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APPLICATION OF ARTIFICIAL NEURAL NETWORK IN BIOMETRIC IDENTIFICATION

KEY WORDS: Biometric identification, ear biometry, thermogram, artificial neural network

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ABSTRACT

The authors tested the influence of neural network settings and the input data format on the success rate of biometric identification. Human ear was chosen as the biometric identifier, and its image was captured with a thermographic camera. The authors employed various scenarios to test the following. Firstly, various numbers of hidden layer neurons were tested. Secondly, various subpixel size of the input image, which directly affects the number of input layer neuron, was tested.

INTRODUCTION

A great number of biometric methods, both physical and behavioural, is used at present. The choice of the method depends on its intended use. Since the authors' research aims at road traffic applications, biometric identification of a car driver using an ear thermogram is tested in this article. The ear is captured from five different angles with a thermal camera placed in the car.

Biometric identification of an ear can be used widely for its versatility, users comfort during image acquisition, its time stability, and reliability.

Personal identification exploiting the ear biometry is based on the unique anatomy and morphology of each individual ear. In general, there are three methods of biometric identification using human ear:

- Methods exploiting the morphometric relations - ear geometry in 2 or 3D
- Methods exploiting the ear print (similarly to the finger prints). This method is however not suitable for practical use for its discomfort. It is used in forensics.
- Methods exploiting thermograms of the ear - a thermographic image mapping body temperature distribution in the ear. The anatomy of subcutaneous veins provides a unique thermogram for each individual.

In their previous research, the authors dealt with driver identification using a face thermogram. However, an ear, in contrast to the face, is not susceptible to changes due to mimics, spacial orientation or due to ageing or cosmetic treatment. The ear is also smaller then the face. Thus, its images have smaller resolution and therefore they can be processed faster and more efficiently. For its position on the side of the head, it is also more accessible for the detection cameras. The image acquisition of an ear, in contrast to the face, is not disturbed by the glasses, beard or by the make-up. An earring, the only possible interference, does not affect the results.

The bare and dry surface of the ear behaves as an almost perfect black body regardless of the skin colour (spectral range above 6 μm; spectral range < 3μm for partially transparent skin surface). Thermographic ear recognition and the ear recognition system uses the ear temperature as input. The images captured with a thermal camera are more suitable for biometric systems. Infrared images are independent from the lighting situation and they are not affected by the objects in the surroundings. The human ear temperature typically varies from 30 to 38°C unless affected by e. g. fever, hypothermia or by distinctive genetics.

BIOMETRIC SAMPLE ACQUISITION - INFRARED CAMERA

The sample (the ear) is scanned with a special optical scanning device from the distance of approx. 0.5 to 1 meter by means of contactless thermography. (Fig 1).

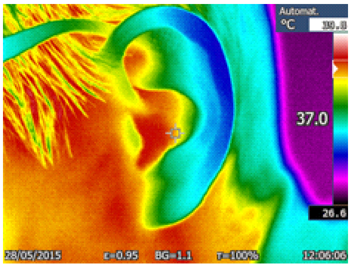

Figure 1: Unnormalised ear thermogram

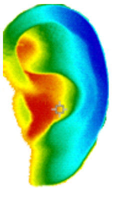

Figure 2: Normalised ear thermogram

For the biometric identification of a person with an ear thermogram, the type of the camera and its settings are of paramount importance. The authors focus on the heat radiation sensitivity of the camera and its temperature range settings.

The thermogram removes the flaws of morphometric and morphoscopic analysis which are caused with hair or other objects covering the ear. The images of the ear are captured in the infrared spectral band. While the human hair temperature ranges from 27.2°C to 29.7°C at normal room ambient temperature of 20°C to 22°C, the ear temperature at the same conditions ranges from 35°C to 38°C. The temperature of the ear varies and the isotherms reflect the anatomy of the ear. [1].

After the thermal image of the ear is acquired, it is processed (normalised) and analysed by the artificial neural network (ANN).

THERMOGRAM PROCESSING

The thermogram of the driver provides information on temperature distribution on the surface of the ear. The thermogram is subjected to an algorithm which detects the shape of the ear and executes primary cropping of the image to a normalised size. The Canny edge detector was used for the ear detection. Canny edge detector achieves very good results even with automatic threshold setting. It uses the Gaussian image convolution and subsequent derivations in the direction of the gradient. The identification of the significant edges requires thresholding of the detector output. Hysteresis thresholding - edge consistence is used. The normalised image is used as the ANN input. (Fig. 2).

Processing the thermogram with the artificial neural network

An Artificial Neural Network is a network containing a number of artificial neurons. It is inspired by the biological neural networks that constitute animal brains. A Multilayer Perceptron with Backpropagation neural network was used for the identification of drivers. It is a multi-layer neural network with an adaptation algorithm of back-propagating of an error. There are three stages in the adaptation algorithm: feedforward propagation of input signal of the training model, back-propagation of an error and an update of weight values on connections. It works with one hidden layer at least. The sigmoid activation function is used with the neurons. [2][3]

A correct setting and tuning of ANN is crucial for a successful identification. The ANN created by the authors consists of three layers of neurons. They are the input layer, the output layer and one inner layer. The neurons of two adjacent layers are fully interconnected. Thus each neuron of the lower layer is connected to each neuron of the higher layer.

Input layer

Number of input neurons depends on dimensions of the input image. Each normalised thermogram consists of a finite number of pixels. When allotting each pixel to a separate neuron, the ANN input layer becomes very numerous. Best results were achieved with sub-pixels that were introduce to group pixels into larger entities and to reduce the number of input neurons needed. Since the authors worked with colour images, the number of input neurons must be multiplied by three – each input neuron holds one of the RGB colour components for each subpixel at given coordinates.

The number of pixels in subpixel has been set and tuned experimentally to maximise the reliability of identification with acceptable size of the ANN.

Example:

- Normalised driver's thermogram: 250px x 460px.
- The number of pixels in subpixel: e.g. 25px x 23px
- Number of output neurons: e.g. 25x23 = 575 x 3 = 1725 + 1 (plus one indicates one fictive neuron with a constant activation value equal to one).

Hidden layer

While solving a multi-layer neuron network model with an adaptive backpropagation algorithm, one must address a crucial issue of a choice of a topology that is suitable for the particular practical problem. Of course the minimisation of the error function is also of a great importance. A multi-layer topology with one or two inner layers is usually employed. It is then expected that the learning algorithm backpropagation will generalise related relations from the training set in weights of individual neuron connections. Even in this case a suitable number of neurons in the inner layers mast be set. In practical applications, the topology is usually set by means of heuristics. In the project of the authors, the best results were obtained with one inner layer of X + 1 neurons (plus one indicates one fictive neuron with a constant activation value equal to one).

Output layer

The number of the output neurons is equal to the number of persons in biometric identification – the drivers. The values of the output neurons indicate the level of the output neuron activation as well as how much the sample matches individual models. That means if the sample matches a model, the output value of the neuron corresponding with the model shows the highest output value. The other neurons will show much lower values on the output.

We should normalise the output value to the probability of positive match:

$$mp = \frac{OUT_i}{\sum_{i=1}^{k} OUT_i} \qquad (1)$$

,where mp = matching probability, OUTi = output value of the neuron I.

The driver is identified successfully if the matching probability is greater than the threshold value. When setting the sensitivity of the system (the threshold value), the authors followed the crossover rate EER (Equal Error Rate) which predetermines the threshold values for FAR (False Acceptance Rate) a FRR (False Rejection Rate). Should this threshold not be exceeded, the process of identification needs to be repeated.

Each sample (the ear image) was obtained from five angles (70°,80°,90°,100°,110°) to simulate a real situation condition when the image is hardly ever captured at the ideal angle of 90°.

When capturing images at the right angle, the threshold value was set to 0.9. For the images captured at 80° and 100°, the value was lowered to 0.7 and for the images captured at 70° and 110°, the value was further lowered to 0.5.

PRACTICAL TESTS

Various ANN settings and input data formats were tested for reliability of successful identification. Individual scenarios tested different numbers of of hidden layer neurons in combination with various input images scalability, that influences the number of input neurons of the ANN. All the images were in colour with 250px by 460px dimensions. The transforming function was a sigmoid.

The ANN was trained on 71 (driver) ear thermogram samples - the ANN training set. The results are presented on three randomly selected drivers. (Subject A, Subject B, Subject C) and on two of their ear thermograms - also selected randomly (therm 1 and therm 2) - the ANN test set.

Test 1

The subpixel size (the number of input layer neurons) was researched in this test. The test was looking for the ideal number of input neurons at 71 + 1 hidden layer neurons. The number of output neurons is 71. (Fig. 3).

Subpixels size:

- 2px x 2px (12 + 1 neurons in the input layer)
- 5px x 5px (76 + 1 neurons in the input layer)
- 20px x 20px (1200 + 1 neurons in the input layer)
- 40px x 40px (4800 + 1 neurons in the input layer)
- 100px x 100px (30000 + 1 neurons in the input layer) – the ANN did not complete the training process

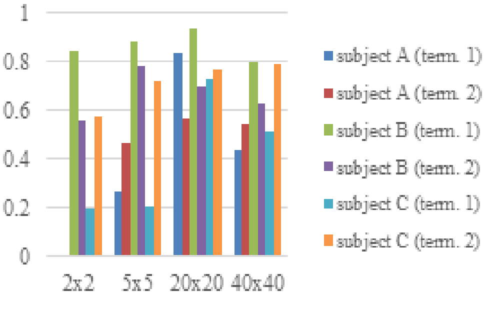

Figure 3: The dependence of the rate of successful identification on the number of input neurons at 72 neurons in the hidden layer.

Test 2

The subpixel size (the number of input layer neurons) was researched in this test. The test was looking for the ideal number of input neurons at 142 hidden layer neurons. (Fig. 4).

Subpixels size:

- 2px x 2px (12 + 1 neurons in the input layer)
- 5px x 5px (76 + 1 neurons in the input layer)
- 20px x 20px (1200 + 1 neurons in the input layer)
- 40px x 40px (4800 + 1 neurons in the input layer)
- 100px x 100px (30000 + 1 neurons in the input layer) – the ANN did not complete the training process and it is not depicted in the graph.

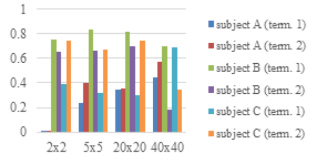

Figure 4: The dependence of the rate of successful identification on the number of input neurons at 72 neurons in the hidden layer.

Test 3

In this test, a person was randomly selected (Subject 6). The results of this subject's identification were compared against all of the 71 other subjects. Since the number of subjects is too large to show all of them in the graph, only the subjects with probability greater than 0.01. are shown in the graph.

The optimal ANN settings as found out in tests 1 and 2 - 71 + 1 hidden layer neurons at 20px by 20px subpixel size (1200 + 1 input neurons) was used in this test. (Fig. 5).

TABLE – 1

Driver	Probability
Subject 6	0,9336
Subject 70	0,0456
Subject 60	0,028
Subject 66	0,0191
Subject 9	0,0173
Subject 17	0,0149
Subject 1	0,0144
Subject 14	0,0127
Subject 46	0,0127
Subject 16	0,012
Subject 34	0,0118

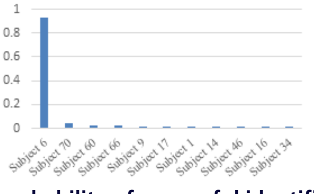

Figure 5: The probability of successful identification of one person (Subject 6) at 1201 input neurons and 72 hidden layer neurons.

CONCLUSIONS

The tests of the ANN on various scenarios shows that doubling the number of hidden neurons does not improve the results of personal identification. On the contrary, the results slightly worsened due to overlearning of the ANN. Speaking of the input thermogram resolution (the number of input subpixels and the input neuron number), the authors are confident to state the following. If the ANN is designed with too few input neurons (76 or less), the ANN does not recognise some of the users. If the opposite happens and there are too many input neurons (4.800 or more), the training becomes too time consuming and the probability of successful identification slightly decreases. If the number of input neurons reaches the critical number of approx. 30.000 neurons, the ANN cannot be trained.

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