

# Face Recognition Using a Neural Network Simulating Olfactory Systems

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**Abstract.** A novel chaotic neural network K-set has been constructed based in research on biological olfactory systems. This non-convergent neural network simulates the capacities of biological brains for signal processing in pattern recognition. Its accuracy and efficiency are demonstrated in this report on an application to human face recognition, with comparisons of performance with conventional pattern recognition algorithms.

## 1 Introduction

Face recognition (FC) plays an increasingly important role in a wide range of applications, such as criminal identification, credit card verification, security system, scene surveillance, etc. However, a straightforward implementation is difficult.

In order to optimize performance, many algorithms of feature extraction are proposed, such as PCA, ICA and so on. Upon the extraction of the proper set of features, a classifier such as nearest neighbor distances, Bayesian statistics, SVM, etc., is applied to collections of facial images. Biologically inspired neural networks are especially widely used, but most are deterministic and time-invariant, and they lack the speed, reliability, and capacities for abstraction and generalization that characterize biological neural systems.

The KIII set is a chaotic neural network mimicking the olfactory system of animals engaged in odorant identification, as revealed by research on the electrical activity recorded in animals trained to identify odors. The KIII model has static nonlinearities that support aperiodic broad-spectrum oscillations from nonconvergent 'chaotic' attractors. The multiple attractors form a landscape, each attractor in a basin that represents a class of input that the system is trained to identify and classify efficiently in image pattern recognition. In this paper, we introduce this novel chaotic neural network and its use for face recognition. First an algorithm for image partition is applied to extract the features of face images. Then the extracted feature vectors are given as inputs to train the KIII set by changing its connection weights, creating a landscape of chaotic attractors. Then independent inputs are given to demonstrate the efficiency of the KIII set as a classifier of facial images, with the potential for use in other types of pattern cognition.

## 2 A Neural Network Mimicking Olfactory Systems — The KIII Set

### 2.1 K Set Hierarchy

In accordance with the anatomic architecture, KIII network is a multi-layer neural network model. The dynamics of every node is described with a second order differential equation (1), which is derived from measurement of open-loop impulse responses [1].

$$\frac{1}{a \cdot b} [x_i''(t) + (a + b)x_i'(t) + a \cdot b \cdot x_i(t)] = \sum_{j \neq i}^N [W_{ij} \cdot Q(x_j(t), q_j)] + I_i(t) \quad (1)$$

$$Q(x_i(t), q) = \begin{cases} q(1 - e^{-(\exp(x(t)) - 1) / q}) & x(t) > x_0 \\ -1 & x(t) < x_0 \end{cases} \quad (2)$$

$$x_0 = \ln(1 - q \ln(1 + 1 / q))$$

In this equation  $x_i(t)$  ( $x_j(t)$ ) represents the state variable of  $i$ th ( $j$ th) neural population while  $W_{ij}$  indicates the connection strength between them.  $I_i(t)$  is an input function. The parameter  $a, b$  reflect two rate constant.  $Q$  is a static nonlinear sigmoid function derived from Hodgkin-Huxley model and  $q$  represents the maximum asymptote of the sigmoid function.

The KIII network describes the whole olfactory neural system. After the parameter optimization, the KIII network generates EEG-like waveform with  $1/f$  power spectra [2]. The KIII system [1] presents an aperiodic oscillation when there is no stimulus and the trajectory of the system soon goes to specific local basin and converges to an attractor when there is a stimulus.

### 2.2 Learning Rule

There are two kinds of learning rules: Hebbian learning reinforces the desired stimulus patterns while habituation decreases the impact of the background noise and the stimuli that are ambiguous, irrelevant or insignificant.

The algorithm is described as follows:

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IF P_M(i) > (1+K)*P_M AND P_M(j) > (1+K)*P_M AND i != j then
W_M(i)->M(j) = h_Heb (i = 1, ..., n)
Else IF i = j
W_M(i)->M(j) = 0
ELSE
W_M(i)->M(j) = h_Hab (i = 1, ..., n)
ENDIF
ENDIF
    
```

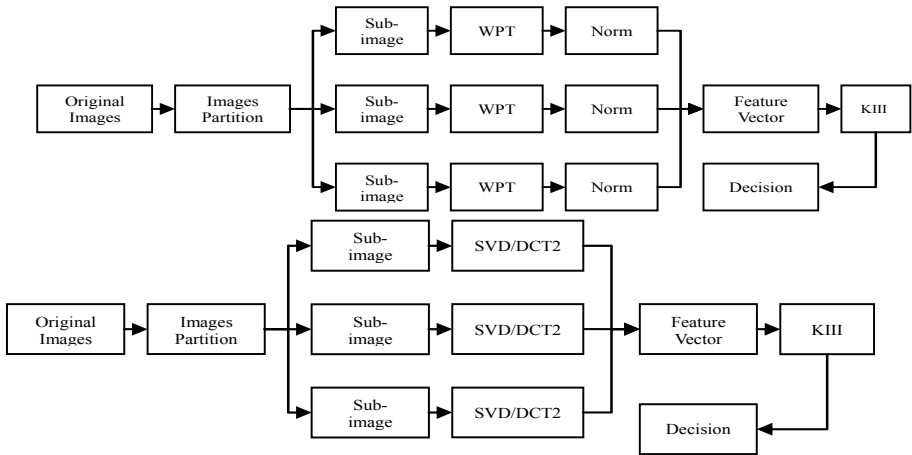


Fig. 1. The flow chart of face recognition

### 3 Application of KIII Model to Face Recognition

#### 3.1 Different Recognition Process

In the process of recognition, 2 different flow charts (Fig.1) are used according to different the extracting methods, SVD (singular value decomposition), DCT (discrete cosine transform) and WPT (wavelet packet transform).

First, the original image is divided into n equal sub-images. In each sub-image, only one feature is extracted. When the feature of sub-image is decomposed, an n-dimension feature vector is generated as the input of KIII model. Fig.1 (upper) shows the flow chart based on SVD or DCT and Fig.1 (lower) shows the flow chart based on WPT.

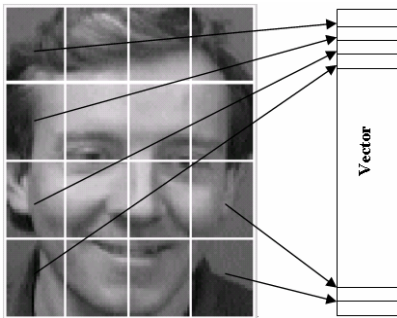


Fig. 2. Image partition

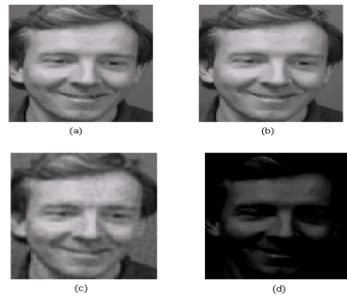


Fig. 3. Face image comparison processed by DCT

### 3.2 Feature Extraction Methods

In extracting a feature vector from the entire image, we divide the original image into sub-images and extract the feature of each sub-image from the whole sub-image (Fig.2). Then, the features are combined to form the whole feature vector of the original image. In our simulation, the face images are divided into 8, 16, 32, 64 and 80 sub-images individually. Either DCT, SVD, or WPT is used separately to extract the feature vector.

DCT can concentrate most of the signal energy effectively. In Fig.3, (a) is the original face image, (b) is the reconstructed image without discarding any coefficient, (c) is the reconstructed image discarding about 90% coefficient and (d) is the reconstructed image only discarding one maximal coefficient.

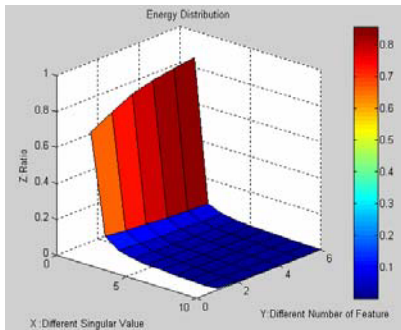


Fig. 4. Energy distribution in SVD

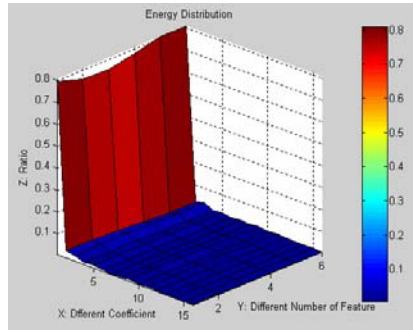


Fig. 5. Energy distribution in WPT

In SVD, the largest singular composes the n-dimension feature vector. In Fig.4, X axis denotes 10 large singular values in each sub-image. Y axis denotes the number of feature, 8\*ly il. Z axis denotes the ratio of singular value to the sum of singular value.

The WPT of image results in an array of wavelet coefficients. In this paper, we use 2 level WPT calculate the coefficients and the norm of all the coefficients of lowest frequency range in sub-bands as the feature. From Fig.5, it is shown that most of the energy of the image concentrates in the lowest frequency range.

### 3.3 Experiment Results

ORL face dataset is used to evaluate the performance. Five images of each person are selected for training and others are used to test. Compared with other ANN, each pattern is only learned 10 times in KIII. The output of OB layer is stored as cognition standard. And the nearest neighbor principle is used to classify new images. From Table 1, it is shown that, the higher is the dimension of the feature vector, the better is the performance. The DCT-based feature seems a little better, but SVD/WPT-based classifier seems more stable. From Table.2, KIII model shows better performance than all of the others.

**Table 1.** Average recognition accuracy for ORL database

Accuracy		Number of feature					
		8	16	32	48	64	80
Method	SVD	0.693	0.815	0.883	0.900	0.908	0.910
	DCT	0.670	0.820	0.885	0.900	0.915	0.910
	WPT	0.695	0.818	0.873	0.898	0.908	0.898

**Table 2.** Comparison the KIII method with other algorithm

Method	MLP[3]	HMM[4]	PCA[4]	WPT+KIII	SVD+KIII	DCT+KIII
Accuracy	84.0%	87.0%	90.0%	90.8%	91.0%	91.5%

## 4 Discussion

KIII network is a kind of chaotic neural network derived from biological neural systems. In this paper, the KIII model is used to face recognition. Based on the feature vectors extracted by DCT/SVD/WPT, the potential of the KIII set for pattern cognition is shown, especially to classify complex images.

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## References

1. Freeman, W.J., Kozma, R.: Biocomplexity: Adaptive Behavior in Complex Stochastic Dynamic Systems, *Biosystems*, 59 (2001), 109-123
2. Li, G., Lou, Z., Wang, L., Li, X., Freeman, W.J.: Application of Chaotic Neural Model Based on Olfactory System on Pattern Recognitions. In: Wang, L., Chen, K., Ong Y.S. (eds.): *Advances in Natural Computation. Lecture Notes in Computer Science*, Vol. 3610. Springer-Verlag, Berlin Heidelberg New York (2005) 378 - 381
3. Pan, Z., Adams, R. and Bolouri, H.: Dimensionality Reduction of Face Images Using Discrete Cosine Transforms for Recognition, *IEEE Conference on Computer Vision and Pattern Recognition* (2000)
4. Samaria, F.: *Face Recognition Using Hidden Markov Models*, PhD Thesis, Cambridge University (1994)