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Computational Intelligence: It's Application in Digital Watermarking

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Abstract: Impersonation and piracy of intellectual properties remain an indispensable problem across the globe. Currently over millions of digital songs, images and videos are copied illegally during file-sharing over the networks, costing loss of revenue to multimedia industries. Digital Watermarking (DW) is an efficient method that embeds an imperceptible message in digital object to protect copyright and authenticate digital media in order to prevent forgery and impersonation. Computational Intelligence (CI); a well-established paradigm is currently gaining attraction in the field of information hiding due to its ability to solve and improve complex problems encountered. CI has been applied in digital watermarking to improve performance in order to curb piracy. This paper brings to view of computational intelligence techniques specifically the Artificial Neural Network (ANN); generalizations of mathematical models based on biological nervous systems and its applications in digital watermarking. Mathematical model of ANN in relation to digital watermarking is indentified, elucidated and simplified. Results of image watermarking using both ANN and no ANN were compared. It was found that ANN based watermarking outperformed the No ANN algorithm in terms of imperceptibility. It is anticipated that this paper will serve as a launch pad for researchers interested in intelligent watermarking.

Key words: Artificial neural networks . backpropagation algorithm . computational intelligence . digital watermarking . multilayer perceptron . transfer function

INTRODUCTION

Commercial and educational importance of digital watermarking has increased research activities, tremendous [1]. Although the main motivation behind the digital watermarking is the protection of copyright and its applications are not that restricted. There are various possible applications on digital watermarking technologies which includes broadcast monitoring, fingerprinting covert communication as well as certification of official documents, such as identity cards or passports [2, 3]. These applications are increasing rapidly and recently, digital watermarking is employed in the e-health environment for teleconsulting and telediagnosis medical safety and protection of pharmaceutical products from counterfeiting [4], in parental control technology which ensures child safety in a digital world as well as in network for content management activities [5-7].

Computational intelligence (CI) is a well-established paradigm, where new theories with a sound biological understanding have been evolving [8]. CI technologies such as neural networks, fuzzy systems, rough sets, evolutionary computation, swarm intelligence, probabilistic reasoning and multi-agent systems, are widely applied for real world problem solving.

Recent works have taken advantage of computational intelligence in Artificial Neural Network (ANN) to design a robust watermarking system. Owing to the inherent characteristics of Neural Network like learning and adaptive capabilities, pattern mapping and classification and ability to generalize, not only to reproduce previously seen data, but also provide correct predictions in similar situations gives the trained networks ability to recover the watermark from the watermarked data. Examples of application of ANN in watermark include capacity estimator [9] error rate prediction [10] embedding and recovery of watermarks [11], detection of alteration [12, 13] and more recently in locating safe region [1].

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MATERIALS AND METHODS

Artificial Neural Networks: Artificial Neural Network (ANN) is a computational structure paradigm modeled on the biological process that is inspired by the way biological nervous systems, such as the brain, processes information [14]. The key element of this paradigm is the novel structure of the information processing system. It composes of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems and it learns by example just as in humans. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. The network adaptable nodes are able to learn from a set of training patterns and minimize the error between its predictions and expected output. During the learning process, the network stores experiential knowledge which is used for subsequent iterations on decision of error decrease and subsequently, predict or classify unseen data. ANN is characterized by its architecture, learning method and activation function.

Architecture of a neural network describes the pattern in which the neurons are interconnected, such as single layer feed-forward, multilayer feed-forward, fully recurrent or competitive network. Learning method are mostly categorized in terms of supervise, unsupervised or re-enforced learning algorithms while activation function are based on transfer function such as sigmoid, transig, tanh and others. Different models of neural network have their own merits and demerits. ANN, as a Machine Learning based technique, has been extensively used in nonlinear controls, address memory optimality, pattern recognition and classification, constraint satisfaction and more recently it has been applied in digital watermarking [15].

In most cases ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. Another important feature of ANN is the training algorithm, although there are also ranges of training algorithms which are normally use in conjunction with the learning type. Such algorithms includes backpropagation (BP) which is a supervised learning based algorithm and is mostly used in training multilayer feedfoward neural networks (MLFFNN). This paper investigates BP algorithm in relation with digital watermarking.

Backpropagation algorithm: One of the common ANN architecture used has been the Multilayer Feedforward Neural Networks (MLFFNN) and it usually trained with Backpropagation (BP) algorithm [16]. The schematic structure of MLFFNN used in this study is shown in Fig. 1, which shows arrangement of the network with a set of nodes and connections in layers. The connections are typically formed by connecting each of the nodes in a given layer to all of the neurons in the next layer. In this way every node in a given layer is linked to every other node in the next layer. BP algorithm is used in either sequential or batch-training, which generally consists of four main steps as follows:

- Initialization: set all weights and threshold level to random number, uniformly distributed in small range.
- Activation: activate the forward phase of the BP algorithm by applying input and desired output.
- Weight training: update weights in the backward phase by propagating the error backwards.
- Iteration: increments iteration number p by one and repeat the cycle from step2 until the overall error value drops below some predetermined threshold.

Assuming the training data inputs are represented by X_i and weights by W, therefore the network diagram for detail explanation can be described as shown in Fig. 1.

Backpropagation scheme: Considering that neurons in each layer are fully connected to others in the next layer, from layer i to j to k. Suppose the network is designed with only one hidden layer neurons with weights, W_{ij}, connecting the i^{th} neuron from input layer to the j^{th} neuron in the hidden layer. The weights: W_{jk}, connecting the j^{th} neuron from hidden layer to the k^{th} neuron in the output layer. In the BP algorithm, the generalization of delta rule involves 2 phases, the forward phase and the backward phase.

The forward phase for hidden layer output: Consider

$$O_j = \Phi(Net_j) \quad (1)$$

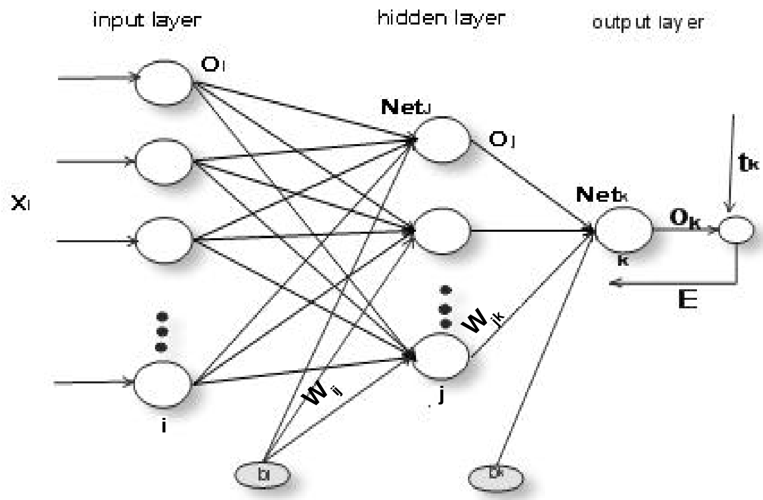

Fig. 2: A multilayer feedforward algorithm with

where

$$Net_j = \sum_j W_{ij} O_i + b_j \tag{2}$$

where b_j is the bias of the hidden node and can be set to zero, Φ is the sigmoid activation function.
For output layer k, the network output is given as;

$$O_k = \Psi(Net_k) \tag{3}$$

where

$$Net_k = \sum_j W_{jk} O_j + b_k \tag{4}$$

but

$$O_j = \Phi(Net_j) = \Phi(\textstyle\sum_j W_{ij} O_i + b_j)$$

Therefore

$$O_k = \Psi \sum_j W_{jk} \Phi(\sum_j W_{ij} O_i + b_j) + b_k \tag{5}$$

where Ψ and Φ are the coefficient of the activation function of output and hidden layer.

The backward phase between output and hidden layer: The backward phase includes the calculation of the signal error and the weight update of the network. The network error 'e' is developed as follow:

$$e = t_k - O_k \tag{6}$$

where t_k is; the desired output and O_k is the output of network. The objective is to find the set of parameters that minimize the sum of the squared of the error function, where the average sum squared error of the network is defined as;

$$E = \frac{1}{N} \sum_{k=1}^{N} (t_k \quad O_k)^2 = \frac{1}{N} \sum_{k=1}^{N} e^2 \tag{7}$$

where N is; the total number of training pattern, e is the error function to be minimised.
The network weight update between the hidden layer j and output layer k is given by;

$$W_{jk}{}^{new} = W_{jk}{}^{old} + \Delta W_{jk} \tag{8}$$

where

$$\Delta W_{jk} = \quad \eta \nabla E|_{W_{jk}} \tag{9}$$

η is the learning rate, $\nabla E|w_{kj}$ is the gradient of the cost function. Therefore, (9) can be re-written as a partial derivative given by:

$$-\eta \nabla E|_{w_{jk}} - -\eta \frac{\partial E}{\partial w_{jk}} \tag{10}$$

In order to use the chain rule to find the gradient of the error function E with respect to W_{jk}, the interdependency of the variables needs to be taken into consideration, the partial derivatives can be written as:

$$\frac{\partial E}{\partial w_{jk}} - \frac{\partial E}{\partial Net_k} \frac{\partial Net_k}{\partial w_{jk}} \tag{11}$$

$$\Delta W_{jk} = \eta(t_k - O_k) O_k (1 - O_k) O_j$$

$$\Delta W_{jk} = \eta \delta_k O_j \tag{12}$$

By substitution, therefore the network weights update for k and j in simplified formula is;

$$W_{jk}{}^{new} - W_{jk}{}^{old} + \Delta W_{jk} - W_{jk}{}^{old} + \eta \delta_k O_j \tag{13}$$

The backward phase between hidden layer and input layer: Adjusting between hidden layer and the input layer by:

$$W_{ij}{}^{new} - W_{ij}{}^{old} + \Delta W_{ij} \tag{14}$$

where ΔW_{ji} is; the rate of change in weight.
But

$$\Delta W_{ij} - -\eta \frac{\partial E}{\partial w_{ij}} \tag{15}$$

where η is; the learning rate,

$$\Delta W_{ij} = \eta \delta_j O_i \tag{16}$$

For sequential weight update

$$\Delta W_{ij} - \eta \sum \delta_j O_i \tag{17}$$

Therefore the new weight update is;

$$W_{ij}{}^{new} - W_{ij}{}^{old} + \Delta W_{ij}$$

$$W_{ij}{}^{new} - W_{ij}{}^{old} + \eta \delta_j O_i \tag{18}$$

APPLICATION OF BP IN WATERMARKING

Figure 2 shows the schematic diagram use of ANN in training selected embedding location coefficients in order to improve the imperceptibility of the watermark image.

The host image was transformed from spatial to frequency domain before a suitable location for embedding was selected. ANN was used to train the selected coefficients location before embedding modulated watermark signal.

RESULTS AND DISCUSSION

Image Fidelity Measure, IFM is used as accuracy indicator for the watermarked image. Technically, IFM is a similarity measurement between two different signals [9]. The value ranges between 0-1. When the result of two

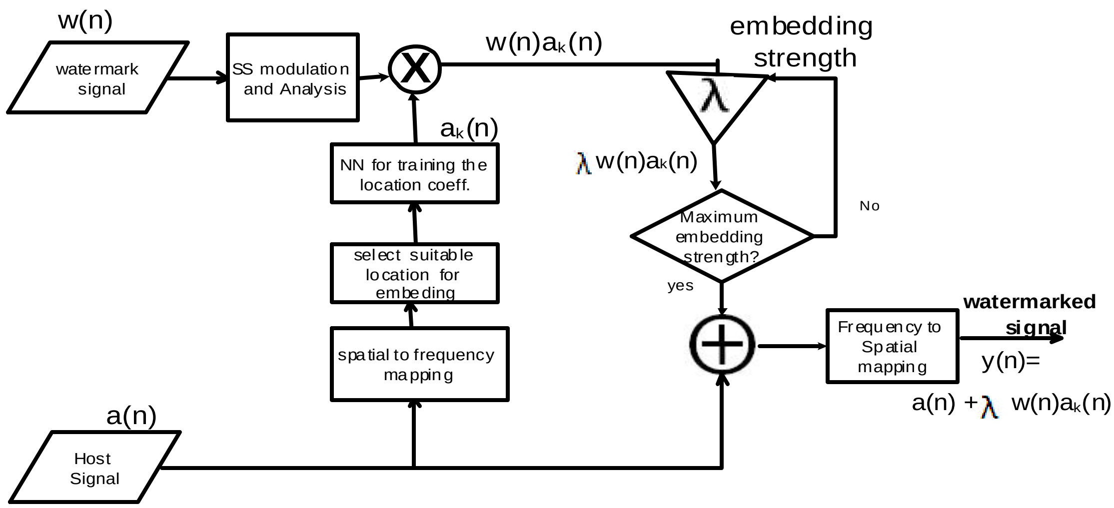

Fig. 2: Schematic flowchart of embedding watermark using NN to train the coefficient location

Table 1: Trained and untrained location coefficients

Test image	Location of embedding	
Fundus	Untrained location	Trained location
No attack	0.8134	0.9588
Compression (80QF)	0.8939	0.9444
	0.9224	0.9350
Weiner (3x3)	0.9072	0.9462
Median filter	0.8611	0.9190
Salt & pepper noise	0.8975	0.9312
Speckle noise	0.8753	0.9246

images is 1, it means they are similar while 0 means dissimilarity, that is, higher value signifies closeness. IFM is defined as:

$$IFM = 1 \quad \frac{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}|U(m,n)-V(m,n)|^2}{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}(U(m,n))^2} \tag{19}$$

where U(m, n) is the original host image/watermark bits and V(m, n) is the watermarked image/extracted watermark.

Test for the image fidelity was carried out and the results in Table 1 confirmed that embedding using ANN to train the location yield better result than embedding in location without training the location coefficients. Using Fundus as the test image, the optimum Image Fidelity, (IFM) obtained was 0.9588 of 1.000 under trained location by NN without any attack applied. However, for untrained location, the IFM values obtained is 0.81345. To check the robustness of the algorithm, attacks were applied on the watermarked image.

When Wiener filter attack was applied to the watermarked image, the value slightly dropped to 0.9462, while JPEG compression IFM 0.9444 and 0.93123 were obtained when Noise attack was applied. This shows that there is significant enhancement in the image fidelity when ANN was used in training coefficients before embedding compared No NN even after the attacks. Literatures have shown that, there are constraints between making the watermark robust as well as achieving better imperceptibility [17].

These constraints are interdependent and in the case of robustness; an increase of the robustness usually increases the visibility of the watermark (visual distortion). On the other side if, due to imperceptibility constrains and the strength of the embedded watermark is lowered, the robustness of the whole system will be jeopardised and affected. However, using NN to train the embedding coefficient has been found to be able to guarantee imperceptibility as well as maintain robustness even after the attacks. This demonstrates, training location coefficients for embedding makes the watermarked image to be robust to attacks and maintain better imperceptibility.

CONCLUSION

This paper explores the use of CI in watermark embedding process. The application of ANN in watermarking is explained. An algorithm for embedding based on ANN trained location coefficient was compare to No ANN based. The result shows that there is significant enhancement in the image fidelity and robustness to attacks using the ANN based embedding procedure.

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