FACE RECOGNITION USING ENSEMBLE OF NEURAL NETWORKS

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Abstract: Authors describe a novel approach for human faces recognition using ensembles (or committee) of artificial neural networks. In the task of human faces recognition there are several problems that should be considered: 1) overlapping of different sets (classes), for example, when distinguishing faces of twins; 2) the training time of neural networks can be limited. In this case it is not possible to reach correct recognition of training set during neural networks training. Therefore, the two-level hierarchical structure is used to recognize objects of examination (testing) set. As a result of neural networks training at the lower level a decisions set is formed. On the basis of the decisions set the final committee solution is constructed at the upper level. A special algorithm of weighted voting is proposed to form the committee decision. The experimental results show that the proposed algorithm is more effective in comparison with other known committee methods, when number of training iterations is limited.

1 INTRODUCTION

The problem of face recognition on a photo and video images is actual in different areas - from commercial sphere to security, etc. During the last two decades researchers have proposed many approaches to human faces recognition.

The techniques of face recognition could be classified by different criteria (Zhao, 2003). In this work the usage of neural networks and ensemble (or committee) decisions is considered. There are known different committee decisions construction algorithms for neural networks as well as its comparative analysis (Sharkey, 1997; Jimenez, 1998; Haykin, 1999; Opitz, 1999; Sharkey, 1999; Whitman, 2006; Mu, 2007; Garcia-Pedrajas, 2007). In the given work the following algoritms are considered: algorithm of plurality voting (Opitz, 1996; Glaz, 1991); algorithm of ensemble averaging (Perrone, 1993); algorithm of weighted voting (Jimenez, 1998). The architecture of such neural network ensemble is shown on Fig. 1.

The set of the neural networks which included in ensemble is generated in the following way: for each i neural network, $i \in [1:T]$, matrixes of initial weights W_i^0, V_i^0 (starting points) are generated randomly from a given interval. Then training (back-propagation algorithm) is conducted on each network. Weights W_i, V_i are obtained during training and are used by each neural network for classification $R_i(X)$ of objects X, which do not belong to the training set.

Achieved decisions $R_i(X)$, $i \in [1:T]$ are used for obtaining an ensemble decision that in case of dichotomy is described by following expression:

$$R^*(X) = \begin{cases} 1, \ if \ \sum_{i=1}^{T} z_i R_i(X) \geq \theta; \\ 0, \ if \ \sum_{i=1}^{T} z_i R_i(X) < \theta; \end{cases} \quad (1)$$

where z_i - weight of decision $R_i(X)$, θ - given threshold.

2 ALGORITMS OF ENSEMBLE DECISION

Different algorithms of ensemble decisions can be obtained from (1) depending on z_i , $R_i(X)$, θ values.

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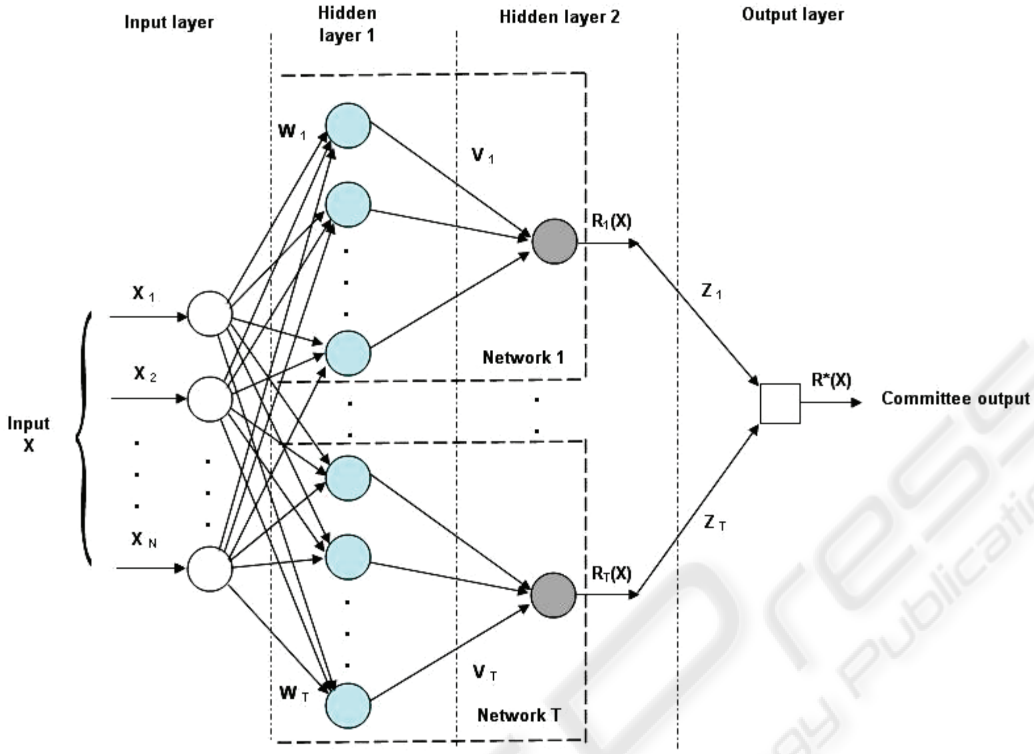

Figure 1: The architecture of neural network ensemble.

2.1 Algorithm of Plurality Voting

In this case weights z_i = 1 and the threshold $\theta = \frac{T}{2}$ (T should be odd), outputs of neural networks $R_i(X)$ can assume only two values: 0 or 1 (it means that threshold function is realized). According to this, the expression (1) is defined as follows:

$$R^*(X) = \begin{cases} 1, \ if \ \sum_{i=1}^{T} R_i(X) \geq \frac{T}{2}; \\ 0, \ if \ \sum_{i=1}^{T} R_i(X) < \frac{T}{2}; \end{cases} \tag{2}$$

2.2 Algorithm of Weighted Voting

For algorithm of weighted voting outputs of neural networks $R_i(X)$ also assume one of the values: 0 or 1, the threshold is $\theta = \frac{1}{2}$, and the weights z_i are defined in the following way:

$$z_i = \frac{q_i}{\sum_{i=1}^{T} q_i}, \tag{3}$$

where q_i – probability of correct classification by i neural network that is estimated by using training set. Also, all weights z_i should satisfy the following condition:

$$\sum_{i=1}^{T} z_i = 1, z_i > 0, i \in [1:T] \tag{4}$$

According to this, the expression (1) assumes the following form:

$$R^*(X) = \begin{cases} 1, \ if \ \sum_{i=1}^{T} z_i R_i(X) \geq \frac{1}{2}; \\ 0, \ if \ \sum_{i=1}^{T} z_i R_i(X) < \frac{1}{2}; \end{cases} \tag{5}$$

2.3 Algorithm of Ensemble Averaging

In this case $R_i(X) \in [0:1]$, it means that the outputs belong to the values of logistic function, the threshold is $\theta = \frac{1}{2}$ and weights $z_i = \frac{1}{T}$. According to this, expression (1) assumes the following form:

$$R^*(X) = \begin{cases} 1, \ if \ \frac{1}{T}\sum_{i=1}^{T} R_i(X) \geq \frac{1}{2}; \\ 0, \ if \ \frac{1}{T}\sum_{i=1}^{T} R_i(X) < \frac{1}{2}; \end{cases} \tag{6}$$

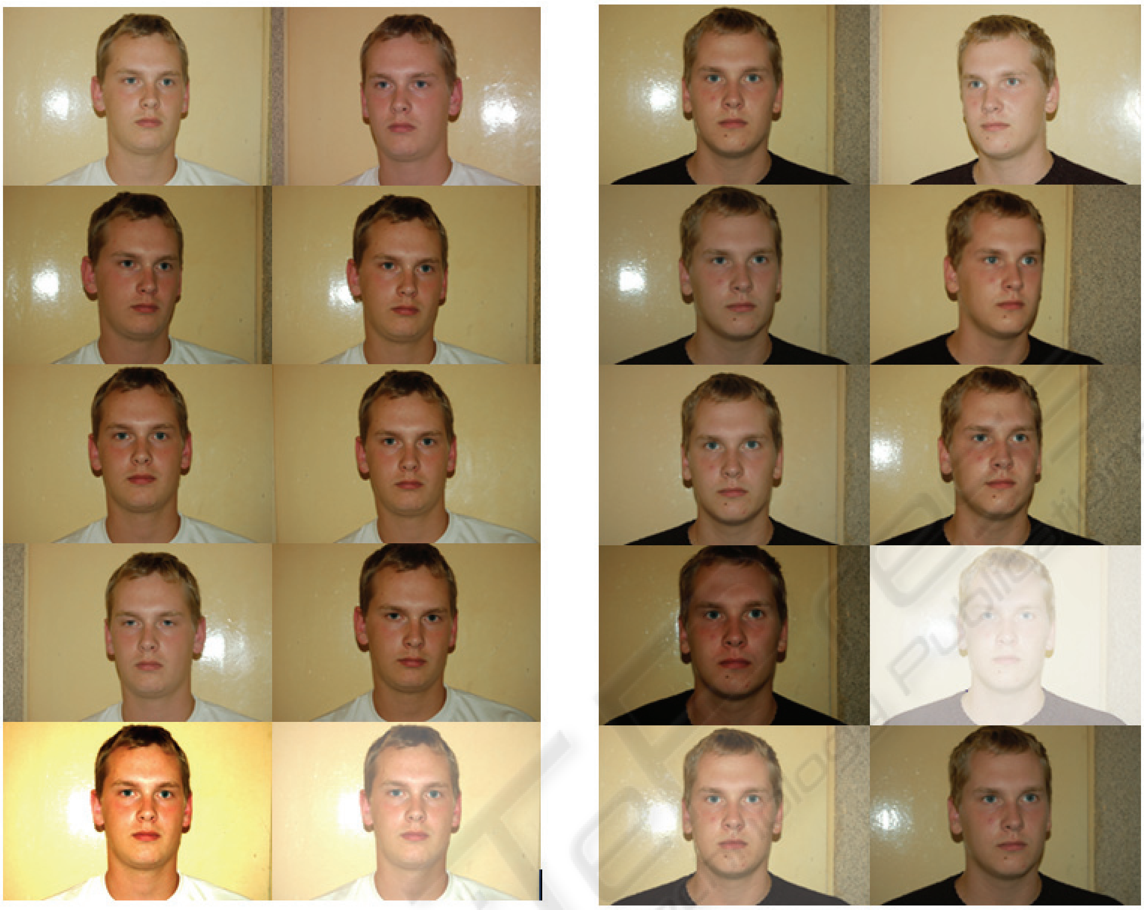

Figure 2: Examples of two classes of faces.

3 PROPOSED ALGORITM

In the result of training, the reliability of training set recognition q_i by i neural network is in the interval $0.5 \leq q_i \leq 1$. That is why in the proposed algorithm of the weighted voting weight z_i is defined as follows:

$$z_i = (q_i - 0.5)*2, \quad i \in [1:T] \tag{7}$$

Thus, weights values are in the interval

$0 \leq z_i \leq 1$ and the threshold θ is defined according to expression

$$\theta = \frac{1}{2}\sum_{i=1}^{T} z_i \tag{8}$$

In this case outputs of neural networks $R_i(X)$ are values of logistic function. It means that $R_i(X) \in [0:1]$ and the proposed algorithm of the weighed voting can be written down in the following form:

$$R^*(X) = \begin{cases} 1, \ if \ \sum_{i=1}^{T} z_i R_i(X) \geq \frac{\sum_{i=1}^{T} z_i}{2}; \\ 0, \ if \ \sum_{i=1}^{T} z_i R_i(X) < \frac{\sum_{i=1}^{T} z_i}{2}; \end{cases} \tag{9}$$

4 EXPERIMENTAL RESULTS

Ensemble methods that are described in this paper have been applied to solve a task of recognition of two classes of faces, which conform to twins.

The initial array included 64 color images (32 in each class). In fig. 2 the fragment of initial array is shown. The initial array of images has been divided into 2 parts: training set (10+10) and examination set (22+22). Each image was coded by a matrix 200x133. Input vector X of each neural network in ensemble included 26600 elements, the number T of

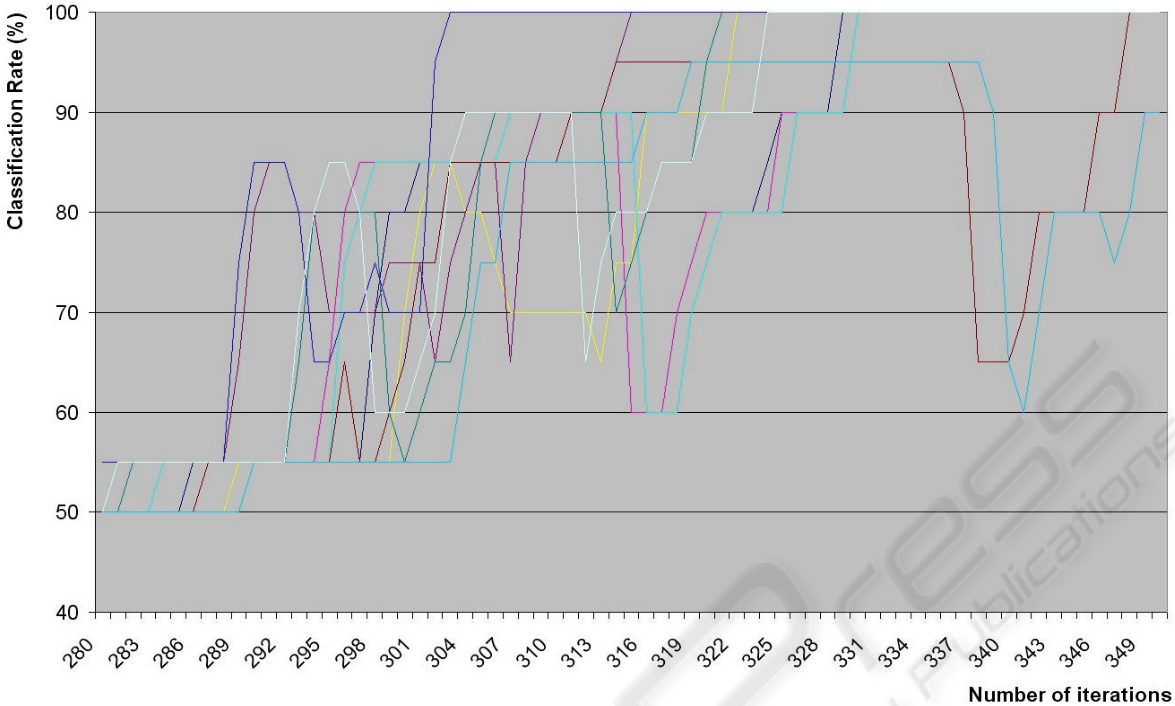

Figure 3: The results of training for 10 neural networks of one training set.

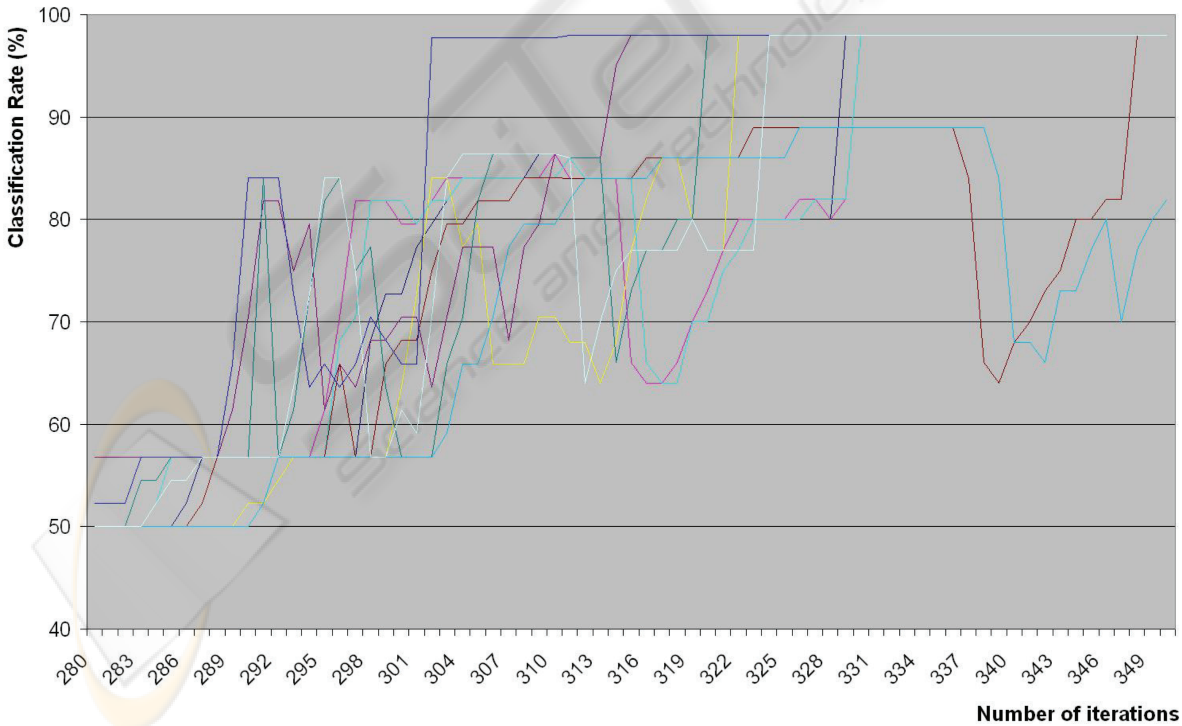

Figure 4: The results of examination for 10 neural networks of one training set.

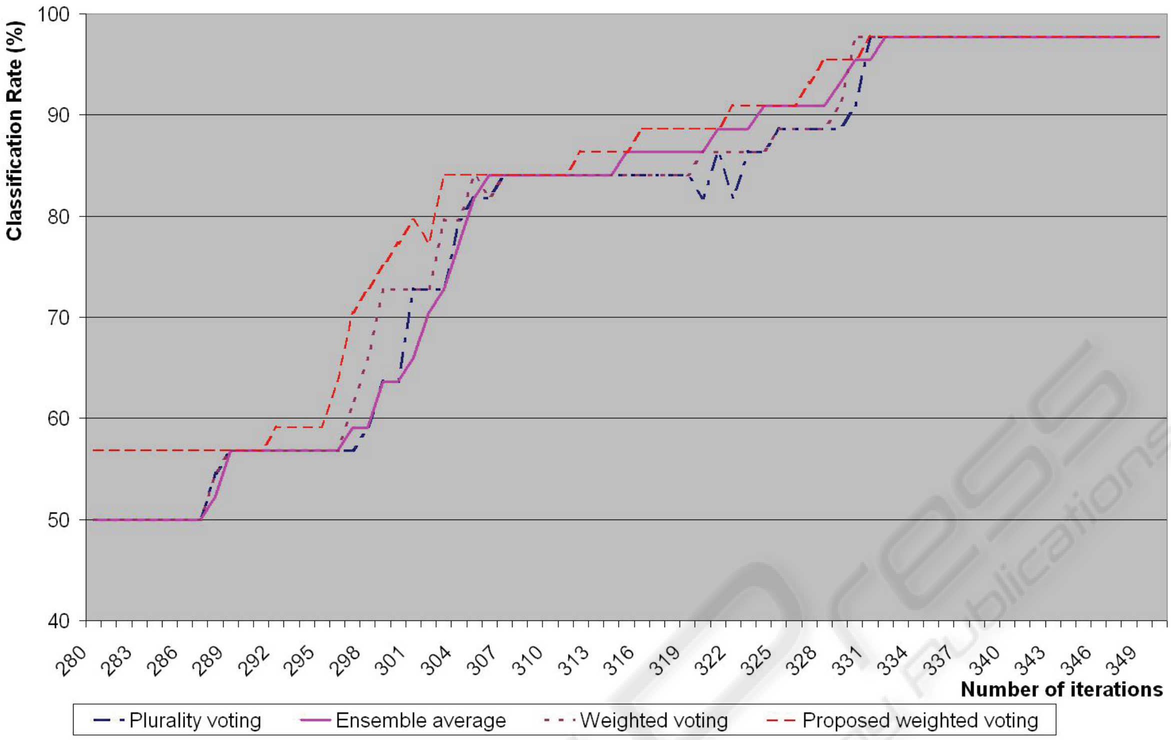

Figure 5: The results of application of ensemble methods for examination.

neural networks (members of ensemble) was 45. Elements of weights matrixes W_i , V_i were randomly distributed in intervals 0 ÷ 0.01 and $i \in [1:45]$. Each element x_j of input vector X , $j \in [1:26600]$, described intensity of the corresponding pixel, which was normalized according to

$$X_j = \frac{256^2 * R_j + 256 * G_j + B_j}{256^3}, \qquad (10)$$

where R_j , G_j , B_j - values of colors in RGB system for j pixel. The algorithm of training (back-propagation) was used for training each neural network. As each image was coded by 26600 elements, it was necessary to limit the time of training (iterations number).

As shown on fig. 3 and 4 the results of training and examination for each neural network can differ. This explains by the random choice of initial values of the weights matrixes W_i and V_i , $i \in [1:10]$.

As seen from the Fig. 5, the proposed algorithm of the weighed voting is more effective in comparison with known methods. Its advantage is especially noticeable, when the number of training iterations is limited. If the number of iterations is not limited, all the algorithms give comparable results. However in this case the training time becomes very long.

The similar situation was obtained in the cases of other training sets.

5 CONCLUSIONS

1. To solve the problem of similar human faces recognition (for example, faces of twins) ensemble methods that are realized in neural networks can be used.
2. The amount of time taken for training such neural networks can be significant, that is why it is necessary to limit the number of training iterations during network training. In these cases the effective method of ensemble decisions is the proposed algorithm of weighed voting.
3. The results of experiments show, that the proposed algorithm of weighed voting is more effective in comparison with known methods: algorithm of plurality voting, algorithm of ensemble averaging and algorithm of weighed voting. Its advantage is especially noticeable, when the number of training iterations is limited.

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