Project Title: Distortion-Free Digital Watermarking for Medical Images (Fundus) using Complex- Valued Neural Network.

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Abstract:

Fundus image is the interior surface of the eye that includes the optic nerves, macula and retinal blood vessels. The optic nerve which is responsible for transmitting of electrical impulses from the retina to the brain is connected to the back of the eye near the macula has a visible portion of the optic nerve called the optic disc. Optic disk has been shown to provide diagnostic information related to diabetic retinopathy (DR) and glaucoma diseases. Since such image are used for early detection of numbers of ocular disease which still remain the legal cause of blindness in working age population. Protection and authentication of such medical images are now becoming increasingly important in an e-Health environment. Though several high-ranking watermarking schemes using neural networks have been proposed in order to make watermark stronger in protection of medical images to resist attacks. However, the current system only deals with real value data. Once the data become complex, the current algorithms are not capable of handling complex data. In this study, a distortion-free digital watermarking scheme based on Complex-Valued Neural Network (CVNN) in transform domain is proposed. Fast Fourier Transform (FFT) was used to obtain the complex number (real and imaginary part) of the host image. The complex values form the input data of the Complex Back-Propagation (CBP) algorithm. Because neural networks perform best on detection, classification, learning and adaption, these features are employed to simulate the Safe Region (SR) to embed the watermark, thus, watermark are appropriately mapped to the mid frequency of selected coefficients. The algorithm was appraised by Mean Squared Error MSE and Average Difference Indicator (ADI). Implementation results have shown that this watermarking algorithm has a high level of robustness and accuracy in recovery of the watermark.

Keywords: Digital Watermarking, Complex Back Propagation Algorithm, Complex-Valued Data (CVD), Complex-Valued Neural Network (CVNN), Fast Fourier Transform (FFT), Fundus.

INTRODUCTION:

Fundus image is the interior surface of the eye that include the optic nerves, macula and retinal blood vessels. This is as shown in Figure 1. The optic nerve which is responsible for transmitting of electrical impulses from the retina to the brain is connected to the back of the eye near the macula has a visible portion of the optic nerve called the optic disc.[1][2]. Optic disk has been shown to provide diagnostic information related to diabetic retinopathy (DR) and glaucoma diseases. Figure 2 and 3 shows the details of the optic nerves. Since such image are used for early detection of numbers of ocular disease which still remain the legal cause of blindness in working age population [3]. Protection and authentication of such medical images are now becoming increasingly important in an e-Health environment where images are readily distributed over electronic networks. Research has shown that medical image watermarking is a relevant process for enhancing data security, content verification and image fidelity [8]. However, it is necessary to preserve the originality of information in the image to avoid performance loss for human (clinician) viewers. Some algorithms have been modified to produce a minimal distortion to the host image [4]-[7], however such small utterance may not be acceptable for medical images which are used for diagnosing and treatment of diseases.. Thus, a distortion free watermarking algorithm is needed. In this study, the solution to the problem of distortion caused by data embedding is been proposed.

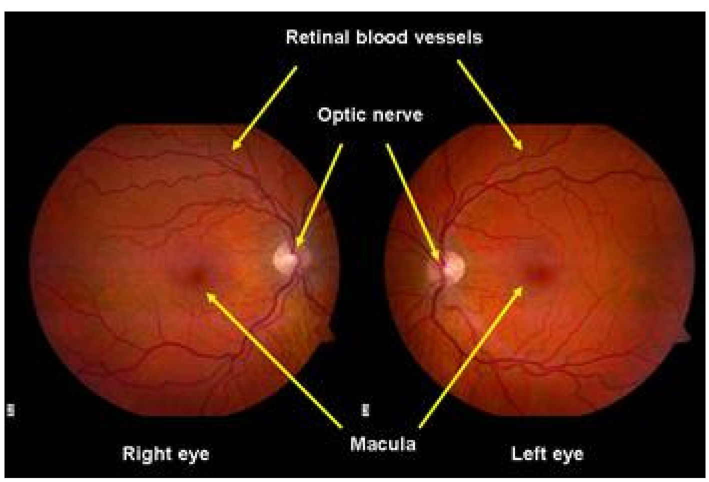

Figure 1: A typical example of the partial area images, the retina fundus image [2].

BACKGROUND:

Health care centers and hospitals are now facing problems of increase in the overhead cost of handling patient information. In patient information, it includes both text and images (patients' information, history, diagnosis information, images of findings etc). Initially these information are store separately in different files, image file and text files. However, in this case, the image can be mistakenly separated from patient information, as this information is stored in a separate header. With the advent of e-Health environment, where patient records are distributed and shared over the electronic network. Security and integration of such information is highly needed. One of the recent research area to integrate text and images together is the Digital Imaging and Communications in Medicine (DICOM) [10].DICOM is a standard file format for the transmission and storage of medical images in health care centers. Most modern ultrasound devices, X-ray photography systems and computer tomography use DICOM image format for storing images. Most of the data management systems in the hospitals are based on DICOM standard [11]. Though DICOM store information of patient with the image, However, it makes use of extra memory space for the text information. DICOM works well when the information is within a unit or department in the clinic, when it involves transmission over the network, the security is not guarantee. Furthermore, this information is not safe from attacks.

Recently, a A$35 million (Australian Dollar) joint venture research in e-health was signed between Commonwealth Scientific and Industrial Research Organization (CSIRO) and Queensland Government to undertake applied research on e-health information management [12]. Therefore a tool that integrates disparate sets of patient records which include diagnostic information, history, biodata as well as image while protecting the privacy and security of patients' data is needed. Due to digital watermarking crucial features such as; imperceptibility, inseparability of the content from the watermark, and its intrinsic ability to undergo same transformation as experienced by the cover work, has made it superior and preferable over other traditional methods of protecting data integrity, authentication of information resources, ownership assertion, confidentiality, copy protection, data monitoring and tracking.

This preference has been proven experimentally [13] to provide improved security. Recently, an approach is proposed by Nayak *et al* [14] a technique based on reversible watermarking. The reversible watermarking technique is embedding data into an image in such a way that the original image can be reconstructed from the watermarked image. Their method is used to store and transmit digital fundus images with an encrypted patient information. That is, the patient data were encrypted and encoded with error control codes before the embedding it into the fundus image. Though the method reported no lost of patient information, however distortion in the fundus image is still a problem need to tackle if the image is to be use for diagnoses.

Woo *et al*. [15] proposed a multiple watermarking method to store the medical images in a digital form and in a secure way in order to avoid the data from being exposed to the unauthorized person. Similarly Giakoumaki *et al.* [16] proposed a wavelet based multiple watermarking schemes in the medical images for secure and efficient health data management. Recently Lou et al. [17], embedded large amount of data, maintained the quality of medical image and restored the original image after extracted by using multiple layer data hiding in spatial domain and Least Significant Bits (LSBs) technique. LSB is known to be vulnerable to geometric attacks and lossy compression [18]. More so, the above watermarking techniques embedded direct into the host image which caused the watermarked image to be distorted hence not suitable for medical diagnoses especially fundus images.

One of the downside of the current watermarking system is the inevitable distortion caused by data embedding. Some algorithms have been modified to produce a minimal distortion to the host image. However such small utterance may not be acceptable for medical images which are used for diagnosing and treatment of diseases. This ultimate intent of the CVNN based algorithm proposed is to solve the problem of distortion caused during patient information embedding by introducing a distortion free method for embedding data in the optic nerves of retina images (fundus) accomplished by Complex-Valued Neural Networks, ensure imperceptibility and to prevent unauthorized manipulation and misappropriation of the Fundus images.

OBJECTIVES

This study has been undertaken based on the following objectives:

1. To develop a distortion-free watermarking technique based on CVNN for authenticating medical images (FUNDUS).
2. To identify the best location in Fundus image to embed the patient's information without affecting the quality of the image.
3. To evaluate the quality of watermarked medical image using the standard benchmark model such as Peak Signal to noise Ratio (PSNR), Weighted Mean Square Error (WMSE), Structural Similarity index (SSIM) and Image fidelity measure (IFM).

METHODOLOGY

The present research is a simulation-based work, which is an attempt to develop an algorithm and implementation code for use as information hiding system for Fundus images. The block diagram of the proposed Distortion-Free watermarking based CVNN (DFW-CVNN) is as shown in figure 2. It consists of a six stage cascade system, namely: Features modelling, data FFT, CVNN, Distortion-free classifier, Embedding and Extracting section

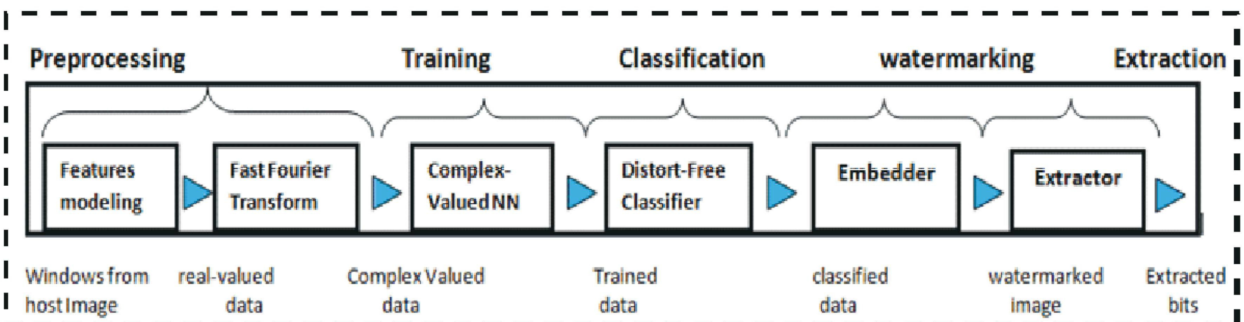

Figure 2: Distortion-Free CVNN based watermarking system

Feature Modeling for DFW-CVNN:

The global shape of retinal vessel structure shown in Fig. 1 is in general form. For better and precise location of region to embed the watermark, the whole image cannot be modeled by a single primitive form. Therefore, the nerve is segmented in small regions as in Fig. 3 in order to

obtain the targeted windows by using block selector. The block selection is based on the length of the watermark. Given a host image *I(m,n)* watermark vector of length *WI* and number of block to be selected *bs* the equation for total possible block that can be selected from
I(m,n) is defined as;

$$TB_s = b_s \leq W_1 : \forall\, Tb_s \in I(m,n) \tag{1}$$

Fast Fourier Transform: Obtaining complex values from host image

The general model of obtaining complex values from. an image *I(x,y)of* size MXN using the fast version of Discrete Fourier Transform (DFT) is represented by *F(u,*v):

$$F(u,v) = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} I(x,y)e^{-j2\pi(\frac{ux}{M}+\frac{vy}{N})} \tag{2}$$

For x=0, 1, 2, ..., M-1, y=0, 1, 2, ... , N-1

Thus given *F(u,v), I(x,Y)* can be obtained back by means of the Inverse 2D DFT (2D IDFT);

$$I(x,y) = \frac{1}{MN}\sum_{u=0}^{M-1}\sum_{v=0}^{N-1} F(u,v)e^{j2\pi(\frac{ux}{M}+\frac{vy}{N})}$$

Where *u,* v are frequency variables and *x, yare* spatial variables

In this work, the FFT is applied on the host image so as to convert the spatial domain image to frequency domain in order to obtain the complex numbers. After selecting a block, before taking the FFT of each block, windowing function is applied. The windowing here is used to further enhance the ability of the FFT to extract spectral data from the host image.

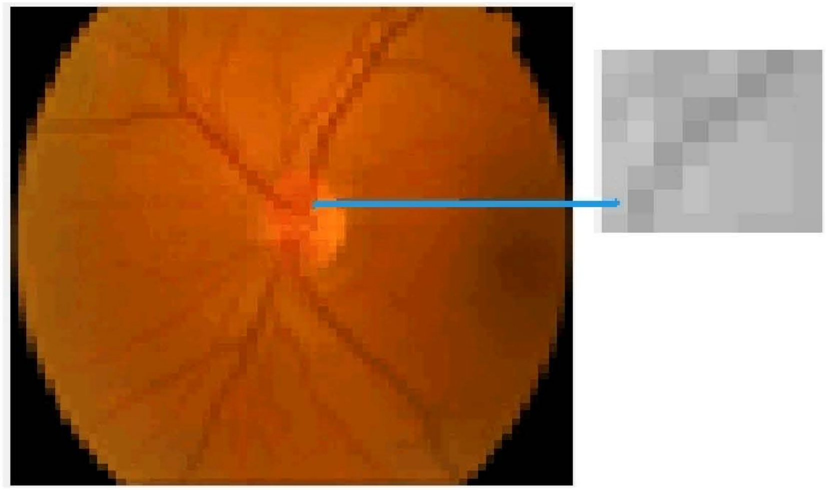

Figure 3: Selected block from nerve end of Fundus image.

The Complex Valued Neural network

In recent times, the use of CVNN has increased the extent and application of ANN. CVNN is use to process complex valued data (CVD) such as in image with real and imaginary component. CVNN is made up of Complex-Valued Feedforward (CVFF) and Complex Back-Propagation (CBP) algorithm as shown in Figure 4. The block diagram of CVFF and CBP is as shown in Figure 5. CVNN has been studied and developed by authors in solving various problems (Aibinu, Salami, Shafie, 2010; Benvenuto & Piazza, 2002; Georgiou & Koutsougeras, 2002; Hanna & Mandic, 2002; Hirose, 2008; Kim & Adali, 2002a, 2002b; Leung & Haykin, 2002; Uncini, Vecci,Campolucci, & Piazza, 2002 and Faijul Amin & Murase, 2009). The CVNN consists of an interconnection of Complex-Valued (CV) neurons and complex valued synaptic weights. It processes information using a connectionist approach to computation in complex domain. CVNN starts with the forward phase by transmitting the complex input signals or data through the connection; each connection has an associated weight that improves the transmitted signal; each neuron transforms the received signals (sums the input multiplied by the connection weight). Inputs are computed based on the complex algebra which results into a complex output through complex weights. The resultant sum is fed into the activation function which maps weighted sum to determine the output signal. The backward phase is trained by Complex Backpropagation (CBP). CBP is a complex version of backpropagation algorithm. This algorithm performs an approximation to the global minimization achieved by the method of steepest descent (Leung & Haykin, 2002). It is applied to multilayer perceptron consisting of many adaptive neurons, each of which has nonlinearity as shown in Figure 5.

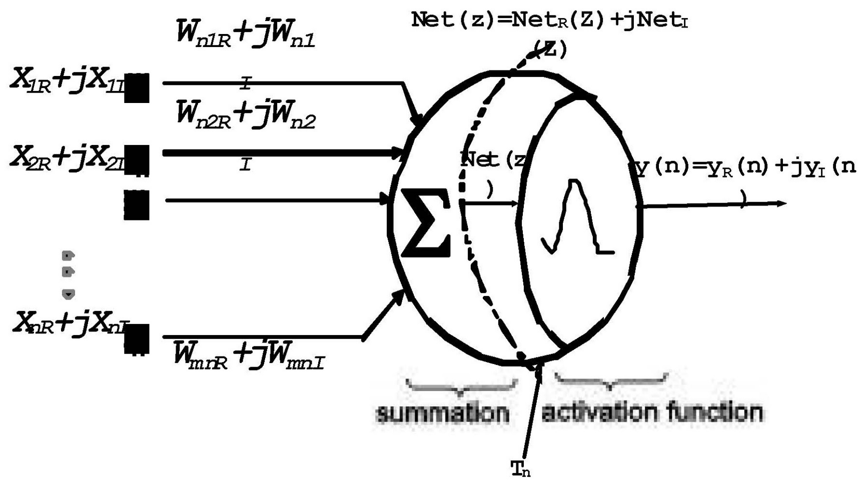

Figure 4: Nonlinear adaptive Complex neuron model

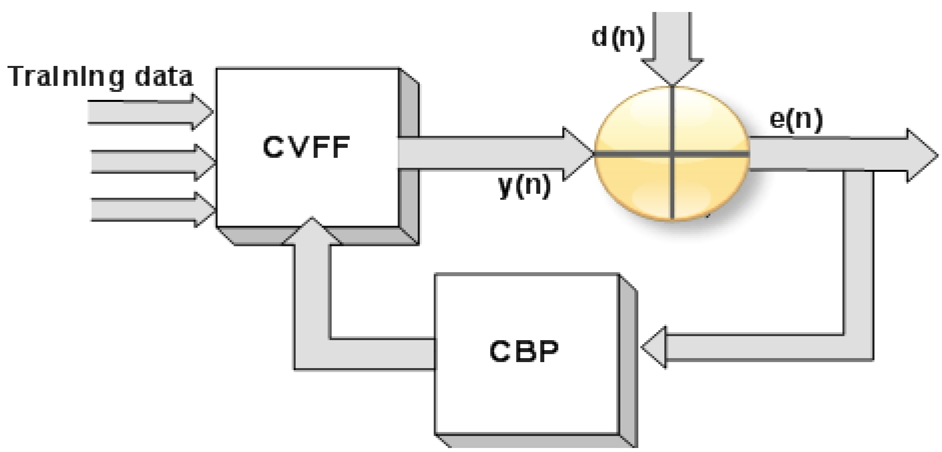

Figure 5: complex valued feed forward (CVFF) and complex back -propagation (CBP) algorithm

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For this study, CBP is applied to a multilayer CVNN, the architecture as shown in Figure 5. The sigmoid activation function used in this work is defined as:

$$Z = \frac{1}{1+\exp^{-zR}} + j\frac{1}{1+\exp^{-zI}} \tag{3}$$

Where *zR* and *zI* are the real and imaginary threshold of the activation function respectively.
From the model neuron shown in 4, the net input/output relationship is characterized by nonlinear recursive equation given by:

$$Net_z = \sum_{i=1}^{j} X_j W_j I + b_i \tag{4}$$

Where W_{ji} is the complex synaptic weight connecting complex-valued neuron *j* in input layer to hidden layer, ~ is the complex input signal from input layer, *j* is the no. of neuron in input layer and *bi* is a bias value (complex-valued) of neuron *i.*

But

$$y(n) = \sum_{m=1}^{q} Net_z V_{q1} + b_m \tag{5}$$

Where *Vq1* is the complex synaptic weight connecting complex-valued neuron *q* in hidden layer to output layer, *Netz* is the output signal from complex hidden neuron.
The CVNN error to be propagated backward is defined as the difference between the desired response *d(n)* and the actual output *y(n).*

In it complex form, it becomes

e(n) = [dR(n) + idjn)] - [YR(n) + iyjn)] (6)

Where *[dR(n) + idjn)]* the desired complex is valued data and *[YR(n) + iyjn)]* is the output of the CVNN.

Distortion Free Classifier:

The main aim of the classifiers is to group the CVNN output into regions with same characteristics that is either positive or negative. The classifier is used in partitioning into K group, [16, 17]. The algorithm finds the most optimum positioning of the K centers and then assigns each point to the most nearest center. The grouping is done by minimizing the sum of squares of distances between CVNN output and the corresponding cluster centroid. The algorithm flowchart is shown in Figure 6.

Watermark Embedding Model: The main step in embedding is sufficient generation of weights (hidden and output) by the CVNN and carefully mapping of the target content (watermark bits) to the input data (host image).

The embedding/mapping procedure is illustrated in Figure 7.

Watermark Extraction Model: Watermark extraction is performed on a block-by-block basis for recovery of the hidden bits. During the training phase of CVNN, hidden nodes and output nodes weights are generated for each block. Those weights are saved for extraction. The block diagram for extraction procedure is shown in Figure 8.

Extractor must receive correct position of each bit.

Only by knowing the proper position of the bit will lead user to proper input values. This serves as a pointer to retrieving the proper network weights and only proper network weights will be able to output correct hidden bits.

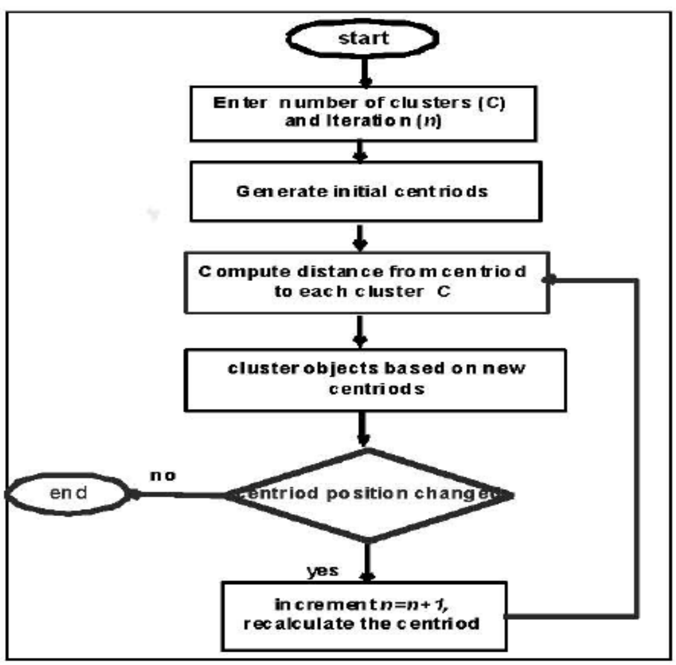

Figure 6. Flow chart of Distortion-free classifier

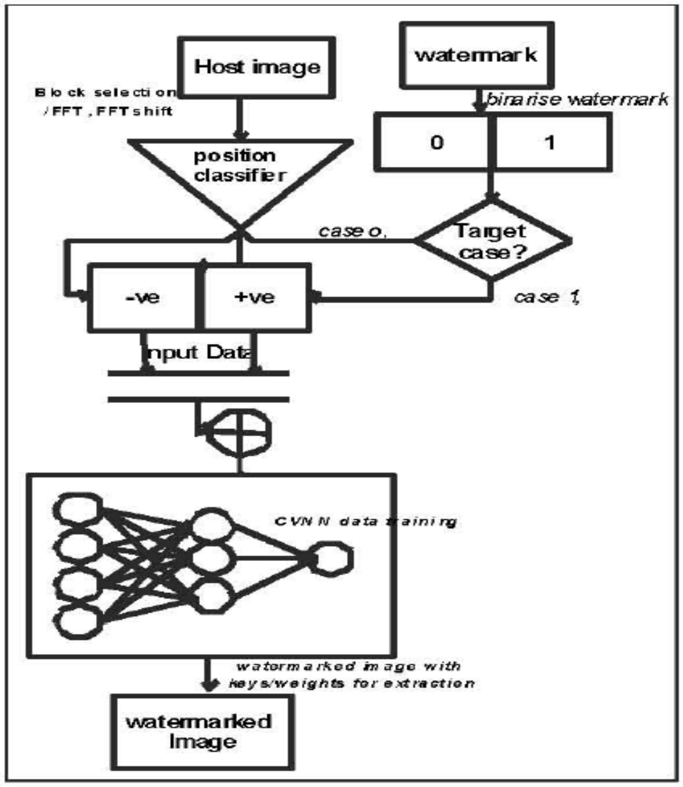

Figure 7. Watemark embedding procedure

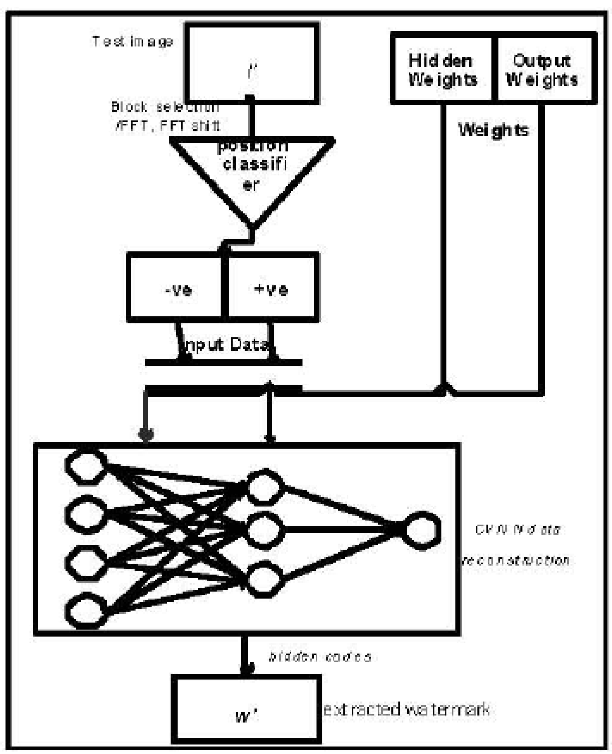

Figure 8. Watermark extracting procedure

FINDINGS

It is found that 40% of the original values were use for training the network, after the network is converged; the next 40% were used as test data while the last 20% were used for validation. The host image 9(a), watermarked image 9(b), histogram of host 9(c) and watermarked image 9(d) is as shown in Fig. 9. From the histogram, both images are alike. In fact, the watermarked image is indistinguishable from the original host image. The watermarked image is highly imperceptible, that is the watermarked image and the host image are indistinguishable without any visual degradation. This is because of the watermarking strategy. In DFW-CVNN, no data was embedded directly into the host image, it rather uses a matching strategy to match the synapse weights of the host image to the watermark position, hence, there is no visual quality degradation to the watermarked image. It can be seen that both host and watermarked image are identical. Therefore, we concentrate on the accuracy of mapping strategy and watermark recovery.

From Table 1, it can be seen that the CVNN has correctly classified the subjects by varying both the epoch (1500-3000) and the learning rate (LR) between 0.4-0.7. 100% mapping accuracy and precision rate is achieved. Also from the table the effect of numbers of neurons use in the hidden layer is observed. Using 5 neurons in hidden layer (RN), it shows that 100% accuracy and precision was obtained for the entire epoch and learning rate used. None of the instance is missed or mis-mapped. However for 4 hidden layer nodes, the watermark bits were mapped with 99% accuracy when learning rate 0.6 and 1500epoch were used. Other learning rates recorded 100% accuracy. This high percentage of classification results has a great effect on the watermark mapping strategy which in turn yielded a good result in retrieval of the watermark. If there were wrong classification, this will lead to mis-mapping of the watermark to the wrong frequency position, consequently, erroneous watermark will be retrieve for incorrect position. For the extracted watermark in Table 2, column 2-4 shows the frequency components of the extracted watermark. After threshold, the entire block with correct weights are correctly recovered. The recovered watermark bits (010) are equal to the mapped watermark bits (010). Column 6 of the table shows IFM between the embedded and the recovered watermarked. IFM value ranges between 0 - 1. When the result of two images is 1 it means they are similar while 0 means dissimilar, that is, higher value signifies closeness, it can be seen that all the values obtained for IFM are between 0.9999 and 0.9625 of 1.0000. This shows that CVNN helps in prevention of loss of information during embedding, hence during extraction, the watermark was correctly recovered with the correct weights.

Table 1: Results of Distortion free Classifier

HN	Epoch.	LR	P	N	TP	TN	FP	FN	ACC	PR	TPR	FPR
5	3000	0.7	1	2	1	2	0	0	1.00	1.00	1.00	1.00
5	3000	0.6	1	2	1	2	0	0	1.00	1.00	1.00	1.00
5	3000	0.5	1	2	1	2	0	0	1.00	1.00	1.00	1.00
5	3000	0.4	1	2	1	2	0	0	1.00	1.00	1.00	1.00
5	1500	0.7	1	2	1	2	0	0	1.00	1.00	1.00	1.00
5	1500	0.6	1	2	1	2	0	0	1.00	1.00	1.00	1.00
5	1500	0.5	1	2	1	2	0	0	1.00	1.00	1.00	1.00
5	1500	0.4	1	2	1	2	0	0	1.00	1.00	1.00	1.00
4	3000	0.7	1	2	1	2	0	0	1.00	1.00	1.00	1.00
4	3000	0.6	1	2	1	2	0	0	1.00	1.00	1.00	1.00
4	3000	0.5	1	2	1	2	0	0	1.00	1.00	1.00	1.00
4	3000	0.4	1	2	1	2	0	0	1.00	1.00	1.00	1.00
4	1500	0.7	1	2	1	2	0	0	1.00	1.00	1.00	1.00
4	1500	0.6	1	2	0	2	0	1	0.9	1.00	0.90	0.10
4	1500	0.5	1	2	1	2	0	0	1.00	1.00	1.00	1.00
4	1500	0.4	1	2	1	2	0	0	1.00	1.00	1.00	1.00

Table 2: Results of extracted watermark with correct hiddin and output layer weights and quality of the extracted watermark

	Frequency components of recovered mark				Measure of Quality
Embedded watermark	Low	Mid	High	Recovered watermark, Thresholded	IFM
010	0.0553	0.9107	0.0443	010	0.9844
010	0.0049	0.9350	0.0465	010	0.9927
010	0.0005	0.9296	0.0608	010	0.9900
010	0.0491	0.8457	0.0875	010	0.9533
010	0.0096	0.9763	0.0266	010	0.9986
010	0.0378	0.9457	0.0424	010	0.9931
010	0.0201	0.9706	0.0238	010	0.9981
010	0.0205	0.9475	0.0582	010	0.9927
010	0.0289	0.9530	0.0304	010	0.9956
010	0.0027	0.9640	0.0436	010	0.9966
010	0.0366	0.9313	0.0560	010	0.9894
010	0.0002	0.9987	0.0104	010	0.9999
010	0.0000	0.9820	0.0327	010	0.9986
010	0.0001	0.9985	0.0162	010	0.9997
010	0.0030	0.9986	0.0374	010	0.9986
010	0.0312	0.9446	0.0084	010	0.9954
010	0.0706	0.8576	0.0502	010	0.9625
010	0.0284	0.9420	0.0223	010	0.9947
010	0.0460	0.9182	0.0207	010	0.9891
010	0.0484	0.8819	0.1029	010	0.9660

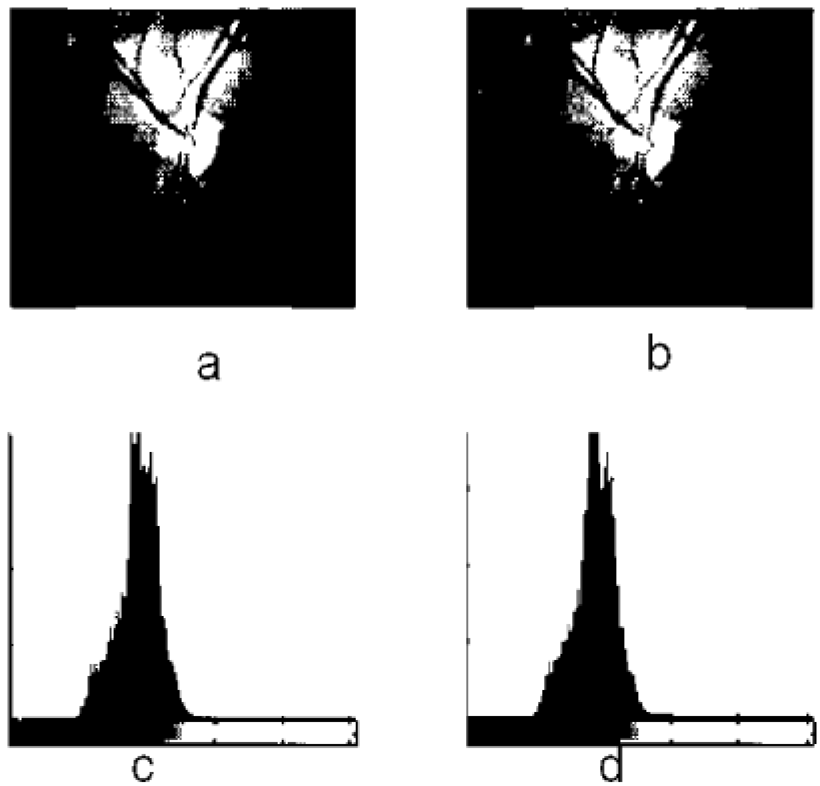

Figure 9. Host image (a) watermarked (b) histogram of the image host (c) and histogram of watermarked fundus (d)

CONCLUSION

This studies suggest an efficient and distortion free digital watermarking algorithm using CVNN and FFT. The major contribution of this work is the innovative application of CVNN in watermarking trained by complex backpropagation which is new in neurowatermarking field. Another contribution is the level of accuracy obtained in the extractor and position classifier,

More so, the system achieved 100% of Imperceptibility because the system used mapping strategy instead of the traditional embedding (+) in to the host image which will make the system suitable for medical and forensic authentication applications. The algorithm can be used for automatic piracy detection, as well as copyright demonstration for intellectual properties. The proposed method has the characteristics of fragile watermarking and can be conditioned with the parameter adjustments. Future work will include application of attacks before extraction of the watermark.

RESEARCH OUTPUT

Publications

1. R. F. Olanrewaju, O. O. Khalifa A. Abdalla and A. A. Aburas, Determining Watermark Embedding Strength using Complex Valued Neural Network: *Journal of Applied Sciences*, 11(16) pages 2907-2915 2011. (Scopus), ISSN 1812-5654.
2. R. F. Olanrewaju, O. O. Khalifa, Aisha- Abdulla, A. A. Aburas and A. M. Zeki, Distortion-Free Embedding in the Optic Disk of Retina Fundus Images using Complex-Valued Neural Network,: *World Applied Sciences Journal WASJ*; 18(6) pages 1295-1301, 2011. (ISI indexed Journal).
3. R. F. Olanrewaju, Othman. O. Khalifa, Aisha- Abdulla, A. A. Aburas and Akram M. Zeki, Forgery Detection In Medical Images Using Complex Valued Neural Network (CVNN), : *Australian Journal of Basic and Applied Sciences.(AJBAS)*, 5(7), pages 1251-1264, 2011. (ISI indexed Journal).
4. R.F. Olanrewaju∗, Othman. O. Khalifa∗, Aisha-Hassan H. Abdalla∗, A.A Aburas‡ and Akram M. Zeki, Watermarking in Safe Region of Frequency Domain Using Complex-Valued Neural Network, 4th International Conference on Mechatronics (ICOM), 17-19 May 2011, Kuala Lumpur, Malaysia
5. R.F. Olanrewaju, Othman Khalifa, Aisha Abdulla, Akram M. Z. Khedher, Detection of Alterations in Watermarked Medical Images using Fast Fourier Transform and Complex-Valued Neural Network , *International Conference on Mechatronic*, presented at Legend Hotel, Kuala Lumpur, Malaysia, 17th -19th May, 2011.(IEEE Xplore® digital library)

FUTURE PLAN OF THE RESEARCH

Using the results obtained from this Type B Research grant, software for detecting altered medical images can be developed to be use in health care system before diagnosis with possible precommercialization phase.

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REFERENCES

[1]. Poonkuntran, S., RS. Rajesh and P. Eswaran, 2009. Imperceptible Watermarking Scheme for Fundus Images Using Intra-Plane Difference Expanding, International J. Computer and Electrical Engineering, 1(4) 1793-8163

[2]. Yarmuzzi, L., M Ober, J. Slakter, R Spaide, Y. Fisher, R Flower and R Rosen, 2004. Ophthalmic fundus imaging: today and beyond American J. OphthalmoL, 137(3) 511-524.

[3]. Li, H. and O. Chutatape, 2000. Fundus image Features extraction, Proceedings of the 22nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society EMBS, 4: 3071-3073.

[4]. Ulutas, M., G. Ulutas and v.v. Nabiyev, 2010. Medical Image Security and EPR Hiding Using Sharnir's Secret Sharing Scheme. J. Systems and Software, pp: 341-353.

[5]. Maeder, A, J. Dowling, A Nguyen, E Brunton and P. Nguyen, 2010. Assuring authenticity of digital mammograms by image watermarking. Digital Mammography, pp: 204-211.

[6]. Zain, J.M., ARM. Fauzi andAA Aziz, 2008. Clinical Evaluation of Watermarked Medical Images. IEEE int Corn. on Engineering in Medicine and Biology Society, pp: 5459-5462.

[7]. Memon, NA, S. Gilani and A Ali, 2009. Watermarking of Chest CT Scan Medical Images for Content Authentication. IEEE lnt. Conf. on Information and CommlUlication Technologies, pp: 175-180.

[8]. Nayak, J., P. Subbarma Bhat, UR Acharya and M. Sathish Kumar, 2009. Efficient storage and transmission of digital flUldus images with patient information using reversible watermarking technique and error control codes. J. Medical Systems, 33(3): 163-171.

[9]. Niranjan, D., 2004. Simultaneous storage of medical images in the spatial and frequency domain: A comparative study. Bio. Medical Engineering OnLine, 3: 17

[10]. Trichili, H., M. Boublel, N. Derbel and L. Kamoun, 2003. A new medical image watermarking scheme for a better telediagnosis. Information And Commmrication Technologies, 1: 1498-1503.

[11]. Ulutas, M., G. Ulutas and v.v. Nabiyev, 2010. Medical Image Security and EPR Hiding Using Shamir's Secret Sharing Scheme. J. Systems and Software, pp: 341-353.

[12]. Wakatani, A, 2002. Digital watermarking for ROI medical images by using compressed signature iniage. Proc. ofthe 35" Annual Hawaii IEEE Int. Corn. on System Sciences, pp: 2043-2048.

[13]. Aibinu, A, M.J.E. Salami and A Shafie, 2010. Determination of Complex Valued Parametric Model Coefficients Using Artificial Neural Network Technique, Advances in Artificial Neural Systems, pp: 1-11.

[14]. Kini, T. and T. Adali, 2002a. Complex Backpropagation Neural Network Using Elementary Transcendental Activation FWlctions. IEEE Proc. Acoustics, Speech and Signal Processing, 2: 1281-1284.

[15]. Faijul Amin, M. and K Murase, 2009. Single layered complex-valued neural network for real valued classification problems. Neurocomputing, 72(4-6) 945-955.

[16]. Hartigan, J. andM. Wong, 1979. Algorithm AS 136: A K-means clustering algorithm. Applied Statistics, 28(1) LOO-L08.

[17]. Wang, H., J. Qi, W. Zheng and M. Wang, 2009. Balance K-Means Algorithm. Int. Conf Computational Intelligence and Software Engineering, pp: 1-3.

[18]. Staal, J.J., M.D. Abramoff, M. Niemeijer, MA Viergever and B. Van Ginneken, 2004. Ridge based vessel segmentation in color images of the retina, IEEE Transactions on Medical Imaging, 23: 501-509.