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Computer Vision and Neuro－Net Based Automatic Grading of a Mushroom(*Lentinus Edodes L.*)

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컴퓨터시각과 신경회로망에 의한 표고등급의 자동판정

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Abstract

Visual features of a mushromm(*Lentinus Edodes L.*) are critical in sorting and grading as most agricultural products are. Because of its complex and various visual features, grading and sorting of mushrooms have been done manually by the human expert. Though actions involved in human grading look simple, a decision making underneath the simple action comes from the result of the complex neural processing of visual image.

Recently, an artificial neural network has drawn a great attention because of its functional capability as a partial substitute of the human brain. Since most agricultural products are not uniquely defined in its physical properties and do not have a well defined job structure, the neuro－net based computer visual information processing is the promising approach toward the automation in the agricultural field.

In this paper, first, the neuro－net based classification of simple geometric primitives were done and the generalization property of the network was tested for degraded primitives. And then the neuro－net based grading system was developed for a mushroom. A computer vision system was utilized for extracting and quantifying the qualitative visual features of sampled mushrooms. The extracted visual features of sampled mushrooms and their corresponding grades were used as input/output pairs for training the neural network. The grading performance of the trained network for the mushrooms graded previously by the expert were also presented.

Key words : mushroom, computer vision, neural network, automatic grading

Introduction

Quality of a dried nushroom(*Lentinus Edodes L.*) depends mainly on the content of the moisture and visually characterized external features which can be affected by the growing environment, drying

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process, handling and so on.

The price difference in the market corresponding to the quality level is rather high compared to other agricultural products. What is worse, the low quality mushroom has a difficulty to be sold.

So far, sorting mushrooms has been roughly done manually and grading has been performed via inspecting randomly selected sample mushrooms by the certified expert. Though grading criterion is specified, its specification is quantitatively rough and includes qualitative description. Besides, it differs from each country such that the classification in Japan is 6 types with 16 grade levels even 3 types with 12 grade levels in Korea. In most cases, the grading criterion of agricultural products can not be specified precisely in the quantitative sense. In a case of a dried mushroom, the ambiguity of the grading criterion increases even more because of the complex and fuzzy external shape factors distributed over the front and back sides of the cap.

Generally, human expert is the best in grading the individual mushroom but he is usually lack of the consistency and the overall productivity becomes low because of the fatigue and the illusion. Therefore, it is required to develop an automatic sorting and grading system which preserves the consistency of grading and improves the efficiency similar to the human like robust visual data processing.

Recent advances in the fields of artificial neural network have opened the way to a new approach to pattern recognition fields. Since the neural network offers many advantages over the previously developed pattern recognition algorithms, many research efforts have been reported related to neuro-net based visual perception and system control[1,3,4,6]. In a word, the neural net is known to be good(poor) at solving problems which human is good(poor) at. High computing rate, a great degree of the fault tolerance provided by massively parallel information processing, and the capability of the learning and the generalization are the most notable advantages.

This paper aims to develop the neuro-net based efficient mushroom grading algorithm utilizing the quantitative features obtained from the computer vision system.

Visual feature oriented neuro-net grading

The computer vision system used is composed of the IBM PC compatible 486DX2/66, ITEX PCvision Plus frame grabber, B/W CCD camera, VGA graphic monitor, and RBG monitor for image output. The functional block diagram of training the grading aspect of the human expert and the process of grading via trained network is shown in fig. 1.

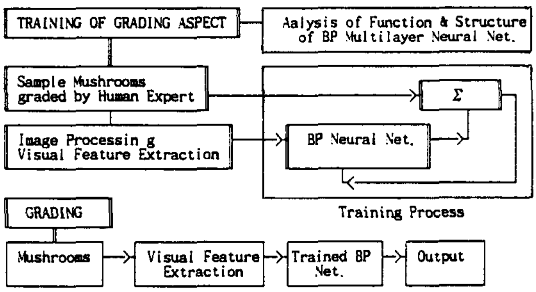

Fig. 1. Block diagram of image processing and grading by BP network.

Recognizing the contents of the raw image directly without extracting any characteristic feature is desirable. Since human, however, often percepts the visual image with ease from the characteristics of the extracted features rather than from the raw image, the network was also trained by inputing the extracted quantitative features obtained from the computer image processing instead of the raw image.

Grading criterion(6 types with 16

grades) specified in Japan was used and sample mushrooms were randomly selected and graded by the expert beforehand. These grading results were used for training network.

1. Generalized error back propagation network

In this section, the structure and learning function of the well known BP network are briefly explained. The error back propagation(BP) network is a muti-layered network generalizing the delta rule for the connection weight adjustment. Delta rule is a kind of the network training algorithm which was developed for networks with linear units whose activation function is defined as linear. The structure of the BP network is the same as multi-layered perceptron but the connection weights among nodes are adjusted by back propagating the output error. And network training is done in the supervised way.

The BP network consists of three or more layers. The bottom layer of the network is called as input, the most upper layer is called as output and intermediate layers are called as hidden layers. Each layer has a number of units, called neurons. Each unit of the input layer may represent an element of a pattern vector given form the outside or independently represent a certain sensory input. Magnitudes of all inputs are usually normalized to have similar ranges. Each unit is connected to all units in the layer above. Given problem, after specifying structures of the input and output layers, the optimum number of intermediate layers and units in each intermediate layer are usually decided as an ad hoc basis.

Each unit of the BP network has a nondecreasing and differentiable semi-linear activation function. A sigmoid type logistic function is frequently used for the activation function. Since the logistic function asymptotically reaches 0 and 1, target output is often set as values near 0 and 1. Except for the units in the input layer, the net input to each unit is the sum of the weighted outputs of the units in the prior layer. The net input to a unit j from the units in the previous layer is defined as follows.

$$net_j = \Sigma w_{ji} o_i \tag{1}$$

where, w_{ji} is the connection weights from unit i of the previous layer to unit j and o_i is the output of the unit i. Initially every connection weight is assigned with small random values to avoid a certain training pathology caused by the weight symmetry[5].

The output of unit j is defined as

$$O_j = f(net_j) \tag{2}$$

where, f is an activation function. A sigmoid type logistic activation function is defined as

$$o_j = \frac{1}{1+\exp[-(net_j+\theta_j)]} \tag{3}$$

where, θ_j is a bias of neuron i and a bias is similar to threshold. Bias offsets the origin of the logistic activation function and has an effect of the rapid convergence of training. Since input units do not have a bias, practically dummy unit whose output is one is assigned at each layer.

Training of the network is done iteratively. Terminating conditions such as maximum number of iterations or tolerance of the total trained error are required. Error at each output unit computed from comparing with desired target value is propagated backward through the network and is used to adjust the connection weight. For given sets of input patterns or images, overall measure of the trained error is defined as

$$E = \Sigma E_p = \frac{1}{2}\Sigma\Sigma(t_{pj} - o_{pj})^2 \tag{4}$$

Where, p denotes a single input pattern.

The idea of the error back propagation learning rule is based on the gradient descent approach which adjusts weights proportional to the negative of the derivative of the ovarall trained error with respect to each weight. Details on implementing the generalized delta rule to the gradient descent approach refer to McClelland and Rumelhart[5].

The connection weight is adjusted such that

$$[w_{ji}]_{NEW}=w_{ji}+\Delta w_{ji}$$
$$\Delta w_{ji}=\zeta\delta_j o_i \quad (5)$$

Where, δ_j is error computed for the output and hidden layers. Details on computing δ_j also refer to McClelland and Rumelhart[5]. And ζ denotes a learning rate. Large learning rate allows fast system learning but usually it brings out the system oscillation caused by the large amount of the change in the weight.

One of the ways to increase the learning rate reducing the learning oscillation has been reported as follows.

$$\Delta w_{ji}(t+1)=\zeta\delta_j o_i+\alpha\Delta w_{ji}(t) \quad (6)$$

Where, α denotes the momentum rate which determines the effect of the past weight changes on the current direction of the movement in the weight space. Great deal of research efforts is still on going to improve the performance of the BP network related to the topics such as training efficiency, optimum structure, network paralysis, local minima, post processing of output, etc.

The BP training is done by two stages forward and backward. At the forward stage, sets of input and output pattern pairs are presented and network output is computed. Then at the backward pass, error signals obtained from the final layer are back propagated. Details on the process refer to McClelland and Rumelhart[5] or Pao[6].

2. Classification of simple geometric primitives

First, the training performance of the BP network was simulated using the sampled simple geometric primitives such as polygons and circle to visualize the capability of the network. Visual features such as complexity, roundness, the ratio of the maximum to the average distance from the centroid to the boundary, and the ratio of the average to the minimum distance from the centroid to the boundary were quantified using the computer vision system. Selected features are independent of scale, location, and orientation of the object image. And each input feature was rescaled to have similar ranges of values.

The structure of the network was formed as 4 input units, 5 hidden units, and 3 output units. Table 1 shows 7 sample primitives used for the network training, corresponding quantitative values of visual features, desired output values for the classification, and output of the trained network for each sample image. In programming, target values of 0 and 1 were converted to 0.05 and 0.95 considering characteristics of a logistic activation function. The normalized system training error which is the squared sum of target and output differences over the total numer of input samples was set 0.001. As shown in table 1, the network was trained well enough to calssify correctly given samples.

Using the trained network, the classification of the untrained and degraded primitives were tested. Table 2 shows the classification results obtained. The generalization property of the network enables to generate the quite reasonable and robust outputs to the fuzzy and degraded inputs.

3. Mushroom grading

Since all the sample mushrooms for each grade were not abailable, 21 sampled mushrooms(3 per each grade) were graded first by the expert as 4 types with 7 grade levels. Seven visual features were selected and quantified via computer vision system and used for the network training. Selected visual features were shape, color, state of the crack, texture of the skin, average radirus, thickness and the membrane state.

Table 1. Training classification of simple geometric primitives(R:roundness, CR:complex Ratio, DO:desired output, M/A:max. to avg. radius ratio, A/M=avg. to min. radius ratio, TNO:trained network output).

Feature / Samples	R	CR	M/A	A/M	DO			TNO		
	1.477	0.834	0.875	0.750	1	1	1	0.952	0.947	1.000
	0.893	1.380	1.308	1.207	1	1	0	0.952	0.940	0.002
	1.413	0.871	0.908	0.764	1	0	1	0.947	0.055	1.000
	0.877	1.405	1.383	1.371	1	0	0	0.949	0.062	0.053
	1.287	0.957	1.033	0.821	0	1	1	0.052	0.951	0.949
	1.103	1.117	1.183	1.071	0	1	0	0.050	0.996	0.052
	1.027	1.200	1.133	1.464	0	0	1	0.049	0.018	0.948

Table 2. Trained network output for unknown degraded samples(R:roundness, CR:complex ratio, M/A: max. to avg. radius ratio, A/M:avg. to min. radius ratio, TNO:trained network output).

Feature / Samples	R	CR	M/A	A/M	TNO		
	1.460	0.844	0.850	0.771	0.952	0.886	1.000
	1.012	1.218	1.300	1.057	0.789	0.997	0.001
	1.377	0.895	0.925	0.843	0.917	0.019	1.000
	0.968	1.272	1.367	1.400	0.855	0.032	0.194
	1.287	0.964	1.017	0.893	0.021	0.984	0.853
	1.162	1.061	1.267	1.007	0.043	0.998	0.038
	1.018	1.210	1.275	1.557	0.330	0.015	0.756

Shape, size, and color(degree of brown color) of a mushroom cap were quantified as roundness, average radius, and overall average gray value respectively. State of the crack on the cap skin was quantified as summed deviation between average gray value of each quadrant and overall intensity of the mushroom cap image. The texture of the skin was evaluated using the weighted sum of overall gray value and the crack state. Thickness and the membrane state were quantified as the amount of rolled skin edge and the average gray value of the membrane respectively, Values of input features were rescaled to have values in the range 0 to around 1. Details on quantifying visual features refer to Han[2].

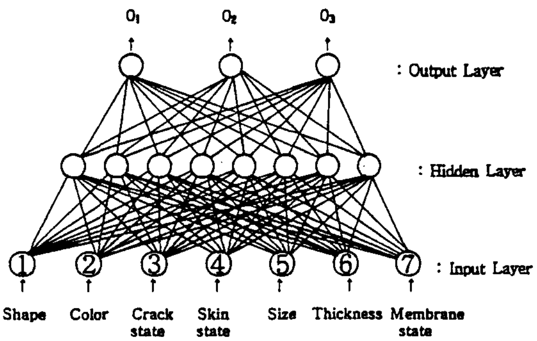

Fig. 2. A sturcture of the generalized error BP network and visual input features.

As shown in fig. 2, the network structure was formed with 7 units for the input, 8 units for the hidden, and 3 units for the output layer. 3 units in the output layer can classify all the input patterns into 8 categories. Learning and momentum rates were assigned as 0.7 and 0.9 respectively, Maximum normalized system training error was set as 0.05 and maximum number of iteration was set as 3000. Table 3 shows the quantitative input features extracted from processing the camera captured visual images of 7 graded 21 sample mushrooms. As shown in table 4, the network was trained well enough to classify sample mushrooms correctly. Grading result of the trained network for the arbitrarily chosen 40 mushrooms from the previously graded ones was perfect. Since network results involved a large amount of numeric data, they were omitted in this paper.

Finally, the network has been trained using 50 sample mushroom data for full grading of 6 types with 16 levels according to the grading criterion specified in Japan. Since samples per every grade level were not available, the visual data for the missing samples were made artificially by carefully inspecting real scaled pictures and descriptions of a mushroom presented in the shitake grading catalog in Japan.

The network struture was formed with 7 units for the input, 8 units for the hidden, and 4 units for the output layer. 4 units in the output layer can classify all the input patterns into 16 categories. Since selecting the optimum number of processing units in the middle layer is not that significant and not critical in the network performance for our task, 8 units for the hidden layer were selected experimentally after trying various numbers of units. Learning and momentum rates were assigned as 0.7 and 0.9 respectively.

To improve the training efficiciency, 50 samples were separated into 5 sets. First, a set having 10 samples was trained and then consecutively next set was added and trained using the pretrained weight data. This consecutive training scheme reduced a great deal of training time compared with training whole samples at one shot. The number of iterations for each training stage is shown in table 5. In this paper because of a large amount of the mumeric results for 50 samples we showed the parts of values of input visual features of 50 sample mushrooms used for training and target output values in table 6. Training was done successfully and table 7 shows parts of the trained results.

Table 3. Input features of 7 graded 21 sample mushrooms(3 per grade level) and target value of each grade level(L:large size M:medium size S:small size HQ:high quality LQ:low quality).

Feature / Samples	Shape	Color	Crack	Skin State	Size	Thickness	Memb. State	Output Target Value		
Hwago (L)	0.833	0.70	0.50	0.73	0.24	1.05	0.81	1	1	1
	0.840	0.72	0.55	0.75	0.25	1.15	0.91			
	0.843	0.81	0.53	0.81	0.25	1.20	0.88			
Hwago (S)	0.737	0.72	0.50	0.73	0.18	0.70	0.85	1	1	0
	0.807	0.70	0.52	0.74	0.18	0.71	0.87			
	0.827	0.80	0.51	0.79	0.18	0.75	0.87			
Donggo (HQ.L)	0.807	0.55	0.28	0.66	0.18	0.90	0.87	1	0	1
	0.811	0.57	0.31	0.67	0.18	0.88	0.88			
	0.800	0.48	0.25	0.65	0.18	0.87	0.85			
Donggo (HQ.M)	0.807	0.53	0.25	0.65	0.22	1.15	0.88	1	0	1
	0.800	0.54	0.27	0.65	0.23	1.08	0.89			
	0.801	0.46	0.33	0.67	0.23	1.34	0.89			
Hyanggo (HQ)	0.830	0.66	0.40	0.60	0.29	1.21	0.85	0	1	1
	0.830	0.64	0.39	0.65	0.34	1.30	0.85			
	0.829	0.67	0.41	0.63	0.32	1.33	0.87			
Hyanggo (LQ)	0.790	0.55	0.28	0.35	0.30	0.42	0.86	0	1	0
	0.820	0.53	0.30	0.35	0.31	0.40	0.86			
	0.830	0.57	0.32	0.38	0.31	0.40	0.85			
Bad	0.560	0.29	0.58	0.19	0.11	0.00	0.60	0	0	1
	0.500	0.35	0.61	0.14	0.21	0.01	0.51			
	0.525	0.25	0.72	0.18	0.41	0.02	0.63			

Table 4. Trained results of 21 sample mushrooms (L:large size M:medium size S:small size HQ:high quality LQ:low quality).

Output / Samples	Output 1	Output 2	Output 3	Target Value		
Hwago (L)	0.9946	0.8795	0.6290	1	1	1
	0.9900	0.8900	0.8536			
	0.9820	0.9092	0.9371			
Hwago (S)	0.9676	0.9402	0.1409	1	1	0
	0.9668	0.9317	0.1313			
	0.9797	0.9397	0.1671			
Donggo (HQ.L)	0.9996	0.0002	0.9945	1	0	1
	0.9999	0.0002	0.7518			
	0.9111	0.0148	0.9063			

(continued)

Output / Samples	Output 1	Output 2	Output 3	Target Value		
Donggo (HQ.M)	0.9999	0.0001	0.0345	1	0	0
	0.9999	0.0003	0.0333			
	0.9626	0.0034	0.0046			
Hyanggo (HQ)	0.2969	0.9484	0.9999	0	1	1
	0.0951	0.9628	0.9999			
	0.0821	0.9608	0.9999			
Hyanggo (LQ)	0.1713	0.9235	0.0183	0	1	0
	0.1596	0.9280	0.0190			
	0.0568	0.9880	0.0273			
Bad	0.0940	0.0000	0.9754	0	0	1
	0.0018	0.0129	0.9946			
	0.0014	0.0096	0.9964			

Table 5. The number of iterations and normalized system errors of each stage training.

Stage	Sample No.	Iterations	Normalized System Errors
1	10	717	0.047826
2	20	934	0.047369
3	30	89	0.047675
4	40	374	0.048761
5	50	618	0.046767

Table 6. Parts of input features of 16 graded 50 sample mushrooms and target values of each grading (L: large size M: medium size S: small size HQ: high quality LQ: low quality).

Feature / Samples	Shape	Color	Crack	Skin STate	Size	Thickness	Memb. State	Output Target Value
Hwago(L)	0.84	0.72	0.55	0.75	0.25	1.15	0.91	1 1 1 1
Hwago(S)	0.81	0.70	0.52	0.74	0.18	0.71	0.87	1 1 1 0
Donggo(HQ.L)	0.80	0.52	0.25	0.65	0.22	1.05	0.86	1 1 0 1
Donggo(HQ.M)	0.81	0.55	0.30	0.68	0.18	0.89	0.87	1 1 0 0
Donggo(LQ.L)	0.80	0.44	0.32	0.27	0.23	0.36	0.88	1 0 1 1
Donggo(LQ.M)	0.80	0.48	0.25	0.25	0.18	0.29	0.85	1 0 1 0
Donggo(S)	0.79	0.45	0.33	0.35	0.19	0.23	0.87	1 0 0 1
Hyanggo(HQ)	0.83	0.64	0.39	0.65	0.34	1.30	0.85	1 0 0 0
Hyanggo(LQ)	0.82	0.53	0.30	0.35	0.31	0.40	0.86	0 1 1 1
Hyanggo(HQ.L)	0.74	0.46	0.25	0.26	0.33	0.21	0.79	0 1 1 0
Hyanggo(HQ.M)	0.75	0.48	0.29	0.29	0.26	0.19	0.78	0 1 0 1
Hyanggo(HQ.S)	0.72	0.49	0.26	0.25	0.15	0.15	0.75	0 1 0 0
Hyanggo(LQ.L)	0.62	0.43	0.35	0.20	0.33	0.12	0.73	0 0 1 1
Hyanggo(LQ.M)	0.60	0.38	0.37	0.26	0.26	0.09	0.74	0 0 1 0
Hyanggo(LQ.S)	0.60	0.41	0.34	0.26	0.16	0.07	0.70	0 0 0 1
Bad	0.46	0.25	0.50	0.17	0.31	0.02	0.55	0 0 0 0
	0.56	0.29	0.58	0.19	0.11	0.00	0.60	

Table 7. Parts of trained results of 50 sample mushrooms (L: large size M: medium size S: small size HQ: high quality LQ: low quality).

Output / Samples	Output 1	Output 2	Output 3	Output 4	Target value
Hwago(L)	0.99987	0.90017	0.97230	0.99995	1 1 1 1
Hwago(S)	0.99999	0.99089	0.97907	0.00010	1 1 1 0
Donggo(HQ.L)	1.00000	0.99997	0.00000	0.94827	1 1 0 1
Donggo(HQ.M)	1.00000	0.99999	0.00012	0.01517	1 1 0 0

(continued)

Output / Samples	Output 1	Output 2	Output 3	Output 4	Target value
Donggo(LQ.L)	0.99927	0.00033	0.99998	0.99947	1 0 1 1
Donggo(LQ.M)	0.99136	0.03110	0.99950	0.00003	1 0 1 0
Donggo(S)	0.99975	0.00002	0.00074	1.00000	1 0 0 1
Hyanggo(HQ)	1.00000	0.09342	0.00003	0.02272	1 0 0 0
Hyanggo(LQ)	0.04268	0.99463	1.00000	0.99735	0 1 1 1
Hyanggo(HQ.L)	0.00000	0.99999	0.99998	0.00114	0 1 1 0
Hyanggo(HQ.M)	0.00000	0.99998	0.04846	0.99329	0 1 0 1
Hyanggo(HQ.S)	0.00265	0.99233	0.00008	0.04442	0 1 0 0
Hyanggo(LQ.L)	0.00000	0.00028	0.99999	0.97879	0 0 1 1
Hyanggo(LQ.M)	0.00000	0.00000	0.96916	0.01943	0 0 1 0
Hyanggo(LQ.S)	0.02629	0.03593	0.00001	0.64039	0 0 0 1
Bad	0.00000	0.00000	0.09049	0.00751	0 0 0 0
	0.00000	0.00000	0.04726	0.00507	

Conclusion

In this paper, we proposed the relatively robust mushroom grading system which can mimic human's grading capability while keeping consistency and improving the productivity, Using multilayer error back propagation network, grading of a dried mushroom(*Lentinus Edodes L.*) was successfully done via inputing quantitative visual features obtained from the computer vision system. Grading capability of the proposed scheme was perfect for samples used for training.

Once the network is trained, grading is performed in a sense of the open loop. To improve the grading accuracy of the network, it is suggested that enough samples per each grade level be trained. Because of the generalization property of the network there will be no problem to grade unknown mushrooms once the network is fully trained with enough samples. Collecting misgraded samples and retraining the previously trained network with previous samples and misgraded ones will improve the grading performance of the network and reduce the training period.

Futher research on direct training of raw image input is suggested to realize the real time implementation of the neuro−net based mushroom grading system.

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요 약

대다수 농산물과 마찬가지로 건조표고의 등급판정은 외관특징에 주로 의존한다. 표고 갓의 전후면에 걸친 복잡하고 다양한 외관특징들로 인하여 표고의 등급판정은 임의로 추출한 표고샘플에 대하여 전문가가 수작업으로 판정하고 있으며, 선별작업 역시 전적으로 수작업에 의존하고 있다. 단순한 반복작업으로 보이는 농산물의 등급판정은 사실 시각과 촉각을 위시한 고도의 감각신경계를 통하여 상호 복잡하게 얽혀 들어오는 정보를 지능적으로 처리하는 고기능의 작업이다.

농산물의 경우, 외관특성을 비롯한 물성은 종류별로 그 경계치를 일괄적으로 명확하게 규정할 수 없기 때문에 대개는 오차를 포함한 통계적 접근에 의하여 규정하고 있다. 따라서 농산작업에 있어서는 농산물 물성이 갖는 모호성을 효율적으로 처리할 수 있는 가변적인 작업구조 및 정보처리가 필수적으로 요구된다.

본 연구에서는 인간 뇌의 정보처리 기능을 부분적으로 구현할 수 있는 인공신경회로망을 컴퓨터시각 시스템에 적용하여 단순 기하도형의 분류 및 표고의 등급판정을 성공적으로 수행하였다. 회로망 입력으로는 컴퓨터시각 시스템을 이용하여 건조표고의 정성적 외관특징을 자동으로 추출한 후 정량화한 특징점 값들을 이용하였다. 신경회로망의 학습은 표본추출한 등급표고와 이들의 정량적 특징점 값들을 입출력쌍으로 하여 수행하였다. 학습한 회로망의 등급판정 성능시험은 표본추출한 미지의 표고에 대한 컴퓨터 영상 특징점 값들을 입력하여 수행하였다.

키 워 드 : 표고, 컴퓨터시각, 신경회로망, 자동등급판정