OptiNeural System for Optical Pattern Classification

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Abstract

An OptiNeural system is developed for optical pattern classification. It is a novel hybrid system which consists of an optical processor and a multilayer neural network. It takes advantages of two dimensional processing capability of an optical processor and nonlinear mapping capability of a neural network. The optical processor with a binary phase only filter is used as a preprocessor for feature extraction and the neural network is used as a decision system through mapping. OptiNeural system is trained for optical pattern classification by use of a simulated annealing algorithm. Its classification performance for grey tone texture patterns is excellent, while a conventional optical system shows poor classification performance.

I. Introduction

One of the most attractive features of optics is its parallel processing of data in two dimensions. Optical matched filters (OMFs) using optical correlation have been used successfully for optical pattern classification in various applications [1]. Binary phase only filters (BPOFs) for optical pattern classification [2] attract considerable interest because they show high optical efficiency and excellent classification performance when compared with OMFs. In addition, BPOFs can be easily implemented on available binary spatial light modulators (SLMs) [3]. E-beam lithography is also a good technology to fabricate accurate BPOFs [4] .

However, conventional optical systems using optical correlation for pattern classification fail in classifying patterns because they are too sensitive to intraclass variation and too insensitive to interclass variation [5]. Recently, neural network systems are used for pattern classification [6]. They show excellent classification performance. In this paper, a novel hybrid system which takes advantages of two dimensional processing capability of optics and nonlinear mapping capability of the neural network is introduced for classification of patterns that are difficult to distinguish by use of the conventional optical system. Hereafter, this system is called an OptiNeural system. As seen in Fig. 1, OptiNeural system consists of an optical processor and a neural network.

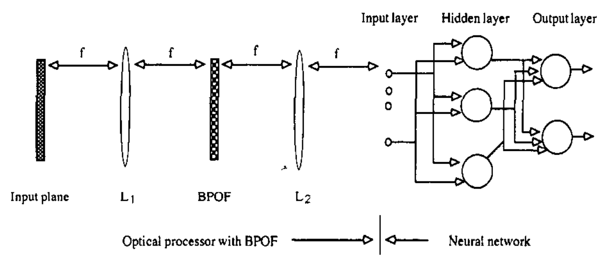

Fig. 1. OptiNeural system. L1 and L2 are Fourier transform lenses and f is their focal length.

The first part of the system is an optical processor with BPOF for preprocessing the input pattern and the second part is a decision system with a multilayer neural network. BPOF in the optical processor and the weights in the neural network are trained to classify patterns. Computer simulation of the system is studied for classification of patterns that are difficult to distinguish by a conventional optical system with BPOF.

In Section II, conventional optical system is analyzed with test patterns for optical pattern classification. In Section III, OptiNeural system is described. In Section IV, training method of OptiNeural system with a learning algorithm is explained and optical pattern classification performance of trained OptiNeural system is presented.

II. Conventional Optical System for Optical Pattern Classification

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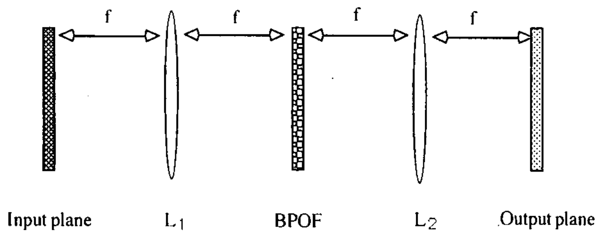

Fig. 2. Conventional optical system with BPOF for optical pattern classification.

Conventional optical system with BPOF (COSB) for pattern classification is shown in Fig. 2 where L_1 and L_2 are Fourier transform lenses, and f is focal lengh of the lenses. Let us represent BPOF, H(u,v), as

$$H(u,v) = [1-\exp(j\phi)]\, B(u,v) + \exp(j\phi) \quad (1)$$

where ϕ is a binary phase and B(u,v) is a binary state which is 0 or 1. Thus,

$$H(u,v) = \begin{cases} 1 & \text{for } B(u,v) = 1 \\ \exp(j\phi) & \text{for } B(u,v) = 0 \end{cases}$$

Let the input pattern on the input plane be g(x,y). After g(x,y) passes the lens L_1 and BPOF, it becomes F(u,v) ;

$$F(u,v) = [1-\exp(j\phi)]\, B(u,v)\, G(u,v) + \exp(j\phi)\, G(u,v) \quad (2)$$

where G(u,v) is Fourier transform of g(x,y) by the lens L_1. When H(u,v) and G(u,v) consist of K x L rectangular pixels and G(u,v) is assumed to be constant over each pixel, F(u,v) becomes

$$F(u,v) = [1-\exp(j\phi)] \sum_{k=-K/2}^{K/2} \sum_{l=-L/2}^{L/2} B_{kl} G_{kl}\, rect\left[\frac{u-k\Delta u}{\Delta u}, \frac{v-l\Delta v}{\Delta v}\right] + \exp(j\phi) \sum_{k=-K/2}^{K/2} \sum_{l=-L/2}^{L/2} G_{kl}\, rect\left[\frac{u-k\Delta u}{\Delta u}, \frac{v-l\Delta v}{\Delta v}\right] \quad (3)$$

where B_{kl} is 1 or 0 [7]. After F(u,v) passes the lens L_2 , the intensity of the output spot on the output plane is $|f(x,y)|^2$ where f(x,y) is Fourier transform of F(u,v) by the lens L_2 [8] ;

$$f(x,y) = [1-\exp(j\phi)]\, C\tilde{f}(x,y) + \exp(j\phi)\, C\tilde{g}(x,y) \quad (4)$$

where

$$C = \Delta u\, \Delta v\, \mathrm{sinc}(x\Delta u, y\Delta v)$$

$$\tilde{f}(x,y) = \sum_k \sum_l B_{kl} G_{kl} \exp[-j2\pi(kx\Delta u + ly\Delta v)]$$

$$\tilde{g}(x,y) = \sum_k \sum_l G_{kl} \exp[-j2\pi(kx\Delta u + ly\Delta v)]$$

When f(x,y) is sampled at intervals of $\Delta u \Delta x = 1/K$ and $\Delta v \Delta y = 1/L$,

$$f(m\Delta x, n\Delta y) = [1-\exp(j\phi)]\, C\tilde{f}_{mn} + \exp(j\phi)\, C\tilde{g}_{mn} \quad (5)$$

where $C = \Delta u\, \Delta v\, \mathrm{sinc}(m/K, n/L)$,

$$\tilde{f}_{mn} = \sum_k \sum_l B_{kl} G_{kl} \exp[-j2\pi(km/K + ln/L)]$$

$$\tilde{g}_{mn} = \sum_k \sum_l G_{kl} \exp[-j2\pi(km/K + ln/L)]$$

We assume that the coefficient C caused by the finite size of the pixel may be set to one [9]. What remains is

$$f_{mn} = [1-\exp(j\phi)]\, \tilde{f}_{mn} + \exp(j\phi)\, \tilde{g}_{mn} \quad (6)$$

where $f_{mn} = f(m\Delta x, n\Delta y)$. When the input pattern is located such that $\tilde{g}_{mn} \approx 0$ for a specific pair (m,n) and the binary phase ϕ is set to π for convenience, Eq. (6) becomes

$$f_{mn} = 2\tilde{f}_{mn} \quad (7)$$

Thus, output spot on the output plane in Fig. 2 has the intensity $|f_{mn}|^2$ that is correlation of the input pattern with BPOF [7].

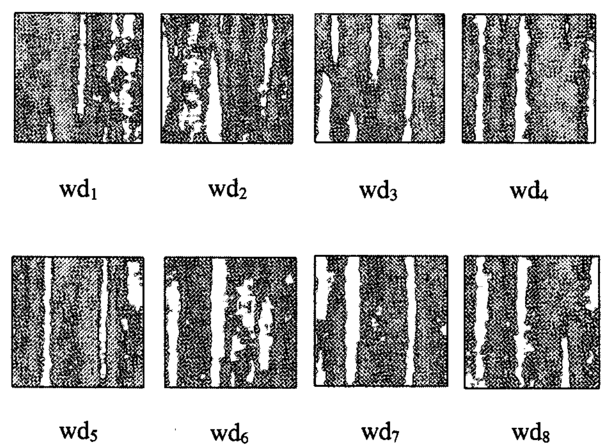

Fig. 3. (a) Wood group patterns to be classified.

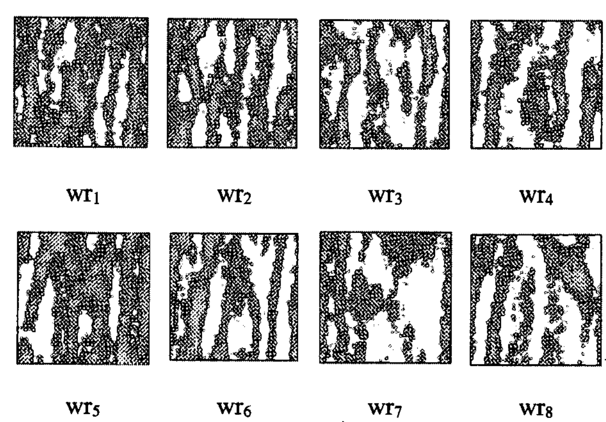

Fig. 3. (b) Water group patterns to be classified.

Fig. 3 is the patterns to test classificaion performance of COSB. The patterns are grey tone texture patterns. The patterns consist of two groups with 16 patterns : a wood group and a water group. Each group consists of eight patterns and each pattern has 32 x 32 pixels with eight bit amplitude. Simulated annealing (SA) algorithm that is one of the most successful algorithms to encode BPOF is used to encode BPOF of COSB in order to classify the test patterns [4]. B_{kl} of BPOF is defined as the system variable for SA algorithm and BPOF is assumed to have 128 x 128 pixels. COSB for optical pattern classfication has used two correlation spots among $|f_{mn}|^2$ which correspond to autocorrelation and crosscorrrelation [8]. The system energy function is defined as follows :

$$E = \sum_{i=1}^{N}\{(T_A - AC[wd_i])^2 + (T_A - AC[wr_i])^2 + (T_C - CC[wd_i])^2 + (T_C - CC[wr_i])^2\} \quad (8)$$

In Eq. (8), AC[wd_i] at the location of the first correlation spot is correlation of BPOF with the training wood pattern wd_i and CC[wd_i] at the location of the second correlation spot is correlation of BPOF with the training wood pattern. AC[wr_i] at the location of the second correlation spot is correlation of BPOF with the training water pattern wr_i and CC[wr_i] at the location of the first correlation spot is correlation of BPOF with the training water pattern. AC[wd_i] (or AC[wr_i]) corresponds to autocorrelation of the input pattern wd_i (or wr_i) with wd_i (or wr_i) on trained BPOF after training of BPOF is finished [10]. Also CC[wd_i] (or CC[wr_i]) corresponds to crosscorrelation of the input pattern wd_i (or wr_i) with wr_i (or wd_i) on trained BPOF after training of BPOF is finished. T_A and T_C are desired correlation intensities for AC[ ] and CC[ ] and $T_A >> T_C$. N is the number of the training patterns in each group, in this case, eight. The cooling schedule T_r is

$$T_r = (D_T)^r\, T_{initial} \text{ and } D_T = (T_{final} / T_{initial})^{1/q} \quad (9)$$

where $T_{initial}$ is initial system temperature, T_{final} is final system temperature, r is the iteration index, q is the total number of the iterations and $D_T > 0.9$. The acceptance probability P($\varDelta$E)

$$P(\varDelta E) = 1 / [1 + \exp(\varDelta E/T_r)] \quad (10)$$

where $\varDelta$E is the energy difference between the current energy and the previous energy. More detailed information about training COSB is available in Ref. 10. For each pattern in the wood group and the water group of Fig. 3, correlation values are obtained as in Table I after training is finished. As seen in Table I, the values of AC[wd_i] and AC[wr_i] are quite comparable to the values of CC[wd_i] and CC[wr_i] so that the two groups of the patterns are hard to classify. Such a poor performance of COSB is due to the inherent drawback of optical correlation for pattern classification that is insensitive to interclass variation of patterns [5]. In order to overcome such a drawback of COSB, OptiNeural system is introduced for pattern classfication.

Table 1. Performance of pattern classification by COSB

Wood group			Water group		
Input pattern	AC[wd_i]	CC[wd_i]	Input pattern	AC[wr_i]	CC[wr_i]
wd_1	1.18	0.91	wr_1	1.16	0.84
wd_2	1.18	0.85	wr_2	1.10	0.83
wd_3	1.18	0.87	wr_3	1.08	0.82
wd_4	1.18	0.91	wr_4	1.08	0.82
wd_5	1.18	0.91	wr_5	1.09	0.85
wd_6	1.18	0.91	wr_6	1.09	0.82
wd_7	1.18	0.88	wr_7	1.08	0.82
wd_8	1.18	0.91	wr_8	1.08	0.82

III. Description of OptiNeural System

As seen in Fig. 1, OptiNeural system is a hybrid system of an optical processor and a neural network. In OptiNeural system to overcome the drawback of COSB for optical pattern classification, the optical processor with BPOF is used as a preprocessor for feature extraction by taking more than two correlation spots. A large amount of data in patterns hinder pattern classification [11]. However, in OptiNeural system, feature extraction by BPOF lessens burden of data processing on the neural network when a small number of the correlation outputs in the optical processor are used as inputs to the neural network through photodetectors. Three layer neural network can be used, which consists of an input layer, a hidden layer, and an output layer. For more sophisticated mapping, it can be expanded to a multilayer neural network with more hidden layers. The input layer of the neural network is just to distribute correlation output spots in the optical processor to the hidden layer through photodetectors. The hidden layer consists of hidden units each of which processes data from the input layer, and the output layer consists of output units each of which processes data from the hidden layer. Mapping of the neural network is obtained by internal representation of the input/output relationship by the hidden layer [6]. The neural network can be implemented on an electronic circuit for simple mapping, or a personal computer for sophisticated mapping [12].

For given patterns to be classified, a desired value is assigned to an output of each unit in the output layer of the neural network. Then the state of BPOF and the weights of the neural network are trained by a supervised learning algorithm in order to obtain the desired value. In one sense, BPOF is a kind of another hidden layer whose weights are binary values implemented with optics.

IV. OptiNeural System for Optical Pattern Classification

The optical processor with BPOF in OptiNeural system is the conventional optical system. The correlation outputs $|f_{mn}|^2$ from the optical processor are used for the inputs to the neural network. As shown in the neural network of Fig. 4, NU_j which is the output of the j-th hidden unit in the hidden layer and NY_i which is the output of the i-th output unit in the output layer are calculated through nonlinear activation functions $\Gamma(\ )$ and $\Lambda(\ )$ as follows [6]:

$$NU_j = \Lambda(U_j) \text{ for the hidden layer}$$

$$NY_i = \Gamma(Y_i) \text{ for the output layer} \qquad (11)$$

where

$$U_j = \sum_{m=0}^{M}\sum_{n=0}^{N} W_{jmn}|f_{mn}|^2 \qquad Y_i = \sum_{j=0}^{J} Z_{ij} NU_j$$

and W_{jmn} is the weight of the j-th hidden unit and Z_{ij} is the weight of the i-th output unit. J is the number of the hidden units, and M and N are the number of the correlation output spots in the optical processor.

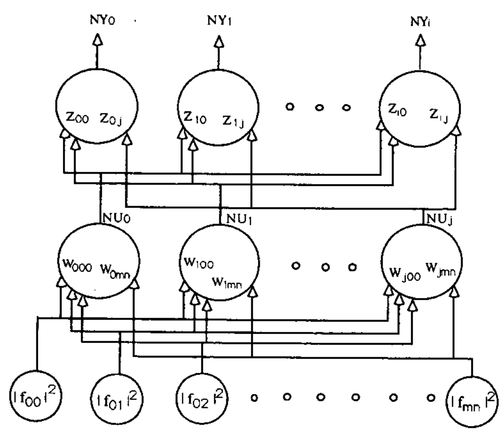

Fig. 4. Neural network.

When SA algorithm is applied to training OptiNeural system, B_{kl}, W_{jmn}, and Z_{ij} are defined as system variables. The system energy is defined as follows :

$$E = \sum_{i=0}^{I}|T_i - NY_i|^2 + \sum_{m=0}^{M}\sum_{n=0}^{N}(F_{mn} - |f_{mn}|^2)^2 \qquad (12)$$

where I is the number of the output units in the neural network, T_i is a desired output of the i-th output unit in the neural network for the current input pattern, and F_{mn} is a desired correlation value at the output in the optical processor. The first term of the system energy in Eq. (12) is introduced to make the actual output of output unit NY_i close to the desired output T_i. The second term of the system energy is introduced to get the correlation values as high as possible. The system temperature in SA algorithm decreases with the cooling schedule as in Eq. (9)

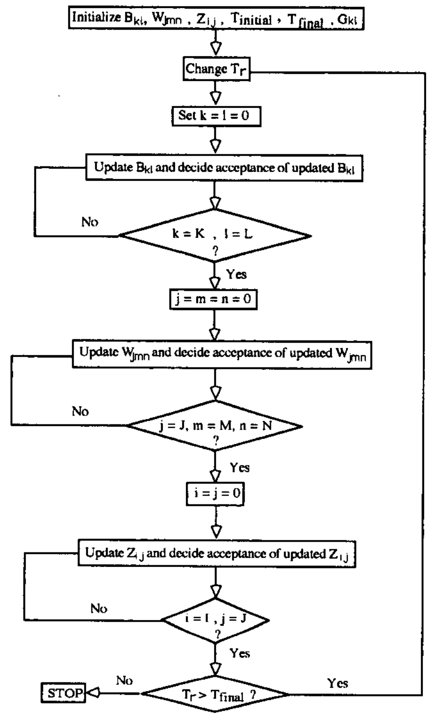

Fig. 5. Flow diagram to train OptiNeural system with SA algorithm

Fig. 5 is a flow diagram of the computer training program for OptiNeural system. The program consists of several loops. In the outer loop, the system temperature decreases according to the cooling schedule. In the first inner loop, each pixel state of BPOF is updated : If the binary state B_{kl} is updated from 1 to 0,

$$f_{mn}^{new} = f_{mn}^{old} - 2\, G_{kl} \exp[-j2\pi(mk/K + nl/L)] \ . \qquad (13)$$

If it is updated from 0 to 1,

$$f_{mn}^{new} = f_{mn}^{old} + 2\, G_{kl} \exp[-j2\pi(mk/K + nl/L)] \qquad (14)$$

Changed B_{kl} is accepted based on the acceptance probability of Eq. (10) after calculation of the system energy. In the other inner loops for the hidden layer and the output layer, each of the weights is updated by random perturbations. The perturbations are accepted according to the acceptance probability of Eq. (10) after calculation of the system energy.

In order to test classification performance of OptiNeural system, the system is trained with the patterns to be classified. The patterns are the same grey tone texture patterns in Fig. 3 as used for COSB. BPOF consists of 128 x 128 pixels. To abridge burden of data processing in the neural network, a small number of correlation spots need to be chosen. Arbitrary correlation spots can be selected, and in this work four correlation spots are selected, which are $|f_{00}|^2$, $|f_{01}|^2$, $|f_{10}|^2$, $|f_{11}|^2$. They are used as the inputs of the neural network through photodetectors. The hidden layer consists of three hidden units and the output layer has one output unit. The nonlinear functions, $\Gamma(\ )$ and $\Lambda(\ )$, for the hidden units and the output unit in the neural network have the same functional form :

$$\Gamma(V) = \Lambda(V) = 1 / [1 + \exp(-V)] \tag{15}$$

Table 2. Performance of pattern classification by Opti-Neural system

Wood group			Water group		
Input pattern	Desired output T	Actual output NY	Input pattern	Desired output T	Actual output NY
wd_1	1.0	1.0	wr_1	0.0	0.001
wd_2	1.0	1.0	wr_2	0.0	0.0
wd_3	1.0	1.0	wr_3	0.0	0.0
wd_4	1.0	1.0	wr_4	0.0	0.0
wd_5	1.0	1.0	wr_5	0.0	0.003
wd_6	1.0	1.0	wr_6	0.0	0.0
wd_7	1.0	1.0	wr_7	0.0	0.0
wd_8	1.0	1.0	wr_8	0.0	0.0

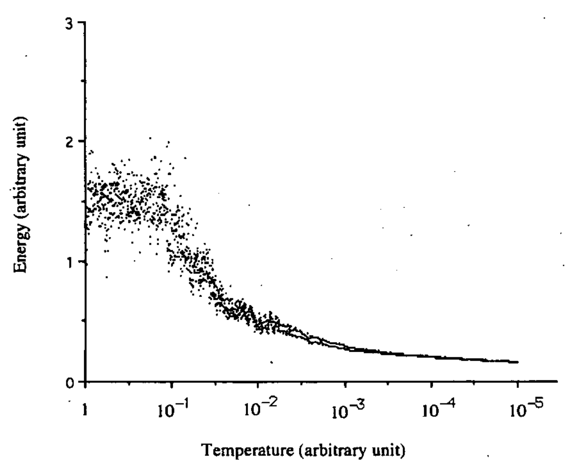

Fig. 6. System energy Vs system temperature.

where V becomes U_j for the hiddden unit or Y_i for the output unit in Eq. (11). The desired output for the eight training patterns in the wood group pattern is 1 and the desired output for the eight training patterns in the water group pattern is 0. Fig. 6 shows how the system energy changes as the system temperature decreases. Table II presents the actual output and the desired output for each pattern in the wood group and the water group of Fig. 3 after training of BPOF in the optical processor and the weights of the neural network is done. As shown in Table II, OptiNeural system trained by SA algorithm classified the grey tone texture patterns easily and excellently, while COSB showed poor classification performance for the same patterns. Therefore, as seen in Table I and Table II, OptiNeural system in which the optical processor takes more than two correlation spots and the neural network processes the spots shows much better classification performance of the patterns than COSB in which two correlation spots of autocorrelation and crosscorrelation are taken.

V. Conclusion

A convenational optical system with a binary phase only filter showes a limited performance in optical pattern classification. A novel OptiNeural system is introduced in this work. It is a hybrid system with an optical processor and a neural network. OptiNeural system takes advantages of two dimensional processing capability of the optical processor and nonlinear mapping capability of the neural network. The optical processor with a binary phase only filter is used as a preprocessor for feature extraction and the neural network is used as a decision system through mapping. OptiNeural system is trained by use of a simulated annealing algorithm. After training is finished, OptiNeural system showed excellent classification performance for grey tone texture patterns while the conventional optical system with a binary phase only filter showed poor classification performance. Further work is to realize OptiNeural system for pattern classification where BPOF in the optical processor is implemented with real-time spatial light modulator and the neural network is implemented with electronic circuitry.

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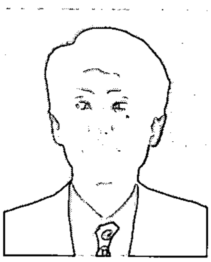

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