World Applied Sciences Journal 29 (Computer Sciences, Engineering and Its Applications): 01-05, 2014
ISSN 1818-4952

DOI: 10.5829/idosi.wasj.2014.29.csea.1

Wavelet Based Loseless Huffman Compression Algorithm for Effective Abnormality Extraction in Medical Thermograms

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Abstract: Digital Infrared Thermal Imaging is a totally non-invasive, painless, contact less clinical imaging procedure for detecting and monitoring a number of diseases and physical injuries thr5ough thermal maps called thermograms. Thermograms are stored on a computer and are sent electronically to a Thermologist for interpretation and reporting. A thermologist has to work with a large image database. It requires a mass storage unit and also a larger bandwidth during image transmission. Hence it necessitates an image compression technique to reduce the average number of bits per symbol. Moreover the compression technique should not result in loss of information for accuracy of abnormality quantification is very important. This paper proposes a novel compression technique that reduces the average bits per symbol but retains the information. The proposed algorithm involves decomposing the image into approximation, horizontal coefficient, vertical coefficient and diagonal coefficient image using Haar wavelets, zeroing the detailed coefficients (approximation image is low resolution image), reconstructing the original image from approximation coefficients and zeroed detailed coefficients, assigning Huffman coding to the reconstructed image pixels. The average bits per symbol are 0.0279 and 0.1145 in contrast to 8 bits per symbol of an arthritis thermogram.

Key words: Thermograms · Huffman · Haar · Average bits per symbol

INTRODUCTION

Medical diagnosis is a process of identifying by signs, symptoms and results of medical imaging. Medical imaging techniques are used to evaluate an area of body that is not externally visible. Various medical imaging techniques include endoscopic imaging, ultrasound imaging, gamma camera imaging, nuclear magnetic resonance technique, Radiography and thermal imaging. Endoscopic imaging uses visible light. The method is painful and is an invasive technique. Ultrasound imaging is based on Ultrasonics and its output needs skilful interpretation. However brain images can not obtained. Gamma imaging uses radioisotopes and requires attenuation correction caused by scattering of photons. Nuclear magnetic resonance is based on magnetic resonance and is less sensitive. It is also not suitable for bone defect detection. X Rays are used in radiography and the technique is harmful. On the other hand Thermal Imaging is non-invasive, painless, hazardless application and its output is thermal image and is easy to interpret. Infrared thermography provides directly a digitized output called thermogram. It provides a thermal pattern of the skin temperature at the area of observation. For a normal person, the thermogram shows uniform and symmetric temperature variations. In case of abnormality, abnormal regions show abrupt variations in temperature. These thermograms are sent to thermologists for interpretation through networks.

The task of thermologist consists of identifying the abnormality and quantitatively evaluating the severity of the disease. The number of bits used for representing these digitized thermograms is the product of rows, columns and the number of bits used to represent the thermogram. Even for a minimum sized thermogram, which is a 256 x 256 pixel matrix with the intensity level represented by 8 bits, the number of bits required to represent a single thermogram is 524288 bits. Thermologist has to work on a very large image database that is generated and transmitted which obviously requires larger memory space. Moreover the required channel capacity for thermogram transmission is also

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more. It necessitates an effective thermogram compression technique. This paper proposes a wavelet based compression algorithm that minimizes the average bits used to represent a pixel.

The paper is organized as follows. Section 2 gives a brief review of Infrared Thermography in Medical diagnosis. Section 3 deals with thermographs depicting arthritis and stress fracture. Section 4 and 5 reviews wavelet transforms and conventional Huffman coding. Section 6 deals with wavelet based image compression algorithm for medical thermograms. Section 7 deals with Results and Discussion. Section 8 is conclusion and future work. The functions are implemented in Mat lab.

Infrared Thermography in Medical Diagnosis: Human body temperature is a complex phenomenon. Man is homoeothermic and produces heat, which must be lost to the environment. The interface between that heat production and the environment is the skin. This dynamic organ is constantly adjusting to balance the internal and external conditions, while meeting the physiologic demands of the body. Digital infrared thermography is a totally non-invasive clinical imaging procedure for detecting and monitoring a number of diseases and physical injuries, by showing the thermal abnormalities present in the body [1-4]. It is based on a careful analysis of skin surface temperatures as a reflection of normal or abnormal human physiology [5]. Infrared or thermal images are produced with Infrared camera. Based on these thermal images, accurate temperature measurements can be made to detect even the smallest temperature differences when looking at human bodies. Over the years thermal images taken using infrared cameras, liquid crystal thermography and infrared tympanic thermometer have proven the human body is symmetrical right to left, extremities are cooler and injuries to nerves, tendons and muscles produce differentiating temperatures [1-2].

Content-based image retrieval system was developed for thermal medical image retrieval. Fractal encoding technique was developed to increase the linear size for fragments of the traced thermal medical images [6]. Computerized technique based on image processing of thermograms was achieved. However noise in thermograms was removed by wavelet based noise removal techniques [7].

Thermograms can be taken of the whole body or just areas being investigated. It diagnoses abnormal areas in the body by measuring heat emitted from the skin surface and expressing the measurements into a thermal map. For a normal person under healthy condition, thermograms depicted uniform and symmetrical pattern. On the other hand abnormality manifests itself either as hot spots or as cold spots. Hot spots correspond to the region of maximum intensity and cold spots correspond to the region minimum intensity and hence the temperature. Several image-processing algorithms were developed for computer-based assessment of medical thermograms. However these techniques are application specific and are developed for that particular group of thermograms.

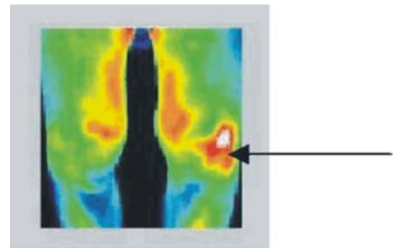

Fig. 1: Arthritis thermogram

Thermograms Depicting Arthritis and Fracture: The thermal maps produced by infrared thermal imaging instruments are called thermograms. Thermogram is defined as a 2D radiance function g (x, y), where x and y denote spatial coordinates and the value of g at any point is proportional to the radiance or energy emitted from the scene at that location. Traditionally, low intensities are represented by dark shades and high intensities by bright shades. Arthritis refers to a condition where there is damage caused to the joints of the body. Arthritis is a group of conditions where there is damage caused to the joints of the body. Arthritis region appears as hot spot in the thermogram as shown in Fig.1.

A stress fracture is a common overuse injury most often seen in athletes. Usually, a fracture, or broken bone, is caused by an acute event, such as a car crash or a fall. When this is the case, the bone experiences a very high force that causes the stress fracture. It when the forces are much lower, but happen repetitively for a long period of time; these injuries are also known as "fatigue fractures." It can occur in any bone, but is commonly seen in the foot and shinbones. Normally X rays do not diagnose it and hence Infrared thermography is the best-suited technique. It also appears as hot spot in thermogram as shown in Fig. 2.

Wavelet Transforms-Revisited: A non-redundant wavelet representation is of the form

$$f(t) = \sum_{-\infty}^{+\infty}\sum_{-\infty}^{+\infty} d(k,l)2^{-k/2}\Psi(2^{-k}t-l) \tag{1}$$

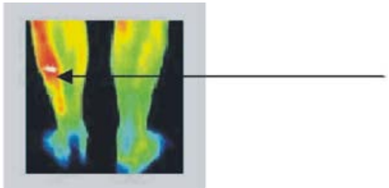

Fig. 2: Stress Fracture thermogram

This equation does not involve a continuum of dilations and translations; instead it uses discrete values of these parameters. The dilation takes values of the form $a=2^k$ where k is an integer. At any dilation 2^k, the translation parameter takes values of the form $2^k l$ where l is again an integer. The values d(k,l) are related to values of the wavelet transform W(a,b)=W[f(t)] at $a=2^k$ and $b=2^k l$. It corresponds to sampling the coordinates (a,b). This process is called dyadic sampling because consecutive values of the discrete scales as well as the corresponding sampling intervals differ by a factor of two. The two dimensional sequence d (k,l) is called as the Discrete Wavelet Transform. The Haar basis is obtained with a multiresolution of piecewise constant functions. The scaling faction is $\phi = 1_{[0,1]}$. The Haar wavelet is

$$\Psi(t) = \begin{cases} -1 & \text{if } 0 \leq t < 1/2 \\ 1 & \text{if } 1/2 \leq t < 1 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

An image is a two dimensional function along the spatial coordinates x,y and f(x,y) is the amplitude along the spatial coordinates. Let f(x,y) be the two dimensional function in the two variables x and y. Wavelet transform on the image produces four subband image coefficients. They are the approximation, horizontal detail coefficients, vertical detail coefficients and diagonal detail coefficients.

Review of Conventional Huffman Coding: Huffman coding is the best-suited lossless compression technique for removing coding redundancy Huffman coding provides the smallest possible number of code symbols per source symbol [8]. Huffman coding algorithm consists of two steps namely creating a source reduction table and assigning codes to the reduced source. In the first step, probabilities of the intensities of the image are arranged in descending order. The two lowest probability symbols are combined into a single symbol that replaces them in the next source reduction. In this way, a source reduction table is formed. The second step is to code each reduced source, starting with the smallest source and working back to the original source. The minimal length binary code for the two-symbol source is '0' and '1'. Let the code of a reduced source symbol is '1'. If combining two probabilities forms that symbol, then those two probability symbols are assigned '10' and '11'. I.e., the initial code '1' is retained and then a '0' or '1' is added to distinguish the symbols. The process is repeated till all the symbols are coded. In this way, the least probability symbol is assigned with a code word consisting of lesser bits and the higher probability symbol is assigned with more bits [4, 5].

Wavelet Based Image Compression Algorithm for Medical Thermograms: Thermograms are to be transmitted to thermologists for interpretation; it is necessary to reduce the number of bits used for representing the image. The number of bits used to represent the image is m*n*k where m and n denote the number of rows and columns in an image respectively and k stands for the number of bits used to represent each pixel. Arthritis and stress fracture thermograms are considered. The number of bits used to represent arthritis and stress fracture images are 45387 and 38976 bytes respectively [6]. The average number of bits per symbol used in both the thermograms is 8 bits. Hence they occupy a large memory space and also require a larger bandwidth. So it is necessary to perform image compression.

The algorithm involves applying Discrete wavelet transform on the thermograms, zeroing the detailed coefficients, reconstructing the thermograms with approximation coefficients and applying Huffman coding on these thermograms. When Discrete Wavelet transform is applied on these thermograms, four different coefficients are obtained namely approximation, horizontal detail, vertical detail and diagonal detail. In thermograms the abnormality appears as a larger region. Hence low-resolution analysis (approximation coefficients) is favored. So the detail coefficients are zeroed. For the reconstructed image Huffman coding is used because Huffman coding is a lossless compression technique.

The effectiveness of image compression is measured in terms of average number o f bits required to represent each pixel. Let r_k represent the gray level of an image and let each rk occurs with the probability $p_r(r_k)$.

$$Pr(rk)=nk/n \quad (3)$$

where k=0,1,2…L-1.L is the number of gray levels, n_k is the number of times that the kth gray level appears in the image and n is the total number of pixels in the image.

Table 1: Comparison between Original thermogram and Wavelet compressed thermogram

	Arthritis		Stress fracture	
Feature vectors/Abnormality	Original Image	Wavelet compressed image	Original Image	Wavelet compressed image
Average bits/symbol (Lave)	8	0.0279	8	0.1145
Major axis length of abnormality (mm)	2.6427	3.4020	2.4907	2.7713
Minor axis length of abnormality (mm)	1.7135	1.7646	1.6064	0.6928
Area of abnormality (mm)	3.2400	4.5000	2.8800	1.4400

If $l(r_k)$ is the number of bits used to represent each value of r_k, then the average number of bits used to represent each pixel is

$$Lavg=\Sigma l(r_k)p_r(r_k) \quad (4)$$

where k varies from 0 to k-1 [8].

Wavelet based thermogram compression is performed at the transmitter side and thermograms are reconstructed at the receiver side. Abnormality region is extracted from these compressed thermograms and also from uncompressed original thermograms and the results are compared. Abnormality is then quantitatively characterized using area, major axis length and minor axis length.

RESULTS AND DISCUSSION

The reconstructed arthritis and stress fracture thermograms are as shown in Fig. 3 and Fig. 4. The abnormality region extracted from the original arthritis and stress fracture thermograms are as shown in Fig. 5 and Fig. 6. The abnormality region extracted from the compressed arthritis and stress fracture thermograms are as shown in Fig. 7 and Fig. 8. The quantitative characterization of thermograms and L_{ave} are as shown in Table 1 for comparison.

The average bits/symbol is much reduced when compared to that of the original image. The abnormality quantification is nearly equal for the original image and compressed image [14].

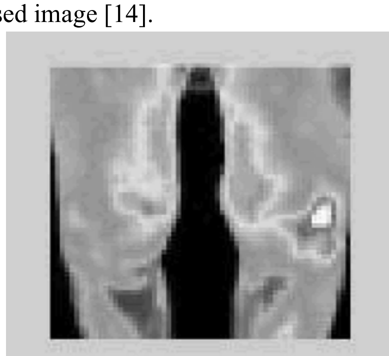

Fig. 3: Reconstructed Arthritis thermogram

Fig. 4: Reconstructed Stress Fracture thermogram

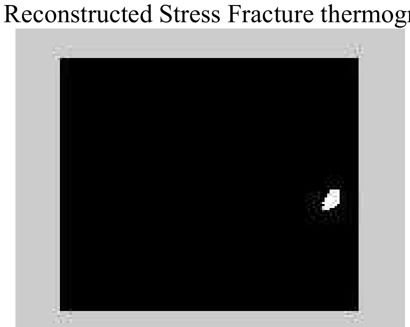

Fig. 5: Arthritis isolation (Original thermogram)

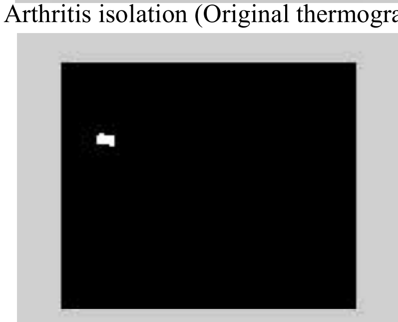

Fig. 6: Stress Fracture Isolation (Original thermogram)

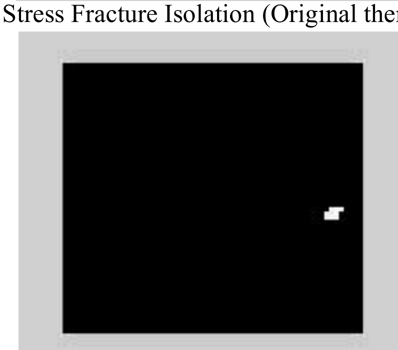

Fig. 7: Arthritis isolation (Compressed thermogram)

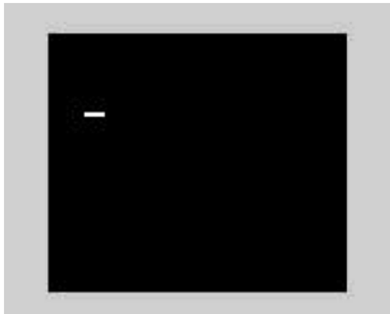

Fig. 8: Stress Fracture Isolation (Compressed thermogram

CONCLUSION

Thermograms of arthritis and stress fracture are considered. A novel Image processing algorithm was developed to compress the thermograms is developed. Abnormality detection and quantification are performed on both original image and wavelet compressed thermograms. The abnormality region is quantified using major axis length, minor axis length and area, which indicate severity of disease. The two results are nearly the same. Moreover the average bits per symbol are also much reduced when compared to original image. In future, the feature extraction algorithm can be fine tuned to provide exactly same results [15].

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