Hybrid Hopfield Neural Network, Discrete Wavelet Transform and Huffman Coding for Image Recognition

Kussay Nugamesh Mutter[†] **Zubir Mat Jafri** [††] **Azlan Bin Abdul Aziz**[†††],

School of Physics, Universiti Sains Malaysia, Malaysia

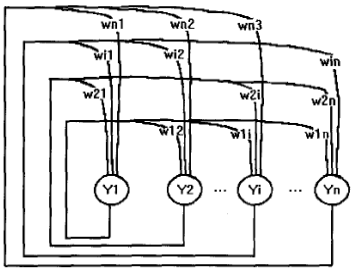
Summary
This work presents a new solution to overcome the obstacle of using Hopfield Neural Network (HNN) with high level images than binary images. While HNN deals with bipolar system for direct input data, still it is not useful for gray-level or color images. Supposing for 8-bit gray-level image consists of 8-layers of bitplanes can be represented as bipolar data. Hence, it is possible to express each bitplane as single image. In this way HNN able to operate on gray level images with good results. However, storing huge data takes large space of storage. Therefore, Discrete Wavelet Transform (DWT) and Huffman Coding will be used in a hybridization system with HNN for reducing the large amount of data. This can be achieved by converting the eight states of bipolar weights for a minimum size of 3-pixels vector into decimal representation to be ready for DWT and Huffman. In converging, the compressed weights will restore and reconverted into bipolar form. Experimental results showed the perfect performing of HNN for gray and color images recognition. This system tested on a large number of different samples of gray level images.

Key words:
Hopfield Neural Network, Discrete Wavelet Transform, Huffman Coding

1. Introduction

Inspired by the structure of the human brain, artificial neural networks have been widely applied to fields such as pattern recognition, optimization, coding, control, etc., because of their ability to solve cumbersome or intractable problems by learning directly from data, [1,2,3]. One of the important types of neural networks is Hopfield network, which is iterative Auto-Associative networks consisting of a single layer of fully connected processing elements. An expanded form of a common representation of the HNN is shown in figure (1). All the processing elements (Y1,Y2,…,Yn : neurons or nodes) are connected in feedback architecture with the connection weights specified in a certain way,[3].

Fig. 1. Hopfield Neural Network Architecture
W_{ij}: weights
Y1,Y2,…,Yn : neurons



If HNN is given by weights and limiting values, then the network will be in dynamic equilibrium when creates a pattern. A network can define various patterns; and can find them by different start vectors in the iteration. Corresponding to the spin-glass theory of solid state physics, such equilibrium functions in Hopfield networks are characterized by the fact, that the total energy (Hamilton function) becomes minimum. This leads here to a "Lyapunov function or energy function", equation (1), which becomes exactly minimum, when creates a pattern. Taking minimum size of pattern (vector) of 3-pixels (elements) rather than the whole image will lead to have only eight possible states for producing weights of learning, table (1). Therefore, multi-path architecture network has to be used here, as shown in figure (2), [4].

$$E = -\frac{1}{2}\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} v_i v_j\right) \quad (1)$$

Where: E: energy function, w_{ij}: the weight from the output neuron i to the input neuron j, and v: input vector.
In table(1) the vector property is the sign of the sum of each vector state used here to create right pattern in HNN, [4,5].

Manuscript received June 5, 2009
Manuscript revised June 20, 2009

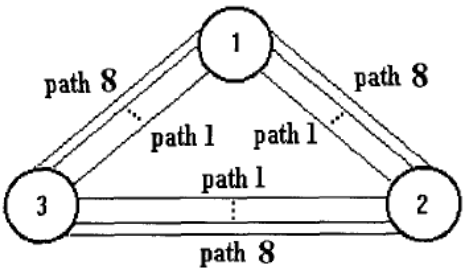


Fig. 2. Multi-path of HNN architecture.

Table 1.Vector states of weights, with the associated vector properties.

State No.	Vector States			Vector Property
1	-1	-1	-1	-1
2	-1	-1	+1	-1
3	-1	+1	-1	-1
4	-1	+1	+1	+1
5	+1	-1	-1	-1
6	+1	-1	+1	+1
7	+1	+1	-1	+1
8	+1	+1	+1	+1

As known, HNN deals only with bipolar system, but not for gray or color images unless a preprocessing operation takes place on the input data. We can solve this problem by supposing, for example, 256 gray-level image consists of 8-layers of bitplanes, each represents as bipolar data. It is possible to express each layer as single binary image for HNN, see figure (3). The 8-bit image consists of 8-layers arranged systematically in proper index in the net memory, [4,5].

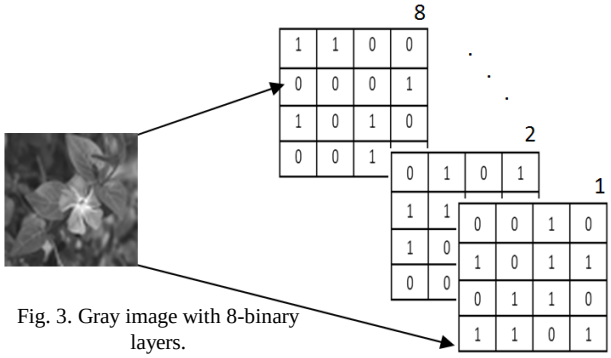


Fig. 3. Gray image with 8-binary layers.

Equation(2) is general form of gray HNN, where feedback to the i'th neuron is equal to the weighted sum of neuron outputs $\mathbf{v_j}$. Here $\mathbf{w_{ij}}$ is weight value connecting output of the j'th neuron with input of the i'th neuron, [6].

$$net_i^k = \sum_{k=1}^{b}\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} v_i + i_i \qquad (2)$$

If the number of neurons is **n=3,** we get simplest and efficient form of HNN. For 8-bit gray images, the number of neuron connections will be **k=8**, figures (4a and 5). The weights that resulted from learning process will look like figure (4-b). Hence, each input image consists of 8-layers corresponds to 8-layers of weights. There is no limitation for the maximum number of stored weights in HNN as it is proved empirically.

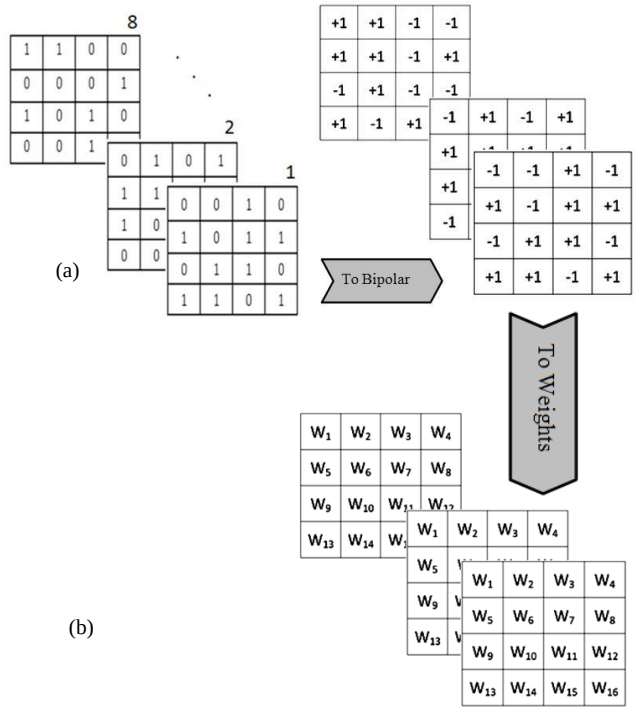


Fig. 4. a- binary layers b- weights of corresponding layers

If n is the maximum number of elements in the vector **V,** and k is the number of bits in the gray-level image, then the general form of Energy Function is:

$$E = -\frac{1}{2}\left(\sum_{k=1}^{b}\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} v_i v_j\right) \qquad (3)$$

Values produced from this equation over all possible vectors are computed for each layer and then an energy landscape with maximums and minimums can be obtained. Now we can see the usefulness of implementing this approach for gray level images; however, there is a weakness associated with this approach which is demonstrated in the next section.

2. Weakness of Gray-HNN

According to above technique, for N number of gray images of same size, HNN will operate 8 times for each image, i.e. 8 x N. If we have, for instance, 10^2 gray images, then HNN will deal with 8 x 10^2 bitplanes. Therefore, there is a burden on the net memory and needs wide storage space to save the weights. Using DWT in hybridization with HNN for compressing weights of each layer can be an excellent solution to overcome this weakness

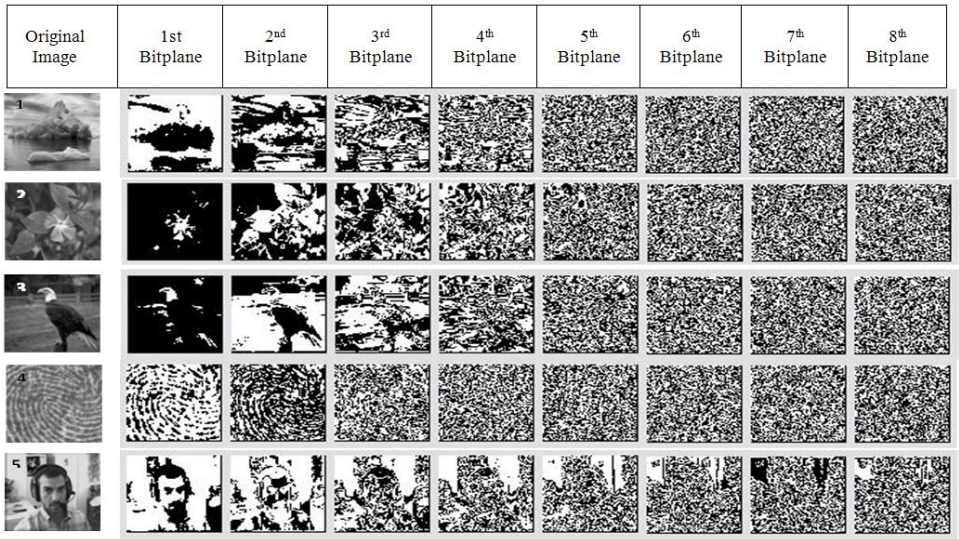


Fig. 5. 8-bit gray images and their 8-bitplanes

3. DWT in Gray HNN

Discrete Wavelet Transform (DWT) can be efficiently used in image coding applications because of their data reduction capabilities [7-12]. Basis of DWT can be composed of any function that satisfies requirements of multiresolution analysis. DWT has some properties, which makes it better choice for image compression than other approaches, especially for images on higher resolutions. A schematic diagram of using DWT with HNN is illustrated in figure (6). An input gray image is divided into 8-layers of bitplanes and each is considered as independent image. These layers will transform into weights and saved in the net memory. Considering table (1) to encode each weight in a single number instead of nine numbers, (3 x 3 array of single weight vector), by taking only the three upper elements in each matrix will help to compress all weights at 1:9 ratio. After that, applying DWT for each layer, where the code book is considered as series of data ready for second compression of Huffman Coding algorithm. Huffman coding is based on the frequency of occurrence of a data item. The principle is to use a lower number of bits to encode the data that occurs more frequently. This algorithm is briefly summarized [7,11-12]:

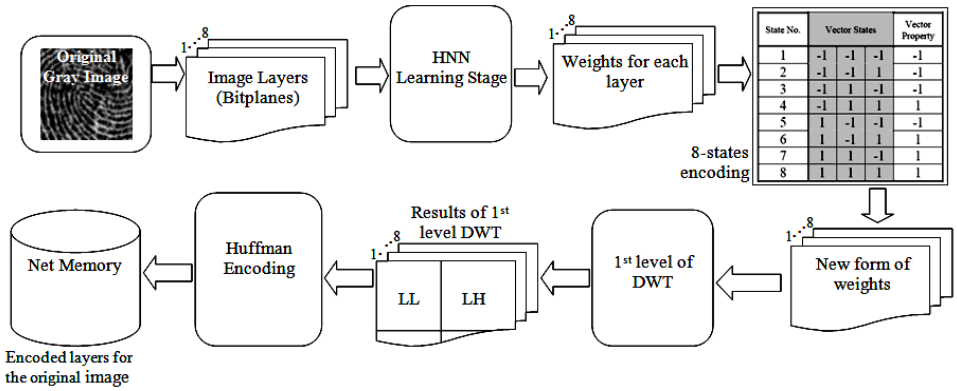
1. Initialization: Put all nodes in an OPEN list, keep it sorted at all times.
2. Repeat until the OPEN list has only one node left:

(a) From OPEN pick two nodes having the lowest frequencies/probabilities, create a parent node of them.

(b) Assign the sum of the children's frequencies/probabilities to the parent node and insert it into OPEN.

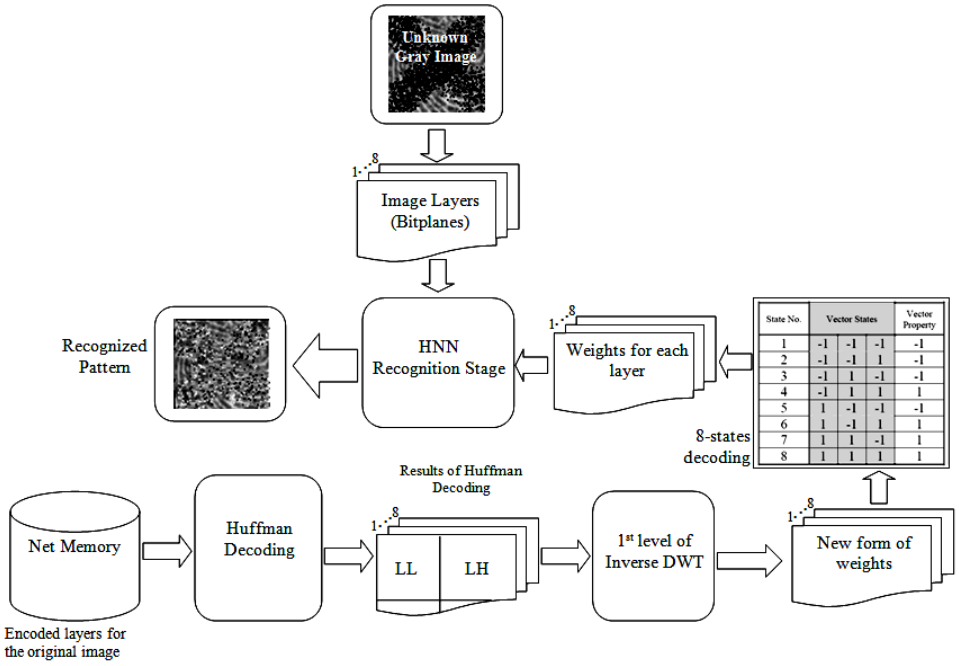
(c) Assign code 0, 1 to the two branches of the tree, and delete the children from OPEN.

The process of Converging (Recognition) is shown in figure (7). The new system able to converge to the nearest pattern after recalling stored images (layer by layer), make Huffman decoding for DWT code book, DWT decoding for the first level, convert weight representation from the 8-states to bipolar form, and running HNN converging with the unknown gray image. The latter is expected to be degraded with noises or has missing in its information, so HNN requested for recognition and reconstruction to recall the right pattern if exists.



State No.	Vector States			Vector Property
1	-1	-1	-1	-1
2	-1	-1	1	-1
3	-1	1	-1	-1
4	-1	1	1	1
5	1	-1	-1	-1
6	1	-1	1	1
7	1	1	-1	1
8	1	1	1	1

Fig. 6. Schematic diagram of the new technique,
(Learning Stage).



State No.	Vector States			Vector Property
1	-1	-1	-1	-1
2	-1	-1	1	-1
3	-1	1	-1	-1
4	-1	1	1	1
5	1	-1	-1	-1
6	1	-1	1	1
7	1	1	-1	1
8	1	1	1	1

Fig. 7 Schematic diagram of the new technique,
(Recognition Stage).

4. Results and Discussion

Empirically, we have found through applying this algorithm on 50 different 8-bit gray images the usefulness of using DWT and Huffman coding to optimize HNN. In order to measure the system activity, we choose 5 different 8-bit gray images that shown in figure (5), and making a comparison between weights with/without using DWT and Huffman techniques, we noticed a very good reduction and saving in storage space of stored weights of images in the net memory. In figure (9) of Appendix, the curves showed sensed differences after compressing processes. The Learning and Converging operations done almost with the same efficiency and quality in compare with the literatures. As illustrated in figure (8) of Appendix, the Converging Ratio for the selected images proportional exponentially with the amount of Noising Ratio.

5. Conclusions

Many conclusions are found according to the results can be listed below:

1. The usefulness of using HNN and DWT in gray-level images recognition which gives good results.
2. Optimization of compression ratio at DWT and Huffman coding dose not affected the final results, and we save about 75% of storage space of the net memory.
3. There is no limitation to the number of 8-bit gray level images which can be stored in the net memory with the same efficient results.
4. Using multilayer gray-level images never affects the net efficiency because each image is considered as binary sub images stored as weights by learning process in the net memory.
5. The new approach does not affect the final results at all except the consuming time which logically increased for DWT and Huffman Coding execution processes.

References

[1] J. J. Hopfield, Neural network and physical system with emergent collective computational abilities, (Proceedings of the National Academy of Sciences USA, vol. 79, pp. 2554-2558, 1982).

[2] Laurence Fausett, Fundamental of Neural Networks, Architectures, Algorithms And Applications, (Prentice-Hall, 1994).

[3] Kussay N. Mutter, Hopfield Neural Network and Genetic Algorithm Techniques for Fingerprint Image Identification and Reconstruction, (M.Sc. thesis, Al-Mustansiryah University, College of Education, Department of Physics, Iraq, 2002).

[4] Kussay Nugamesh Mutter, Imad I. Abdul Kaream, and Hussein A. Moussa, Gray Image Recognition Using Hopfield Neural Network With Multi-Bitplane and Multi-Connect Architecture; (IEEE, Proceedings of the International Conference on Computer Graphics, Imaging and Visualisation (CGIV'06), July-2006).

[5] Kussay Nugamesh Mutter, Zubir Mat Jafri, and Azlan Abdul Aziz. Hopfield Neural Network (HNN) Improvement for Color Image Recognition Using Multi-Bitplane and Multi-Connect Architecture; (Proceedings of the Forth International Conference on Computer Graphics, Imaging and Visualisation (CGIV'07), Thailand, pp. 403 – 407, 2007).

[6] Kussay N. Mutter, Zubir Mat Jafri, and Azlan Abdul Aziz, Automatic Fingerprint Identification Using Gray Hopfield Neural Network Improved by Run-Length Encoding; (Proceedings of the Fifth International Conference on Computer Graphics, Imaging and Visualisation (CGIV'08), Malaysia, pp. 205-210, 2008).

[7] Rafael C. Gonzalez, and Richard E. Woods, Digital Image Processing, (Addison-Wesley publishing company, 1992).

[8] Sonja Grgic, Kreiimir Keri, Mislav Grgic, Image Compression Using Wavelets, (University of Zagreb, Faculty of Electrical Engineering and Computing, IEEE, p.p. 99-104, 1999).

[9] Domagoj Kovacevic and Sven Loncaric, Ct Image Labeling Using Hopfield Neural Network, (Department of Electronic Systems and Information Processing, Faculty of Electrical Engineering and Computing, University of Zagreb, Croatia, 1998).

[10] Cornelius T. Leondes, Algorithms and Architectures, Neural networks systems techniques and applications, (Academic press, 1998).

[11] Scott E. Umbaugh, Computer Vision and Image Processing: A Practical Approach Using CVIP Tools, (Prentice Hall PTR, 1998).

[12] R. Ahmed, Wavelet-based Image Compression using Support Vector Machine Learning and Encoding Techniques, (ACTA Press, Australia, 2005).

Kussay nugamesh Mutter is a lecturer in the University of Al-Mustansiryah-Baghdad. He received the B.Sc. in Physics in 1997 and M.Sc. degree in Artificial Intelligence and Image Processing in 2002 from University of Al-Mustansiryah-Baghdad. Now he is Ph.D. student at Universiti Sains Malaysia. His research interest in fields of Neural Networks, Digital Image Processing, Optical Computing.

Mohd. Zubir MatJafri is a lecturer and researcher at the School of Physics, Universiti Sains Malaysia. He obtained his B. Sc. (1984) with first class honours in Physics from Universiti Kebangsaan Malaysia, M Sc. (1991) in Microprocessor Technology and Applications from Brighton Polytechnic, UK, and his Ph D. (1996) from University College of Swansea, Wales, UK, in the research area of algorithms development for detecting curves

from digital images. He has more than fifteen years teaching experience in the area of physics, optical communication, digital image processing, digital and analogue electronics and also microprocessors. His research interest includes the area of microprocessor-based systems, automation visual inspection systems, optical sensors, digital image processing and remote sensing.

Azlan Abdul Aziz did his MSc degree in microelectronics material and device technology in 1994 and PhD degree in GaAs-based and InP-based high electron mobility transistor (HEMT) grown by MBE in 1999 at University of Manchester Institute of Science and Technology, U.K. He worked as a lecturer in applied physics at School of Physics, Universiti Sains Malaysia (USM) since 1999 and now working as senior lecturer in engineering physics. Since 1992, he has been actively engaged in the research field of solid state physics and materials science. The research fields are amorphous and nanostructure materials, thin films, semiconductor optoelectronics material and devices and semiconductor sensors; in particular, IV-IV, III-V and III-Nitride based material. Under his guidance, two PhD, five MSc by research and numerous MSc by dissertation candidates have successfully graduated from Universiti Sains Malaysia since 2000. He has published and presented at least 80 research papers in national and international journals and conferences. He is a life member of The Malaysian Solid State and Technology Society (MASS) and a member of SPIE since 2004. He is currently attached to Nano-Optoelectronics Research and Technology Laboratory (N.O.R) in USM.

Appendix

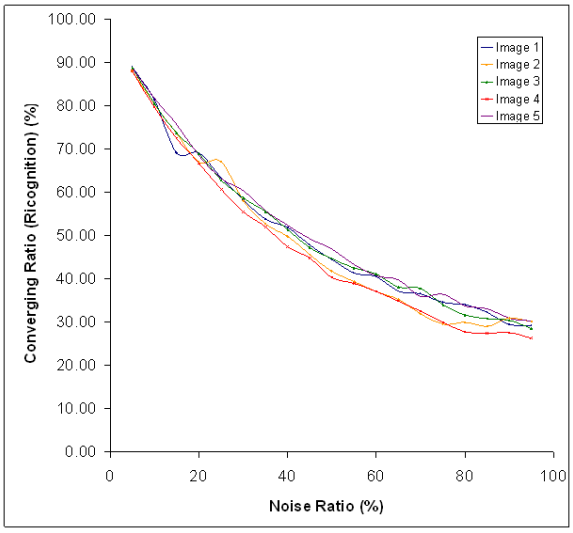


Fig. 8. Converging Ratio for the 5-different images

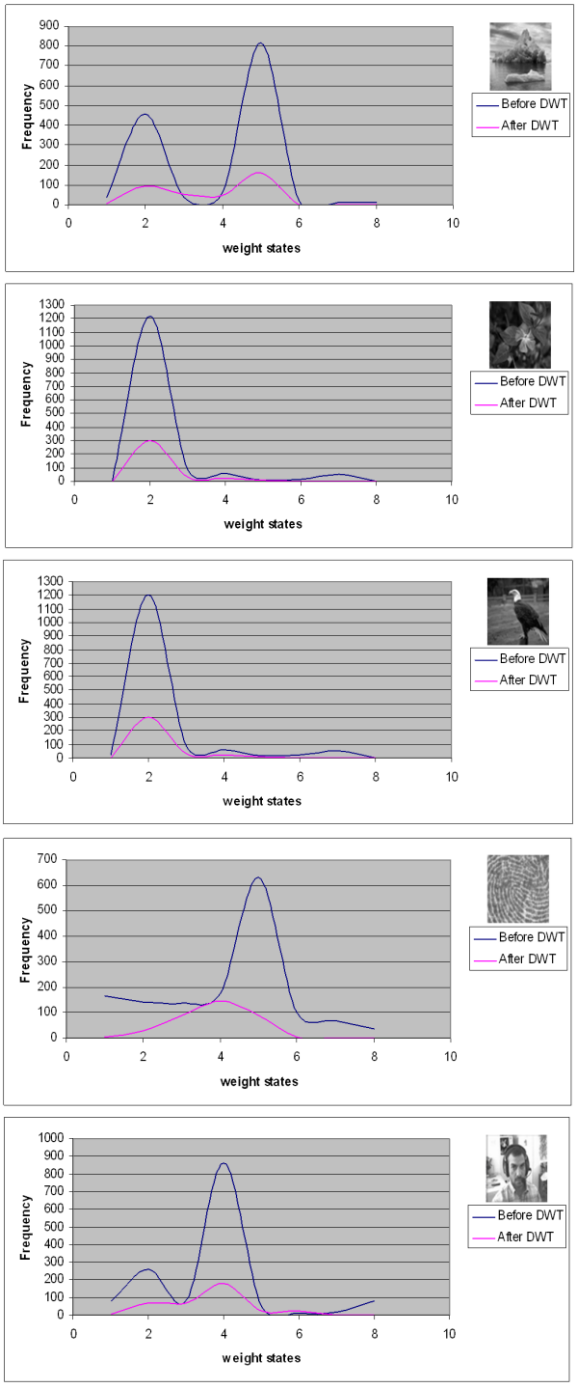


Fig. 9. Weights before and after using DWT