

## テクスチャ解析による夜間海面波浪状態の ニューラルネットワーク学習

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### Texture Analysis for Training of a Neural Network in Identification of Ocean Surface Wave Conditions at Night

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**Abstract :** A system for automatic monitoring of wave conditions in littoral waters was constructed. Based on previously reported findings using daytime ocean surface images, the ability of the system to use nighttime images was investigated. Texture analysis of ocean surface images was performed on infrared images, and the characteristic quantities of these results were compared with wind force. Two analytical methods were used to extract the image characteristics of the quantitative result: the spatial gray-level dependence method and the gray-level difference method. A multilayer neural network was trained to predict ocean wind velocity by error back-propagation. The specified conditions and optimal ocean surface images were then compared to the network structure and learning conditions to evaluate the effectiveness of this system and to assess its limitations.

**Key words :** measurement, sea surface, texture, neural networks, winds

#### Introduction

For members of the fishing industry, as well as ship operators and marine safety authorities, a knowledge of ocean wave conditions is very important. Ocean surface conditions have an inestimable impact on the efficiency and safety of fishing and maritime activities in the coastal waters of Japan; such activities extend from the automated navigation of trawlers to the more mechanical tasks of fishing, as well as the installation, maintenance and management of moored floating equipment, aquaculture rafts and fixed nets. This study attempted to develop a system that automatically detects ocean wave conditions using images of the ocean surface. A previous report addressed surface conditions during the day<sup>1</sup>). However, in this study,

infrared nighttime images were used to facilitate the measurement and monitoring of ocean wave conditions for a full 24-hour period. The wave conditions were subjected to texture analysis and digitized, and these data were then used to train a neural network that could be applied to recognizing and predicting wave conditions.

#### Texture Analysis

“Texture” refers to the large- and small-scale patterns in an image. As such, texture is not restricted to being a characteristic of highly ordered artificial objects, such as rows of blocks etc., rather, it can also be used to characterize natural phenomena, such as trees or the surface of water. Thus, monochromatic

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surfaces can have textures with no variation in color density.

These structural and statistical analyses of texture can be used to derive the characteristic quantities of the texture in the image<sup>2),3)</sup>. In texture analysis at the structural level, the basic elements constituting straight lines, points and other textural components are extracted from the image and characteristic quantities are revealed using rules that describe their spatial relationships. In this way, the constituent elements of the target image can readily be distinguished from artificial textures. In texture analysis at the statistical level, the color density of each pixel is examined for uniformity, directionality, variations in contrast, and other characteristic quantities. Since structural regularities, with respect to points and lines, were not observed in the data captured at the ocean surface in this study, the statistical level of texture analysis was considered appropriate for the current case.

**Spatial gray level dependence method**

Figure 1 shows the frequency at which the color densities (gray levels) of a pair of pixels  $(x_1, y_1)$  and  $(x_2, y_2)$  in a specified spatial relationship  $(d, \theta)$  match with a density pair  $f(x_1, y_1)=i, f(x_2, y_2)=j$ . The probability of this match is defined by  $S_\theta(i, j)$ .

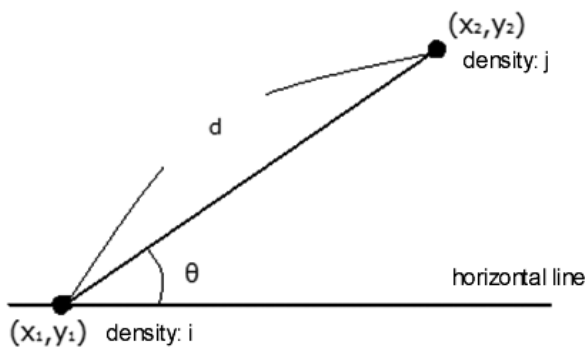


Figure 1 Pair of pixels

$\theta$ , which is the angle between a line joining the pixel pair and a horizontal line, can take the four values of  $0^\circ, 45^\circ, 90^\circ$  and  $135^\circ$ . The distance between the pixel pair under consideration is  $d$  in the  $\theta$  direction. The procedure for creating the gray level cooccurrence matrix  $P(i, j|d, \theta)$  is as follows. A pair of pixels is selected as the density pair when a second point lies at distance  $d$  in the  $\theta$  direction from the first point. Next,

the color density values of the pair are determined; if these densities are  $i, j$ , then the terms are summed to correspond to the terms of  $P(i, j|d, \theta)$ . Either of the two members of the pair is allowed to have either gray level. The gray level cooccurrence matrix then has the size  $N \times N$ , where  $N$  is the number of gray levels in the image.

The values of the characteristic quantities found by texture analysis can be determined using the following equations.

Energy;

$$E(d) = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \{S_\theta(i, j|d)\}^2 \quad \dots \dots \dots (1)$$

Entropy;

$$H(d) = - \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} S_\theta(i, j|d) \log_\theta(i, j|d) \quad \dots \dots (2)$$

Correlation;

$$H(d) = - \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} S_\theta(i, j|d) \log_\theta(i, j|d) \quad \dots (3)$$

Local infirmity;

$$L(d) = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{S_\theta(i, j|d)}{1 + (i - j)^2} \quad \dots \dots \dots (4)$$

Momentum;

$$I(d) = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i - j)^2 S_\theta(i, j|d) \quad \dots \dots \dots (5)$$

where,

$i, j$ : Pixel color density

$S_\theta$ : Probability that a pixel at distance  $d$  in the  $\theta$  direction from a pixel of density  $i$  in the image will have density  $j$

$\theta$ : Angle with respect to the horizontal by a straight line between two pixels

$d$ : Distance from a pixel of density  $i$  to a pixel of density  $j$

$v_x, v_y$ : Mean color densities

$\sigma_x, \sigma_y$ : Variance of color density

**Gray level difference method**

We find the probability  $f(i, \delta)$  that the difference  $i$  in the densities of two points separated by a constant displacement  $\delta = (d, \theta)$  (see Figure 1), and use this probability to calculate the characteristic quantities. The characteristic quantities identified by texture analysis can be identified using the following equations:

Contrast;

$$C = \sum_{i=0}^{N-1} i^2 f(i|\delta) \quad \dots \dots \dots (6)$$

Angular second moment;

$$M_{as} = \sum_{i=0}^{N-1} \{f(i|\delta)\}^2 \quad \dots \dots \dots (7)$$

Entropy;

$$H = \sum_{i=0}^{N-1} S_{\theta}(i|\delta) \log f(i|\delta) \quad \dots \dots \dots (8)$$

Mean ;

$$M = \sum_{i=0}^{N-1} if(i|\delta) \quad \dots \dots \dots (9)$$

Inverse differential moment;

$$M_{id} = \sum_{i=0}^{N-1} \frac{f(i|\delta)}{i^2+1} \quad \dots \dots \dots (10)$$

where

$N$ : Color density of pixel

$i$ : Difference between density value  $L$  at  $(x_1, j_1)$  and density value  $M$  at  $(x_2, j_2)$

$f$ : Probability that the color density difference will be  $i$

### Neural Network

An ‘‘artificial neural network’’ refers to mimicking the data processing that occurs in the cells (neurons) of the human brain using a computer. Numerical models perform the role of neurons, and the data-processing structure consists of a network of interconnected models<sup>4</sup>. This process facilitates numerical modelling of a system based directly on sets of input and output data, without equations. Figure 2 shows a model of a neuron.

$x_1, x_2, x_3, \dots, x_n$  in the figure correspond to the inputs,

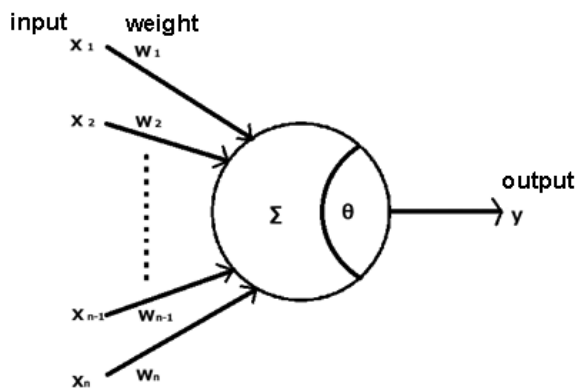


Figure 2 Numerical model of neuron

$w_1, w_2, w_3, \dots, w_n$  correspond to the combination loads of the paths, and  $y$  represents the output. If  $x_i$  ( $i=1, 2, 3, \dots, n$ ) represents the input signal from the  $i$ <sup>th</sup> neuron,  $w_i$  ( $i=1, 2, 3, \dots, n$ ) represents the combination load,  $S$  is the sum of input signals from all other neurons, and  $f_h$  is the sigmoid function, then we can obtain the following expression:

$$S = \sum_{i=1}^n x_i w_i \quad \dots \dots \dots (11)$$

Output  $y$  is,

$$y = f_h \left( \sum_{i=1}^n x_i w_i - \theta \right) \quad \dots \dots \dots (12)$$

A multilayer neural network shown in Figure 3 consists of an input layer, an intermediate layer and an output layer. There are no interconnections

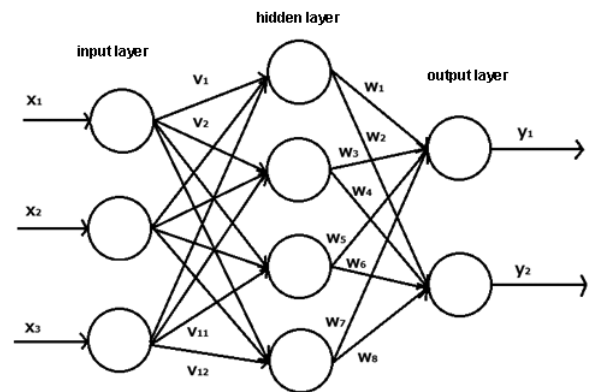


Figure 3 Multilayer neural network

within a layer in this type of neural network; a signal proceeds in a single direction, from the input layer through the intermediate layer to the output layer. This characteristic enables the network to learn faster than an interacting neural network.

### Experiments and Results

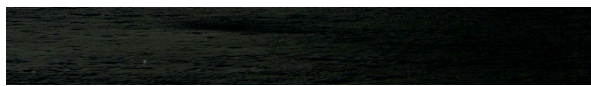
#### Textural analysis of wave images

The Beaufort wind scale<sup>5</sup>) shown in Table 1 was used as an indicator of the wave conditions shown in the different images. Figures 4 provide images of training patterns.

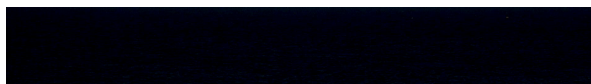
Using image analysis software, the training images were analyzed using both the spatial gray level dependence method and the gray level difference method. Portions samples of the images were employed, as shown in Figure 5. The sample size was  $500 \times 200$  (width x height) pixels.

**Table 1** Beaufort scale of wind force

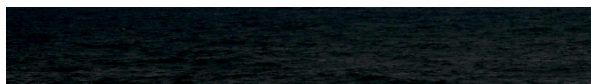
Wind force class	Wind speed		Sea surface	Wave ht. [m]
	[kt]	[m/s]		
1	1~3	0.3~1.5	Waves resemble fish scales	0.1
2	4~6	1.6~3.3	Small waves created, but crests do not break	0.2
3	7~10	3.4~5.4	Larger waves created, occasional whitecaps	0.6
4	11~16	5.5~7.9	Small-medium waves. Frequent whitecaps.	1
5	17~21	8.0~10.7	Medium waves, numerous whitecaps.	2



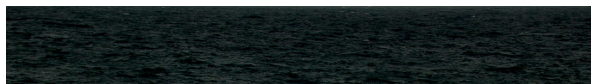
(a) wind scale 1



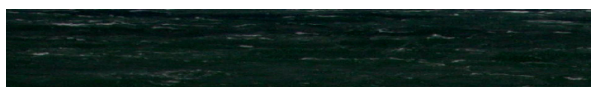
(b) wind scale 2



(c) wind scale 3



(d) wind scale 4

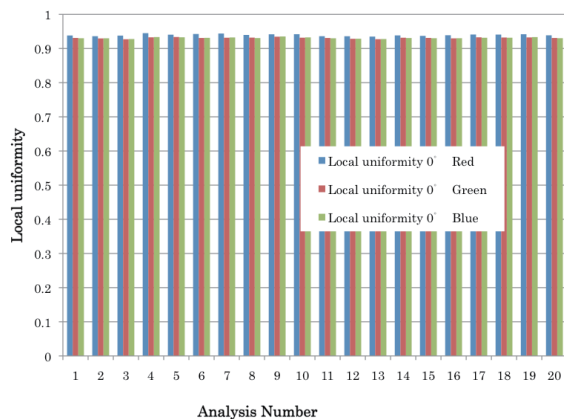


(e) wind scale 5

**Figure 4** Training images A - E



**Figure 5** Training image E marked to show cut-out portion



**Figure 6** Local uniformity of colors

Learning was performed using a neural network. The values for the characteristics of extracted energy, entropy, correlation, local uniformity and inertia were calculated. The color indices were classified as red, green or blue during analysis, but these were limited to just one color for comparison in Figure 6. No particularly prominent characteristics were found in this analysis, so red was employed as an index for the remainder of the experiment.

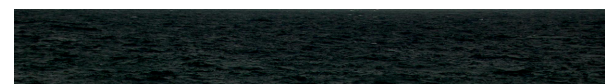
A network with inputs that consisted of energy, entropy, correlation, local uniformity and inertia, and an output of wind scale was created. Once the neural network had been trained, the prediction was calculated as output. The learning conditions were set for the neural network, which was trained to assess the relation between the wave image and wind scale. Table 2 shows the parameters for learning conditions.

**Table 2** Learning conditions used for the neural network

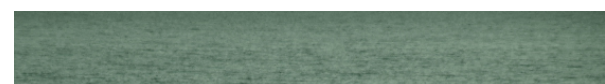
Learning iterations	10000
Permissible error	0.1
Number of hidden units	10
Random numbers	1
Fraction	100.0%
Lower limit	-1
Upper limit	1

### Texture analysis of unclassified images

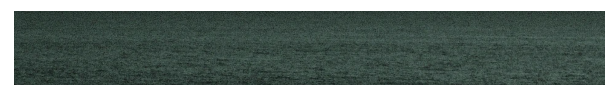
An analysis of images with unknown wave conditions was performed using the same procedure as described for the training data. Figures 7 show wave images F, G and H for which the wind scale was unknown.



(a) Image F



(b) Image F



(c) Image H

**Figure 7** Unclassified images

Learning with neural network and predicting winds

The analytical results from the training images were used for training. Figure 8 shows the predicted wave conditions based on the teaching and unclassified images. There are some concerns about the numerical stability of the predictions inferred from images A – C, but the scatter was low in the unclassified image F, and the values were relatively stable.

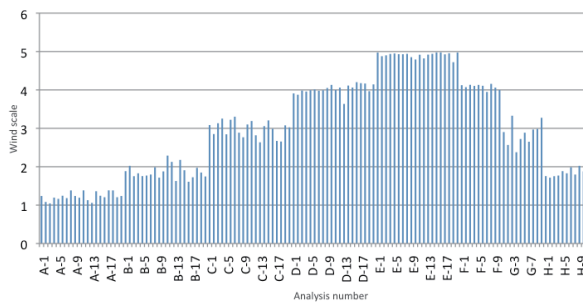


Figure 8 Wind scales of training images and prediction results from teaching and unclassified images

Predictions with gray level difference method

The neural network was trained using the data obtained with the spatial gray level dependence method. The contrast, angular second moment, entropy, mean, and inverse difference moment obtained with the gray level difference method were used for training using the same procedure described above. Figure 9 shows the results.

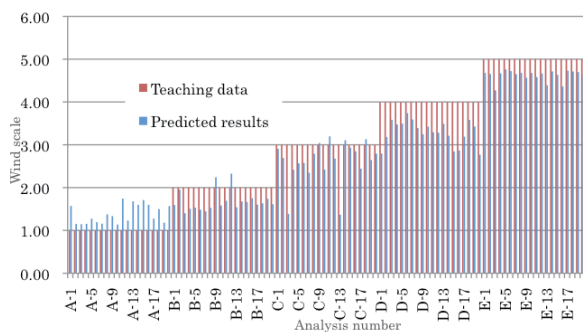


Figure 9 Predicted results using the gray level difference method

In this study, the gray level difference method was found to be less suitable for training than the spatial gray level dependence method. Still, since the greater the wind scale, the greater the precision achieved by the gray level difference method, the gray level difference method may well be effective for predicting wave conditions under high winds, despite the lack of

robust findings observed in this study.

Predictions for analytical regions of varying sizes

Instead of using an image measuring  $500 \times 200$  pixels, we increased the size of the image to  $1000 \times 200$  pixels, and show the results in Figure 10. The results showed that the findings obtained from the analysis were stable when the size of the image area was doubled. Interesting, more precise predictions were obtained for cases A – C, whose values had not been very stable when images measuring  $500 \times 200$  pixels were measured.

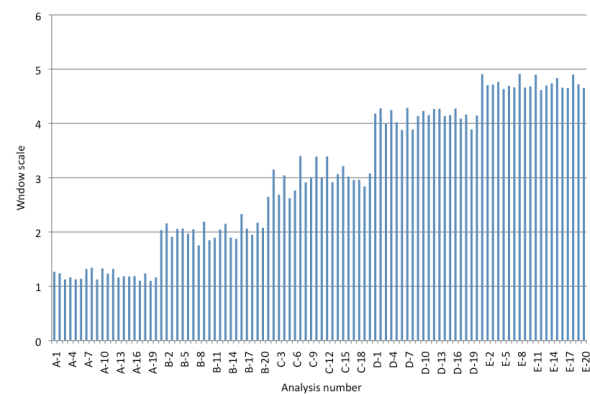


Figure 10 Predicted results obtained using a  $1000 \times 200$  pixel image method

Predictions obtained from unclassified images after changing analytical region size

Figure 11 shows the predictions of the trained network obtained from unclassified images F, G and H. Although the results shown in image G were not considered very stable, the values obtained from image H were stable. When these findings were compared with the Beaufort wind scale, image G was classified as wind scale 3, and image H, as wind scale 2, essentially

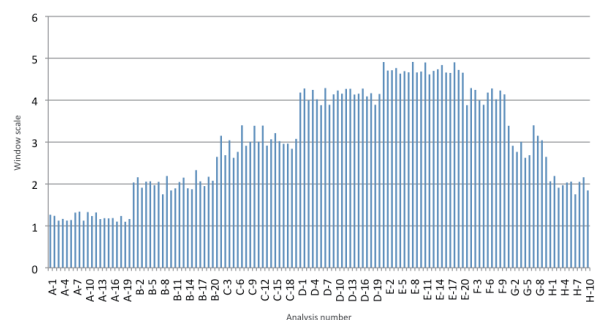


Figure 11 Prediction results using  $1000 \times 200$  unclassified images

matching the predicted results.

**Effect of changing the number of units in the intermediate layer**

The number of units comprising the intermediate layer of the three-layer neural network was increased from 5 to 15 and then to 20 units, and the obtained results were compared in Figure 12.

Figure 12(c) shows the error between the predicted values and the estimates based on visual observations when the number of units in the intermediate layer was changed from  $500 \times 200$  to  $1000 \times 200$ . When the number of units in the intermediate layer was 5 units and the image was  $500 \times 200$  pixels, convergence

was 75% at 10,000 learning cycles, so learning was forcibly terminated at this cycle number. No notable changes were observed in the results obtained using an intermediate layer with other sizes.

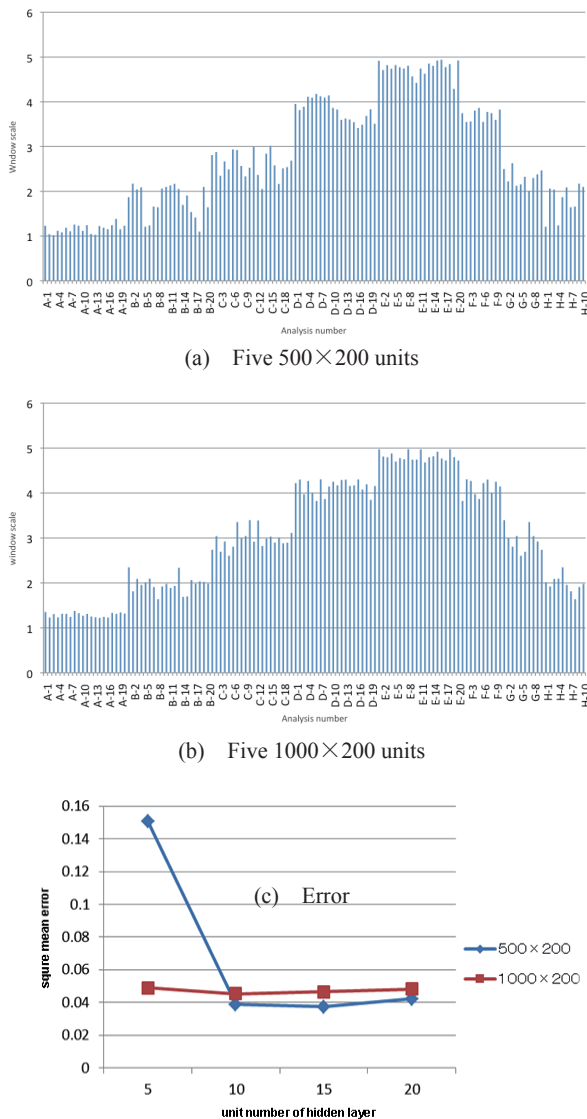
**Summary**

Although this experiment employed nighttime images of ocean surface waves, which provide comparatively little detail of the photographed. Two analytical methods were used here, spatial gray level dependence and gray level difference; within the present range, the spatial gray level dependence method showed superior predictivity. The gray level difference method did not provide satisfactory results in the present study. This is probably because of the difficulties associated with extracting characteristics using that method and nighttime images, which typically have characteristic quantities that are relatively poorly defined. However, the accuracy of the gray level difference method did improve as the wind scale increased. It is therefore possible that that method could be used, with appropriate pre-processing, to improve prediction accuracy.

Some improvement in accuracy was observed under calm conditions when the size of the analytical region was increased. This improvement was attributed to obtaining more accurate values for the characteristic quantities from larger extracted portions. However, when the wind conditions were strong, the accuracy deteriorated as convergence increased.

Provided that convergence was obtained in this experiment, the number of units in the intermediate layer did not have any particular affect on accuracy. Although color did not markedly affect analytical results, larger extracted images could be beneficial, as images with  $1000 \times 200$  pixels provided more accurate data than images measuring  $500 \times 200$  pixels, at lower wind scales.

The following are recommended topics for future research: The efficacy of both analytical methods used in this study should be reviewed at higher wind scales; the minimum practicable size for an image to provide accurate predictions should also be identified.



**Figure 12** Effect of changing number of units in intermediate layer

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