]. The biometrics with lower FAR/FRR is assigned with higher weight.

LWSR Weighting Strategy:

The biometric model with lower value of FAR is assigned higher weight [17].

The weighting method based on EER degrades badly when used with two different models while method based on score distribution degrades as modality is increased [17]. As values of FAR and GAR are governed by threshold, if there is change in threshold then there is corresponding change in weights and hence method in [17] not only assigns a weight efficiently but also adaptively changes the weight based on values of FAR and GAR [17].

From all these techniques that has been studied above, widely employed techniques are sum rule, product rule and majority voting rules [5,6,8,10,11,12,13,14,15,16]. The literature survey of all this rule based methods has been summarised in table III. In Table III, S_u is for sum, P_r is for product and M_v is for majority voting. This method of fusion is simple, computationally efficient and no training session is required [5, 8, 9]. It can be observed that product rule performs better than sum rule when multiple representations of a single biometric are available for fusion. When product rule is used with two different biometric modalities, then sum rule outperforms product rule as can be seen in [11]. Thus, product rule is well suited for multi-sample systems. Majority voting rule depends upon individual matchers output. Thus, majority voting rule is suitable for multi-algorithmic systems i.e. multiple classifiers for a given single trait. In [11] sum rule outperforms product rule as well as majority voting rule when these methods are used with different biometric traits.

A common theoretical framework for combining classifiers is developed in [10] using various combination schemes, e.g. Product, Sum, Min, Max, Median rules and Majority Voting are compared. In [10] Kittler proved that sum rule outperforms all other rule based techniques as it is dependent upon error rates of individual systems. The effectiveness of the Sum rule is further justified by Ross and Jain's research in [5].The authors in [5] have used equal weights for all the three models and concludes that this fusion rule outperforms the complicated Decision Trees and the Linear Discriminant Analysis (LDA) fusion methods. Thus, sum rule is simple, efficient and robust as compared to product rule and majority voting rule.

Table III Literature review of rule based methods

Method	Biometric employed
Product rule	
	Ear and profile face ($S_u > P_r$) [11]
	Face($P_r > S_u$) [12]
	Face ($P_r > S_u$) [13]
	Hand shape and palmprint ($P_r > S_u$) [14]
	Palm print ($P_r > S_u$) [15]
Majority voting rule	Ear and profile face ($S_u > M_v$) [11]
Sum rule	face, fingerprint and hand geometry [5]
	3D face and hand biometrics [6]
	Face and Fingerprint [8]
	Face and speech [10]
	Ear and profile face ($S_u > P_r > M_v$) [11]
	Iris and ear (S_u) [16]

LWSR does not require any training session for its implementation. Hence it is less time consuming and computationally efficient. Fusion using sum rule and LWSR results in higher performance of a multi-modal system as compared to other methods. Thus, LWSR fusion is widely used rule based fusion technique as it is computationally efficient, simple and robust. Classification based methods treats the scores from different biometric models as feature vectors. This category of fusion involves various classifier techniques such as Support vector machines (SVM), Bayesian classifier, neural networks, decision trees, Linear Discriminant analysis (LDA) etc. for fusion of scores. The fusion in this application is therefore viewed as a classification problem. A classifier is used to construct a separation boundary between the genuine user and impostor in a verification system

[8]. The classifier used for this purpose includes K Nearest Neighbours, Decision Trees, Neural Networks, Support Vector Machine, etc. [8].

For KNN classifier method, no advance training session is required. By referring to the distances from the testing sample to *k* nearest reference points, the sample is then assigned to the category that has the majority of nearest neighbours [8]. Although no training session is required, the distances from the testing sample to all the reference points have to be found and hence this process is time-costly.

Decision Tree method categorises the biometric samples according to a series of tests on a specific attribute of the data [8]. These hierarchical tests lead to a particular class. Each of the tested attributes is found based on maximising the information gain at the particular node. This method has the advantage that it provides direct insight into the predictive structure [8]. However, it is very sensitive to small changes in the dataset [8]. Well-known C4.5 classifier is devised by Quinlan [8]. This is the most widely employed Decision Trees algorithm as is used in [5].

Another classification method that can be used for biometrics fusion is Artificial Neural Network (ANN). An ANN is composed of many artificial neurons that are interlinked by synaptic connections [8]. Each of these connections is assigned with some synaptic weights. To train an ANN the weights are adjusted according to the error between the predicted and actual outputs. This process is performed mostly by a back-propagation algorithm. These weights and the relative biometric scores are then used by a function to transform this information into a meaningful output [8]. The Multilayer Perceptron (MLP) and Radial Basis Function are two commonly used transform function in the literature [8]. MLP uses a linear transform function whereas the RBF uses a non-linear one. In [8], it is commented that RBF is preferred because their experiment shows better fusion performance than MLP and RBF kernel can learn from genuine user as well as impostor samples [8].

K Nearest Neighbours, Decision Tree and ANN operating thresholds are not adjustable because their output is not a score but a class label, which is threshold independent [8]. Although Support Vector Machines and Discriminant Analysis operating thresholds are also non-adjustable, these algorithms can be modified to generate a score value but not a class label [8]. So a threshold can be used to classify these biometrics samples associated with confidence value.

The fusion therefore is viewed as a classification problem. A classifier is used to construct a separation boundary between the genuine user and impostor in a verification system. In the biometrics fusion problem for verification (two class classification problem), given a set of training samples, a Support Vector Machine constructs a separation boundary so the distance from it to the nearest data points which are termed as support vector on each side is maximised. Such a classifier is a linear classifier. A non-linear Support Vector Machine can be built by applying this algorithm in a transformed feature space [18]. This feature space can be created through a kernel function to project the samples to higher dimensional space. Polynomial and Radial Basis Function kernels are employed in [18] for multimodal biometrics fusion problems. In [18], significant fusion performance difference is obtained by using the Polynomial and Gaussian kernel. Therefore it can be said to choose a suitable kernel function is the main challenge of this fusion approach. The SVM has been reported to have the best fusion performance in [8 18-26] compared to the methods including decision level fusion approach, Sum rule, K Nearest Neighbours, Decision Trees and ANN. Instead of using the output class label by SVM, the signed distance from the tested sample to the Support Vector Machine's separating surface can be used as output score [8]. Another classification based fusion uses Bayesian method as a classifier. First it transforms the scores of biometrics into probability densities. These probabilities can then easily be combined using the product rule. Unlike the scores used in rule based fusion, these densities can be applied directly without normalisation. Furthermore, provided that the underlying densities are known, the optimal fusion performance is directly achieved. Since this method is probability based, additional information (e.g. the probability based quality) that aids the fusion process can also be incorporated without having to modify the fusion algorithm. Some individuals might not possess certain biometrics or its measurements are not reliable. This causes Bayesian algorithm cannot be applied as sufficient input is not available. This missing data problem can also be easily solved in this fusion method. The work in [27] shows that biometrics quality can be easily incorporated for such fusion. They directly use the joint density modelling conditioned on the identity (genuine user and impostor) and biometrics quality. This is modelled by using Gaussian, Gamma, Log-normal or beta distribution. These joint densities are applied in their developed Bayesian Belief Network (BBN) which is shown to outperform the Sum fusion rule.

Bayesian networks get confused when mutually exclusive hypothesis are used for fusion [9]. As for example Bayesian networks cannot distinguish between fuzzy fast walking and slow running [9]. Bayesian networks cannot handle both events with same probabilities and hence it gets confused. As for example, if in a gesture recognition system sign of two fingers will confuse the system whether it is a victory sign or a count of 2.

The disadvantage of Bayesian networks over Support vector machine is that if the underlying probabilities of the scores are not known or not properly estimated then the classifier may be inefficient to provide the proper classification of individuals [9]. For effective multimodal fusion, Support Vector Machines algorithm is modified to generate a score value but not a class label [8]. So a threshold is used to classify these biometrics samples associated with score value. In Bayesian classifiers such score values cannot be calculated and hence it can be used as a classifier and not a fuser.

IV.CONCLUSION

Multimodal biometric system results in more secured and accurate applications. As can be seen from the simulation results, the performance of a fused model is more efficient as compared to that of individual modalities.

When the qualitative weight assignment is done using the proposed method based upon the EER and GAR values of the individual modalities the resulting performance of the fused model using LWSR outperforms the performance of individual modalities. The model with the lowest value of EER is assigned higher weight. From the ROC curve it is clearly observed that the total error rate for the fused model reduces to a much greater extent as compared to total error rate of individual modalities as well as the GAR of fused system increases as compared to individual models. Thus, it is observed that the performance of a fused model will be high as compared to individual models i.e. more genuine acceptance is accomplished by a fused model. Rule based methods like LWSR are hard decision methods whereby a fixed rule has to be applied on scores from different models in order to develop a multimodal system.

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