Watermarking using Lifting Wavelet Transform (LWT) and Artificial Neural Networks (ANN)

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Abstract

Background/Objectives: In recent times internet has become a primary means of communication between the medical center and the some remote doctor present at hospital. With the usage of internet, there comes the issue of data integrity and therefore the responsibility of the medical specialist to preserve sensitive data of patients contained within the medical images relevant with that exact patient. Methods and Analysis: Thus we have created an experiment to preserve the data integrity by using different watermarking techniques used for conventional images. For medical images quality conservation is imperative. We have used 2D Lifting Wavelet Transform (LWT) for watermarking. Findings: As lifting wavelets has the advantage of less computing time and the less memory requirements. Application/Improvement: Here lifting scheme of wavelet transform (LWT) is used for watermarking different types of medical images along with Artificial Neural Network for better security.

Keywords: Artificial Neural Networks, Medical Image Watermarking, Lifting Wavelet Transform (LWT)

1. Introduction

Watermarking is a subsidiary of data obscuring which is used for hiding data in digital media like photos, music, etc. The Image watermarking techniques can also be employed to digital videos as well. The comfort regarding the digital data that can be commenced through the Internet has created copyright violation issues. Excluded material can also be effortlessly exchanged through networks, and this has led to major involvement to such content suppliers who bring up these digital contents. For preserving the activity of the content providers, the respective digital information has to be watermarked. In order to acquire any attack from assailant, the medical image is taken into account as watermark and is embedded in to a natural image. A multiobjective development approach is planned to take care of the fidelity of the watermark (medical image) because it contains valuable diagnostic data. This multi–objective approach ensures that there is an optimum trade-off between lustiness, imperceptibility and structural integrity of watermark. Controlling the structural integrity of the watermark is necessary by the fact that most of the diagnostic paths in medical image take into account the linguistic factors of the image to let out precious data regarding the diagnosis of a selected analytic condition. Different type of performance parameters such as Normalized cross coefficient (NCC), Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), is employed to frame an objective action. A lifting scheme is added in addition to hike the performance of the selected preferred wavelet family. The watermarked image is tested for various forms of attacks like sharpening, smoothening, rotation, cropping and distinct forms of noises that add speckle noise, Gaussian noise and Poisson noise. A new improved watermarking scheme is suggested adopting lifting wavelet transform (LWT) for medical data. The medical data of patients are watermarked with the image of that particular patient that is extracted at the doctor’s end of identification. Lifting wavelets have peculiar advantage that is explored and is incomprehensible in conventional wavelet transform. With the lifting wavelets the inverse transformation is down-falling the operations of forward transform that scale back the artefacts throughout transformation. Here, in this concept we provide a

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watermarking technique, employed with Artificial Neural Networks to watermark images.

2. LWT Watermarking (Lifting Wavelet Transform)

This is one of the recently used watermarking technique. The Lifting scheme could be a new mode for constructing bi-orthogonal wavelets\(^6\). The most contrast with classical constructions is that they do not admit the Fourier Transform\(^7\). In this approach lifting will be accustomed to construct second generation wavelets. These wavelets are not essentially translates and dilates of one function. The latter we tend to talk over with as initial generation wavelets\(^8\).

Lifting wavelets belongs to the category of second generation wavelets that have peculiar advantages over initial generation wavelets. The lifting wavelets cut back the computing time associated memory necessities as they adopt an in position realization of wavelet transform\(^9\). Conflicting traditional wavelets the computations for lifting wavelets achieve performance in integer domain instead of real domain. The inverse method in lifting wavelets is abolishing of the processes performed during the forward transformation\(^10\).

The Lifting Wavelet Transform (LWT) constitute of three elemental steps for integer domain: Split, Predict and Update as shown in the figure below:

- **Split**: In this stage the image is decomposed into even and odd components.
  
  The Z-transform of even component is
  
  $f_e(z_1, z_2) = \sum_{n=1}^{N} \sum_{m=1}^{M} f(2n_1, 2n_2) z_1^{-n_1} z_2^{-n_2}$

  The Z-transform of odd component is
  
  $f_o(z_1, z_2) = \sum_{n=1}^{N} \sum_{m=1}^{M} f(2n_1 + 1, 2n_2 + 1) z_1^{-n_1} z_2^{-n_2}$

  The consolidation of the Predict operation and Subtraction operation is replaced by the odd sample $f_o(z_1, z_2)$. And in the place of the even sample, the Predict operation is taken as the average of two neighbouring even components.

  $$P[.] = 1/2 [f_e(z_1, z_2) + f_e(z_1+1, z_2+1)]$$

  Where $f_e(z_1, z_2)$ and $f_e(z_1+1, z_2+1)$ are two consecutive samples in integer domain and $f_e(n_1, n_2)$ and $f_e(n_1+1, n_2+1)$ are analogous inverse transforms in spatial domain. The Predict process computes the detailed coefficients and the operation implies high pass filters.

  The Update operation updates the even samples $f_e(n_1, n_2)$ using the detailed coefficients $d(n_1, n_2)$ figured out in the prediction process. The Update stage alternate the even samples $f_e(n_1, n_2)$ with the approximate coefficients $a(n_1, n_2)$ of the original image $f(x, y)$. The inverse transform is quite reverse of the forward transform\(^11\).

2.1 Embedding Process

1. Frequency conversion for the target image.

2. Feature values are selected based on the feature extraction key.

3. Preparing the bit patterns that are to be hidden.

4. Generating the classifier to the output hidden bit patterns using the algorithm used by the neural networks.

5. Finally save the generated classifier as the watermark extraction key.

Figure 2 is the reconstruction of the Lifting Wavelet Transform (LWT). In this process the signal input that has undergone the stages of Split, Predict and Update are reconstructed back into the original signal input.

2.2 Extracting Process

1. Firstly we should obtain the feature extraction key and the watermark extraction key.

2. The feature extraction for the target image is done by the feature extraction key.

3. Using watermark extraction key, we have to build a classifier.
4. Examine the output bit patterns from the classifier when the extracted feature values are given as input values for the classifier.

Figure 3 is the extracted image of the input image that has undergone the process of 1st level of LWT that is approximately, horizontally, vertically and diagonally.

3. Artificial Neural Networks (ANN)

ANN is a data processing archetype activated by the Human nervous system. Medical images contain health report of the patient. As they lack to show the information clearly or due to the lack of experts, they tend to send the medical images through unsecured networks. To provide security for this unsecured networks watermarking images are used generally. Here, to justify the medical images, the patient image is embedded as watermark into the medical image. The watermarking will probably alter the composition of pixels resulting to the quality contraction of respective medical image. This dis-advantage can have conflicting effects on the life of the patient. To avert these issues, watermarking is composed with Artificial Neural Networks (ANN). ANN fix up the depraved pixel data that is disoriented during transmission or watermarking.

ANNs are taken out from the biological neural systems. The soma of cell body accepts inputs from the other various neurons through the synapses to the dendrites. At times when the neurons get excited, the impulses from the soma are disseminate through the axon to the synapses of various other neurons. The neurons here are the processing elements.

3.1 Types of ANNs

There are majorly two categories of ANNs. FFNNs (Feed-Forward Neural Networks) and RNNs (Recurrent Neural Networks). FFNNs don't have any feedback loops wherein the RNNs, said to have the feedback loops. There are also many other types of ANNs.

Here, we are training with feedback Neural Networks, nothing but the Recurrent Neural Networks. These feedback Neural Networks can also possess signals moving in both directions bringing up loops in the networks.
These networks are said to be dynamic. These are also said to be referred to as interactive.

3.2 Architecture of Neural Networks

Artificial Neural Networks are mostly built of three layers. Input layer, Hidden layer and the Output layer.

3.2.1 Input Layer

This layer gets activated when the input modules represent raw information which is being fed to the network.

3.2.2 Hidden Layer

This layer gets activated when each and every hidden input is constrained by working of inputs and weights on connections amidst input and hidden modules.

3.2.3 Output Layer

The act of the output modules depend on the functioning of the hidden modules. The weights amidst the hidden nodes and the output modules.

ANN is composed of processing elements called perceptrons. Each perceptron receives inputs, processes inputs and finally delivers a single output. A perceptron takes the vector of the real valued input, calculates the linear combination of these inputs and then outputs. A single perceptron can be used to represent many Boolean functions like AND and OR functions. But for XOR function it takes the two-layered network of perceptrons. Here we propose the Back Propagation algorithm for hiding the cover image.

3.3 Approach for using Back-Propagation Neural Network

3.3.1 Embedding Process

1. The target watermark image is chosen to deliver as an output image to a Back-propagation Neural Network.
2. A Back-propagation neural network is conscripted with an input, a hidden layer and an output.
3. For the input layer, the cover image is armed as an input to the network. At the output layer for producing the respective target image, weights are held to them adopting the Back-propagation method.
4. The trained weight matrices are hidden in the cover image itself undergoing special techniques.

In Figure 5 Embedding process of the medical image using BPNN (Back Propagation Neural Network) method. Initially the cover image is taken and it is subjected to the 1st level of LWT. Then the watermarked image is taken and these two images are subjected to BPNN. Finally we get the Embedded Image and the Extraction key.

3.3.2 Extracting Process

1. From the cover image the watermark is obtained and the hidden weights of the neural network are extracted. This is done using some special techniques and produces the reconstruction of the trained neural network.
2. The watermarked image is equipped to the input layer of the neuron network layer and the output layer shows the resulted watermark image.
3. The output watermarked image corresponded to the target watermarked output image for determining the PSNR of the resulted watermark image.

In Figure 6, the watermarked image is taken and LWT is applied. The extraction key is used in BPNN and thereon this is subjected to ILWT (Inverse LWT) for the extraction of data from the image.

3.3.3 Neural Network Application Development

The development process for an ANN has the following eight steps:
3.3.3.1 Data Collection
The data that is required for training and also for testing of the network is possessed. The considerations that are to be made are whether that particular problem is responsive for the neural network so that the relevant data exists and it can be obtained.

3.3.3.2 Data Separation for Training and Testing
The data that is to be trained must be classified and a strategy must be made for testing the act of the corresponding network. This feasible data must be made into two partitions for training and testing.

3.3.3.3 Network Architecture
A particular network and a learning method are chosen. The considerations to be looked up are the number of perceptrons and the layers.

3.3.3.4 Tuning Parameters and Weight Initialization
The network should be tuned to the desired learning performance level. Tuning and them adding weights for the parameters, followed by modifying the parameters as training feedback is received. It should be kept in mind that the initial values are crucial for determining the effectiveness of the training.

3.3.3.5 Data Transformation
The data should be transformed into a format acceptable by the ANN.

3.3.3.6 Training
Training is attended constantly by displaying input and known or desired output data to the ANN. Then the ANN enumerates the outputs and accustom the weights until the computed outputs are interior to the acceptable strengths of the known outputs for the input cases.

3.3.3.7 Testing
Once the training is said to be completed, the next step to be done is testing the network. This testing verifies the performance of the network with the desired weights. Black box testing is the initiative method for verifying the inputs and the appropriate outputs. Black box testing is nothing but comparing test results with the horizontal results.

3.3.3.8 Implementation
Now a set of desired outputs are obtained by the network with the given inputs.

The network can also be used as a stand-alone network system or as a part of another software system.

4. Results
The Figure 7 shows the input that is to be applied to the neural network. Initially the image is loaded into the mat-lab with the help of the ANN code.

The Figure 8 is the architectural view of the neuron network showing the no of layers and the no of inputs, hidden layers and the outputs we have consumed. Here we have considered 8 inputs, 5 hidden layers and 1 output at the output layer.

The Figure 9 above shows the parameter performance of the image that is gone through BPNN algorithm. We
are using Levenberg-Marquardt training method for training the parameters. These calculations are done in MATLAB.

Figure 10 describes the watermarked image that has undergone the training of Artificial Neural Networks.

5. Conclusion

Here in this concept, we propose the Lifting Wavelet Transform (LWT) with the Artificial Neural Networks (ANN) using numerous types of medical images like MRI images, CT images etc. Experimental results are expected to define the image parameters more accurately and exactly. The Back Propagation algorithm used in this concept minimizes the error function between the original image and the watermarked image. Experiments are also done to simulate the attacks that shows the robustness of the Lifting Wavelet technique for watermarking approaching attacks.

6. References


