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Modified Hopfield Neural Network Algorithm (MHNNA) for Chlorophyll Mapping in Penang Strait, Malaysia

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ABSTRACT

Water pollution is big problem in the world. The objective of this study was to modify Modified Hopfield Neural Network Algorithm (MHNNA) with remote sensing image for water quality mapping. The using of remote sensing technologies for environmental monitoring gives a low-cost, reducing time, low efforts. Without using the traditional ship sampling method for environmental monitoring that requires a high survey cost, long time consuming, and exerting great efforts. In this study we classify one of the water pollutants which is chlorophyll of polluted water in Penang strait, Malaysia by applying (MHNNA) on THEOS (Thailand Earth Observation System) image. This done after modifying Hopfield neural network to be appropriate with color images such as satellite images. The collected samples from study area were simultaneously with the image acquisition by the airborne. The samples locations were determined by usage of a handheld global positioning system (GPS), and the measurement of chlorophyll concentrations was conducted in the lab to be validation data (sea-truth data). The mapping (classification) has been achieved by using (MHNNA) to classify the concentrations according their varied values to produce the desired map. The map was color-coded for visual interpretation. The efficiency of the proposed algorithm was investigated based on dividing the validation data into two groups, the first one refers to standard samples for supervisor classification by the used algorithm, and the second one for test. Where after getting classification we detected the second group positions in the produced classes, then calculation of the correlation coefficient (R^2) and (RMSE) between the two groups according to their locations in the classes. The observations were high (R^2= 0.981) with low (RMSE=0.9621). This study indicates that chlorophyll mapping of polluted water can be carried out using remote sensing technique by the applying of (MHNNA) on THEOS satellite data over Penang strait, Malaysia.

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INTRODUCTION

Water is one of the most precious natural resources and the lifeblood for sustained economic development in each country. Environmental management and water resources are essential for sustaining quality of life on earth planet (Bhatti, A.M., 2008). Water quality has been affected via pollutants delivered to a water body from either point or nonpoint sources. Point sources can be traced to a single source, for example a pipe or a ditch. Non- point sources are diffuse and associated with the scene and its response to the movement of water, human activities on the watershed, land use and management, and natural influences. Industrial, agriculture, and urban areas are anthropogenic sources of point and nonpoint materials. Water pollutants that lead to deterioration of water quality affect ecosystems, estuarine, and most freshwater in the world (Dekker, A.G., 1995). The changes of water quality in the surface water bodies create several health problems for the creatures life (Alaguraja, P.,). The solution requires identifying the reasons of water pollution and detecting its trace to treat or reduce this problem, beginning from the most important places in the world that have the great effect on the live creatures.

The study area in this research is Penang strait, which is important location to have good environment and ecosystem care because it has central location between the two parts of Penang state where people live on the

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both parts, but because human activities and natural influences continue to increase pollution levels, to solve this problem, at first the solution requires monitoring study and analysis of water bodies and determine the pollution sources. The best techniques for all these requirements are remote sensing techniques (Kzar, A.A., M.Z. MatJafri, 2013).

Neural Networks (NNs) are considered important techniques in the remote sensing applications, (NNs) perform several useful methods such as recognizing, classification, analyzing, estimation and prediction. Many studies have been performed to achieve tasks in the water quality topic. In this study the focus was on classification. Among the several types of neural networks, Hopfield's model, is suitable for solving optimization problems . In this study we modify the Modified Hopfield Neural network (MHNN) [5] to classify chlorophyll in Penang strait, Malaysia.

The problem observed when HNN use with multicolor images that have high information, when these images are converted into black and white in order to be compliant with HNN, the information is reduced. Thus, this can be considered as a challenge for high resolution images like satellite images where each pixel as a significant piece of information used to interpret a certain phenomenon. Furthermore, a solution for usage HNN with high resolution images will be presented via dealing with the pixel depth in this type of images, this technique named as Modified Hopfield Neural Network (MHNN), it has been presented by (Mutter, K.N., 2010).

In this study the (MHNN) technique has been developed for classification of water pollutant (chlorophyll), where the adaptive image with HNN will be sliced for each band into binary layers called bit planes (Gonzalez, R.C. and R.E. Woods, 2002; Sonka, M., 2008). Each band in the color image is converted to eight layers via the conversion of each band value in the pixel from decimal to binary, then take vector of three bit consist of the three bands, this means for each pixel we have eight vector, and stored in a lookup table, to be dealt directly with HNN. So modify the energy function through considering each layer weight without using the same dealing for lowest, highest and graded layers weight. The now technique named as Modified Hopfield Neural Network Algorithm (MHNNA).

The new algorithm has been achieved by the following steps:

A. Using Validation Data:

The validation data (real data) have been used as samples in supervisor classification by the new algorithm for identification of chlorophyll concentrations, where the learning of the new algorithm (MHNNA) depends on bands values (R,B,G) that are at these samples location, and they match with adopted image data (bands of R,G, B) then decision making to choice the corresponding or the nearest class. Also, for accuracy of the new algorithm, we have been separated the real data into two parts, the first part used as classification samples and the second part used as test samples through detection of their position in the produced classes to calibrate the new algorithm.

B. Depending on More than Two Samples:

The used samples that used in just two samples, here the real data (samples) that have been used were thirteen samples, they gave wide range of samples that is appropriate for the classification success and for calibration of the new algorithm.

C. New Representation for the Used Vector:

New representation for the adaptive vector (Sample Vector and Image pixel Vector that match each other in the matching step) gives good results for classification, where the vector consist of three elements, that are the three binary numbers of (R, G, B) from the three bands layers in one order, this means each image pixel has eight vectors, *equation (1) represents of (SV_L) the Sample Vector in the certain layer L, so in the same way we represent (IPV_L) the Image pixel Vector in the certain layer L, as in equation (2):*

$$SV_L = [R, G, B] \qquad \ldots\ldots(1)$$

$$IPV_L = [R, G, B] \qquad \ldots\ldots(2)$$

D. Never Using the Iteration of Matching in (MHNNA):

Matching iteration never used, in this case the decision making about the class will be done when the image pixel fellows the class (sample) which has the lowest value of the summation of the eight values of the energy function, without problem of the local minimum.

E. Modifying the Energy Function:

The Weight of each Layer Order (WLO) in the binary system, has been considered in the energy function. It gives the best results, when the energy function through each matching is multiplied by the weight of each

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sample vector (WSV) in each layer order with image pixel vector which is the counterpart in the same layer order, equation (3) represents (WLO), so table (I) shows the (WLO) value of each layer order (L), and equation (4) represents (WSV) which is called Hebb rule (Mutter, K.N., 2010; Fausett, L., 1994; Samarasinghe, S., 2007).

$$WLO = 2^{L-1} \tag{3}$$

WLO is the Weight of a Layer Order in the binary system, L is the Layer order (Kzar, A.A., 2013).

Table 1: The Layers Orders with their Weights in the Binary system.

Layer order (L)	1	2	3	4	5	6	7	8
(WLO)	1	2	4	8	16	32	64	128

$$WSV = \left(\sum_{i,j=1}^{3} SV_{Li} * SV_{Lj}\right) SSVG_L \tag{4}$$

Where SV_{Li} is sample vector in a certain Layer order (L), SV_{Lj} is the transpose of SV_{Li}, e.g. $SV_{Lj} = SV_{Li}^T$, $SSVG_L$ the summation of sample vector signs in a layer order (L) which is represented in the following equation:

$$SSVG_L = sgn\left(\sum_{i=1}^{3} SV_{Li}\right) \tag{5}$$

Also, we need summation of image pixel vector signs in a layer order L, as the following equation:

$$SIPVG_L = sgn\left(\sum_{i=1}^{3} IPV_{Li}\right) \tag{6}$$

The considering of (WLO) in the energy function is to keep the value of this function for each matching (for image pixel vector and the weight of sample vector in each layer order L). The value of the binary number in the layer increases according to the increasing in the order from lowest order to the highest order, without (WLO) the energy function value of a certain layer will be nearest or the same value of the energy function of other layer without respecting the increasing of the binary number in layers ascending, therefore each layer order has effect more than other order layer on the summation value of the eight energy functions.

Where the selected sample (class) for image pixel, is the sample which gives the lowest summation of energy functions, because it denotes the corresponding or nearest class, but without the weight of layer order (WLO) in the binary system is very important to correct results, so avoiding the error in summation of the energy functions values, without this variable, this causes improper effect on the summation value. Equation (4) for the matching between (IPV_L) and (WSV_L). Equation (7) illustrates the modified energy function.

$$M = (IPV_L * WSV_L) * SIPVG_L \tag{7}$$

IPV_L is the image pixel vector of layer order L, WSV_L is the weight of the sample vector in the same layer order L, $SIPVG_L$ is the summation of image pixel vector signs in the same layer order (L).

$$Mn = \begin{cases} +1, & M \geq 0 \\ -1, & M < 0 \end{cases} \tag{8}$$

$$E = -\frac{1}{2} * \left(Mn * IPV_L{}^T\right) * WLO \ldots.. \tag{9}$$

E is energy function, $IPV_L{}^T$ is the transpose of IPV_L , WLO is the weight of a layer order (L) in the binary system .

2. Study Area and Data Sources:

The study area is Penang strait, Malaysia. the used image of the study area has location between latitudes 5^o 19’ N to 5^o 26’ N, and longitudes 100^o 17’ E to 100^o 24’ E. Penang state has two parts: the first part an island, and the second part a coastal strip on the mainland which is called Wellesley Province (Seberang Perai)(Daraigan, S.G., 2007). Penang Island has an equatorial climate which is uniform during the whole year (Mutter, K.N., 2010). The climate is described as warm and humid. The temperature range from 25^{o}C (night time) to 33^{o}C (day time) (Daraigan, S.G., 2007; San, L.H., 2009). The average of the annual relative humidity varies between 70 - 90 %. For the rainfall, the average annual rainfall is approximately 267 cm, during the annual total can be as high as 624.

Penang has monsoon winds, during the period of these winds, the condition becomes totally different. Thus, the conditions of the city will be changeable to be sunshine during the day, but rainy in the evenings (Mutter, K.N., 2010). Fig.1. shows the study area.

Methodology:

Determine of the locations (longitudes and latitudes) for samples collection in the study area by a handheld GPS. Then samples collection from these locations simultaneously with the airbone passing for the image acquisition, the samples analaysis in the lab to measure the validation data that represented by chlorophyll

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concentration of unit (mg/m^3) belong each location. Fig.2. shows the raw satellite image and sampling locations for validation data. Table 2 illustrates the chlorophyll concentrations values with their indices.

Results:

The applying result of the new algorithm (MHNNA) on the satellite image (THEOS) is shown in the fig.3, which shows the zeros giving for the non-water pixels. Fig.4, where the mapping of Chlorophyll concentrations has been achieved. The map was color-coded for visual interpretation.

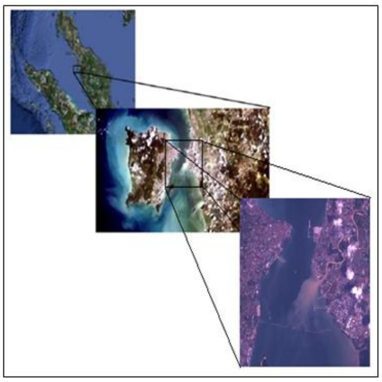

Fig. 1: The study area.

Table 2: The Samples Values of the Real Data and their Indices.

Sample index	Sample value (mg/m^3)
1	8.5
2	3.6
3	3.3
4	3.1
5	2.5
6	4.3
7	5.2
8	9.2
9	10.2
10	12.3
11	11.3
12	4.9
13	2.8

Fig. 2: The raw satellite images and sampling locations.

The applying MHNNA on the dopted satellite image (RGB image) is explained the following steps:

Modified Hopfield Neural Network Algorithm (MHNNA):

1- Consider each pixel bands values of non water region equal to zeros.

2- Pick samples of size (3x3) pixels from the image, then take the average value to be the centers of this samples, where the centers of the samples locations (longitude and latitude) are exact the same locations of collected samples (real data) from the study area.

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3- Analyze each sample pixel (center pixel) to the RGB bands, and for each band do:
4- Converting each digital numder of each band from decimal to binary representation, to replace the digital numder of the band by eight binary layers called bit planes. This means each binary bit (0 or 1) represented by one layer.
note: for small binary value eg. (11), the remaining six bits (layers) at the left have the value of zero.
5- For each sample (S) Initialize vectore of size (1x3) for the three binary bits (R,G,B) for each layer (L) to be known vector for learning, as in equation (1). this means each sample pixel have eight vectors of binary bits.
6- For each vector, find the summation of the sample vector signs in the layer (L) by equation (5).
7- Find weight to each vector by using equation (4).
8- For all image pixels:
If pixel bands values equal to zeros then the results of bands values equal to zeros, else, (water pixels) do:
9- For all image pixels (water pixels) repeat Steps (3-6), except replacing equations (1) and (5) by equations (2) and (6) respectively for getting IPV_L (image pixel vector which is considered unknown vector of the layer order L), and $SIPVG_L$ (summation of image pixel vector signs in the layer order L).
10-For each water pixels do:
11-Convergeing between the image pixel and the first sample through: For each unknown vector of the eight unknown vectors: Converge the unknown vector of the each layer with the weight of the known vector of the corresponding layer in the order by using equation (7).
12- Verify equation (8).
13- Find the energy function value by equation (9).
14- Find summation of the energy function values of the eight convergences above.
15- Repeat steps (11-14) for the other samples.
16- Select the lowest summation value of the energy function and consider the image pixel follow the sample (class) that gives this lowest summation of the energy function values.

Fig. 3: Zeros values giving for the non-water pixels.

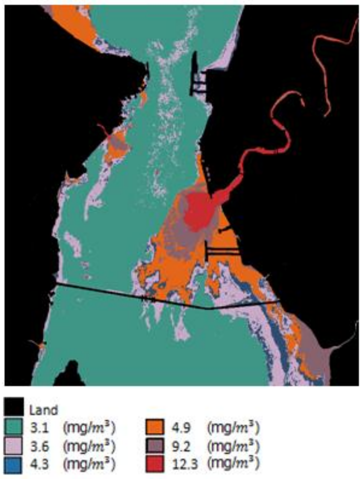

Fig. 4: Chlorophyll mapping.

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The finding of the efficiency investigation of the used algorithm (MHNNA) we divided the validation data (Chlorophyll concentrations) into two groups, first group which has even indices to use them as standard samples for supervisor classification by the used algorithm, the second group which has odd indices for test, where after classification achievement, we detect the second group data positions in the produced classes, then calculation of the correlation coefficient (**R^2**) and the root-mean-square-error (***RMSE***) between the first and the second group data. Fig.4. illustrates the result of the classification of Chlorophyll concentrations that used (even indices) in the classification by applying (MHNNA) on the used image. Table. 2 and fig.5. shows the results of the test for the depended and test samples.

Table 3: The Source and Test Samples values of chlorophyll

Source samples ($mg/_{m^3}$)	Test samples ($mg/_{m^3}$)
9.2	8.5
3.1	3.3
3.1	2.5
4.9	5.2
12.3	10.2
12.3	11.3
3.1	2.8

Where the correlation coefficient is (R^2 = 0.981) with low (RMSE=0.9621).

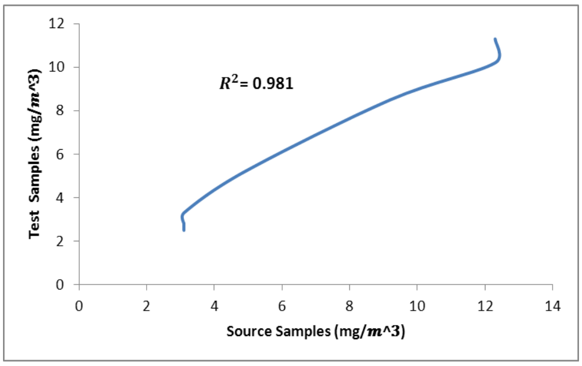

Fig. 5: The correspondence of the source and test samples.

Conclusion:

This study gives a brief overview of the Chlorophyll mapping in Penang strait, Malaysia. The satellite imagery can be used to provide information for effective planning management purpose. The application of THEOS data for chlorophyll mapping in this area produced reliable and good results.

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