ISSN 2229-5518

De-Noising Thermal Image Based On Haar Wavelet Transform Using Soft Threshold Technique

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Abstract: The concept of thermal imaging is inspiring the attention of many researchers, corporate companies and medical fields recently owing to its wide applications. The thermal camera captures the image of an object irrespective of the lighting condition. It can even picture the object in the dark environment, which is an added advantage. As a result, we can use the thermal image for object detection and classification process. A datasets of thermal image is created by using Fluke VT02 thermal camera for observation. But the thermal image has some noise signals as it depends only on the temperature of the environment. For de-noising the thermal image, the Haar wavelet transform is used in the proposed model and further the images were experimented on soft threshold technique. The thermal image is retained nearly 90% with minimum loss and hence the thermal image can be utilized for image processing applications.

Keywords: thermal image, Haar wavelet, soft threshold, image processing.

1. Introduction:

The application of the digital images and the thermal images are increasing steadily in recent times due to its nature of adaptability. The thermal images are grabbing the attention recently in COVID-19 situation, because it detects the object based on their emissivity of the heat. Thermal image depends on the temperature of the object rather than the lighting condition [5, 6]. For locating an object, thermal cameras don't require even the minimum lighting condition whereas the visible images [3] requires minimum of 30% of light as mandatory. Initially the thermal image was employed in military applications but now it is widely used in various fields such as medical, computer vision, deep learning, machine learning, agriculture etc. [4, 7]. The thermal image must be pre-processed as it contains some noisy and unwanted signals. Those noisy signals must be removed to enhance the pixel quality of the image and it helps for contouring the edges of the object in the image.

Plenty of techniques such as Fourier Transform (FT), Discrete Cosines Transformation (DCT), and Discrete Wavelet Transformation (DWT) are available for deforming the signals of the image. At earlier days, DCT was used to transform the thermal images. This DCT method [12] will remove the signals, which depend only on the time domain, and it ignores the signals, which depend on the frequency. To overcome this drawback DWT method [2, 4, 7] appeared as it concentrates on both time and frequency domain. The wavelet functions process not only the frequency of the input signal but also it deals with the time accompanying the frequency domain. It generates the wavelet filter by decomposing the wavelet coefficients ω.The wavelet transform de-noise the image after the decomposition of the signal's coefficients at different levels. Mostly the noise signal is scattered in small coefficients, so the undesirable signals are removed easily by setting those coefficients to zero. The estimated coefficients are used for both compression and de-noising process because the data are correlated using their statistics. This wavelet transform [8] deals with both time and frequency of the corresponding signal so it retains the quality of the image without blurring.

This research article is partitioned as follows: In section 2 the Digital Wavelet Transform is briefed and the proposed techniques and methods are discussed in the section 3. The validating parameters for the proposed model are discussed and its efficiency is justified in section 4. In section 5 the conclusion of this research article and future work is discussed.

2. Discrete Wavelet Transform (DWT):

The DWT transfers the signals through high and low pass filter [12] to extract the approximated details of the input image respectively. This process is known as decomposition of the signals and further those signals are reconstructed without loss in the energy of the signals. Mathematically the decomposition process is called as discrete wavelet transforms and the reconstruction of those signals is known as inverse discrete wavelet transform.

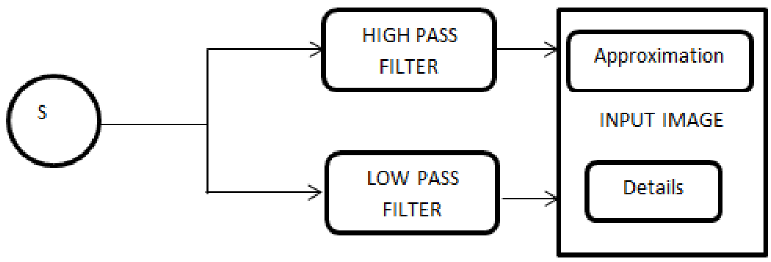

Fig.1 Overview of the DWT process

This wavelet function is capable of processing the images with different resolution. The DWT passes the signal S in both high and low pass filter to extract the features and details of the input image (Fig.1). The signals of the input image are processed by identifying their colour pattern distribution. From the signal the high and low frequency coefficients are marked for normalizing the distribution. The coefficients are fused together to produce an inverse discrete wavelet transform (IDWT) [2, 4, 10] without loss in terms of energy. Then the de-noising in the wavelet transform happens based on the two threshold methods such as hard and soft. The threshold becomes the deciding parameter for isolating the noisy signals from the signal of the input image. The edges of the image are contoured by using this threshold values. Even though hard thresholding method segments the object from the image, it sometimes fails to map the interference of the signals. In this condition, a discontinuity occurs in the signal transformation due to some external force known as Pseudo Gibbs. This hindrance is addressed by the soft thresholding technique where the visual distortion is neglected.

In the proposed work the thermal image dataset is created on own and those images are processed in wavelet transform application. The input thermal signal is decomposed at a fixed level using HAAR features [9] and later the images are subjected to both hard and soft thresholding. Their results are analysed to arrive at an optimum solution for de-noising [1, 2] the thermal image. Finally the images are reconstructed using the new coefficients without losing the energy field which can be used for object classification [11, 13].

3. Proposed Methodology:

In this proposed technique, the images are captured through the Fluke VT02 thermal camera, which is depicted in the Fig.2. Once the images are captured in the indoor environment, they are subjected to the pre-processing techniques to enhance their picture quality. In this working model, we have chosen the objects such as chair, key, phone and spectacles (Specs) for experimental purpose and the dataset is created by placing them at different distances.

Fig.2 Fluke VT02 Thermal camera

The images have some percentage of noise signals irrespective of their versatile formats. These noise signals are removed by utilizing various kinds of techniques, algorithms and methods. Especially the Gaussian noise is well handled by the wavelet transform and so it is widely used in many image pre-processing methods. As the wavelet transform considers both time and frequency, domain it is able to determine the energy of the signal within short duration. The flow of the process is carried out in three major steps as follows:

I. Initially the input image is transformed into the orthogonal domain by decomposing it in different levels.
II. Later the wavelet coefficients of both high and low frequencies deal with the hard or soft thresholding.
III. The de-noised image is obtained by inverse discrete wavelet transform.

Digital Wavelet Transform (DWT) replicates the input image in the spectral form for analysing it in the dimensional space based on the application. While decomposing the 2D image in the proposed system, it undergoes N level and 3N+1-frequency bands which are represented as LL, LH, HL and HH. The bands are divided further depending on the horizontal, vertical and diagonal details. The coefficients of low frequency wavelet eradicate the Gaussian noise from the input image and further the thresholding process is focused only on the coefficients of the high frequency wavelet. In this proposed methodology, the image of size 480 × 480 is chosen as the input and they are processed by using the Haar wavelet. The computation of this process is very low, so it is widely used in feature extraction and image processing field. They perform well in two-dimensional signals because of its default wavelet structure. Consider $H(n)$ and $H(n)^T$ as the wavelet and inverse wavelet matrix of Haar transform respectively. In two-dimensional the matrix of the wavelet signal is denoted as follow

$$Spectrum\ matrix\ SM = a.H(n) \cdot IM \ \cdot \ \mathrm{a} \cdot H(n)^T$$

$$Image\ Matrix\ IM = b \ \cdot \ H(n)^T \cdot \ SM \ \cdot b \ \cdot H(n)$$

Here a and b are parameters which has the default value as $\frac{1}{N}$ and $n = \log_2 N$. All the images are inferred as matrix and the wavelet coefficients are represented in rows and columns. SM consists of the values of the trained image whereas IM consists of the values of the test image. Hence, these matrices are in square format and so their product is commutative. The matrix of the image value is multiplied so that the features of the object are extracted from the image. The product of the wavelet coefficients value identifies the edges of the object present in the pixel.

3.1 Flow of the proposed model

Step 1: The decomposition of the 2D Haar wavelets are carried out in different levels which is denoted as N. The features from the image are extracted based on the values of the matrix. This transform provides the spectral distribution of the edges in the two dimensional space. The values of the coefficients are compressed to reduce their magnitude. During the reconstruction process, the low coefficients are removed with small errors, which are not a major issue. The high coefficients value identifies the all the possible edges of the target image. The decomposition pattern of the sample thermal object key at the level $N = 2$ is represented in Fig.3.

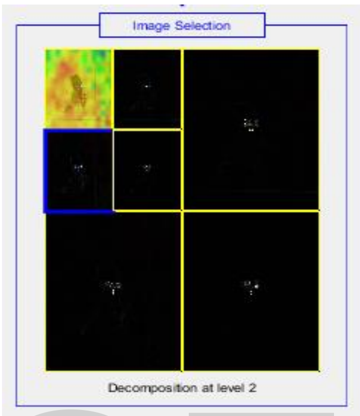

Fig.3 2D Haar wavelet based decomposition of the object key at level 2.

Fig.3 briefs the square shaped decomposition of the input image at the particular frequency bands. The horizontal, vertical and diagonal details of the target image are considered an ideal factor for edge detection (Fig.4). The product of the matrices with respective wavelet coefficients predicts the edges of the object in the image effectively.

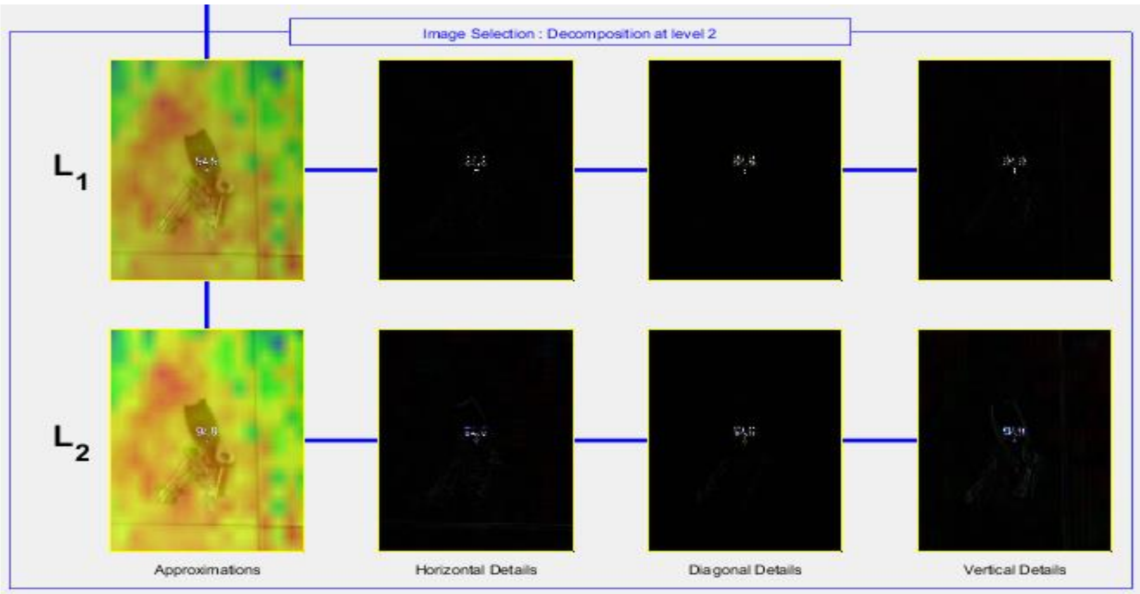

Fig.4 Edge Detection of the object key

Step 2: After predicting the edges using the decomposition process, further the thresholding algorithm is applied for de-noising the image. The thresholding algorithm is classified into hard and soft thresholding. The Haar spectrum is analysed using this algorithm for enhancing the image. If the basic requirement is only to remove the noise signal then we can simply set threshold value to zero. But if the requirement is to remove the noise signal and enhance the pixel quality then we need to cling to the thresholding technique. The Hard thresholding keeps only the high frequency (Larger magnitude coefficients) and kills the remaining coefficients by setting it to zero. The Hard threshold is mathematically defined as follows

ISSN 2229-5518

$$\omega_{i,j} < T \; then \; \omega_{i,j} = 0$$
$$\omega_{i,j} > T \; then \; \omega_{i,j} \; is \; retained$$

Here $\omega_{i,j}$ represents the wavelet coefficients of high ω_i and low ω_j frequency.

The major drawback of this method is the external oscillation will disturb the performance of the system and therefore the visual distortion take places. Technically this process of hindrance is termed as Pseudo Gibbs. In order to overcome this tricky situation the soft thresholding came into existence. The soft thresholding deals with energy of the signal by retaining the input image with minimum loss. If the frequency of the signal is below the threshold value then it is marked as zero but if the frequency is above the threshold value the particular function is taken into account. The frequencies of the signal are altered based on that function and it identifies the probability of occurrence of the colour pattern in that image. It is defined as

$$\omega_{i,j} < T \; then \; \omega_{i,j} = 0$$
$$\omega_{i,j} > T \; then \; sign(\omega_{i,j})(|\omega_{i,j}| - T)$$

Hence, the threshold becomes the major deciding pattern in this wavelet transform. The term $\omega_{i,j}$ represents the high and low frequency coefficients and the deviation from the threshold value T is estimated using $|\omega_{i,j}|$. The magnitude of the signal is provoked by the parameter *sign*, which takes care of the vector of the predicted values. The hard threshold badly filters the noise signal whereas the soft threshold filters eliminates the the low frequency value of the image under certain situation.

Step 3: Finally, the image is reconstructed by filtering the noises in the image. The threshold method is used to segment the pixels of the input image by analysing its intensity values (Fig.5). In this proposed work, global thresholding method is employed, which sets the same threshold value for the entire image's pixel. In the wavelet analyser package, the global segmentation is carried out by choosing "Remove nearby 0" option. This option will keep alive only the signals, which have values greater than the threshold values, and the remaining signals are marked as zero in the matrix. The threshold value is set as 3.5 in order to retain the 100% energy of the signal and the number of zeros is about 83.74%. The default threshold techniques will always balance the percentage between the retained energy and the number of zeros. By varying the threshold values, the optimum results can be achieved. Fig.5 illustrates that the retained percentage of the signal is enhanced by altering the values of the threshold manually.

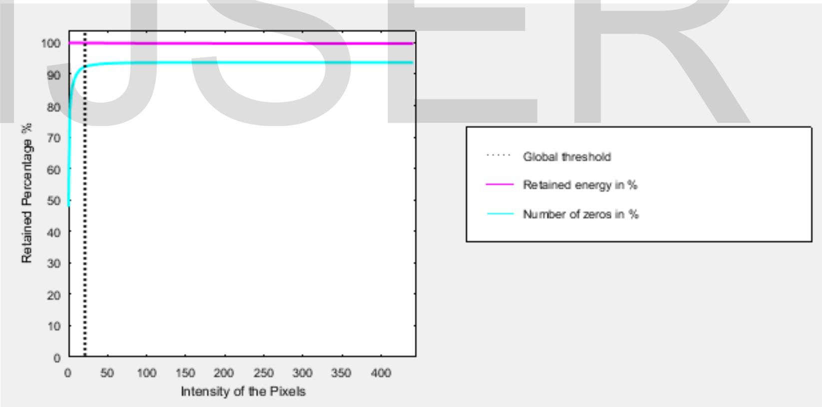

Fig.5 Comparison of Retained energy and Intensity of the Pixel

The reconstruction of this pixel results in the de-noised image, which is, retained nearly 100% with minimum loss of energy. The resultant de-noised image (Fig.6) is further implemented for the object detection and classification, which can be widely used in various fields of interest.

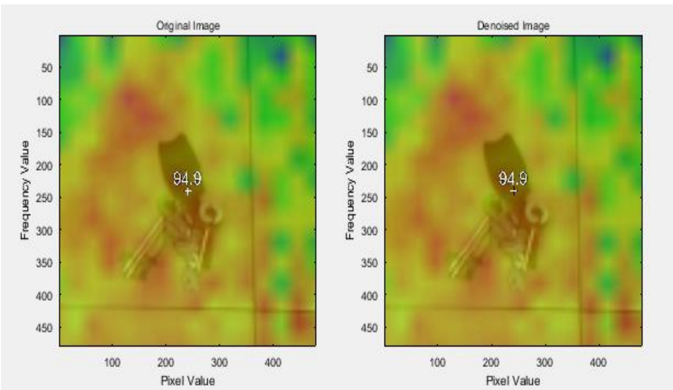

Fig.6 De-noise image using soft thresholding technique

4. Evaluation Metrics:

Mean Square Error (MSE) denotes the difference between the original input image and the processed image. It explains relation between the set of points and the regression line. The MSE value is calculated by squaring the mean value μ of the input image. A good model should have low MSE value. The Root Mean Square (RMSE) it predicts the error by the standard deviation. It resembles how the data points are fitted in the best fit line. The R^2 value in the RMSE determines the quality of the model and a good model should have high R^2 value.

$$\mathrm{MSE} = \sum_{i=1}^{n} \frac{(Y_i - \overline{Y}_i)^2}{n}$$

In the above equation n denotes the number of data points in the cluster, Y_i represents the observed value and $\overline{Y}_i$ denotes the predicted value

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(Y_i - \overline{Y}_i)^2}{n}}$$

Simply by taking the square root of the MSE we can predict the RMSE. In RMSE R^2 value predicts the quality of the proposed system.

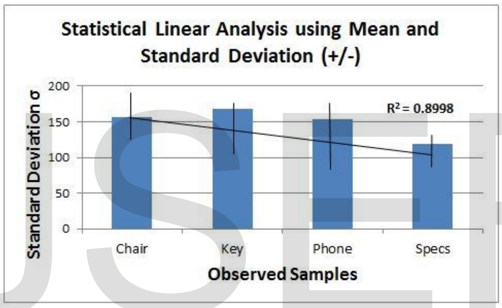

Fig.7 Statistical Analysis of the thermal image using RMSE

From the above comparative analysis, we can infer that the objects key and spectacle are accurately detected approximately to 99%. This analysis is done by monitoring the fitting line, which is perfectly placed in their respective class of objects. When comparing the other objects, the object pone has better fitting line when comparing the object chair. In the proposed model, the R^2 value is 0.8998, which indicates that nearly 90% of the image is retained with minimum loss. Hence, the proposed model is suitable for analysing the thermal image for object detection and classification.

5. Conclusion:

The thermal image dataset is created by using Fluke VT2 thermal camera and the proposed hybrid algorithm enhances them. The captured image is filtered for removing the annoying noise signal to improve its efficiency. The Haar wavelet transform is applied to decompose the signals in the process of de-noising. In digital, image the frequency represents the pixel value of that image whereas the threshold T is the chosen value, which we are selecting from that particular scale. The soft thresholding technique deals with Gaussian as well as white noise effectively in our proposed model. As a result, the proposed model achieves the accuracy of 90% of prediction of noise signals and the input signals. Hence, the soft thresholding is suitable for de-noising the thermal image and helps in the object detection and classification task. In future planning to identify the object and classify it by combining the proposed de-noising filter and the deep learning technique.

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