The Face Recognition Processes - Neurofuzzy Approach

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Abstract: The paper deals with the novel neuro-fuzzy approach for face recognition problem. A proposed method consists of two steps. The first one means image preprocessing (face detection and landmarks extraction). In particular, this concerns points on the face such as the corners of the mouth, points along the eyebrows, on the eyes, nose and jaw. In the second step, based on extracted features, neurofuzzy system recognizes to whom detected face belongs. Classical fuzzy controllers need an expert knowledge to define set of rules and/or defuzzification process. Main concept of neurofuzzy approach is to replace expert with neural networks. This paper shows that, neurofuzzy system can suit face recognition process and provide better results than other popular techniques.

1 INTRODUCTION

Facial appearance is definitely very important biometric characteristic as the most decisive way to recognize and distinguish people. Since photography was invented it is used in passports or identity cards as it guarantees unambiguous identification. Nowadays, there exist a lot of archival photos databases, which can be automatically searched. Therefore, large variety of applications for face recognition process, opens up, e.g. looking for suspects in police database, physical and logical access to protected resources and humanoid robots. Face recognition process is intuitive and obvious for humans, whereas it can be very challenging for computers and artificial intelligence , because it is impossible to create simple rules leading to mathematical model of this complicated process. Usually face recognition systems begin with image processing in order to detect if there is a face and where is it localized. There are many methods of face detection, based on face anatomy. Using standard image processing operations like shifts, scaling and rotations, face image can be normalized to simplify next steps of recognition. There are defined two categories of methods which can be applied for image processing (Bolle et al., 2004): based on facial appearance, face geometry or hybrids. Approach presented in this paper deals with face geometry method, which closely depends on position and geometrical relations between face details, like eyes, mouth, nose etc. In this case, recognition is a matter of comparison with layouts of details stored in database of known faces. Feature-by-feature comparison may be inefficient and lacks generalization and there is a need for more optimized solution. Another promising concept that could be apply for face recognition is so called "computing with words" introduced by (Zadeh, 1996). Its origin dates back to his famous article „Fuzzy Sets" (Zadeh, 1965, p. 338-353) where he introduced new approach for describing not precise and many-meanings concepts as opposed to well-known mathematical methods, which use classical divalent. Inspiration for creating fuzzy logic was human's brain, which use not precise terms of natural language and can create very complicated models of complex reality, making good decisions and deal with many complicated tasks without any measures and calculations. Computing with words is particularly useful when: i) available information has low accuracy level, ii) there is a toleration for inaccuracy and task can be done with low cost, iii) problem cannot be solved using classical methods or it is just too complicated to define it numerically. In theory, it suits very well face recognition problem, because people usually describe others using not precise terms like „big/small eyes/nose" etc. The main drawback of this approach is that systems based on fuzzy logic have no ability to learn and everything must be defined explicitly by creating set of rules manually.

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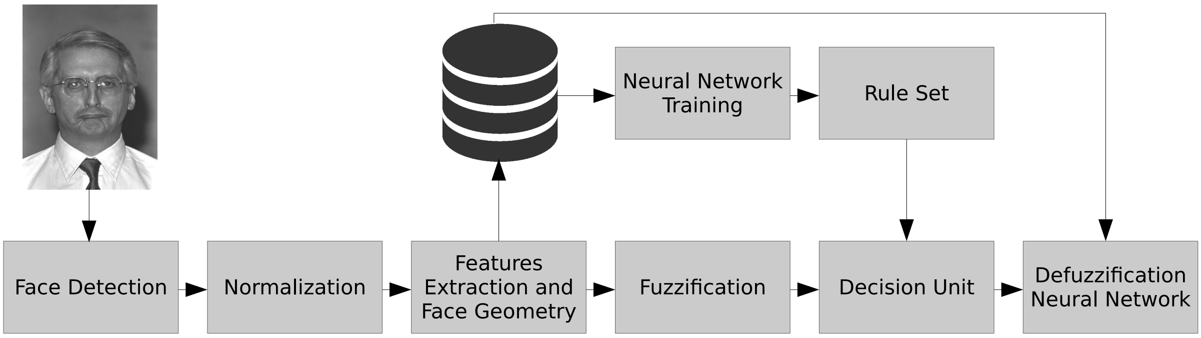


Figure 1: Steps of recognition process.

Face recognition process requires self-learning tool like neural network. Therefore, combining complementary solutions of fuzzy logic and neural network appears to be a very promising path (Dhavalikar and Kulkarni, 2014). However, in general fuzzy logic and neural networks approach the design of intelligent systems from quite different perspectives. Fuzzy logic allows making definite decisions based on imprecise or ambiguous data, whereas neural networks tries to incorporate human thinking process to solve problems without mathematically modeling them (Yuan et al., 2004). Even though both methods can be used to solve nonlinear problems, and problems that are not properly defined, they are fully independent (Vyas and Garg, 2012). Both neural networks and fuzzy logic are powerful design techniques that have their strengths and weaknesses summed up in Table 1. This paper presents neurofuzzy approach in face recognition process. Presented solution consist of two main step: image processing and face recognition. Figure 1 shows flow chart of presented process in details.

Table 1: Properties of neural networks and fuzzy logic (Makhsoos et al., 2009).

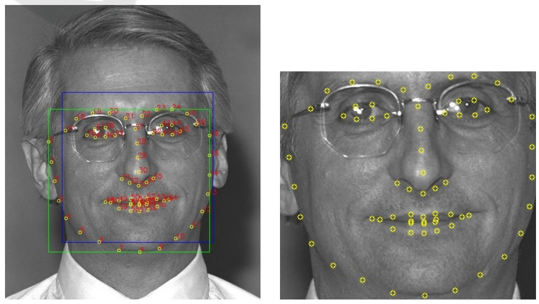
	Neural Networks	Fuzzy Logic
Knowledge Representation	Implicit, the system can not be easily interpreted or modified	Explicit,verification and optimization are very easy and efficient
Trainability	Trains itself by learning from data sets	None, everything must be defined explicitly

2 METHOD DESCRIPTION

In this section all elements of presented process will be explained. In particular this concerns: image preprocessing, face detection and neuro-fuzzy system.

2.1 Image Preprocessing

Image preprocessing is responsible for finding human faces in an image, estimating landmarks and normalizing face image to selected size. Face detector and landmark estimator is already implemented in dlib http://dlib.net/. Face detector is made using the standard Histogram of Oriented Gradients (HOG) feature combined with a linear classifier, an image pyramid and sliding window detection scheme. Blue frame in figure 2a marks the result of the detection step, which is just estimation where the face is located. Based on this estimation, landmarks positions are detected. Landmark Detector was created by using dlib's implementation after *One Millisecond Face Alignment with an Ensemble of Regression Trees* (Kazemi and Sullivan, 2014). Green frame in figure 2a is a region which contains all detected landmarks and a role model for normalization shown in figure 2b. This process is very important, because it automatically creates reference system for landmarks coordinates, so it is possible to analyze every case in the same way.

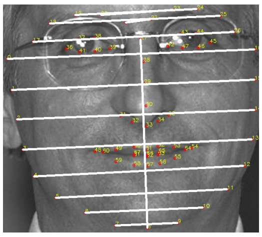


(a) Face detection and landmarks (b) Normalization

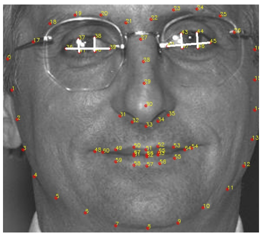
Figure 2: Steps of image preprocessing.

2.2 Face Geometry

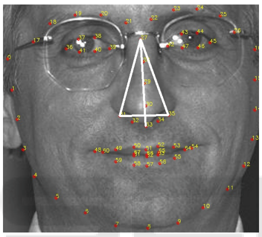
Landmarks detector provide positions of 68 landmarks arranged on the face. Based on detected landmarks it is possible to separate selected regions such as the mouth, left and right eye, nose and face shape, which consists of jaw and eyebrows. This approach makes the fuzzy representation of features more useful and understandable and as a consequence the *computing with words* strategy. It is also possible to measure distance between selected points and regions. This solution should give more precision in the whole process, because it includes region arrangement relative to each other. Features can be combined in many different ways.



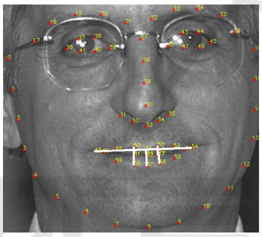
(a) Face shape features



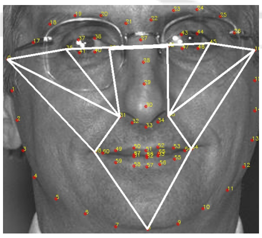
(b) Eyes features



(c) Nose features



(d) Mouth features



(e) Distances between regions

Figure 3: Example of possible features set.

Figure 3 shows exemplary combination of geometrical features for selected regions (figures: 3a, 3b, 3c, 3d) and spatial relations between regions (figure 3e).

2.3 Neurofuzzy System

Classical fuzzy controllers need predefined membership functions and set of rules linked with them. This is made usually by human expert.

Face recognition process is a problem that requires specially defined solution, that will fit specified cases, with no need for human expert. The

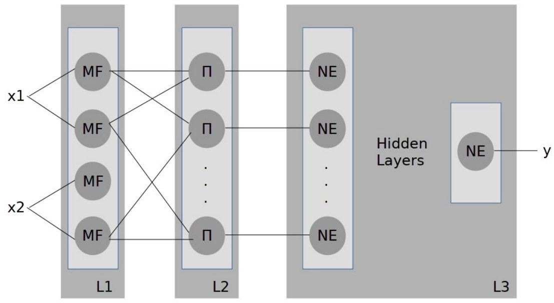


Figure 4: Structure of neurofuzzy network (MF - Membership function, NE - Neuron).

best way to create neurofuzzy system is to represent it as multilayer network with one output node (neuron). Figure 4 shows a scheme of an exemplary controller. Presented solution uses singleton as fuzzification method and neural network as defuzzification block (Rutkowska et al., 1999). This scheme can be mathematically described using following expression:

$$y = \bar{w}^T \left(\prod_{i=1}^{n} exp \left[- \left(\frac{\bar{x}_i - \bar{x}_i^k}{\sigma_i^k} \right)^2 \right] \right), \qquad (1)$$

where:

- $\bar{w}$ is a vector of neural network weights,
- i is a number of input variables,
- k is a number of membership functions for each variable universe,
- n is a number of all possible rules, which is a product of number of input variables with number of membership function,
- $\bar{x}^k$ is a mean value of normal distribution, which is used here as membership function,
- σ^k is a sigma parameter (standard deviation) for a normal distribution.

In the structure of neurofuzzy controller shown in figure 4 we can separate two specific functional modules. First one consists of layers L1 and L2, which represent fuzzification using singleton method and fuzzy inference blocks in classical fuzzy controller. Layer L3 is a neural network which realizes defuzzification part. Output of L1 consists of values of membership functions existing in input variables universe. One of the most popular membership function is Gaussian function, which appears in many contexts in the natural sciences.

Of course, it is possible to use another membership functions - this can be a subject of further research. Shape of Gaussian function depends on two parameters: x is a mean value (central value)and σ responsible for width of the distribution. Figure 5

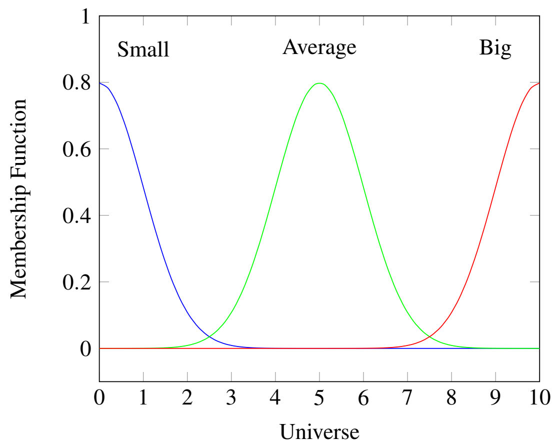


Figure 5: Universe of fuzzy variable with standard distribution membership functions.

shows exemplary universe of fuzzy variable. These parameters can be set precisely, depending on universe of each variable. Variable universe can be defined as difference between its largest and smallest value observed in training set. The easiest way to start is to convert universe of input and output variables into linguistic domain like „small/average/big nose", set them evenly into variable space and learning in the iterative way. Result of this step is set of parameters pairs (x_i, σ_i) which describe all membership functions for each fuzzy set in the whole variable space. Layer L2 is a representation of fuzzy inference. Each element in this layer is specific combination of L1 outputs. Size of this layer depends on number of input variables and number of membership functions for each variable universe. Layer L3 represents defuzzification block of the system using neural network. Number of neurons in input layer is equal to outputs from layer L2. It is also possible to define specific parameters like number and size of hidden layers, number of learning epochs, activation function.

3 EXPERIMENTAL RESULTS AND DISCUSSION

The experimental investigation of proposed approach was divided into three stages. The first one covers the aspect of defining how input features determine results of the whole system. Reducing the number of input features can be beneficial for system ability to generalize, because in the case of too many features the classifier will overfit. The second one was performed in order to show how size of the data set influences classification process. The last one is a comparison with other classification methods. Neurofuzzy system will be compared with k-nearest neighbors, naive Bayes, decision tree and neural network approaches which are standard tools used for face recognition.

Training set used in this case, comes from FERET (Phillips, 2016) database. In total 248 people which have at least three frontal photos of their faces, were selected. This means that the number of elements *(L)* of the training set ranges from 248 to 744. As a training algorithm, back propagation method was used. Test set consists of one photo of each person chosen randomly from available samples (248 elements). Presented solution using input vector of features with structure:

$$X = (x_1, x_2, \cdots, x_{47}, x_{48})^T, \tag{2}$$

where $x_1, x_2, \cdots, x_{48}$ are single features read from face image. The result of the operation of the system is the number of the class to which the object belongs. There are 248 classes (one for each person).

3.1 Features Selection

Way to check how input features influence final result is to increase number of used features in each iteration. In this case there are about 48 features. While iterating from 1 to 48 selected number of features we need to check final correct recognition of whole system. Result of this experiment is presented in Figure 6. The biggest difference in the correct recognition value can be seen between 1 and 10 selected features. The correct recognition increases strongly with the number of features for low values, much slower in the range of 10-48 features (20% increase) and saturates for larger number of features. Therefore, face recognition process based on neurofuzzy system needs at

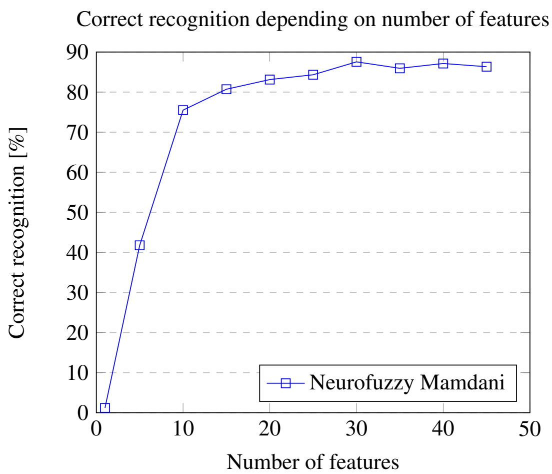


Figure 6: Correct recognition depending on number of features.

least 10 input features to get about 80% correct recognition. It is also possible to determine which features are dominant. Figure 7 shows most dominant features listed below marked on exemplary face. It is noteworthy that the most decisive features are those related to face geometry (width and height) and distances between separated regions - for example distance between corners of the eyes. The dominant features, in decreasing order of use, are as follows:

1. face9 (points 8 - 27),
2. general2 (points 36 - 45),
3. face14 (points 21 - 22),
4. face6 (points 5 - 11),
5. face11 (points 18 - 25),
6. general5 (points 16 - 35),
7. general7 (points 0 - 31),
8. face4 (points 3 - 13),
9. mouth1 (points 48 - 54),
10. general8 (points 0 - 48).

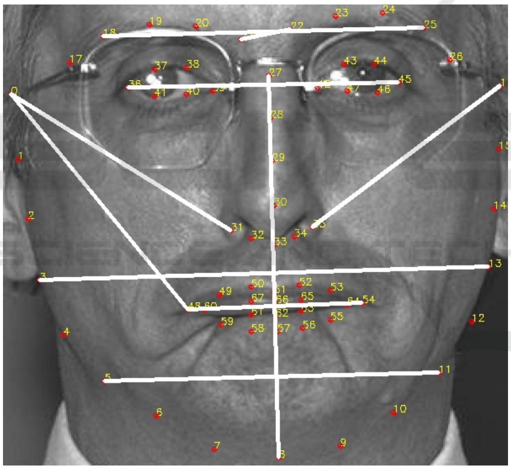


Figure 7: Face with selected 10 most dominant features.

3.2 Influence of Size of the Input Data

This experiment studies how number of people in the input set influences the final result. Figure 8 shows the correct recognition value depending on size of input set for learning. Each iteration of this experiment has been performed for 1 to 248 faces.

In Figure 8 results for different size of samples per person, corresponding to 1, 2 or 3 photos, are presented. In all cases the correct recognition values decreases with the size of the input set by 10%-15%. It is obvious that set with three photos per person guarantees the best correct recognition, which decreases when the number of photos per person for learning is decreased.

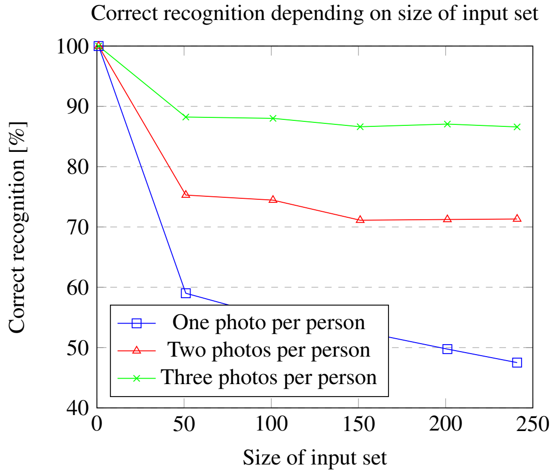


Figure 8: Correct recognition depending on size of input set.

3.3 Comparison with other Classification Methods

There are many methods of solving classification problem. Comparison with other classification methods is a way to verify if method works correctly. It is not possible to easily assign classifier to specific problem. The best way to select suitable method is by comparison. This paper compares neurofuzzy approach with k-nearest neighbors (for $k = 5$ neighbors), naive Bayes using normal distribution function, decision tree and neural network. As a comparative criterion, the value of the correct classification was used. Figure 9 shows result of this comparison. Developed and presented in this work neurofuzzy approach gives the best correct recognition with the value over 85%. This is probably caused by fuzzification process, which normalizes input values and naive Bayes is based on normal distribution. Presented result depends on initialization of input parameters and can change in some specific cases, which can be investigated in future work.

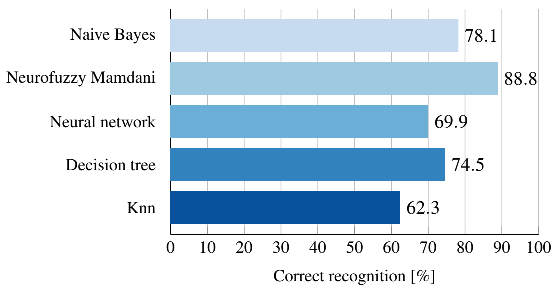


Figure 9: Neurofuzzy correct recognition comparison with other classification methods.

4 CONCLUSIONS

Obtained results confirms that neurofuzzy system can suit face recognition process. The approach was verified by features selection experiment and influence of size of the input data. Finally, neurofuzzy approach was compared with other classification methods, which shows presented system works better. The proposed work can be further extended by adding different types of membership functions or checking others parameters of the system. Try to use different features reduction techniques is also worth attention. A comparison of the presented approach with deep learning methodology will be analyzed in the future too. Presented system has a wide range of applications in research and human-computer interfaces. Based on the obtained results, we can say that neurofuzzy approach fits better face recognition process than other most popular classification techniques, especially neural network, which is also a part of neurofuzzy system.

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