Decision Level Fusion by Clustering algorithms for Person Authentication

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ABSTRACT

In this paper, the use of clustering algorithms for decision level data fusion is proposed. Person authentication results coming from several modalities (e.g. still image, speech), are combined by using the fuzzy k-means (FKM) and the fuzzy vector quantization (FVQ) algorithms, two modification of them that use fuzzy data FKMfd and FVQfd, and a median radial basis function (MRBF) network. The modifications of the FKM and FVQ algorithms are based on a novel fuzzy vector distance definition, and they utilize the quality measure of the results, that is provided by the authentication methods. Simulations show that the proposed algorithms have better performance compared to classical clustering algorithms and other known fusion algorithms.

1 Introduction

The problem of processing and combination of information provided by different knowledge sources is usually referred as *multisensor data fusion*. Decision level fusion involves fusion of sensor information that is preliminary determinated by the sensors. Examples of decision level fusion methods include weighted decision methods, classical inference, Bayesian inference and Dempster-Shafer's method [1]. In this paper the use of fuzzy clustering and median radial basis function (MRBF) algorithms for decision level fusion, is proposed.

Classical clustering methods refer to a wide variety of methods that attempt to subdivide a data set into subsets (clusters). Fuzzy clustering algorithms, such as the *fuzzy k-means (FKM)* [2, 3] and the *fuzzy vector quantization (FVQ)* [4], consider each cluster as a fuzzy set, while a membership function measures the possibility that each training vector belongs to a cluster. The FKM and FVQ are used to combine results coming from various single modality person authentication algorithms (e.g. from speech, video, still images) [5, 6, 7, 8]. The methods provide results accompanied with a degree of quality. The quality measure will be used to fuzzify the data. Two modifications of the FKM and FVQ algorithms, based on a novel fuzzy vector distance definition and named *FKM for fuzzy data (FKMfd)* and *FVQ for fuzzy data (FVQfd)*, will be proposed to handle the fuzzy data and utilize the quality measure.

A Radial Basis Function (RBF) network is also proposed to be used for fusion. RBF network is a two-layer feed-forward neural network in which various clusters are grouped together in order to describe classes [9]. The algorithm employed for training the RBF network is based on robust statistics and is called Median RBF (MRBF) [10].

The paper has the following structure. In Section 2 the person authentication problem is described and the modalities used are mentioned. In Section 3 the clustering methods FKM, FVQ the modifications FKMfd, FVQfd and the MRBF network are described. Experimental results are presented in Section 4 and Conclusions are drawn in Section 5.

2 Description of the person authentication problem and solutions

In an authentication system the candidate claim his identity and a feature set, that corresponds to biometric or other features of the candidate, is compared only to the feature set of the client that he claims. An authentication system is much faster than an identification system and moreover deals with the imposter problem. In this study, five different methods for person authentication were used. The feature sets are based on grey-level and shape information of the persons face and on voice features. The first face recognition technique used was "Morphological Dynamic Link Architecture (MDLA)" [7] that employs both grey-level and shape information. Two more methods for person authentication which employ shape and grey level information coming from the profile of a person were used: the "Profile Shape Matching (PSM)" that uses the shape of the profile and the "Grey Level Matching (GLM)" that uses its grey-level values [8]. The fourth method employed was the use of Gabor filters responses to create a feature vector and implement the Dynamic Link Architecture (GDLA)[5]. Finally a speech authentication algorithm based on hidden Markov models (MSP) was used [6].

All of the above mentioned methods were applied on

Table 1: The False Rejection (FR) and False Acceptance (FA) rates, when MDLA, GDLA, PSM, GLM and MSP methods are applied for person authentication.

Modality	FR %	FA %
MDLA	8.09	10.36
GDLA	7.39	3.71
PSM	15.54	4.56
GLM	26.35	1.29
MSP	0.00	6.70

the M2VTS database of 37 persons. All these authentication algorithms provide results in the range $[0,1]$. The values near zero show that the candidate is totally different from the client and values near one stress that the candidate and the client are similar. Moreover, the applied algorithms provide a degree of *quality* for every result, that is a measure of the reliability of the result. The quality is also a value in the range $[0,1]$, where the values near zero mean that the result is unreliable, and the values near one that the result can be considered reliable. The qualities can easily be transformed to provide measures of *fuzziness*, through the rough qualitative relation "fuzziness $= 1 -$ quality". The individual performances of the five modalities tested on M2VTS database are presented on Table 1. These results were obtained in a joint experiment organized within ACTS M2VTS project.

3 Description of the clustering algorithms

3.1 The fuzzy clustering algorithms

The well known classical k-means algorithm classifies each training vector to a certain cluster in order to minimize a distance measure. The performance of the algorithm strongly depends on the initialization of the codebook vectors. Since the codebook is designed, any data is classified into a cluster based on a classical distance criterion.

The fuzzy k-means algorithm (FKM) classifies each vector to all clusters with different values of membership between 0 and 1 [2]. This membership value indicates the association of a vector to each of the k clusters. Notice that the fuzzy k-means algorithm does not classify fuzzy data, but crisp data into fuzzy clusters. The algorithm is derived from the constrained minimization of the following objective function:

$$J_m = \sum_{j=1}^{k}\sum_{i=1}^{M} u_j(\mathbf{x}_i)^m ||\mathbf{x}_i - \mathbf{y}_j||^2 \qquad 1 < m < \infty \quad (1)$$

where $\mathbf{x}_i$ are the training vectors, $\mathbf{y}_j$ are the codebook vectors and $u_j(\mathbf{x})$ are the membership functions of the clusters. The fuzziness of the clustering procedure is controlled by the parameter m, which is always greater than one. When m tends to one, the clustering tends to the one provided by theclassical k-means algorithm. When a vector $\mathbf{x}_i$ is an outlier, which means that it is far from all cluster centers, their membership functions take very small values and that vector does not practically modify the cluster centers.

The fuzzy vector quantization algorithm (FVQ) is a clustering algorithm based on soft decisions, that leads to crisp decision at the end of the codebook design process [4]. First, a membership function $u_j(\mathbf{x}_i)$ should be constructed, such that it approaches unity as the distance $||\mathbf{x}_i - \mathbf{y}_j||^2$ approaches zero, and decreases monotonically to zero as the distance increases from 0 to the maximum, for all codebook vectors, distance value $d_{max}(\mathbf{x}_i)$. Such a membership function can be of the form:

$$u_j(\mathbf{x}_i) = \left(1 - \frac{||\mathbf{x}_i - \mathbf{y}_j||^2}{d_{max}(\mathbf{x}_i)}\right)^{\mu} \quad (2)$$

where μ is a positive integer. The advantages of fuzzy vector quantization versus fuzzy k-means are the elimination of the effect of the initial codebook selection on the quality of clustering and the avoidance of *a priori* assumptions for the level of the fuzziness needed for a clustering task. Similarly to the fuzzy k-means algorithm, the fuzzy vector quantization algorithm does not classify fuzzy data.

In the following, we propose two modifications of the FKM and FVQ algorithms, based on a fuzzy vector distance measure, that will provide us a way to handle fuzziness and classify fuzzy data. Since a crisp data point can be considered as a vector, the fuzzy data can be considered as a fuzzy vector, which is an extension of the notion of a fuzzy number to n-dimensions [11]. A fuzzy vector $\mathbf{X}$ can be symbolized as $\mathbf{X} = \bigcup_\theta \bigcup_\alpha \cdot [\mathbf{x}_l^{\theta\alpha}, \mathbf{x}_r^{\theta\alpha}]$ where $\mathbf{x}_l^{\theta\alpha}$ and $\mathbf{x}_r^{\theta\alpha}$ are the lower and upper points that limit the α-cuts of the corresponding 1-d X^θ fuzzy numbers defined on a certain direction θ. The union of all 1-d fuzzy numbers for all the $n-1$ angles $\theta = (\theta_1, \theta_2, \ldots, \theta_{n-1})$, which is symbolized by $\bigcup_\theta$, reconstructs the n-dimensional fuzzy vector. Then, a distance norm $D_n[\mathbf{X}, \mathbf{Y}]$ between fuzzy vectors X, Y is defined as [11]:

$$D_n[\mathbf{X}, \mathbf{Y}] = c \cdot \int_{\theta,\alpha} (||\mathbf{x}_l^{\theta\alpha}, \mathbf{y}_l^{\theta\alpha}|| + ||\mathbf{x}_r^{\theta\alpha}, \mathbf{y}_r^{\theta\alpha}||) d\alpha d\theta \quad (3)$$

where c is a constant used for normalization and $||.,.||$ denotes a distance norm between classical vectors. When the Euclidean norm is chosen, the *Euclidean fuzzy distance* is defined. Let us describe fuzzy vectors by using α-cuts. For a given α and a vector of angles $\theta = (\theta_1, \theta_2, \ldots, \theta_{n-1})$, two points $\mathbf{x}_l^{\theta\alpha}$ and $\mathbf{x}_r^{\theta\alpha}$ are defined, which are the lower and the upper limits of the corresponding $\theta\alpha$-cut. The proposed Euclidean fuzzy distance is the normalized integral of all the distances $d_e^2(\mathbf{x}_l^{\theta\alpha}, \mathbf{y}_l^{\theta\alpha})$ between the lower limits, and the distances $d_e^2(\mathbf{x}_r^{\theta\alpha}, \mathbf{y}_r^{\theta\alpha})$ between the upper limits, for every $\alpha \in [0,1]$ and $\theta_i \in [0, \pi)$, $i = 1, 2, \ldots, n-1$.

Let us symbolize as $d_{lx}^{\theta\alpha}$ the Euclidean distance between the lower limit $\mathbf{x}_l^{\theta\alpha}$ of the $\theta\alpha$-cut and the center $\mathbf{x}_c$ of a fuzzy vector $\mathbf{X}$, as $d_{rx}^{\theta\alpha}$ the Euclidean distance between the upper limit, $\mathbf{x}_r^{\theta\alpha}$ of the $\theta\alpha$-cut and the center $\mathbf{x}_c$, and as d_{xy} the distance between the centers of two fuzzy vectors $\mathbf{X}, \mathbf{Y}$. It can be proven that the Euclidean fuzzy distance between two fuzzy vectors X, Y is given by [11]:

$$D_{e_n}[\mathbf{X}, \mathbf{Y}] = d_{xy}^2 + d_{f_{xy}}^2 \tag{4}$$

where:

$$d_{f_{xy}}^2 = c \cdot \int_{\theta,\alpha} [(d_{lx}^{\theta\alpha} - d_{ly}^{\theta\alpha})^2 + (d_{rx}^{\theta\alpha} - d_{ry}^{\theta\alpha})^2 + $$
$$+ 2d_{xy} \prod_{i=1}^{n-1} \cos(\theta_i)(d_{lx}^{\theta\alpha} - d_{ly}^{\theta\alpha} - d_{rx}^{\theta\alpha} + d_{ry}^{\theta\alpha})] d\alpha d\theta \tag{5}$$

The above equation shows that the Euclidean fuzzy distance is the classical Euclidean distance between the centers of two fuzzy vectors $\mathbf{X}, \mathbf{Y}$, modified by a factor that depends on the fuzziness that every fuzzy vector holds. The Euclidean fuzzy distance can be considered as a generalized Euclidean distance since (5) equals to 0 when the vectors are crisp.

The fuzzy classification algorithms FKM and FVQ can now be modified to incorporate the Euclidean fuzzy distance and classify fuzzy data. The modified algorithms, *fuzzy k-means for fuzzy data (FKMfd)* and *fuzzy vector quantization for fuzzy data (FVQfd)*, use the proposed fuzzy distance measures to evaluate the membership values of a fuzzy vector in a cluster. The need for crisp decisions at the end of the training procedures, force us to chose crisp codebook vectors. Thus, the centers of the fuzzy vectors should be used for all arithmetic operations.

During the training procedure, these methods take into account not only the presence of outliers, but also the reliability of the result. Then, when a test is performed, the outputs of the modalities are combined to form a vector, which is classified to the authentication or the imposture cluster based on a crisp distance criterion.

3.2 The Median Radial Basis Function network

The inputs of the RBF network consist of the results provided by the various modalities employed. Each hidden unit implements a Gaussian function which models a cluster :

$$\phi_j(\mathbf{x}) = \exp[-(\mathbf{x} - \mathbf{y}_j)^T \mathbf{S}^{-1} (\mathbf{x} - \mathbf{y}_j)] \tag{6}$$

where $\mathbf{x}$ is the entry vector, $\mathbf{y}_j$ is the mean vector and $\mathbf{S}_j$ is the covariance matrix and $j = 1, \ldots, L$, where L is the total number of hidden units. Each hidden unit models the location and the spread of a cluster.

The output unit consists of a weighted sum of hidden unit outputs which are fed into a sigmoidal function :

$$\psi(\mathbf{x}) = \frac{1}{1 + \exp[-\sum_{j=1}^{L} \lambda_j \phi_j(\mathbf{x})]} \tag{7}$$

where λ_j are the output weights associated with the hidden units. The output consists of a decision function $\psi(\mathbf{x}) \in (0, 1)$.

A very common approach for estimating the parameters of an RBF network consists of an adaptive implementation of the k-means clustering algorithm. For the covariance matrix estimation, a 2-D extension of this algorithm is employed. In [10] a robust statistics algorithm called Median RBF (MRBF) was proposed for estimating parameters of RBF networks. It was proved that this algorithm provides better parameter estimates when the clusters are overlapping or in the presence of outliers [10]. MRBF assigns an incoming data vector to a cluster which is the closest in the Euclidean distance :

$$\|\mathbf{x}_i - \mathbf{y}_j\| = \min_{k=1}^{L} \|\mathbf{x}_i - \mathbf{y}_k\|. \tag{8}$$

After assigning a set of vectors to the same cluster, we calculate the center of the cluster using the marginal median algorithm :

$$\mathbf{y}_j = \text{Med}\{\mathbf{x}_{j,0}, \mathbf{x}_{j,1}, \ldots, \mathbf{x}_{j,n}\} \tag{9}$$

where $\mathbf{x}_{j,i}$ for $i = 0, \ldots, n$ are the person modality feature vectors assigned to the hidden unit j. In order to limit the computational complexity we consider only a limited set of data samples and the formula (9) is calculated from a running window. For the dispersion we employ the median of the absolute deviations algorithm :

$$\mathbf{S}_j = \frac{\text{Med}\ \{|\mathbf{x}_{j,0} - \mathbf{y}_j|, \ldots, |\mathbf{x}_{j,n} - \mathbf{y}_j|\}}{0.6745} \tag{10}$$

where the covariance matrix $\mathbf{S}$ is considered diagonal. The output weights are calculated from the backpropagation algorithm :

$$\lambda_j = \sum_{i=0}^{n} [F(\mathbf{x}_i) - \psi(\mathbf{x}_i)] \psi(\mathbf{x}_i) [1 - \psi(\mathbf{x}_i)] \phi_j(\mathbf{x}_i) \tag{11}$$

where $F(\mathbf{x}_i)$ is the decision function associated with each modality feature vector in the training set.

4 Experimental results

The algorithms that are described in Section 3 were used to fuse the results provided from five different modalities in groups of two. Since a "yes/no" answer was desirable, the clustering algorithms were apllied for two clusters ($k = 2$). The quality of the data was utilized by using the modified fuzzy clustering algorithms FKMfd and FVQfd. The results are presented in Table 2.

The fuzzy clustering algorithms have better performance than classical k-means. Moreover, the quality of the results, used by the proposed fuzzy clustering algorithms for fuzzy data FKMfd and FVQfd, improves the performance in cases where the results are not good enough, and preserves the performance of the fuzzy clustering techniques when the results are good. A 0% False

Table 2: The False Rejection (FR) and False Acceptance (FA) rates, by using the results from the five modalities combined by two, fused by k-means (KM), fuzzy k-means (FKM), FKM for fuzzy data (FKMfd), fuzzy vector quantization (FVQ), FVQ for fuzzy data (FVQfd) and median radial basis function (MRBF).

Modalities Combined	KM		FKM		FKMfd	
	FR %	FA %	FR %	FA %	FR %	FA %
MDLA,GDLA	6.76	2.12	0.68	2.36	0.68	2.42
MDLA,PSM	5.41	4.05	2.70	3.68	0.68	3.60
MDLA,GLM	12.84	2.65	2.03	3.60	0.00	2.57
MDLA,MSP	0.68	2.21	0.00	2.08	0.00	2.05
GDLA,PSM	6.08	1.48	1.35	1.63	0.68	1.73
GDLA,GLM	9.44	1.01	1.35	1.56	1.35	1.86
GDLA,MSP	2.01	0.73	0.00	0.81	0.00	0.86
PSM,GLM	20.27	2.63	6.76	6.16	4.73	5.56
PSM,MSP	2.70	1.16	0.00	1.05	0.00	1.13
GLM,MSP	6.76	0.73	0.00	0.64	0.00	0.66
Modalities Combined	FVQ		FVQfd		MRBF	
	FR %	FA %	FR %	FA %	FR %	FA %
MDLA,GDLA	2.70	2.85	2.70	2.85	7.64	2.03
MDLA,PSM	4.73	4.26	4.73	4.22	7.32	5.78
MDLA,GLM	12.16	2.74	11.49	2.70	5.97	2.98
MDLA,MSP	0.00	2.63	0.00	2.57	0.68	0.60
GDLA,PSM	4.05	1.69	4.05	1.75	9.68	0.60
GDLA,GLM	5.41	1.22	5.41	1.20	8.40	0.60
GDLA,MSP	1.35	0.98	1.35	0.98	1.33	0.15
PSM,GLM	20.27	3.04	20.27	3.04	10.81	5.99
PSM,MSP	2.70	1.26	2.70	1.22	3.38	0.06
GLM,MSP	6.76	0.62	6.76	0.62	**0.00**	**0.53**

Rejection rate and 0.53% False Acceptance rate was achieved by using the results coming from GLM and MSP algorithms, fused by MRBF algorithm, shown in Figure 1, where the clustering methods are also compared with the known OR and AND fusion techniques.

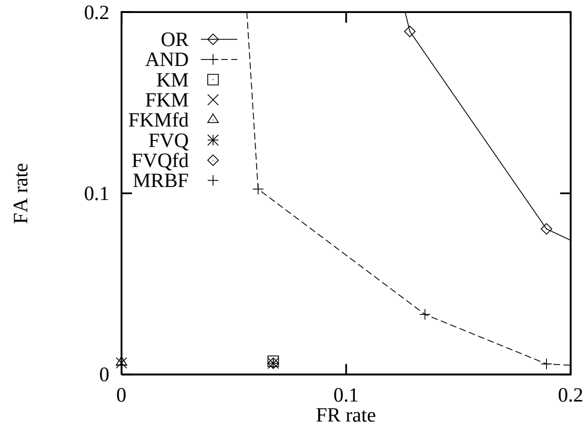

Figure 1: The False Rejection (FR) and False Acceptance (FA) rates, using or (OR), and (AND), classical k-means (KM), fuzzy k-means (FKM), FKM for fuzzy data (FKMfd), fuzzy vector quantization (FVQ), FVQ for fuzzy data (FVQfd) and median radial basis function (MRBF) methods for fusing the results of GLM and MSP methods.

5 Conclusions

The use of fuzzy clustering algorithms for decision level data fusion in a person authentication system was proposed. Results coming from five person authentication methods were fused by fuzzy k-means and fuzzy vector quantization. The quality measure was used to fuzzify the data, and two modifications of the FKM and FVQ algorithms, based on a novel fuzzy vector distance definition, were proposed to utilize the quality. Simulations results showed that fuzzy clustering algorithms have better performance compared with classical k-mean and other known fusion algorithms. It was also shown that the median radial basis function network provides an alternative reliable way for fusion. Moreover, the proposed fuzzy clustering algorithms for fuzzy data, which utilize the quality of the results, increases in most cases the performance of the fusion system.

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