A Complete Analysis of K-SVD_DWT Algorithm for Improvising the PSNR Ratio in Image Denoising

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Abstract

The important component of the developing countries economic growth is agriculture. The eminence of the crop is solely based on the plant's growth and the plant's involvement is exceedingly imperative for the surrounding as well as human life. Like humans, the plants also endure from diseases. The numerous varieties of diseases affect the plants and its growth. The parts of the plant like stem, bud, leaf or the entire plant may get affected by this type of diseases. The plant may die when this problem is not effectually identified and treated. Hence, some sort of disease diagnosis is required to recognize the disease. In this work, leaf disease detection problem is taken and resolved by image processing methods. There are several procedures for analyzing, identifying and classifying the leaf disease. The process includes pre-processing of an image, image segmentation, feature extraction and classification. In the projected work, the denoising technique is examined for the leaf disease detection and it can be made effectual by performing denoising phenomena which is known to be noise reduction technique. This feature can be executed by incorporating the method called K-SVD_DWT which improves the speed, accuracy and PSNR ratio when compared to the existing techniques. The K-SVD is the singular value decomposition and the generalized view of k-means clustering for indicating the signal from the group of signals and helps to obtain a dictionary to estimate every signal with a meager

permutation of the atoms. The Peak Signal to Noise Ratio (PSNR) of the Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT) and K-SVD_DWT are compared and the result proves its effectiveness.

Keywords: Leaf Disease, DCT, DWT, K-SVD_DWT

1. Introduction

The continuous progress in the expansion of the developing countries is due to agriculture. When there is a lack in agriculture, the entire economy of the country gets affected. Hence the cautious supervision of all the sources like water, soil, fertilizers are required in order to maintain sustainability. The disease recognition plays an imperative part since the diseases are foreseeable. The observation through eyes and tagged along with the chemical examinations is the major thing in detecting and categorizing the leaf disease [3].

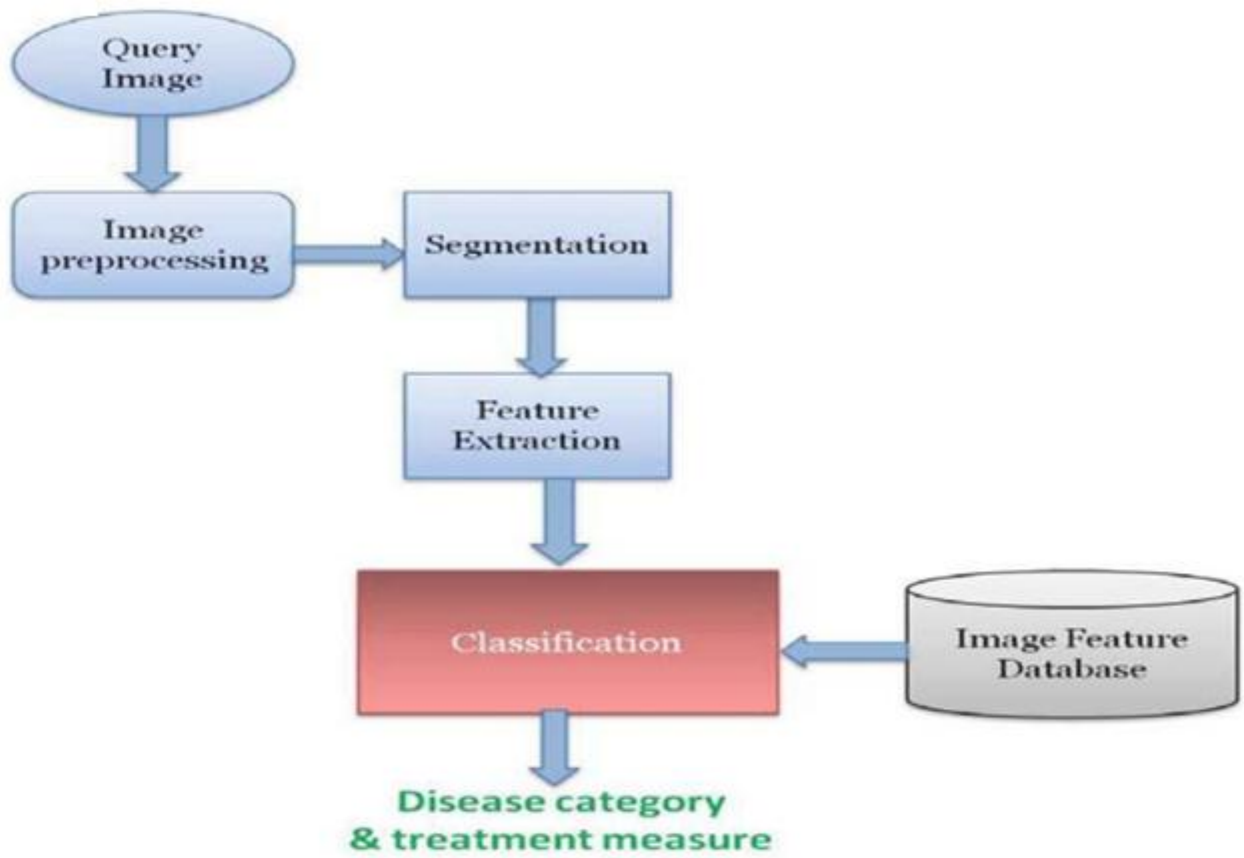

Figure 1.1 Stages in detection and classification of leaf disease

In developing countries, farming land may be abundant and farmers cannot observe every plant, every day. Farmers are unaware of non-native diseases. Consultation of specialists for this can be long & expensive. Also, inessential use of pesticides can be dangerous for natural resources like water, soil, air, organic phenomenon etc. Also, it is predicted that there must be less contamination of food merchandise with pesticides [5]. There are two main characteristics of disease detection machine-learning strategies that have got to be achieved, they are speed and accuracy. There is a necessity for developing technologies like automatic disease detection and classification by leaf image process techniques. This may be a helpful technique for farmers and can alert them at the correct time before spreading the sickness over an oversized space. A solution is found and it consists of four main sections; within the initial phase, produce a color transformation structure for the RGB leaf image and so, tend to apply color transformation for the color transformation structure. The image is divided by the K-means cluster technique. In the second section, the inessential half (green space) intervals a leaf area is removed. In the third section, texture parameters are computed for the divided infected object. Finally, in the fourth section, the extracted options are executed and the stages are mentioned in figure 1.1.

The projected work mainly focuses on the preprocessing step, where denoising technique is enabled to minimize the noise for affording consistent results in the area of image processing. Here, the denoising feature is performed by examining the pixel ratios of the healthy leaves with the help of MATLAB and the pixel values of an exaggerated leaf image are compared with the healthy leaf. The method is examined with the help of K-SVD_DWT method. The method is significant for attaining quicker and exact recognition of leaf diseases at the beginning stage.

Denoising is a noteworthy feature of image processing. In the most recent decades, a few denoising methods have been proposed. One class of such methods contains those which take benefit of the examination of the image in a (repetitive) frame. For instance, in this subset, the threshold value of the image coefficients can be denoted in an orthonormal basis, similar to the cosine basis, a wavelet basis, or a curvelet basis. In this type, the features can be involved which try to recover the main structures of the signal by using a dictionary (which basically consists of a possibly redundant set of generators). The matching pursuit algorithm and the orthogonal matching pursuit are of this type. The efficiency of these methods comes from the fact that natural images can be sparsely approximated in these dictionaries. The variational methods form a second class of denoising algorithms. Among them the total variation (TV) denoising is preferred where the chosen regularity model is the set of functions of bounded variations. In another class, one could include methods that take advantage of the non-local similarity of patches in the image. The most famous things are NL-means, BM3D, and NL-Bayes. The K-SVD based denoising algorithm merges some concepts coming from these three classes, paving the way of dictionary learning. Indeed, the efficiency of the dictionary is encoded through functional criteria which are optimized taking profit of the non-local similarities of the image. It is divided into three steps: a) sparse coding step, where, using the initial dictionary, sparse approximations are used for the computation of all patches (with a fixed size) of the image; b) dictionary update, where updation is performed in the dictionary in such a manner that the quality of the sparse approximations is increased; and next, c) reconstruction step which recovers the denoised image from the collection of denoised patches. Actually, before getting to c), the algorithm carries out K iterations of steps a and b. The K-SVD method can also be useful in other image processing tasks, such as non-uniform denoising, demosaicing and inpainting.

In de-noising, single orthogonal wavelets with a single-mother wavelet function have played an important role. De-noising of natural images corrupted by Gaussian noise using wavelet techniques is very effective because of its ability to capture the energy of a signal in few energy transform values. Crudely, it states that the wavelet transform yields a large number of small coefficients and a small number of large coefficients. Simple de-noising algorithms that use the wavelet transform consist of three steps.

• Calculate the wavelet transform of the noisy signal.

• Modify the noisy wavelet coefficients according to some rule.

• Compute the inverse transform using the modified coefficients.

The projected method combines both the terminologies termed as "K-SVD_DWT" for improving the performance of disease detection in terms of PSNR.

2. Related Work

Identification and classification of plant leaf disease is a complicated task to perform. Many researchers have worked on both traditional and soft computing approach for the segmentation of infected area of leaves from the disease. The healthy crop production is the main requirement of the farmers. Therefore, disease diagnosis and correct treatment is essential for the healthy crop production process as early as possible. The farmer's wrong diagnosis of crop disease causes insecticides spray inappropriately. Various image processing and data mining techniques are significantly applied to observe the crop growth progress and disease diagnosis. The plant occur diseases in several parts. Generally, unhealthy plant leaves change their shape, color, size, texture etc. Hence, disease detection and proper expert treatment suggestions can be find by using image processing techniques and everyone can be apply these techniques by using android application very easily.

Traditional methods such as neural network, back propagation and other pattern recognition concepts described by Kaur and Singla (2016) [1]. The responses of traditional methods are accurate but slow. Hence, there is a need of some nature inspired technique for the high speed detection efficiency of the results. The innovative, efficient & fast interpreting machine learning algorithms could be developed by Patil and kumar [2] in 2011 for detecting plant disease. They suggested that the speed and accuracy of disease detection method must be achieved by applying machine learning methods. It is difficult to determine the accurate disease in noisy image. Image should be noise free for processing. Therefore, noise reduction techniques and image enhancement are required for desirable processing. Valliammai and Geethalakshmi (2012) [3] have found that the appropriate feature extraction of leaf can be possible if input image is noise free. The leaf vein edges are not exactly visible in Gaussian noise method. The speckle noise affected the leaf size, shape and pattern. Therefore, Gaussian and speckle noise removal techniques are essential to restore the noise free leaf images for further process. This Hybrid filter method is developed to eliminate the noise, improve the quality of image and thereby produces better results compared to other traditional filters.

An automatic genetic algorithm based image segmentation and classification technique have explained by Singh and Mishra (2016) [4] for leaf diseases detection with very less computational efforts. This method can be identified the plant diseases at early stage or the initial stage. Artificial Neural Network, Bayes classifier, Fuzzy Logic and hybrid algorithms can also be used to increase recognition rate in classification process. The android applications to control the irrigation system and plant disease detection are also developed. The Android Software

Development Kit (Android SDK) consist the tools and Application Programmable Interface (API) to start developing applications on the Android platform using the Java programming language. This application used the GPRS [General Packet Radio Service] feature of mobile phone as a resolution for irrigation control system and GSM (Global System of Mobile Communication) for communication. This communication was established using the miss call and SMS.

In 2015, Xia and Li [5] have proposed the android design of intelligent wheat diseases diagnose system. In this process, users collect images of wheat diseases using Android phones and send the images across the network to the server for disease diagnosis. After receiving disease images, the server performs image segmentation by converting the images from RGB color space to HSI color space. The color and texture features of the diseases are to be determined by using color moment matrix and the gray level co-occurrence matrix. The preferred features are input to the support vector machine for recognition and the identification results are fed back to the client. The comparative results of RGB and Grayscale images in leaf disease finding process suggested by Padmavathi and Thangadurai (2016) [6]. Color could be change for infected leaves so that color of the leaf is an important feature to find the disease intensity. They have considered Gray scale and RGB images. The median filter for image enhancement and segmentation for extraction of the diseased portion are used to identify the disease level.

3. Existing System

3.1 Discrete Cosine Transform (DCT)

Digital images are often contaminated by noise during the acquisition. Image denoising aims at attenuating the noise while retaining the image content. The topic has been intensively studied during the last two decades and numerous algorithms have been proposed and lead to brilliant success. This work presents an image denoising algorithm, arguably the simplest among all the counterparts, but surprisingly effective. The algorithm exploits the image pixel correlation in the spacial dimension as well as in the color dimension [9]. The color channels of an image are first decorrelated with a 3-point orthogonal transform. Each de-correlated channel is then denoised separately via local DCT thresholding: a channel is decomposed into sliding local patches, which are denoised by thresholding in the DCT domain, and then averaged and aggregated to reconstruct the channel. The denoised image is obtained from the denoised decorrelated channels by inverting the 3-point orthogonal transform. This simple, robust and fast algorithm leads to image denoising results in the same ballpark as the state-of-the-arts. Due to its simplicity and excellent performance, this contribution can be considered in addition as a baseline for comparison and lower bound of performance for newly developed techniques.

A signal $f \in R^N$ is contaminated by a noise $w \in R^N$ that is often modeled as a zero-mean Gaussian process independent of f

$$Y = f + w \qquad \text{(Equation 3.1)}$$

where $y \in R^N$ is the observed noisy signal. Signal denoising aims at estimating f from y.

Let $B = \{\varphi_n\}$ $1 \leq n \leq N$ be an orthonormal basis, whose vectors $\varphi_n \in C^N$ satisfy

$$\langle \phi_m, \phi_n \rangle = \begin{cases} 1, & \text{if } n = m \\ 0, & \text{otherwise.} \end{cases} \qquad \text{(Equation 3.2)}$$

A thresholding estimator projects the noisy signal to the basis, and reconstructs the denoised signal with the transform coefficients larger than the threshold T and it is a threshold operator.

$$\tilde{\mathbf{f}} = \sum_{n=1}^{N} \rho_T(\langle \mathbf{y}, \phi_n \rangle)\phi_n,$$

$$\rho_T(x) = \begin{cases} x, & \text{if } |x| > T \\ 0, & \text{otherwise,} \end{cases} \qquad \text{(Equation 3.3)}$$

The mean square error (MSE) of the thresholding estimate can be written as

$$E[\|\mathbf{f} - \tilde{\mathbf{f}}\|^2] = \sum_{n:|\langle \mathbf{y}, \phi_n \rangle| \leq T} |\langle \mathbf{f}, \phi_n \rangle|^2 + \sum_{n:|\langle \mathbf{y}, \phi_n \rangle| > T} \sigma_n^2, \qquad \text{(Equation 3.4)}$$

It is well known that local Discrete Cosine Transform basis, applied in the most popular image compression standard JPEG, gives sparse representations of local image patches. Consider an 8 ×

8 DCT basis. The denoising algorithm decomposes the image into local patches of size $\sqrt{N}=16\times16$, and denoises the patches with thresholding estimate in the DCT domain. The 16×16 DCT window leads, on average, to the best denoising results [10]. While it gives similar performance as smaller window size when the noise level is low ($\sigma < 30$), when the noise level is high it outperforms significantly smaller window, the gain with respect to window size of 8×8 from on average 0.5 to 2 dB as σ goes from 50 to 100. A window size larger than 16×16 does not bring further significant improvement. It has been shown that introducing translation invariance considerably improves the thresholding estimate in an orthonormal basis. Following a common practice, translation invariant DCT denoising is implemented by decomposing the image to sliding overlapping patches, calculating the DCT denoising in each patch, and then aggregating the denoised patches to the image averaging the overlapped pixels. The translation invariant DCT denoising significantly improves the denoising performance, typically from about 2 to 5 dB, and removes the block artifact, at a cost of $\sqrt{N} \times \sqrt{N}$ times calculation with respect to estimation with non-overlapping patches. But the main disadvantage of using method is prone to the problem of blocking artifacts. Hence this problem can be circumvented by Discrete Wavelet Transform (DWT).

3.2 Discrete Wavelet Transform (DWT)

The Discrete Wavelet Transform (DWT) of image signals produces a non-redundant image representation, which provides better spatial and spectral localization of image formation, compared with other multi scale representations such as Gaussian and Laplacian pyramid. Recently, Discrete Wavelet Transform has attracted more and more interest in image denoising. The DWT can be interpreted as signal decomposition in a set of independent, spatially oriented frequency channels. The signal S is passed through two complementary filters and emerges as two signals, approximation and Details. This is called decomposition or analysis. The components can be assembled back into the original signal without loss of information. This process is called reconstruction or synthesis [7]. The mathematical manipulation, which implies analysis and synthesis, is called discrete wavelet transform and inverse discrete wavelet transform.

All digital images contain some degree of noise. Image denoising algorithm attempts to remove this noise from the image. Ideally, the resulting denoised image will not contain any noise or added artifacts. Denoising of natural images corrupted by Gaussian noise using wavelet techniques is very effective because of its ability to capture the energy of a signal in few energy transform values. The methodology of the discrete wavelet transform based image de-noising has the following three steps as shown in figure 3.1.

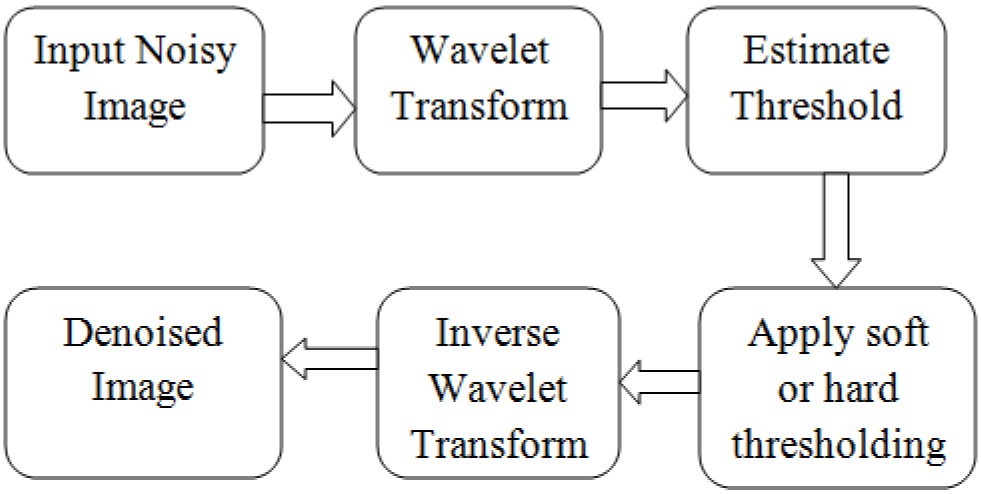

Figure 3.1 Discrete Wavelet Transform for Image Denoising

1. Transform the noisy image into orthogonal domain by discrete 2D wavelet transform.

2. Apply hard or soft thresholding the noisy detail coefficients of the wavelet transform

3. Perform inverse discrete wavelet transform to obtain the de-noised image.

Here, the threshold plays an important role in the denoising process. Finding an optimum threshold is a tedious process. A small threshold value will retain the noisy coefficients whereas a large threshold value leads to the loss of coefficients that carry image signal details. Normally, hard thresholding and soft thresholding techniques are used for such de-noising process. Hard thresholding is a keep or kill rule whereas soft thresholding shrinks the coefficients above the threshold in absolute value. It is a shrink or kill rule.

Threshold T can be calculated using the formulae,

$$T = \sigma\sqrt{2\log n^2} \qquad \text{(Equation 3.5)}$$

This method performs well under a number of applications because wavelet transform has the compaction property of having only a small number of large coefficients. All the rest wavelet coefficients are very small. This algorithm offers the advantages of smoothness and adaptation. However, it exhibits visual artifacts.

Let d (i, j) denote the wavelet coefficients of interest and B (i, j) is a neighborhood window around d (i, j). Also let $S^2 = \sum d^2$ (i, j) over the window B(i,j). Then the wavelet coefficient to be threshold is shrinked according to the formulae,

$$d(i, j) = d(i,j) * B(i,j) \qquad \text{(Equation 3.6)}$$

where the shrinkage factor can be defined as $B(i,j) = (1 - T^2 / S^2 (i,j))+$, and the sign + at the end of the formulae means to keep the positive value while set it to zero when it is negative.

During experimentation, it was seen that when the noise content was high, the reconstructed image using threshold shrink contained mat like aberrations. These aberrations could be removed by wiener filtering the reconstructed image at the last stage of IDWT. The cost of additional filtering was slight reduction in sharpness of the reconstructed image. However, there was a slight improvement in the PSNR of the reconstructed image using wiener filtering. The de-noised image using threshold shrink sometimes unacceptably blurred and lost some details. The reason could be the suppression of too many detail wavelet coefficients. This problem will be avoided by reducing the value of threshold itself. So, the shrinkage factor is given by

$$B(i, j) = (1 - (3/4) * T^2 / S^2 (i,j))+ \qquad \text{(Equation 3.7)}$$

Still the accuracy can be enhanced by combining this method with the K-SVD technique and also improve the PSNR ratio.

4. Projected Work

4.1 Incorporating K-SVD and DWT

The main purpose of this research is to build an over complete dictionary system by enhancing K-SVD_DWT for image denoising, as well as using this algorithm to gain faster image denoising process than the ordinary K-SVD. The dataset is based on classifying the leaves into one of the following types: 'Alternaria Alternata', 'Anthracnose', 'Bacterial Blight', 'Cercospora Leaf Spot' and 'Healthy Leaves'.

It is now time to present the method to adapt the grayscale algorithm to color images. To address this problem, a first suggestion would be to apply the K-SVD algorithm to each channel R, G and B separately. This naive solution gives color artifacts. They are due to the fact that in natural images there is an important correlation between channels. Another suggestion would be to apply a principal component analysis on channels RGB, which would uncorrelate them, and then to apply the first suggestion in this more appropriate environment. This solution has not been tried because the new proposition seems even more promising.

In order to obtain the colors correctly, the algorithm previously described will be applied on column vectors which are the concatenation of the R,G,B values. In this way, the algorithm will better update the dictionary, because it is able to learn correlations which exist between color channels.

The Orthogonal Matching Pursuit (OMP) algorithm is a greedy algorithm with attempts to find a sparse representation of a signal given a specific dictionary [8]. The algorithm attempts to find the best basis vectors (atoms) iteratively such that in each iteration the error in representation is reduced. This achieved by selection of that atom from the dictionary which has the largest absolute projection on the error vector. This essentially implies that we select that atom, which adds the maximum information and hence maximally reduces the error in reconstruction. Given a signal vector y and a dictionary D the algorithm attempts to find the code vector x in three steps :

1. Select the atom which has maximal projection on the residual

2. Update $x^k = \arg\min x^k \|y - Dx^k\|_2$

3. Update the residual $r^k = y - y^k$.

A pre-specified dictionary D is present which is used to find a sparse representation for a given signal. However, as mentioned before, the design of this dictionary is not trivial. One can of course use a fixed dictionary of over complete basis like wavelets, curvelets, contourlets, steerable wavelet filters, and short-time Fourier transform basis. However, such basis may not be the best over complete dictionary for all kinds of signals and hence, depending on the application, a data dependent dictionary may be the best option. Researchers have proposed many methods which perform this form of data dependent dictionary selection. Probabilistic methods aim to construct a dictionary which maximizes the probability of reconstruction assuming a known estimate of the noise along with some Apriori information which can be turned into an optimization problem that ensures minimum error as well as sparsity of representation. Other MAP approaches are also reported in literature. Another method, the Method of Optimal Directions bases its outline on the celebrated K-Means algorithm and attempts to identify a dictionary which is a close representation of the different classes that every patch in the image can be classified into. Another Method of Orthonormal Bases considers the dictionary to be composed of unions of orthonormal bases. This method is quite simplistic and calculates the SVD to update orthonormal basis of D sequentially.

The K-SVD algorithm attempts to minimize the cost function iteratively, by first finding a coding for the signals in question using the OMP algorithm using an initial estimate of the dictionary [11]. This coding is sought such that it minimizes the error in representation, and at the same time maintains a sparsity constraint. Once this sparse coding stage is done, the algorithm proceeds to update the atoms of the dictionary, one atom at a time, such that the error term is further reduced. Proceeding in such an iterative method, the algorithm reduces, or at worst maintains, the error of representation in the iteration. Having defined a general view of the steps of the algorithm, we proceed to detail the steps and the mathematical basis behind the method. We make an initial guess of the atoms of the dictionary which can be either from a set of over complete basis vectors or from the observed data itself. Given such an initial estimate D, the cost function can also be broken down into multiple optimization problems in the form

$$\min x_i \|y_i - Dx_i\|^2 \text{ subject to } \|x_i\|_0 \; i = 1, 2, ..., N. \qquad \text{(Equation 4.1)}$$

Now the problem of sparse coding is that of finding the code vector x_i for each input signal y_i.

5. Results and Discussion

The input taken for the proposed work is shown in figure 5.1.

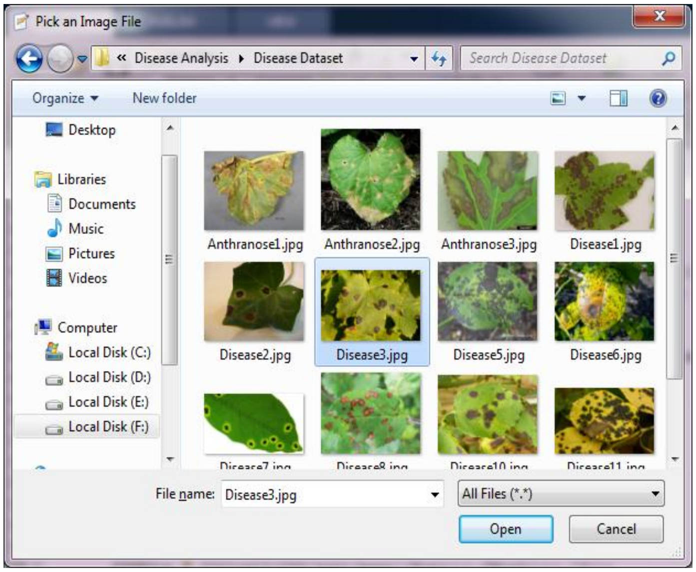

Figure 5.1 Input Image Selection

The image denoising is performed by DCT method and then by DWT method. DCT has less accuracy level and the denoised images for DCT, DWT and K-SVD are shown in figure 5.3, 5.4, and 5.5 and also the PSNR ratios are mentioned in table 5.1.

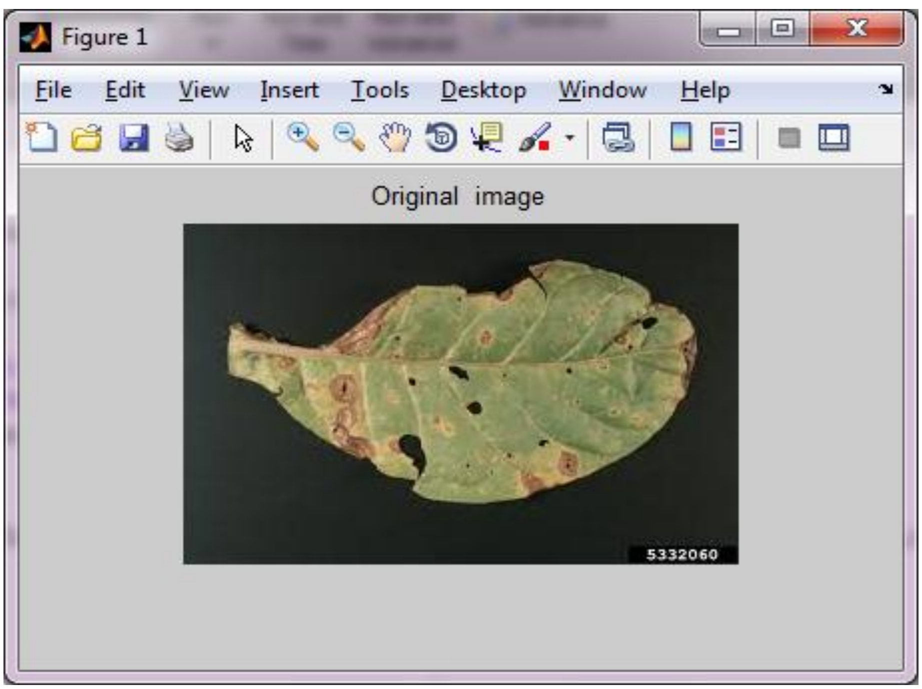

Figure 5.2 DCT Based Denoising Image

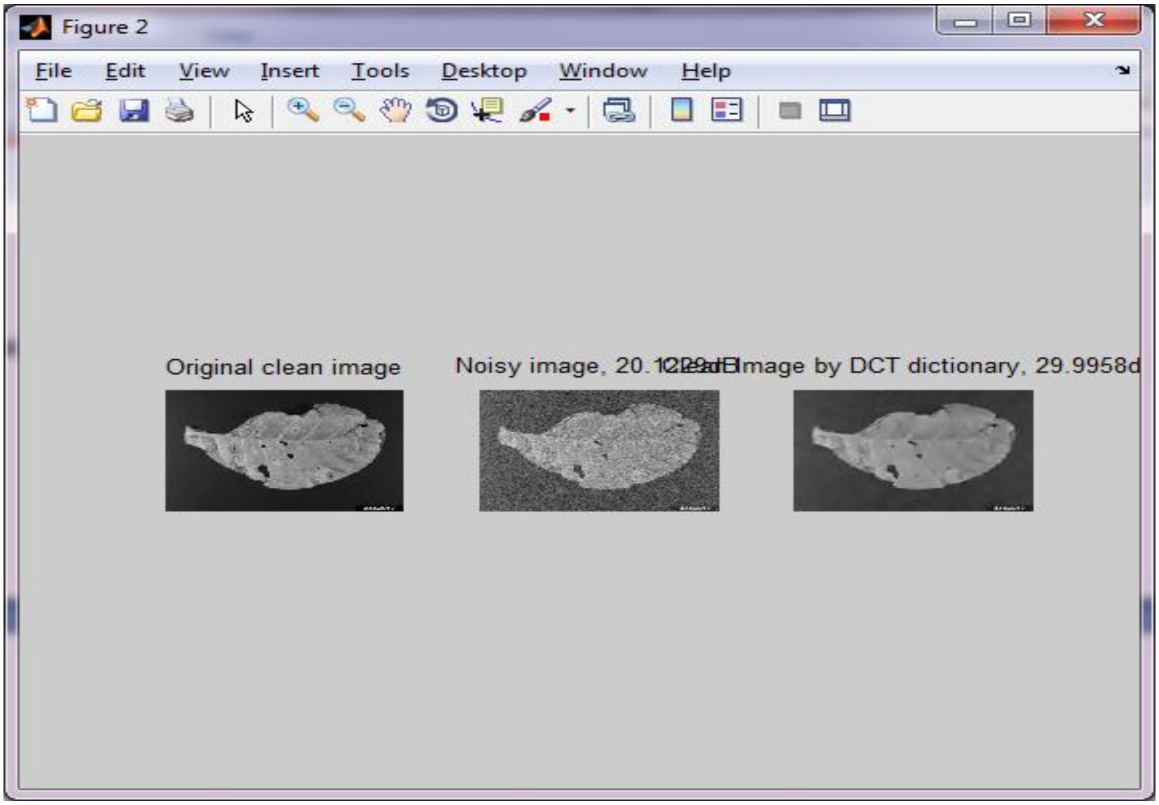

Figure 5.3 DCT based Denoising Image

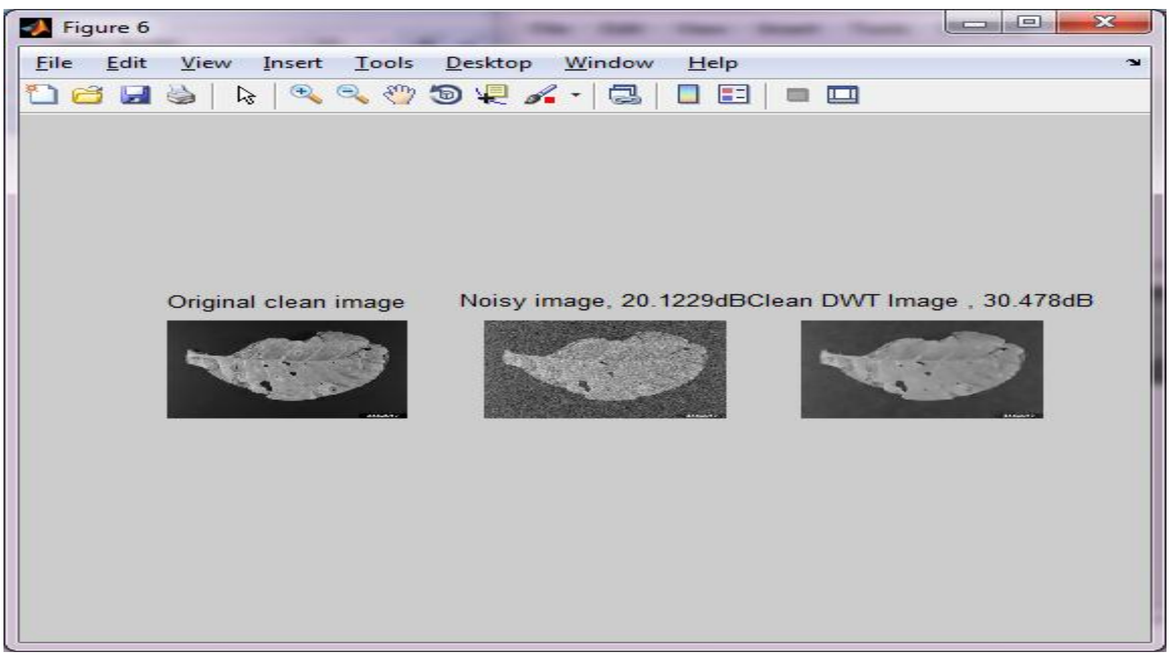

Figure 5.4 Clean DWT image 30.478 db

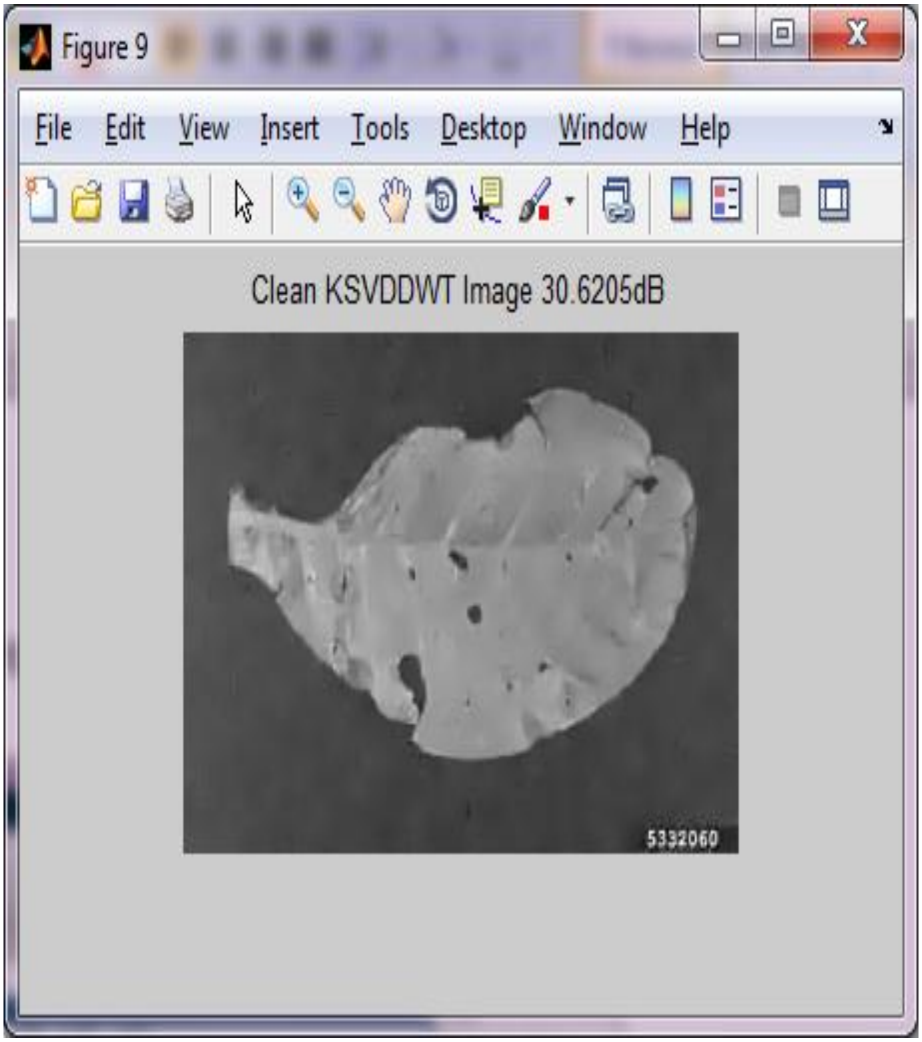

Figure 5.5 K-SVD based Denoising Image

PSNR is most easily defined via the mean squared error (*MSE*). Given a noise-free $m \times n$ monochrome image I and its noisy approximation K, *MSE* is defined as:

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2$$

(Equation 5.1)

$$
\begin{aligned}
PSNR &= 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \\
&= 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \\
&= 20 \cdot \log_{10}(MAX_I) - 10 \cdot \log_{10}(MSE)
\end{aligned}
$$

(Equation 5.2)

The PSNR values for the different algorithms are denoted below in table 5.1.

S.NO	**Algorithm**	**PSNR**
1	DCT	28.6
2	DWT	29.56
3	K-SVD_DWT	33

Table 5.1 PSNR Ratio

The PSNR metric values are analyzed and the results are shown in figure 5.6.

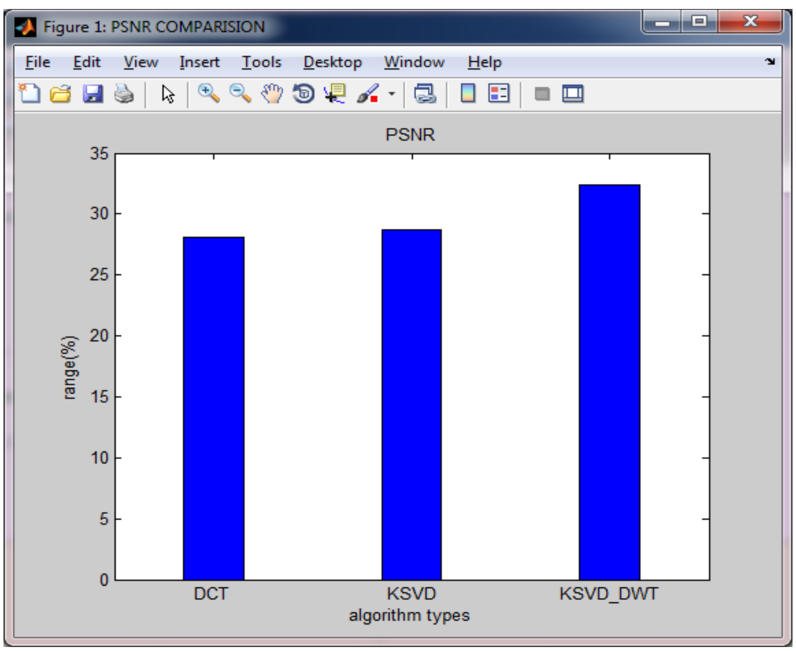

Figure 5.6 PSNR Value Comparisons

The K-SVD_DWT algorithm presented, find its use in multiple applications. One of which is the problem of compression where the sparse coding technique can be directly applied. It explored other applications like denoising and inpainting. The application of the K-SVD_DWT algorithm is used to denoising of images. Before that can be addressed, the discussion about how the method can be scaled up to address image denoising of arbitrary sizes. From the theory it is obvious that if the signal vectors have a high dimensionality, the size of the dictionary needs to be large for a stable acceptable reconstruction. This may not be the most suitable thing to do as the computational complexity scales up with the size of the vectors and the number of atoms in the dictionary. To address this issue it is proposed to break up the noisy image into patches and treat the vectorized version of each patch as signals, thereby restricting the dimensionality of each atom in the dictionary. However, the size of the patch has to be chosen such that it encodes enough details of the underlying signal. It is also natural to select these patches to be overlapping in nature in order to reduce blocking artifacts that might result at the boundaries. Dealing with patches as signals, the K-SVD_DWT algorithm can be effectively scaled to denoise large images.

6. Conclusion

In this work, the image de-noising using discrete wavelet transform is analyzed. The experiments were conducted to study the suitability of different wavelet bases and also different leaf disease detection sizes. Among all discrete wavelet bases, it performs well in image de-noising. But to improve the ratio of PSNR it can be combined with K-SVD. From this experiment, it is concluded that the time consuming process for dictionary learning was faster in K-SVD_DWT method than in K-SVD method. However, the error reduction was merely quite the same for both methods. It is concluded that the K-SVD_DWT is the most effective choice for denoising process by seeing its PSNR value.

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