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TRANSFERRING HUMAN SENSIBILITIES TO MACHINES
- SENSITIVITY ANALYSIS OF LAYERED NEURAL NETWORKS AND ITS APPLICATION TO PEARL COLOR EVALUATION -

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ABSTRACT

This paper proposes a new framework for acquiring the sensibilities (*kansei*) of human experts, and applies it to the design of a pearl color evaluation system. The fundamental concept behind the proposed framework is that a system which imitates human sensibilities can be realized based on deriving factors from experts. A factors identification method using sensitivity analysis of layered neural networks finds the influential factors as the input units which have the greatest influence on any outputs. This method has been applied to the network mapping between spectral reflectance of pearls and the pearl color categories evaluated by experts, and allowed some specific wavelength bands to be identified as the essential factors contributing to the evaluation. Based on this result, a pearl color evaluation system has been designed using multi-bands images (MBI) acquired by combining a monochrome CCD camera with several interference filters corresponding to the identified major wavelength bands factors. Experimental results verify the usefulness and feasibility of this method.

INTRODUCTION

Such tasks as the complicated inspection and quality evaluation of products in manufacturing processes are usually done by human experts. They perform these tasks, which require the qualitative evaluation of objects with high resolution, by intuitive discrimination. They have acquired this expert intuition, namely, a sophisticated sensibility, from past learned experiences. To automate these tasks, it is necessary to develop a technique which can identify human sensibility and transfer it to machines.

One of the major difficulties in transfering human sensibilities is that experts cannot exactly and quantitatively describe their evaluative sense, because as they become experienced they become able to perform tasks without being aware of the detailed relationship between sensory information and their evaluation. Another difficulty is that when dealing with such objects as pearls, where the tasks are multi-dimensional and required highly resoluting, the relationship between the sensory information and the evaluation results is not easy to explain.

In order to solve these problems the authors have proposed a new instrumentation technique framework called 'Kansei Instrumentation'[1], which acquires the sensibilities (*kansei*) of experts. In this paper, we propose a factors identification method, based on this framework, and its application to design a pearl color evaluation system. The method we propose here is of employing sensitivity analysis of a layered neural network for finding the influential set of factors contributing to the evaluation, by deriving the sensitivities between candidates of factors (physical parameters) given to the input units and the evaluations by an expert given to the output units. The pearl color evaluation system we have designed based on the results of this method are also presented.

KANSEI INSTRUMENTATION

Methods to acquire human complex sensations, have been previously developed[2], however, few studies have tried to develop practical equipment. Also, so far most of the developed methods have dealt with linear models, but methods for flexible nonlinear models are more desirable.

The new Kansei Instrumentation technique framework, as shown in Figure 1, consists of three stages. In the first stage, by analyzing the responses of human experts, essential sense factors (conscious and subconscious) and essential physical factors can be extracted. In the second stage, a sensing system is tentatively designed based on the extracted factors. In the last stage, the responses of the system are compared with those of experts, and the differences are fedback to the first and second stages. Therefore the responses of the system gradually approach those of experts.

FACTORS IDENTIFICATION USING SENSITIVITY ANALYSIS OF NEURAL NETWORK

Neural networks are teachable systems and information is stored in the strengths of the connections between units (i.e. weights). So far many studies have been made on analysis of weights and hidden units [4][5]. We are concerned by the input layer and output layer sensitivities that have been adjusted after a learning process. This method is unique because it uses sensitivities not of the hidden layer but of the input layer, and furthermore uses neural networks as an analysis method in finding which factors are critical to a problem.

Sensitivity of neural networks

A schema of the multi-layered neural network architecture is shown in Figure 2. The output of the mth unit of the Lth layer can be described by

$$o_m^L = f(net_m^L) \qquad \cdots(1)$$

where
$$net_m^L = \sum_k w_{mk}^L o_k^{L-1} + \theta_m^L$$
$$net_m^1 = i_m$$

where net^L_m is the net input to mth unit of the Lth layer, θ^L_m is the bias of the mth unit of the Lth layer, f is the non-linear input-output function of the units, and w^L_{mk} is the weight from the kth unit of the L-1th layer to the mth unit of the Lth layer. Now, partial diffenciation of the output o^L_m with respect to i_j gives derivative D^L_{mj}

$$D^L_{mj} = \frac{\partial o^L_m}{\partial i_j} = \frac{\partial o^L_m}{\partial net^L_m}\frac{\partial net^L_m}{\partial i_j}$$
$$= f'(net^L_m) \sum_k w^L_{mk} \frac{\partial o^{L-1}_k}{\partial i_j} \qquad \cdots(2)$$

In (2), $\frac{\partial o^{L-1}_k}{\partial i_j} = D^{L-1}_{kj}$. Then, the derivatives of any output with respect to any input are computable by the following formulas.

$$D^2_{mj} = f'(net^2_m)\, w^2_{mj}$$
$$D^L_{mj} = f'(net^L_m) \sum_k w^L_{mk} D^{L-1}_{mj} \qquad \cdots(3)$$

Also, let us consider f to be a sigmoid function, we have

$$f'(x) = f(x)\,(1 - f(x)) \qquad \cdots(4)$$

By applying (4) to (3) and substituting L=3, we get the derivative

$$D^3_{mj} = \frac{\partial o^3_m}{\partial i_j} = o^3_m(1 - o^3_m) \sum_k w^3_{mk} o^2_k\,(1 - o^2_k)\, w^2_{kj} \qquad \cdots(5)$$

After learning, the weights are determined, this derivative is computable for an appropriate input pattern .

Identification of contributing factors

In the network after learning, the derivatives of all the outputs with respect to all the inputs can be calculated using (5) for all possible input patterns. The normalized maximum of the absolute values of all the derivatives for an input j is the sensitivity

$$S_j = \frac{\max_{c,m} |D^3_{cmj}|}{M} \qquad \cdots(6)$$

where $M = \max_{c,m,j} |D^3_{cmj}|$

By calculating all the sensitivities of all the outputs with respect to any input j can be calculated.

So, we can find two types of input: those which show higher sensitivities, and those which show lower sensitivities independent of any output. The former may be contributing to the input-output relationship, however, it may be seen that removing such inputs as the latter would have no effect on the input-output relationship.

we try again to train the network with these input units eliminated , and if the network can be seen to have the same relationship as before elimination, namely, that the errors of the network do not increase, then we can remove these inputs from the network. This procedure can be applied continuously while maintaining the initial ability as the networks are reduced, until finally we can find the most influential set of factors as the rest input units.

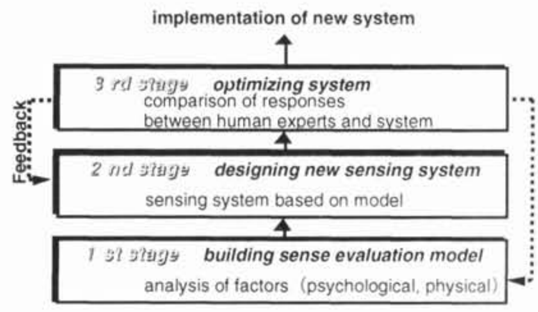


Figure 1. Kansei Instrumentation framework.

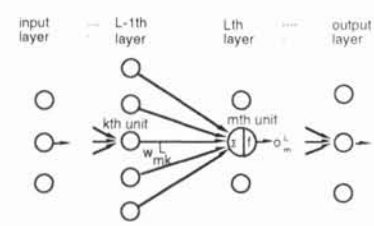


Figure 2 Layered neural network architecture

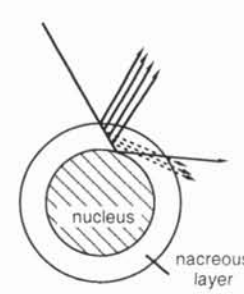


Figure 3. optical characteristics of incident light of pearl

APPLICATION TO DESIGN A PEARL COLOR EVALUATION SYSTEM

Based on the framework of Kansei Instrumentation, the design of the pearl color evaluation system will be discussed. That is, first, factors identifification is done to the network mapping between the physical appearance and the evaluation by experts. Second, a sensing system is tentatively designed based on the extracted factors. And last, the system is optimized to approach the responses to an expert.

Before discussing, the quality evaluation of pearls are explained briefly.

Quality evaluation of pearls

Pearls are famous for being unique in their colors and lusters. This uniqueness occurs because the pearl layers are composed of more than 1000 fine, translucent films of 0.3 micron-thick nacreous material deposited on a spherical surface, which causes optical effects such as interference colors resulting from multiple reflections, and psychological effects such as the sensation of gloss (see Figures 3). Although a number of studies of these optical characteristics have been made e.g.[3], a model integrating such effects has not been reported.

Yet in spite of the complexity of a pearl's structure, experts inspecting them can provide accurate evaluations based on sensibilities they hold in common which has been cultivated from their experience. Currently emphasis is placed on about several evaluation items including flaws, the shape, the luster, and the color. However it is supposed that the each of them are composite items and many more factors, including those which are subconscious, contribute to the perception of the evaluation of pearls.

Factors identification on evaluation of pearl color

We now apply the above method to the pearl color evaluation problem. The problem which is to gradually evaluate pearls into 10 categories by their color from category 1 (white) to category 10 (cream) is not simple because the difference between categories is very slight and non-linear. Spectral reflectance is used here as the physical appearance because of this slightness.

The network architecture consists of a three layered back-propagation network. It takes as the input layer, 81 units which correspond to the spectral reflectance from 380nm to 780nm with a 5nm sampling cycle, and as the output layer, 10 units which corresponds to the output pattern which represents the pearl categories evaluated by an expert, for example, a vector $(0, 0, 0, 0.5, 1, 1, 1, 1, 1, 1)^T$ for the category 3. Figure 4 shows sample input patterns.

The networks are trained by a back-propagation learning algorithm by using 10 samples from each category, in total 100 pearl samples. The judgment for the completion of training is done by the Cross Validation method[6], namely, by stopping the training when the MSE (Mean Square Errors) for testing data indicates a minimum. Also the number of hidden units are decided by trial and error selecting the minimum MSE network for 10, 20, 40 and 60 units and are finally selected the networks with 20 hidden units. In this case, the network correctly dictates the categories to approximately 65% for training data, and to 52% for testing data.

Sensitivities of trained network

Next, the sensitivities of input units are calculated using the weights of the network constructed as described above. Figure 5 shows the sensitivities obtained from the derivatives by using each input pattern (combining the mean values of input patterns belonging to the same categories in the training set).

For the purpose of finding the wavelength factors contributing to pearl color evaluation, we execute the reduction procedure as described above. Finally, it is confirmed that the reduced network composed of 20 input units of the initial network has the same ability as the initial network, and these input units (i.e. wavelength factors) are the most influential physical factors in this evaluation.

The wavelength factors obtained finally are divided into 9 wavelength bands. Table 1 shows the center wavelengths of those bands. We regard this information as the specifications for interference filters whose transmittance has a Gaussian distribution. Thus it seems that a simple sensing system consisting of 9 interference filters and a

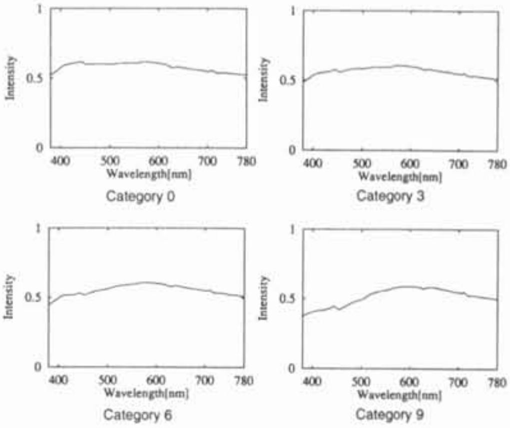


Figure 4. Sample input patterns

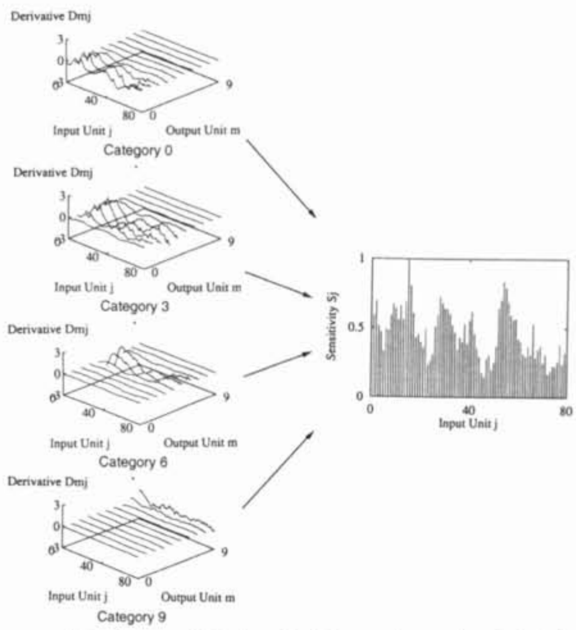
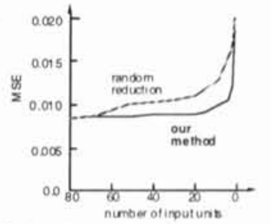


Figure 5 sensitivities by calculating maximum value of derivatives.

Table 1 Center wavelength of bands.

No.	wavelength[nm]
1	390
2	428
3	455
4	520
5	540
6	580
7	648
8	710
9	768



Figre 6 Number of input units and mean square errors of each network.

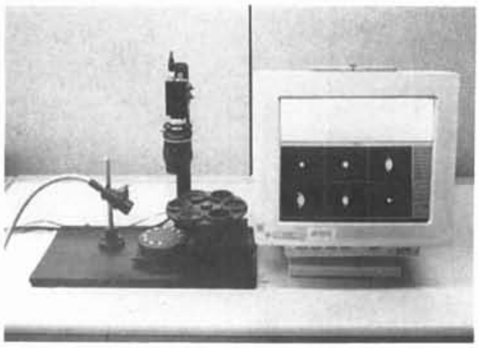


Figure 7 pearl color evaluation system

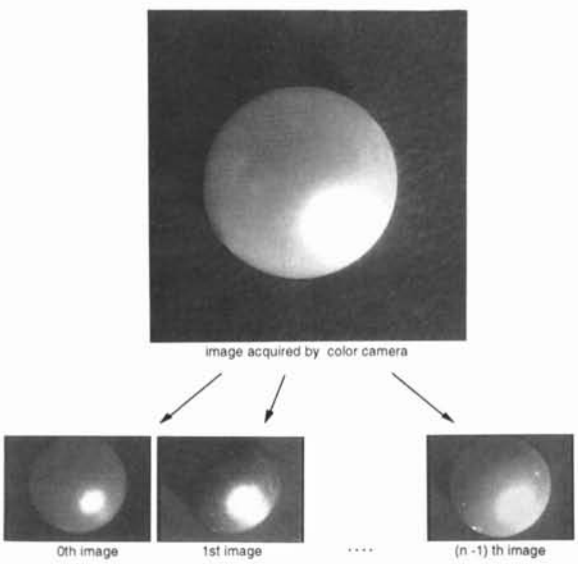


Figure 8 an example of multi-band image

monochrome CCD camera can be designed.

Furthermore the relationship between the number of input units of the reducing network and the mean square errors (MSE) of each network are examined as shown in Figure 6. In comparison with the MSE when the input reduction is selected randomly, the MSE when selected by our method is low. It is shown that the contributing factors are identified appropriately.

Pearl color evaluation system by using multi-band images (MBI)

Based on the result above, a sensing system is tentatively designed, as shown in Figure 7. It consists of a standardized white light source, a rotating filter holder supporting several interference filters, a monochrome CCD camera, and an EWS with an image processor board. A pearl object is illuminated by the white light source which makes an angle of 45 degree with the axis pearl - CCD camera. Reflected light from the pearl surface passes through one of the selected interference filters and reaches the CCD camera. A gray image of 512x480 pixels is taken by the image processor board through each of the interference filters on the filter holder. Such a set of gray images called a multi-band image (MBI), an example of which is shown in Figure 8, is a unit of data corresponding to an object. An MBI is acquired for each of the 100 pearl samples which have also been used in the factors identification. In order to evaluate the MBIs, a smaller sized network than that used in the analysis was constructed. The input layer consists of 9 units which correspond to the mean intensity value of a 16x16 pixels area in each image of the MBI. Finally, after a similar training period, the network correctly dictates the categories to approximately 90% for training data, and to 71% for testing data. This confirms that the images constituting the MBI effectively describe the characteristic features of the pearl color.

Moreover, by using again the factors identification method, it is expected to further reduce the number of images in the MBI, and also to find the best position for taking the mean intensity value in each image of the MBI.

CONCLUSION

A new framework for transferring human sensibility to machines has been introduced. A new method for identifying factors by using the sensitivity analysis of the neural network and its application to design a pearl color evaluation have been presented. We have identified the wavelength factors which contribute most in the pearl color evaluation, and succeeded in tentatively designing a pearl color evaluation system.

The ultimate goal of this research is to develop effective techniques for building optimized sensing systems for practical manufacturing processes. We came a step closer to this goal, by developing a factors identification method which prooves effective in finding which sensors are critical to a task.

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