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Neural Network Learning of Ocean Wave Condition by Texture Analysis

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Abstract : In this study, littoral wave conditions were transformed into image data and used to assess the applicability of the method to constructing a system for automatically digitizing and monitoring wave conditions. An image of ocean wave conditions was treated as a texture and its characteristics were examined as texture feature quantities representing the surface conditions in response to wind. These feature quantities were input to a hierarchical neural network for learning. The network, which had a multilayer structure adapted for the back-propagation algorithm, facilitated the study of the influence of learning conditions on the network structure . In addition, digital sensitivity analysis was performed to identify optimal calculation conditions for presenting an optimal image of the sea surface . Analyses were also performed using spatial color concentration dependence, with texture feature quantities consisting of energy, entropy, correlation, local uniformity, and inertia.

Key words : wave measurement, texture, neural networks, wind force

Introduction

It is vital that people who are responsible for the operation of ships, such as fishermen, as well as people living on or near the coast, keep abreast of the wave conditions at sea. As a consequence, a variety of techniques, including SBM, spectral analysis and other methods, have been developed[1)] to plan littoral fishing expeditions, prepare for storms, and plan other activities that affect people's lives. Given the importance of obtaining information about current wave conditions in real time, several methods employing direct information have been deployed, particularly in coastal fisheries, to anticipate the effects of waves on fixed nets and aquaculture equipment or support decisions related to whether of not to issue warnings regarding whether it is safe to leave or return to port. If it were possible to perceive ocean conditions as an image, then it would be possible to convey information such as wind direction and force, wave height, etc. immediately to fishermen. Indeed, it is considered that developing a system capable of visualizing and analyzing the ocean in real time would be very useful.

In the present study, wave conditions were interpreted using image textures. The texture feature quantities of the sea surface were then calculated and input into a neural network for learning[2-4)], and the ability of the network to detect and predict the wind force class was investigated.

Texture Analysis

The word "texture" refers to patterns consisting of two-dimensional variations of color and color depth. On this basis, regions can be characterized based on the extent of their uniformity. In the field of image analysis, two kinds of texture analysis exist: structural and statistical[5)]. Structural level texture analysis relies on extracting the fundamental elements in the image that determine texture (i.e. straight lines, points, etc.) from the picture elements, and then to find the rules governing how these are aligned with each other. In statistical level

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texture analysis, we focus on the pixel color depth and calculate the texture feature quantities expressing the nature of the image in terms of uniformity, orientation, changes in contrast, etc. Natural ocean waves, the topic of this study, are like wood grain, sandy regions and grassy regions in that they show fine detail and have irregular patterns. Thus, in order to characterize such areas, the texture of the ocean surface was analyzed at the statistical level and classified based on the statistical characteristics of color depth distribution of the pixels. The wave characteristics were calculated using a color depth co-occurrence matrix created on the basis of spatial color concentration dependence. The texture feature quantities were found using the following equation[5] ;

Energy ; $E=\sum\sum P(i,j)^2$

Entropy ; $H=-\sum\sum P(i,j)\log P(i,j)$

Correlation ; $C=\dfrac{\sum\sum(i-v_x)(j-v_y)P(i,j)}{(\sigma_x\sigma_y)}$

Local uniformity ; $L=\sum\sum\dfrac{P(i,j)}{1+(i-j)^2}$

Inertia ; $I=\sum\sum(i-j)^2P(i,j)$

where N was the color depth level of the image, v_x and v_y were the mean color depths, and σ_x and σ_y were the corresponding variances.

Experiment and Observations

First, the image was analyzed using the color depth co-occurrence matrix. Each wave image was divided into a grid of regions and the wind force was classified into the five classes of the Beaufort scale as shown in Table 1. The analytical direction was 0°. Although the color indices included red, green and blue, this study only used the red index to extract and calculate texture feature values for of energy, entropy, extent of correlation, local uniformity, and inertia. Ten values for each of these features were input into the neural network as teacher patterns and the learning process of the program was initiated. Next, the textures of wave images of with unknown wind force classes were analyzed and the extracted texture feature values were input to the neural network to predict the wind force classes. The predicted values were then evaluated using the results for the wind force scale predicted from the wave image in the teacher patterns originally used to teach the neural network. When values corresponding to the wave images were obtained, the neural network was considered to have learned correctly and that it was capable of conducting accurate evaluations.

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

Wave images used as teacher patterns

Figure 1 shows the wave images used as teacher patterns for wind force classes1–5. The classes used as teacher patterns in the neural network ranged from 1.0 to 5.0 rather than 1 to 5. Figure 2 shows the wave images used as neural network inputs to predict wind force classes, and Table 2 shows the learning conditions employed for the neural network. Table 3 shows the results of the neural network predictions after learning the wind force classes from each wave image. out 1 is the teacher data and out 2 is the predicted result. It is clear from the Table 3 that satisfactory results were obtained for all the wind force scales.

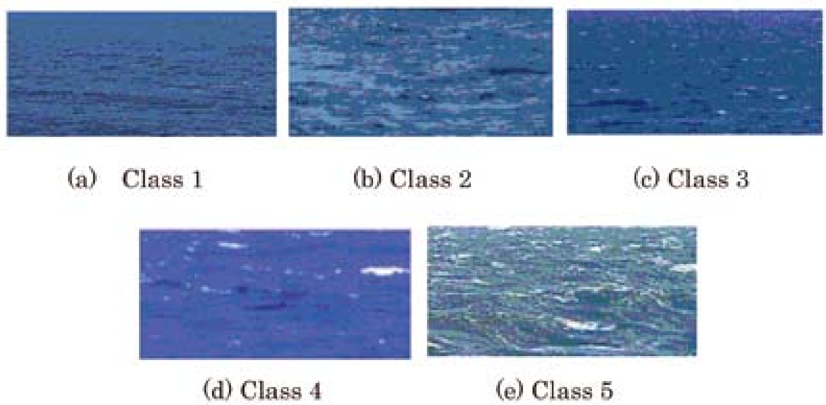

Fig. 1. Teacher patterns

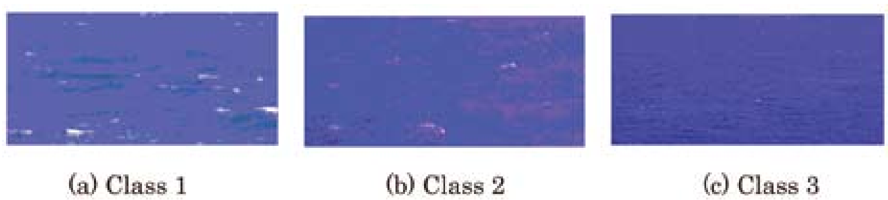

Fig. 2. Neural network inputs

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	100.00%
Lower limit	-1
Upper limit	1

Table 3. Prediction by learned networks

No.	Input					Output	
	Energy	Entropy	Correlation	Local uniformity	Inertia	Wind force class	Predicted value
1	0.0272	3.905	0.6679	0.5159	2.65	1	1.12
2	0.0286	3.834	0.6555	0.5233	2.521	1	1.09
3	0.0347	3.65	0.6941	0.5655	1.973	1	1.09
4	0.0179	4.38	0.954	0.638	1.694	2	1.95
5	0.0223	4.136	0.9268	0.6339	1.556	2	1.73
6	0.0204	4.167	0.9706	0.7034	1.033	2	2.03
7	0.0875	2.875	0.8227	0.753	0.757	3	3.18
8	0.0729	3.107	0.8179	0.7206	1.071	3	2.96
9	0.0633	3.066	0.8585	0.7365	0.73	3	2.74
10	0.0811	3.315	0.9396	0.7224	1.45	4	3.92
11	0.0763	3.393	0.9559	0.718	1.415	4	3.9
12	0.0725	3.569	0.9498	0.7109	1.636	4	3.99
13	0.0141	4.785	0.8099	0.4688	5.48	5	4.88
14	0.021	4.712	0.7097	0.4741	9.393	5	5
15	0.0132	4.907	0.8363	0.503	6.425	5	4.99

Structure of learned network and predicted results

Figure 3 shows the structure of the network after the learning process. The numbers with plus or minus sign in the figure indicate positive and negative combination loads, respectively. The findings show that inertia contributed strongly to the observed results, while energy had only a weak effect on the results . The results of the neural network predictions revealed that the wave images could be used to learn wind force classes and that the results predicted by the network were correct. The first test wave image was assessed by the neural network at a wind force class of 3.736. This was higher than a class 3 wind force and slightly less than a class 4 wind force. Comparing this value visually with the wave images used as teacher patterns revealed that this average was close to the image used to depict the class 4 wind force . The neural network was thus capable of making a reasonably correct prediction without the knowledge of the wind force class used to derive the wave images. The mean value of the second test image was 3.385, which is close to that derived from the wave image used to learn a class 3 wind force, and the mean value for the third test image was 1.915, which was close to the wave image used to learn a class 2 wind force. These were all classified by the neural network with reasonable accuracy.

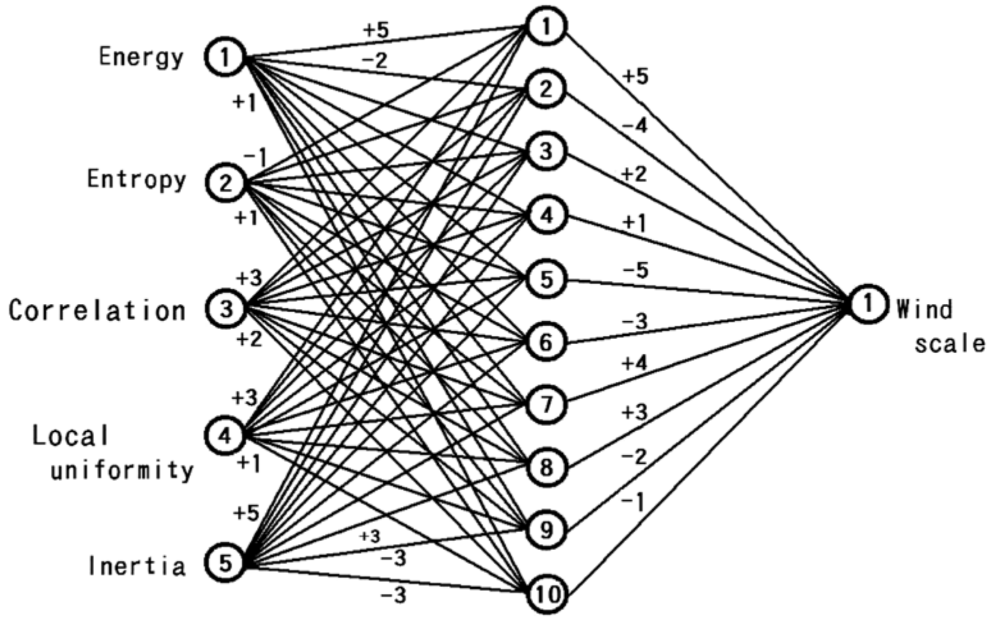

Fig. 3. The Structure of neural network after leaning

Learning Conditions for the Neural Network

The influence of the number of hidden units, number of learning iterations and allowable error were examined in order to improve the predictive capacity of the neural network. The influence of varying the number of hidden units, was studied first. The number was set to 3, 5, 10, 15 and 20, and the predictions of the neural network after learning were examined to determine which of the results most closely reflected the teacher data. On closer visual examination, no differences were apparent between the obtained results irrespective of how many hidden units, there were. Since the analysis with 10 units best reflected the teacher data, this number was employed in the following analyses.

Regarding the number of iterations , no improvement in prediction accuracy was found by increasing this, because, irrespective of how high the maximum number of iterations was set, the neural network completed learning in 760 iterations.

The allowable error was set to values ranging between 0.01 and 0.0001 to assess for its influence on convergence by the neural network. As a result, no great differences were found in the predictions while varying this parameter, but the rate of convergence diminished as the allowable error was reduced. A rate of convergence of 70-100% was considered desirable, so the allowable error was left unchanged for further learning.

Effect of Setting Texture Region

Methods for setting the region in the wave image as the object for texture analysis were also investigated. Since the image of the sea region can be cut either vertically or horizontally, these orientations were compared for their effect on network learning. Figure 4 shows the image cut vertically to give 10 texture regions that were equal in size. The red signal was analyzed and texture was analyzed in the 0o direction. Conversely, Figure 5 shows the image cut horizontally into 10 texture regions that were equal in size. As before, the red signal was analyzed and the texture was examined in the 0o direction. Table 4 shows the results of this analysis and Table 5 summarizes the results of neural network learning under the two conditions described above.

Data Nos. 1-10 in the Table 5 show the learning results derived from teacher data using wave image E, which was used previously for learning. The items listed vertically in the table (Data Nos. 1-10) correspond to the cases when the image was divided vertically for the texture analysis and learning, while the items listed horizontally (Nos. 1–10) refer to those cases in which the image was divided horizontally for texture analysis and learning. Figure 6 presents the predicted results obtained after learning by the neural network. Data Nos. 1–10 in the figure are the results derived from the teacher data in the wave image and Data Nos. 11–20 (in yellow) represent the results predicted by the neural networks from the vertical divisions of the image. Data Nos. 21–30 (light blue) represent the results predicted from horizontal divisions of the image. When the results were compared, the mean predicted value derived from the vertical divisions was 4.91, while that derived from the horizontal divisions was only slightly less at 4.85. Data Nos. 22 and 23 were found to have relatively high errors due to the lower perspective of the texture region in the vertically divided image than in the horizontally divided image, which resulted in a lower error in the depth of image color. We therefore conclude that better predictions can be obtained if the image is divided vertically when setting the texture regions.

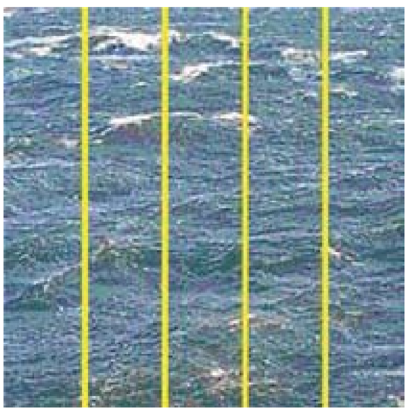

Fig. 4. Vertical cut image

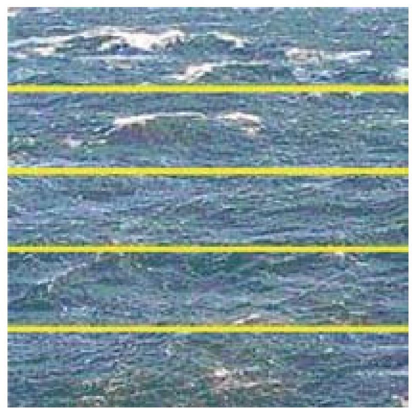

Fig. 5. Horizontal cut image

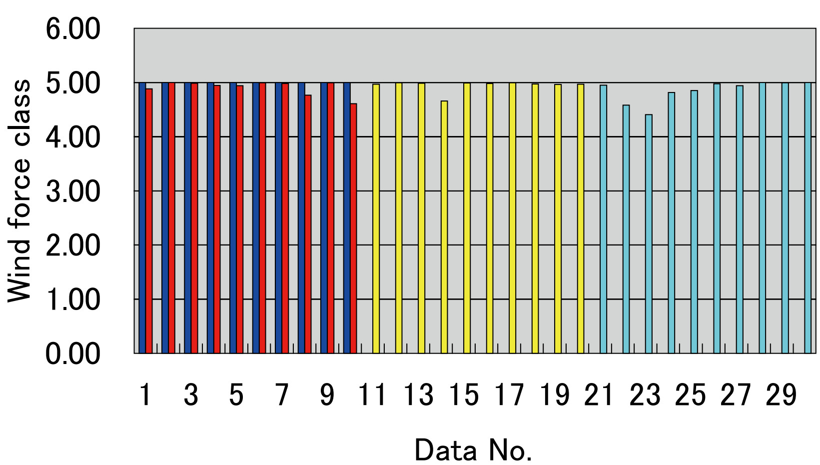

Fig. 6. Prediction by learned neural network

Table 4. Properties for image dividing direction

	Energy	Entropy	Correlation	Local uniformity	Inertia
Vertical 1	0.0147	4.726	0.8016	0.5349	5.903
Vertical 2	0.0139	4.886	0.828	0.508	7.012
Vertical 3	0.0128	4.902	0.8323	0.5069	6.545
Vertical 4	0.0148	4.721	0.8073	0.5396	4.567
Vertical 5	0.011	5.037	0.8528	0.4794	6.798
Horizontal 1	0.0144	4.84	0.852	0.462	5.769
Horizontal 2	0.0169	4.618	0.8323	0.5001	4.523
Horizontal 3	0.0168	4.612	0.8284	0.5018	4.355
Horizontal 4	0.0143	4.754	0.8491	0.4953	4.93
Horizontal 5	0.0161	4.668	0.832	0.5207	4.979

Table 5. Prediction by neural networks

	Energy	Entropy	Correlation	Local uniformity	Inertia	Out 1	Out 2
1	0. 0141	4. 7850	0. 8099	0. 4688	5. 4800	5. 00	4. 88
2	0. 0210	4. 7120	0. 7097	0. 4741	9. 3930	5. 00	5. 00
3	0. 0132	4. 9070	0. 8363	0. 5030	6. 4250	5. 00	4. 99
4	0. 0134	4. 8400	0. 8185	0. 4740	5. 8460	5. 00	4. 95
5	0. 0132	4. 8630	0. 8274	0. 4457	5. 9320	5. 00	4. 94
6	0. 0248	4. 5430	0. 7298	0. 5124	7. 9580	5. 00	5. 00
7	0. 0163	4. 7450	0. 7919	0. 4874	6. 5360	5. 00	4. 98
8	0. 0166	4. 6630	0. 8332	0. 4934	4. 8380	5. 00	4. 76
9	0. 0144	4. 8610	0. 7894	0. 4914	7. 2410	5. 00	4. 99
10	0. 0195	4. 5170	0. 7969	0. 4994	4. 6560	5. 00	4. 61

Summary

We used a neural network to predict wind force by analyzing the texture on an image of waves. The neural network was trained using these images of ocean waves, and comparisons with other teacher patterns revealed that the method provided accurate predictions. Thus, if a neural network is trained using wave images with known wind force classes, then it can be used to assess and predict wind force classes based on the texture of a wave image with an unknown wind force class. Using the texture analysis of a wave image provides the network with sufficient texture feature quantities for analysis, and no calculations of other elements, such as the wavelength, frequency or wave height, are necessary. Data for analysis and learning by a neural network are straight

forward to acquire. It was found that the data generated by the neural network were slightly more robust when the texture regions sampled for texture analysis were taken in the vertical direction. However, neural networks have an extremely complicated structure, and the equations describing such networks are complicated. It was therefore impractical to make any adjustments to the neural network and conduct trial runs of the modified network in order to improve the prediction results. In the future, this system should be optimized to analyze an increased number of images and to improve the accuracy of the predictions.

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テクスチャ解析による海面波浪状態のニューラルネット学習

森元映治・中村誠

本研究は、沿岸海域の海面波浪状態を画像情報としてとらえ、特徴を自動的に数値化する監視システムの構築について基礎的検討を行ったものである。海面の波浪状態をテクスチャとしてとらえ、風力に応じた海面状態を特性値に対応させ、階層型ニューラルネットワークの入力として学習させた。ネットワークは誤差逆伝播法による多層構造型を用いた。これにより学習条件、ネットワーク構造の及ぼす影響を調べ、最適な計測条件を数値的に感度解析した。また解析データとして最適な海域画像の設定方法についても複数の方法を比較検討した。解析には空間濃度レベル依存法を用い、特徴量としてエネルギー、エントロピー、相関、局所一様性、慣性の各量を用いた。