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Model of Identity Verification Support System Based on Voice and Image Samples

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Abstract: The increasing need to implement systems as identity verification meant that safe and effective verification systems have become one of the main branches of modern scientific research. In this paper, the idea of identity verification support system is presented. The main novelty of this work is to present the technique of feature extraction that can be implemented simultaneously for processed image files as well sound ones. Proposed method was tested due to achieve the highest possible accuracy of the selected neural classifier. The obtained results were discussed in terms of advantages and disadvantages for practical applications.
Key Words: Neural nets, Heuristic methods, Interactive systems
Category: I.2.8, I.5.1, I.5.5

1 Introduction

The elimination of the amount of documents and papers caused the automatic systems became an important element of the currently conducted research. Reduction of documents results in the introduction of electronic data into the circulation of everyday life. One of the most popular digital data types today is the money that has disappeared from the use of ATMs and credit cards. Security is also becoming increasingly popular in this field. The reason is to remove barriers in identity documents for quick identification by the use of our unique features. Such an elegant solution brings with it many problems. Such an elegant technique eliminates many problems that anyone can encounter. An example is the disappearance or loss of our cards which can be impeccable used by another person. The construction of a system that will verify identity will be strongly dependent on the extraction of data from different samples and their classification. Moreover, simply and fast became a determinants of efficient identity verification process. The ideal solution assumes that a person will came to computer/machine and it will make a immediate decision if that person is who said to be. Such a solution should be fast and not to create any queue. For make it true, system should take a few features which can be called as unique for that person. A unique feature may be voice, fingerprints or eye iris.

One of the unique features used in identity identification process is the iris of our eye. In [Tan C-W. et al.(2014)], the authors presented the idea of iris verification based on geometric key-based encoding. Again in [Rai H. et al.(2014)], the iris verification was made by the application of hamming distance approach and support vector machine as method of data classification. Not only the iris but whole face can be used for this purpose what can be seen in [Ren J. et al.(2013)]. The proposed solution has been modeled in three stages (face detection, alignment and verification) and it was designed to secure our mobile phones. However, the proposed solution can be used in a much broader perspective.

Voice is another feature that can be used as a human identifier. In [Alegre F. et al.(2013)], the idea of preventing counterfeiting for the protection of automated voice verification from a conversation was presented and discussed in terms of advantages and disadvantages. Again in [Graves A. et al.(2013), Abdel-Hamid O. et al.(2014)], different types of neural networks were used for the purpose of voice recognition of concurrent individuals. The use of two different neural classifiers has shown that another technique for extracting important information from a similar samples are needed. Moreover, the results and accuracy are dependent on them. Voice verification can also be combined with automatic facial matching [Wang S. et al.(2013)].

Identity verification is often understood as a signature check which is shaped throughout our whole live, making it a recognized unique feature. This type of signature distinguishes two types of characteristics local like slope of signature fragment and global like length or slope of the entire signature. An example of automatic signature analysis is shown in [Diaz M. et al.(2017)]. Another application is the verification of foot prints [Variani E. et al.(2014)] or the movement of the computer mouse [Zheng N. et al.(2016)]. Verification technique must be used in decision support system, which application is shown in [Połap D. et al.(2016)], where the use of voice and image analysis were presented as a main tools for active assistance system. Another idea is to use mobile phones as verification tools. In [Damaševičius R. et al.(2016)], the gait characteristics has been used in a verification process. Moreover, the idea of cloud computing is very important due to transfer of calculations from the device [Wei W. et al.(2016)]. The same is with some technique that can be used to decrease the amount of calculation and processing time [Wei W. et al.(2017), Wei W. et al.(2017), Włodarczyk-Sielicka M. et al. (2017), Włodarczyk-Sielicka M. (2016)].

The main problem is to model one method which will consist few features for the verification process. In this paper, I presents the idea of identity verification system model that joins iris eye and voice features by the use of one method based on heuristic and neural approach.

2 Features Extraction

The proposed technique for obtaining features from sound and graphic samples causes that the sound sample must be be converted to graphic form. Having two graphics samples, the swarm intelligence locates the important features of images that will be used to create the vector (pattern) representing the specific person.

2.1 Audio sample

Signal is understood as a process of change over time caused by certain systems or phenomena. Mathematically, the signal is a function, so the sound signal is understood as a wave. It can be presented as

$$s(t) = \sum_{i=1}^{N} A_i(t) \sin[2\pi F_i(t)t + \omega_i(t)], \tag{1}$$

wherein t means time, $A(t)$ is the value of the amplitude, $F(t)$ is frequency and $\omega(t)$ means a phase of the wave, so it determine an interval where the point is located.

Signal analysis in its original form is impossible to analyze. To enable this operation, the signal must be transformed. Fourier transform is one of the most popular and most widely used in signal theory. For computer signal processing (so-called digital signals), the calculation of the transform takes place through its discrete version. Let $s(n) = (s_0, s_1, s_2, \ldots, s_{N-1})$ where $s_i \in \mathbb{R}$ and N is the number of all sequence. Process which converts $s(n)$ in a harmonic form defined as $(S_0, S_1, S_2, \ldots, S_{N-1})$ where $S_i \in \mathbb{C}$ is called as *Discrete Fourier Transform* and it is defined as

$$S_k = \sum_{n=0}^{N-1} s_n \exp\left(-\frac{2\pi ink}{N}\right) \quad 0 \le k \le N-1. \tag{2}$$

Reverse action is called as *Inverse Fourier Transform* what can be described as

$$s_n = \frac{1}{N} \sum_{k=0}^{N-1} S_k \exp\left(\frac{2\pi ikn}{N}\right) \quad 0 \le n \le N-1. \tag{3}$$

In the sixties of the previous century, the computing power of computers and calculating machines were too weak to cope with the calculation of such a transform. To enable calculating of the transformations in finite, short time, James W. Cooley and John W. Tukey proposed an algorithm called *Fast Fourier Transform* [Cooley J. et al.(1965)]. Proposed technique is a recursive algorithm that works on a divide and conquer rule, so algorithm divides the transform into smaller and smaller parts (this action does not reduce the number of calculations, but shows some symmetry that indicates that only half of the calculation must be done) what can be shown as

$$\begin{aligned} S_k &= \sum_{n=0}^{N-1} s_n \exp\left(-\frac{2i\pi nk}{N}\right) = \sum_{m=0}^{N/2-1} s_{2m} \exp\left(-\frac{2i\pi k(2m)}{N}\right) \\ &+ \sum_{m=0}^{N/2-1} s_{2m+1} \exp\left(-\frac{2i\pi k(2m+1)}{N}\right) = \sum_{m=0}^{N/2-1} s_{2m} \exp\left(-\frac{2i\pi km}{N/2}\right) \\ &+ \exp\left(-\frac{2i\pi k}{N}\right) \sum_{m=0}^{N/2-1} s_{2m+1} \exp\left(-\frac{2i\pi km}{N/2}\right). \end{aligned} \tag{4}$$

The result of applying Fourier transform can be visualized in a graphical form of spectrogram. It is two-dimensional space spread over two axes – time and frequency. Amplitude is imaged as a point on a plane that is described by a specific shade of color called density. Spectrogram analysis involves finding the darkest areas composed of several to a dozen pixels (depending on the size) that can be understood as a feature of voice for a given sample.

2.2 Eye iris image processing

In the case of eye iris images, samples must be prepared for feature extraction by iris segmentation and image processing technique. In this subsection, both things are described due to the proposed method of extraction.

To detect iris, the edge detection algorithm can be used. One of the most known is called Canny edge detection algorithm [Canny J.(1986)]. The algorithm assumes a noise reduction that is made through the convolve the image and the Gaussian filter, resulting in a slightly blurry image. Gaussian filter of size $(2k+1) \times (2k+1)$ is defined as

$$H_{ij} = \frac{1}{2\pi\omega^2} \exp\left(-\frac{(i-(k+1))^2 + (j-(k+1))^2}{2\omega^2}\right), \qquad 1 \le i, j \le (2k+1). \tag{5}$$

Using Eq. (5) for size of 5×5 and $\sigma = 1.4$, the whole operation may be presented as

$$B = \frac{1}{159} \begin{bmatrix} 2 & 4 & 5 & 4 & 2 \\ 4 & 9 & 12 & 9 & 4 \\ 5 & 12 & 15 & 12 & 5 \\ 4 & 9 & 12 & 9 & 4 \\ 2 & 4 & 5 & 4 & 2 \end{bmatrix} * A. \tag{6}$$

The next step is to find the intensity gradient of the image. For this purpose, four filters are used, respectively for horizontal, vertical and diagonal detection. Formulas describing operators for gradient and direction are

$$G = \sqrt{G_x^2 + G_y^2}, \tag{7}$$

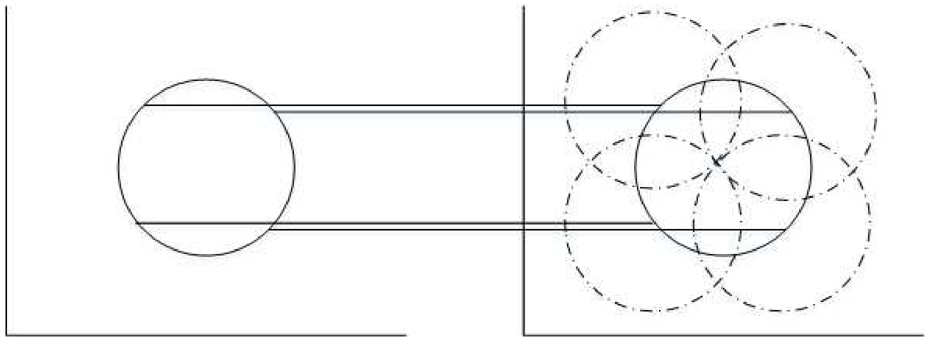

Figure 1: Visualization of Circular Hough Transform application.

$$\Theta = \arctan\left(\frac{G_y}{G_x}\right), \tag{8}$$

where G_x is the first derivative for the horizontal direction and G_y for the vertical direction. Then, the resulting edges are shedding to get their continuity. We call this operation as *non-maximum suppression*. This is to compare the edge strength around the current pixel by checking the positive and negative directions of the gradient. If the strength is greater than around, the pixel is preserved. Otherwise, it is suppressed. The last step is edge tracking by hysteresis. The process is to merge weak pixels with strong ones, which will cause that the noise will not be connected. For that purpose, blob analysis is applied ie 3×3 grid analysis where the analyzed pixel is in the middle. If one of the neighbors is a strong one, the middle pixel should not be removed.

Applying the Canny algorithm only allows the edge to be detected and the result of all these actions should be the eye iris. For this purpose, Circular Hough Transform is applied. Notice that the iris is a circle and such an equation looks as follows

$$r^2 = (x-a)^2 + (y-b)^2, \tag{9}$$

where (a, b) is the center of a circle with a radius r. Algorithm assumes, that the space of parameters a and b will be the set of circles of the same radius r. Such an approach causes that all circles with such radius and a center located on the circumference of the suspicious circle will intersect in one point. In this way, circles are found by the use of a Circular Hough Transform. The visualization of this process is shown in the Fig. 2.2. Now, the found iris can be cut from the original image.

The segmentation method returns only the iris of the eye. An important element of the current image is a pupil that does not store important identifying features. Removal is understood as replacing the black pupil color (located exactly in the center of the image) into white.

2.3 Feature Extraction

Having an image area, feature extraction involves searching for specific areas. In both cases, dark areas will be most desirable. In order to locate it, swarm intelligence will move around the image so to find a unique sequence of characteristics (pixels) that will represent the values from all samples for a specific person.

2.3.1 Artificial Ant Colony Algorithma

Artificial Ant Colony Algorithm (AACA) is one of the swarm intelligence algorithm which modeling the behavior of ants while searching for the best source of food. Each ant in the swarm moves in the environment (here it is an image) to leave a pheromone trace that is amplified. Other ants may follow the same path and increase the amount of pheromone – such an action will increase the quality of searched food source. Over time, the pheromone slowly evaporates and the path becomes forgotten.

The proposed algorithm requires several assumptions to improve its performance

- all pixels are potential food localizations,
- the initial population of ants is stacked on the image randomly,
- each ant is understood as a point $\mathbf{x_i}$, where i is its numerical designation,
- the initial pheromone level for each pixel is set as 0.3,
- The number of ants in the swarm is constant,
- Ants are evaluated by the fitness function defined as

  $$f(\mathbf{x}) = \left| \frac{\max R(\mathbf{x}), G(\mathbf{x}), B(\mathbf{x}) - \min R(\mathbf{x}), G(\mathbf{x}), B(\mathbf{x})}{2} - 1 \right| = |B(\mathbf{x}) - 1|, \tag{10}$$

  where $B(\cdot)$ means brightness value, $R(\cdot)$, $G(\cdot)$ and $B(\cdot)$ are the color components, respectively red, green and blue.
- 30% of the best individuals at the end of the iteration are moved to the next iteration and the rest is selected in random way.

The pheromones level is updated in t iteration as

$$f^{t+1}(\mathbf{x_i}, \mathbf{x_j}) = (1-\rho) f^t(\mathbf{x_i}, \mathbf{x_j}) + \Gamma_i^t, \tag{11}$$

where ρ is constant evaporation rate and n is total number of individuals that travel to $\mathbf{x_i}$ over Γ_i^t distance calculated as

$$\Gamma_i^t = \sum_{i=1}^{n} \frac{1}{L_{ij}^t}, \tag{12}$$

and L_{ij}^t is the distance between two individuals $\mathbf{x}_i$ and $\mathbf{x}_j$ described as a Cartesian metric that is

$$L_{ij}^t = \|\mathbf{x_i}^t - \mathbf{x_j}^t\| = \sqrt{\sum_{k=1}^{2}(x_{i,k}^t - x_{j,k}^t)^2}, \tag{13}$$

where k is the components of the spatial coordinates. Moreover, the probability of choosing the path to ant $\mathbf{x_j}$ by $\mathbf{x_i}$ is determined by

$$p^t(\mathbf{x_i}, \mathbf{x_j}) = \frac{[f^t(\mathbf{x_i}, \mathbf{x_j})]^\alpha \left[\frac{1}{L_{ij}^t}\right]^\beta}{\sum_{\alpha \in N_i^k}\left([f^t(\mathbf{x_i}, \mathbf{x}_\alpha)]^\alpha \left[\frac{1}{L_{i\alpha}^t}\right]\right)}, \tag{14}$$

where α is constant value described as pheromones impact factor, N_i^k is a collection of places not visited by k which leads to $\mathbf{x_i}$.

Through all the information determined by the above equations (especially the probability given in Eq. (14)), the ant moves in accordance with the following formula

$$\mathbf{x_i}^{t+1} = \lfloor \mathbf{x_i}^t + sign(\mathbf{x_i}^t ind(t) - \mathbf{x_i}^t) \rfloor \tag{15}$$

where $ind(t)$ where $ind(t)$ Is a collection of sorted indexes of neighbors. A full algorithm is presented in Algorithm 1.

2.3.2 Method of extraction through the use of swarm intelligence

N random samples are selected and merged. The merge is made by averaging all values from each sample, ie for each pixel, the new value is constructed by

$$\mathbf{x}_c = \frac{1}{N}\sum_{i=0}^{N} \mathbf{x}_c, \tag{16}$$

where c is the color component. Having two, averaged samples for a given person, the swarm intelligence search for the features according to the Eq. (10). For each image, set of points (ants position) will be returned. We denote $\{(x_0, y_0)_{img}, (x_1, y_1)_{img}, \ldots, (x_{n-1}, y_{n-1})_{img}\}$ as a set of iris features, and as a $\{(x_0, y_0)_{snd}, (x_1, y_1)_{snd}, \ldots, (x_{n-1}, y_{n-1})_{snd}\}$ set of features taken from the

Algorithm 1 Artificial Ant Colony Algorithm

Define all coefficients – α, ρ, $best\_ratio$, T_{max} and n,
Create a random population of ants,
$t := 0$,
while $t \leq T_{max}$ **do**
    Recalculate pheromone values by (11),
    Calculate the distance between individuals in the population using (13),
    Calculate the probability of choosing a road from i to j by (14),
    Move the ant using (15),
    Sort population by (10),
    the best ones take to next iteration, the rest replace with new individuals selected by random,
    $t++$,
end while
Return the best ones from last iteration.

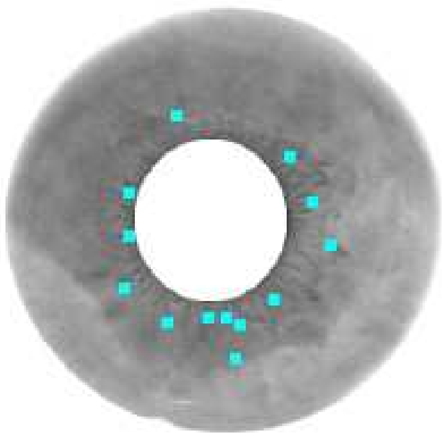

Figure 2: Iris image (after segmentation) with localized ants, which indicate important features of a given sample.

spectrogram. Then, the vector (pattern) representing the person can be created by merging both sets and adding the identifier as follows

$$[(x_0, y_0)_{img}, \ldots, (x_{n-1}, y_{n-1})_{img}, (x_0, y_0)_{snd}, \ldots, (x_{n-1}, y_{n-1})_{snd}, id_0, \ldots, id_k], \tag{17}$$

where $(id_0, \ldots, id_k)$ is a bit string with length k. The value of k is dependent on the number of people in the database. Such vectors are used in training and classifying using neural networks.

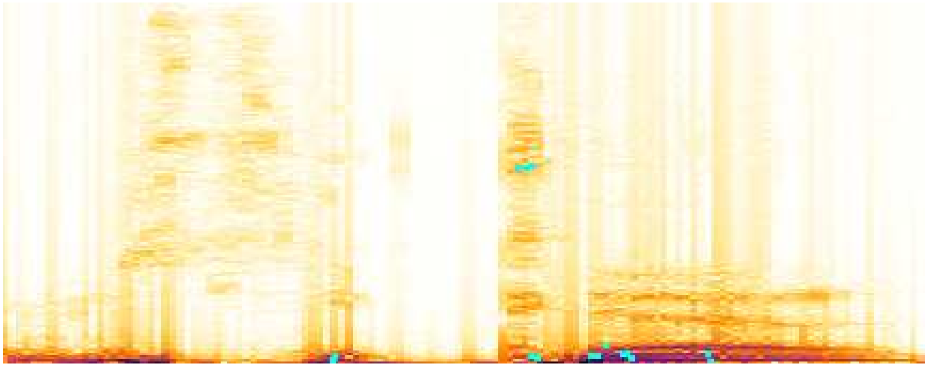

Figure 3: Fragment of a spectrogram with localized ants, which indicate important features of a given sample.

3 Neural classification technique

Natural neurons are made up of three elements such as dendrite, soma and axon. Soma is the body that stores the nucleus surrounded by dendrites, and axons connect two neurons together. The transmitted signal is called an impulse, which is the reason for forwarding the information further. Such stimulation is called a spike voltage or simply an impulse that is produced after a change of the neuron's state (so-called value of the membrane potential). Mathematically, the impulse is generated when a threshold value is exceeded, which is the same for all neurons in the network.

Neurons are the smallest unit of the network and they build the layers from which the network is composed. Let denote Ξ_j as a set of neurons from the earlier layer to j-th neuron, which receives impulses from the previous layer at time t_i. Neurons generate a impulse upon reaching a threshold value ν. The state of neuron $x_j(t)$ is determined as

$$x_j(t) = \sum_{i \in \Xi_j} w_{ij} \epsilon(t - t_i), \tag{18}$$

where w_{ij} is the weight between two connected neurons i-th and j-th and $\epsilon(t)$ is a function understood as impulse response modeled as

$$\epsilon(t) = \frac{t}{\tau} \exp\left(1 - \frac{t}{\tau}\right), \tag{19}$$

where τ is the constant value known as membrane potential.

The time between two states of the neuron (generating and reproducing the impulse) is called the delay d^k on the k-th connection and it is described by

$$y_j^k(t) = \epsilon(t - t_j - d^k), \tag{20}$$

where t_j is a time to generate impulse if the threshold value ν has been exceeded by $x_j(t)$ for the first time.

Using Eq. (18), (19) and (20), the state of x_j neuron may be presented as

$$x_j(t) = \sum_{i \in \Xi_j} \sum_{k=1}^{m} w_{ij}^k y_i^k(t). \tag{21}$$

As in classical neural networks, the network is composed of three types of layers – one input, multiple hidden and one output.

3.0.1 Training algorithm

The neurons between the layers are connected, and the connections are weighed w. In [Bohte S. et al.(2002)], the classic back-propagation algorithm is modified for this type of network and it is called *SpikeProp*. Denote types of layers in the following way – H – input, I – hidden and J – output. Input data entered into the input layer can be described as $\{[t_1, \ldots, t_h], \ldots\}$, and the time to generate the impulse in neuron $j \in J$ as $\{t_j^d\}$. The least squares method may be used as error function defined as

$$E = \frac{1}{2} \sum_{j \in J} \left(t_j^a - t_j^d\right)^2, \tag{22}$$

where t_j^a is the last time the impulse was generated and t_j^d is called the expected time. The training algorithm involves modifying the weights between the neurons for the output layer

$$\Delta w_{ij}^k = -\eta y_i^k(t_j^a)\delta_j, \tag{23}$$

where η is the constant coefficient, and δ_j is calculated using

$$\delta_j = \frac{\partial E}{\partial t_j^a} \frac{\partial t_j^a}{\partial x_j(t_j^a)}. \tag{24}$$

And the equation for modifying weights in hidden layers is as follows

$$\Delta w_{hi}^k = -\eta y_h^k(t_i^a)\delta_i, \tag{25}$$

where

$$\delta_i = \frac{\sum_{j \in \Xi^i} \delta_j \left[\sum_k w_{ij}^k \left(\frac{\partial y_i^k(t_j^a)}{\partial t_i^a} \right) \right]}{\sum_{h \in \Xi^i} \sum_l w_{hi}^l \left(\frac{\partial y_h^l(t_i^a)}{\partial t_i^a} \right)}. \tag{26}$$

4 Proposed Decision Support System In Identity Verification Purposes

The proposed technique was developed for use in decision support systems during identity verification. A person approaching the terminal scans the iris of the eye and speaks his name. The system quickly verifies and confirms or denies the identity of the person standing in front of the terminal.

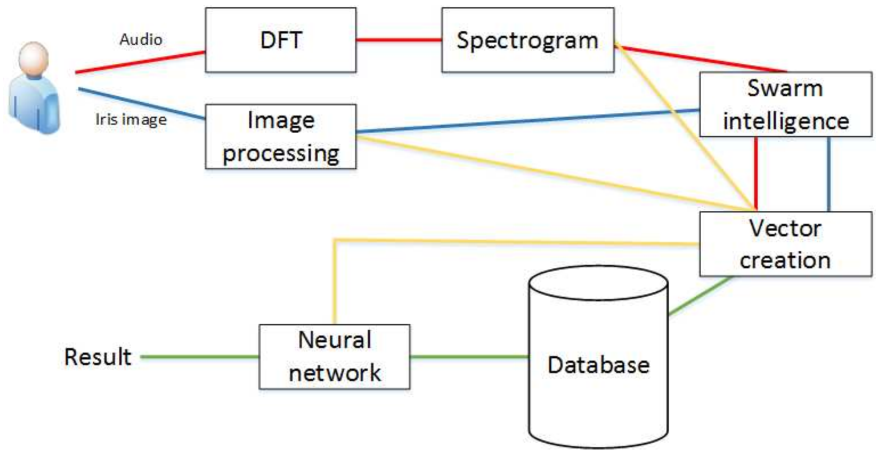

Figure 4: Visualization of the decision support model to verify identity. The green line indicates the process of adding the vector to the database, and the yellow one the verification without the use of the swarm intelligence algorithm.

The system gets two samples - an image and a sound file. Both files are converted in accordance with Sec. 2. Due to the use of a classifier that require training, the system must offer two pathways of action. For a new user, a vector representing the person must be created and added into database. For this purpose, the system takes a large number of samples, creates its merged version and by the use of swarm intelligence, location of important features are found. The next step is to train neural classifier to identify a given persons. Another way of action is the verification – it is possible after the classifier is already trained. The terminal accepts two files which are processed, but swarm algorithm is no longer useful. The vector for this person is retrieved from the database and on this basis, the data is extracted from the processed files. Data is calculated by a neural network that returns a decision. The graphical version of the system is shown on Fig. 4.

5 Experiments

Model described in Sec. 4 was implemented and tested for various parameters to measure the efficient of the methods. For testing purposes, CUHK Iris Image Dataset (available on *http://www2.acae.cuhk.edu.hk/~cvl/database.htm* from Chinese University of Hong Kong) was used. This collection contains 1120 images from 224 persons. Of course, 224 people causes that the number of bit characters in the vector described by Eq. (17) should be equal 8. Not forgetting that the proposed technique uses voice samples, the samples been prepared by 15 people resulting in $15 * 20 = 300$ samples. For each set of voice samples, a random set of iris images was chosen. In this way, a set of data was prepared for the tests.

For each person a representative vector was created and inserted into the database. Each of the samples was processed and prepared a dozen training sets for the neural network - their number is dependent on the length of the vector. Moreover, the network was trained according to the minimum error and the data were shuffled as $40\% - 60\%$ (training to verifying). Network performance is defined as the number of correctly classified samples in the database. All obtained results are averaged based on 10 different tests with the same parameters.

The average effectiveness of classifier trained to obtain 0.1 error is presented in Fig. 5. The greater the length of the vector, the efficiency is higher. The efficiency at level of 90% was obtained for a vector composed of 36 numbers. Moreover, the efficiency of the classifier increases when the obtained error is smaller what is shown in Fig. 6. It can be seen that besides two cases (exceptions may be cased by overfitting), this is a linear trend. Exceptions may be due to network overruns.

6 Conclusion

Proposed technique for identity verification based on image processing, swarm intelligence and spiking neural network was described as a main tool to use in decision support system. The same method for feature extraction can be applied to different input files such as sound or graphics files. The premise was to convert the audio file to graphics and subjected to various image processing technique. The proposed method was implemented in the form of a small identity verification system and tested for accuracy as well the possibility of improvement.

The tests showed that the effectiveness of the method is quite large and the average value was 90%. Increasing the length of the vector and reducing the error of the classifier affect not only on the accuracy but also on the training time. This is the biggest drawback of the proposed solution despite good results. Adding a new user to the system can be done by adding a new network or retraining. In large corporations, where the rotation of users is very often, the use

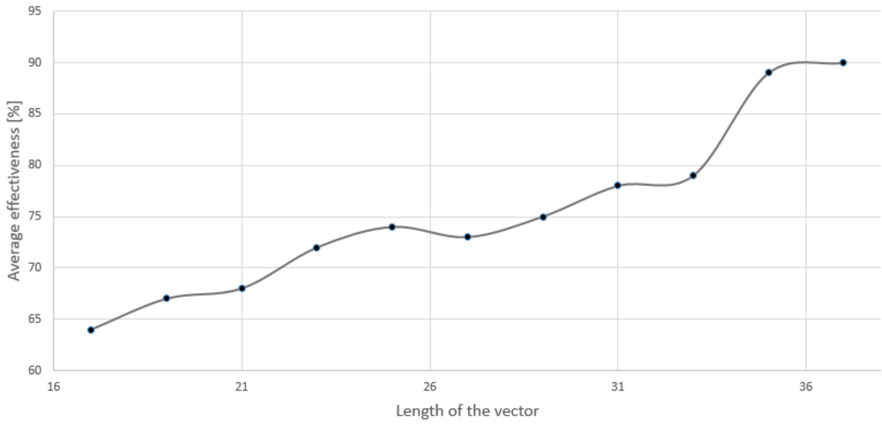

Figure 5: The averaged effectiveness of the neural classifier (error was 0.1) for all samples in the database to the length of the learning vector for error 0.01.

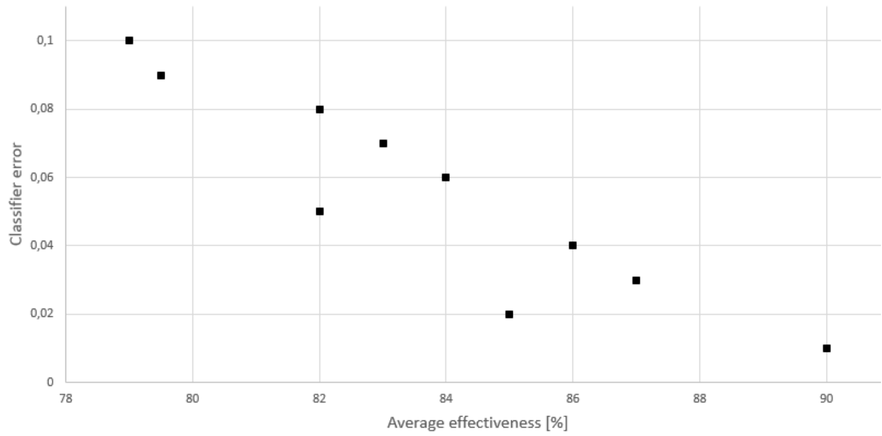

Figure 6: Dependency of the resulting classifier error to the averaged effectiveness based on 10 tests for vectors length 33.

of neuron classifiers is not beneficial. Choosing a decision-making technique is an open question. Changing methodology is just one of the issues, the other is the ability to the possibility of parallelization. This type of actions will be considered in future research to improve the proposed technique.

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