

# Improvement of Text Dependent Speaker Identification System Using Neuro-Genetic Hybrid Algorithm in Office Environmental Conditions

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## Abstract

In this paper, an improved strategy for automated text dependent speaker identification system has been proposed in noisy environment. The identification process incorporates the Neuro-Genetic hybrid algorithm with cepstral based features. To remove the background noise from the source utterance, wiener filter has been used. Different speech pre-processing techniques such as start-end point detection algorithm, pre-emphasis filtering, frame blocking and windowing have been used to process the speech utterances. RCC, MFCC,  $\Delta$ MFCC,  $\Delta\Delta$ MFCC, LPC and LPCC have been used to extract the features. After feature extraction of the speech, Neuro-Genetic hybrid algorithm has been used in the learning and identification purposes. Features are extracted by using different techniques to optimize the performance of the identification. According to the VALID speech database, the highest speaker identification rate of 100.000 % for studio environment and 82.33 % for office environmental conditions have been achieved in the close set text dependent speaker identification system.

**Key words:** *Bio-informatics, Robust Speaker Identification, Speech Signal Pre-processing, Neuro-Genetic Hybrid Algorithm.*

## 1. Introduction

Biometrics are seen by many researchers as a solution to a lot of user identification and security problems now a days [1]. Speaker identification is one of the most important areas where biometric techniques can be used. There are various techniques to resolve the automatic speaker identification problem [2, 3, 4, 5, 6, 7, 8].

Most published works in the areas of speech recognition and speaker recognition focus on speech under the noiseless environments and few published works focus on

speech under noisy conditions [9, 10, 11, 12]. In some research work, different talking styles were used to simulate the speech produced under real stressful talking conditions [13, 14, 15]. Learning systems in speaker identification that employ hybrid strategies can potentially offer significant advantages over single-strategy systems.

In this proposed system, Neuro-Genetic Hybrid algorithm with cepstral based features has been used to improve the performance of the text dependent speaker identification system under noisy environment. To extract the features from the speech, different types of feature extraction technique such as RCC, MFCC,  $\Delta$ MFCC,  $\Delta\Delta$ MFCC, LPC and LPCC have been used to achieve good result. Some of the tasks of this work have been simulated using Matlab based toolbox such as Signal processing Toolbox, Voicebox and HMM Toolbox.

## 2. Paradigm of the Proposed Speaker Identification System

The basic building blocks of speaker identification system are shown in the Fig.1. The first step is the acquisition of speech utterances from speakers. To remove the background noises from the original speech, wiener filter has been used. Then the start and end points detection algorithm has been used to detect the start and end points from each speech utterance. After which the unnecessary parts have been removed. Pre-emphasis filtering technique has been used as a noise reduction technique to increase the amplitude of the input signal at frequencies where signal-to-noise ratio (SNR) is low. The speech signal is segmented into overlapping frames. The purpose of the overlapping analysis is that each speech sound of the input

sequence would be approximately centered at some frame. After segmentation, windowing technique has been used. Features were extracted from the segmented speech. The extracted features were then fed to the Neuro-Genetic hybrid techniques for learning and classification.

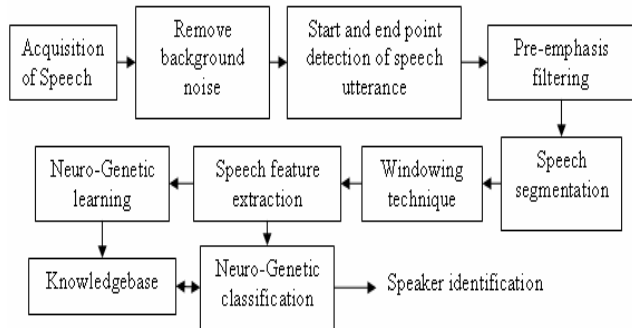


Fig. 1 Block diagram of the proposed automated speaker identification system.

### 3. Speech Signal Pre-processing for Speaker Identification

To capture the speech signal, sampling frequency of 11025 Hz, sampling resolution of 16-bits, mono recording channel and Recorded file format = \*.wav have been considered. The speech preprocessing part has a vital role for the efficiency of learning. After acquisition of speech utterances, wiener filter has been used to remove the background noise from the original speech utterances [16, 17, 18]. Speech end points detection and silence part removal algorithm has been used to detect the presence of speech and to remove pulse and silences in a background noise [19, 20, 21, 22, 23]. To detect word boundary, the frame energy is computed using the sort-term log energy equation [24],

$$E_i = 10 \log \sum_{t=n_i}^{n_i+N-1} S^2(t) \quad (1)$$

Pre-emphasis has been used to balance the spectrum of voiced sounds that have a steep roll-off in the high frequency region [25, 26, 27]. The transfer function of the FIR filter in the z-domain is [26]

$$H(Z) = 1 - \alpha \cdot z^{-1}, \quad 0 \leq \alpha \leq 1 \quad (2)$$

Where  $\alpha$  is the pre-emphasis parameter.

Frame blocking has been performed with an overlapping of 25[%] to 75[%] of the frame size. Typically a frame length of 10-30 milliseconds has been used. The purpose of the overlapping analysis is that each speech sound of the input sequence would be approximately centered at some frame [28, 29].

From different types of windowing techniques, Hamming window has been used for this system. The purpose of using windowing is to reduce the effect of the spectral artifacts that results from the framing process [30, 31, 32]. The hamming window can be defined as follows [33]:

$$w(n) = \begin{cases} 0.54 - 0.46 \cos \frac{2\pi n}{N}, & -\left(\frac{N-1}{2}\right) \leq n \leq \left(\frac{N-1}{2}\right) \\ 0, & \text{Otherwise} \end{cases} \quad (3)$$

### 4. Speech parameterization Techniques for Speaker Identification

This stage is very important in an ASIS because the quality of the speaker modeling and pattern matching strongly depends on the quality of the feature extraction methods. For the proposed ASIS, different types of speech feature extraction methods [34, 35, 36, 37, 38, 39] such as RCC, MFCC,  $\Delta$ MFCC,  $\Delta\Delta$ MFCC, LPC, LPCC have been applied.

### 5. Training and Testing Model for Speaker Identification

Fig.2 shows the working process of neuro-genetic hybrid system [40, 41, 42]. The structure of the multilayer neural network does not matter for the GA as long as the BPNs parameters are mapped correctly to the genes of the chromosome the GA is optimizing. Basically, each gene represents the value of a certain weight in the BPN and the chromosome is a vector that contains these values such that each weight corresponds to a fixed position in the vector as shown in Fig.2.

The fitness function can be assigned from the identification error of the BPN for the set of pictures used for training. The GA searches for parameter values that minimize the fitness function, thus the identification error of the BPN is reduced and the identification rate is maximized [43].

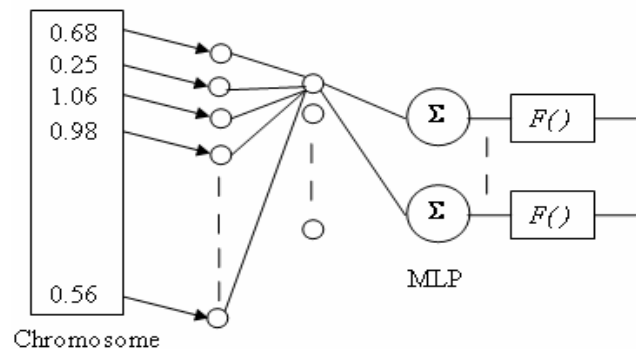


Fig.2 Learning and recognition model for the Neuro-Genetic hybrid system.

The algorithm for the Neuro-Genetic based weight determination and Fitness Function [44] is as follows:

Algorithm for Neuro-Genetic Weight determination:

```
{
i ← 0;
Generate the initial population Pi of real coded
chromosomes Cij each representing a weight set for the
BPN;

Generate fitness values Fij for each Cij ∈ Pi using the
algorithm FITGEN();
While the current population Pi has not converged
{

Using the cross over mechanism reproduced offspring
from the parent chromosome and performs mutation on
offspring;

i ← i+1;

Call the current population Pi;

Calculate fitness values Fij for each Cij ∈ Pi using the
algorithm FITGEN();
}
Extract weight from Pi to be used by the BPN;
}
```

Algorithm for FITGEN():

```
{Let (  $\overline{I}_i, \overline{T}_j$  ), i=1,2,.....N where  $\overline{I}_i = ( \overline{I}_{1i}, \overline{I}_{2i}, \dots, \overline{I}_{li} )$  and  $\overline{T}_j = ( \overline{T}_{1j}, \overline{T}_{2j}, \dots, \overline{T}_{lj} )$ 
represent the input-output pairs of the problem to be
solved by BPN with a configuration l-m-n.
{
```

```
Extract weights  $\overline{W}_i$  from Ci;
```

```
Keeping  $\overline{W}_i$  as a fixed weight setting, train the BPN for
the N input instances (Pattern);
```

```
Calculate error Ei for each of the input instances using the
formula:
```

$$E_i = \sum_j (T_{ji} - O_{ji})^2 \quad (3)$$

```
Where  $\overline{O}_i$  is the output vector calculated by BPN;
```

```
Find the root mean square E of the errors Ei, I = 1,2,.....N
```

$$\text{i.e. } E = \sqrt{\sum_i E_i} / N \quad (4)$$

Now the fitness value F<sub>i</sub> for each of the individual string of the population as F<sub>i</sub> = E;

```
}
Output Fi for each Ci, i = 1,2,.....P; }
}
```

## 6. Optimum parameter Selection for the BPN and GA

### 6.1 Parameter Selection on the BPN

There are some critical parameters in Neuro-Genetic hybrid system (such as in BPN, gain term, speed factor, number of hidden layer nodes and in GA, crossover rate and the number of generation) that affect the performance of the proposed system. A trade off is made to explore the optimal values of the above parameters and experiments are performed using those parameters. The optimal values of the above parameters are chosen carefully and finally find out the identification rate.

#### 6.1.1 Experiment on the Gain Term, $\eta$

In BPN, during the training session when the gain term was set as:  $\eta_1 = \eta_2 = 0.4$ , spread factor was set as  $k_1 = k_2 = 0.20$  and tolerable error rate was fixed to 0.001[%] then the highest identification rate of 91[%] has been achieved which is shown in Fig.3.

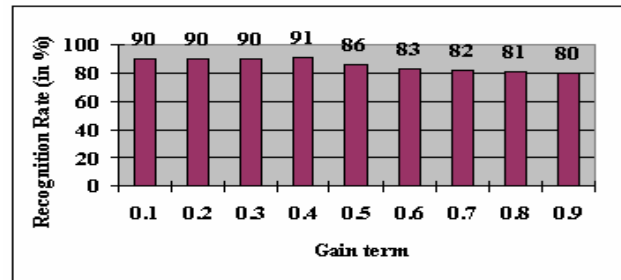


Fig. 3 Performance measurement according to gain term.

#### 6.1.2 Experiment on the Speed Factor, $k$

The performance of the BPN system has been measured according to the speed factor,  $k$ . We set  $\eta_1 = \eta_2 = 0.4$  and tolerable error rate was fixed to 0.001[%]. We have studied the value of the parameter ranging from 0.1 to 0.5. We have found that the highest recognition rate was 93[%] at  $k_1 = k_2 = 0.15$  which is shown in Fig.4.

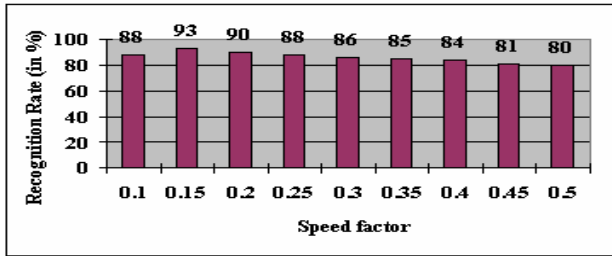


Fig. 4 Performance measurement according to various speed factor.

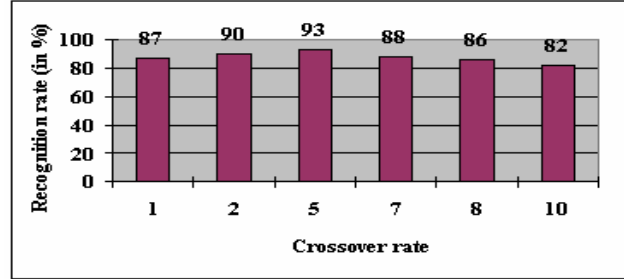


Fig. 6 Performance measurement according to the crossover rate.

### 6.1.3 Experiment on the Number of Nodes in Hidden Layer, $N_H$

In the learning phase of BPN, We have chosen the hidden layer nodes in the range from 5 to 40. We set  $\eta_1 = \eta_2 = 0.4$ ,  $k_1 = k_2 = 0.15$  and tolerable error rate was fixed to 0.001[%]. The highest recognition rate of 94[%] has been achieved at  $N_H = 30$  which is shown in Fig.5.

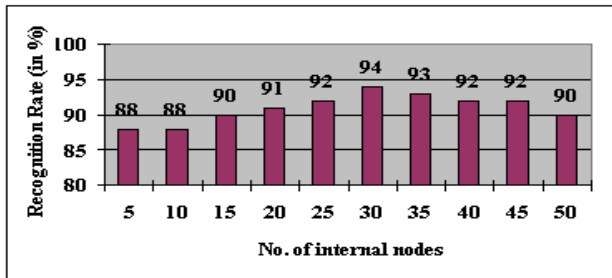


Fig. 5 Results after setting up the number of internal nodes in BPN.

### 6.2.2 Experiment on the Crossover Rate

Different values of the number of generations have been tested for achieving the optimum number of generations. The test results are shown in the Fig.7. The maximum identification rate of 95[%] has been found at the number of generations 15.

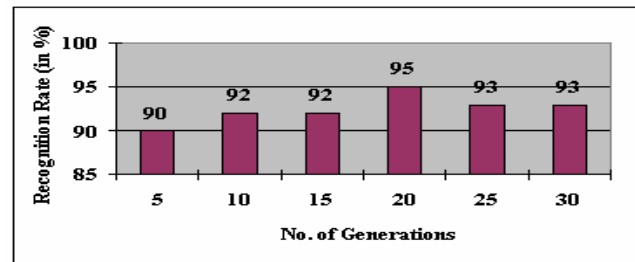


Fig.7 Accuracy measurement according to the no. of generations.

## 6.2 Parameter Selection on the GA

To measure the optimum value, different parameters of the genetic algorithm were also changed to find the best matching parameters. The results of the experiments are shown below.

### 6.2.1 Experiment on the Crossover Rate

In this experiment, crossover rate has been changed in various ways such as 1, 2, 5, 7, 8, 10. The highest speaker identification rate of 93[%] was found at crossover point 5 which is shown in the Fig.6.

## 7. Performance Measurement of the Text-Dependent Speaker Identification System

VALID speech database [45] has been used to measure the performance of the proposed hybrid system. In learning phase, studio recording speech utterances were used to make reference models and in testing phase, speech utterances recorded in four different office conditions were used to measure the accurate performance of the proposed Neuro-Genetic hybrid system. Performance of the proposed system were measured according to various cepstral based features such as LPC, LPCC, RCC, MFCC,  $\Delta$ MFCC and  $\Delta\Delta$ MFCC which are shown in the following table.

Table 1: Speaker identification rate (%) for VALID speech corpus

Type of environments	MFCC	$\Delta$ MFCC	$\Delta\Delta$ MFCC	RCC	LPCC
Clean speech utterances	100.00	100.00	98.23	90.43	100.00
Office environments	80.17	82.33	68.89	70.33	76.00

speech utterances					
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Table 1 shows the overall average speaker identification rate for VALID speech corpus. From the table it is easy to compare the performance among MFCC,  $\Delta$ MFCC,  $\Delta\Delta$ MFCC, RCC and LPCC methods for Neuro-Genetic hybrid algorithm based text-dependent speaker identification system. It has been shown that in clean speech environment the performance is 100.00 [%] for MFCC,  $\Delta$ MFCC and LPCC and the highest identification rate (i.e. 82.33 [%]) has been achieved at  $\Delta$ MFCC for four different office environments.

## 8. Conclusion and Observations

The experimental results show the versatility of the Neuro-Genetic hybrid algorithm based text-dependent speaker identification system. The critical parameters such as gain term, speed factor, number of hidden layer nodes, crossover rate and the number of generations have a great impact on the recognition performance of the proposed system. The optimum values of the above parameters have been selected effectively to find out the best performance. The highest recognition rate of BPN and GA have been achieved to be 94[%] and 95[%] respectively. According to VALID speech database, 100[%] identification rate in clean environment and 82.33 [%] in office environment conditions have been achieved in Neuro-Genetic hybrid system. Therefore, this proposed system can be used in various security and access control purposes. Finally the performance of this proposed system can be populated according to the largest speech recognition database.

## References

- [1] A. Jain, R. Bole, S. Pankanti, **BIOMETRICS Personal Identification in Networked Society**, Kluwer Academic Press, Boston, 1999.
- [2] Rabiner, L., and Juang, B.-H., **Fundamentals of Speech Recognition**, Prentice Hall, Englewood Cliffs, New Jersey, 1993.
- [3] Jacobsen, J. D., "Probabilistic Speech Detection", **Informatics and Mathematical Modeling**, DTU, 2003.
- [4] Jain, A., R.P.W.Duin, and J.Mao., "Statistical pattern recognition: a review", **IEEE Trans. on Pattern Analysis and Machine Intelligence** 22 (2000), pp. 4–37.
- [5] Davis, S., and Mermelstein, P., "Comparison of parametric representations for monosyllabic word recognition in continuously spoken sentences", **IEEE 74 Transactions on Acoustics, Speech, and Signal Processing (ICASSP)**, Vol. 28, No. 4, 1980, pp. 357-366.
- [6] Sadaoki Furui, "50 Years of Progress in Speech and Speaker Recognition Research", **ECTI TRANSACTIONS ON COMPUTER AND INFORMATION TECHNOLOGY**, Vol.1, No.2, 2005.
- [7] Lockwood, P., Boudy, J., and Blanchet, M., "Non-linear spectral subtraction (NSS) and hidden Markov models for robust speech recognition in car noise environments", **IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)**, 1992, Vol. 1, pp. 265-268.
- [8] Matsui, T., and Furui, S., "Comparison of text-independent speaker recognition methods using VQ-distortion and discrete/ continuous HMMs", **IEEE Transactions on Speech Audio Process**, No. 2, 1994, pp. 456-459.
- [9] Reynolds, D.A., "Experimental evaluation of features for robust speaker identification", **IEEE Transactions on SAP**, Vol. 2, 1994, pp. 639-643.
- [10] Sharma, S., Ellis, D., Kajarekar, S., Jain, P. & Hermansky, H., "Feature extraction using non-linear transformation for robust speech recognition on the Aurora database.", in **Proc. ICASSP2000**, 2000.
- [11] Wu, D., Morris, A.C. & Koreman, J., "MLP Internal Representation as Discriminant Features for Improved Speaker Recognition", in **Proc. NOLISP2005**, Barcelona, Spain, 2005, pp. 25-33.
- [12] Konig, Y., Heck, L., Weintraub, M. & Sonmez, K., "Nonlinear discriminant feature extraction for robust text-independent speaker recognition", in **Proc. RLA2C, ESCA workshop on Speaker Recognition and its Commercial and Forensic Applications**, 1998, pp. 72-75.
- [13] Ismail Shahin, "Improving Speaker Identification Performance Under the Shouted Talking Condition Using the Second-Order Hidden Markov Models", **EURASIP Journal on Applied Signal Processing** 2005:4, pp. 482–486.
- [14] S. E. Bou-Ghazale and J. H. L. Hansen, "A comparative study of traditional and newly proposed features for recognition of speech under stress", **IEEE Trans. Speech, and Audio Processing**, Vol. 8, No. 4, 2000, pp. 429–442.
- [15] G. Zhou, J. H. L. Hansen, and J. F. Kaiser, "Nonlinear feature based classification of speech under stress", **IEEE Trans. Speech, and Audio Processing**, Vol. 9, No. 3, 2001, pp. 201–216.
- [16] Simon Doclo and Marc Moonen, "On the Output SNR of the Speech-Distortion Weighted Multichannel Wiener Filter", **IEEE SIGNAL PROCESSING LETTERS**, Vol. 12, No. 12, 2005.
- [17] Wiener, N., **Extrapolation, Interpolation and Smoothing of Stationary Time Series with Engineering Applications**, Wiley, Newyork, 1949.
- [18] Wiener, N., Paley, R. E. A. C., "Fourier Transforms in the Complex Domains", **American Mathematical Society**, Providence, RI, 1934.
- [19] Koji Kitayama, Masataka Goto, Katunobu Itou and Tetsunori Kobayashi, "Speech Starter: Noise-Robust Endpoint Detection by Using Filled Pauses", **Eurospeech 2003**, Geneva, pp. 1237-1240.
- [20] S. E. Bou-Ghazale and K. Assaleh, "A robust endpoint detection of speech for noisy environments with application to automatic speech recognition", in **Proc. ICASSP2002**, 2002, Vol. 4, pp. 3808–3811.
- [21] A. Martin, D. Charlet, and L. Mauuary, "Robust speech / non-speech detection using LDA applied to MFCC", in **Proc. ICASSP2001**, 2001, Vol. 1, pp. 237–240.

- [22] Richard. O. Duda, Peter E. Hart, David G. Strok, **Pattern Classification**, A Wiley-interscience publication, John Wiley & Sons, Inc, Second Edition, 2001.
- [23] Sarma, V., Venugopal, D., "Studies on pattern recognition approach to voiced-unvoiced-silence classification", **Acoustics, Speech, and Signal Processing, IEEE International Conference on ICASSP'78**, 1978, Vol. 3, pp. 1-4.
- [24] Qi Li, Jinsong Zheng, Augustine Tsai, Qiru Zhou, "Robust Endpoint Detection and Energy Normalization for Real-Time Speech and Speaker Recognition", **IEEE Transaction on speech and Audion Processing**, Vol. 10, No. 3, 2002.
- [25] Harrington, J., and Cassidy, S., **Techniques in Speech Acoustics**, Kluwer Academic Publishers, Dordrecht, 1999.
- [26] Makhoul, J., "Linear prediction: a tutorial review", in **Proceedings of the IEEE 64**, 4 (1975), pp. 561-580.
- [27] Picone, J., "Signal modeling techniques in speech recognition", in **Proceedings of the IEEE 81**, 9 (1993), pp. 1215-1247.
- [28] Claudio Beccchetti and Lucio Prina Ricotti, **Speech Recognition Theory and C++ Implementation**, John Wiley & Sons. Ltd., 1999, pp.124-136.
- [29] L.P. Cordella, P. Foggia, C. Sansone, M. Vento., "A Real-Time Text-Independent Speaker Identification System", in **Proceedings of 12th International Conference on Image Analysis and Processing**, 2003, IEEE Computer Society Press, Mantova, Italy, pp. 632 - 637.
- [30] J. R. Deller, J. G. Proakis, and J. H. L. Hansen, **Discrete-Time Processing of Speech Signals**, Macmillan, 1993.
- [31] F. Owens., **Signal Processing Of Speech**, Macmillan New electronics. Macmillan, 1993.
- [32] F. Harris, "On the use of windows for harmonic analysis with the discrete fourier transform", in **Proceedings of the IEEE 66**, 1978, Vol.1, pp. 51-84.
- [33] J. Proakis and D. Manolakis, **Digital Signal Processing, Principles, Algorithms and Applications**, Second edition, Macmillan Publishing Company, New York, 1992.
- [34] D. Kewley-Port and Y. Zheng, "Auditory models of formant frequency discrimination for isolated vowels", **Journal of the Acoustical Society of America**, 103(3), 1998, pp. 1654-1666.
- [35] D. O'Shaughnessy, **Speech Communication - Human and Machine**, Addison Wesley, 1987.
- [36] E. Zwicker., "Subdivision of the audible frequency band into critical bands (frequenzgruppen)", **Journal of the Acoustical Society of America**, 33, 1961, pp. 248-260.
- [37] S. Davis and P. Mermelstein, "Comparison of parametric representations for monosyllabic word recognition in continuously spoken sentences", **IEEE Transactions on Acoustics Speech and Signal Processing**, 28, 1980, pp. 357-366.
- [38] S. Furui., "Speaker independent isolated word recognition using dynamic features of the speech spectrum", **IEEE Transactions on Acoustics, Speech and Signal Processing**, 34, 1986, pp. 52-59.
- [39] S. Furui, "Speaker-Dependent-Feature Extraction, Recognition and Processing Techniques", **Speech Communication**, Vol. 10, 1991, pp. 505-520.
- [40] Siddique and M. & Tokhi, M., "Training Neural Networks: Back Propagation vs. Genetic Algorithms", in **Proceedings of International Joint Conference on Neural Networks**, Washington D.C.USA, 2001, pp. 2673- 2678.
- [41] Whiteley, D., "Applying Genetic Algorithms to Neural Networks Learning", in **Proceedings of Conference of the Society of Artificial Intelligence and Simulation of Behavior**, England, Pitman Publishing, Sussex, 1989, pp. 137- 144.
- [42] Whiteley, D., Starkweather and T. & Bogart, C., "Genetic Algorithms and Neural Networks: Optimizing Connection and Connectivity", **Parallel Computing**, Vol. 14, 1990, pp. 347-361.
- [43] Kresimir Delac, Mislav Grgic and Marian Stewart Bartlett, **Recent Advances in Face Recognition**, I-Tech Education and Publishing KG, Vienna, Austria, 2008, pp. 223-246.
- [44] Rajesskaran S. and Vijayalakshmi Pai, **G.A., Neural Networks, Fuzzy Logic, and Genetic Algorithms-Synthesis and Applications**, Prentice-Hall of India Private Limited, New Delhi, India, 2003.
- [45] N. A. Fox, B. A. O'Mullane and R. B. Reilly, "The Realistic Multi-modal VALID database and Visual Speaker Identification Comparison Experiments", in **Proc. of the 5th International Conference on Audio- and Video-Based Biometric Person Authentication (AVBPA-2005)**, New York, 2005.



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