Neuro-Fuzzy Logic Decision in a Multimodal Biometrics Fusion System

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Abstract :

Verification using biometrics has become in the last few years a key issue in security and privacy. Intensive search is being focusing on improving verification performance and quality by fusing multi biometric modalities. Several fusion techniques have been proposed in the current literature. This paper proposes hybrid artificial intelligent tools such as neuro-fuzzy systems for their powerful capabilities of learning and fuzzy expression to insure high quality of verification through multi-modal biometrics fusion. Experimental investigation under various data conditions reveals outstanding results over existing fusion techniques.

Keywords:

Multi-modal biometrics fusion, score-level fusion, neuro-fuzzy systems, biometric verification.

1. INTRODUCTION

Verification of individuals is key issues in security. Biometrics have proven their efficiency over conventional recognition techniques, especially when multiple modalities are involved. It has been reported that the most appropriate and effective approach to multimodal biometrics is through the fusion of data at the score level [Indovina, *et al.*, 2003]. To date, a number of score-level fusion techniques have been developed for this task [Rodriguez, *et al.,* 2008; Sanderson and Paliwal, 2004]. These range from the use of different weighting schemes that assign weights to the information streams according to their information content, to support vector machines which use the principle of obtaining the best possible boundary for classification, according to the training data.

Due to the advantages offered by the fuzzy logic techniques as well as neural networks for enhancing the recognition accuracy in the field of multimodalities , the discussions are focused on these types of fusion techniques.

Several approaches are proposed in the current literature to improve biometrics fusion using fuzzy logic. A fuzzy system has been proposed to dynamically alter the weight of three biometrics taking into account the variations during data acquisition [Hui *et al.,* 2007]. Another study [Lau *et al.,* 2004] uses a fuzzy logic decision fusion of three biometrics based on majority vote. In [Rodrigues et al., 2009], the likelihood ratio based fusion scheme and the fuzzy logic for fusion have been proposed. Another study by [Lee *et al.,* 2004] proposes a fusion scheme that uses fuzzy linear discriminant analysis (LDA) method for the face recognition. It is an expanded version of the Fisherface method using the fuzzy logic which assigns fuzzy membership to the LDA feature values.

On the other hand, neural networks has also been introduced into the field of multimodal biometrics. A Multi-Layered Perceptron for integrating face and voice data has been used in [Czyz *et al.,* 2003]. The results of the study showed that using Multi-Layered Perceptron as the fusion process has led to considerable improvement. Another study [Alsaade *et al.,* 2009] proposes a method that combines neural networks and genetic algorithms to enhance fusion performance. The study demonstrated that the capabilities provided by such combination can significantly improve the accuracy of fused biometrics.

This paper presents a hybrid approach to fuse biometrics scores. An Adaptive Neuro-Fuzzy Inference Systems (ANFIS) is used for fusion of multimodal biometrics (face and voice) and trained toward a decision level. The underlying idea of hybridizing is to take advantage of their mutual advantageous properties, respectively training, fuzzy expression, and global optimization. The proposed fusion technique is conducted on a sample data set of scores (XM2VTS, TIMIT, NIST and BANCA) and compared to two well known fusion techniques in the field of multimodal biometric fusion. These are Brute Force Search (BFS) and Support Vector Machine (SVM).

The rest of the paper is structured as follows. Section 2 describes the neuro-fuzzy hybrid systems. Section 3 describes the proposed model along with the experimental investigations, and the overall conclusions are presented in Section 4.

2. NEURO-FUZZY HYBRID SYSTEM

2.1 Overview

The neuro-fuzzy hybrid system combines the advantages of fuzzy logic system and neural networks [Rahmoun and Benmohammed, 1998; Rahmoun and Berrani, 2001]. The fuzzy logic system, in the proposed technique, deals with explicit knowledge that can be explained and understood. Whilst neural networks deal with implicit knowledge, which can be acquired by learning.

Neural networks and Fuzzy logic have some common features such as distributed representation of knowledge, model-free estimation, ability to handle data with uncertainty and imprecision. Fuzzy logic has tolerance for imprecision of data, while neural networks have tolerance for noisy data . A neural network's learning capability provides a good way to adjust expert's knowledge and it automatically generates additional fuzzy rules and membership functions to meet certain specifications. This reduces the design time and cost. On the other hand, the fuzzy logic approach possibly enhances the generalization capability of a neural network by providing more reliable output when extrapolation is needed beyond the limits of the training data.

The neuro-fuzzy system consists of the components of a conventional fuzzy system except that computations at each stage is performed by a layer of hidden neurons. In such system, the neural network's learning capacity is provided to enhance the system knowledge. It can be said that the basic idea behind the proposed neuro-adaptive learning technique is to benefit from the fuzzy modeling procedure to learn from data. This is used to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. The training uses the training schemes of the neural networks. For example, given an input/output data set, the ANFIS system generates a fuzzy inference system (FIS) whose membership function parameters are tuned. The training phase , in this paper, is performed using a backpropagation algorithm in combination with a least squares type of method [Rahmoun and Benmohammed, 1998; Rahmoun and Berrani, 2001]. The FIS is implemented in neural network structure which maps inputs through input membership functions and associated parameters, and then through output membership functions (mfs) and associated parameters to outputs. Consequently, the number of fuzzy rules will be limited by keeping only rule nodes with higher weights links; weak connections will be removed. Figure 1 illustrates general structure of an ANFIS with 2 inputs (face score/ voice score), 1 output (final decision).

The input layer in Figure 1 consists of two nodes, one for each biometrics score. Both are defined by five membership functions ranging as follows: very low, low, medium, high and very high of the form bell function uniformly distributed over the range (0,1). We construct all possible rules (combinations), each rule is a node which inputs are synaptic weights provided by the corresponding input score nodes to fuse. These weights are tuned during the training phase through the backpropagation algorithm. The training will generate the best-fit parameters for the fuzzy inference systems in terms of mfs parameters, number of rules and output values. The size of the rule base can be reduced drastically in some cases during training as mentioned earlier.

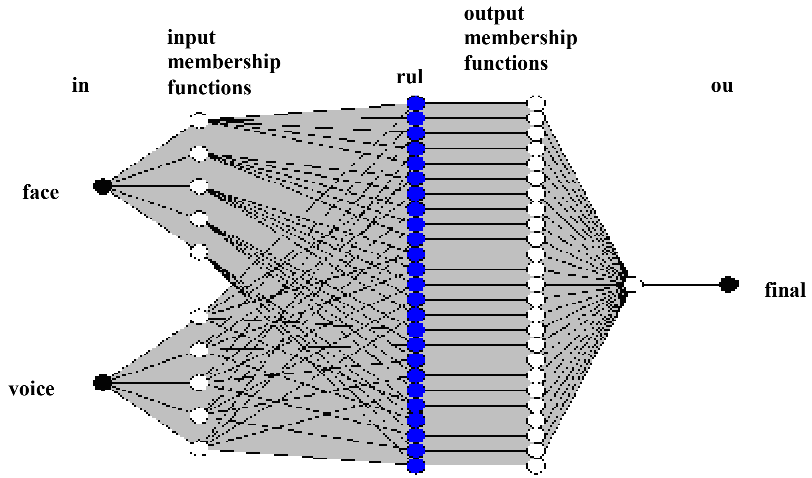

Figure 1: General structure of ANFIS with 2 inputs, 1 output.

The nodes of the hidden layer represent fuzzy rules, as for example:
If face score is very high and voice score is very high then fused score = constant.

The corresponding output for each rule will be either 1 or 0 depending respectively on whether the candidate should be accepted (client) or rejected (impostor).

As constraints for the proposed technique, ANFIS only supports Sugeno-type systems [Rahmoun and Berrani, 2001], and these must have the following properties:

- be first or zeroth order Sugeno-type systems,
- have a single output,
- obtained using weighted average defuzzification,
- all output membership functions must be the same type and either be linear or constant,
- have no rule sharing,

- different rules cannot share the same output membership function, namely the number of output membership functions must be equal to the number of rules, and
- have unity weight for each rule.

The proposed fusion scheme is illustrated by Figure 2 as follows:

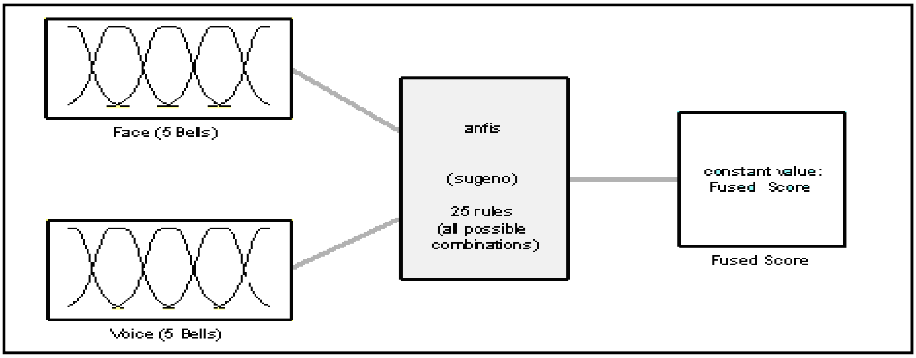

Figure 2: The proposed ANFIS structure.

The proposed algorithm is as follows:

1- Load data (face and voice biometric scores: development and test data).
2- Range normalize data using min-max method.
3- For each client, do the following three steps:
  - Generate an anfis structure.
  - Train anfis with development data forcing output to 1(decision).
  - Evaluate anfis output based on the test data of the indiviual modalities involved (face and voice) before the fusion process. The evaluation process is acheieved by computing EERs for the individual modalities involved.
4- Compute the EER for the fused scores.

3. EXPERIMENTAL RESULTS AND DISCUSSIONS

The experimental studies are concerned with the score-level fusion of face and voice biometrics. The modeling and pattern matching approaches used with each modality is not discussed here, as these are outside the scope of this paper. The investigations involve three different data conditions. The first two are formed by using scores for clean face images together with scores for either clean or degraded utterances. The third one is based on the use of scores for degraded face images and degraded utterances.

In each experiment, the individual biometric score types involved are subjected to the range equalization process using the Min-Max normalization

[Indovina, et al., 2003]. The process of score-level fusion for decision purpose is based on the use of adaptive neuro-fuzzy inference system. The procedures for speech feature extraction and speaker classification are as detailed in [Ariyaeeinia, et al., 2006 ; Fortuna, *et al.*, 2004]. The face recognition scores are based on the approach detailed in [Zafeiriou, *et al.*, 2006; Bengio, *et al.,* 2002].

3.1 Fusion under Clean Data Conditions

This part of the study investigates the efficiency of the proposed method of fusion and decision scheme in enhancing the reliability of multimodal fusion when the biometric datasets are free from degradation. The datasets considered for the face and voice modalities in this investigation are extracted from the XM2VTS and TIMIT databases respectively [Zafeiriou, et al., 2006; Alsaade, et al., 2005]. Using these biometric datasets, a total number of 140 client tests and 19460 (i.e. 140×[140-1]) non-client tests is used from the development data. While the total number of client and non-client tests used in investigating the performance for the proposed schemes is 140 and 19460 respectively.

The ANFIS structure is generated automatically with the following properties. Both range normalized biometrics scores are defined by five membership functions ranging from "very low" to "very high" of the form bell function uniformly distributed over the range (0,1) as shown in Figure 3.

The used fuzzy methods for the experimental implementation in this section are : the AND method is the minimum; the implication method is the product; and the aggregation method is the maximum. The Sugeno type is used with output member functions of linear type. The defuzzification method is centroid. The training scheme of the ANFIS, on the other hand, is performed using the backpropagation algorithm in combination with the least squares. The training is performed over 10 epochs, resulting in the following adjusted membership functions for both biometrics (Figure 4).

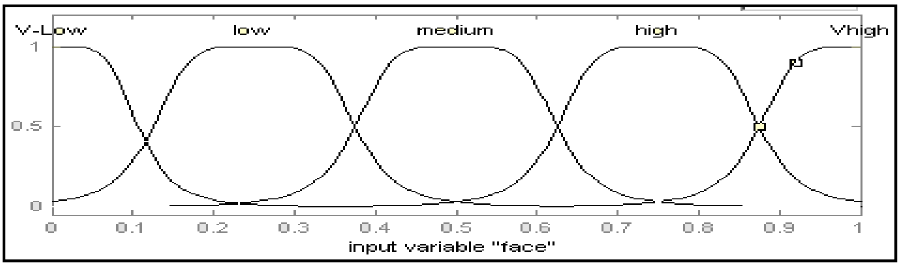

Figure 3: membership functions distribution over the range normalized scores.

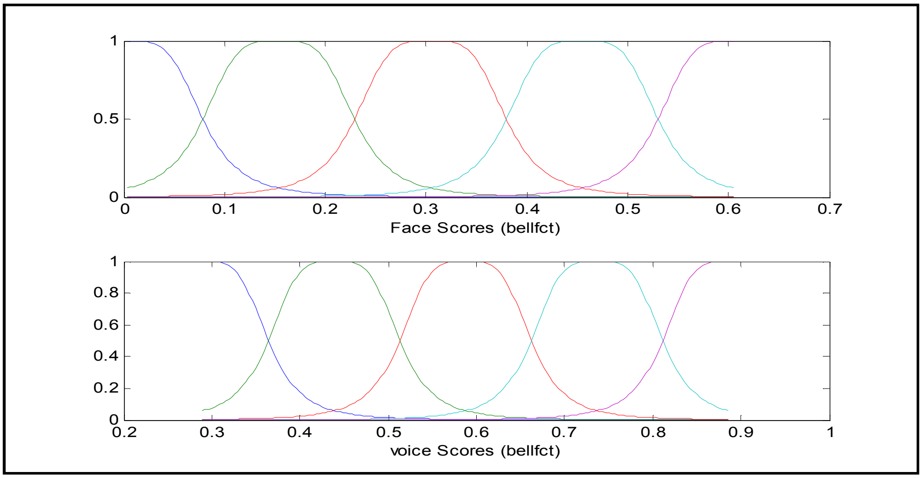

Figure 4: Membership functions for both biometric scores after tuning using ANFIS training.

Figure 5 shows the performance of the ANFIS acting as decision system when tested with test data. The pick value at the back corner in Figure 5 shows that only high scores for both biometrics can be accepted as "clients", others are "impostors". In order to clarify such situation, the paper presents two sample test cases. Sample test case 1: medium face score (0.58 for example) and high voice score (0.82), the decision output fused score is 0.87; it is "almost" accepted as being a "client" at 87%.

Sample test case 2: case where even with medium face score (0.55) and high voice score (0.72), the output decision score is 0; this is refuted as being a client.

The experimental results are presented as equal error rates (EERs) in Table 1. It is observed from the results in Table 1, that using ANFIS as a fusion scheme leads to better performance than the individual modalities and the other fusion methods (BFS and SVM). It is also noted that the use of ANFIS reduces the error rates of the fused scores to zero.

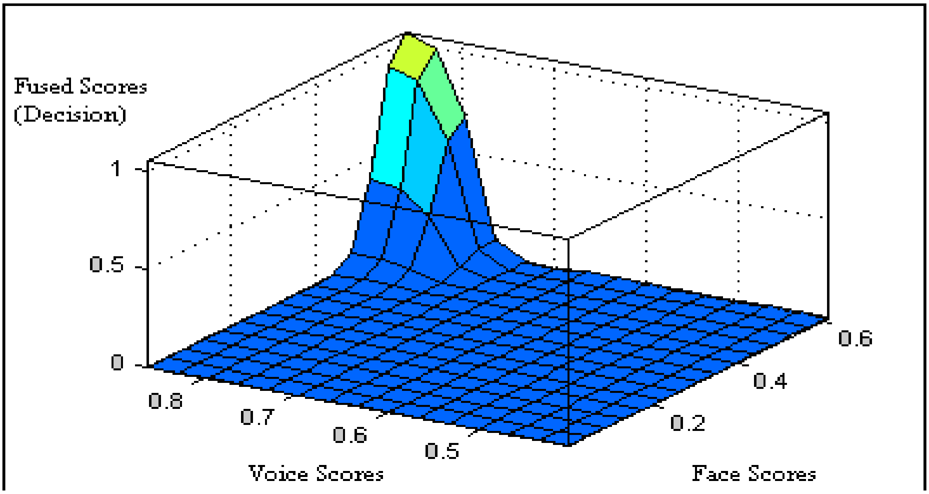

Figure 5: Surface view of decision output scores against inputs face and voice scores.

Table 1: Effectiveness of BFS, SVM and ANFIS in Multimodal biometric verification based on clean biometric data.

Modality	EER%
Voice (TIMIT)	2.55
Face (XM2VTS)	3.57
Fused: voice and face by BFS	0.05
Fused: voice and face by SVM	0.68
Fused: voice and face by ANFIS	0

3.2 Fusion under Varied Data Quality Conditions

The purpose of the experiments presented in this section is to investigate the usefulness of the ANFIS decision fusion scheme in multimodal fusion when the qualities of the biometric data types are considerably different. The datasets considered for the face modality in this case is the same as previous, and the voice modality is extracted from the 1-speaker detection task of the NIST Speaker Recognition Evaluation 2003 (degraded speech) database [Fortuna, *et al.*, 2004]. Using these datasets, again a total number of 140 client tests and 19460 (i.e. 140×[140-1]) non-client tests is used from the development data. While the total number of client and non-client tests used in investigating the performance for the proposed schemes is 140 and 19460 respectively. Furthermore, the same ANFIS structure is used to investigate the effectiveness of the method when one of the modalities is degraded. Figure 6 shows membership functions adjustments.

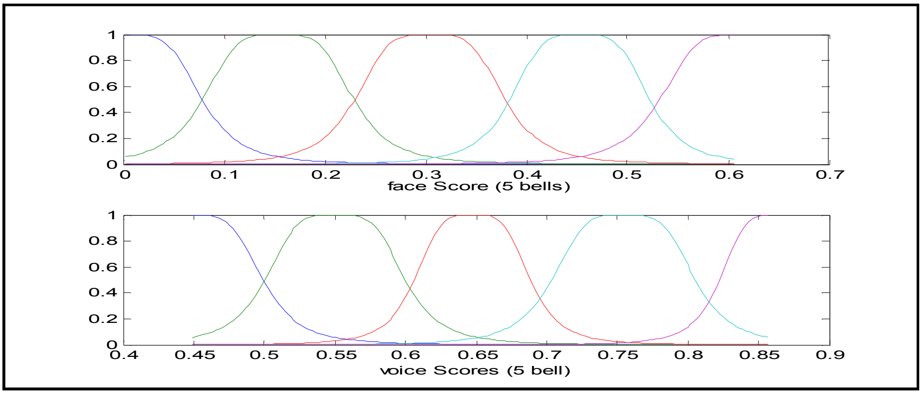

Figure 6: Membership functions for both biometric scores after tuning using ANFIS training.

Because of the highly degraded voice development data; distributions of low scores are further shifted to the right as a consequence of training. The experimental results for this part of the study are presented in Table 2. It can be observed that the fusion processes (BFS and SVM) outperform the best individual modality involved. For example, the use of BFS and SVM results in improvement of the EER associated with the better modality by about 14% and 18%. On the other hand, it is seen that the verification accuracy offered by the face modality (better modality) is increased significantly (by about 99%) through the use of ANFIS. The reason for such significant results offered by ANFIS is shown to be due to the characteristic of this fusion method. Such technique takes into account the statistical distribution of the modalities (in terms of fuzziness), and hence uses the best-fit fuzzy rules to generate the proper output (decision).The 'learning' capabilities (offered by neural networks) of such system makes this possible in combination with the power of expression of fuzzy rule and inferencing.

Table 2: Effectiveness of BFS, SVM and ANFIS in Multimodal biometric verification based on clean face and degraded voice data.

Modality	EER%
Voice (NIST)	31.43
Face (XM2VTS)	3.57
Fused: voice and face by BFS	3.06
Fused: voice and face by SVM	2.94
Fused: voice and face by ANFIS	0.005

3.3 FUSION UNDER DEGRADED DATA CONDITIONS

The aim of the experiments in this part of the study is to investigate the effectiveness of ANFIS fusion scheme in enhancing the reliability of multimodal fusion when the biometric datasets are contaminated. The datasets considered for the face and voice modalities in this investigation are extracted from the BANCA [Bengio, *et al.,* 2002] and the NIST Speaker Recognition Evaluation 2003 [Fortuna, *et al.,* 2004] databases respectively. Using these biometric datasets, a total of 26 subjects have been used for the experiments. The face recognition scores are obtained based on images captured in four sessions, and affected by two different forms of distortion [Bengio, *et al.,* 2002]. Based on these and the corresponding score data for NIST, a development score dataset is formed for the experiments. This consists of 104 client tests and 2600 (i.e. 4×{26×(26-1)}) non-client tests. While the total number of client and non-client tests used in investigating the performance for the proposed schemes is 104 and 2600 respectively. The ANFIS model uses 9 bell membership functions for both modalities. Notice for such case that the properties of membership functions are different than previous. Several tests have been performed to get the best results. The same ANFIS properties and training conditions are applied also in this case. Figure 7 shows the distributions of both score modalities after training (tuning).

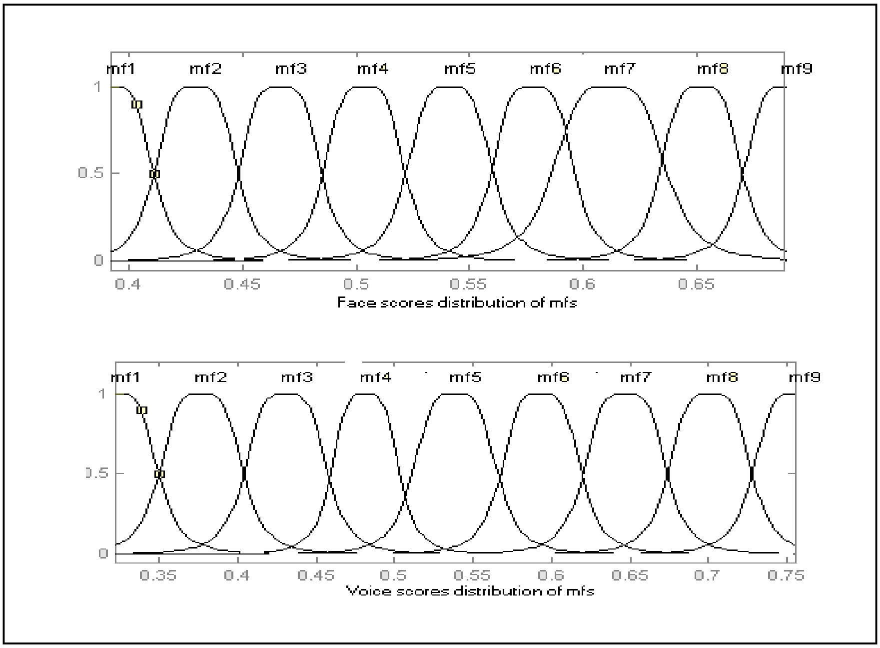

Figure 7: Membership function distributions for both degraded modalities .

The results of verification for this part of the study are presented in Table 3 as EERs.

Table 3: Effectiveness of ANFIS in Multimodal verification at a decision level based on clean face and degraded voice data.

Modality	EER%
Voice (NIST)	45.84
Face (BANCA)	50
Fused: voice and face by BFS	47.23
Fused: voice and face by SVM	39.09
Fused: voice and face by ANFIS	27.88

It is observed that even in the presence of highly degraded data, the ANFIS fusion scheme outperform BFS, and makes an improvement of performance of about 15% than the one obtained with the best single modality. Furthermore, as previous, the surface view of the ANFIS in Figure 8 reveals an acceptable 'behavior' of the decision system even in the presence of very degraded data scores.

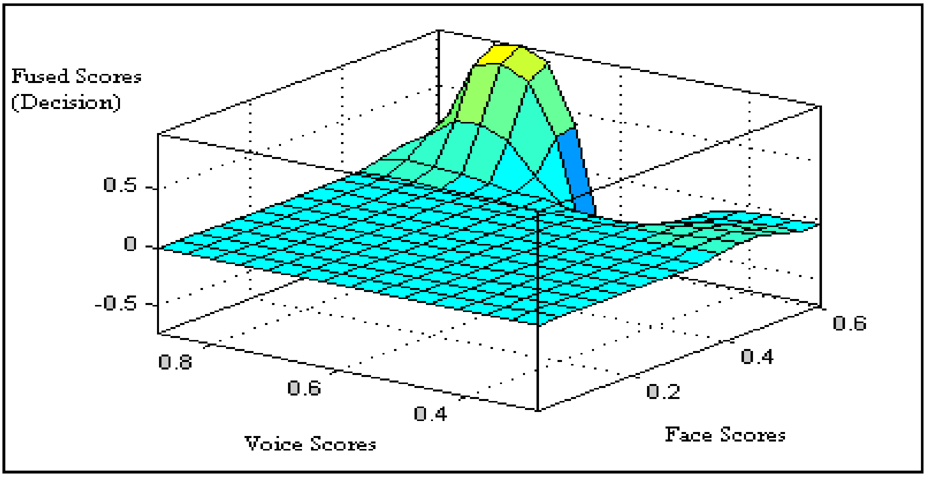

Figure 9: Surface view of the decision ANFIS in case of fusion under degraded conditions

Another important outcome of the experimental investigations can be observed by considering the results in all the tables shown above. From these results, it is clearly seen that in all three data conditions, ANFIS leads to the best performance compared to the other two fusion schemes (BFS and SVM). This is thought to be due to some reasons. ANFIS takes into account the statistical distribution of the modalities (in terms of fuzziness), and hence uses the best-fit fuzzy rules to generate the proper output (decision). The 'learning' capabilities of such system makes this possible in combination with the power of expression of fuzzy rule and inferencing.

4. CONCLUSION

This paper has presented a new fusion scheme that relies on neuro-fuzzy techniques. In order to investigate the effectiveness of the proposed approach, it was compared to well-known fusion techniques such as BFS and SVM. The experimental investigations have been carried out under three different data conditions. As expected in the three cases of data condition (for all modalities), the results have shown that the use of neuro-fuzzy scheme leads to the highest accuracy. This is shown to be due to the characteristics of this neuro-fuzzy hybrid system such that ANFIS takes into account the statistical distribution of the modalities (in terms of fuzziness), and hence uses the best-fit fuzzy rules to generate the proper output (decision). The 'learning' capabilities of such system makes this possible in combination with the power of expression of fuzzy rule and inferencing. However, the effectiveness of neuro-fuzzy techniques relies strongly on the parameter settings of the ANFIS structure and training conditions. Future work focuses on enhancing fusion multimodal biometrics performance. Efforts will focus on using GA-Based hybrid intelligent systems. Search and optimization capabilities of Genetic algorithms will certainly help automate the process of generating the best-fit settings for an Adaptive fuzzy inference system for fusion-decision purposes.

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استخدام Neuro-Fuzzy Logic Decision
في نظام دمج القياسات البيولوجية

فواز بن وصل الله الصاعدي

كلية علوم الحاسب وتقنية المعلومات - جامعة الملك فيصل

الأحساء - المملكة العربية السعودية

المستخلص :

التحقق باستخدام القياسات البيولوجية قد أصبح في السنوات القليلة الماضية قضية رئيسية في مجال الأمن والخصوصية. والبحث في هذا المجال مركز على تحسين أداء وجودة طرق التحقق من الأشخاص وذلك بدمج بعض من هذه القياسات البيولوجية مع بعض. هناك العديد من وسائل الدمج والتي بدورها طرحت للنقاش من خلال الدراسات الحديثة في هذا المجال. هذه الورقة العلمية تقترح أدوات ذكاء صناعي هجين مثل neuro-fuzzy systems لقدراتها القوية في التعلم والتي تضمن جودة عالية في عملية التحقق من الأشخاص من خلال استخدام عملية دمج وحدات القياسات البيولوجية. هذه التجارب والتي تمت باستخدام بيانات مختلفة الجودة (النوعية) أظهرت نتائج باهرة مقارنة بطرق الدمج الموجودة.

الكلمات الرئيسية :

دمج القياسات البيولوجية المتعددة - دمج على مستوى الدرجة - أنظمة عصبية ضبابية - التحقق من الهوية.