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Development of Robust Feature Recognition and Extraction Algorithm for Dried Oak Mushrooms+

건표고의 외관특징 인식 및 추출 알고리즘 개발

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적 요

표고의 외관 특징들은 표고의 재배시 생육상태의 정량적 측정을 위해서, 표고의 건조시 건조 성능을 나타내는 정량적 지표로서, 그리고 건표고의 품질을 판정하는 요인으로서 중요한 역할을 한다. 본 논문에서는 컴퓨터 시각시스템 및 신경회로망 기술을 적용하여 표고의 갓 및 내피에 고루 분포되어 있는 외관특징을 정량적으로 추출하는 알고리즘을 개발하였다. 기존의 영상 처리 과정에서 유도되는 경험적 판정규칙 또는 명확한 수치적 판정조건에 의한 등급판정은 입력데이타의 결핍 또는 애매모호성에 따른 오차가 발생하기 쉽다. 신경회로망을 이용한 영상인식 기능을 도입함으로써 다양하고 애매모호한 표고의 외관 영상특징들을 효율적으로 처리하여 기존 영상처리 알고리즘에서 발생하는 오차를 개선하였다. 본 논문에서 제안하는 알고리즘은 표고의 갓과 내피면의 인식 및 특징 분할, 꼭지부의 검출, 제거 및 재생 등을 포함한다. 제안한 알고리즘에 의거하여 건표고의 등급판정에 주요한 품질인자들을 추출하고 정량화하였다. 그리고 알고리즘의 개발은 흑백의 다치입력영상을 이용하여 수행하였다.

주요 용어(Key Words) : 외관특징추출(Visual Feature Extraction), 건표고(Dried Oak Mushrooms), 컴퓨터시각(Computer Vision), 형상인식(Feature Recognition), 신경회로망(Neural Network)

1. INTRODUCTION

Quality of a dried oak mushroom(*Lentinus Edodes L.*) depends mainly on the content of the moisture and external features which are visually characterized and affected by the growing environment, the drying process, handling etc. Automatic quality evaluation of dried oak mushrooms is one of the challenging tasks because of its complex external characteristics.

It is very important to identify the stipe, the protruding portion, or the certain shaped joint part of agricultural products such as carrot, onion, strawberry, tomato etc. for the automation of the related processing and the correct measurement of some quality features. Researches on this topic have been reported for various agricultural products(Batchelor et. al., 1988, Giacomelli et. al., 1981, Langers, 1991). But as far as the identification rule depends on the

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quantitative geometrical or visual features of the given image, it has a deficiency in the robust identification. Since most agricultural products have their own unique but irregular visual features, none are exactly the same. Therefore, it is required to develop feature extraction algorithms which preserve the consistency of robust visual data processing. In this paper, artificial neural network was adopted to overcome this deficiency.

2. MATERIALS AND METHOD

A B/W CCD camera was used for the image sensing and PFG board(Imaging Technology Inc.) was used to digitize and store the incoming video signal. To obtain the geometrical information of oak mushrooms, Freeman's chain coding and Kitchin's vector searching algorithm were modified to ensure the continuous boundary extraction and to obtain directly real scaled values of features.

Primary qualitative visual features of a dried oak mushroom are the overall size and shape of the cap, texture state(color, crack and pattern) of the cap, thickness of the cap, the rolled state (shape and amount) of the cap edge in the back side and the state(standing and color) of the inner membrane around the stipe. The back (gill) side denotes a side having a stipe and membrane.

In this paper, algorithms to recognize and extract the primary features of a dried oak mushroom were developed considering the real time system implementation. Functional block diagram of overall processes of the developed algorithms was shown in fig.1.

Various algorithms are known in determining an optimum threshold value automatically to segment the desired object(Gonzalez et al, 1992) from the given image. Histograms of oak mushrooms showed the bimodal shape for the front(cap) side and mostly trimodal shape for the back side image. In some cases, back side image showed the unimodal pattern. A combined type automatic thresholding algorithm was adopted to sequentially extract the overall size, shape, and skin texture of oak mushrooms. The algorithm takes an advantage of two simple algorithms, the window extension and the maximum depth finding methods based on the histogram mode. Details on the algorithm refer to Hwang et al.(1993).

A. Surface State Identification

1) Rule based approach via texture descriptor

First of all, the surface identification was tried based on the rules set up with some experimental heuristics using the quantitative features such as geometry and the texture extracted from the segmented image of oak mushroom. The captured image was converted first to the segmented binary image via combined type automatic thresholding. To identify the surface state, following texture descriptors were adopted. Four element a_{11}, a_{12}, a_{21}, a_{22} represent the percentage of the number showing the gray level relations between the basis and neighborhood pixels on the path mask (0,0), (0,255), (255,0) and (255,255) with respect to the total scan times respectively.

$$A=\begin{bmatrix} a_{11}. & a_{12} \\ a_{21}. & a_{22} \end{bmatrix} \quad C=\frac{A}{n}$$

Where, n is the total number of point pairs from the path mask in the scanning region and C is the normalized gray value co-occurrence matrix.

① Maximum probability : max(C)

② Element-difference moment(EDM) of order k : $\sum_i \sum_j (i-i)^k C_{ij}$

③ Entropy : $-\sum_i \sum_j C_{ij} \log C_{ij}$

④ Uniformity : $\sum_i \sum_j C_{ij}^2$

A descriptor EDM(Element-difference moment) has a relative low value when the high value of C are near the main diagonal since the difference $(i\text{-}j)$ is smaller there. Entropy is a measure of randomness, achieving its highest value when all element of C are equal. Uniformity is the lowest when C_{ij} are all equal. The condition for the surface identification was determined by classification of descriptor. In this research, EDM and C_{11} was selected for identification descriptor.

2) Neuro-net approach

Extracting geometrical features of the object requires time consuming and complex processes and may yield the inaccurate feature data and lose some important information due to the enhancement and the simplification of the image information. If a pattern is recognized without extracting quantitative features, the real time processing can be achieved more easily.

Neuro-net based surface(side) recognition was tried without extracting any quantitative features. Two types of network inputs were tested primarily. Segmented binary image from the combined type automatic thresholding was tested first for network input. And then gray valued raw input image was directly input to the network. Since the segmented binary image by the combined type thresholding may lose some important details of the gray valued image or may distort some information, the recognition performance of the network with the binary image input was worse than the network with the raw gray valued image.

In this paper, recognition results of neuro-net approach were presented for the case of gray valued image as a network input. Well known error back propagation(BP) multi-layer network was used for the surface recognition.

B. Stipe State Recognition

The overall size and shape of the cap could be extracted regardless of the front or the back side image. However, a stipe is not usually raised up vertically but lies along the radial direction. When measuring the size and the shape of a cap, a portion of the stipe located outside of the cap boundary should be avoided. After the stipe was removed, the corresponding missing boundary should be regenerated.

Considering the curvature continuity of the cap boundary of an oak mushroom, Overhauser curve formulation(Brewer et. al., 1977) was applied to regenerate the boundary of the removed stipe region. It required at least 4 points to generate the Overhauser curve. Two points were selected by shifting the specified number of pixels forward and backward from the end points of the stipe region defined previously. The number of pixels to be shifted was varied automatically based on the cap size and the conditional value was prespecified empirically. Details on the algorithm refer to Hwang et al.(1993). Once new boundary was generated, the chain coding was executed again and area, centroid, and perimeter of the oak mushrooms were recomputed.

1) Rule based approach

The boundary of the oak mushroom was obtained via modified real scale chain coding. From the chain coded boundary, moment with respect to x and y axis, perimeter, area, roundness, complex ratio and centroid were computed. And the extracted boundary was divided into the predefined number of line segments so that each segment had an equal number of pixels. Radial distance from the centroid to each divided boundary point was computed and compared with the distance of the opposite radial line. If the magnitude difference of the two radial lines exceeded the specified portion of the length of the opposite radial line, the boundary was considered to have a stipe. And more detailed process to locate the stipe was executed.

The boundary segment of the stipe was detected using the fixed length contour trace algorithm which gave the maximum curvature point. Since the segment length used to find the maximum curvature was too large, the segment of the boundary to be removed were determined precisely again. Determining the portion of the stipe to be removed was done as following.

First, two boundary points were obtained by shifting the predefined number of pixels backward and forward sequentially from the midpoint of the maximum curvature segment. And the distance from the centroid to the line connecting two boundary points was obtained and the length of the line was set as the initial basis. Another two boundary points were obtained from the previous points by shifting the same amount of pixels along the boundary, and those points were connected. Again the distance from the centroid to the line and the length of the line were computed. The length difference was compared iteratively by renewing its basis. The distance from the centroid to the line was also compared with the average radius.

2) Neuro-net approach

Input image was determined as either cap or gill side from the surface identification procedure. The surface identification procedure was done using neuro-net with cap or gill side image. The image of the mushroom was first bounded by the retagular window and 66 grids along the 8 directions were formed from the bounded image and used as network input. In order to train the network, images of sample mushrooms were captured approximately at every 45 degree rotation. Total number of images used for the network training was 100. 80 images were the stipe outside of the cap and 20 images were not. The number of units in the output layer was set as 4(for cap surface) and 3(for gill surface). For the cap surface, one of output units was for identifying whether there resided a stipe outside of the cap or not, and the other three units were used to classify 8 different orientations of the stipe outside of the cap.

C. Extraction of Quantitative Features

1) Size and shape

After stipe recognition, removal, and contour regeneration were done, the overall cap size was estimated by averaging radial lengths excluding the maximum and the minimum magnitudes obtained from the centroid to the specified number of equally spaced perimeter pixel coordinates. The overall shape of the oak mushrooms was quantified by the roundness and the complex ratio.

2) Cap state via texture analysis

To extract local cracks and severe wrinkles on the cap surface, average intensities of four quadrants and the overall average intensity of the cap were obtained from the binary image generated after the combined type thresholding. To quantify the degree of local cracks and wrinkles, the amount of intensity deviation per quadrant was obtained, which was obtained after subtracting average intensity of each quadrant from the overall average intensity. Texture of the cap surface was analyzed via statistical approach(Haralick,1979) including relative positions of pixels having equal or nearly equal intensity values with respect to each other. Fig.2 shows four types of path masks used to extract the quantitative texture data. Fig. 3 shows results of the average values of the co-occurrence matrix elements obtained from four types of path masks. 10 oak mushrooms per representative grading levels such as Hwago, Gureum Hwago, Donggo, Hyanggo and Hyangsin were arbitrarily chosen.

3) Thickness and rolled state

Amount of the thickness of the cap works as an index of the degree of the ripeness. And thickness of the cap is an important factor in evaluating the quality of oak mushrooms. It is impossible, however, to measure the thickness from the 2-D planar top viewed image. Empirically, it was seen that the amount of the thickness was almost proportional to the rolled amount of the front skin edge, though the exact correlation between the two features was not investigated. After the stipe removal process was done, the rolled skin amount was measured from the back side image utilizing coordinates of the centroid and the boundary computed from chain coding. And the back side image was obtained from the combined type thresholding. In measuring the amount of the rolled skin edge, the stipe portion should be excluded. First, boundary pixels were divided into the specified number of segments, where each segment had the same number of pixels.

Once the stipe was identified previously, a certain portion of the boundary before and behind the identified stipe coordinate were not considered in measuring thickness. In a case that the stipe was feeble and was not recognized, the stipe position was identified by radially scanning the selected region from the centroid. And the size of the scanning region was adjusted automatically with respect to the average radius of the oak mushroom.

Image smoothing was applied to the binary image obtained from the combined type thresholding to remove the noise effects on the inside membrane image. The amount of the rolled skin was traced along the radial direction from the selected boundary pixels to the centroid by evaluating the continuity of pixels on the scan line. To select the proper pixel quickly on the radial scan line, simple digital differential analyzer(SDDA) scan line conversion algorithm was adopted. From the results of the radial scans, the average value, the variance, and the number of severe disconnectivities which quantify size, shape and crack of the rolled skin edge were computed respectively.

4) Gill state

Membrane of the gill side should stand in order neatly and free of severe cracks and damage and color should be bright. Inspecting 3-D state of the membrane standing was impossible using the top viewed 2-D planar image. From the fact that membrane in good standing looked bright, the average intensity value of the membrane was computed using the input gray level image.

Previously identified region occupied by the stipe and a square region around the centroid were excluded in scanning. The size of square was varied according to the size of the average radius. The intensity scan was performed along x-axis from the inside boundary pixels identified from the thickness quantization to the centroid axis.

3. RESULTS AND DISCUSSIONA.

A. Surface Identification

Texture data were computed from the binary image obtained from the combined automatic thresholding. The element of the co-ocuurence matrix C_{11} obtained from the path mask 1 was selected to recognize the front and back sides. Recognition criteria was set up as following. If C_{11} is higher than 0.5, the side was identified as the back side and if not, it was identified as the front side. Since C_{11} of both sides of Hwago categories were higher than 0.5, additional condition was adopted using EDM. When EDM is higher than 0.05 and C_{11} is lower than 0.7, the side was determined as back side. 60 oak mushrooms images were randomly selected regardless of the front and the back sides and tested under the mentioned criteria. And the recognition success rate showed 88.3%.

Most of the error occurred in the back side images of Hwago. Color of the rolled skin edge of Hwago was ivory white with scattered dark brown spots. The inner membranes of the mushrooms were hidden a lot by the rolled edge and the stipe. Since the binarization of the image enhanced a certain feature of the object but it lost lots of information because of its simplification. The combined type automatic thresholding resulted in the undesirable binary image for the irregular shape of mushrooms, which was somewhat obscure and fuzzy to recognize its side.

The network was trained independently using input structures as shown in fig.4. Structure of the network input was formed using 66 rectangular grids composed of the 8 directions in the rectangular window. Grid output was normalized in the range of 0 and 1 after averaging gray values of pixels in each grid. Since the brightness level of the camera input gray level image varied very sensitively to the lighting condition, the average brightness of the input window was measured. And then according to the predefined value at the initial stage of training, gray values of input image were compensated. The compensation process provided nearly the external lighting invariant consistent input image to the trained network. Training experiment was done using 40 oak mushrooms images including the front and the back sides. The number of processing nodes in the hidden and output layer was set to 10 and 1 respectively. The momentum and the learning rates were assigned as 0.9 and 0.7 respectively. The normalized system error(RMS error) which is the root of squared sum of target and network output differences over the total number of input samples was set 0.0001. In programming, target values of 0 and 1 were converted to 0.05 and 0.95 considering characteristics of a sigmoid type logistic activation function.

Visual images of 40 oak mushrooms used for the training were newly obtained again for the recognition test. Networks with both types of input structure gave 100% recognition success for the trained samples. Using the trained network, 60 untrained oak mushrooms were tested and again it showed 100% recognition success rate.

B. Stipe State Recognition

The algorithm which identified a portion of the stipe outside of the cap boundary based on the geometrical data extracted from the oak mushrooms image was already mentioned previously. Using the proposed algorithm, 60 oak mushrooms images were randomly captured and tested for recognizing the existence and the orientation of the stipe. The proposed stipe recognition process gave wrong results for 6 oak mushrooms.

The proposed algorithm perfectly identified and removed the stipes when they resided outside of the cap. It, however, misidentified caps of very unusual and irregular shape which in fact did not have stipe outside of the cap as a portion of the stipe and removed.

As shown in fig.5-a, given front side gray level images of oak mushrooms were tested using BP network. Total 100 captured images were used to train the network, 80 images with the stipe outside of the cap and 20 images without, .

The number of nodes in the hidden layer was set as 15 and number of the input grids was 66. The momentum and the learning rates were assigned as 0.6 and 0.1 respectively and the normalized system training error was set as 0.000 01. Trained network showed 100% recognition rate for the newly captured images for the samples used for training. For 60 untrained oak mushrooms images, the trained network recognized successfully all except 2 images resulting into 96.7% recognition rate. Two oak mushrooms which network made an error in recognition showed very abnormal shape patterns in their caps and stipes.

For gill side images, the stipe portion should be excluded in measuring the amount of the rolled edge and the state of the inner membrane. The orientation of the stipe can be recognized from the back side image regardless of the portion of the stipe being outside of the cap. As shown in fig.5-b, input structures of the network were formed the same as that of the network used for the front side stipe recognition. Sample oak mushrooms were rotated around 45 degree interval and images were captured. Total 100 captured images were used to train the network, where 80 images had the stipe residing outside the cap and 20 images did not.

The number of nodes in the output layer was set to be 3 to classify 8 different orientations of the stipe. The number of nodes in the hidden layer was set as 15. The momentum and the learning rates were assigned as 0.7 and 0.2 and the normalized system training error was set as 0.0001. Trained networks showed 100% recognition success for the newly captured images used for training. The trained network with 8 directional 66 grid inputs misrecognized 2 images resulting into 96.7% recognition rate for untrained 60 sample image. For the given gray image, according to the results of the front and back side recognition, the corresponding network can be selected for the stipe state recognition from the two networks, one for the front side image and the other for the back side image.

C. Extraction of Quantitative Features

Table 1 shows results of averaging 10 measurements using proposed visual feature extraction algorithms. The measured value was normalized between 0 and 1.

4. CONCLUSIONS

In this paper, computer vision based algorithms for the automatic visual feature recognition and extraction algorithm were developed. The developed algorithm could be utilized to the mushroom sorting system, growth state measuring of mushrooms and the performance evaluation of the oak mushroom drying.

Algorithms were developed and integrated with the neural network processing to deal with various feature patterns in a robust way. The neuro based image processing successfully recognized the cap surface and wrinkle sides and states of the stipe from the camera captured raw B/W images without extracting quantitative features.

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SUMMARY

Visual features are crucial for monitoring the growth state, indexing the drying performance, and grading the quality of oak mushrooms. A computer vision system with neural net information processing technique was utilized to quantize quality factors of a dried oak mushrooms distributed over the cap and gill sides. In this paper, visual feature extraction algorithm were integrated with the neural net processing to deal with various fuzzy patterns of mushroom shapes and to compensate the fault sensitiveness of the crisp criteria and heuristic rules derived from the image processing results. The proposed algorithm improved the segmentation of the skin features of each side, the identification of cap and gill surfaces, the identification of stipe states and removal of the stipe, etc. And the visual characteristics of dried oak mushrooms were analyzed and primary visual features essential to the quality evaluation were extracted and quantized. In this study, black and white gray images were captured and used for the algorithm development.

Keywords : Visual Feature Extraction, Dried Oak Mushroom, Computer Vision, Neural Network, Feature Recognition

Table 1 Results of measurement using proposed algorithms

Feature \ Grade	12 Grade Classification of Oak Mushrooms											
	1	2	3	4	5	6	7	8	9	10	11	12
Size	0.642	0.428	0.615	0.50	0.623	0.507	0.250	0.944	0.608	1.00	0.641	0.457
Roundness	0.836	0.810	0.807	0.791	0.796	0.749	0.766	0.841	0.768	0.724	0.712	0.470
Gray Value	1.00	0.960	0.820	0.745	0.597	0.677	0.537	0.830	0.670	0.577	0.612	0.560
Thickness	1.00	0.64	0.985	0.930	0.675	0.683	0.474	0.885	0.363	0.183	0.106	0.011
Membrane	0.974	0.951	1.000	0.963	0.928	0.869	0.795	0.838	0.970	0.747	0.608	0.03

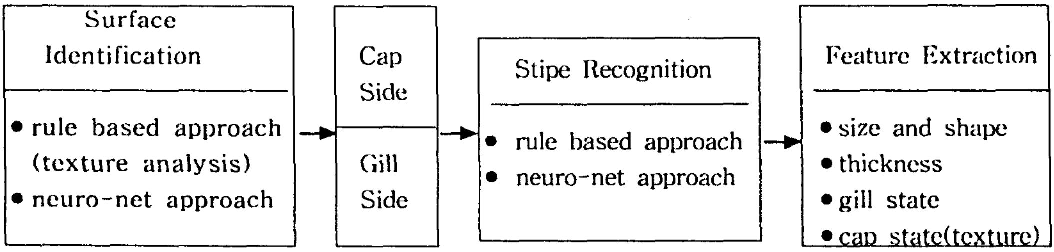


Fig.1 Functional block diagram of the developed feature recognition and extraction algorithms.

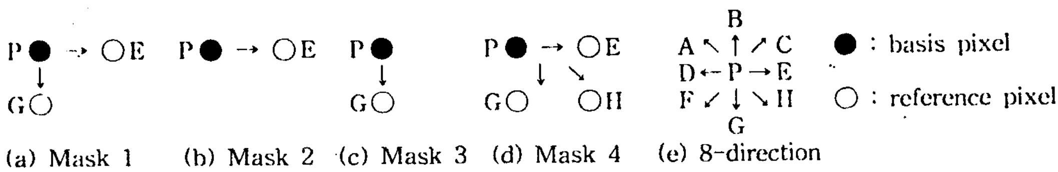


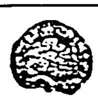
Fig. 2 Four types of path mask operators.

Mask		Hwago	C11	C12	C21	C22	Max(C)	EDM	Entropy	Uniformity
F	1		0.652	0.030	0.036	0.282	0.652	0.066	0.452	0.543
	2		0.628	0.074	0.074	0.224	0.628	0.149	0.340	0.479
	3		0.635	0.067	0.067	0.231	0.635	0.133	0.335	0.490
	4		0.723	0.025	0.033	0.219	0.723	0.058	0.265	0.603
B	1		0.728	0.021	0.025	0.226	0.728	0.046	0.400	0.600
	2		0.641	0.058	0.059	0.242	0.641	0.117	0.331	0.497
	3		0.646	0.053	0.054	0.247	0.646	0.107	0.327	0.505
	4		0.718	0.019	0.024	0.239	0.718	0.043	0.267	0.600

Mask		Gureum Hwago	C11	C12	C21	C22	Max(C)	EDM	Entropy	Uniformity
F	1		0.472	0.031	0.026	0.471	0.472	0.057	0.547	0.457
	2		0.427	0.070	0.072	0.431	0.427	0.142	0.392	0.386
	3		0.433	0.064	0.064	0.439	0.439	0.128	0.387	0.396
	4		0.477	0.029	0.024	0.470	0.477	0.052	0.347	0.461
B	1		0.760	0.016	0.018	0.207	0.760	0.057	0.547	0.457
	2		0.702	0.043	0.048	0.208	0.702	0.090	0.299	0.552
	3		0.707	0.038	0.039	0.217	0.707	0.076	0.296	0.561
	4		0.772	0.014	0.016	0.198	0.772	0.030	0.241	0.650

Mask		Donggo	C11	C12	C21	C22	Max(C)	EDM	Entropy	Uniformity
F	1		0.338	0.026	0.018	0.618	0.618	0.043	0.524	0.512
	2		0.318	0.054	0.054	0.575	0.575	0.107	0.357	0.451
	3		0.324	0.047	0.047	0.581	0.581	0.094	0.351	0.461
	4		0.341	0.024	0.016	0.620	0.620	0.040	0.319	0.516
B	1		0.684	0.021	0.019	0.276	0.684	0.040	0.431	0.568
	2		0.626	0.049	0.052	0.274	0.626	0.100	0.334	0.488
	3		0.630	0.044	0.044	0.281	0.630	0.088	0.330	0.497
	4		0.697	0.019	0.017	0.267	0.697	0.036	0.279	0.583

Mask		Hyanggo	C11	C12	C21	C22	Max(C)	EDM	Entropy	Uniformity
F	1		0.138	0.035	0.024	0.803	0.803	0.059	0.384	0.676
	2		0.144	0.067	0.083	0.706	0.706	0.150	0.297	0.544
	3		0.150	0.061	0.061	0.729	0.729	0.121	0.289	0.573
	4		0.131	0.032	0.021	0.816	0.816	0.053	0.227	0.694
B	1		0.720	0.015	0.018	0.246	0.720	0.033	0.393	0.604
	2		0.664	0.044	0.052	0.239	0.664	0.097	0.313	0.522
	3		0.672	0.036	0.037	0.254	0.672	0.074	0.307	0.538
	4		0.730	0.014	0.017	0.239	0.730	0.031	0.257	0.616

Mask		Hyangsin	C11	C12	C21	C22	Max(C)	EDM	Entropy	Uniformity
F	1		0.137	0.028	0.020	0.815	0.815	0.048	0.367	0.698
	2		0.141	0.064	0.059	0.737	0.737	0.122	0.283	0.585
	3		0.155	0.049	0.051	0.745	0.745	0.100	0.275	0.598
	4		0.131	0.027	0.018	0.824	0.824	0.044	0.216	0.711
B	1		0.837	0.015	0.015	0.132	0.837	0.031	0.276	0.732
	2		0.768	0.054	0.043	0.136	0.768	0.097	0.258	0.629
	3		0.788	0.034	0.034	0.145	0.788	0.068	0.241	0.657
	4		0.847	0.013	0.014	0.125	0.847	0.028	0.185	0.747

F: front(Cap) side B: back(Gill) side
Max(C): maximum value of element of normalized co-occurrence matrix C
Cij: element of matrix C
EDM: element difference moment of order 2

Fig.3 Average texture values of the 5 types of oak mushrooms.

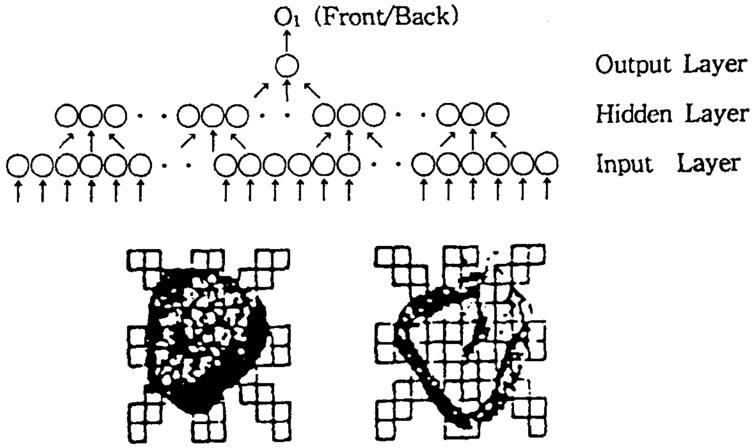


Fig.4 Network and image input structure for the surface identification.

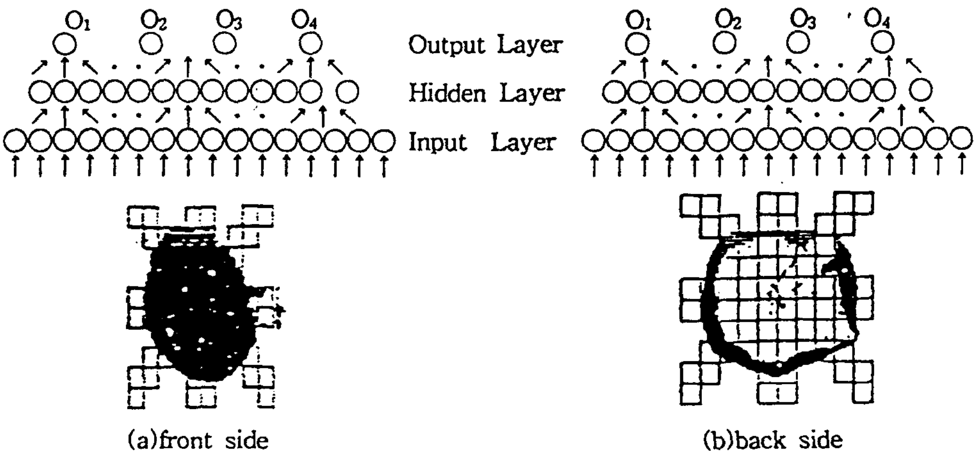


Fig.5 Network input structure for the stipe state recognition