Fingerprint Recognition for Distorted Image Applications Using Three-Rate Hybrid Kohonen Neural Network

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Abstract: - One of the most difficult problems in fingerprint recognition has been that the recognition performance is significantly influenced by distorted fingertip surface condition, which may vary depending on environmental or personal causes. Addressing this problem, this paper presents the three-rate hybrid Kohonen neural network (TRHKNN) for distorted fingerprint image processing. The received TRHKNN consists of "fast" Kohonen neural network (FKNN), "middle" Kohonen neural network (MKNN) and "slow" Kohonen neural network (SKNN). The received TRHKNN has not only high speed of image recognition, but also high speed of image restoration. This approach demonstrates that the proposed TRHKNN is capable not only to identify the distorted image of fingerprint but also to restore the undistorted image of fingerprint. The simulations for TRHKNN were carried out in a MATLAB/Simulink environment. This example shows the computing procedure and applicability of TRHKNN for fast-acting image recognition in real-time conditions.

Key-Words: - Fingerprint, hybrid systems, image processing, multirate, neural networks, simulation.

1 Introduction

Multirate dynamical models appropriately describe many physical and engineering problems. The study of multirate systems began in the late 1950s.

Sandell et al. reviewed the previous research and divided it into four categories: Model Simplification, Interconnected Systems, Decentralized Control, and Hierarchical Control [1]. In opinion of these authors, we do not believe that the existing mathematical tools are powerful enough to define a preferable structure for decentralized and/or hierarchical control. It was claimed that with respect to designing decentralized controllers for many physical large-scale systems a good combination of engineering judgment and analysis can be used to define in a reasonable way a special structure for the dynamic system.

Kokotovic et al. showed that the singular perturbation theory for difference equations involves a list of ingredients-order reduction, separation of time scales, and boundary layer phenomena [2]-[3]. Sufficient conditions are given under which the solution of the original problem tends to the solution of a low-order problem.

The lifting method [4] is used to analyze the multirate system in the state-space framework. It is clear that the fast sampled model can be easily identified from the input excitation of an open-loop process running under a multirate sampling scheme with slow output sampling and fast control.

Tornero et al. studied the multirate controller [5], which updates the controller output faster than the measurement sampling frequency by a factor of N. The controlled system is continuous, and the discrete time controller is obtained as its zero order hold equivalent. The simplest case of $N = 2$ has been examined in some details.

Extensive research has been done to solve the problem of three-rate NN control of stochastic model of an experimental fighter aircraft in the short approach to landing task [6].

In contrast to the above approaches, in this paper we discuss the image processing and analysis of images of complex structure such as fingerprints by means of the TRHKNNs.

Performance evaluation is important for all pattern recognition applications and particularly so for biometrics, which is receiving widespread international attention for citizen identity verification and identification in large-scale applications. Recently, the topic of fingerprint image processing has been developed by various researchers.

Cappelli et al. discussed the data collection and testing protocols and introduced a simple but effective method [7] for comparing algorithms at the score level to isolate difficult images and to study error correlations and algorithm “fusion”. The huge amount of information obtained, including a structured classification of the submitted algorithms on the basis of their features, makes it possible to better understand how current fingerprint recognition systems work and to delineate useful research directions for the future.

Chen et al. proposed a novel algorithm [8], normalized fuzzy similarity measure (NFSM), to deal with the nonlinear distortions. The proposed algorithm was evaluated on fingerprints databases of Fingerprint Verification Competition 2004 (FVC2004) [9]. Experimental results confirm that NFSM is a reliable and effective algorithm for fingerprint matching with nonlinear distortions. This algorithm gives considerably higher matching scores compared to conventional matching algorithms for the deformed fingerprints. In fingerprints databases DB1 and DB3 of FVC2004, the distortion between some fingerprints from the same finger is large, but this algorithm performs well. The equal error rates are 4.37% and 1.64% on DB1 and DB3, respectively.

The problem of automatic fingerprint matching involves determining the degree of similarity between two fingerprint impressions by comparing their ridge structure and the spatial distribution of the minutiae points. However, the image acquisition process introduces nonlinear distortions in the ridge structure due to the nonuniform finger pressure applied by the subject and the elastic nature of the skin. Ross et al. have developed a deformation model for estimating the distortion effects in fingerprint impressions based on ridge curve correspondence. The proposed deformation model [10] based on ridge curves leads to a better alignment of two fingerprint images compared to a deformation model based on minutiae patterns.

This paper concentrates on issues related to the area of three-rate control [6], but demonstrates another field for application of these ideas, e.g., three-rate image processing.

The goal of this paper is to show the applicability of the proposed TRHKNNs for processing of distorted images of fingerprints.

Our purpose here is not only to search for the best possible three-rate image processing of distorted fingerprints, but also to enhance the obtained results with the case of single-rate image processing of distorted fingerprints.

The contribution of the paper is twofold: to develop new schemes appropriate for three-rate image processing by the TRHKNNs in real-time conditions, and to present the results of three-rate image processing of distorted fingerprints for chosen model of the TRHKNN in simulation form.

The rest of the paper is organized as follows. Section 2 provides a brief description of Kohonen algorithm. Experimental results with real fingerprint are described in section 3. Finally, in section 4 the conclusions are given.

2 Kohonen Algorithm

The salient steps of the Kohonen algorithm [11] are as follows.

Step 1. Set the small casual values for the weighted coefficients of this network.

Step 2. Present a new entrant signal of this network.

Step 3. Calculate the distance d_j in the manner

$$d_j = \sum_{i=1}^{N} \left(x_i(t) - w_{ij}(t)\right)^2 \qquad (1)$$

where $x_i(t)$ is the entrant signal at element i and time t, $w_{ij}(t)$ is the weight of communication of an entrant signal at element i and neuron j and time t.

Step 4. Choose a neuron $\overset{*}{j}$ with minimum value of d_j.

Step 5. Adjust the weights for a neuron $\overset{*}{j}$ and for neurons from his neighborhood $D_{j^*}(t)$ in the manner

$$w_{ij}(t+1) = w_{ij} + \eta\left(x_i(t) - w_{ij}(t)\right) \qquad (2)$$

where η is the step of training $0\langle\eta\langle 1$.

Step 6. Return to the **Step 2.**

Kohonen’s learning rule can be described as

$$w_{ij}(t) = w_{ij}(t-1) + \alpha\left(y_i^{(q-1)} - w_{ij}(t-1)\right) \qquad (3)$$

where $y_i^{(q-1)}$ is the target value at neuron i and layer $(q-1)$, $w_{ij}(t)$ and $w_{ij}(t-1)$ are the weight coefficients of the synapse at iterations t and $(t-1)$, respectively; α is the coefficient of training rate, q is the arbitrary layer of a network.

The rule (3) minimizes the difference between the entrant signals of a neuron, which acting from outputs of neurons of the previous layer $y_i^{(q-1)}$, and weight coefficients of his synapses.

3 Example

In this section, we present illustrative example to design the TRHKNN for three-rate processing of fingerprint.

A structure of the designed TRHKNN is illustrated in Fig. 1.

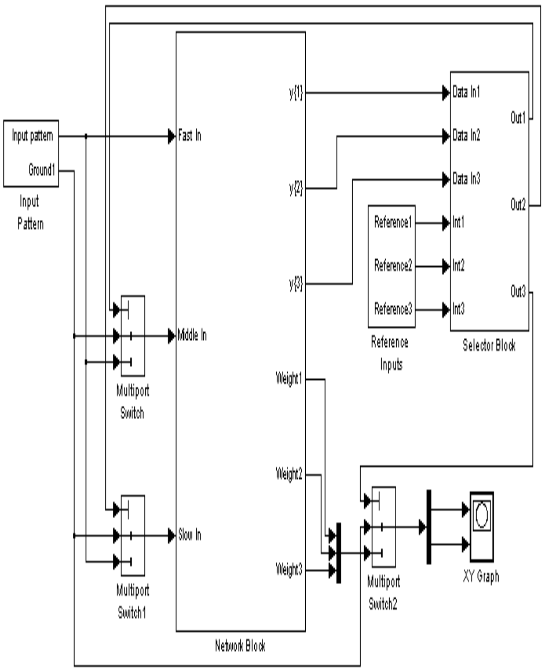

Fig. 1. Structure of TRHKNN.

A block diagram of the Network Block from Fig. 1 is given in Fig. 2 and the FKNN, MKNN and SKNN parts of this hybrid network are designed.

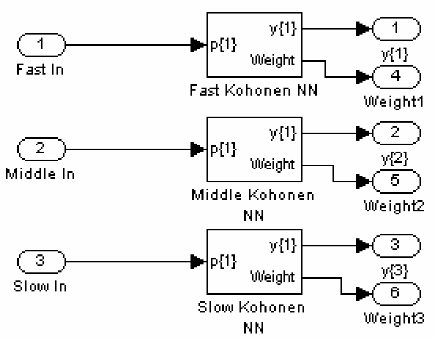

Fig. 2. Design Model of Network Block.

A detailed block diagram of the FKNN is given in Fig. 3.

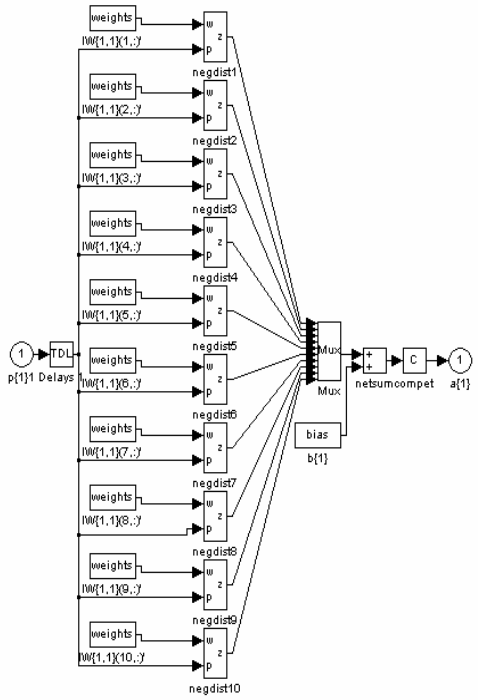

Fig. 3. Block diagram of FKNN.

The "fast" part of TRHKNN distinguishes an image of fingerprint, and the "middle" and "slow" parts of this NN restore this image.

The vector of attributes was formed. In order to evaluate the recognition of given image of fingerprint we measured the accuracy of this recognizer. Note that, if the accuracy does not correspond to the given criterion, there is only unrecognized image. If the "middle" network does not cope with restoration precisely enough then the “slow" network starts to operate.

The "fast" network has rather simple structure than the "middle" and "slow" networks. The additional decoding addresses-inputs of the "middle" and "slow" subnetworks have been entered for successful work of these subnetworks. The additional controlled multiplexing and demultiplexing segments of the "middle" and "slow" subnetworks and synchronization of all TRHKNN also are entered.

The procedure in [6] is, however, ad-hoc in nature and can result in decomposition of NN on two or more subsystems. It is assumed that

$$T = \tau_f + \tau_m + \tau_s , \tag{4}$$

where T is the operating time of the TRHKNN, τ_f,

τ_m and τ_s are the operating times of the "fast", "middle" and "slow" parts of TRHKNN, respectively.

The purpose of Selector Block from Fig. 1 is to compare a target signal with the standard signal of this network. We assume that the network has correctly distinguished an entrant image with the error value below 1% . After that, the "middle" and "slow" part of the TRHKNN for restoration of an image are activated.

The Kohonen NN demonstrates the ability to obtain the regular grid of topographical distribution of the data. These data can be restored by weight coefficients of neurons.

It is assumed that the "slow" part of TRHKNN is available not only for restoration of an entrant image, but also for his additional recognition.

The accuracy of recognition is

$$a_{\text{TRHKNN}} = 100\left(1 - \left(1 - a_f\right)\left(1 - a_m\right)\left(1 - a_s\right)\right) \quad (5)$$

where a_f, a_m and a_s are the accuracies of the "fast", "middle" and "slow" parts of TRHKNN, respectively.

Before identifying the distorted image of fingerprint (see Fig. 5) using TRHKNN containing the proposed three subsystems, we first train this NN using original fingerprint image (see Fig. 4).

The goal of the following simulations is twofold. First, we verify that the TRHKNN is able to identify the fingerprint. Second, we examined the effect of restoration.

Fig. 4 shows the arbitrary image of original fingerprint [12].

Fig. 4. Image of original fingerprint.

The distorted image of this original fingerprint as an input data in memory block is presented in Fig. 5.

Fig. 5. Distorted image of original fingerprint.

We continue to achieve the second procedure of our image processing goal, i.e., restoration of image of fingerprint (see Fig. 6).

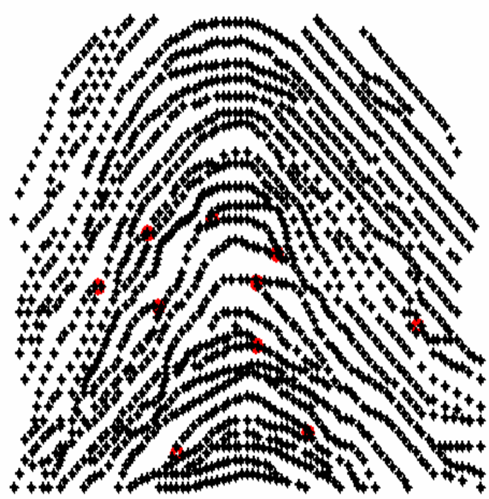

Fig. 6. Restored image of fingerprint.

However, as shown in Fig. 6, restoration of image for this fingerprint can be closed to reality.

Note that good results were obtained using only simple NNs (FKNN, MKNN and SKNN) for the subsystems. These results support the theoretical predictions well and demonstrate that this research technique would work for real systems.

4 Conclusions

From the applications viewpoint, we believe this research technique illustrates that TRHKNNs furnish a powerful approach for image processing problems.

In this paper, the three-rate processing of distorted fingerprint image by means of TRHKNN is proposed.

Note that the analysis of the obtained three-rate subnetworks (FKNN, MKNN and SKNN) can be produced by means of the modern computer software.

From the simulation studies of TRHKNN, the following can be observed.

In a TRHKNN, the data have presentation as a bidimensional array.

TRHKNN is very useful for graphic representation of the entrant, recognized and restored images.

The received TRHKNN consists of FKNN with 10 neurons, MKNN with 15 neurons and SKNN with 20 neurons.

These subnetworks (FKNN, MKNN and SKNN) have various speeds of actuation (fast, middle and long times of data processing) and are completely shared in time.

The maximum of 330 epochs for TRHKNN is smaller than the maximum of epochs for the others single-rate NNs.

The TRHKNN is capable not only to distinguish the entrant fingerprint image, but also is capable to restore the entrant fingerprint image.

The trained TRHKNN works more quickly than the others single-rate NNs.

TRHKNN studies to understand structure of graphical representation.

The distorted image of original fingerprint has been recognized with the error value of 0.007%, i.e., less than 0.01%.

The possible application of TRHKNN for recognition and restoration of distorted fingerprints, which act from various scanners, extends the potentiality for fast-acting image processing and analysis in real-time conditions.

We expect that the proposed technique makes possible highly reliable fingerprint matching for fingerprint images captured from fingertips with difficult conditions (e.g., dry fingertips, rough fingertips, allergic-skin fingertips) in the near future.

References:

[1] N. R. Sandell, P. Varaiya, M. Athans and M. G. Safonov, Survey of Decentralized Control Methods for Large Scale Systems, *IEEE Trans. Automatic Control*, Vol. 23, No. 2, 1978, pp. 108-128.

[2] P. V. Kokotovic and R. A. Yackel, Singular Perturbation of Linear Regulator: Basic Theorems, *IEEE Trans. Automatic Control*, Vol. 17, No. 1, 1972, pp. 29-37.

[3] P. V. Kokotovic, R. E. O'Malley and P. Sannuti, Singular Perturbations and Order Reduction in Control Theory - an Overview, *Automatica*, Vol. 12, No. 2, 1976, pp. 123-132.

[4] D. Li, S. L. Shah, T. Chen and R. Patwardhan, System Identification and Long-Range Predictive Control of Multi-Rate Systems, *Proc. American Control Conference*, San Diego, USA, 1999, pp. 336-340.

[5] J. Tornero, Y. Gu and M. Tomizuka, Analysis of Multi-Rate Discrete Equivalent of Continuous Controller, *Proc. American Control Conference*, San Diego, USA, 1999, pp. 2759-2763.

[6] I. Astrov, Simulation of Three-Rate Neural Network Control for Stochastic Model of a Fighter Aircraft, *Proc. IEEE Canadian Conference on Electrical and Computer Engineering,* Montreal, Canada, 2003, pp. 1711-1714.

[7] R. Cappelli, D. Maio, D. Maltoni, J.L. Wayman and A.K. Jain, Performance Evaluation of Fingerprint Verification Systems, *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 28, No. 1, 2006, pp. 3-18.

[8] X. Chen, J. Tian and X. Yang, A New Algorithm for Distorted Fingerprints Matching Based on Normalized Fuzzy Similarity Measure, *IEEE Trans. Image Processing*, Vol. 15, No. 3, 2006, pp.767-776.

[9] *Biometric Systems Lab., Pattern Recognition and Image Processing Lab. Biometric Test Center,* [Online]. Available: http://bias.csr.unibo.it/fvc2004/, 2004.

[10] A. Ross, S.C. Dass and A.K. Jain, Fingerprint Warping Using Ridge Curve Correspondences, *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 28, No. 1, 2006, pp. 19-30.

[11] T. Kohonen, *Self-Organizing and Associative Memory*, New York: Springer-Verlag, 1984.

[12] G. Soroka, *Dactyloscopy,* [Online]. Available: http://www.iks.ru/~soroka/otpehatk.htm/, 2007.