Physiological Neuro-Fuzzy Learning Algorithm for Face Recognition

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Abstract—This paper presents face features detection and a new physiological neuro-fuzzy learning method by using two-dimensional variances based on variation of gray level and by learning for a statistical distribution of the detected face features. This paper reports a method to learn by not using partial face image but using global face image. Face detection process of this method is performed by describing differences of variance change between edge region and stationary region by gray-scale variation of global face having featured regions including nose, mouse, and couple of eyes. To process the learning stage, we use the input layer obtained by statistical distribution of the featured regions for performing the new physiological neuro-fuzzy algorithm.

Index Terms— face recognition, neuro-fuzzy learning algorithm, 2-D blob feature.

I. INTRODUCTION

The problem of face recognition, one of the most remarkable abilities of computer vision, is considered in stages of face detection in human body, of extraction of face features, and learning of the face features by neural fuzzy system. Face recognition is practical importance in many applications, such as criminal identification, credit card verification, and authentication in security system. In general, we can recognize hundreds of faces which we have learned during our life time different specific techniques have been proposed or recomposed recently. Among those, one may cite neural networks, elastic template matching, 3-D representation of face shape, and description of principal component by region -vector for extracting geometric structure of face features. Typically, the relation of these techniques with standard approaches and their relative performance has not been characterized well or not. Even absolute performance has been rarely measured with statistical significance on meaningful data base[1].

In the recent trend of face image recognition research, some papers has been presented to perform an active-camera real time system for tracking, shape description, and classification of the human face[2]. Some paper report the face recognition system by using partial template matching method using face features like eyes, nose, and ears[3], however we can not ensure that the recognition system has real-time processing because of preprocessing process in acquiring the partial face.

In this paper, the process focuses on implementation of accurate tracking for the active-camera real-time system in category of the face recognition. The system of this paper is based on use 2-D blob features, which are spatially compact clusters of pixels that are similar in terms of low-level image properties. Face patterns can be classified in real-time processing using both two-dimensional variances of distribution obtained in gray-scale variation and learning of the neural fuzzy algorithm employed a new physiological neuro-fuzzy algorithm. We extract 2-D blob features represented by the two-dimensional variances in global region of a face. The 2-D blob features represented by the variance can represent characteristics of gray-scale variation for distinct region on face like eyes, nose, and mouse regions. Because the variances are computed from gray-scale variation in local region, properties of the 2-D blob features are independent from brightness change of light sensor and a restricted behavior of human to acquire in the comparing to the partial face recognition system. Therefore, learning stage by input layer suing the 2-D blob feature is robust for any kinds of face image. The distribution parameters can be obtained by describing correlation for a gray scale variation in local region corresponding to distinct face features. The gray-scale variation in brightness region corresponding to the face features can be represented geometrical structure of face features in the view point of day time. The two variance values in the stationary region of skin represent zero mean, while the values, due to rapid change of gray scale, of the face featured regions in nose, mouse, and eyes of face can not has zero means[4]. For input layer in learning stage of the proposed neuro-fuzzy algorithm, we extract 2-D blob feature corresponding the two variance value of two orthogonal directions in spatial region. Those variances are able to describe the geometric features of face part that have rapid change of gray-scale variation.

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II. CLASSIFICATION OF FEATURED REGION IN FACE

We employ to estimate the variance value of distribution parameter in whole region of image. We know that the variance value is closed to zero value in a stationary region, in contrast, the value obtained in noise and edge regions is not similar to zero value. Computational description to detect 2-D blob feature in a local region *of (N, N)* kernel are shown as follows:

$$|(N^2-1)I(x,y)-\sum_{1\le i\le(N-1)}I(k,l)|>1$$

where *I(x, y)* represents the gray level at central point and *I(k, l)* corresponds to the gray level of the neighboring pixels shown by:

$$k=x\pm1,\quad l=y\pm1$$

whose positions represent the neighboring pixels in local region. Further change of gray level is more complicated, for those, more detail constraints to detect small spike noise and speckle noise for the purpose of preserving edge line, are considered using two dimensional variances shown as follows:

$$\sigma_x^2=\frac{1}{n}\sum_i\|I_i(x,y)-\mu_i\|^2$$
$$\sigma_y^2=\frac{1}{n}\sum_j\|I_j(x,y)-\mu_j\|^2$$

where μ is the mean value in a local region, $(I_i(x,y),I_j(x,y))$ and n represent the intensity of gray level and the number of pixels along the x and y axis in a local region, respectively. Classification of a signal and a noise by the variance can be performed by:

$$additive\ \ noise: \sigma_x\approx\sigma_y and(\sigma_x,\sigma_y)>c,$$
$$edge\ \ signals: \sigma_x\ne\sigma_y and(\sigma_x,\sigma_y)>c,$$
$$stationary\ \ signal: \sigma_x\approx\sigma_y and(\sigma_x,\sigma_y)\approx 0$$

where *c* is an integer value. In learning stage, we employ parameters of input layer by using the variance value of edge signals. The variance value is used to get the 2-D blob feature corresponding to the featured region of face.

In this paper, we showed a method to obtain 2-D blob features of face. The features are computed by description of the variance in a local region where variation of gray scale is rapid. In general, a method using a sort of the variance parameter is known robust in digital signal processing[7,8]. By using the 2-D blob features corresponding to the meaning regions of face, we perform the learning stage by proposed physiological learning algorithm. The input layer is obtained by determining the median value for peak area of 2-D blob featured face.

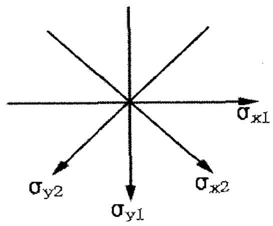


Fig. 1 The estimation of two dimensional variances (σ_x,σ_y)

III. NEW PHYSIOLOGICAL NEURO-FUZZY ALGORITHM

A. A Neuro-Fuzzy Learning Based On a Physiological Neuron Structure

Physiological neuron organization structure is composed of excitatory neuron and inhibitory inter-neuron, which are each activated by agonistic neuron and inactivated by antagonistic neuron.

Agonistic neuron is the one that directs to forward and antagonistic neuron does to backward. Inhibition is classified into antagonistic inhibition, forward inhibition and backward inhibition. Antagonistic inhibition makes on inhibitory synapse through an inter-neuron which control the antagonistic neuron. Forward inhibition is inhibited without previous excitation of an antagonistic neuron. Backward inhibition is inhibited backwards in case that on inhibited inter-neuron acts upon the cell which activated itself[5].

The physiological neuron is shown in Fig. 2.

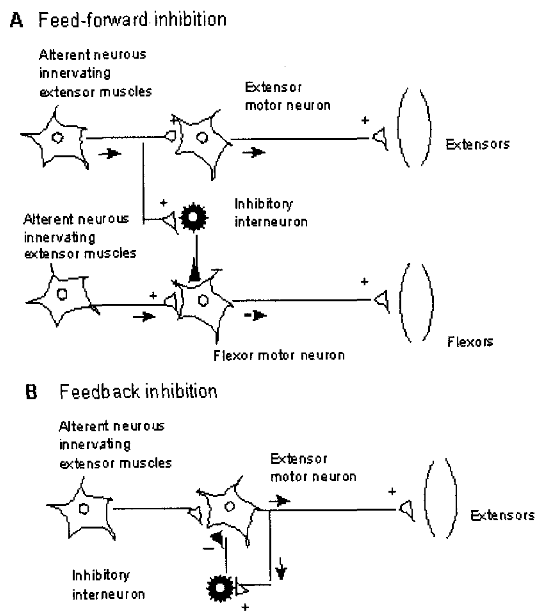


Fig. 2 A physiological neuron structure

B. A Physiological Neuro-Fuzzy Learning Model

We defined a fuzzy OR structure by analyzing excitatory neuron in the physiological neuron organization. We also defined a fuzzy AND structure by classifying the inhibitory neuron structure as the forward inhibitory neuron structure and the backward inhibitory neuron structure. The inter-neuron is defined as fuzzy NEGATION.

The proposed learning structure is shown in Fig. 3.

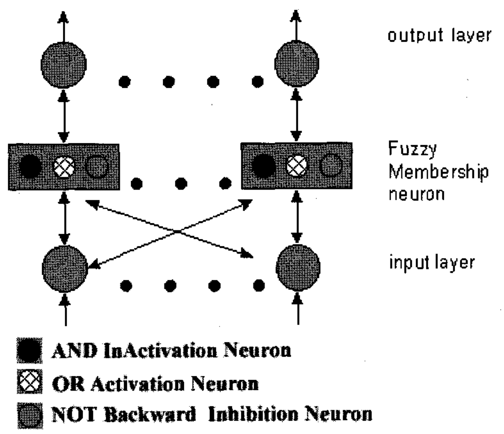


Fig. 3 Physiological neuro-fuzzy learning model

C. Physiological Neuro-Fuzzy Learning Algorithm

The learning steps are classified as the forward step and the backward step in the proposed neuro-fuzzy algorithm. The actual output values are calculated through the fuzzy neuron membership function in the forward steps. The initial weight range is established by [6].

We use fuzzy logic operator Max & Min instead of sigmoid function, with these operators, Max operator can be used if target value is '1' or Min operator if '0'.

The weight is adjusted by dividing each neuron into excitatory neuron and inhibitory neuron in accordance with the fuzzy neuron membership function in the backward steps.

The proposed algorithm as follows:

Step 1: Initialize Logic_value, Logic_weight, and Logic_mark

. Logic_weight: $W_{ANDij} = 1$, $W_{ORij} = 1$, $W_{NTij} = 1$
. Logic_value : $V_{ANDij} = 1/I$, $V_{ORij} = 1$, $V_{NTij} = -1$
. Logic_mark : $ON_{ANDp\,ij} = 1$, $ON_{ORp\,ij} = 1$, $ON_{NTp\,ij} = 1$

where W_{ANDij} : forward inhibitory operation
W_{ORij} : forward excitory operation
W_{NTij} : backward inhibitory operation

Step 2: Read input pattern

Step 3: Select target bit j for input pattern

Step 4: Calculate and normalize Synapse_value from 0 to 1

$$Synapse_{ij} = Synapse_{ij} + (ON_{ANDp\,ij} \times x_{pi} \times V_{ANDij} \times W_{ANDij}) + (ON_{ORij} \times x_{pi} \times V_{ONij} \times W_{ORij})$$

if $(Synapse_{ij} > 1.0)$ $Synapse_{ij} = Synapse_{ij} + V_{NTij}$

Step 5: Determine Soma_value for output value

if $(target_{pj} = 1.0)$ $Soma_j = \vee(Synapse_{ij})$;
if $(target_{pj} = 0.0)$ $Soma_j = \wedge(Synapse_{ij})$;
at $1 \le p \le P$, P: *Number of pattern*
$\vee$: Fuzzy MAX operation
$\wedge$: Fuzzy MIN operation

Step 6: Update Logic_weight and Logic_mark value

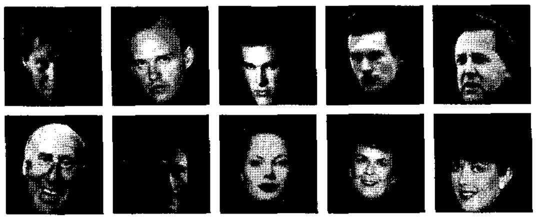
if $((W_{ANDij} \le 1.0)$ and $(ON_{ANDpij}) = 1)$
$W_{ANDij} = W_{ANDij} + \beta \times error_{ij} \times (x_\pi / insize)$
$ON_{ANDij} = 1$
if $((W_{ANDij} \le 1.0)$ and $(ON_{ANDpij}) = 1)$
$W_{ANDij} = W_{ANDij} - 1.0$, $ON_{ANDij} = 0$
if $((W_{ORij} \le 1.0)$ and $(ON_{ORpij}) = 1)$
$W_{ORij} = W_{ORij} + \beta \times error_{ij} \times (x_\pi / insize)$
$ON_{ORij} = 1$
if $(W_{ORij} > 1.0)$ $W_{ORij} = W_{ORij} - 1.0$, $ON_{ORij} = 1$
at β: Learning rate, *insize* : Gravity Center

Step 7: Repeat step 3, until it process all target bits

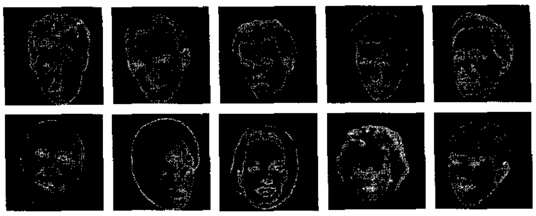
Step 8: Repeat step 2, until it process all input patterns

IV. EXPERIMENTAL RESULTS

In this paper, we showed a method to obtain 2-D blob of face. The features are computed by description of the variance in a local region where variation of gray is rapid. In general, a method using a sort of the variance parameter is known robust in digital signal processing. Even though, we did not implement to experiment the method by many set of face image, we ensure this method by using the variance parameter used for building input layer in learning stage is suitable because of an ability of a real-time processing and unrestricted pose of human behavior while acquiring the face image from image sensor. By using the 2-D blob features corresponding to the meaning regions of face, we perform the learning stage by proposed neuro-fuzzy learning algorithm. The input layer is obtained by determining the median value for pear area of 2-D blob feature. We simulated our method on IBM Pc/586 with Delphi 3.0. Training set face image data consists of 10 male face image and 10 female face images. After training, the performance of classification was tested with a test image set that presented randomly. The proposed neuro-fuzzy learning algorithm in the classification test was 96% of recognition rate. The example images we used are shown in Fig. 4. The face recognizer using the proposed neuro-fuzzy learning algorithm is shown Fig. 5.



(a) Original face images



(b) Training face images by the proposed preprocessing

Fig. 4 Original face images and training face images

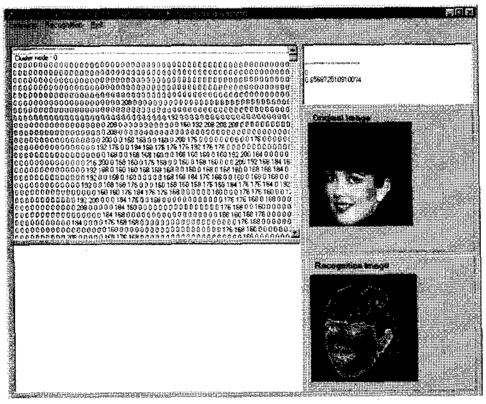


Fig. 5 The face image recognition using a physiological neuro-fuzzy learning algorithm

V. CONCLUSIONS

We proposed the neuron-fuzzy learning algorithm on the theoretical basis of fuzzy logic and physiological neural networks. The proposed algorithm is the learning algorithm which contains logic operations to imitate the structure of human brains.

In this paper, we presented method of 2-D blob feature represented by two dimensional variance and new physiological neuro-fuzzy algorithm for training the 2-D blob feature of meaning region in a face. However, it is necessary to compare with other fuzzy neural networks and other recognition method, and to examine the generality in different situation.

Further studies are required to apply it in real world situation. And the author will develop the novel physiological learning and recognition algorithm.

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