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ACCESS CONTROL BY FACE RECOGNITION USING NEURAL NETWORKS*

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A Multilayer Perceptron Neural Network (NN) is considered for access control based on face image recognition. We studied robustness of NN classifiers with respect to the False Acceptance and False Rejection errors. A new thresholding approach for rejection of unauthorized persons is proposed. Ensembles of NN with different architectures were studied too. Advantages of the ensembles are shown, and the best architecture parameters are given. The explored NN architectures may be used in real-time applications.

Introduction

Access control by face recognition has the following advantages in comparison with other biometrics systems. There are no requirements for expensive or specialized equipment, a system may be built using a simple video camera and a personal computer. The system is passive. There is no need to touch something by fingers or palm, no need to say any word or lean eye to a detector. Any person just may walk or stay before the camera, and the system performs recognition. It is especially useful in everyday usage. Also it has advantages in different extremal or non-standard situations, when it is impossible or inconvenient to took other biometric characteristics, for example when catching criminals.

The recognition performance of a simple face recognition system is not the best in comparison with other biometric-based systems, and such a system can be relatively easy deceived. But using a face thermogram or output of an infrared camera, the system can achieve very high recognition rate and robustness to deceiving. The face thermogram is strictly individual for every person, it does not change when lighting condition are changed, and it is impossible to deceive even by plastic operation. The ultra-high security access is based on face thermogram recognition.

There are many works devoted to the face recognition problem. But most of them are oriented on obtaining higher recognition rate for some test face databases in the prejudice of identification robustness and stability for real applications. The rejections of misclassified or unauthorized persons are not studied well. We tested the ORL face database (www.cam-orl.co.uk/facedatabase.html). It has 40 persons and 10 different images for each person, 92x112 pixels with slightly varying lighting conditions, pose, scale, face expression and presence or absence of glasses. No attempts to normalize these images were made.

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In work [1] the multilayer perceptron neural network was used. It has one hidden layer with number of hidden units varying from 60 to 80. The input of neural network was a set of discrete cosine transform coefficients. The first 30 coefficients from 10304 were used. The achieved recognition rate was from 94% to 97%.

In work [2] the convolution neural network were used. It has sophisticated architecture for image recognition. The input of such network was whole image. Reported recognition rate was from 96% to 98.5%. The Pseudo-2D Hidden Markov Models (P2D-HMM) were used in work [3]. Reported recognition rate was from 98% to 100%. All this works used ORL database. The first five images of each person were used for training, and the last five – for testing. There were no any attempts neither to estimate the reliability of classification, nor to develop the rejections for unauthorized persons or for unreliable cases for authorized persons. For neural networks and P2D-HMM's there were used the maximum response rule, when a unit of the output layer (or particular model for HMM's) with maximum value indicates recognized person.

The main question is how reliable such classification? For example, when distinctiveness between classes is small, the system may perform well during one run, and fail during another one due to random fluctuations of training process. Can the mentioned algorithms give robust distinctiveness between classes of people, particularly for previously unseen persons? When system is trained only on positive examples (i.e. authorized persons) it may fail on unauthorized person, considering such one as known class. For example, Hidden Markov Models are trained only on positive examples [3], each model corresponds to its own class. In work [4] a sophisticated algorithm for rejecting unauthorized persons were developed. It exploits fact that unauthorized persons are not similar to training examples, and statistical properties for output of models will differ. And what will be when an unauthorized person is similar to some training classes simultaneously? In this article we attempting to cope with such situation.

In our study we are considering two different thresholding approaches for rejecting unauthorized persons and unreliable cases. The neural network discriminative power in conjunction with thresholding-based rejection is explored.

Also we have explored different architectures of neural networks ensembles and their stability for classification and robustness for rejection unauthorized and unreliable cases.

1. Theory

Multilayer Perceptron (MLP) Neural Network is a good tool for classification purposes [5,6]. It can approximate almost any regularity between its input and output. The NN weights are adjusted by supervised training procedure called backpropagation. Backpropagation is a kind of the gradient descent method, which search an acceptable local minimum in the NN weight space in order to achieve minimal error. Error is defined as a root mean square of differences between real and desired outputs of NN.

During the training procedure MLP builds separation hypersurfaces in the input space. After training MLP can successfully apply acquired skills to the previously unseen samples. It has good extrapolative and intrerpolative abilities.

Typical architecture has a number of layers following one by one [5,6]. MLP with one layer can build linear hypersurfaces, MLP with two layers can build convex hypersurfaces, and MLP with three layers – hypersurfaces of any shape.

In experiments we have used one hidden layer with 20 and 30 units in it. The number of units in the input layer is equal to the number of image pixels, 2576 in our case (i.e. 46x56). We have used images scaled down by factor 2 in order to speed up learning. Our previous experiments [7] has showed that such scaling did not change recognition rate on the ORL database. Gray level of every pixel was linearly scaled from range [0; 255] to [-0.05; +0.05] in order to avoid paralysis or surfeit of the network. The number of output units is equal to the number of classes, i.e. 40, the number of persons in the ORL database. Each output unit has corresponding "own" class.

We have used hyperbolic tangent as an activation function. It has output range [-1; +1] and outperforms the standard sigmoid function [5,6]. Each unit in the output layer is trained to give respond "+1" for the own class and "-1" for others. Thus MLP remaps the input space into the output space $\{O_i\},\ O_i = \begin{cases} +1, i = class \\ -1, i \neq class \end{cases}$. In practice, real outputs are not exactly "+1" or "-1". They vary in the range [-1; +1] and the vicinity to the ideal values depends on the NN confidence. The closer output values to ideal, the more confidence to the NN decision. Recognition is performed by finding output neuron with the maximal value. The input image is considered as belonging to the class corresponding to this neuron. Then a thresholding algorithm is applied. It can reject or confirm decision of the NN.

For the training we have used a modification of the standard backpropagation procedure, an adaptive step suggested by Golovko [6]. When learning rate is small, training takes a long time. When learning rate is big, learning may never converge. Main advantage of this approach is that no need to manually select learning rate. Learning process is converged stable and fast (Fig. 1). In our experiments it takes from 50 to 100 training cycles to obtain the best performance and we used 100 cycles almost in all experiments, if otherwise is not mentioned. For the standard division of ORL (first five images of every person are used for training, last five – for testing) our system has recognition rate from 90% to 94%. Also we performed experiment to choose the number of hidden units for best performance (Fig. 2). As can be seen, adding more than 30 hidden units has no effect.

After training neural network produces practically ideal output for training samples (Fig. 3). Typical output for test sample is given on Fig. 4.

The typical output of NN for the case of unreliable classification, misclassification person looks like in Fig. 5. However, there can be cases such as in Fig. 6, where one person is more similar to another person than to itself (possibly due to similar pose or lighting conditions). For unauthorized persons in access control task output of the NN looks more diverse if there are no special algorithms were used for training.

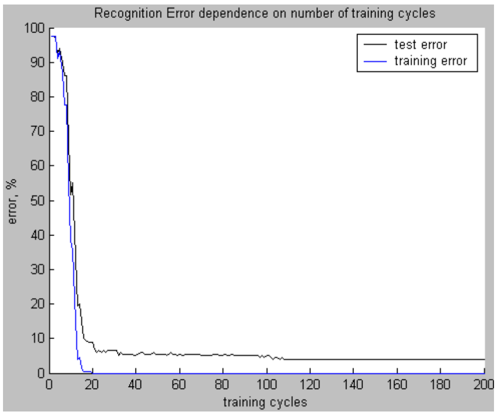

Fig. 1. Changing of recognition rate with training cycles.

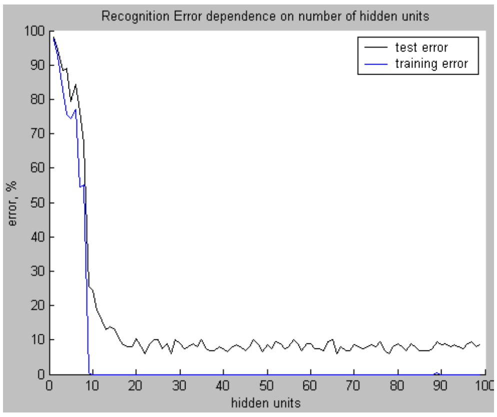

Fig. 2. Changing of recognition rate with number of hidden units.

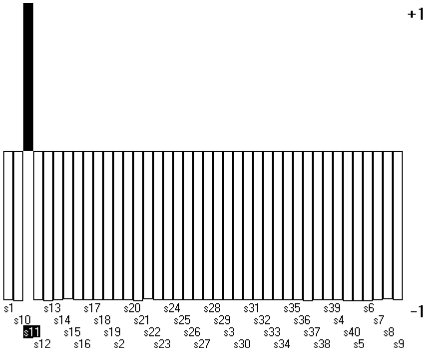

Fig. 3. Recognition of training sample, class “s11”. (output of NN)

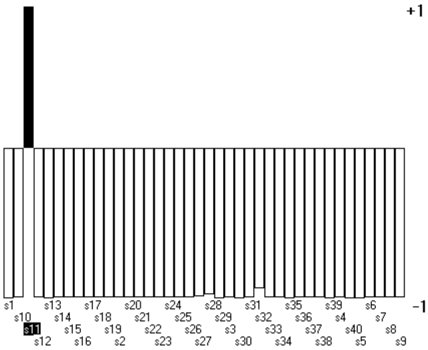

Fig. 4. Recognition of test sample, class “s11”. (output of NN)

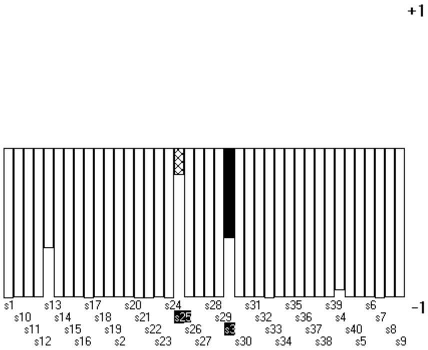

Fig. 5. Misclassification, class “s3” (black bar) recognized as “s25” (crossed bar).

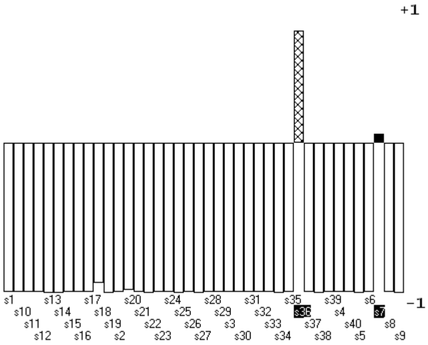

Fig. 6. Strong misclassification, class “s7” (black bar) recognized as “s36” (crossed bar).

2. Experimental results

For this set of experiments ORL database were divided on two parts. First part represented authorized persons and has 20 persons, from which random 5 images were used for training (total 100 images), other 5 for testing (total 100 images). Second part represented unauthorized persons. It has 20 persons and 10 images per person (total 200 images) only for testing purposes. Thus system has 100 images for training, and 300 for testing (100 authorized and 200 unauthorized).

In order to measure performance of algorithms we have used following factors. False Acceptance Rate (***FAR***), the number of unauthorized persons, considered as authorized, divided by total number of unauthorized attempts. False Rejection Rate (***FRR***), the number of authorized persons, considered as unauthorized, divided by total number of authorized attempts. FAR/FRR midpoints, the ratio when FAR and FRR is approximately equal. Recognition Rate, sum of misclassified authorized persons, false acceptance cases, false rejection cases divided by total number of access attempts. Also we considered stability of this factors. The system can achieve different recognition results on different training runs due to the probabilistic character of NN training. Stability is calculated as root mean square deviation (***RMSD***) of these factors on different runs from an average value. The less is ***RMSD*** the more stability the training algorithm has.

2.1. Experiment 1 – exploring thresholds

Besides the cases of correct and reliable classification the cases system must handle are misclassification, unreliable classification or attempt to access by unauthorized person for access control task. In this experiment we have explored two thresholding algorithms for rejection of such cases. The recognition system must reject such cases as much as possible, but perform well for authorized persons.

First thresholding algorithm (labeled ***'min'***) compares value of the maximal output neuron $\boldsymbol{O_{max}}$ with threshold ***t***. When this output is lower than threshold, the decision of NN is rejected and person considered as unauthorized. Otherwise person considered as authorized. If we consider the output of NN as *n*-dimensional space (*n* – number of classes), then this algorithm will represent so-called ***"chess"*** metric. The value of threshold can be in range from "-1" (the lower value of NN output) to "+1" (the highest value of NN output).

The drawback of ***'min'*** algorithm is that it can't deal with situation such as on Fig. 6, when some class is similar to more than one class. Second thresholding algorithm (labeled ***'sqr'***) uses values of all output units and can cope with such situations. It calculates root mean square deviation from the real NN output to the ideal NN output: $d = \sqrt{\sum_{i=1}^{n} (O_i - \begin{Bmatrix} +1, i = \max \\ -1, i \neq \max \end{Bmatrix})^2}$. If ***d*** is less than threshold ***t***, then NN decision is rejected, and person considered as unauthorized. Otherwise the person is authorized for access. This algorithm can be considered as Euclidean distance in NN output space, where each class has area, bordered by quarter of circle with radius ***t*** and center in its ideal position $\{O_i\}$ (Fig. 7). The minimal value of threshold is 0 and maximum is infinity, but practice has showed that for ***t*** > ***2*** there are can be no false rejections and we have used range [0; +2].

The comparative performance measure is shown on Fig. 8, 10, 11. Because the threshold ranges is different, we labeled ranges from 0 to 20 in order to place values in one graph. The graphs are showing averaged values for three different database divisions. For each division were performed three NN trainings with different initial weight seedings.

As can be seen, ***'sqr'*** thresholding algorithm gives better recognition rate for all threshold ranges and better FAR/FRR midpoints. Also ***'sqr'*** has significantly lower FAR and slightly higher FRR. In other words it much stricter to unauthorized persons and slightly stricter for authorized persons.

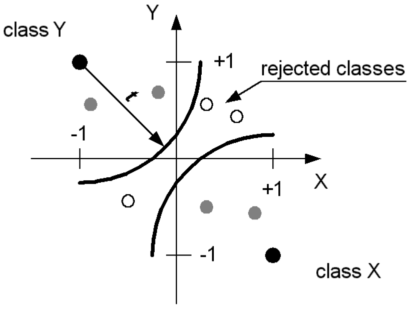

Fig. 7. NN output space and ***'sqr'*** thresholding algorithm.

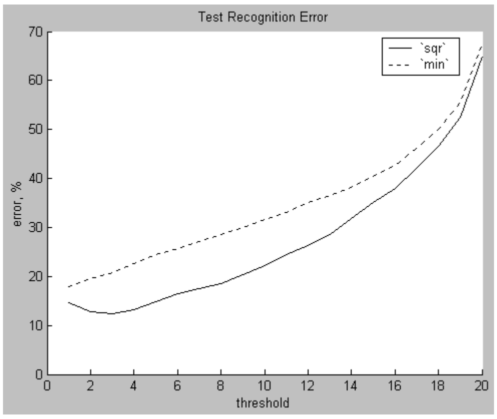

Fig. 8. Recognition Rate for both thresholding rules.

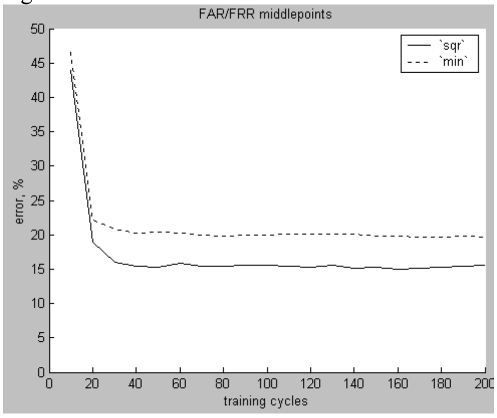

Fig. 9. FAR/FRR midpoints for both thresholding rules.

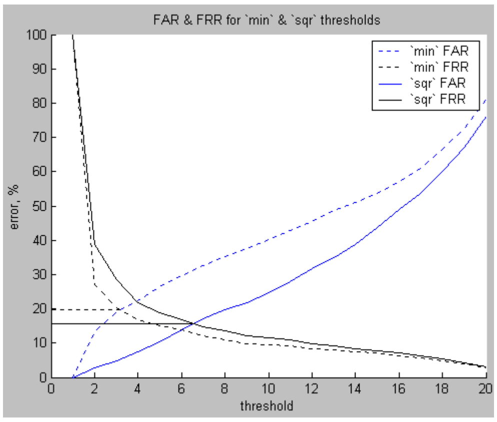

Fig. 10. FAR and FRR for both thresholding rules.

2.2. Experiment 2 – exploring ensembles of neural networks

In this set of experiments we have measured performance of four different architectures of NN.

First architecture (labeled ***'mlp'***) was usual multilayer perceptron with ***'sqr'*** thresholding rule.

Second architecture (***'one-one'***) is ensemble from 40 MLPs. Every MLP have one "own" class assigned with it. Each MLP have 2 layers, 20 hidden unit and one output unit. An output unit was trained to give "+1" for own person and "-1" for other persons. Outputs of ensemble were forming an aggregate network output, for example output of first MLP in ensemble were representing first output unit of aggregate NN. Then output of aggregate NN was considered as output of uniform MLP and ***'sqr'*** thresholding rule was applied as usual.

Third architecture (***'one-two'***) is like ***'one-one'***, but it has additional second output unit which was trained to give "-1" for own classes and "+1" for other classes. However in aggregate NN were considered only first output unit. By this architecture we have checked a statement that more different goals NN has, the eases the learning process and better the performance.

Fourth architecture (***'all-all'***) is an ensemble of NN of first (***'mlp'***) architecture. Voting makes the decision of such ensemble. Every MLP in ensemble gives one voice for person recognized by this ensemble. When the confidence for certain

MLP is low, such MLP can abstain and give no voice at all. Confidence is checked by ***'sqr'*** thresholding rule. The threshold for abstaining was chosen experimentally and is equal to ***1.2***. Then decision rule is counting the number of voices for all persons. The person with maximum voices (it must be at least two voices) considered as recognized. Then we have compared the percent of voices for recognized person with thresholding percent (range [0; +1]). If the person has fewer voices than threshold, it considered as unauthorized and rejected. We have experimentally checked the performance of this architecture depending on number of ensembles. The performance was increasing with the number of MLPs and reaches optimum value for seven MLPs.

First, we have explored the ability of all architectures to classify face images (Fig. 11). All classes were used both for training and testing. Graph shows an averaged data for different database divisions and NN seedings. As can be seen from Fig. 11, the fourth architecture has best recognition performance. Second and third architectures are worse than usual MLP. As we expected the third architecture performs better than second. The stability of recognition results (RMSD) is the same. The behavior of FAR/FRR midpoints is practically the same, but the third architecture slightly better than second.

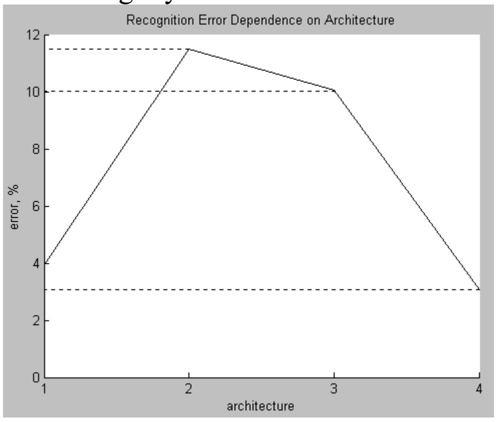

Fig. 11. Recognition performance for classification, all architectures.

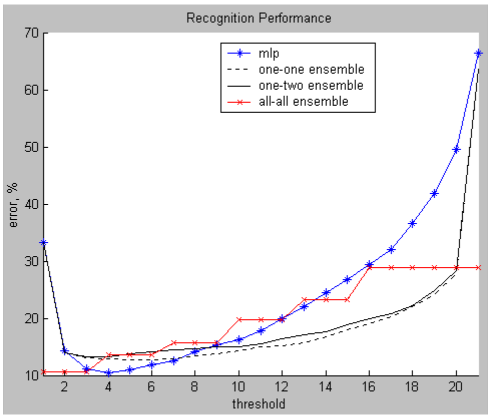

Fig. 12. Recognition performance for access control, all architectures, full thresholds range.

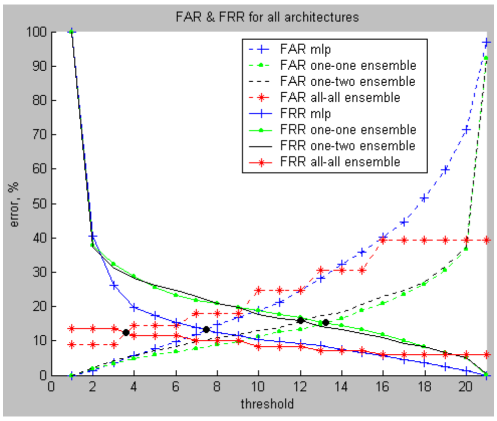

Fig. 13. FAR and FRR for all architectures, full thresholds range.

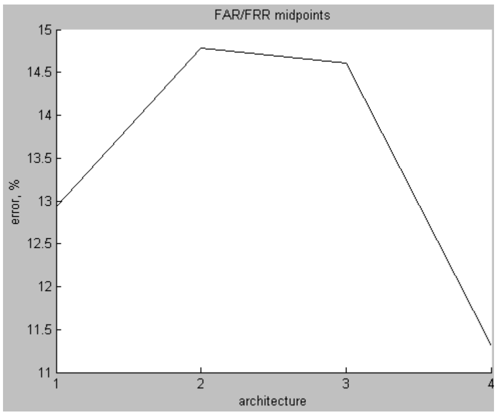

Fig. 14. FAR/FRR midpoints for all architectures.

Second, we have explored the performance of these architectures for access control task. For the training were used 20 classes from 40 with five samples per class. Results can be seen on Fig. 12-15. First and fourth architecture has best recognition performance (Fig. 12). Fourth architecture has the best FAR/FRR relation (Fig. 14). Then follows first architecture. The second and third architectures is very strict to unauthorized persons (low FAR) but also strict for authorized persons.

Fourth architecture has significantly best performance as for recognition task either for access control. However it has less stability (RMSD) in recognition results than other architectures. The second and the third architectures are very strict to attempts for unauthorized access, but they have low performance for authorized persons (Fig. 13, 14).

Conclusion

As can be seen from the experimental results, the more different goals NN have to learn, the better performance is. A collective decision is better than a decision of one network. Also the introduced ***'sqr'*** thresholding rule has better performance for rejection an unauthorized persons than ***'min'*** thresholding rule.

Improvements presented in the paper are insufficient for creation a real access control system. First, an image must be normalized in brightness and contrast, face orientation and scale to bring it to uniform conditions. This is required to exclude systems reaction on similar shooting conditions that may be greater than difference between two different persons.

The second improvement lies in the domain of the better NN training. NN needs a set of negative examples to narrow areas with unauthorized persons. Also most of the NN ensemble errors are due to the fact that individual networks are mistaken similarly. We will try to decorrelate NN errors during the training process.

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