論 文

2차원 신경회로망 모델에 근거한 광연상 메모리의 실현

準會員 韓 鍾 旭* 準會員 朴 仁 虎* 正會員 李 丞 玄*

正會員 李 禹 相* 正會員 金 恩 洙*

Optical Implementation of Associative Memory Based on Two-Dimensional Neural Network Model

Jong Wook HAN*, In Ho PARK*, Seung Hyun LEE*, Woo Sang LEE*

Eun Soo KIM* ***Regular Members***

要 約 본 논문에서는 2차원 Hopfield 신경회로망 모델에 근거한 새로운 광 연산 메모리 시스템을 구현하였다. 2차원 영상의 실시간 처리를 위하여 입력 공간광변조기와 메모리 마스크는 상용 LCTV를 사용하고 특히, 4차원 메모리 행렬은 2차원 부행렬 마스크의 2차원적 배열로 구성하였으며 임의의 입력 패턴과 메모리 행렬간의 내적 계산은 multifocus hololens를 사용하여 처리하였다. 출력 영상은 전자적으로 thresholding 된 후 2차원 CCD 카메라를 사용하여 다시 연상 메모리 시스템의 입력으로 궤환되도록 루프를 구성하였다. 본 시스템의 연상 기억 및 오류 정정 능력에 대한 실험결과를 통해 본 논문에서 제시된 새로운 2차원 신경회로망 모델의 광학적 구현 시스템은 앞으로 패턴 인식, machine vision 등과 같은 분야에 실질적 응용이 가능하다.

ABSTRACT In this paper, optical inplementation of the Hopfield neural network model for two-dimensional associative memory is described For the real-time processing of two-dimensional images, th e commercial LCTVs are used as a memory mask and an input spatial light modulator. A 4-D memory matrix is realized with a 2-D mask of a matrix arrangement and the inner-products between arbitrary input pattern and memory matrix are carried out by using the multifocus hololens. The output image is then electronically thresholded and fed back to the input of the associative memory system by 2-D CCD camera. From the good experimental results for the high error correction capability, the proposed system can be applied to practical pattern recognition and machine vision systems

I. Introduction

It is well known that neural network in brain system process information in parallel with the

*光云大學校 電子工學科
Kwangwoon Univ., Dept. of Electronic Eng.
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aid of large number of simple interconnected processing elements, the neurons. Moreover, the collective properties of this system include some capacity for content addressable memory, pattern recognition, error correction, optimization and categorization, etc. [1]

Recently, it has received considerably increased attention because of Hopfield's detailed exposition of its simple model as associative memory.[2] And the model has been implemented mostly in the form of optical systems based on the optical vecter-matrix multiplier to process one-dimensional(1-D) binary vectors.[3] The main stimuls for such implementation has come from the huge parallelism and global interconnections feasible in optical systems.[4]

However, for the massive parallelism of optics to be utilized fully and for the application in fields such as machine vision and pattern recognition, the real-time two-dimensional(2-D) oiptical associative memory may be of practical interest.[5]

Recently, Jang et al.[6] reported the realization of Hopfield model by using an unfocused holograpic interconnection to process 2-D binary images, and Lin et al.[7] reported optical implementation of the Hopfield model for a 2-D associative memory based on incoherent multiple imaging and correlation.

But, those systems can not be applicable to real-time applications because they used the fixed film mask for memory matrix and the LED array for input display.

Another important feature of a neural network is its capability to learn by changing interconnection weights between neurons. Therefore, to provide the network with learning capability, a programmable spatial light modulator (SLM) is needed as a real-time weighting mask. Fisher et al.[8] used MSLM (Microchannel SLM) to perform optical associative memory of vectors with six elements using the LMS (least-mean-square) learning algorithm and Jang et al.[9] proposed a programmable high-order optical interconnections between 2-D array of neurons by using holographic lenslet array and LCTV SLM. Recently, T.Lu et al.[10] reported a 2-D hybrid optical neural network using a high resolution vedio monitor as a programmable associative memory and optical interconnection systems using photorefractive dynamic holograms[11],[12] are also proposed.

In this paper, we propose a new real-time optical implementation of the Hopfield model for 2-D associative memory by using the multifocus hololens and liquid-crystal television (LCTV) spatial light modulators.

Ⅱ. 2-D Associative Memory System

A digital optical associative memory is a method of optically implementing the associative memory algorithms developed for electronic digital computers. An example of such an algorithm, with a relatively straightforward structure, is the Hopfield neural network model.

The Hopfield model can be considered as a content-addressable memory of auto-associative memory in which the inputs and outputs are same vectors. The 1-D Hopfield model can be summarized as follows. Let $V_i^{(m)}$ be binary vector that is N bits long. M such vectors are stored in a synaptic matrix T_{ij} in accordance to the outer-product recipe

$$T_{ij}=\begin{cases}\sum_{m=1}^{M}(2V_i^{(m)}-1)(2V_j^{(m)}-1) & \text{for } i\neq j\\ 0 & \text{for } i=j\end{cases}\quad(1)$$

where $i,j=1,2,\cdots$, N. and $V_i^{(m)}$ is referred to as the nominal state vector of the memory.

If the memory is addressed by multiplying the matrix T_{ij} with one of the state vectors, say $V_i^{(in)}$, then the output is defined as a vector $V_i^{(out)}$. where

$$V_i^{(out)}=\begin{cases}1 & \text{for } \sum_j T_{ij} V_j^{(in)} \geq 0 \\ 0 & \text{for } \sum_j T_{ij} V_j^{(in)} < 0\end{cases} \quad (2)$$

The dynamics of the model are such that this thresholded output, $V_i^{(out)}$ is then reentered into the system as an input vector. In this manner, information is iterated around the system and ultimately converges to a stable state.

This occurs when vector is unalterd by the operation of Eq.(2), and this condition is satisfied only if that vector has previously been stored in the memory. Therefore, an input vector is associated with one particular memory vector, which becomes the output.

Generally the number of M of state vectors of length N that can be stored at any time in the interconnection matrix T_{ij} is limited to a fraction of N. An estimate of $M \leq 0.15N$ is indicated in simulations involving a hundred neurons or less[2] and a theoretical estimate of $M \leq N/4 \ln N$ for the outer product memory matrix and $M \leq N/(2\pi \ln N)$ for the clipping memory matrix have been obtained.[13][14]

From Eq.(2) it can be seen that there are three processes involved with the association of the input with a memory, namely, multiplication of the input vector $V_j^{(in)}$ with the memory matrix T, thresholding of the resultant vector, and iteration of the information in the system.

Now, we consider the possibility of 2-D optical associative memory system. Compatibility with two-dimensional data format may be of practical interest in applications such as machine vision, and the potential exists for the optical implementation of networks containing larger numbers of neurons if they are arranged in two-dimensions. The scheme is a direct extension of the procedure for formation and readout of memories in 1-D Hopfield model.

Let $V_{ij}^{(m)}$ be M binary images($N\times N$) to be stored, then these images can be stored in a four-dimensional (4-D) memory interconnection in accordance to the outer-product recipe

$$T_{ijkl}=\begin{cases}\sum_{m=1}^{M} (2V_{ij}^{(m)}-1)\ (2V_{kl}^{(m)}-1) & \text{for } i,j\neq k,l \\ 0 & \text{for } i,j=k,l\end{cases} \quad (3)$$

where $i,j,k,l=1,2,\cdots N$, $m=1,2,\cdots M$.

Since we have only three spatial coordinates to work with in an optical system, it is difficult to implement such a fourth-rank system directly. This problem has been approached in several ways.[15][16] One possibility is the use of either wavelength multiplexing and/or time domain processing systems.[16] However this solution may add complexity to the system.

On the other hand, the Hopfield model can be made applicable to 2-D images without any extension. Architectures for optical implementation of 2-D networks must contend with the task of realizing a fourth-rank memory matrix. Here a scheme is presented that is based on the partitioning of the 4-D matrix into an array of 2-D $N\times N$ submatrices and this scheme enables to store 4-D memory matrix in a flat 2-D SLM for use in optical implementation as shown in Fig. 1.[15]

Information is retrieved from this memory by forming the product of an input $V_{ij}^{(in)}$ with the 4-D matrix,

$$V_{ij}^{(out)} = \begin{cases} 1 & \text{for } \sum_{k,l} T_{ijkl} V_{kl}^{(in)} \geqq 0 \\ 0 & \text{for } \sum_{k,l} T_{ijkl} V_{kl}^{(in)} < 0 \end{cases} \quad (4)$$

This thresholded N×N matrix is then used to replace $V_{ij}^{(in)}$ in Eq.(4) for subsequent iterations. The procedure is repeated until the resulting matrix converges to the stored entity closest to the initiating matrix $V_{ij}^{(in)}$,

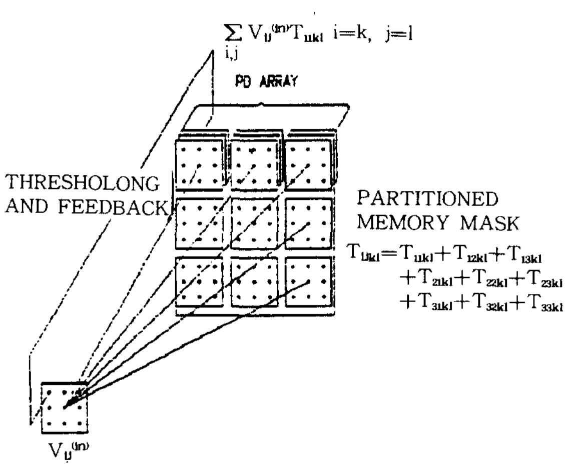


Fig. 1. Partitioning of the 4-D matrix into an array of 2-D N×N submatrices

Several architectures for optical implementation of 2-D Hopfield model have been reported, [6] [7] but those systems could note be applicable to the real-time applications because the fixed memory mask and LED array input were used.

The most distinctive feature of a neural network is learning capability and in many respects it is this aspect that gives neural computation an advantage over alternative conputational strategies. Recently, some optical architectures with high programmability which in principle can be made highly adaptive are reported.[8-12]

Therefore, in this paper, a new real-time optical implementation of the Hopfield model for 2-D associative memory is proposed, in which the commercial LCTVs for real-time memory mask & input spatial light modulator and the multifocus hololens for easy multiplication of input image by each of the partitioned submatrices are used.

The proposed system diagram is shown in Fig.2.

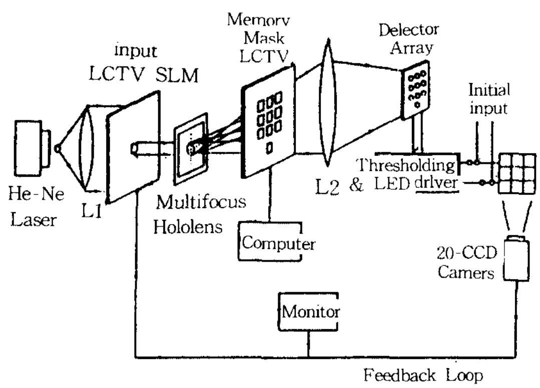


Fig. 2. The proposed system diagram

The operation in Fig.2 can be interpreted as follows. The N×N input entity $V_{ij}^{(in)}$, in Fig.2, is displayed on a LCTV SLM by using the computer graphics. Then the LCTV display of $V_{ij}^{(in)}$ is multiplied by the transmittance of each partition submatrix displayed on the LCTV real-time memory mask by multiple-imaging the input display on each of these with exact registration of pixels by means of a multifocus hololens.

In this system, the multifocus hololens is used to exactly and simply perform the inner-product between input image and memory matrices.[17] Then, the input image multiplied by a corresponding block of the memory mask is focused on the N×N detector array. The output of each photodetector is thresholded, amplified and fed back to the system input by using the 2-D CCD camera.

Since it is inconvenient to build an optical system that contains both positive and negative T_{ijkl} connections, we following Jang et al., [6] add a constant to T_{ijkl} to obtain unipolar T^*_{ijkl} and compensate it with an input-dependent thresholding operation as

$$V_{ij}^{(out)} = \begin{cases} 1 & \text{for } \sum_{k,l} T^*_{ijkl} V_{kl}^{(in)} \geq \sum_{k,l} V_{kl}^{(in)} \\ 0 & \text{otherwise} \end{cases} \qquad (5)$$

where $T^*_{ijkl} = T_{ijkl} + 1$ for all i,j,k,l and T_{ijkl} is assumed to be clipped.

Since T^*_{ijkl} is unipolar(0, 1, 2), it can be optically implemented with intensity modulation or area modulation of the memory mask. The input-dependent thresholding level can be also optically obtained by addition of one thresholding matrix to memory mask. Therefore, only N×N+1 detectors and N×N+1 connection patterns are needed for an N×N-neuron system.[18]

Ⅲ. Experiments

1. Multifocus Holographic Lens

The optical system for making a multifocus hololgraphic lens (hololens) is shown in Fig. 3.[16]

In this system, a specific grating 2-D contact screen S placed at one focal length f_1 in front of the Fourier transform lens L_1 is illuminated by a collimated laser beam. At the back focal plane P_1 of L_1, the Fourier transform of the screen pattern is obtained. As a result of the specific design of the screen an array of spectra foci of nearly the same intensity appears at P_1. A certain pattern of the spectra according to our choice can be selected by spatial filtering. The chosen pattern can then be reimaged at plane P_3 through lens L_2.

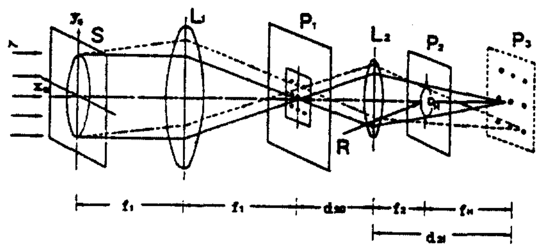
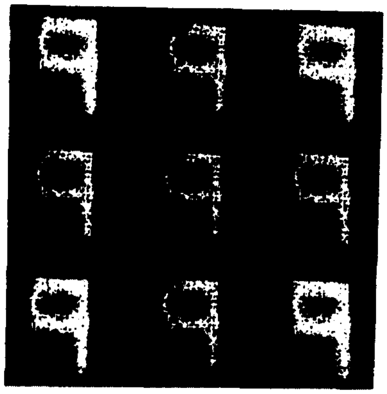


Fig. 3. Optical system diagram for making a multifocus hololens.

For example, in Fig.3, a spatial filter with a square aperture is used for the selection of 9(a 3×3 array) spectra foci at P_1. If we simultaneously introduce a collimated reference beam R and expose a film at plane P_2, a 9-focus holoens with a common aperture of diameter D_H can be obtained. The number of foci and their positions can be varied within certain limts by varying the spatial filtering process.

In this paper, we made a 3×3 multifocus hlolens in holographic film (Agfa 10E75) by using a new methjod of bleaching for high diffreaction efficiency.[19] The hololens has 2.3cm of diameter and about 13.03% of diffraction efficiency.

In Fig.4, we have shown the multiple-image reconstruction using the 9-focus hololens with a LCTV input of character "9" and each light intensity of 3×3 image array which is measured by optical power meter (NRC Model 8 15).



(a)

1.45	1.07	1.43
1.10	0.96	1.07
1.44	1.08	1,42

(b)

Fig. 4. (a) 3×3 image reconstruction using 9-focus hololens
(b) Measured each light intensity of 3×3 image array (unit: 10μW)

From Fig.4(b), it can be seen that each 3×3 image has a little bit of different intensity. But, we can compensate for the nonumiformity of each intensity of 3×3 image array just by adjusting the variable resistors of electronic cirucits containing CdS photodetector array in Fig.2.

2. System description

We have built a 3×3 neuron system employing a LCTV input spatial light modulator, 3×3 multifocus hololens, LCTV memory mask and a photodetector array as shown in Fig. 2. In this system, we use two commercial LCTVs as a 2-D input SLM and a realtime memory mask. Thus, we can simply change the representation of memory mask and input image display through the computer graphics connected to the LCTVs. Accordingly, this proposed system is more feasible in real-time processing of 2-D associative memory than any other systems.

Our experiments have been performed with a black-and-white LCTV (Model CASIO TV-200) with a 5.4 cm by 4.4 cm screen. The resolution is typically 146 horizontal elements by 120 vertical elements that are each 370μm by 370μm square. The dimension of 3×3 input image is 8.5 mm by 8.5mm composed of 23 by 23 pixels of LCTV SLM.

Because the built-in polarizers of commercial LCTV is not optically flat and poor in quality, there is a phase distortion and reduction of contrast. Therefore for our application, commercial LCTV has been modified by replacing the two polarizers attached to the LCTV with a high quality external polarizer and polarized input He-Ne laser beam (NEC Model GL G5 350, 10mW).

The connectivity weights in this system were stored in a realtime LCTV memory mask which was formed with the help of computer graphics connected to the LCTV in the following manner; starting from a set of unipolar binary matrix V_{ij} to be stored in the net, the required 4-D connectivity tensor was obtained by computing the sum of the outer-products of the bipolar binary versions, the resulting connectivity was partitioned and stored at their appropriate locations in a LCTV memory mask placed in the image plane of the multifocus hololens by computer graphics.

A CdS photodetector array (Model 2 PK-62L, diameter: 6.5mm) is used to detect inner-product between input matix and each of the submatrixes of the partitioned memory mask. A 2-D LED array is used to initialize input matix and display the outputs after electronic thresholding operation. Thresholded outputs are feedback to the input LCTV SLM by using 2-D CCD camera. In this way, next iteration is excuted successively in real-time.

3. Experimental results

In our experiment, two binary images which represent the letters "T", "L" are stored in the 3×3 neuron system.

$$T=\begin{bmatrix}1 & 1 & 1\\ 0 & 1 & 0\\ 0 & 1 & 0\end{bmatrix} \quad L=\begin{bmatrix}0 & 0 & 0\\ 1 & 0 & 0\\ 1 & 1 & 1\end{bmatrix}$$

The 4-D memory matrix T^*_{ijkl}, which is a biased version of T_{ijkl}, can be calculated from two binary images, where i,j,k,l=1,2,3, and partitioned into a 2-D array of 2-D submatrices; T^*_{11kl}, $T^*_{12kl},\cdots,T^*_{32kl}$, T^*_{33kl}. These nine 3×3 interconnection patterns with a thresholding mask are shown in Fig.5. Each 3×3 interconnection pattern is displayed onto the LCTV real-time memory mask using computer graphics. Each biased binary levels of 0,1,2 can be represented by gray levels of 0, 127, 255 respectively by computer graphic programming and optically implemented by using the ligth transmittance modulation of LCTV spatial light modulator based on computer gray levels.[18]

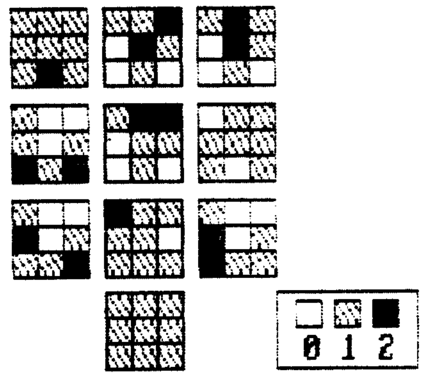


Fig. 5. Nine 2-D memory matrices and one thresholding mask.

We set LED arraty to display initial input matrix and the input is fed back to a LCTV input SLM.

Mulifocus hololens is used to spatial multiplex and project the input display onto each of the submatrixes of the partitioned memory mask. The product of the input matrix with each of the weights stored in each submatrix is formed with the help of a spatially integrating square photodetector of suitable size positioned behind the imaging lens L_2 followed by each submatrix. Input-dependent thresholding level can be obtained from the zeroth-order diffracted beam multiplied with a thresholding mask.[5]

The results of the inner-product is focus on each CdS array by large imaging lens L_2 (focal length: 9cm, diameter: 10.2cm) as shown in Fig.2.

The output of each CdS array is thresholded, amplified and displayed on LED array. The results displayed on LED array is fed back to the input LCTV by using the 2-D CCD camera (SONY Model XC-38). In this way, next iteration is excuted successively in real-time. Experimental results of the associated

(a)

(b)

(c)

Fig. 6. Experimental results:
(a) erroneous input "L" and "T" displayed on input LCTV SLM
(b) associated output of "L" and"T" in front of CdS photodetedctor array before thres holding
(c) associated output of "L" and "T" fed back to input LCTV SLM after thresholding.

outputs to the partial and erroneous input images of letters "T", "L" are shown in Fig. 6.

We set LED array to display initial erroneous input matrix and the input is fed back to input LCTV as a system input by using 2-D CCD camera. Fig. 6(a) shows initial erroneous input matrix displayed on LCTV SLM. The input matrix is multiplied to memory matrices by multifocus hololens and ten of inner-products are occurred. The inner-products are imaging on CdS photodetector array. Fig.6(b) shows ten of inner-products in front of CdS photodetector array before thresholding; nine of them are the inner-products between input matrix and memory matrices and the other is the inner-product between input matrix and thresholding level. The inner-products between input matrix and memory matrices are compared with inner-product between input matrix and thresholding level and are electrically thresholded. After thresholding, the associated output image is fed back to input LCTV SLM. Fig. 6(c) shows final associated output displayed on input LCTV SLM. We can see the mesh pattern of LCTV in Fig. 6. Because the number of input bits is small, erroneous input image is corrected after one iteration in our experiment.

It is seen that although memory capacity is decreased by clipping for easy optical imple nentation, this system shows a error correction capability, Therefore, when an initial input contains a few errors, this system finds the stored image that has the shortest Hamming distance from the output images.

From this experimental reuslts, it can be seen that using commercial LCTV as a memory mask makes possible real-time processing and the parallel inner-product betwwen input image and memory matrices by multifocus hololens is demonstrated.

Ⅳ. Conclusion

The optical implementation of associative memory has recently received considerable attention. In particular, for the massive parallelism of optics to be utilized fully and for the application in fields such as machine vision and pattern recognition, the real-time 2-D optical associative memory may be of practical interest.

Therefore, in this paper, a new real-time optical implementation of the Hopfield model for 2-D associative memory was proposed, in which the commercial LCTVs for programmable memory mask and 2-D input spatial light modulator were used.

From our experimental results, it is shown that although memory capacity is decreased by clipping the memory matrix for easy optical implementation, this proposed system still shows a error-correction capabiltiy and can be applicable to real-time processing of 2-D associative memory.

We also discussed the advantages of this sytstem and demonstrated its capability of error-corrective association.

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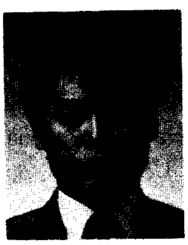
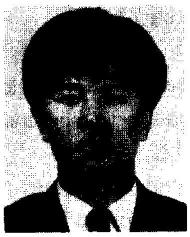
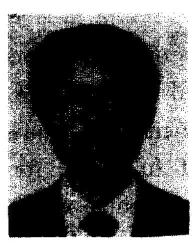


韓 鍾 旭(Jong Wook HAN) 準會員
1965年 9 月17日生
1989年 2 月 : 光云大學校 電子工學科 卒業. 工學士 取得.
1989年~現在 : 光云大學校 大學院 電子工學科 碩士課程 在學中.
※主關心 分野는 Optical Neural Network, 光情報處理, 光패턴認識, Optical Computing 等임.

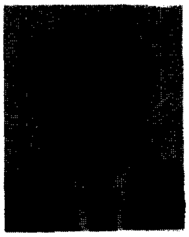
朴 仁 虎(In Ho PARK) 準會員
1965年 3 月15日生
1988年 2 月 : 光云大學校 電子工學科 卒業. 工學士 取得.
1990年 2 月 : 光云大學校 大學院 電子工學科 卒業. 工學碩士 取得.
1990年 3 月~現在 : 泰光產業株式會社 開發部 研究員.
※主關心 分野는 Optical Neural Network, 光情報處理, 光패턴認識, Optical Computing等임.



李 丞 玄(Seung Hyun LEE) 正會員
1961年12月25日生
1984年 2 月 : 光云大學校 電子工學科 卒業. 工學士 取得.
1986年 2 月 : 光云大學校 大學院 電子工學科 卒業. 工學碩士 取得.
1989年 3 月~現在 : 光云大學校 大學院 電子工學科 博士過程 在學中
※主關心 分野는 Optical Neural Network, 光情報處理, 光패턴認識, Optical Computing等임.



李 禹 相(Woo Sang LEE) 正會員
1956年10月 3 日生
1983年 2 月 : 光云大學校 電子工學科 卒業. 工學士 取得.
1985年 2 月 : 光云大學校 大學院 電子工學科 卒業. 工學碩士 取得.
1985年 8 月~現在 : 光云大學校 大學院 電子工學科 博士過程 在學中
※主關心 分野는 Optical Neural Network, 光情報處理, 光패턴認識, Optical Computing等임.



金 恩 洙(Eun Soo KIM)　　正會員

1955年 8月 1日生

1978年 2月 : 延世大學校 電子工學科 卒業.

1980年 2月 : 延世大學校 大學院 電子工學科 卒業. (工學碩士)

1984年 2月 : 延世大學校 大學院 電子工學科 卒業.(工學博士)

1987年 2月～1988年 8月 : Caltech 電氣工學科 客員教授.

1981年 3月～現在 : 光云大學校 電子工學科 副教授.

※主關心 分野는 Optical Neural Network, 光情報處理, Learning Algorithm, Optical Computing, 光패턴認識 等임.