Vis Comput (2013) 29:123–130
DOI 10.1007/s00371-012-0741-9

ORIGINAL ARTICLE

A multi-modal approach for high-dimensional feature recognition

Kushan Ahmadian · Marina Gavrilova

Published online: 30 October 2012

Abstract Over the past few decades, biometric recognition firmly established itself as one of the areas of tremendous potential to make scientific discovery and to advance state-of-the- art research in security domain. Hardly, there is a single area of IT left untouched by increased vulnerabilities, on-line scams, e-fraud, illegal activities, and event pranks in virtual worlds. In parallel with biometric development, which went from focus on single biometric recognition methods to multi-modal information fusion, another rising area of research is virtual world's security and avatar recognition. This article explores links between multi-biometric system architecture and virtual worlds face recognition, and proposes methodology which can be of benefit for both applications.

Keywords Neural networks · Face recognition · Biometric · Security · Avatars · Virtual worlds

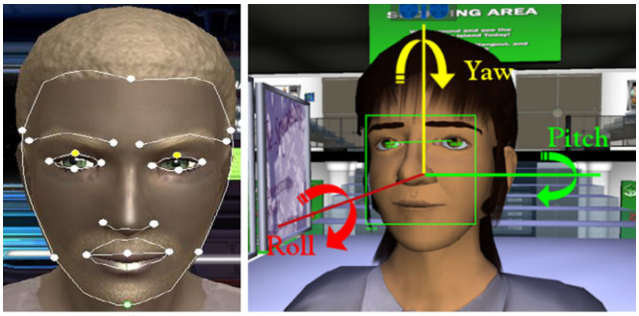
1 Introduction and motivation

Over the past 10 years or so, primarily in response to growing security threats and financial fraud, it has become necessary to be able to accurately authenticate identity of human beings using biometrics. Using modern technologies, design, and implementing secure access control systems based on physical or behavioral traits are becoming more and more crucial. Within the process of recognition/identification, it usually happens that a set of features are extracted from the input patterns/images of the user and afterward compared to a set of features stored in the database. Recognition of a system user based on fingerprints, iris, face, voice, gait, or typing pattern are common in many commercial or personal applications. Recently, such technologies made their way into the virtual world, where biometric approaches and multi-model schemes are successfully applied to virtual entity recognition [11, 15].

As a very important biometric feature, facial biometrics plays a significant role in user authentication. It is usually comprised of a large set of high-dimensional vectors representing topological, color, or texture information, which makes it a hard biometric pattern to learn [8, 12]. Many of the earlier face recognition algorithms are based on feature-based methods. Some of them go through the process by detecting a set of geometrical features on the face such as distance between the eyes, eyebrows length, nose shape, and mouth width [1]. However, there is no distinction made between more or less prominent features, or analysis of how easy or hard it is to extract them. As an alternative, appearance-based face recognition algorithms are used as a tool to extract representation of an image by projecting it onto the subspace and then finding the closest point set [3]. One of well-known linear transformation methods that are used vastly for dimensionality reduction and feature extraction in images is Principal Component Analysis (PCA) [2]. PCA is based on the linear projection of highly correlated features on the subspaces based on the higher eigenvalues of the covariance matrix [2]. The PCA could be used over raw face image to extract the features or on the eigenface to obtain the discriminant eigenfeatures [2]. There are several methods designed based on PCA in order to overcome the shortcomings of the PCA in different feature sets. LDA (Linear Discriminant Analysis) [4], Kernel PCA [5],

K. Ahmadian · M. Gavrilova (✉)
Department of Computer Science, University of Calgary, Calgary, Canada
e-mail: marina@cpsc.ucalgary.ca

K. Ahmadian
e-mail: kahmadia@cpsc.ucalgary.ca



(a) (b)

Fig. 1 (**a**) Feature-points in avatar face. (**b**) Tolerance of roll, pitch, and yaw [15]

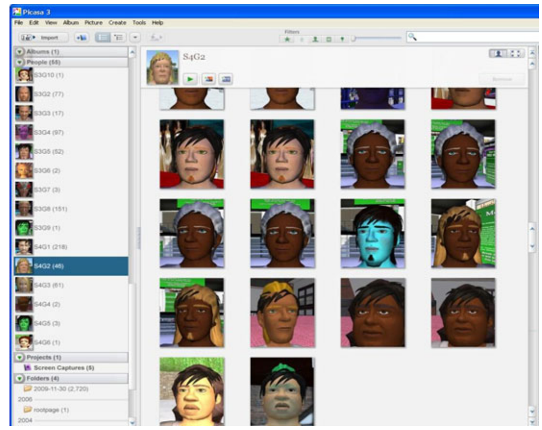


Fig. 2 Screen shot of PICASA avatar face recognition software [15]

and Generalized Discriminant Analysis (GDA) using a kernel approach [6] are all among such methods. On the other side, face recognition techniques based on graph matching [7] and support vector machines (SVMs) [9] have been used as alternatives of dimensionality reduction methods. In addition, methods that use a combination of two groups of methods discussed above have been proposed [10, 12].

One of the novel directions for facial recognition which can potentially yield a significant improvement is overcoming high-complexity and high-dimensionality of biometric data, especially if various features of a single or multiple biometrics must be taken into account. This becomes increasingly important not only for biometric, but also for avatar face recognition, which emerged recently [15] as one of novel directions of research in the virtual reality domain. As with traditional approaches, both geometric feature point extraction (see Fig. 1a) and appearance-based methods taking into account roll, pitch, and yaw (Fig. 1b) are employed to tackle the problem. Preliminary experimentation conducted on commercial PICASA software [15] reports that combining both methods yields improved avatar face recognition results rather than resorting to single face recognition approach (see Fig. 2).

The current paper investigates this topic in the context of multi-modal security system. Numerous security threats in both on-line and virtual worlds require more sophisticated resources, and better analysis of features important for face recognition. In this paper, dimensionality reduction methods are employed for this task. The goal is to transform data from a high-dimensional space into a lower-dimensional one without loss in the information. Normally, the lower dimension maximizes the variance of data. High-dimensionality of data is a common problem in recognition systems where a set of features from the training samples are used to create a learner. The complexity of designing algorithms for the recognition purpose grows significantly as the number of dimensions grows. A common set of methods to reduce the dimensionality of space is the clustering approach. In this paper, we utilize the concepts discussed above in order to create a secure and precise system (compared to other dimensionality reduction methods) to recognize individuals based on their face and ear features. The unique characteristic of such system is that it is based on a novel representation of data and embedding it into a newer subspace in a way that maximizes the covariance of the obtained features and hence increasing the recognition rate by identifying the uniquely selected features and also using neural network for selection and training. This paper is an extended version of the conference paper [18] invited for special issue of the Journal of Visual Computer.

2 Proposed methodology

The proposed system consists of training different chaotic learners based on different biometric coming from a single source (i.e. a single subject). Note that this approach is currently being extended to avatar face feature recognition, with preliminary results for single biometric recently appeared in [16].

2.1 Overall system architecture

The simplified training structure of the proposed system is shown in Fig. 3.

As shown above, the vectors of different biometrics (here, ear and face) are combined and fed into the dimensionality reduction phase after conventional normalizations process (correcting illumination, removing noise, and adjusting rotations). Afterward, the chaotic neural model is used to learn the obtained pattern. The input vector to the subspace clustering method is defined as $x = (x_1, \dots, x_d)^T$. In the case of the multimodal biometric system, the vector is a combination of all the features from different biometrics. By other means,

$$x = (x_1, \dots, x_d, u_1, \dots, u_m, v_1, \dots, v_n)^T \quad (1)$$

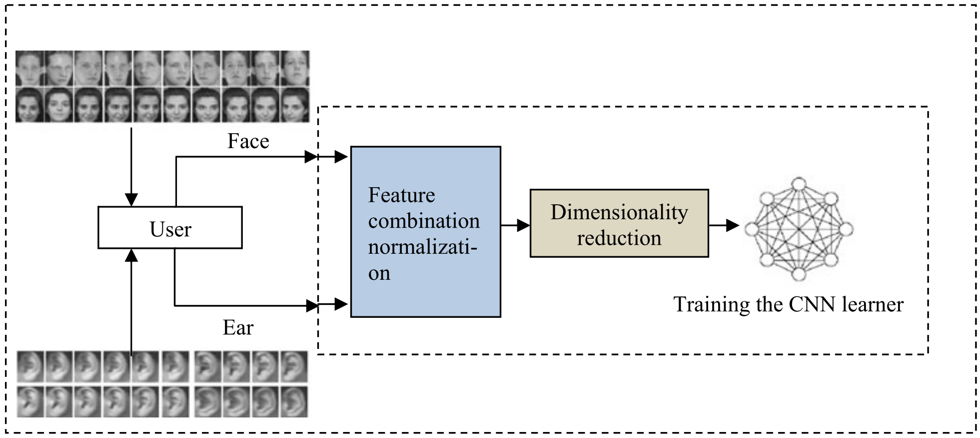


Fig. 3 The training phase of the proposed system

where x, u, and v are different input biometrics and d, m, and n are their dimensions, respectively. The new subspace is labelled as follows:

$$x' = \left(x'_1, \ldots, x'_{d'}\right)^T \tag{2}$$

where $d' \ll d + m + n$.

The chaotic neural network is trained by the whole new features subspace. After training the neural network, test patterns are fed into the system. The testing phase is illustrated in Fig. 4. First, the input pattern is introduced to the system. Different biometric features are collected from the user and analysed through the system. If the learner converged the input pattern into a stored pattern within a reasonable threshold, then the person is verified and access to the system is granted. Otherwise, the person would be rejected.

2.2 Face detection

To detect the face area inside the face images, we chose well-known Haar-like feature based face detector which was originally implemented by open source project library OpenCV. The Haar-like feature based face detector is designed based on the idea of finding features that are a candidate for a certain object class [14]. The area of interest is detected in a similar manner to the coefficient in Haar wavelet transformations. Afterward, the obtained features are used to detect the face area in the images.

In order to detect the faces, the images have been scaled down to 128 × 128 pixel images for efficient processing. The detector was mostly successful on finding the face area except for a few of the samples. In addition, to avoid the false detection problem, a larger area of the candidate square has been chosen.

2.3 Ear detection

Similar to face detection process, to detect the ear area, the images have been scaled down to 90 × 72 pixel images. In some of the cases, a later detector area has been chosen to avoid the problem of false detected samples. Unlike the face detector, ears are invisible in some of the cases due to occlusions of ears by hair.

A common way to overcome this problem is simply avoiding the features related to ears and considering other features. We have used a similar approach in our method and for the invisible ear images we have just considered the faces.

2.4 Single biometrics

After finding the area of interest, in face and ear biometrics, a second phase of processing has been applied to images in order to remove extra width of the obtained images from the images of the first phase. In order to compare the results of the proposed method, we have used the PCA (Principle Component Analysis) method. PCA is a successful dimensionality reduction method in statistics, and consequently in face and ear biometric recognition [2]. By using PCA, we translate the pixels of the images into principle components. In other words, the pixel space is transferred into feature space. Eigenspace of such a features space is determined by the corresponding Eigenvectors of the covariance matrix [2].

2.5 Multimodal biometrics

Multimodal biometric systems are designed to overcome the usual problems of conventional single biometric systems. As with any information processing system, the accuracy of the outcome is highly dependent on the quality of data, system architecture, training of the operator and proper equipment. The issues which are inherent to biometric field are revolve around variability of data samples (highly subjective to noise, illumination, distance to sensing devise, orientation, etc.), as reliability of underlying methods in the presence of temporal variance in data (i.e. template aging, equipment being outdated, etc.), or intentionally sabotage

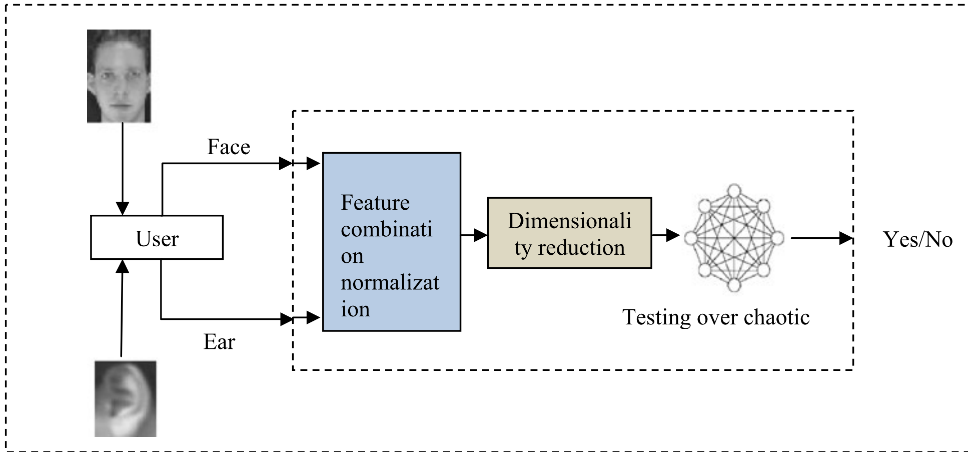


Fig. 4 Testing phase of the proposed system

(i.e. data spoofing, information falsification, template tampering etc). Over the past decade, the multi-modal approach evolved from vaguely defined concept to one of the most advanced method to alleviate the problems listed above. It allows increasing the accuracy of recognition while at the same time with lowering the False Rejection Rate (FRR), thus making system more error-proof and reliable [19, 20]. In our proposed method, we develop a multi-modal biometric system where we introduce chaotic neural networks as learners for each of the individual biometrics.

The final result is obtained by aggregating the single biometric outcomes utilizing information fusion approach. The maximum vote method is used, where the person is recognized based on the number of matches as identified by each of single biometric modules. This is one of basic information fusion techniques, with a proven record of good performance in variable biometric systems. However, the outcome is binary (Yes/No) and in systems with small variations of data samples but high requirements for precision, this method is not ideal. Thus, we augment these information fusion methods by considering the distance of the saved pattern in the chaotic neural network (corresponding to the person being verified) to the given input pattern (see Fig. 5). With that modification, we can not only report match/mismatch (or Yes/No) outcome, but also can report level of confidence and have control over precision rates through adjusting threshold parameters. To the best of our knowledge, this is the first application of chaotic neural network learner to feature-level multi-modal biometric system.

3 Chaotic neural network learner

The proposed system consists of training different chaotic learners based on different biometric coming from a single source (i.e. a single subject). The key feature of the method is in using the Chaotic Hopfield network for storing the biometric patterns. When a new pattern is introduced to the network, the network tries to converge the introduced pattern to the closest pattern saved in the memory. In order to train the network, we first obtain a set of vectors and then feed them as features of the new pattern. Clustering is performed to group feature vectors with similar features and to reduce complexity of feature vector space further. Having the vector of weights from the candidate clusters, the next step in the proposed methodology is defining an energy model for the associative memory to learn the data patterns. The benefit of this approach is that this is a learner system that converges the given set of vectors to the stored pattern.

We now describe the chaotic neural learner in more details. Having the vector of weights, the next step is to define an energy model for the associative memory to learn the vectors. It is well known that the NCNN (Noise Chaotic Neural network) based methods suffer from a blind noise injection policy. In order to overcome the problem of blind noise injection in NCNN-based models, which results in lower memory capacity for the huge amount biometric data, we use a new class of non-autonomous chaotic networks where the key idea is that the chaotic noise injection is based on the behavior of neighbor neurons. This method is especially useful for a class of optimization problems in which state changing of neurons affects neuron with limited logical distances. Hereby, we will first look at the chaotic dynamics of single neuron of noise chaotic neural network. This model is described as follows:

$$
\begin{aligned}
x_{jk}(t) &= \frac{1}{1+e^{-y_{jk}(t)/\varepsilon}},\\
y_{jk}(t+1) &= k y_{jk}(t)\\
&\quad + \alpha\left\{\sum_{i=1,i\neq j}^{N}\sum_{l=1,l\neq k}^{M} w_{jkil}x_{jk}(t) + I_{ij}\right\}\\
&\quad - z(t)\big(x_{jk}(t) - I_0\big) + n(t),\\
z(t+1) &= (1-\beta_1)z(t),\\
n(t+1) &= (1-\beta_2)n(t).
\end{aligned}
\tag{3}
$$

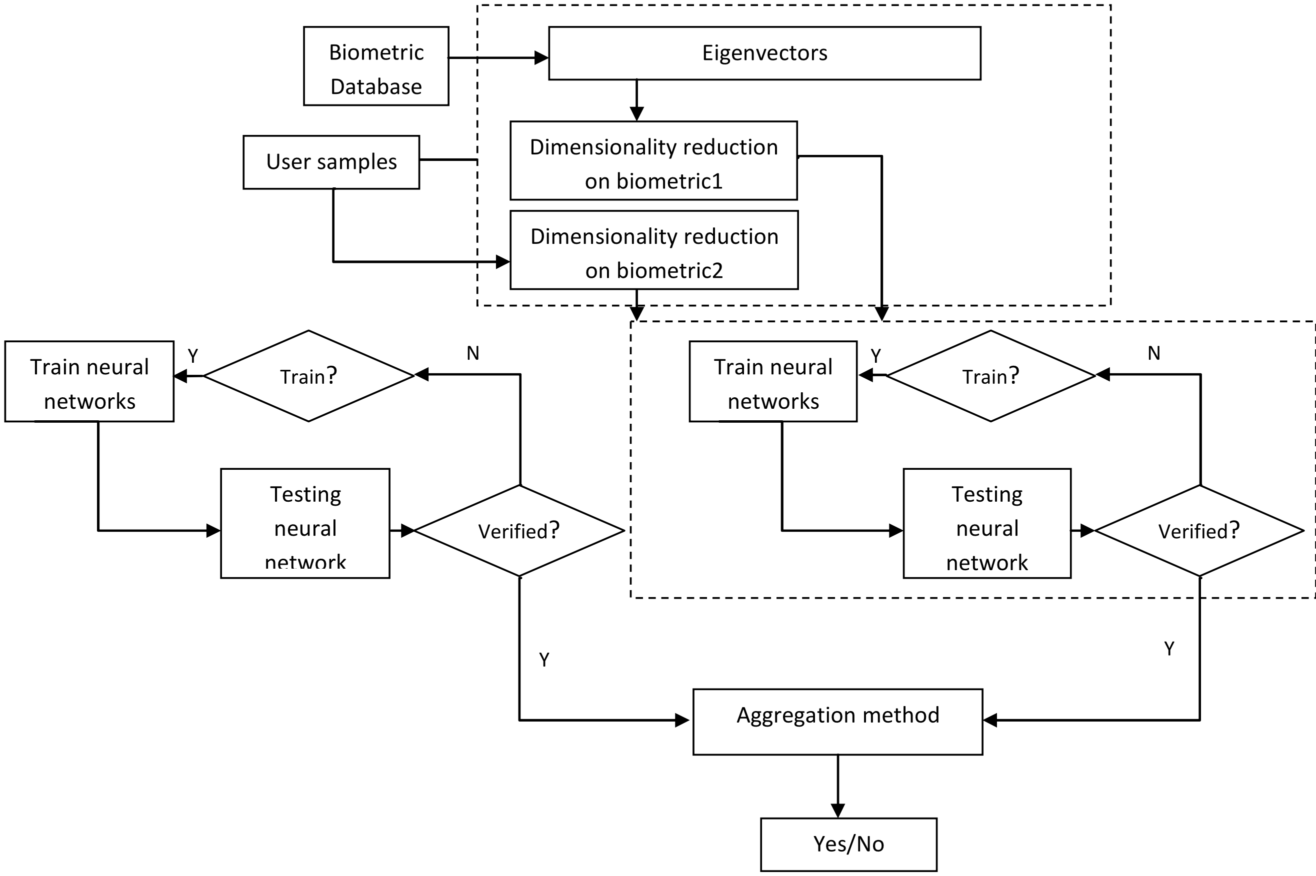


Fig. 5 Chaotic neural network learner in multi-modal security system

Here, x_{jk} and y_{jk} are outputs and inputs of neuron jk respectively and w_{jkil} is the weight of the connection between neuron jk and il. K is the damping factor. I_{ij} is the input bias of neuron ij and β_1 and β_2 are damping factors of neural self-coupling and stochastic noise, α is a positive scaling factor and ε is steepness parameter of the output function, $n(t)$ is the random injected noise and $I0$ is the initial value which controls the chaotic behavior [12].

To overcome the shortcomings of classic Hopfield neural networks, chaotic dynamics have been applied to HNN networks by many authors, including well-known stochastic chaotic simulated annealing (SCSA) method [17] that works by adding decaying stochastic noise into the Chen and Aihara's transiently chaotic neural network. A well-known deficiency of such an approach is a blind noise-injecting strategy. This is due to the structure of noise function which is temporal function and is independent of the neighbor neurons. In such methods, the chaotic or stochastic noises are injected into the network regardless of neuron's previous behavior. In the developed system, and in order to rationalize the process of noise injection, we use the adjacency matrix to evaluate the chances of a neuron to receive chaotic noise. When a sufficient number of neighbors—which are indicated by the adjacency matrix—change their state, a chaotic noise is injected into the current neuron to escape local minima. This is beneficial due to the fact that changes of one neuron state may not need to change a global modification of all states which depends on the shape of the resulted graph. This method was first developed in 2009 in application to a single biometric and details can be found in [12].

4 Optimization through subspace clustering

While utilizing the chaotic neural network learner allows to focus on most important pattern, and thus leads to significant improvement in recognition rates (as will be shown in experimental section), another aspect that should not be overlooked is reducing data complexity. Obtaining features from row biometric data results in large amount of information, where not all of it might be necessary for neural network learner. Thus, the good optimization approach is to reduce complexity of data by further processing initial biometric samples. The approach taken in our system development is dividing datasets into subsets (clusters), where objects in the same subset are similar to each other with respect to a given similarity measure, whereas objects in different clusters are dissimilar. Thus, only selected subset of most critical features which maximizes recognition rate will be given to neural learner.

A common way to overcome problems of high-dimensional data spaces where several features are correlated or only some features are relevant is to perform feature selection. Due to the problem of local feature relevance and local feature correlation, usually no global feature selection can be applied to overcome the challenges of clustering high-dimensional biometric data. Instead of a global approach to feature selection, we propose to use a local approach accounting for the local feature relevance and/or local feature correlation problems, and develop a novel method which integrates feature analysis into the clustering process.

The method proven to be quite effective for biometric system is to project a d-dimensional vector of biometric feature points in the parameter space through a $(d-1)$-dimensional hyperplane [13]. In order to detect those linear hyperplanes in the data space, the task is to search for points in the parameter space where many sinusoidal curves intersect. Since computing all possibly interesting intersection points is too expensive, we discretize the parameter space by grid and search for grid cells with which many sinusoidal curves intersect. Note that in such discretization of the parameter space, exact intersections are no longer considered. The higher the grid resolution is, the more accurate the recognition of the line segments is. The given method transforms the original subspace clustering problem (in data space) into a grid-based clustering problem (in parameter space).

5 Experimental results

In this section, we describe the proposed multi-modal biometric system training and testing results of applying the proposed method over the FERET dataset in order to showcase the benefits of the proposed approach. The objective was to develop a novel multi-biometric system architecture and evaluate performance of resulting security system for the face/ear biometric. This section validates the proposed methodology by providing experimentation results. The novel multi-biometric architecture is compared against commonly used match score level multi-modal biometric system. The experiments demonstrate that the proposed combination of dimensionality reduction and associative memory training methodology outperforms other commonly used techniques in both FAR (False Accept Rate) and FRR (False Reject Rate) parameters both individually and when those two methodological approaches used together. The proposed system utilizing combined features from face and ear biometric is also validated against commonly used match score fusion methods.

The system is implemented on a Windows 7 running desktop computer with i3 core and 4 GBs of memory, on Matlab and Java programming languages. For the experimental results, we have used the FERET database of facial images. The database images were collected in 15 sessions between 1993 and 1996. The database samples represent different facial expressions and different lightning conditions. IIT Delhi ear image database has been acquired in IIT Delhi campus during October 2006–June 2007 using a simple imaging setup. All the images are acquired from a distance (touchless) using simple imaging setup and the imaging is performed in the indoor environment. After normalizing the images, the next step is feature extraction. There are several techniques to retrieve features from ear images like geometrical distances and Haar wavelet transform.

We now compare the developed system based on subspace clustering (SC) method for reducing the number of features and on chaotic neural network learner for training against one of the most popular multi-modal biometric system architecture: match level fusion. Note that uniqueness of the system is in using combined feature vector, which is not limited to one single biometric source, but instead is comprised of the most important for identification features, strategically selected across different biometrics. The number of features for each individual biometric does not have to be the same, and the combined vector can be of different size based on the various environments during system operational or deployment modes. For instance, quality of data, enrollment time, cost of replacement of equipment necessary to collect user samples play an important role and result in different set of biometrics featured. In order to validate the whole system, we now compare the final identification outcome, including FAR and FRR, against other leading multi-biometric systems. For comparison, we implement the match level fusion biometric system.

The match level fusion is one of the most popular, reliable and easy to implement methods when a number of outcomes (accept/reject) from different biometrics obtained and the final answer (accept/reject) must be reported by using fusion techniques. We compare the proposed system based on combined biometric feature vectors from face and ear with match score level fusion methods, which utilize simple-sum (SS), min-score (MIS) and max score (MAS) fusion methods. As a normalization method, SC (subspace clustering) is compared against known methods such as min-max (MM), zero-score (ZS), Tanh (TH), and Quadratic Linear Quadratic (QLQ). While utilizing these methods, the raw eigenvectors obtained from samples from the FERET database has been used (see Fig. 6).

We have carried out all possible permutations of normalization and fusion method computation on the database of 972 subjects. Table 1 shows the obtained Equal Error Rate (EER) values for these permutations. In order to carry

Fig. 6 Eigenvectors for samples from FERET database

Table 1 EER values for (normalization, fusion) permutations (%)

Normalization method	SS	MIS	MAS	CNN
MM	0.99	5.43	0.86	0.54
ZS	1.71	5.28	1.79	2.27
TH	1.73	4.65	1.82	3.18
QLQ	**0.94**	5.43	0.63	0.58
SC	1.64	**4.43**	**0.61**	**0.51**

out these experiments, we created a multi-modal biometric system framework where we could substitute any normalization method (including SC) with any system architecture (i.e. match level fusion or proposed CNN method). The best, namely the lowest, Equal Error Rate (EER) values in individual columns are indicated with bold typeface in Table 1. The fused scores that have been used are Simple-Sum, Min-Score, and Max Score which are compared to dimensionality-reduction (normalization) methods, including proposed Chaotic Neural Network method (rightmost column). One can clearly see that subspace clustering method outperforms all other alternatives for all combinations of methods (except for Simple-Sum match level fusion architecture). Furthermore, the lowest EER value of 0.51 % is reached when combining our original SC and proposed CNN method.

The data from Table 1 has been plotted in Fig. 7. Here, the x axis corresponds to normalization (dimensionality-reduction) method used, while the y axis corresponds to system architecture used (match level fusion or chaotic neural network), with z axis standing for EER values. As it can be seen from Fig. 7, the EER values are low using CNN and MM combination, as well as CNN and QLQ combination. However, it is the unique combination of proposed CNN learner and subspace clustering method (SSC) which results in the lowest EER value across all permutation of methods at 0.51 %.

Generally speaking, CNN outperforms all other methods. The subspace clustering method (SC) is advantageous over the normalization methods together with the most of fusion methods (MIS, MAS, UW, and CNN). The results show that the dimensionality reduction method and the chaotic associative memory in combination are the best tools for the multi-modal security system. The aggregation of these two

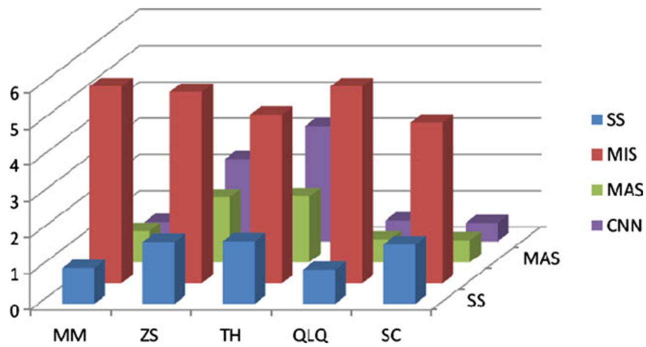


Fig. 7 EER values of different normalization and fusion methods. Lowest EER rates (best results) are achieved when subspace clustering is combined with chaotic neural network learner

methods also provides the best (lowest) EER rates among all combinations. It is worth noting that the testing has been done on not-perfect data. The data samples were not free from deformations, inconsistent orientation, illumination, and noise. Thus, the proposed system shows very high results in the presence of noisy and low quality data.

6 Conclusion

In this paper, we have demonstrated that embedding data dimension reduction techniques within a multimodal biometric system, and combining this with a new way of learning biometric patterns as chaotic neural networks, provides a significant increase in recognition detection rates and resistance to noise and low quality data. The multi-modal biometric system based on face and ear biometrics was fully developed and implemented. We have validated the performance of new multi-modal architecture based on Chaotic Neural Network Learner and received exceptionally good results with the EER rate of 0.5 %. In the future, we plan to extend the testing to the avatar image database and compare results with the database containing only human faces.

Acknowledgements Authors of the paper would like to acknowledge support of NSERC and GEOIDE for partially sponsoring this research, as well as Biometric Technologies Laboratory at the University of Calgary. We also would like to acknowledge Prof. Roman Yampolskiy for his collaboration on avatar recognition methodology and for sharing avatar images.

References

1. Gao, Y., Leung, M.K.H.: Face recognition using line edge map. IEEE Trans. Pattern Anal. Mach. Intell. **24**(6), 764–779 (2002)
2. Belhumeur, P.N., Hespanha, J.P., Kriegman, D.J.: Eigenfaces vs. Fisherfaces: recognition using class specific linear projection. IEEE Trans. Pattern Anal. Mach. Intell. **19**(7), 711–720 (1997)
3. Bartlett, M.S., Movellan, J.R., Sejnowski, T.J.: Face recognition by independent component analysis. IEEE Trans. Neural Netw. **13**(6), 1450–1464 (2002)

4. Lu, J., Plataniotis, K.N., Venetsanopoulos, A.N.: Face recognition using LDA-based algorithms. IEEE Trans. Neural Netw. **14**(1), 195–200 (2003)
5. Kim, K.I., Jung, K., Kim, H.J.: Face recognition using kernel principal component analysis. IEEE Signal Process. Lett. **9**(2), 40–42 (2002)
6. Baudat, G., Anouar, F.: Generalized discriminant analysis using a Kernel approach. Neural Comput. **12**(10), 2385–2404 (2002)
7. Wiskott, L., Fellous, J.M., Krüger, N., von der Malsburg, C.: Face recognition by elastic bunch graph matching. IEEE Trans. Pattern Anal. Mach. Intell. **19**(7), 775–779 (1997)
8. Rowley, H.A., Baluja, S., Kanade, T.: Neural network-based face detection. IEEE Trans. Pattern Anal. Mach. Intell. **20**(1), 23–38 (1998)
9. Phillips, P.J.: Support vector machines applied to face recognition. Adv. Neural Inf. Process. Syst. **11**, 113–123 (1998)
10. Li, S.Z., Lu, J.: Face recognition using the nearest feature line method. IEEE Trans. Neural Netw. **10**(2), 439–443 (1999)
11. Gavrilova, M., Yampolskiy, R.: Applying biometric principles to avatar recognition. In: International Conference on Cyberworlds, Singapore, pp. 179–186. IEEE Comput. Soc., Los Alamitos (2010)
12. Ahmadian, K., Gavrilova, M.: Chaotic neural networks for biometric pattern recognition. Adv. Artif. Intell. **2012**, 124176 (2012). doi:10.1155/2012/124176
13. Gavrilova, M., Ahmadian, K.: Dealing with biometric multidimensionality through novel chaotic neural network methodology in issue on advances and trends in biometrics. Int. J. Inf. Techn. Manag. Inderscience **11**(1–2), 18–34 (2011)
14. Jones, M., Viola, P.: Fast multi-view face detection. Mitsubishi Electric Research Laboratories, TR2003-96 July (2003)
15. Yampolskiy, R., Cho, G., Rosenthal, R., Gavrilova, M.: Evaluation of face recognition algorithms on avatar face datasets. In: Proc. of Cyberworlds 2011, Oct, Banff, pp. 9–16. IEEE Comput. Soc., Los Alamitos (2011)
16. Tenenbaum, J.B., de Silva, V., Langford, J.C.: A global geometric framework for nonlinear dimensionality reduction. Science **290**, 2319–2323 (2000)
17. Wang, L., Smith, K.: On chaotic simulated annealing. IEEE Trans. Neural Netw. **9**, 716–718 (1998)
18. Ahmadian, K., Gavrilova, M.: A novel multi-modal biometric architecture for high-dimensional features. In: IEEE Proceedings Cyberworlds, Banff, Canada, pp. 9–16 (2011)
19. Monwar, M., Gavrilova, M.: A multimodal biometric system using rank level fusion approach. IEEE Trans. Syst. Man Cybern.—TSMC **39**(4), 867–878 (2009)
20. Wecker, L., Samavati, F., Gavrilova, M.: A multiresolution approach to iris synthesis. Comput. Graph. J. **34**(3), 468–478 (2010)

Kushan Ahmadian obtained Ph.D. from the Department of Computer Sciences, University of Calgary in 2012 and joined Calgary industrial sector. He graduated from Iran University of Science and Technology in 2008, where he obtained a degree in the artificial intelligence field. His research interests include Biometrics, Artificial Neural network and Chaotic dynamics. He also held teaching positions at the University of Calgary for Advanced programming techniques and Information structure courses.

Marina Gavrilova is an Associate Professor in the Department of Computer Science, University of Calgary. Dr. Gavrilova is founder and co-director of two research laboratories: the Biometric Technologies Laboratory: Modeling and Simulation and the SPARCS Laboratory for Spatial Analysis in Computational Sciences. Prof. Gavrilova publication list includes over 150 refereed journal and conference papers, edited special issues, books and book chapters. Prof. Gavrilova acted as a Co-Chair of the International Workshop on Biometric Technologies BT 2004, Calgary, Alberta, Canada, 2004, an Overall Chair of the 3rd and 8th International Conference on Voronoi Diagrams in Science and Engineering, and as Organizational Chair of WADS 2009. Prof. Gavrilova is an Editor-in-Chief of the LNCS Transactions on Computational Science Journal, Springer and serves on numerous Journal Editorial Board and International Steering and Program Committees.