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# New invariant pattern recognition system based on preprocessing and reduced second-order neural network

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## ABSTRACT

We propose a new method for shift, scale, rotation invariant pattern recognition system using a normalization algorithm and a shift invariant neural network of order two with reduced input dimension. The normalization scheme normalizes the scale and rotation of deformed patterns using Principal Component Analysis (PCA). The reduced second-order neural network using the combinations of input pattern pixels and PCA has only (2 N)/5 input nodes, where N is the dimension of the input patterns. Experimental results with four types of aircraft data indicate the superiority of the proposed method to the compared system in terms of both learning speed and recognition rates.

## I. Introduction

An important aspect of human visual system is the ability to recognize an object despite changes in the object's shift, its scale, or its orientation. Computer vision system is the implementation of human visual system onto computer. For many industrial applications, computer vision systems must also have the ability to recognize geometrically distorted patterns. In computer vision, there are three basic forms of geometric distortion. They are shift, scale and rotation. Figure 1 shows various geometrical deformations of a airplane pattern. Thus, pattern recognition systems need to recognize a pattern despite changes in the pattern's shift, scale and rotation [4].

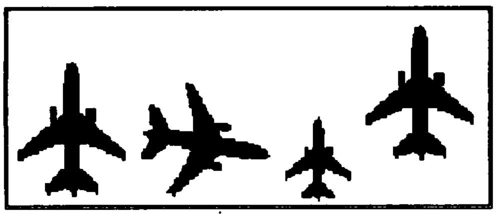


Figure 1. Various deformations of a airplane

Traditionally, pattern recognition systems have separated the pattern recognition task into two independent subtasks : feature extraction and recognition. The feature extraction task extracts relevant features from an pattern. In the recognition step, an pattern is classified to a class based on the extracted features. The feature extraction can be divided into two major categories : global feature extraction and local feature extraction. However, the global feature extraction methods are not good for the recognition of patterns with large distortions. The local feature extraction methods require large computation time [2].

Recently, the neural network approach was frequently used for pattern recognition. The first-order network trained by EBP (Error Back Propagation) learning rule is by far the most commonly used neural network. However, first-order neural network (FON) is inefficient for pattern recognition of geometrically distorted patterns because its training needs the distorted patterns as well as the original patterns [1, 7].

In a high-order neural network (HONN), geometrically motivated nonlinear combinations of pattern pixels are exploited and the desired invariances are built directly into the architecture of the network [9]. But straightforward use of HONNs is limited because the number of input nodes required by HONN increases in O(NR), where N is the number of input pixels and R is its order. This is the major obstacle to implementation of HONN[5, 8, 9].

In this paper, we present a new invariant pattern recognition system based on HONN. The proposed system consists of preprocessing module and postprocessing module. In the preprocessing module, PCA(principal component analysis) is used to transform input patterns into rotation and scale invariant patterns. The transformed patterns are fed into the postprocessing module, a second-order neural network. The number of input nodes of the second-order neural network is reduced using PCA and pixel combinations to absorb shift and shape distortions caused by the preprocessing module. The main idea is to combine the preprocessing and input nodes reduction strategy for effective use of invariant properties of HONN.

## II. Proposed recognition system

Figure 2. shows the block diagram of the proposed system.

In the preprocessing module. PCA is used to transform input patterns into rotation and scale invariant patterns. The original coordinates of each pixel in the pattern can be interpreted as variables with mean $m_x$ and covariance matrix $C_x$

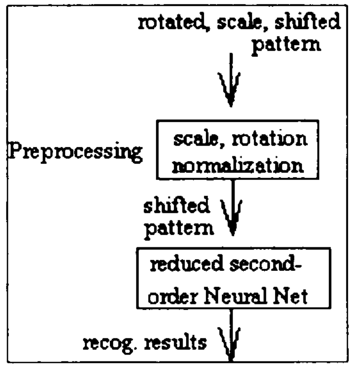



Figure 2. Block diagram of the proposed system

$$m_x = \frac{1}{P} \sum_{i=1}^{P} x_i \quad \text{and} \quad C_x = \frac{1}{P} \left[ \sum_{i=1}^{P} x_i x_i' \right] - m_x m_x' \qquad (1)$$

where P is the number of pixels in the

〈Table 1〉. Rotation and scale normalization

step 1. Compute the mean vector and the covariance matrix of the original image

$$m_x \cong \frac{1}{P} \sum_{i=1}^{P} x_i$$

$$C_x \cong \frac{1}{P} \left[ \sum_{i=1}^{P} x_i x_i' \right] - m_x m_x'$$

step 2. Alligin the coordinates with eignvectors of $C_x$

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} e_{11} & e_{12} \\ e_{21} & e_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

step 3. Rescale the coordinates according to the eignvalues of $C_x$

$$\begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \frac{B}{\sqrt{\lambda_1}} & 0 \\ 0 & \frac{B}{\sqrt{\lambda_2}} \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}, B = constant$$

pattern to be rotated and $x_i$ is the coordinates of the ith pixel. Since the eigenvectors of $C_x$ point in the directions of maximum variance, a logical choice is to select the new coordinate system so that it will aligned with these eigenvectors. Scale normalization for output of rotation normalization is then performed by the eigenvalues of eigenvectors [2]. Scale normalization for output of rotation normalization process is then performed by the eigenvalues of eigenvectors. We summarized the normalization algorithm for scale and rotation in Table 1.

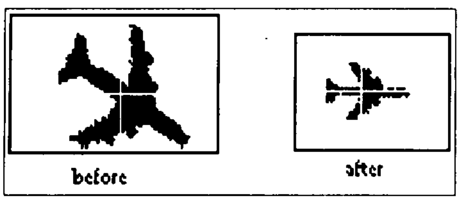
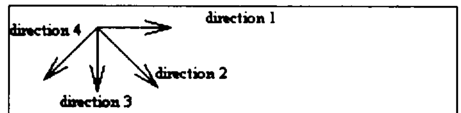



Figure 3. Result of the normalization

We gave the value 4 to constant B for the normalization in experiments. Figure 3 shows the results of scale and rotation normalization using the above algorithm.

The normalized patterns are fed into the postprocessing module, a reduced shift invariant second-order neural network. Shift invariant second-order neural network can be implemented by multi-layer perceptron (MLP) with (2{EMBED Equation |}N) number of second- order feature (SOF), which is the cumulative value of all the combinations of two pixels for equi-distance [5]. Figure 4 shows the example of the SOFs.




| | | | vector size |
|---|---|---|---|
| direction 1 | 2 1 0 0 0 | 2 1 0 0 0 | |
| direction 3 | 2 1 0 0 0 | 2 1 0 0 0 | |
| direction 2 | 1 0 0 0 0<br>1 0 0 0 0<br>0 0 0 0 0<br>0 0 0 0 0<br>0 0 0 0 0 | 1 0 0 0 0<br>1 0 0 0 0<br>0 0 0 0 0<br>0 0 0 0 0<br>0 0 0 0 0 | |
| direction 4 | 1 0 0 0 0<br>1 0 0 0 0<br>0 0 0 0 0<br>0 0 0 0 0<br>0 0 0 0 0 | 1 0 0 0 0<br>1 0 0 0 0<br>0 0 0 0 0<br>0 0 0 0 0<br>0 0 0 0 0 | |

Figure 4. Example of SOFs

So, it is desirable to reduce the number of input nodes of second-order neural networks as much as possible using PCA. In the PCA, the principal components can be obtained by using the diagonal terms from the diagonalized covariance matrix. They are equivalent to the variance of each dimension of the pattern [3].

As can be seen in Figure 5 for distribution of SOF values for aircraft patterns (X axis : horizontal distance between two pixels, Y axis : vertical distance between two pixels, Z axis : variance value of each dimension), features with small variance differ very little for most patterns. By eliminating these features, about 20% of second-order features ($(2 \times N)/5$ input nodes) are sufficient for recognition of aircraft patterns [1].

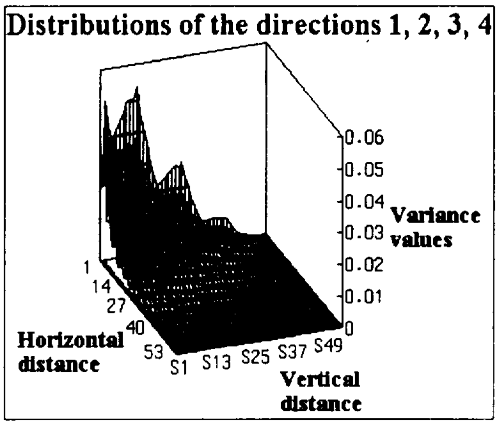



Figure 5. Distribution of SOFs

## III. Experimental results

We evaluated the performance of the proposed system on the recognition of aircraft data. Figure 6 shows the 4 kinds of airplane images.

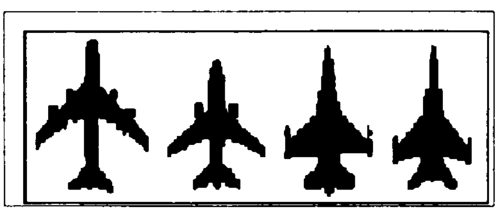


Figure 6. Data used in the experiment

The selected airplane images were digitized using a scanner and normalized to 128X128 size. After the original patterns were scaled by factors from 0.5 to 1.5, these scaled-patterns were rotated by various degrees and shifted 10 to 15 pixel distance randomly from centroid to yield the test patterns. Through these processes, 150 deformed airplane patterns (10 patterns for each deformation per aircraft pattern and 10 patterns for composite deformation per airplane pattern) were obtained. The recognition rate of the proposed system is compared with (Log-polar + FFT + MLP). The comparisons were made in term of recognition rates, recognition speed, learning speed and number of iterations.

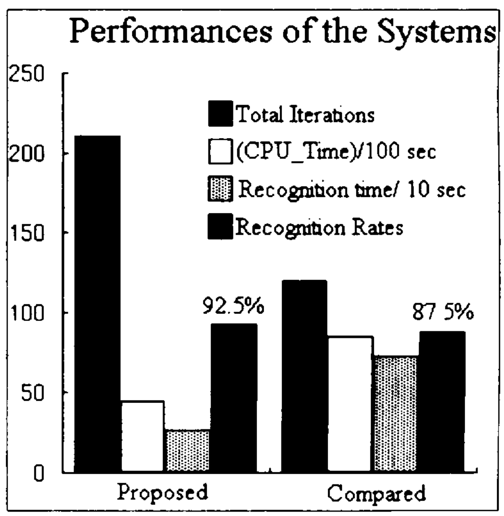



Figure 7. Performances of the two systems

Figure 7 shows the performances of the two systems. The recognition results in Figure 7 show the proposed system produces higher recognition rate than the compared system. The proposed system also produces higher performance than the compared system in terms of learning and recognition speed.

## IV. Conclusion

In this paper, for effective use of invariant properties and powerful computational capabilities of high-order neural networks, we present a reduced second-order neural network with preprocessing module. The preprocessing using PCA transforms a pattern into a scale and rotation normalized pattern. The reduced second-order neural network recognizes shift-and-shape distortion patterns resulted from preprocessing. The experimental results show that the proposed system enables invariant properties of the high-order neural network to be used for real time pattern recognition.

The main advantages of the proposed system are as follow :.

1. Lower storage requirements over the original second-order neural network.

2. The preprocessing is simple and doesn't need much computation.

3. The system has a two-step architecture which is simpler than existing models.

So, we observe that the proposed system is able to recognize geometrically deformed patterns effectively.

## References


[1] Giles, C.L. and Maxwell, T. (1987). Learning, invariance and generalization in high-order neural networks. Applied Optics, 25, pp. 4972 - 4978.

[2] Gonzales, R.C. and Wiatz, P. (1987). Digital image processing. Addision-Wesely.

[3] Hertz, J., Krogh, A. and Palme, R.G. (1991). Introduction to the Theory of Neural Computation. Addision-Wesely.

[4] Jeng, S. C. and Tasi, W. H. (1991). Scale-and orientation-invariant generalized Hough transform- A New approach. Pattern Recognition, v. 24, pp. 1037-1051.

[5] Lee, B.K., Cho, Y.K. and Lee, H.H. (1994). Reduction of Input Nodes for Shift Invariant Second Order Neural Networks using PCA. Proc. of WCNN, vol 3, pp. 144-149.

[6] Pei, S. C. and Lin, C. N. (1992). Normalization of Rotationally symmetric shapes for pattern recognition. Pattern Recognition, v. 25, pp. 913-920.

[7] Perantonis. S.J. and Lisboa. P.J.G. (1992). Translation. Rotation and Scale Invariant Pattern Recognition by Higher order Neural Networks and Moment Classifier. IEEE Transactions on Neural Network. March. v. 3. pp. 241-251.

[8] Reid. M.B.. Spirkovska. L. and Ochoa. E. (1989). Rapid training of higher-order neural networks for invariant pattern recognition. Proc of IJCNN. vol. I. pp. 689-692.

[9] Schmidt. W. and Davis. J.P. (1993). Pattern Recognition Properties of various feature spaces for higher order Neural Networks. IEEE Trans. on PAMI. 1993. 15. (8). pp. 795 - 801.