GENETIC ALGORITHM BASED FEATURE SELECTION LEVEL FUSION USING FINGERPRINT AND IRIS BIOMETRICS

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An accuracy level of unimodal biometric recognition system is not very high because of noisy data, limited degrees of freedom, spoof attacks etc. problems. A multimodal biometric system which uses two or more biometric traits of an individual can overcome such problems. We propose a multimodal biometric recognition system that fuses the fingerprint and iris features at the feature extraction level. A feed-forward artificial neural networks (ANNs) model is used for recognition of a person. There is a need to make the training time shorter, so the feature selection level should be performed. A genetic algorithms (GAs) approach is used for feature selection of a combined data. As an experiment, the database of 60 users, 10 fingerprint images and 10 iris images taken from each person, is used. The test results are presented in the last stage of this research.

Keywords: Multibiometric; feature selection; genetic algorithms; artificial neural networks.

1. Introduction

Biometrics, which measures a physiological or behavioral characteristic of a person, such as fingerprints, iris, voice, etc., provides an effective and reliable way to achieve personal authentication. A biometric system is essentially a pattern recognition system that acquires biometric data from an individual, extracts a feature set from the data, compares this feature set against the feature set(s), and executes an action based on the result of the comparison. Therefore, a simple biometric system as shown in Fig. 1 has a sensor module, a feature extraction module, a matching module and a decision module.

1. Sensor stage includes acquiring the biometric data of an individual such as fingerprints by using a scanner that captures the fingerprints image of a user.
2. Feature extraction stage in which the acquired data is processed extracts feature values. For example, the geometric shapes (lines, freckles etc.) in an iris image would be extracted in the feature extraction module of an iris system.

3. Matching stage in which the feature vectors are compared with the template from the database generates the matching score. For example, the similarity values of feature vectors between input face image and database face image will be computed and treated as a matching score.

4. Decision-making stage in which the user’s identity is recognized is either accepted or rejected based on the matching score generated in the matching stage.

Several studies have shown that the biometric authentication system based on recognizing the unimodal biometric template; suffer from insufficient accuracy caused by noisy data, limited degrees of freedom, nondistinctive and nonuniversal biometric traits and performance limitations. Further, if the biometric trait being sensed or measured is noisy (for example, a fingerprint with a scar), the resultant matching score computed by the matching module may not be reliable. To overcome those problems, biometric systems can also be designed to recognize a person based on information acquired from multiple biometric sources. Such systems, known as multibiometric systems, can be expected to be more accurate due to the presence of multiple pieces of evidence. A multimodal biometric system can be defined as the fusion of multiple biometric traits such as face, iris, fingerprint etc. to identify a person. Hence, the reliability and performance of the authentication system can be increased by using such a system.

While implementing a multimodal biometric system, it is necessary to determine the level that the system will be integrated in. There are several different levels to which the fusion of the multiple biometric traits would be applied. These are:

- **Fusion at Sensor Level:** The acquired data from multiple sensors are combined to generate new input data in sensor level fusion. An example of sensor level fusion is the mosaicing of multiple fingerprint impressions of a subject in order to construct a more elaborate fingerprint image.

- **Fusion at Feature Extraction Level:** The feature vectors obtained from each template can be fused to create new feature set. When the feature sets are homogeneous (e.g. multiple measurements of a person’s fingerprint), a single resultant feature vector can be calculated as a weighted average of the individual feature vectors. When the feature sets are nonhomogeneous (e.g. features of different
biometric modalities like fingerprint and iris), we can concatenate them to form a single feature vector.

- Fusion at Matching Score Level: The matching scores taken from each matching system can be combined to make a resulting decision. This is also known as fusion at the measurement level or confidence level. Next to the feature vectors, the match scores output by biometric matchers contain the richest information about the input pattern. Also, it is relatively easy to access and combine the scores generated by the different matchers. Consequently, integration of information at the match score level is the most common approach in multibiometric systems.\(^4\),\(^27\)

- Fusion at Decision Level: The decision classes (accept/reject) obtained from the output of the matching stage can be fused as a single decision by employing techniques like majority voting. Integration of information at the decision level can take place when each biometric system independently makes a decision about the identity of the user or determines if the claimed identity is true or not. Since most commercial biometric systems provide access to only the final decision output by the system, fusion at the decision level is often the only viable option.

Prior to matching, integration of information from multiple biometric sources can take place either at the sensor level or at the feature level. We presented a multimodal biometric recognition system that fuses the fingerprint and iris features at the feature extraction level in this study. Obtained features are input to ANNs for multibiometric recognition. In general, ANNs can produce robust performance when a large amount of data is available. However, it may not be possible to train ANNs or the training task cannot be effectively carried out without data reduction when a data set is too large. Under these conditions, data reduction techniques can be achieved in many ways such as feature selection.\(^16\),\(^20\) Among those, GAs have proven to be an effective computational method, especially in situations where the search space is highly dimensional.

In this study, we applied a method for feature selection of the training multibiometric data which have the highest selective power using a Gas in the feature selection level. The genetic algorithm is applied for feature selection for decreasing the training time of a neural network.

The rest of this paper is organized as follows. The general information about basic and multimodal biometric system is introduced in Sec. 1. The feature extraction levels of iris and fingerprint templates are given in Sec. 2. Also, the process of a fusion of iris and fingerprint features is explained in this section. In Sec. 3, the feature selection using genetic algorithms is described. Experimental results are given in Sec. 4. Conclusions and the direction for future research are given in Sec. 5.

1.1. Related works

The recent studies on multibiometric authentication system based on fingerprint and iris modalities are shown in Table 1. Hong and Jain\(^8\) used public domain face database and MSU fingerprint database in multimodal biometric recognition
system in 1998. They proposed a multimodal personal identification system which integrates face and fingerprints that complement each other. The fusion algorithm operates at the expert (soft) decision level, where it combines the scores from the different experts under statistically independence hypothesis, by simply multiplying them. In this study, test results were taken as 1% FAR (False Accept Rate) and 1.8% FRR (False Reject Rate) results.

Wang et al.\textsuperscript{31} purposed a combined system of face and iris biometrics for identification. They used two different strategies for fusing iris and face classifiers. The first strategy was to compute either an unweighted or weighted sum of two matching distances and compare the distances to a threshold. The second strategy was to treat the matching distances of face and iris classifiers as a two-dimensional feature vector and use a classifier such as the Fisher’s discriminant analysis or a neural network with radial basis function (RBFNN) to classify the vector as being genuine or an impostor. Accordingly, the test results were shown that minimum total error (FAR + FRR) rate is 0.024%.

In 2003, Ross and Jain\textsuperscript{26} applied face, hand and fingerprint templates in this multimodal recognition system, tried to solve the problem of information fusion in biometric verification systems by combining information at the matching score level and obtained 0.03% FAR and 1.78% FRR results.

The researchers, Nandakumar et al.,\textsuperscript{24} purposed a multibiometric system that includes iris and fingerprint modalities in 2006. They proposed a likelihood ratio-based fusion scheme that takes into account the quality of the biometric samples while combining the match scores provided by the matchers. Instead of estimating the quality of the template and query images individually, they estimated a single quality metric for each template-query pair based on the local image quality measures. Their experiments on a database of 320 users with iris and fingerprint modalities demonstrate the advantages of utilizing the quality information in multibiometric systems. Thus, they applied a quality based likelihood ratio fusion technique and obtained an error rate of 0.01% FAR and 94.8% GAR (Genuine Accept Rate).

2. Feature Extraction

Feature extraction is the process of defining a set of features, or image characteristics, which will most efficiently or meaningfully represent the information that is important for analysis and recognition. The goal of feature extraction is to improve
the effectiveness and efficiency of analysis and recognition. In this work, the feature extraction process is explained in two stages: iris feature extraction and fingerprint feature extraction.

2.1. Iris feature extraction

Feature extraction allows us to obtain the most discriminating information of an image. This information can be presented as a feature vector. A feature vector that includes global and local features of an iris image should be encoded so that the comparison between iris templates can be made.

In the preprocessing step, inner and outer boundaries of the iris are located by using the Daugman’s method, integro-differential operator with Hough transform. Then, cartesian to polar coordinate transform method was used for converting the ring shaped iris pattern to the rectangular form. Histogram equalization technique is employed to make the iris patterns more distinctive before feature extraction.

The Hough transform is designed to find lines, since a line can be defined as a collection of edge points. This transform is an algorithm that will take a collection of edge points as found by an edge detector.

If we define the line trigonometrically:

\[ x \sin \theta + y \cos \theta = r \]  \hspace{1cm} (1)

where \((x, y)\) denotes the coordinates in the spatial domain and \((r, \theta)\) denotes the transform parameters. The circular Hough transform, employed by Wildes et al., can be used for detection of the circular lines. The equation for circular Hough transform can be defined as:

\[ x_c^2 + y_c^2 = r^2 \]  \hspace{1cm} (2)

where \((x_c, y_c)\) are center coordinates of a circle and \(r\) is the radius. A maximum point in the Hough space will correspond to the radius and center coordinates of the circle best defined by the edge points.

The cartesian to polar coordinate transform, suggested by J. Daugman, allows us to transform the circular images to the rectangular shaped images with fixed dimensions. This method remaps each point within the iris region to the polar coordinates \((r, \theta)\), where \(r\) is the radius calculated as subtraction of inner circle radius from outer circle radius, and \(\theta\) is an angle. The transform can be defined as:

\[ I(x(r, \theta), y(r, \theta)) \Rightarrow I(r, \theta) \]  \hspace{1cm} (3)

Here, \(x(r, \theta)\) and \(y(r, \theta)\) can be found in Eq. (4):

\[ x(r, \theta) = (1 - r)x_p(\theta) + rx_i(\theta) \]
\[ y(r, \theta) = (1 - r)y_p(\theta) + ry_i(\theta) \]  \hspace{1cm} (4)

where \(I(x, y)\) represents the iris image, \(x_p, y_p\) and \(x_i, y_i\) are the coordinates of the pupil and iris boundaries.
The gray-level histogram of an image is the distribution of the gray level values in an image. The histogram equalization is a popular technique to improve the appearance of a poor contrasted image. So, it is applied to iris templates for making the iris features distinctive. The process of equalizing the histogram of an image consists of four steps: (1) Find the sum of the histogram values. (2) Normalize these values dividing by the total number of pixels. (3) Multiply these normalized values by the maximum gray-level value. (4) Map the new gray level values.

After determining the iris boundaries, the noisy regions such as eye lids, eyelashes etc. should be eliminated. So, we defined imaginary horizontal lines from the center of the pupil to the lower direction of the iris image with the size of predetermined pixel number from the centers of the pupil. We obtained the locating 80 × 40 pixel iris images after preprocessing of iris images. The sample image, the eye image including the inner and outer boundaries marked with white line, the iris region image that was obtained from cartesian to polar coordinate transform and histogram equalized iris image were shown in Fig. 2.

The next process of determining the feature vector of iris templates is encoding the gray level iris image. It can be supposed that the gray level value of every pixel in iris image can be encoded as in iris feature set. But, in this method, the iris feature vector is very huge, so the training time of ANN will be very long. To cope with this problem, the iris image should be divided into subimages and then every subimage should be encoded. In the proposed approach, the feature vector of every subimage was encoded by using Average Absolute Deviation (AAD) algorithm. This algorithm is defined as:

\[
V = \frac{1}{N} \left( \sum_{N} |f(x, y) - m| \right)
\]  

where \(N\) is the number of pixels in the image, \(m\) is the mean of the image and \(f(x, y)\) is the value at point \((x, y)\). The determining process of iris feature set by using AAD is shown in Fig. 3.

In this study, the 80 × 40 pixel iris images were divided into 4 × 4 pixel subimages. Each subimage was encoded by using AAD algorithm. The feature vectors with the length of 200 bytes are obtained. Then, the feature values are normalized to the values between −1 and +1.

![Fig. 2. Iris localization and segmentation.](image-url)
2.2. Fingerprint feature extraction

The feature vectors called FingerCode were extracted from the fingerprint images using a filter-bank based method. The algorithm set a registration point in a given fingerprint image and tessellated it into 48 sectors (4 bands and 12 sectors). Then, it transformed the fingerprint image using the Gabor filter of eight directions (0°, 22.5°, 45°, 67.5°, 90°, 112.5°, 135° and 157.5°). The general form of the even symmetric Gabor filter is:

$$h(x, y : \phi, f) = \exp\left\{ -\frac{1}{2} \left[ \frac{(x \cos \phi)^2}{\delta_x^2} + \frac{(y \sin \phi)^2}{\delta_y^2} \right] \right\} \cos(2\pi fx \cos \phi)$$ (6)

where \(\phi\) is the orientation, \(f\) the estimated frequency (can be empirical), \(\delta_x, \delta_y\) are constants. Practically, it can be computed by:

$$E(i, j) = \sum_{u=-w_g/2}^{w_g/2} \sum_{v=-w_g/2}^{w_g/2} h(u, v : O(i, j), F(i, j)) G(i - u, j - v)$$ (7)

where \(O\) is the orientation image, \(F\) is the frequency image, \(G\) is the normalized input fingerprint image. This method was proposed in Ref. 12, and is widely used. The four main steps in this feature extraction algorithm are:

- determine a reference point for the fingerprint image,
- tessellate the region around the reference point,
- filter the region of interest in eight different directions using a bank of Gabor filters, and
- compute the average absolute deviation from the mean (AAD) of gray values in individual sectors in filtered images to define the feature vector.\(^{11,13}\) The system diagram mentioned above is shown in Fig. 4.

AADs were computed on 48 sectors for each of the eight transferred images in order to generate the 384-dimensional feature vector called FingerCode. As in iris feature extraction, the feature values of fingerprint template are normalized to the values between −1 and +1.

2.3. Fusion of fingerprint and iris features

The feature vectors extracted from encoded input images can be combined into the new feature vector by fusing them at the feature extraction level. The fusion at this
level is much less preferable in literature\textsuperscript{24,25} This is because the feature vectors may be incompatible and score generation may be difficult. Also the relationship between the feature spaces may not be linear. Therefore the classification of the feature vectors may result in a false authentication.

The structure of the multibiometric recognition system including fusion at feature extraction level is basically shown in Fig. 5.

In the proposed system, the fusion of fingerprint and iris features is integrated at the feature extraction level. The feature vectors of fingerprint and iris images are combined by adding consecutively. Let the fingerprint feature vector be \( \{a_1, a_2, \ldots, a_n\} \), the iris feature vector be \( \{b_1, b_2, \ldots, b_m\} \) and the resulting vector \( C = \{a_1, a_2, \ldots, a_n, b_1, b_2, \ldots, b_m\} \). The new feature vector, \( C \) has very long dimension. Therefore, this may increase the training time of ANNs. So the dimensionality reduction should be performed. The feature selection process using GAs is performed at the feature selection level for this purpose.

3. Feature Selection Using Genetic Algorithms

Feature selection is the process of identifying and removing as much irrelevant and redundant information as possible. This reduces the dimensionality of the data and may allow learning algorithms to operate faster and more effectively. Finding an
optimal set of features from a large set of candidate features is a problem which occurs in many contexts such as biometrics data.

Searching the space of feature subsets within reasonable time constraints is necessary if a feature selection algorithm is to operate on data with a large number of features. One simple search strategy, called greedy hill climbing, considers local changes to the current feature subset. Often, a local change is simply the addition or deletion of a single feature from the subset. When the algorithm considers only additions to the feature subset it is known as forward selection; considering only deletions is known as backward elimination.\textsuperscript{22,28} An alternative approach, called stepwise bidirectional search, uses both addition and deletion. Within each of these variations, the search algorithm may consider all possible local changes to the current subset and then select the best, or may simply choose the first change that improves the merit of the current feature subset. In either case, once a change is accepted, it is never reconsidered.

Genetic algorithms (GAs) introduced by Holland\textsuperscript{7} are a well-known searching algorithm in a large space. GAs are used in feature selection problems.\textsuperscript{16,20} They employ a population of competing solutions — evolved over time — to converge to an optimal solution. Effectively, the solution space is searched in parallel, which helps in avoiding local optima.

For feature selection, a solution is typically a fixed length binary string representing a feature subset — the value of each position in the string represents the presence or absence of a particular feature.

In this case, let $C$ be a total number of features, there exist $2^C$ possible feature subsets. Each individual is represented by an $C$-bit string. Value “1” or “0” of any bit means present or absent of the corresponding feature, respectively (Fig. 6).

The initial set of possible solutions or population with a fixed number of population or population size is randomly constructed. After the initialization step, each chromosome is evaluated by the fitness function. Given a particular chromosome, the fitness function returns a single numerical “fitness” which is supposed to be proportional to the “utility” or “ability” of the individual which that chromosome represents. In general, feature selection methods use generalized regression neural networks (GRNN) for regression problems or probabilistic neural networks.

![](image)

**Fig. 6.** $C$-dimensional binary vector determined according to fingerprint feature sets.
(PNNs) for recognition and classification problems because they train quickly and have proved to be sensitive to the irrelevant inputs. In this study, PNNs are used as fitness function for feature selection using GAs because PNNs are trained quickly and have proved to be sensitive to the irrelevant inputs.

The PNNs, introduced by D. Specht in 1988, are a three-layer, feed-forward, one-pass training algorithm used for classification and mapping of data. Unlike other ANNs, like the back-propagation neural network, it is based on well-established statistical principles derived from Bayes’ decision strategy and non-parametric kernal based estimators of probability density functions. An advantage of the PNNs is that it is guaranteed to approach the Bayes’ optimal decision surface provided that the class probability density functions are smooth and continuous.

The PNNs use Parzen (or Parzen-like) probability distribution function estimators that asymptotically approach the true underlying parent density, provided that it is smooth and continuous. The PNNs operate by using spherical Gaussian radial basis functions centered at each training vector. The likelihood of an unknown vector belonging to a given class can be expressed as

$$f_i(x) = \frac{1}{(2\pi)^{p/2}\sigma^p M_i} \sum_{j=1}^{M_i} \exp\left(-\frac{(x - x_{ij})^T(x - x_{ij})}{2\sigma^2}\right)$$  \hspace{1cm} (8)

where $i$ is the class number, $j$ is the pattern number, $x_{ij}$ is the $j$th training vector from class $i$, $x$ is the test vector, $M_i$ is the number of training vectors in class $i$, $p$ is the dimension of vector $x$, $s$ is the smoothing factor (the standard deviation), and $f_i(x)$ is the sum of multivariate spherical Gaussians centered at each of the training vectors $x_{ij}$ for the $i$th class probability density function estimate.

Classification decisions are consequently made in accordance with the Bayes’ strategy for decision rule, which is $d(x) = C_i$, if

$$f_i(x) > f_k(x) \text{ for } k \neq I$$  \hspace{1cm} (9)

where $C_i$ is the class $i$. According to the value of the fitness function, the chromosomes associated with the fittest individuals will be reproduced more often than those associated unfit individuals. New individuals (offspring) for the next generation are formed by using two main genetic operators, crossover and mutation. Mutation changes some of the values (thus adding or deleting features) in a subset randomly. Crossover combines different features from a pair of subsets into a new subset. They provide the means for introducing new information into the population. Finally, the GAs tend to converge on optimal or near-optimal solutions.

GAs are used for feature selection to evaluate the fitness of subsets of attributes. Figure 7 shows a general framework for the application of a feature selection algorithm using GAs for combined feature vectors. In this study, GAs are performed to improve the robustness of feature selection without sacrificing too much computational efficiency.
The following GA parameters are used for the selected features of combined feature vectors.

- Population size = 100
- Generations = 50
- Crossover probability = 0.9
- Mutation probability = 0.01
- Fitness function = Determined by PNNs

The feature selection method starts with a random population of input configuration. Input configuration determines which inputs are ignored during performance test. At each following step (called generation), a process analogous to natural selection to select superior configurations is used. Generations, then, are used to generate a new population. Each step successively produces better input configuration. In 50 generations, GAs always find the global optimum in the constrained search space. At the last step, the best configuration is selected. Thus, feature mask of the best network is determined as a string like “010000011001111…”. Here, value of “1” or “0” suggests that the feature is selected or removed respectively.

In this study, the fusion of feature selection using GAs is applied to the combined feature set (the iris feature set (200 features) and the fingerprint feature set (384 features) 584 features totally). As a result of fusion at the feature selection level, the number of the new feature set is 298. The GAs for the feature selection provided good results since it reduced available features almost 50%. These selected feature vectors are fed to artificial neural networks (ANNs) for training and used to test the performance of the person recognition method. The GAs-based method proved to be quite effective in improving the robustness of the feature selection over the combined feature vectors.

4. Experimental Results

In this study, we used 600 iris images and 600 fingerprint images taken from 60 users (10 samples per user per biometric) by using CCD camera and optic scanner. The iris images have a dimension of 200 × 150 pixel and fingerprint images have a dimension of 512 × 512 pixel. The images were preprocessed with methods mentioned above to get the region of interest. Then the feature extraction process is implemented to the fingerprint images and iris images, separately. As a result of feature extraction, the fingerprint feature set including 384 features and iris feature set including 200 features are obtained.
The fusion at feature extraction level was chosen for integration to the multibiometric system. In the feature selection level, the feature set was applied to the feature selection unit using GAs and a new feature set including 298 selected feature was obtained. In the matching step, feed-forward artificial neural network was performed for recognition. Back-propagation learning algorithm was used for training the neural network.

The ANNs structure was determined by using heuristic methods. For combined feature vector (iris + fingerprint (IF)), the structure of ANNs has an input layer with 584 neurons same as the number of feature vectors obtained from multibiometrics; one hidden layer with 86 neurons and an output layer with 10 neurons same as the number of person. The structure of ANNs for feature selected vector (iris + fingerprint + GAs (IFGA)) has an input layer with 298 neurons; one hidden layer with 52 neurons and an output layer with 10 neurons same as the number of persons.

100 iterations were performed for input sets of both combined feature vector (IF) and feature selected vector (IFGA). The ANNs were trained on the 42 training samples but were then validated and tested on a set of nine samples from the validation and test sets, respectively. The validation set is a part of combined feature vector used to tune network topology or network parameters other than weights. For example, it is used to define the number of hidden units to detect the moment when the neural network performance started to deteriorate. In addition, this 60 feature set was also used to evaluate the fitness of the population. The population size was selected as 100. As in the experiment, the probability of crossover was selected as 0.9 and the mutation probability as 0.01. The two best individuals in a generation were kept unchanged for the next generation.

In Table 2, the training time, the correct classification rates (CCR) and the ANNs structure are shown. In verification systems, performance characteristics are summarized by two measures: false accept rate (FAR) and false reject rate (FRR). CCR stands for Correct Classification Rate and is used in classification tasks as a qualitative characteristic. This rate is calculated by dividing the number of correctly recognized records by the total number of records. CCR is measured in relative units or in percents.

The training times obtained in our experiments by using the configuration of computer with Intel® Pentium® 4 3.0 Mhz, 1 GB DDR RAM. As it can be seen from the Table 2, the training time of the network for IF feature set is longer in

<table>
<thead>
<tr>
<th>Feature Set</th>
<th>Structures of ANN (input:hidden:output)</th>
<th>Training time (hour:minute:second)</th>
<th>CCR (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iris + Fingerprint</td>
<td>584:86:100</td>
<td>00:23:38</td>
<td>Training 100 99.2</td>
</tr>
<tr>
<td>Iris + Fingerprint + Gas</td>
<td>298:52:100</td>
<td>00:05:45</td>
<td>Test 100 99.3</td>
</tr>
</tbody>
</table>

(00:02:18 for GAs)
comparison to the training time for IFGA feature set. However, a trained ANN requires only 3 to 6 milliseconds for testing. So, it can be mentioned that the training time was reduced without any performance loss.

The best results are taken after training 100 iterations of the ANNs. The schemes of CCR for feature set of IF and IFGA were shown in Figs. 8(a) and 8(b), respectively. After the training process of 100 iterations, the success rate of 100% is obtained both normal features and selected features using GAs for training feature vectors. By considering of test feature vectors, the success rate is 99.2% for IF and is 99.3% for IFGA. In addition, although the training time for normal features is

![Graph A](a)

![Graph B](b)

Fig. 8. (a) The CCR for IF data set (b) The CCR for IFGA data set.
00:23:38, for selected features is only 00:05:45. Hence, the training time is reduced nearly four times for selected features using GAs.

5. Conclusion

We have proposed a multimodal biometric system using iris and fingerprint modalities. In preprocessing phase, the fingerprint and iris images were segmented to get the region of interest. Then, the feature extraction level was implemented for both fingerprint and iris templates. The feature vectors extracted from encoded input images were fused at feature extraction level to get a new feature vector. However, there is a need to make the recognition process faster and accurate using the minimum number of features which primarily characterize the biometric traits.

The biometric traits were extracted to the feature sets and the combined feature sets were reduced by performing genetic algorithms. This consequently minimizes the input number of the neural network, so the training time can be reduced.

As a result of experimental applications, the genetic algorithms were applied to the combined feature vector (IF — including 584 features) and a new reduced feature vector (IFGA — including 298 features) was obtained. Both the feature vectors were trained by using feed forwarded ANN. It has been observed from the experiments that the training time of the neural network was decreased from approximately 24 minutes to 8 minutes without any performance loss. By analyzing the test results, it can be said the correct classification rate is almost the same for both IF and IFGA feature sets.

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References


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