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Optimized Neural Networks Using Principal Component Analysis for Automatic Road Extraction from Remote Sensing

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Abstract: Remote sensing imagery has become an invaluable tool to observe and study the earth's surface. With the increasingly availability of multi-spectral remote sensing images, color provides another important feature extracting road net works. From a scientific perspective, the extraction of roads in complex environments is one of the challenging issues in photogrammetry and computer vision since, many tasks related to automatic scene interpretation are involved. The aim of this study is to show the ability of satellite imagery in road mapping by using Artificial Neural Networks (ANN) and Principal Component Analysis (PCA) of multi Spectral SPOT imagery. The results demonstrate that the elimination of correlated information in the sample data by PCA improve the MLP estimation performance and reduce the required training time. We have obtained very accurate results (<0.03) for the MSE. This approach is distinguished from previous work by the choice of the structure of multilayer neural networks input based mainly on two PCA and the neighbors of the pixel influencing greatly the quality of output (extracted road network image). The system includes different modules: data pre-processing and PCA transformation, neural networks for road extraction, procedure of road centerline and vectorization. The results show that the proposed method for road extraction is very effective and demonstrate its performance.

Key words: Road extraction, image processing, remote sensing, principal component analysis, neuronal networks

INTRODUCTION

Automatic extraction of urban roads from remote sensing imagery is still a challenging problem in digital photogrammetry and computer vision. The main reason is that the diverse road surfaces and the complex surrounding environments such as trees, vehicles and shadows induced by high buildings make the urban roads take on different textures and gray levels in images. Road extraction in urban areas from remotely sensed images has been the purpose of many researches in the image processing field and because its complexity is still a challenging topic. In recent years, mainly the rapid development of urban areas makes it urgent to provide up-to-date road maps. The timely road information is very useful for the decision-makers in urban planning, traffic management and car navigation fields, etc. Now a days, we are experiencing an explosion in the amount of satellite image data which provides us abundant data and also brings challenges to the road extraction task at the same time. The conventional road extraction methods by manual are time consuming and tedious and cannot meet the increasing requirement for such tremendous data. Therefore, it has drawn considerable attention of many researchers on how to develop automatic road extraction systems and much work has been done for this task. However, automatic extraction of urban roads from high resolution remote sensing imagery is still a challenging problem in digital photogrammetry and computer vision. The problems currently involved in the features extraction like road presents the following issues: first, the roads may be partially hidden; second, some stretches of road may not be registered due to limitations of the orbital images; third, the radiometric resolution of the selected road. The first issue is due to clouds that may be present in the images and shadows of structures such as buildings, bridges and cars as well as vegetation can hide parts of the road feature. The second question is a function of spatial resolution of the images used for extraction. The third question refers to the similarity

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between different features for example, roads without pavement may present a feature similar to exposed soil. In fact, many researches on this topic have been presented (Mena, 2003) but the manual intervention of the operator in extracting, defining and validating cartographic objects for GIS update is still needed. Nevertheless, important advances have been achieved. The literature contains a variety of schemes which are mainly based on a local criterion, involving the use of local operators or a global criterion, incorporating additional knowledge about the structure of the objects to be detected. The methods based on local criteria evaluate local properties on the image by using morpholoical operators (Ma *et al*., 2008). The performance of these methods can be greatly increased by using techniques that introduce some global constraints in the image analysis process. However, most of them focus on extracting roads in rural or open areas. Some researches on automatic road extraction in urban area from high resolution satellite images used a based machine learning approach and model reconstruction based on aerial images using SVM and Gabor filter (Jin *et al*., 2011). The other semi-automatic methods have been the subject of several studies such as active contour (or snake) (Ksantini *et al*., 2013; Marikhu *et al*., 2007) and dynamic programming (Tournaire and Paparoditis, 2009). The methods of road extraction in satellite and aerial images based on stochastic geometry and dynamics reversible jump MCMC are presented in (Cai *et al*., 2006; Stoica *et al*., 2004). One can find an excellent survey paper by Mokhtarzade *et al*. (2008) on road network extraction using the organizing maps applied to classified images. A road detection strategy based on the neural network classifiers was introduced by Mokhtarzade and Zoej (2007) where a variety of input spectral parameters were tested on the functionality of the neural network for both road and background detection. Those involving texture analysis, fuzzy clustering and genetic algorithms have been treated by Mokhtarzade *et al*. (2007) and Mohammadzadeh *et al*. (2006) and fuzzy logic and mathematical morphology in (Mohammadzadeh *et al*., 2004). In road extraction was performed on multispectral satellite images characteristics of the pixel from SPOT imagery, using Artificial Neural Networks (ANNs) with a vector of 27 neurons. The principal problem of this method was that of the time of training due to the dimension of the input vector.

Most of the real-world data samples used to train Artificial Neural Networks (ANNs) consist of correlated information caused by overlapping input instances. Correlation in sampled data normally creates confusion over ANNs during the learning process and thus, degrades their generalization capability. To solve this problem, the study proposes the Principal Component Analysis (PCA) Method for elimination of correlated information in data. The uncorrelated PCA data were used to train a Multi-Layer Perceptron (MLP) ANN system. The results demonstrated that the elimination of correlated information in the sample data by way of the PCA Method improved the MLP's estimation performance and reduced the required training time.

As the neural networks require a large coded data base in their training stage, we have used a set of road net manually drown using special software. To perform road centerline a procedure based on mathematic morphology operations was implemented. The results show that the proposed method for road extraction is very effective and demonstrate its performance. The proposed system for road detection includes different modules:

- Data pre-processing and non linear PCA computing
- Artificial neuronal networks with back propagation algorithm for road extraction
- Mapping based mathematical morphology to extract road centerline

MATERIALS AND METHODS

Hypothesis of this work: Road networks in high resolution satellite and aerial images are presented as elongated homogenous areas having a distinct brightness from the background. Road detection can be considered as the first step in road extraction: it is the process of assigning a value to each pixel that can be used as criteria of road and not-road pixels. The problem of road detection from satellite images is performed using artificial neuronal networks based on Principal Component Analysis. In fact, the non linear PCA transform produces an orthogonal basis (generated by the eigenvectors of the sample covariance matrix that correspond to the largest eigenvectors). It is based on the assumption that the most relevant information corresponds to the highest variances.

In our research, input requirements and the following hypothesis have been considered: road characteristics can be classified in five groups: geometrical, radiometrical, topological, functional and contextual characteristics:

- Roads are elongated (geometry)
- Roads have a maximum curvature (geometry)
- The road surface usually is homogeneous (radiometry)
- The road surface often has a good contrast with the adjacent areas (radiometry)

- Roads do not stop without a reason (topology)
- Roads intersect and build a network (topology)
- Roads connect cities (functional)
- Higher roads (fly-overs) may cast a shadow (contextual)
- Trees may occlude the road surface but on the other hand, an array of trees may also indicate a road (contextual)

The characteristics describe many features that are used by a human operator to recognize and map roads. Especially, the functional and contextual characteristics require quite some intelligence in order to exploit them in the image interpretation process. In our research, three characteristics have been considered: the radiometry, the geometry and the topology. The origin of the motivation is the homogeneity of roads in high-resolution satellite images, since homogeneity is a characteristic that can be recognized with respect to neighbor pixels and their spectral information.

Data pre-processing

Orthoimages: The first task consists in obtaining the rectified and geo-referenced image. The rectification process is indispensible because it avoids the accumulation of errors when big surfaces are analyzed. In order to evaluate the functionality of the road extraction method proposed in this research, a sub-sample of VHR SPOT5 image bands (1-4) acquired from ISIS scientific project of CNES (n°122) on March 26, 2007 covering Laghouat (Algeria) was used as case study. Table 1 shows the spectral characteristics of the used image.

Median filter: In order to smooth the image noise, a median filter is applied considering the window (3×3) for each pixel. This operation could be substituted for filtering technique described by Zhang *et al.* (2011) which is based on texture properties. In this technique, the texture unit comprising of height neighborhood elements is decomposed into two separable texture units, namely cross texture unit diagonal texture unit of four elements each. For each pixel cross and diagonal texture matrix is evaluated using several types of combinations of cross and diagonal texture units. Using the median technique with (3×3) window best result in the reduction of noise in satellite data has been obtained.

Principle components analysis: Principal component analysis is a popular linear technique in statistical analysis for data compression and has been successfully used as initial step in many computer vision tasks: data analysis, signal processing, statistics, pattern recognition, change detection and neural networks (Zhang *et al.*, 2011).

Table 1: Characteristics of the SPOT image

Mode	Band	Wave length (μm)	Spectral band	Resolution (m)
Multi spectral	B1	0.50-0.59	Green absorption	10×10
	B2	0.61-0.68	Red absorption	10×10
	B3	0.79-0.89	Near infrared of red	10×10
	SWIR	1.58-1.75	Middle infra red	20×20
Mono spectral	PAN	0.51-0.73		5×5 (ou 2.5 en super mode)

Table 2: Correlation matrix

Bands	Band 1	Band 2	Band 3	Band 4
1	1	0.906244	0.788480	0.897033
2	0.906244	1	0.939589	0.874732
3	0.788480	0.939589	1	0.726066
4	0.897033	0.874732	0.726066	1

Table 3: Principal component analysis

PCA	PCA1	PCA2	PCA3
Variance (%)	93.71	5.10	0.97
Eigen vector	596.99	32.47	6.20

Because digital remote sensing images are numeric, their dimensionality can be reduced using this technique. In multi-band remote sensing images, the bands are the original variables. Some of the original bands may be highly correlated and to save on data storage space and computing time such bands could be combined into new, less correlated eigen images by PCA.

The principal components are then the eigen vectors of C. These eigen vectors can be computed in several ways. In our system we compute these eigenvectors using the implementation provided by Matlab.

Because all correlation coefficients are close to 1 in Table 2, there is a strong correlation between each pair of data columns. Principal components analysis on the bands of SPOT5 image produces a new set of images or components that are uncorrelated with each other and explain progressively less of the variance found in the original set of bands. The technique is used for data compression since, the first two or three components explain 93-99% of the variance in the original set of bands (Table 3). In cases like this, the components explaining less than a certain percent of the variance can be dropped.

We use PCA1 and 2, since they contain a total of 98.8% of the variance in the data, PCA3 and 4 are ignored. Eigen values and factor loadings of the principal components from the original (raw) image data are as shown in Table 3.

Figure 1 represent the sub-sample image used in our study and the corresponding color composite image (PCA1 and 2) where roads are well highlighted.

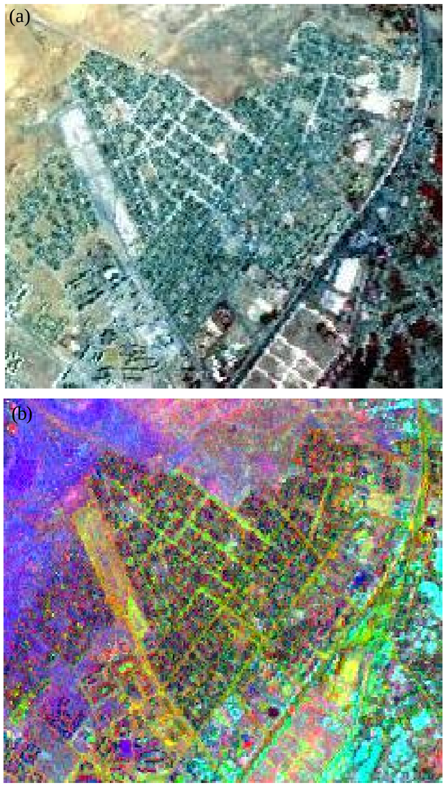

Fig. 1: Sub scene of SPOT image: a) The sub-sample of SPOT image; b) Color composite image of PCA1 and 2

Neural networks road detection method: Neural networks are made up of simple processing units called neurons which are usually organized into layers with fully or partially connections. One of the most important advantages of neural networks as compared to conventional statistical methods is that they are distribution-free operators because the learning and recalling depend on the linear combination of data pattern instead of the statistical parameters of the input. The principal task associated with a neuron is to receive the activation values from its neighbors, compute an output based on its weighted input parameters and send that output to its neighbors. Neural networks are also highly capable of dealing with multi-source data because they do not require explicit modeling of the data from different sources. There is therefore, no need to treat them independently as in the case of many statistical methods. It is also clear in a problem of statistical multi-source analysis of specifying how much influence each data source should have in classification (Bhattacharya *et al*., 2001). Learning (training) a network is the process of adapting or modifying the connection weights between neurons, so that the network can fulfill a specific task. Back propagation, the most common learning algorithm was used with an iterative gradient decent algorithm designed to minimize error function expressed in Eq. 1:

$$E = \frac{1}{2}\sum_{j=1}^{N}\left(D_j - D_j^M\right)^2 \tag{1}$$

Where:

D_j and O_j = The desired output and the current response of the neurons
j = The output layer, respectively
N = The number of neurons in the output layer

In the iterative method, corrections to weight parameters are computed and added to the previous values as illustrated below:

$$\begin{cases} \Delta w_{i,j} = -\eta \dfrac{dE}{dw_{i,j}} \\ \Delta w_{i,j}(t) = \Delta w_{i,j} + \alpha \Delta w_{i,j}(t) \end{cases} \tag{2}$$

Where:

$w_{i,j}$ = The weight parameter between neuron
I and j = Neurons i and j
η = A positive constant that controls the amount of adjustment and is called learning rate and
α = Momentum factor that can take on values between 0 and 1
t = The iteration number

The parameter α can be called smoothing or stabilizing factor as it smoothes the rapid changes between the weights.

Normalized spectral information in a window (3×3) around each pixel is extracted as 9 PCA1 and 2 to constitute the input vector of 18 neurons. The homogeneity is a characteristic that can be defined with respect to neighbor pixels. The system output is represented by one neuron normalized representing the road or not-road characteristic. As the neural networks require a large coded data base in their training stage, we have used a set of 200 road net manually drawn using a special software for the learning stage. It is recommended to have representative pixels of all present objects in the training set.

A back-propagation neural network with one hidden layer is implemented. The output layer consists of one neuron that represents the network's output by a number between 0 and 1 as not road and road pixel, respectively. After the trained network is performed on entire pixels, a matrix called output matrix of the same size as input image is obtained. An adaptive strategy is used to avoid trial and error learning rate and momentum assignment. Therefore, initial learning rate and momentum are not crucial to the success of training stage. Also, training speed is increased because the learning rate is adjusted to the highest value that does not cause instability.

The dataset is divided into training, cross validation and testing datasets. The training dataset is presented to the network for learning. Cross-validation dataset is used to measure the training performance during training and stop training if necessary. The testing dataset is not used in any way during training and hence, provides an independent measure of training performance.

RESULTS AND DISCUSSION

The combination of both 18 input parameters makes the network powerful in the detection of road and background, reducing also the request hidden layer and size iteration time. We have used as a first step a set of different neural networks architectures with 5, 10, 15 and 20 neurons in the hidden layer to test the performance of the neural networks. We have found that a layer of 15 neurons in the hidden layer is sufficient. The choice of window size (3×3) is related to the resolution of the multispectral SPOT image (10 m); a window size (5×5) gives a noisy result because of taking road surrounding into account. All computations (filtering, PCA and morphologic treatments) are carried out in MATLAB environment and thus coding is done in M language.

Accuracy assessment: In order to evaluate the performance of the proposed method and accuracy assessment, we consider four parameters: the Mean Square Error (MSE), the Kappa coefficient, the BCC and RCC coefficients:

- The MSE error is computed by comparing network responses in the output neuron (multiplied by 255) and desired value from manually produced reference map
- The Kappa coefficient, overall accuracy parameter is obtained by the same way as conventional classification methods where the network response of each pixel uses a threshold value
- The BCC (Background Correctness Coefficient)
- The RCC (Road Correctness Coefficient)
- RCC and BCC, stand for "Road/Background Detection Correctness Coefficient", respectively are the average of correct neural network response for road and background detection by comparing the manually produced reference

Table 4 shows that the presented accuracy assignment parameters for both road and background detection ability of spectral information of the proposed ANN based PCA inputs. ANN-PCA Proposed Method is improved comparing of the method based ANN spectral information (ANN-RGB) proposed by Benkouider and thus, the efficiency of the proposed road detection methodology in this research is improved too.

Road mapping: Mathematical morphology is a theory introduced in 1964 by Matheron and Serra. Its initial goal is the analysis of objects in images via their structure (shape, size, relationship with their neighborhood in particular topological texture, grayscale or color). To cartography roads, a set of morphological operations is applied to the RNN extracted image in order to obtain road centerline and vectorization. The method is organized as follow.

Application of morphological erosion to the gray scale image extracted by the RNN with a chosen structuring element (disk of 2 pixels radius according to the resolution if the image (10 m) in order to smoothing roads by shrinking image objects: Erosion generally decreases the sizes of objects and removes small anomalies by subtracting objects with a radius smaller than the structuring element. With grayscale images, erosion reduces the brightness (and therefore the size) of bright objects on a dark background taking the neighborhood minimum when passing the structuring element over the image (Fig. 2c).

The obtained image is then transformed to binary image by threshold. In the thresholding process, individual pixels in an image are marked as "object" pixels if their value is greater than some threshold value (assuming an object to be brighter than the background) and as "background" pixels otherwise. A simple method will be to choose the mean or median value as threshold. A more sophisticated approach may create a histogram of the image pixel intensities and use the valley point as the threshold. The histogram approach assumes that there is some average value for the background and object pixels but the actual pixel values have some variation around these average values. However, this may be computationally expensive and image histograms may not have clearly defined valley points, often making the selection of an accurate threshold difficult. In our case of study, we have used the iterative method that is relatively

Table 4: Accuracy measurement: MSE, BCC, RCC, Kappa coefficient and last iteration

Coefficients	MSE	BCC	RCC	KAPPA	Last iteration
ANN-RGB	0.036	0.83	0.82	0.86	5200
ANN-ACP	0.027	0.86	0.90	0.90	1100

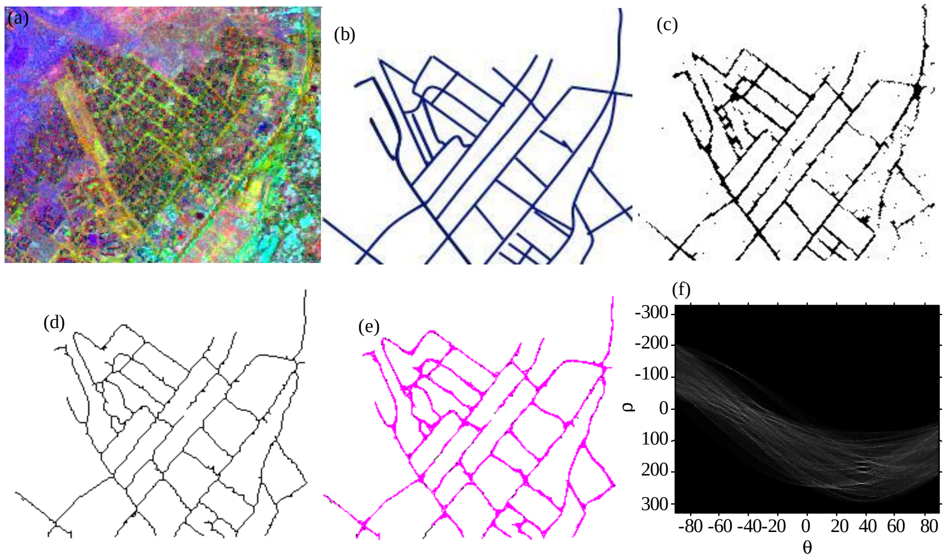

Fig. 2: Note how the caption is centered: a) Composed PCA of sub image (urban); b) Manually road map produced; c) Road detected by RNN-ACP; d) Road centerline; e) Reconstructed road network with hough transform; f) Hough peaks

simple and does not require much specific knowledge of the image and it is robust against image noise. A squelitesation algorithm is then applied to extract road centerlines (Fig. 2d).

Finally, Hough transform is carried out for road vectorization. Post processing above is used to reduce false alarms and the sensitivity of the Hough transform to local variations. Corresponding detected peaks and troughs in the Hough space are shown in (Fig. 2f).

CONCLUSION

In this study, we present an optimization of extraction and vectorization of road network from remote sensing based on neuronal networks strategy. This method is based on spectral characteristics of the pixel from satellite image. As the neuronal net requires a large coded data bases in their training stage, we use a set of road net manually drown using a special software. We propose the uncorrelated PCA data to train a Multi-Layer Perceptron (MLP) ANN system. The results demonstrated that the elimination of correlated information in the sample data by way of the PCA Method improved the MLP estimation performance and reduced the required training time. We have obtained very accurate results <0.03 for the MSE. This approach is distinguished from previous research by the choice of the structure of multilayer neural networks input based mainly on two PCA and the neighbors of the pixel influencing greatly the quality of output (extracted road network image). These results are very accurate since the method can extract the road despite the low resolution of the image (10 m). A set morphological operation is applied in order to obtain the road center line and vectorized: grayscale erosion is applied to road extracted by the proposed RNN-PCA system, followed by a binarization process which is followed by the application of morphological edge to extract road centerline. For further research, we propose using geometric characteristics of road for network's training and texture in order to improve its ability in road detection. Figure 2a represent the composed PCA sub-image test and (Fig. 2b) the corresponded manually road network.

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REFERENCES

Bhattacharya, A.K., P.K. Srivastava and A. Bhagat, 2001. A modified texture filtering technique for satellite image. Proceedings of the 22nd Asian Conference on Remote Sensing, November 5-9, 2001, Singapore.

Cai, X., A. Sowmya and J. Trinder, 2006. Learning parameter tuning for object extraction. Proceedings of the 7th Asian Conference on Computer Vision, January 13-16, 2006, Hyderabad, India, pp: 868-877.

Jin, H., Y. Feng and Y. Shen, 2011. Accurate urban road model reconstruction from high resolution remotely sensed imagery based on Support Vector Machine and Gabor filters. Proceedings of the Joint Conference on Urban Remote Sensing Event, April 11-13, 2011, Munich, Germany.

Ksantini, R., B. Boufama and S. Memar, 2013. A new efficient active contour model without local initializations for salient object detection. EURASIP J. Image Video Process., 10.1186/1687-5281-2013-40.

Ma, H., Y. Zhao and Y. Chen, 2008. Road extraction from high resolution remote sensing image based on mathematics morphology. Proceedings of the Geoinformatics 2008 and Joint Conference on GIS and Built Environment: Classification of Remote Sensing Images, November 07, 2008, Guangzhou, China.

Marikhu, R., M.N. Dailey, S. Makhanov and K. Honda, 2007. A family of quadratic snakes for road extraction. Proceedings of the 8th Asian Conference on Computer Vision, November 18-22, 2007, Tokyo, Japan, pp: 85-94.

Mena, J.B., 2003. State of the art on automatic road extraction for GIS update: A novel classification. Pattern Recog. Lett., 24: 3037-3058.

Mohammadzadeh, A., A. Tavakoli and M.J.V. Zoej, 2004. Automatic linear feature extraction of Iranian roads from high resolution multi-spectral satellite imagery. Proceedings of the 20th ISPRS Congress, July 12-23, 2004, Istanbul, Turkey, pp: 764-768.

Mohammadzadeh, A., A. Tavakoli and M.J.V. Zoej, 2006. Road extraction based on fuzzy logic and mathematical morphology from pan-sharpened IKONOS images. The Photogram. Record, 21: 44-60.

Mokhtarzade, M. and M.J.V. Zoej, 2007. Road detection from high-resolution satellite images using artificial neural networks. Int. J. Applied Earth Observ. Geoinform., 9: 32-40.

Mokhtarzade, M., H. Ebadi and M.J. Valadan Zoej, 2007. Optimization of road detection from high-resolution satellite images using texture parameters in neural network classifiers. Can. J. Remote Sens., 33: 481-491.

Mokhtarzade, M., M.J.V. Zoej and H. Ebadi, 2008. Automatic road extraction from high resolution satellite images using neuronal net work, texture analysis, fuzzy clustering and genetic algorithm. Int. Arch. Photogramm. Remote Sens. Spatial Info. Sci., 37: 549-556.

Stoica, R., X. Descombes and J. Zerubia, 2004. A gibbs point process for road extraction from remotely sensed images. Int. J. Comput. Vision, 57: 121-136.

Tournaire, O. and N. Paparoditis, 2009. A geometric stochastic approach based on marked point processes for road mark detection from high resolution aerial images. ISPRS J. Photogramm. Remote Sens., 64: 621-631.

Zhang, D., S. Mabu, F. Wen and K. Hirasawa, 2011. A supervised learning framework for PCA-based face recognition using GNP fuzzy data mining. Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, October 9-12, 2011, Anchorage, AK., pp: 516-520.