METHOD OF RECURSIVE-CONTOUR PREPARING FOR IMAGE NORMALIZATION

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ABSTRACT

The work offers the methods for invariant representation of images against a variety of distorting factors including *2D* and *3D* rotation, changes in brightness, contrast and scale.

It also deals with the procedure of recursive contour preparation consisting of step-by-step preparation of differences among the pixels of grey-scale image and formation of positive, negative and zero preparations. Thus at the first step the contour preparation is effected for the first differences, at the second step, for the second differences, and so on, with a step-by-step definition of the criterial function of distribution of binarized preparations. So it is possible to identify objects in different lighting conditions which simplifies the implementation of similar approaches. This relative simplicity of this method extends the range of its possible application for recognition purposes and for its implementation in the parallel-hierarchical network in particular.

1. INTRODUCTION

During the last 15 years the problem of facial recognition has been given more and more attention by researchers. The latest improvements in this field use a great variety of methods. Although each method has its own specific quality, the reliable recognition has not been practically achieved yet, even for the narrow range of conditions. The basic specific problems to be solved are as follows: *3D* rotations, the invariance to facial expression, various sights and the integration of information from different scales.

The main goal of this research is to solve the problem of the integration of the high-level information into the low-level facial presentation [1]. This will result in higher recognition efficiency. The advantage of such recognition is compact face presentation which considers the reduced size of the data sets and faster efficiency.

A human being tends to concentrate upon some high level peculiarities while recognizing unfamiliar faces. On the contrary, most automatic systems process faces as a whole. Kirby and Sirovich [2], Lanitis and others [3] performed the analysis of principal components considering a face as a whole. Blackwell and others [4] noted that the preliminary processing of the whole image cannot solve the problems connected with the integration of large data sets.The other system class processes located descriptors. Lades and others [5] recognized faces without integrating the regularity of a facial class. Penev and Atick [6] performed the analysis of a local peculiarity on the basic of each human's individual view.

To create effective image converters that function in the Real Time Scale (RTS) some special methods are required. They have to provide optical input, fast and compact processing, flexible and simple image classification. Modern computing devices are productive enough (up to 10^{14} operations per second). However, this index doesn’t include the time required for data entering.

Besides, computing devices process data taking into account time consequence. The commands are given and executed according to tree-like laws. This means that all intellectual procedures based on the hierarchical principle only. Therefore, there are tasks within the scope of which fast image processing throughout the whole RTS is impossible even with the help of the most advanced technologies. These devices are not able to provide *apriori* the combined productivity required to implement RTS. The possible solution of this problem is the concept of specialized parallel optoelectronic converters. This concept makes it possible to use parallel optic channels to enter and process images. The further processing needs such an arrangement of parallel channels that would provide noiseproof and fast pre-processing compact description and flexible image classification.

2. METHODOLOGY

In the course of the research into the problems of invariant image representation, for the network identification of objects a portrait gallery of test facial images $I_1, \ldots, I_k$ was used, each being defined by the lighting function $F_1^L, \ldots, F_k^L$ and dependent on the co-ordinates i, j :

$$I_1 = F_1^L(i,j),\ I_2 = F_2^L(i,j), \ldots, I_k = F_k^L(i,j) .$$

It is necessary to obtain such functions $\Phi^L(\ )$ for L classes of facial images that would allow the following approximation:

$$\Phi^L(I_1) \approx \Phi^L(I_2) \approx \ldots \approx \Phi^L(I_k) = \Phi^L(I)$$

Thus the functions $\Phi^L(I_1), \ldots, \Phi^L(I_k),\ L = \overline{1,l}$ should be classified into corresponding L classes of the facial images gallery, each class correlating with its own normalised function $\Phi^L(\,I\,)$.

The preprocessing scheme is based upon the separate segment analysis and includes image preparing, i.e. transforming the image into the matrix of 3-level binary preparations (positive, negative and zero) and their subsequent transformation by means of forming local and general equalization functions. Further correlation analysis of those functions is provided as well. The preliminary processing includes all subsequent operations. The input *2D* grey-scale image is presented by the matrix of light intensity pixels $A = \left[a_{i,j}\right]$, $i = 1 \div N$, $j = 1 \div M$, where $M \times N$ is the input image dimensions. The general mean of the present matrix A is found as:

$$\bar{a} = \frac{1}{NM} \sum_{i,j} a_{i,j} \tag{1}$$

Then sets of differences between pixels and obtained means of the whole image or its segments, are determined:

$$R_{i,j} = a_{i,j} - \bar{a} \tag{2}$$

In order to obtain the set of preparations this differences are compared with the threshold δ [7, 8, 9]:

$$q_{i,j} = \begin{cases} 1, \text{ if } R_{i,j} > \delta \\ -1, \text{ if } R_{i,j} < (-\delta) \\ 0, \text{ if } \left|R_{i,j}\right| \le \delta \end{cases} \tag{3}$$

The experiments have shown that the usage of the function that equally distributes positive, negative and zero preparations is most useful for the facial image preparing. It makes it possible to mark areas with and without brightness differences (according to the threshold) in a proper way. The threshold itself is adapted to the image. It results in segmenting separate fields of an initial image for their further analysis. The threshold δ is chosen from the following condition [8]:

$$\Phi = MAX\left(N_t^{(1)}, N_t^{(-1)}, N_t^{(0)}\right) \tag{4}$$

where $N_t^{(1)}, N_t^{(-1)}, N_t^{(0)}$ is the number of positive, negative and zero preparations within each grey level -*t*.

Some methods of invariant image representation are offered with regard to different distorting factors such as *2D* rotation, brightness, contrast and scale. After having sequentially applied the contour preparing operation to the differences (2) and solved the criterial function of contour preparations distribution (4), let us perform the operation of recursive contour preparing.

The operation of recursive contour preparing consists of step-by-step preparing of differences. At the first step the contour preparing of the first differences takes place, at the second step, of the second differences, at the *j*-step, of *j*-th differences with step-by-step definition of the criterial function of distribution (4).

To represent an image with three types of contour preparations (3) a relatively rough its description is generated. It is done due to the fact that a wide spectre of the pixels image falls within the zone of zero contour preparations and all of them are encoded in a similar way, i.e. by zero preparations. In this case both lighter and darker areas of an image fall within the same code zone thus resulting in the loss of some informative areas. To avoid this effect, a multilevel procedure of formation of contour preparations is offered. It presupposes that after the first step of contour preparing the pixels represented in the transformed image by negative preparations are excluded from the second step. Thus at the second step another threshold is chosen for those pixels which at the first step of preparing had zero or positive preparations. Further procedure is similar to the first step, that is new positive, negative and zero preparations are generated in relation to the newly calculated threshold. A certain *k*-step covers zero and positive preparations of *k-1* step, with the negative preparations being omitted. It is true that the operation of the pyramid-like general contour preparing can be performed to exclude light spots of an image represented by positive preparations, with the subsequent exclusion of newly-determined positive preparations at each subsequent to follow.

Thus the operation of pyramid-like general contour preparing is a recursive formation of image areas with negative (positive) preparations that correspond to darker (lighter) of grey levels. This subsequent formation of the image areas is none other than a multilevel process of segmentation of an image into the areas with negative (positive) distribution of contour preparations.

Mathematically the choice of the threshold for *k* steps of pyramid-like generalised contour preparing may be presented as follows [10].

$$\begin{cases} N_{t,1}^{(0)} \times N_{t,1}^{(-1)} \times N_{t,1}^{(1)} = Max \\ N_{t,2}^{(0)} \times N_{t,2}^{(-1)} \times N_{t,2}^{(1)} = Max \\ \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \\ N_{t,(k-1)}^{(0)} \times N_{t,(k-1)}^{(-1)} \times N_{t,(k-1)}^{(1)} = Max \\ N_{t,k}^{(0)} \times N_{t,k}^{(-1)} \times N_{t,k}^{(1)} = Max \end{cases}, \tag{5}$$

where $N_{t,k}^{(0)}$, $N_{t,k}^{(-1)}$, $N_{t,k}^{(1)}$ - is the distribution of zero, negative and positive preparations at *k*-th step of pyramid-like generalised contour preparing (*k*=1,2,...*n*), *n* is the number of segmentation levels, *t* is the number of grey levels. By calculating the threshold for each of grey level *t* the criterial system (5) makes it possible to represent the tested image with corresponding contour preparations at *k* levels of segmentation.

With the use of the criterial system (5) we can describe the algorithm of pyramid-like contour generalised preparing as follows. At the first level of segmentation (*k*=1) we sort out all of grey levels to define the value of *t* when $N_{t,1}^{(0)} \times N_{t,1}^{(-1)} \times N_{t,1}^{(1)} = Max$. At an a certain *k*-th level we also sort out all of grey levels to define the value of *t* when $N_{t,k}^{(0)} \times N_{t,k}^{(-1)} \times N_{t,k}^{(1)} = Max$. Consequently, at each level of segmentation a unique value of the threshold is calculated with the use the criterial system (5). Thus we achieve the adaptability of the algorithm of the pyramid-like generalised contour preparing, i.e. for each newly generated image a certain individual threshold is calculated, being defined by the distributed of grey levels.

3. EXPERIMENTAL RESULTS

Fig. 1 and 2 accordingly show facial images (with rotation step $\varphi = 20^0$) and the results of the execution of recursive contour preparing algorithm at its four steps. Note that at each step of algorithm the criterial correlation is satisfied (4). Fig. 3 illustrates the functions of the distance minimum (Euclidean distance - *d*), initial and rotated ($\varphi = 5^0$) facial images - $d(N)$ for the four steps of the recursive contour preparing algorithm.

Fig. 1 Example of rotated images.

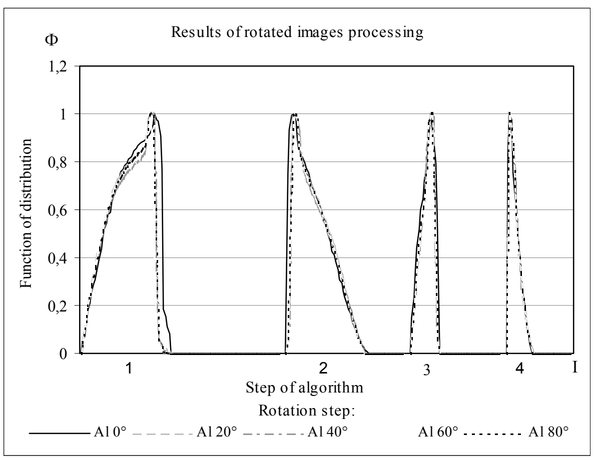


Fig. 2 Normalised functions of rotated images preparations distribution at four steps of recursive contour preparing algorithm.

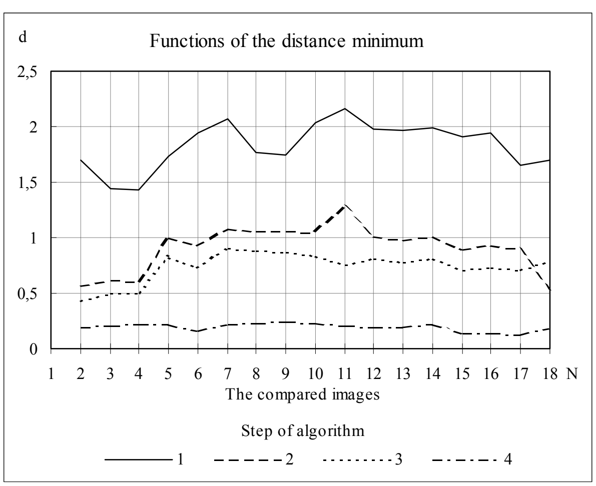


Fig. 3 Functions of the distance minimum for 2D rotated images at four steps of the recursive contour preparing algorithm.

Fig. 4 illustrates the results of processing of the recursive contour preparing algorithm applied to a test facial image with different values of brightness (Fig. 5a) and contrast (Fig. 5b). Judging on the appearance of the functions of distribution of contour preparations (Fig. 4) of the same facial image, these functions are absolutely identical.

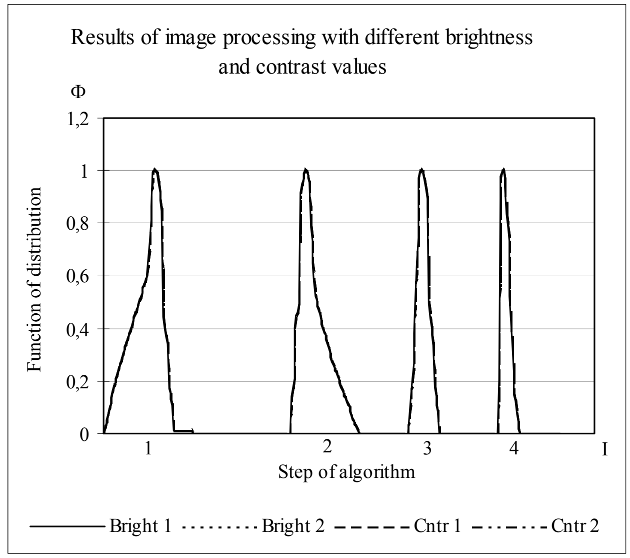


Fig. 4 Normalised functions of image preparations distribution with different contrast and brightness values.

a) b)

Fig. 5 Examples of test images with different brightness and contrast values.

Fig. 7 shows the results of four steps of the recursive contour preparing algorithm applied to a scaled facial image (Fig. 6), and Fig. 8 shows the corresponding functions of the distance minimum for the functions of contour preparations distribution for a scaled image.

To compare the degree of invariance of image representation with the use of the functions of preparations distribution for various types of distortion, let us see estimate the relevant changes of the functions of distance minimum for different non-distorted facial images. Fig. 9 gives the example of the functions of distance minimum for eight such facial images.

Fig. 6 An example of scaled facial images.

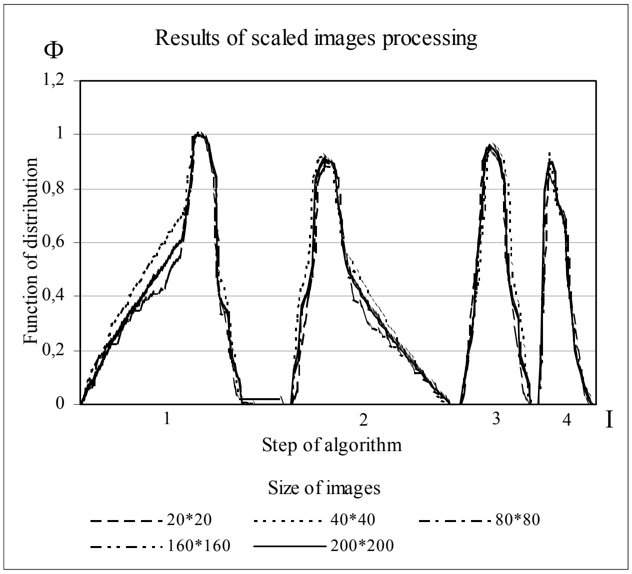


Fig. 7 Normalised functions of preparations distribution for a scaled facial image.

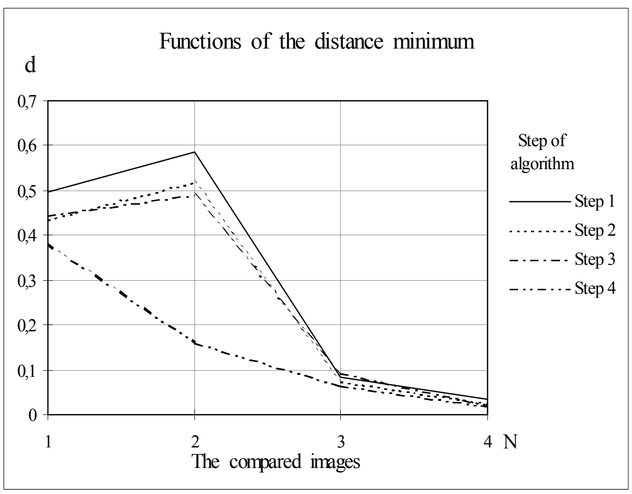


Fig. 8 Functions of the distance minimum for the compared images derivatives at different scales.

As it follows from the comparison of the functions of distance minimum when processing scaled facial images (Fig. 8) and the functions of distance minimum for different facial images (Fig. 9) their average values are more than twice as different.

Good results have been also obtained for this approach to be used when processing *2D* rotated images. Thus when comparing the functions of distance minimum for processing facial images with different *2D* orientation (Fig. 3) and the functions of distance minimum for different facial images (Fig. 9), their average values differ more than 1,5 times.

It testifies to the expediency of the use of the approach offered when scaling and *2D*-locating objects over a wide range, and this expands the limits of its application.

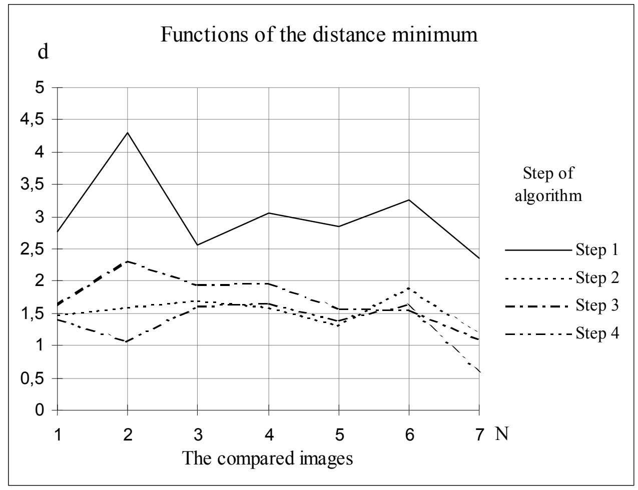
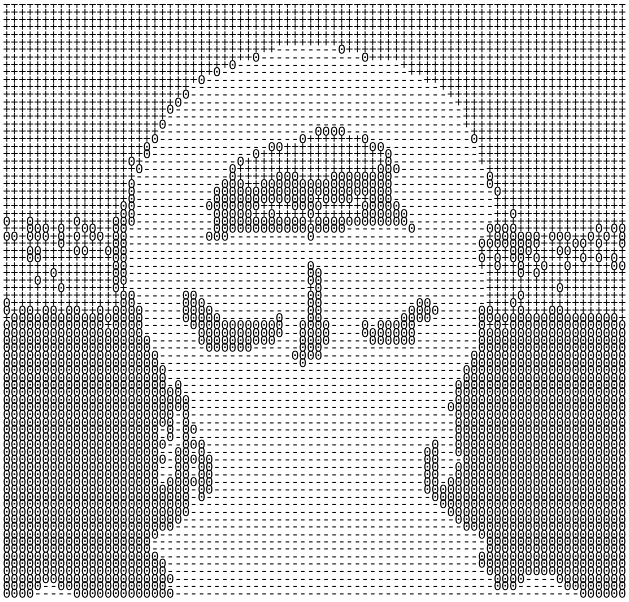


Fig. 9 Functions of distance minimum for eight different facial images.

The virtue of the method of image representation based on the use of the function of preparations distribution (4) lies in the integral nature of such image representation, as for each threshold δ, the sums of positive, negative and zero preparations are calculated individually. Such an integral value allows to achieve the invariancy of representation of an image against scaling, on account of normalisation of the function all readings rather its maximum value.

a)

Fig. 10 The results of execution of the first step of the algorithm of preparing (+ positive preparations, 0 zero preparations, – negative preparations).



b)

Fig. 10 The results of execution of the second step of the algorithm of preparing (+ positive preparations, 0 zero preparations, – negative preparations).

Fig. 10 a, b shows the results of segmentation on the basis the pyramid-like generalised contour preparing at the 1-st and 2-nd levels. As is seen in the Fig. 10, the facial sections of the haircut, mouth and eyes are filled with negative preparations. At the 2-nd level (Fig. 10b) the nose section is already filled with zero preparations. This feature makes it possible to automate the coarse scheme of processing by picking out individual facial segments.

4. CONCLUSIONS

The virtue of the method of image representation based on the use of the functions of preparations distribution lies in the integral nature of such image representation, as for each threshold, the sums of positive, negative and zero preparations are calculated individually. Such an integral value allows to achieve the invariancy of image representation against scaling, on account of normalisation of this function rather its maximum value.

It allows us to identify objects in different lighting conditions thus, on the one hand, significantly simplifying the implementation of similar approaches, as far as in this case we need not use labour-consuming DLA [5] neural network that require hierarchy graph positioning, and on the other hand, due to this relative simplicity of implementation, extending the possible application range in the problems of recognition.

5. REFERENCES

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