17

Face Recognition Using Self-Organizing Maps

Qiu Chen, Koji Kotani, Feifei Lee and Tadahiro Ohmi
Tohoku University
Japan

1. Introduction

As an active research area, face recognition has been studied for more than 20 years. Especially, after the September 11 terrorist attacks on the United States, security systems utilizing personal biometric features, such as, face, voice, fingerprint, iris pattern, etc. are attracting a lot of attention. Among them, face recognition systems have become the subject of increased interest (Bowyer, 2004). Face recognition seems to be the most natural and effective method to identify a person since it is the same as the way human does and there is no need to use special equipments. In face recognition, personal facial feature extraction is the key to creating more robust systems.

A lot of algorithms have been proposed for solving face recognition problem. Based on the use of the Karhunen-Loeve transform, PCA (Turk & Pentland, 1991) is used to represent a face in terms of an optimal coordinate system which contains the most significant eigenfaces and the mean square error is minimal. However, it is highly complicated and computational-power hungry, making it difficult to implement them into real-time face recognition applications. Feature-based approach (Brunelli & Poggio, 1993; Wiskott et al., 1997) uses the relationship between facial features, such as the locations of eye, mouth and nose. It can implement very fast, but recognition rate usually depends on the location accuracy of facial features, so it can not give a satisfied recognition result. There are many other algorithms have been used for face recognition. Such as Local Feature Analysis (LFA) (Penev & Atick, 1996), neural network (Chellappa et al., 1995), local autocorrelations and multi-scale integration technique (Li & Jain, 2005), and other techniques (Goudail et al., 1996; Moghaddam & Pentland, 1997; Lam & Yan, 1998; Zhao, 2000; Bartlett et al., 2002 ; Kotani et al., 2002; Karungaru et al., 2005; Aly et al., 2008) have been proposed.

As a neural unsupervised learning algorithm, Kohonen's Self-Organizing Maps (SOM) has been widely utilized in pattern recognition area. In this chapter, we will give an overview in SOM-based face recognition applications.

Using the SOM as a feature extraction method in face recognition applications is a promising approach, because the learning is unsupervised, no pre-classified image data are needed at all. When high compressed representations of face images or their parts are formed by the SOM, the final classification procedure can be fairly simple, needing only a moderate number of labeled training samples. In this chapter, we will introduce various face recognition algorithms based on this consideration.

The chapter will be organized as follows: Section 1 contains an introduction to the chapter. Section 2 presents a review of conventional face recognition currently. Section 3 gives a brief introduction on Self-Organizing Maps (SOM). Section 4 presents in details on various face recognition applications using SOM, including analyses and discussions of their advantages and demerits, and refer to the direction of research of SOM-based face recognition in future. Section 5 gives a conclusion of the chapter.

2. Review of Face Recognition

A number of face recognition algorithms have been proposed (Chellappa et al., 1995; Zhao, 2003; Li et al., 2005; Tan et al., 2006; Abate et al., 2007). These algorithms can be roughly divided into two approaches, namely, structure-based and statistics-based.

In the structure-based approaches (Brunelli & Poggio, 1993; Wiskott et al., 1997; Ben & Nandy, 1998; Lam & Yan, 1998; Li & Lu, 1999), recognition is based on the relationship between human facial features such as eye, mouth, nose, profile silhouettes and face boundary. Statistics-based approaches (Turk & Pentland, 1991; Zhao, 2000) attempt to capture and define the face as a whole. The face is treated as a two dimensional pattern of intensity variation. Under this approach, the face is matched through finding its underlying statistical regularities.

2.1 Structure-based Face Recognition Algorithms

In Wiskott et al. (Wiskott et al., 1997), an elastic graph-matching algorithm is used with a neural network for face recognition. Faces are stored as flexible graphs or grids with characteristic visual features (Gabor features) attached to the nodes of the graph (labeled graphs). The Gabor features are based on the wavelet transform, and have been shown to provide a robust information coding for object recognition (invariance against intensity or contrast changes). Furthermore, Gabor-features are less affected by pose, size and facial expression than raw grey level features. For image matching against a stored graph, the graph location in the image is optimized. It has been shown that Elastic Bunch Graph Matching (EBGM) can successfully recognize faces from facial line drawings. The efficiency of the Gabor-wavelets in recognizing line drawings is due to the fact that line drawings have dominant orientations of bars and step edges, and the Gabor-code is also dominated by orientation features. Gender classifications experiments performed on line drawings resulted in a correct-decision rate of better than 90%.

Perronnin & Dugelay (Perronnin & Dugelay, 2003) proposed a further deformable model, whose philosophy is similar to the EBGM. They introduced a novel probabilistic deformable model of face mapping, based on a bi-dimensional extension of the 1D-HMM (Hidden Markov Model). Given a template face F_T, a query face F_Q and a deformable model M, the proposed method try to maximize the likelihood $P(F_T|F_Q,M)$. There are two main differences between this method and the original EGM. First of all the HMM is extended to the 2D case to estimate $P(F_T|F_Q,M)$, automatically training all the parameters of M, so taking into account for the elastic properties of the different parts of the face. Secondly, the model M is shared among all faces, so the approach works well also when little enrolment data is available.

In Ref. (Lam & Yan, 1998), an analytic-to-holistic approach is introduced for identification of faces at different perspective variations. The ORL-database is used in the experiments. Only one upright frontal face is selected for each of 40 individuals. Among the rest of the faces, they selected 160 images as a testing set. About half of the faces are upright and have a small rotation on the y-axis. The other half show different amounts of perspective variations. Fifteen feature points are located on a face. A head model is proposed, and the rotation of the face can be estimated using geometrical measurements. The positions of the feature points are adjusted so that their corresponding positions for the frontal view are approximated. A similarity transform is then used to compare the feature points with pre-stored features. In addition to that, eyes, nose and mouth are correlated with corresponding patterns in a database. Under different perspective variations, the overall recognition rates are over 84% and 96% for the first and the first three likely matched faces, respectively.

In Ref. (Li & Lu, 1999), a classification method, called the Nearest Feature Line (NFL), is proposed for face recognition. The line passing through two feature points in the eigenspace of the same class is used to generalise any two featurepoints of the same class. The derived FL can capture more variations of face images than the original points. A nearest distance-based classifier is used. The nearest feature line method achieved an error rate of 3.125%, and the authors claim that it is the lowest reported rate for the ORL database. The authors expect this improvement to be due to the feature lines' ability to expand the representational capacity of available feature points, and to account for new conditions not represented by original prototype face images. The error rate of the proposed method is 43.7–65.4% of that of the standard Eigenface method.

2.2 Statistics-based Face Recognition Algorithms

The Eigenface approach described by Turk and Pentland (Turk & Pentland, 1991) is one of the most popular approaches for face recognition. The principal component analysis is applied on the training set of faces. The Eigenface approach assumes that the set of all possible face images occupies a low-dimensional subspace, derived from the original high-dimensional input image space. The Eigenface space is an approximation of face patterns in the training set using data clusters and their principal components. An unknown face is classified if its distance to the clusters is below a certain threshold, using an appropriate classifier. Turk and Pentland (Turk & Pentland, 1991) reported a correct recognition rate of 95% in the case of the FERRET database, containing about 3000 different faces. The tested face images seem to be taken with little variation in viewpoint and lighting, although with significant variation in facial expression. The major drawback of the Eigenface approach is that the scatter being maximised is due not only to the 'between-class scatter' that is useful for classification, but also to the 'within-class scatter' that, for classification purposes, is unwanted information.

Many other researchers have implemented the Eigenface approach for comparison purposes. Belhumeur et al. (Belhumeur et al., 1997) used the Fisherface method to project face images into a three dimensional linear subspace. The projection is based on Fisher's Linear Discriminant in order to maximise the 'between-class scatter' while minimising the 'within-class scatter'. This approach is proved to be more efficient than the Eigenface approach, especially in the case of variable illumination. The experiments were performed on only 150 faces from 15 subjects selected from the ORL database. The results show that the Eigenface approach is quite robust when dealing with glasses and facial expressions, but sensitive to scale, pose and illumination. The correct recognition rate achieved is 95% for only 150 images, selected from the 400 images of the ORL database.

The LDA (Linear Discriminant Analysis) (Lu et al., 2003; Martinez and Kak, 2001) has been proposed as a better alternative to the PCA. It expressly provides discrimination among the classes, while the PCA deals with the input data in their entirety, without paying any attention for the underlying structure. Indeed the main aim of the LDA consists in finding a base of vectors providing the best discrimination among the classes, trying to maximize the between-class differences, minimizing the within-class ones.

3. Self-Organizing Maps (SOM)

In this section, we will give a brief introduction on Self-Organizing Map (SOM) (Kohonen, 1985). SOM has been proposed by Kohonen in the early eighties (Kohonen, 1985). Since that time, it has been used most widely for data analysis in some areas such as economics physics, chemistry or medical applications. As a general purpose clustering tool with topology preserved from input data, Self-Organizing Map (SOM) has been widely utilized in various areas now (Kohonen, 1996).

The SOM provides an orderly mapping of an input high-dimensional space $\Re^n$ in much lower dimensional spaces, usually one or two dimensions. As it compresses information while preserving the most important topological and metric relationships of the primary data items, it can be thought to produce some kind of abstractions of information. So it can be utilized in a number of ways in complex tasks such as pattern classification, process analysis, machine perception, control, and communication.

The Kohonen neural network consists of two layers; the first one (input layer) is connected to each vector of the dataset, the second one (output layer) forms a two-dimensional array of nodes. In the output layer, the units of the grid (virtual sites) give a representation of the distribution of the sample units in an ordered way. For learning, only input units are used, no expected output data is given to the system; we are referring to unsupervised learning. The learning steps are well known (Kohonen, 1996) but will be described in some detail.

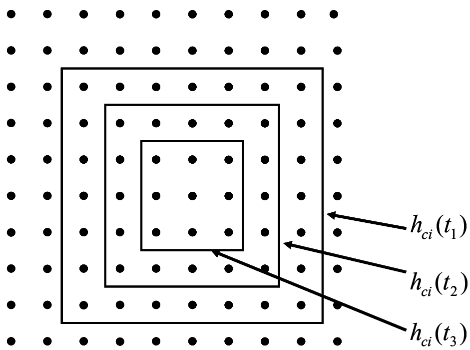

Fig. 1. An example of a two-dimensional SOM

An example of a two-dimensional SOM is show in Figure 1. With each *i*, a reference vector in the input space,

$$W_i = [w_{i1}, w_{i2}, \ldots, w_{in},]^T \in \Re^n ,$$

is assigned to each node in the SOM. During training, each input x, is compared to all of the W_i, obtaining the location of the close match

$$\left|x - W_c\right| = \min\left|x - W_i\right| \tag{1}$$

The input point is mapped to this location in the SOM. Nodes in the SOM are updated according to:

$$W_i(t+1) = W_i(t) + h_{ci}(t)\left[x(t) - W_i(t)\right] \tag{2}$$

Where t is the time during learning and $h_{ci}(t)$ is the neighbourhood function, a smoothing kernel which is maximum at W_c. Usually,

$$h_{ci}(t) = h(\| r_c - r_i \|, t), \tag{3}$$

where r_c and r_i represent the location of the nodes in the SOM output space. r_c is the node with the closest weight vector to the input sample and r_i ranges over all nodes. $h_{ci}(t)$ approaches 0 as $\| r_c - r_i \|$ increases and also as t approaches ∞. A widely applied neighbourhood function is:

$$h_{ci} = \alpha(t)\exp\left(-\frac{\| r_c - r_i \|^2}{2\sigma^2(t)}\right) \tag{4}$$

where $\alpha(t)$ is a scalar valued learning rate and $\sigma(t)$ defines the width of the kernel. They are generally both monotonically decreasing with time. The use of the neighborhood function means that nodes which are topographically close in the SOM structure activate each other to learn something from the same input x. A relaxation or smoothing effect results which leads to a global ordering of the map. Note that $\sigma(t)$ should not be reduced too far as the map will lose its topographical order if neighboring nodes are not updated along with the closest node. The SOM can be considered a non-linear projection of the probability density, *p(x)* (Kohonen, 1995).

4. Face Recognition Using SOM

In this section, we presents in details on various face recognition applications using SOM, including analysis and discussions of their advantages and demerits.

4.1 Overview

Figure 2 shows a general procedure of face recognition algorithm using Self-Organizing Map (SOM). For face recognition algorithm, Self-Organizing Map (SOM) usually fills the role of dimension reduction and feature extraction.

Self-Organizing maps (SOMs) (Kohonen, 1985; Kohonen, 1996) have been successfully used as a way of dimensionality reduction and feature selection for face space representations (Lawrence et al., 1997; Tan et al., 2005; Kumar et al., 2008).

In Lawrence et al. (Lawrence et al., 1997), both a convolutional neural network and a self-organising feature map classifier were used for invariant face recognition. This system was tested on the ORL database, and resulted in a correct recognition rate of 96.2% for the case of a training set, including five faces per person and a test set including five faces per person.

Neagoe (Neagoe & Ropot, 2002) present a new neural classification model called Concurrent Self-Organizing Maps (CSOM), representing a winner-takes-all collection of small SOM networks. Each SOM of the system is trained individually to provide best results for one class only. They obtained a recognition score of 91% with CSOM (40 small linear SOMs) on the ORL database.

Tan (Tan et al., 2005) proposed a Self-Organizing Map (SOM) based algorithm to solve the one training sample face recognition problem. As stated in Ref. (Tan et al., 2005), the SOM algorithm can extract local facial features even with a single image sample due to its unsupervised, nonparametric nature, resulting in a lower recognition error rate compared to PCA.

Kumar et al. (Kumar et al., 2005) integrated the two techniques for dimensionality reduction and feature extraction and to see the performance when the two are combined. Simulation results show that, though, the individual techniques SOM and PCA itself give excellent performance but the combination of these two can also be utilized for face recognition. The advantage in combining the two techniques is that the reduction in data is higher but at the cost of recognition rate.

Oravec et al. (Oravec & Pavloicova, 2007) present an original method of feature extraction from image data using MLP (multilayer perceptron) and PCA (principal component analysis). This method is used in human face recognition system and results are compared to face recognition system using PCA directly, to a system with direct classification of input images by MLP and RBF (radial basis function) networks, and to a system using MLP as a feature extractor and MLP and RBF networks in the role of classifier. Also a two stage method for face recognition is presented, in which Kohonen self-organizing map is used as a feature extractor. This method uses feature extraction method from image data, which is based on vector quantization (VQ) of images using Kohonen self-organizing map for codebook design. The indexes used for image transmission are used to recognize faces.

Aly et al. (Aly et al., 2008) present an appearance-based method for face recognition and evaluate its robustness against illumination changes. Self-organizing map (SOM) is utilized to transform the high dimensional face image into low dimensional topological space. However, the original learning algorithm of SOM uses Euclidean distance to measure similarity between input and codebook images, which is very sensitive to illumination changes. In Ref. (Aly et al., 2008) , they present Mahalanobis SOM, which uses Mahalanobis distance instead of the original Euclidean distance. The effectiveness of the proposed method is demonstrated by conducting some experiments on Yale B and CMU-PIE face databases.

Lefebvre & Garcia (Lefebvre & Garcia, 2008) present a method aiming at quantifying the visual similarity between an image and a class model. This kind of problem is recurrent in many applications such as object recognition, image classification, etc. In Ref. (Lefebvre & Garcia, 2008), they proposed to label a Self-Organizing Map (SOM) to measure image similarity. To manage this goal, they feed local signatures associated to the regions of interest into the neural network. At the end of the learning step, each neural unit is tuned to a particular local signature prototype. During the labeling process, each image signature presented to the network generates an activity vote for its referent neuron. Facial recognition is then performed by a probabilistic decision rule. This scheme offers very promising results for face identification dealing with illumination variation and facial poses and expressions.

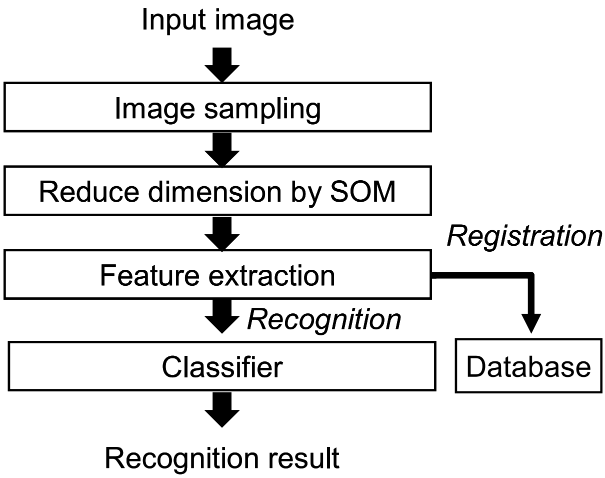

Fig. 2. General procedure of face recognition algorithm using Self-Organizing Map (SOM)

4.2 Some Typical Face Recognition Approaches Using SOMs

4.2.1 Hybrid Neural-Network method using SOM and CNN for Face Recognition

Lawrence et al. (Lawrence et al. 1997) proposed a hybrid neural-network method which combines local image sampling, a self-organizing map (SOM) neural network, and a convolutional neural network (CNN).

In Ref. (Lawrence et al. 1997), both a convolutional neural network and a self-organizing feature map classifier were used for invariant face recognition. The system was tested on the ORL database, and resulted in a correct recognition rate of 96.2% for the case of a training set, including five faces per person and a test set including five faces per person. On the contrarily, testing the Eigenface method resulted in 89.5% correct recognition rate.

The overview of this method is described as follows.

1. In their system, firstly, a window is stepped over the image and a vector is created from a local window on the image using the intensity variation given by the difference between the centre pixel and all other pixels within the square window. For the images in the training set, a fixed size window (e.g. 5 x 5) is stepped over the entire image and local image samples are extracted at each step. At each step the window is moved by 4 pixels.

2. The Self-Organizing Map (SOM) provides a quantization of the image samples into a topological space where inputs that are nearby in the original space are also nearby in the output space, thereby providing dimensionality reduction and invariance to minor changes in the image sample. A Self-Organizing Map (SOM) (e.g. with three dimensions and five nodes per dimension, $5^3 = 125$ total nodes) is trained on the vectors from the previous stage. The SOM quantizes the 25-dimensional input vectors into 125 topologically ordered values. The three dimensions of the SOM can be thought of as three features.

The SOM is used primarily as a dimensionality reduction technique and it is therefore of interest to compare the SOM with a more traditional technique. Hence, experiments were performed with the SOM replaced by the Karhunen-Lo`eve transform. In this case, the KL transform projects the vectors in the 25-dimensional space into a 3-dimensional space.

3. The same window as in the first step is stepped over all of the images in the training and test sets. The local image samples are passed through the SOM at each step, thereby creating new training and test sets in the output space of the self-organizing map. (Each input image is now represented by 3 maps, each of which corresponds to a dimension in the SOM. The size of these maps is equal to the size of the input image (92x112) divided by the step size (for a step size of 4, the maps are 23x28).
4. The convolutional neural network provides for partial invariance to translation, rotation, scale, and deformation. The convolutional network extracts successively larger features in a hierarchical set of layers, which is trained on the newly created training set. Training a standard MLP was also investigated for comparison.

The main objective of this algorithm is how to improve the robustness of recognition system using a five-layered convolutional neural network (CNN). So it can not provide a general representation for one sample per person problem.

4.2.2 SOM and Soft k-NN Ensemble for Single Training Image per Person

Towards the one training sample face recognition problem, Tan proposed a similar Self-Organizing Map (SOM) based algorithm (Tan et al., 2005) to solve it. Based on the work of Martinez's (Martinez, 2002), which used a local probabilistic method to recognize partially occluded and expression variant face from a single sample per class, Tan extended it by proposing an alternative way of representing the face subspace with SOMs instead of a mixture of Gaussians. As stated in Ref. (Tan et al., 2005), the SOM algorithm can extract local facial features even with a single image sample due to its unsupervised, nonparametric nature, resulting in a lower recognition error rate compared to PCA.

The overview of this method is described as follows.

1. Localizing the face image

   The original face image is firstly divided into M nonoverlapping subblocks with equal size. Then the M low dimensional local feature vectors (LFVs) are obtained by concatenating the pixels of each subblock.
2. SOM projection

   A SOM network is then trained using all the obtained subblocks from all the available training images irrespective of classes. After the SOM map has been trained, each subblock R_i of the same face image I are mapped to its corresponding best matching units (BMUs) by a nearest neighbor strategy, whose location in the 2D SOM topological space is denoted as a location vector $l_i = \{x_i, y_i\}$. All the location vectors from the same face can be grouped as a set, which is called SOM-face. The merit of SOM-face is that even when the sample size is too small to faithfully represent the underlying distribution, the SOM algorithm can still extract all the significant information of local facial features due to the algorithm's unsupervised and nonparametric characteristic, while eliminating possible faults like noise, outliers, or missing values. Therefore, the compact and robust representation of the subspace can be reliably learned. In Ref. (Tan et al., 2005), based on the localization of the training images, two strategies of learning the SOM topological space are proposed, namely to train a single SOM map for all the samples and to train a separate SOM map for each class, respectively.

3. Identifying face based on SOM-face

   A soft nearest neighbor (soft -NN) ensemble decision method, which can effectively exploit the outputs of the SOM topological space and can avoid the losing of information, is used to identify the unlabeled subjects.

This algorithm was tested on the FERET database (Phillips et al., 2000), which a single SOM map was trained using all 1196 images in the gallery set. And the recognition rate of the system on 1195 probe images is measured, resulted in a correct recognition rate which outperformed the standard Eigenface technique (Turk & Pentland, 1991) and 2-DPCA (Yang et al., 2004) by 10%–15%.

However, the performance of these approaches was evaluated using frontal face patterns where only small variations are considered. If more complex variations such as aging-, illumination- and pose-variations are included, the recognition performance may be still in question (Wang et al., 2006).

4.3 Discussions

The Self-organizing Map (SOM) provides a quantization of the image samples into a topology preserving space where inputs located nearby in the original space also appear nearby in the output space. The SOM achieves dimensionality reduction and provides partial invariance to translation, rotation, scale, and deformation in the image sample.

However, when the number of people increases, the computation expenses become more demanding. In general, neural network approaches encounter problems when the number of classes (i.e., individuals) increases. Moreover, they are not suitable for a single model image recognition task because multiple model images per person are necessary in order to train the systems for optimal parameter settings (Kong et al, 2005). Tan et al. (Tan et al., 2005) have proposed a SOM-face representation to resolve the one training sample face recognition problem. Fusion of multiple neural networks classifiers improved the overall performance of face recognition (Gutta et al., 2000; Lawrence et al., 1997; Tan et al., 2005; Kumar et al., 2008).

5. Conclusions

In this chapter, various face recognition approaches using Self-Organizing Map are reviewed. The Self-Organizing Map (SOM) provides an orderly mapping of an input high-dimensional space in much lower dimensional spaces, so it can play the role of dimension reduction and feature extraction for face recognition algorithm. Furthermore, because it can provides partial invariance to translation, rotation, scale, and deformation in the image sample, combined with other neural networks methods, more and more face recognition algorithm using SOM will be studied in the future.

6. References

Abate, A.F.; Nappi, M.; Riccio, D. & Sabatino, G. (2007). 2D and 3D Face Recognition: A Survey, *Pattern Recognition Letters*, Vol. 28, pp. 1885-1906

Aly, S. ; Tsuruta, N. & Taniguchi, R. (2008). Face Recognition under Varying Illumination Using Mahalanobis Self-organizing Map, *Artificial Life and Robotics*, Vol. 13, No. 1, pp. 298-301

AT&T Laboratories Cambridge, The database of faces, at http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html

Bartlett, M. S. ; Movellan, J. R. & Sejnowski, T. J. (2002). Face Recognition by Independent Component Analysis, *IEEE Trans. on Neural Networks*, Vol. 13, No. 6, pp. 1450-1464

Belhumeur, P.; Hespanha, J. & Kriegman, D. (1997). Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection, *IEEE Trans. on Pattern Analysis and Machine Intelligence*, Vol. 19, No.7, pp. 711–720

Ben, A. J. & Nandy, D. (1998). A Volumetric/iconic Frequency Domain Representation for Objects with Application for Pose Invariant Face Recognition, *IEEE Trans. on Pattern Analysis and Machine Intelligence*, Vol. 20, No. 5, pp. 449–457

Bowyer, K.W. (2004). Face Recognition Technology and the Security Versus Privacy Tradeoff, *IEEE Technology and Society*, pp. 9-20

Brunelli, R. & Poggio, T. (1993). Face Recognition: Features Versus Templates, *IEEE Trans. on Pattern Analysis and Machine Intelligence*, Vol. 15, No. 10, pp. 1042-1052

Chellappa, R. ; Wilson, C. L. & Sirohey, S. (1995). Human and Machine Recognition of Faces: A Survey, *Proc. IEEE*, Vol. 83, No. 5, pp. 705-740

Filippone, M.; Camastra, F.; Masulli, F. & Rovetta, S. (2008). A Survey of Kernel and Spectral Methods for Clustering, *Pattern Recognition*, Vol. 41, pp. 176 -190

Goudail, F. ; Lange, E. ; Iwamoto, T.; Kyuma, K. & Otsu, N. (1996). Face Recognition System Using Local Autocorrelations and Multiscale Integration, *IEEE Trans. on Pattern Analysis and Machine Intelligence*, Vol. 18, No. 10, pp. 1024-1028

Gutta, S. ; Huang, J. R. J. ; Jonathon, P. & Wechsler, H. (2000). Mixture of Experts for Classification of Gender, Ethnic Origin, and Pose of Human Faces, *IEEE Trans. on Neural Network*, Vol. 11, Issue. 4, pp. 948–960

Karungaru, S.G.; Fukumi, M. & Akamatsu, N. (2005). Face Recognition in Colour Images Using Neural Networks and Genetic Algorithms, *International Journal of Computational Intelligence and Applications*, Vol. 5, No. 1, pp. 55-67

Kohonen, T. (1985). *Self-Organizing Maps*, Springer-Verlag, Berlin

Kohonen, T. (1996). Engineering Applications of the Self-Organizing Map, *Proceedings of the IEEE*, Vol. 84, No. 10, pp. 1358-1384

Kong, S. G.; Heo, J.; Abidi, B. R.; Paik, J. & Abidi, M. A. (2005). Recent Advances in Visual and Infrared Face Recognition - A Review, *Computer Vision and Image Understanding*, Vol. 97, pp. 103-135

Kotani, K. ; Chen, Q. & Ohmi, T. (2002). Face Recognition Using Vector Quantization Histogram Method, *IEEE 2002 International Conference on Image Processing*, II-105-108

Kumar, D.; Rai, C.S. & Kumar, S. (2005). Face Recognition Using Self-Organizing Map and Principal Component Analysis, *International Conference on Neural Networks and Brain 2005 (ICNN&B '05)*, Vol. 3, pp. 1469-1473

Lam, K.-M. & Yan, H. (1998). An Analytic-to-holistic Approach for Face Recognition Based on a Single Frontal View, *IEEE Trans. on Pattern Analysis and Machine Intelligence*, Vol. 20, No. 7, pp. 673-686

Lampinen, J. & Oja, E. (1995). Distortion Tolerant Pattern Recognition Based on Self-Organizing Feature Extraction, *IEEE Trans. on Neural. Network*, Vol. 6, pp. 539-547

Lawrence, S.; Giles, C. L.; Tsoi, A. C. & Back, A. D. (1997). Face Recognition: A Convolutional Neural Network Approach, *IEEE Trans. on Neural Networks*, Vol. 8, No.1, pp.98-113.

Lefebvre, G & Garcia, C. (2008). A Probabilistic Self-Organizing Map for Facial Recognition, *19th International Conference on Pattern Recognition*, Florida, USA

Li, S. Z. & Lu, J. (1999). Face Recognition Using the Nearest Feature Line Method, *IEEE Trans. on Neural Networks*, Vol. 10, No. 2, pp. 439–443

Li, S. Z. & Jain, A. K. (2005). *Handbook of Face Recognition*, Springer, New York

Lin, S. H. ; Kung, S. Y. & Lin, L. J. (1997). Face Recognition/detection by Probabilistic Decision-based Neural Network, *IEEE Trans. on Neural Networks*, Vol. 8, No. 1, 114–132

Martinez, A. M. (2002). Recognizing Imprecisely Localized, Partially Occluded, and Expression Variant Faces from a Single Sample per Class, *IEEE Trans. on Pattern Analysis Machine Intelligence*, Vol. 25, No. 6, pp. 748-763

Moghaddam, B. & Pentland, A. (1997). Probabilistic Visual Learning for Object Representation, *IEEE Trans. on Pattern Analysis and Machine Intelligence*, Vol. 19, No. 7, pp. 696-710

Neagoe, V. E. & Ropot, A. D. (2002). Concurrent Self-Organizing Maps for Pattern Classification, *Proceedings of the First IEEE International Conference on Cognitive Informatics (ICCI02)*

Oravec, M. & Pavloicova, J. (2007). Face Recognition Methods Based on Feedforward Neural Networks, Principal Component Analysis and Self-Organizing Map, *Radioengineering*, Vol. 16, No. 1, pp. 51-57

Penev, P. S. & Atick, J. J. (1996). Local Feature Analysis: A General Statistical Theory for Object Representation, *Network: Computation in Neural Systems*, Vol. 7, No. 3, pp. 477-500

Perronnin, F. & Dugelay, J.-L. (2003). An Introduction to Biometrics and Face Recognition, *Proc. IMAGE'2003: Learning, Understanding, Information Retrieval, Medical*, Cagliari, Italy

Phillips, P. J.; Moon, H.; Rizvi, S. A. & Rauss, P. J. (2000). The FERET Evaluation Methodology for Face-Recognition Algorithms, *IEEE Trans. on Pattern Recognition and Machine Intelligence*, Vol. 22, No. 10, October 2000, pp. 1090-1104

Tan, X.; Chen, S.; Zhou, Z. & Zhang, F. (2005). Recognizing Partially Occluded, Expression Variant Faces from Single Training Image per Person with SOM and Soft k-NN Ensemble, *IEEE Trans. on Neural Networks*, Vol. 16, No. 4, pp. 875-886

Tan, X.; Chen, S.; Zhou, Z. & Zhang, F. (2006). Face Recognition from A Single Image per Person: A Survey, *Pattern Recognition*, Vol. 39, pp. 1725-1745

Tolba, A. S. & Abu-Rezq, A. N. (2000). Combined Classifiers for Invariant Face Recognition, *Pattern Analysis & Applications*, Vol. 3, pp. 289-302

Turk, M. & Pentland, A. (1991). Eigenfaces for Recognition, *Journal of Cognitive Neuroscience*, Vol. 3, No. 1, pp. 71-86

Wang, J.; Plataniotis, K. N.; Lu, J. & Venetsanopoulos, A. N. (2006). On Solving the Face Recognition Problem with One Training Sample per Subject, *Pattern Recognition*, Vol. 39, pp. 1746 -1762

Wiskott, L.; Fellous J. M.; Kruger, N. & Malsburg, C. von der. (1997). Face Recognition by Elastic Bunch Graph Matching, *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 19, No. 7, pp. 775-779

Yang, J.; Zhang, D.; Frangi, A. F. & Yang, J. (2004). Two-dimensional PCA: A New Approach to Appearance-based Face Representation and Recognition, *IEEE Trans. on Pattern Analysis Machine Intelligence*, Vol. 26, No. 1, pp. 131–137

Zhang, D. ; Peng, H. ; Zhou, J. & Pal S. K. (2002). A Novel Face Recognition System Using Hybrid Neural and Dual Eigenspaces Methods, *IEEE Trans. on System Man Cybernetics-Part A*, Vol. 32, No. 6, pp. 787-793

Zhao, W. (2000). Discriminant Component Analysis for Face Recognition, *Proceeding of International Conference on Pattern Recognition*, Track 2, pp. 822-825

Zhao, W. ; Chellappa, R. ; Rosenfeld, A. & Phillips, P.J. (2003). Face Recognition: A Literature Survey, *ACM Computing Surveys*, Vol. 35, Issue 4, pp. 399-458