A feed-forward Hopfield neural network algorithm (FHNNA) with a colour satellite image for water quality mapping

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Abstract. There are many techniques that have been given for water quality problem, but the remote sensing techniques have proven their success, especially when the artificial neural networks are used as mathematical models with these techniques. Hopfield neural network is one type of artificial neural networks which is common, fast, simple, and efficient, but it when it deals with images that have more than two colours such as remote sensing images. This work has attempted to solve this problem via modifying the network that deals with colour remote sensing images for water quality mapping. A Feed-forward Hopfield Neural Network Algorithm (FHNNA) was modified and used with a satellite colour image from type of Thailand earth observation system (THEOS) for TSS mapping in the Penang strait, Malaysia, through the classification of TSS concentrations. The new algorithm is based essentially on three modifications: using HNN as feed-forward network, considering the weights of bitplanes, and non-self-architecture or zero diagonal of weight matrix, in addition, it depends on a validation data. The achieved map was colour-coded for visual interpretation. The efficiency of the new algorithm has found out by the higher correlation coefficient ($R=0.979$) and the lower root mean square error ($RMSE=4.301$) between the validation data that were divided into two groups. One used for the algorithm and the other used for validating the results. The comparison was with the minimum distance classifier. Therefore, TSS mapping of polluted water in Penang strait, Malaysia, can be performed using FHNNA with remote sensing technique (THEOS). It is a new and useful application of HNN, so it is a new model with remote sensing techniques for water quality mapping which is considered important environmental problem.

1. Introduction

Water is essential to humans, animals and plants. especially for human being, it has important in many different ways like for food production, drinking, domestic and industrial activities [1]. Water is one of the most important natural resources and the lifeblood for sustaining economic development in any country [2]. Water pollution can come from both point and non-point sources. Point sources can be traced to a single source, such as a pipe or ditch. Non-point sources are diffused and typically associated with a watershed and its response to the water movement, human activities, land use and management, and natural influences. Industrial, agriculture and urban areas are anthropogenic sources of point and non-point pollutants. Water pollutants that deteriorate water quality affect many estuarine
and freshwater ecosystems on earth [3]. Water quality changes in surface water bodies can create various health problems for living creatures [4]. To solve water pollution issues, we must identify the causes and detect their locations, beginning with major pollution sources that impact places of significant interest or importance.

Penang strait is used as our study area. The area was chosen because of its urgent need for environmental and ecosystem protection. The area is centrally located between the two sections of Penang state, with people living in both areas. Thus, human activities and natural influences continue to increase pollution levels. We must apply monitoring techniques, analyse water bodies and determine pollution sources to solve pollution problems. All of these requirements can be satisfied via remote sensing techniques [5]. The use of artificial neural networks (ANNs) is an important technique in remote sensing applications. ANNs help to provide several useful processes, such as recognition, classification, enhancement, analysis, estimation and prediction. Many studies have been carried out related to water quality. In this study, we focus on water quality mapping. Among several types of ANNs, the Hopfield neural network (HNN) is found suitable for solving optimization problems. In this study, we modify the modified Hopfield neural network (MHNN) [6] for TSS mapping over Penang Strait, Malaysia. The drawback associated with using an HNN with high information, multi-colour images is that information is reduced when these images are converted into white and black, which is required by HNN. Therefore, this drawback is a challenge for colour images, such as satellite images, where each pixel is considered a significant piece of useful information used to interpret a certain phenomenon. To use HNN with colour images, a modified Hopfield neural network (MHNN) has been presented by [6]. This algorithm focuses on the pixel depth of colour images, such as colour satellite images.

In this study, the MHNN technique has been developed for mapping total suspended solids (TSS). Depending on the modification technique, each band of the adaptive HNN image was sliced into binary bitplanes [6-8]. Each band in the colour image is converted to eight bitplanes by converting each band value in the pixel from decimal to binary, then, to a bipolar system, which is convenient for HNN. The new algorithm is named Feed-forward Hopfield Neural Network Algorithm (FHNNA).

2. FHNNA

The FHNNA has two phases: Learning phase and Converging phase. The modification was with both of these phases.

2.1. Learning phase

This phase depend totally on the network vector, called the known vector, and the learning weight. The adopted vector of this network consists of three elements (three bipolar numbers), which are extracted from one band. The sample vectors which are considered known vectors are used for initializing the learning weights according to equation (1). This means the weight will be a matrix of nine elements. The weight initializing occurs in the learning phase of this neural network, and these weights are stored in a look-up table to be ready for the converging phase of the HNN with the unknown vectors, which also consist of three elements from the image data. The weight equation is called the Hebb rule [6, 9, 10].

\[ W_{ij} = \sum_{j=1}^{3} V_i V_j \]  

Then, it is multiplied by the majority description of the known vector \( mdkv(V_j) \):

\[ W_{ij} = \sum_{j=1}^{3} V_i V_j \cdot mdkv(V_j) \]  

Where \( V_j \) is the known vector and \( V_i \) is the transpose of \( V_j \).

\[ mdkv(v_j) = sgn(\sum_{j=1}^{3} v_j) \]
In addition, the initialized weight has been determined with zero-diagonal architecture (non-self-connection architecture). The majority description is very important in this network for avoiding similar weights produced by orthogonality phenomenon. Table 1 shows the possible cases of the adopted vector (known or unknown) and its weights, with the correction by \( m_{dv}(V_j) \).

Table 1: All the possible vectors cases with their weight matrices.

| Index (decimal) | Vector states (binary) | Vector states (bipolar) | Learning Weight states | majority description \( m_{dv}(v) \) | Corrected Weight states |
|----------------|------------------------|-------------------------|------------------------|--------------------------------|------------------------|
| 0              | 0 0 0                  | -1 -1 -1                | 0 1 1                  | 0 -1 -1                        | -1 0 0                |
| 1              | 0 0 1                  | -1 -1 +1                | 0 1 1                  | 0 -1 +1                        | -1 0 1                |
| 2              | 0 1 0                  | -1 +1 -1                | 0 -1 -1                | 0 1 -1                         | 1 0 1                 |
| 3              | 0 1 1                  | -1 +1 +1                | 0 -1 -1                | 0 1 +1                         | 1 0 1                 |
| 4              | 1 0 0                  | +1 -1 -1                | -1 0 -1                | 0 1 +1                         | 1 0 1                 |
| 5              | 1 0 1                  | +1 -1 +1                | -1 0 -1                | 0 1 -1                         | 1 0 1                 |
| 6              | 1 1 0                  | +1 +1 -1                | -1 0 -1                | 0 1 +1                         | 1 0 1                 |
| 7              | 1 1 1                  | +1 +1 +1                | 0 1 1                  | 0 1 1                          | 1 0 1                 |

2.2. Converging phase

The convergence phase of this network is represented by the energy function equation. It provides the value that denotes the amount of convergence between the known vector (from the sample), which is represented by the learning weight, and the unknown vector (from the image). The energy function equation of the Hopfield neural network is given below [11]:

\[
E = -\frac{1}{2} \sum_i \sum_j v_i w_{ij} v_j + \delta v_j \quad \ldots \ldots (4)
\]

Where \( E \) = energy function, \( n \) = number of vector elements, \( v_i \) = unknown vector = \( v_i^T \) or \( v_i = v_j^T \), \( W_{ij} \) = learning weight of the known vector which is the counterpart of the unknown vector \( v_j \), where this weight from the output of neuron \( i \) to the input of neuron \( j \) and \( \delta = \) the limiting value, which equals zero in the Hopfield neural network because it is a single layer. Because HNN here in this study is single layer, the \( \delta \) will be equal to zero, then the energy function equation becomes:

\[
E = -\frac{1}{2} \sum_i \sum_j v_i w_{ij} v_j \quad \ldots \ldots (5)
\]

In the FHNNA, the energy function is modified by considering weights for the bitplanes (\( W_b \)) to keep the energy function level of each of the eight bitplanes. Furthermore, the energy function equation must be multiplied by the majority description of the unknown vector, \( m_{duv}(v_j) \), to avoid producing the reverse result for the energy function [12]. For this, the equation for \( E \) becomes:
\[ E = -\frac{1}{2} \sum_{i}^{n} \sum_{j}^{n} v_i w_{ij} v_j * W_b * mduv(v_j) \quad ... (6) \]

\[ mduv(v_j) = \text{sgn}(\sum_{j=1}^{3} v_j) \quad \ldots \quad (7) \]

The weight of a bitplane (\( W_b \)) is represented by the following equation:

\[ W_b = 2^{L-1} \quad \ldots \quad (8) \]

Where \( W_b \) is the weight of a bitplane in the binary system and \( L \) is the bitplane order [5], so that these weights will be equal when the binary system is converted to the bipolar system, which is suitable for the HNN.

| \( L \) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|-------|---|---|---|---|---|---|---|---|
| \( W_b \) | 1 | 2 | 4 | 8 | 16 | 32 | 64 | 128 |

According to the energy function value, we can know how similar to, or different from, the unknown vector the known vector is, according to the sequence of energy values (-3, -1, +1, +3). The investigation of the energy function value in the case of a non-self connection architecture (weight of zero on the diagonal) for all states between the unknown vectors and the weights of the known vectors are 64 states of energy function values, this number comes from all cases that produced from the 8 possible cases weights of the known vectors and the 8 possible cases of the unknown vectors, as shown in table 3.

Table 3: All possible energy function values of the FHNNA.

| W | V | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|
| -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 | -3 |
| -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 |
| -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 |
| -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

3. The study area

The Penang Strait, Malaysia is the study area of this work. The image used for the study is located between latitudes 5° 19’ N and 5° 26’ N and longitudes 100° 17’ E and 100° 24’ E. Penang state is divided into two parts. The first is an island and the second part is a coastal strip on the mainland, which is called Wellesley Province (Seberang Perai) [13]. Penang Island has an equatorial climate, which is uniform throughout the year [6]. The area has a warm, humid climate. The temperature ranges from 25 °C (night time) to 33 °C (day time) [13, 14]. The average annual relative humidity varies between 70% and 90%. The total annual rainfall can be as high as 624 cm, and the average annual rainfall is approximately 267 cm.

Penang state is faced by monsoon winds. During this period, the weather conditions become rainy at night and sunny during the day. Figure 1 shows the study area.
4. The used data

The data in this study is divided into two essential parts: the remote sensing image (THEOS) and the validation data, which related with samples that took simultaneously with capturing the satellite image.

4.1. The satellite image

In this study, the used remote sensing (satellite) image is Thailand earth observation system (THEOS). There are technical specifications for this type that make it able to achieve several applications; Figure 2 shows THEOS [15]. Table 4 demonstrates these specifications [16], and Table 5 gives characteristics about THEOS satellite orbit parameters.
4.2. Validation data

The location for sample collection (longitudes and latitudes) in the study area were determined using a handheld global positioning system (GPS). Samples from these locations are collected simultaneously with satellite (THEOS on 29-1-2010) image acquisition. The samples were analysed in the lab to measure the validation data, represented by TSS concentrations in milligrams per litre (mg/L) for each location. The raw satellite imagery and sampling locations used for validation data and the TSS concentrations with indices are shown in Figure 3.

| Sample index | Longitude       | Latitude       | Sample value (mg/L) |
|--------------|-----------------|----------------|---------------------|
| 1            | 100d20'20.6002"E | 5d23'56.0900"N | 75                  |
| 2            | 100d19'45.9098"E | 5d22'16.9400"N | 70                  |
| 3            | 100d20'22.2601"E | 5d21'50.5000"N | 50                  |
| 4            | 100d22'17.1098"E | 5d22'15.2800"N | 98                  |
| 5            | 100d22'11.3300"E | 5d22'40.0700"N | 91                  |
| 6            | 100d22'03.0698"E | 5d22'56.6000"N | 101                 |
| 7            | 100d21'25.0600"E | 5d22'58.2000"N | 71                  |
| 8            | 100d21'33.3202"E | 5d23'21.3800"N | 62                  |
| 9            | 100d20'59.4398"E | 5d23'13.1200"N | 50                  |
| 10           | 100d20'09.8700"E | 5d23'37.0800"N | 71                  |

Figure 3: THEOS and validation data: a- Raw satellite images and sampling indices. b- Samples locations and their concentrations values.

5. Methodology

It is important to mention the FHNNA architecture, that is demonstrated in the Figure 4 [6]. This architecture consists of three neurons, where each node is connected with every other neuron but not with itself, as a result we used architecture called non-self-architecture (zero diagonal weight matrices). The possible number of vectors is $2^3$, the small number of neurons gives FHNNA the ability for computing faster than other size, in addition to ability of dealing with a big number of patterns.
Modification of the FHNNA was conducted via the following contributions:

5.1. The validation

The validation is very important in studies like that related with water quality, where the validation data (real data) representing TSS concentrations are divided into two equal groups. The first group is used to classify samples (source samples) through the converted red, green, and blue values of these samples locations for using in the FHNNA. The second group is used as test samples by finding out their position in the produced classes. The band values are converted from decimal to binary representation, then to a bipolar representation as known vectors. They produce the learning weights in the learning phase of the FHNNA. The weights will then combine with the unknown vectors from the image bands by the energy function value to test the corresponding or nearest class. The concentration values will not be used in the proposed algorithm, but instead for determining accuracy through calculating the $R$ and $RMSE$ between the concentrations from the produced classes and those are found out in the produced class locations. Previous studies [6] have used only two samples. In this study, twelve real samples were used. They give a better range of samples, which is ideal for satellite image classification success and algorithm accuracy. Matching then occurred between the image pixels vectors (unknown vectors) and the counterparts weights of the samples vectors (known vectors). This matching is an important step in providing the energy function value.

5.2. FHNNA as a feed-forward associative memory

In the new algorithm, HNN is represented as a feed-forward network, which acts in one direction. It is not recurrent because this artificial neural network has been determined as ideal for classification purposes. Two types of convergence methods exist [12, 17, 18]:

**Type one**: Detection method – used to detect the corresponding vector by calculating the value of the energy function. This method is related to a feed-forward net (non-iterative net) and is typically used for pattern classification.

**Type two**: Generating method – used to generate the lost vector based on the energy function value calculation. This method is a recurrent net (iterative net) and is typically used for several applications such as enhancement or restoring purposes.

We have adopted a detection method using satellite (THEOS) images to classify pollutants concentrations and contribute to water quality mapping. FHNNA in converging phase as detection method (without iterations) provides two advantages: (1) The network will not face local minimum problems, which produce errors in the results; and (2) It will increase algorithm speed, i.e., reduces the algorithm run time. In addition, because [6] used an HNN generating method for dealing and optimizing colour images and we used the HNN for dealing and classifying colour images, a comparison will be made between the minimum distance classifiers, which have been used to classify satellite images in many previous studies [19, 20].
5.3. Considering weights of bitplane in the energy function

The binary number value in the bitplane increases as the order increases from lowest to highest. But Without $Wb$, the energy function value of a bitplane will be based on the nearest or similar value of the energy function of another bitplane, without considering the binary number level of the bitplane. Therefore, each bitplane has a differing effect on the summation value of the eight energy functions. The selected sample (class) for image pixels, as a result of classification, is the sample which gives the lowest summation of energy functions because the Hopfield neural network denotes the corresponding or nearest class. The $Wb$ in the FHNNA is very important for correcting the results. This variable avoids error in the summation value of energy functions values.

Thus, we have modified the HNN, a simple network, to be suitable with modern techniques (satellite imagery) to analyse an important topic, water pollution. Where, each image band has been contributed in the algorithm depending on its ratio as shown in the table 6. These ratios gave the best results.

| Band  | Ratio |
|-------|-------|
| Red   | 0.42  |
| Green | 0.38  |
| Blue  | 0.20  |

The methodology of this work is demonstrated clearly in the following figure:
Figure 5 shows the methodology of using FHNNA with remote sensing image for water quality mapping, but the main steps of the new algorithm (FHNNA) are explained below:

**FHNNA:**

Step 1– Collect samples to be validation data (in situ data) from the study area, the collection is simultaneously with the acquisition of the satellite imagery, fixing the position of these data via a handheld global positioning system (GPS).

Step 2– Determine the pollutant concentration values of the collected samples in the lab.

Step 3- Order the pollutant concentration values in ascending or descending order. Then, separate them into two groups. The first group includes values that have even indexes, which are used as classes for supervised classification. The second group includes odd values, which are used to validate the algorithm accuracy.

Step 4– Use the satellite image and give the non-water pixels a black colour (Red=0, Green=0, Blue=0).

Step 5- **Learning phase:** For water pixels, analyse each pixel of the RGB bands and multiply each band by its ratio through table 6, then for each band, do:

Step 6- Convert each digital number from decimal to binary representation (eight bits), i.e., replacing the band with eight binary bitplanes (eight binary images). Each pixel in a bitplane will be 0 or 1. Note that for small binary values (e.g., 3 is equal to binary 11), the remaining six bits (bitplane) to the left will have zero values (e.g., 00000011).

Step 7– Convert the bitplane numbers from binary to bipolar representation by consider each (0) to be (-1) and each (1) to be (+1), or via the following equation:

\[
N_{\text{bipolar}}(x, y) = 2 \times N_{\text{binary}}(x, y) - 1 \quad \ldots(9)
\]

Step 8- Choose 3x3 pixel x 8 bitplane sample sizes for each image band, which represent the samples for supervised classification. The locations of these samples are the exact locations (longitudes and latitudes) of collected samples (real data) from the study area.

Step 9- Initialize 1x3 vectors by dividing each sample size in each band in each bitplane by the 1x3 size (i.e., each chosen sample size will have 3 vectors) to be included in the known (learning) vector.

Step 10- For each known vector, find the learning weight via equation (2) and depending on the vector information. These weights are given sequentially symbols and saved in the lookup table:
Where $s$ is number of samples in band $b$ in bitplane $p$ of number of known vector $c$.

Step 11- **Converging phase**: Starting from the beginning of the water pixels in image $I$, for each band $b$ and each bitplane $p$, obtain a 3x3 sample size, then divided these samples into three 1x3 vectors, which will be unknown vectors: $V_{ij}^{bpc}$.

Step 12- Find the energy function values for each vector in the first sample and its counterpart vector from the image, as shown in:

$$E^{bpc} = -\frac{1}{2} \sum_i \sum_j V_{ij}^{ibpc} W_{ij}^{sibpc} V_{ij}^{ibpc} \ast W^{bp} \ast md(V_{ij}^{ibpc}) \quad \ldots \quad (11)$$

Step 13- Calculate the Energy Function summation values for the eight bitplanes of each band. Then, find the SEF value for the three bands (Red, Green, and Blue) related convergence of the first sample.

$$SEF = E^r + E^g + E^b \quad \ldots \quad (12)$$

Where $E^r$, $E^g$, and $E^b$ are the Energy Function summation values for the red, green and blue bands, respectively.

Step 14- Repeat steps (12) and (13) for all other samples.

Step 15- Find the minimum summation value ($SEF$) from all summations values. Then, note the image size of the sample (class) that produced this minimum value.

Step 16- After producing the classified image, validate the results through identifying the class values that cover the location of the second group values (e.g., each value that represents its class and the value from the second group it covers). Then, find the correlation coefficient, $R$, and $RMSE$ between them.

6. **Results and discussion**

The results obtained by applying the proposed algorithm to the adaptive satellite image are shown in Figure 6.
The results are visually clear for evaluating FHNNA and its comparison with Min-dis, where the latter gives a classification but is not synoptic for all classes. There are classes that have not been classified, especially with the two classes of TSS=78 mg/l and TSS=105 mg/l. This outcome does not give a completed mapping for the TSS. When we look at the FHNNA map, we find that all of the
classes have been classified, which gives a completed mapping with respect to TSS. With respect to a visual comparison, more accuracy can be given by the tables (Tables 7 and 8).

Table 7: The accuracies of the produced classes by FHNNA and Min-dis.

|                | Min-dis |                | FHNNA  |
|----------------|---------|----------------|--------|
| Classification | Samples (mg/l) | Test samples (mg/l) | Classification | Samples (mg/l) | Test samples (mg/l) |
| 50             | 50      | 50             | 50     | 50      |
| 68             | 62      | 68             | 71     | 70      |
| 98             | 71      | 75             | 98     | 91      |
| 98             | 101     | 98             | 98     | 101     |

Table 7 denotes the concentration values of the classes produced via each method. Although the majority of the test samples are located in the correct classes, some were inaccurately classified, particularly within the Min-dis results. This proves that the proposed algorithm is better than Min-dis. The FHNNA is capable of high quality TSS mapping (classification). Regarding the efficiency of the proposed algorithm, we calculated the correlation coefficient ($R$) and the root mean square error ($RMSE$) between the first and the second groups of validation data (real data). Table 8 displays the accuracy results.

Table 8: Accuracy Results.

|                | $R$ | RMSE  |
|----------------|-----|-------|
| FHNNA          | 0.979 | 4.301 |
| Min-dis        | 0.846 | 11.740 |

This table provides evidence that FHNNA yields a more accurate result, and this result is the first that proves the FHNNA efficiency with the remote sensing image by the band ratios method, where the different ratios for the bands refer to the physical meaning of the water surface phenomenon, which gives these bands values and has a relationship with the reflectance of the water surface and the conditions above the studied area.

7. Conclusion

This study provides a brief overview of TSS mapping at the Penang Strait, Malaysia. Satellite imagery can be used to provide information for effective planning management. Applying the FHNNA to THEOS data for TSS mapping in the study area produced reliable, high quality results. Our results exhibit successful evidence of applying the new algorithm to the water quality mapping of colour images, which is considered a new application of HNN. In addition, FHNNA is considered a new model with remote sensing techniques for water quality that is critical environmental problem.

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