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# ENERGY COMPACTION ALGORITHM FOR ENHANCING FOOTPRINT IMAGE QUALITY USING DISCRETE WAVELET TRANSFORMATIONS

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**ABSTRACT**

A new energy compaction algorithm that compresses the image of a foot print based on Discrete Wavelet Transformation (DWT) using 2-D Haar Wavelet Transform of the gray scale image is proposed. The foot print image is resized to 256 x 256. Wavelet Transforms are used for noise reduction in order to improve the image quality. This is accomplished through Wavelet Decomposition followed by selective compression of undesirable noise components. Use of a Bi-Lateral filter to smoothen the ridges of the foot print and filtering the image without blurring the sharp edges. The reconstruction of the image is done using Inverse Discrete Wavelet Transformation (IDWT) with the maximum correlation of adjacent scales. The image is further used to match identity of the person's foot print from data base by measuring the Euclidean distance.

**Keywords:** energy compaction, discrete wavelet transform, 2-d haar wavelet, bi-lateral filter.

## 1. INTRODUCTION

A foot print is a set of ridges and furrows which follow a common feature pattern, which is differentiated by abnormal points called the minutia or the bifurcation points that differs from person to person. To perform matching of footprint images and its recognition, both accuracy and the processing time are critical. A database may contain more number of images and the processing time becomes very important at this stage. Accuracy in mapping the input image with that of the images present in the data base is also important as shown in Figure-1.

**Figure-1.** A footprint image acquired by an Optical Sensor.

## 2. ENERGY COMPACTION TECHNIQUE

2-D Haar Wavelet is a loss less image compression technique or algorithm that possess the property of orthogonality, which splits low and high frequencies and thus filtering without duplicating them. One of the key properties is that image after compression and its reconstruction does not loose the number of pixels. The energy is conserved after this transformation. A suitable filter is found to remove the Gaussian noise that is introduced during the image capturing device.

## 3. USE OF BI—LATERAL FILTER

The use of Bi--Lateral filter blurs the image without the loss of crucial ridges which is utmost important for pattern recognition. . The image is then reconstructed through the Inverse Discrete Wavelet transformation (IDWT). A linear construction of the regions of interest preserves all details of the original image which is both time and memory efficient. Image matching is done by applying Euclidean distance in order to identify the image ID of the person.

## 4. DESIGN AND IMPLEMENTATION OF ENERGY COMPACTION ALGORITHM

The energy compaction algorithm uses DWT and IDWT. The use of Bi-Lateral filter to smoothen the image and finally the use of Euclidean Distance for foot print recognition is explained as follows:

### a) Preprocessing

Convert the foot print image that is captured by the device to gray scale image. Resize the image to 256 x 256.

### b) Image compression using 2-D Haar wavelet

To calculate the 2-D Haar wavelet transform of an array of n samples of foot print images.

Foot print image is compressed using the following steps:

**Step-1:** Find the average of each pair of samples (n/2 averages).

**Step-2:** Find the differences between each average and the samples. It is calculated from (n/2 differences).

**Step-3:** Fill the first half of the array with averages.

**Step-4:** Fill the second half of the array with differences.

**Step-5:** Repeat the process on the first of the array (the array length should be a power of two ).

This algorithm conserves energy even after compression without much loss of pixels. The compression of the image reduces the time to process the image for decomposition and image smoothening techniques.

**c) Image decomposition**

In wavelet decomposition of an image, decomposition is done row by row and the column by column. Down scaling of the foot print image is done for N x M (size of matrix) where (M ≥ N ). Filter each row and then down scale to obtain two N x (M/2) images. Then down scaling to obtain four (N/2) x (M/2) images. We can see clear information in the low frequency sub bands as shown in the Figure-2.

LL LH

HL HH

**Figure-2.** Foot print image sub bands HH-High High, HL-High Low, LH-Low High, LL-Low Low sub bands**.**

**d) Image smoothening**

The image after decomposition is then smoothened by a special filter called the bilateral filter. This filter is a non-iterative and non-linear in nature. The key feature of this filter is to blur the image by preserving the edges and sharpening them leaving an acceptable image i.e. further used for pattern reorganization. The intensity value of each pixel in an image is replaced by the weighted average of the intensity values of its nearby pixels. These weights are based on Gaussian distribution, which depends not only on the Euclidean distance of each of the pixels present.

This filter preserves the sharp edges by symmetrically looping through each pixel and adjusting weights of the adjacent pixels accordingly.

The bilateral filter is defined as in Equation (1):

$$I^{\text{filtered}}(x) = \frac{1}{W_p} \sum_{x_i \in \Omega} I(x_i) f_r(\|I(x_i) - I(x)\|) g_s(\|x_i - x\|), \quad (1)$$

Where,

$I^{\text{filtered}}$ is the filtered image. $I$ is the original input image to be filtered. $x$ are the coordinates of the current pixel to be filtered. $\Omega$ is the window centered in $x$. $f_r$ is the range kernel for smoothing differences in intensities. $g_s$ is the spatial kernel for smoothing differences in coordinates. This function can be a Gaussian function. Where the normalization ensures that the filter preserves image energy.

$$W_p = \sum_{x_i \in \Omega} f_r(\|I(x_i) - I(x)\|) g_s(\|x_i - x\|) \quad (2)$$

The weight $W_p$ used in Equation (2) is assigned using the spatial closeness and the intensity difference. Consider a pixel located at $(i, j)$ which needs to be de-noised in image using its neighbouring pixels and one of its neighbouring pixels is located at $(k, l)$. Then, the weight assigned for pixel $(k, l)$ to de-noise the pixel $(i, j)$ is given in Equation (3):

$$w(i,j,k,l) = e^{\left(-\frac{(i-k)^2+(j-l)^2}{2\sigma_d^2} - \frac{\|I(i,j)-I(k,l)\|^2}{2\sigma_r^2}\right)} \quad (3)$$

where $\sigma_d$ and $\sigma_r$ are smoothing parameters and I (i, j) and I(k, l) are the intensity of pixels $(i, j)$ and $(k, l)$ respectively. After calculating the weights, normalize them.

$$I_D(i,j) = \frac{\sum_{k,l} I(k,l) * w(i,j,k,l)}{\sum_{k,l} w(i,j,k,l)} \quad (4)$$

$I_D$ is the de-noised intensity of pixel $(i, j)$ used in Equation (4).

**e) Inverse Discrete Wavelet Transformation (IDWT)**

The image then undergoes inverse wavelet transformation for pattern recognition after the image has been reconstructed and it is free from Gaussian noise. Only the required features that are important to pattern recognition remains .These features are then required to be loaded in the database for identifying the foot prints of each individual.

**f) Foot print recognition**

The image is matched from the database by using Euclidean Distance d (p, q) between points p and q formula in Equation (5) :

$$d(p,q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2}. \tag{5}$$

Hence matching of the ridges or the minutia are successful by equating the distances between each pair p1 and p2 points of one image with the q1 and q2 points of the image present in the database image.

## 5. EXPERIMENTAL RESULTS AND DISCUSSIONS

The gray scale values of the foot print image has been plotted in a graph before and after compression showing the pixel densities in each case. The following graph is an original image before undergoing Discrete Wavelet Transformations (DCT) .The image represents the Gray scale values on the Y axis and the pixel density range on the X axis .The image is not compressed at this stage. The gray scale values lies between 140 to 260 and pixel density from 0 to 160.

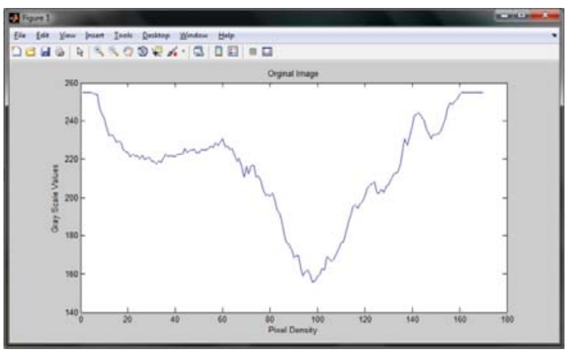


**Figure-3.** Pixel density of original foot print image before DWT.

The following graph shows the image after Discrete Wavelet Transformation. The image represents the gray scale values on the Y axis and the pixel density range on the X axis .The image is compressed at this stage. The gray scale values lie between from 250 to 255 and pixel density from 0 to 240.

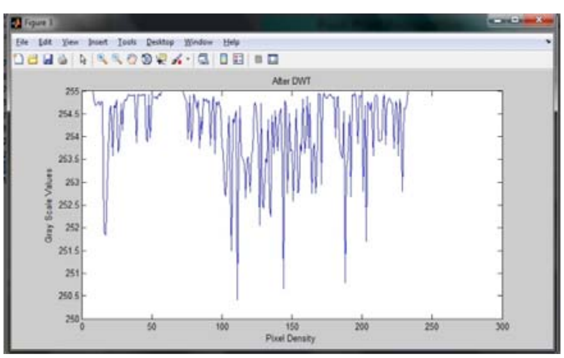


**Figure-4.** Pixel density of the foot print image after DWT.

The image has been compressed considerably without loss of pixel intensities.

## 6. CONCLUSIONS

The performance of the Energy Compaction algorithm used for compressing the images was found to be efficient in both memory and time complexity. This algorithm is cost efficient. The following properties of wavelet function such as (a) Linear Time Complexity: Transforming a wavelet that is represented linearly can generally be accomplished faster, allowing time complexity to reduce. (b) Sparsity: The simplest functions can be calculated easily, the coefficients in a wavelet representation are either zero or small. Thus we can compress the data using wavelets.(c)Flexibility: Wavelets are very adaptable .They are suited to solve problems involving images open or close curves and surfaces .These properties make the DWT very efficient in pattern recognition. Use of a Bi-Lateral to enhance the foot print used which is both non-iterative and non-linear in nature preserves the ridges even after filtration. This processes the image for pattern identification.

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