Inspiring Excellence

# An Efficient Way to Convert 1D Signal to 2D Digital Image Using Energy Values


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# DECLARATION

We, cordially declare that every result, research included in this thesis is found by the experiments and work done by ourselves. We took some references from other researchers which are mentioned in the reference section. This Thesis, neither in whole or in part, has been previously submitted for any degree.

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To conclude, we would like to express our heart full joy and appreciation to our beloved parents, brothers and sisters for their love and care. We are grateful to all of our friends who helped to complete this thesis.

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# LIST OF ABBREVIATIONS

**EMD** Empirical Mode Decomposition

**IMF** Intrinsic Mode Functions

**1D** One Dimension

**2D** Two Dimension

**SVM** Support Vector Machine

**SFTA** Segmentation Fractal Texture Analysis

# Abstract

Image processing and feature extraction techniques are mandatory for any image based application. Basically, major goals of texture research in computer vision are to understand, model and process texture and ultimately to simulate human visual learning process using computer technologies. Our proposal is to create a new efficient approach for converting 1D signal to 2D digital image. Here we will be using 1D signal, which will be converted into 2D digital image using energy values.

In the past, all approaches of the signal processing techniques, the signal is always processed in one dimension (1-D) representation; therefore, a huge relationship information between time and frequency coefficients is easily lost. To eradicate these problems, two dimensions representation of the signal using energy values is evaluated in this thesis.

The main goal of this thesis is to focus on developing an efficient way for converting 1D signals to 2D digital image to get a perfect accuracy than other approaches. It includes some important steps by which we will find our result. Signal acquisition is the first part of our work, then comes the signal reprocessing. After that we extract the feature from the image to justify the different textures and finally the classification part, being done with these steps we are finding out the accuracy with a new efficient approach by which we created the 2D digital image.

In the proposed system, at first it takes 1D fault motor signals and then we are applying Empirical Mode Decomposition algorithm to detect the low frequency which basically represents noise and remove it from the signal. After obtaining the processed signal we have calculated energy values of each signal frame and converted into 2D gray-level images. After that we are using Segmentation-based Fractal Texture Analysis method to extract the feature vectors. Then we have classified our gray level images using support vector machine which has high classification ability.

Finally the performance of this proposed approach is compared to other techniques of feature extraction methods by providing the accuracy and thus our proposed approach is one of the efficient techniques for feature extraction methods .

# CHAPTER 1

# Introduction

## 1.1Motivations

The field of signal processing is a very important field of study and one that makes possible various other fields such as communications. MP3 music files contain processed, transformed, and compressed music signal data. Speech recognition systems such as dictation software need to analyze and process signal data to identify individual words in a spoken sentence. Neural interface devices, such as various medical prostheses must read the complicated signals of neurons, process those signals to determine the important features, and then convert those features to digital data. Signal processing enables high-speed data communication, even in the presence of interference or noise [2][13].

We all want to see a perfect image. The view of on image depends on the good quality of the image and the good quality refers to the perfect texture combination. So by representing texture in a perfect way we can easily make a perfect image. And it is a must for the viewers to see a good quality image. Basically our motive is to create a perfect good quality image which will be useful in business sectors and in the industries to detect the basic elements with clarity.

For a developing country like us there are many industries where productivity depends on the reliability and efficiency of the machines, motors. In order to monitor if they are working without any disturbance or not their signals need to be checked. For this kind of reason image processing from signal and their feature extraction has become very popular subject in a modern era like this. In recent years two dimensional (2D) representation of 1D signal has been used in a variety of sectors. These images can be processed and features are extracted which plays an important role in many applications which shows the significance of the process of conversion of 1D signal to 2D image and feature extraction from it. While doing it people faced many difficulties and complexities as they went to define significant features of the texture [18].2D representation from 1D signals has been widely researched and came out with desired results but the feature extraction of texture images is still in research. The drawbacks of these process has motivated us to come up with a more efficient method of 2D representation of 1D signal and feature extraction of the texture image [3].

## 1.2 Description of feature extraction

Transforming the input data into the set of features is called feature extraction [2]. Basically it is a process of deriving new features from the original features in order to reduce the cost of feature measurement, increase classifier efficiency, and allow higher classification accuracy feature extraction involves reducing the amount of resources required to describe a large set of data [15]. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power, also it may cause a classification algorithm to over fit to training samples and generalize poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy [7]. Many machine learning practitioners believe that properly optimized feature extraction is the key to effective model construction.

## 1.3 Contribution summary

In our proposed technique for converting 1D signal to 2D gray-level image, at first we convert the 1D signal into 2D gray-level image by taking each pixels normally, then we convert it by taking the mean of some pixels and later on convert the 1D signal to 2D gray level image by fourier analysis technique, We have done it these ways just to check the difference between the converted images. After that we have extracted feature vector using SFTA, and then train the classifier by giving test data. In this proposed system, the samples of a signal are normalized into the range 0-255 of a gray image and assembling into the 2D space, forming an image. Our efficient method is to take the energy of the pixels and make a 2D gray-level image. Finally compare it with the other feature extraction approaches by providing the accuracy [5].

## 1.4 Thesis organization

- Chapter 2 includes the necessary background information regarding the proposed approach of the efficient feature extraction method for 2D digital image.
- Chapter 3 includes the methodology of our new proposed model for 2D digital image
- Chapter 4 includes the experimental analysis, results of the new efficient model which shows the performance.
- Chapter 5 includes the social impact of why we are doing this research and future works and plans regarding this research.
- Chapter 6 summarizes and concludes this thesis in short.

# CHAPTER 2

# Background study

## 2.1 The Time Domain Features

Time domain of a signal is representing the signal highlighting the amplitude of the signal at different instances of time. In the time domain, the signal's value is known for all real numbers, for the case of continuous time or at various separate instants in the case of discrete time. A time domain graph shows how a signal changes with time.

## 2.2 The Frequency Domain Features

The frequency domain refers to the analysis of signals with respect to frequency rather than time. A frequency-domain representation can also include information on the phase shift that must be applied to each sinusoid in order to be able to recombine the frequency components to recover the original time signal. Frequency domain of signal is representing the signal as a pair of amplitude and phase values at each component frequency.

## 2.3 Energy of a signal

The energy spectral density of a signal gives the distribution of the energy of the signal at various frequencies of the signal. Energy of a signal x(t) is calculated using this equation:

$$E=\int_{-\infty}^{\infty}|x(t)|^2 \, dt \qquad (1)$$

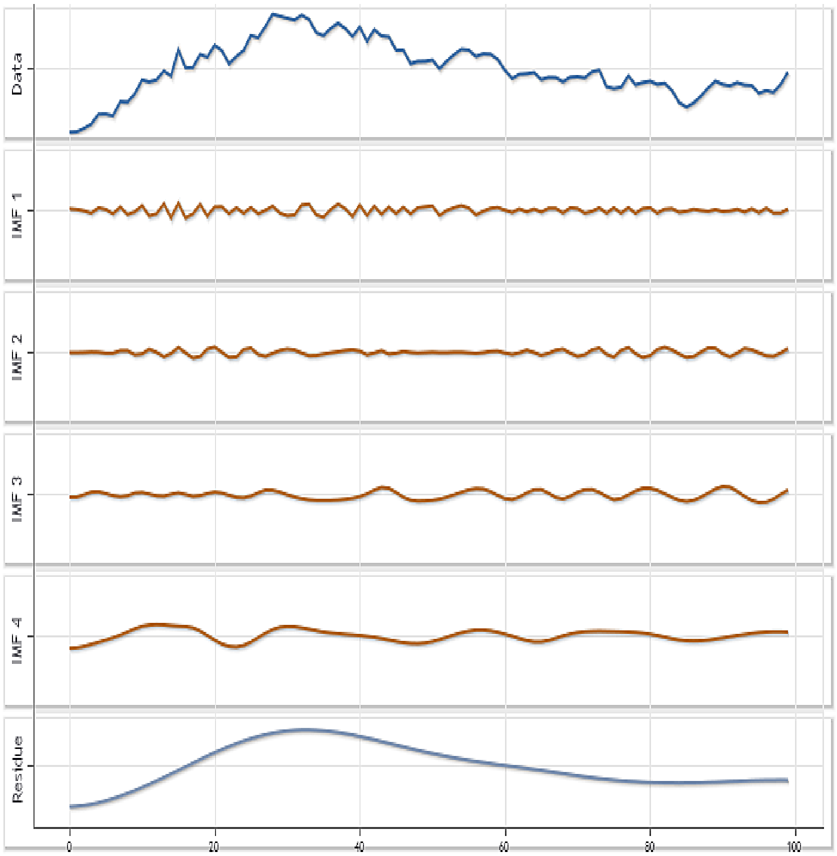
## 2.4 Empirical Mode decomposition (EMD)

EMD (Empirical Mode Decomposition) is an adaptive time-space analysis method suitable for processing signals that are non-stationary and non-linear. EMD performs operations that partition a series into 'modes' (IMFs; Intrinsic Mode Functions) without leaving the time domain. It can be compared to other time-space analysis methods like Fourier Transforms and wavelet decomposition. Like these methods, EMD is not based on physics. However, the modes may provide insight into various signals contained within the data. In particular, the method is useful for analyzing natural signals, which are most often non-linear and non-stationary [14].

The Empirical Mode Decomposition (EMD) was proposed as the fundamental part of the Hilbert–Huang transform (HHT). The Hilbert Huang transform is carried out, so to speak, in 2 stages. First, using the EMD algorithm, we obtain intrinsic mode functions (IMF).Then, at the second stage, the instantaneous frequency spectrum of the initial sequence is obtained by applying the Hilbert transform to the results of the above step. The HHT allows to obtain the instantaneous frequency spectrum of nonlinear and no stationary sequences. These sequences can consequently also be dealt with using the empirical mode decomposition.

EMD filters out functions which form a complete and nearly orthogonal basis for the original signal. Completeness is based on the method of the EMD; the way it is decomposed implies completeness. The functions, known as Intrinsic Mode Functions (IMFs), are therefore sufficient to describe the signal.

frequency




time

Figure 2.1Decomposing a signal data into a series of IMF's [15]

The fact that the functions into which a signal is decomposed are all in the time-domain and of the same length as the original signal allows for varying frequency in time to be preserved. Obtaining IMFs from real world signals is important because natural processes often have multiple causes, and each of these causes may happen at specific time intervals. This type of data is evident in an EMD analysis, but quite hidden in the Fourier domain or in wavelet coefficients.

An IMF resulting from the EMD shall satisfy only the following requirements:

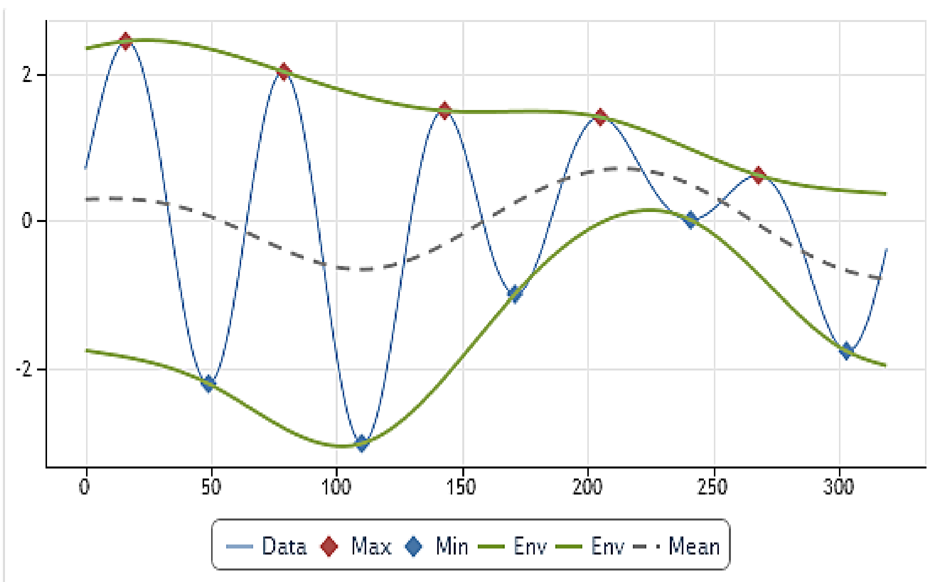
I. The number of IMF extrema (the sum of the maxima and minima) and the number of zero-crossings must either be equal or differ at most by one.

II. At any point of an IMF the mean value of the envelope defined by the local maxima and the envelope defined by the local minima shall be zero.

Decomposition results in a family of frequency ordered IMF components. Each successive IMF contains lower frequency oscillations than the preceding one [6]. And although the term "frequency" is not quite correct when used in relation to IMFs, it is probably best suited to define their nature. The thing is that even though an IMF is of oscillatory nature, it can have variable amplitude and frequency along the time axis.

The algorithm as proposed by Huang is based on producing smooth envelopes defined by local maxima and minima of a sequence and subsequent subtraction of the mean of these envelopes from the initial sequence. This requires the identification of all local extrema that are further connected by cubic spline lines to produce the upper and the lower envelopes.

frequency




\

time

Figure 2.2 Obtaining process of IMF by subtracting mean values from initial sequence [6]

This Figure gives the analyzed sequence in the thin blue line. The maxima and minima of the sequence are shown in red and blue, respectively. The envelopes are given in green. The mean is calculated based on the two envelopes and is shown in Figure 2.2 as the dashed line. The mean value calculated is further subtracted from the initial sequence. The above steps result in the extraction of the required empirical function in the first approximation. To obtain the final IMF, new maxima and minima shall again be identified and all the above steps repeated. This repeated process is called sifting. The sifting process is repeated until a certain given stoppage criterion is met. If the sifting process is successfully completed, we will get the first IMF. The next IMF can be obtained by subtracting the previously extracted IMF from the original signal and repeating the above described procedure once again. This continues until all IMFs are extracted. The sifting process usually stops when the residue, for example, contains no more than two extrema [6].

## 2.5 Segmentation-based Fractal Texture Analysis (SFTA)

Segmentation-based fractal texture analysis is an efficient feature extraction method which executes in two stages. Firstly an input image is being decomposed into a set of binary images. Using the binary images we can measure fractal dimensions of boarders of the region of the binary images which help to describe the segmented texture patterns. Before we can get the binary images which is done by segmenting the input image is done by Two Threshold Binary decomposition Algorithm [8]. Some brief ideas of these two processes are mentioned below.

### 2.5.1 Two Threshold Binary Decomposition (TTBD)

This algorithm is being used to process an input image by partitioning it into a set of binary images. It takes gray-scale image I(x, y) as input and after processing give us a set of binary images. Initially TTBD algorithm calculates a set T of threshold values. TTBD uses a different kind of approach for calculating threshold values compared to other threshold value computing algorithms. It puts multi-level Otsu algorithm is use [7]. The multi-level Otsu algorithm consists in finding the threshold that reduces the input image intra-class variance .Repeatedly ,the Otsu algorithm is used upon each image until the expected number of threshold $n_t$ is found. Here, $n_t$ is a parameter which is selected by the user. Later, The TTBD algorithm segments the input image into a set of binary image which is done by choosing pairs of thresholds from T and also using the following two-threshold segmentation formula [8]:

$$I_{b(x,y)} = \begin{cases} 1 \text{ if } t_l < I(x,y) \le t_u \\ 0, \text{otherwise} \end{cases} \quad (2)$$

Here, $t_l$ and $t_u$ represents lower and higher threshold values respectively.

The set of binary images is obtained by applying the two threshold segmentation(equation) to the input image using all pairs of contiguous thresholds from T union $\{n_l\}$,t belongs to T, where $n_l$ corresponds to the maximum possible gray level in I(x; y). Thus, the number of resulting binary images is $2n_t$.

### 2.5.2 SFTA extraction algorithm

Following to the use of Two Threshold Binary Decomposition the input gray-scale image is being converted into a set of binary images. Now, The SFTA feature vector is computed by finding the values of the image size, mean gray level and boundaries fractal dimension [8].The region boundaries of a binary image $T_b(x,y)$ are represented as a border image expressed as $\Delta(x,y)$ and calculated in the following way:

$$\Delta(x,y) = \begin{cases} 1 \ \text{ if } \ \exists (x',y') \in N_8[(x,y)] : \\ \qquad I_b(x',y') = 0 \ \wedge \\ \qquad I_b(x,y) = 1, \\ 0, \ \text{otherwise.} \end{cases} \quad (3)$$

With the help of box counting algorithm the fractal dimension D is calculated from each border image [9].Along with the fractal dimension D,the mean gray level and size are also calculated to extract the feature of the image.Calculating mean gray level and size is not a time consuming process so it does not effect the computaion time of the program that much [13].Feature vectors size is thus 3 times of the number of the threshold as we have 3 component for each threshold which are mean gray level,seze and fractal dimension.

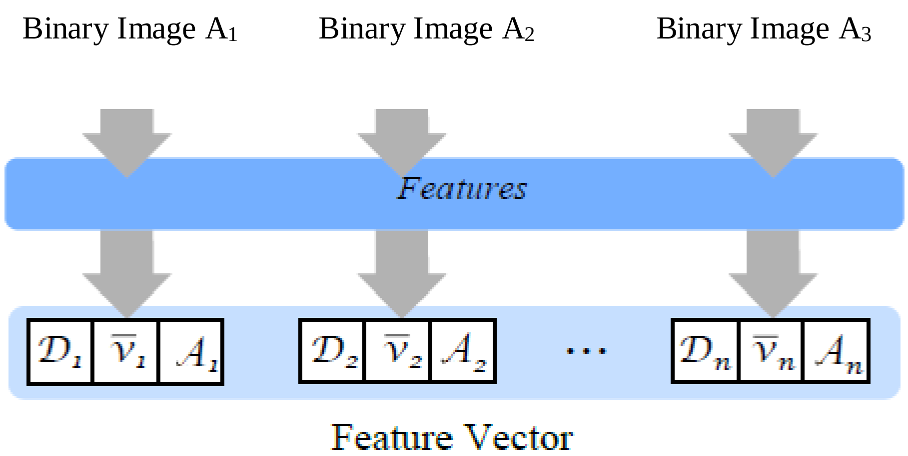



Figure 2.3 Extraction of feature vector from binary images using SFTA [8].

## 2.6 Support Vector Machine

In order to classify we prioritized support vector machine amongst all the classifier. Support vector machine is usually the first choice for many applications as people mostly choose it for its robustness and its high classification ability which ensures most accuracy. Further to that, it is a dimension insensitive algorithm and has fast development pace in training data process [10].

The very first support vector machine was proposed by Vapnik [11] which is mainly a binary classifier model used for classifying dataset into two sub-classes. Conceptually this algorithm analyses training data and locates optimal hyper-plane that has the largest distance from training object to support vectors. The hyper-plane is illustrated by pair parameters, which are direction vector W and offset b, (W,b). The distance measurement is applied to decide given data follow the class one or class two as a follow example:

$$x_i \Rightarrow \begin{cases} W^T.x_i + b \geq 1 & \text{for } y_i = +1 \text{ (class one)} \\ W^T.x_i + b < -1 & \text{for } y_i = -1 \text{ (class two)} \end{cases} \quad (4)$$

The optimal hyper-plane is formed form the training data $X_i$ and target $y_i$ based on solving a maximize Langrangian problem with two constraints.

$$L_D = \sum_i \alpha_i - \frac{1}{2}\sum_{i,j} \alpha_i \alpha_j y_i y_j x_i x_j \quad (5)$$

$$w = \sum_i \alpha_i y_i x_i \quad (6)$$

$$\sum_i \alpha_i y_i = 0 \quad (7)$$

Basically, SVM structure just has productive response when it deals with separable space in which two classes ideally allocate in two different locations. However, popular applications are in inseparable space in which almost the pattern locations of two classes are mixed together. In this case, kernel functions are proposed to project patterns from the low dimensional space to high dimensional space, where the chance to find an optimal hyper-plane is higher. These are a lot of kernel functions proposed as Polynomials, Radial-Basic-Function, Two Layer Perception and Three layer neural network, etc [12].

## 2.7 Multi-class Support Vector machine

In order to apply for multi-classes problem, three proposed solutions were announced which are One-Against-All method (WTA_SVM), One-Against-One method (MWV_SVM) and Directed-Acyclic-Graph (DAGSVM) . In WTA_SVM, each SVM structure will deal with a mission that classifies one class from the others; the final decision is confirmed by the SVM that has highest output value. On the other hand , in MWV_SVM, one SVM structure classifies between two classes, so with N-classes problem, MWV_SVM structure involves N(N-1)single SVM structures. The final decision is the class that the highest number of single SVM structures goes with. DAGSVM was developed based on MWV_SVM structure; it creates an acyclic graph among each single SVM structure. In order to make a classification decision, testing sample has to encounter each binary decision function under an acyclic graph rule; it starts from the root node (starting single SVM structure) and finishes where the class of testing data is detected in a leaf node [12].

# CHAPTER 3

# Proposed methodology

## 3.1 Introduction

The diagram in Figure 3.1 shows the detailed demonstration of our proposed model and how the algorithm is going to work to efficiently extract features and detect their classes. At first we have collected different types of fault wave signals for our experiment .After applying empirical mode decomposition we found different IMF's from the signal and from those IMF's we cut off few lower IMF's of lower frequencies which made our signal smoother as lower frequencies are considered as noise. Then we calculated the energy of our signals which we have used for converting into 2-D images. Then we converted the energy spectrum of the signal into 2-D image. We normalized the energy values into a range of 0-255.We also created 2-D images using different techniques done in previous research. Followed by converting the signals into 2-D image we extracted features of the 2-D images using SFTA algorithm in which we segmented the images into a sets of binary images. We measured 21 features for each images of our training dataset. We have used SVM binary classifier for the purpose of classification of our images as it is one of the efficient and accurate classifiers. The feature vectors obtained from our 2-D images were used to train the classifier SVM. The trained classifier was able to efficiently detect our test images and label their class accurately.

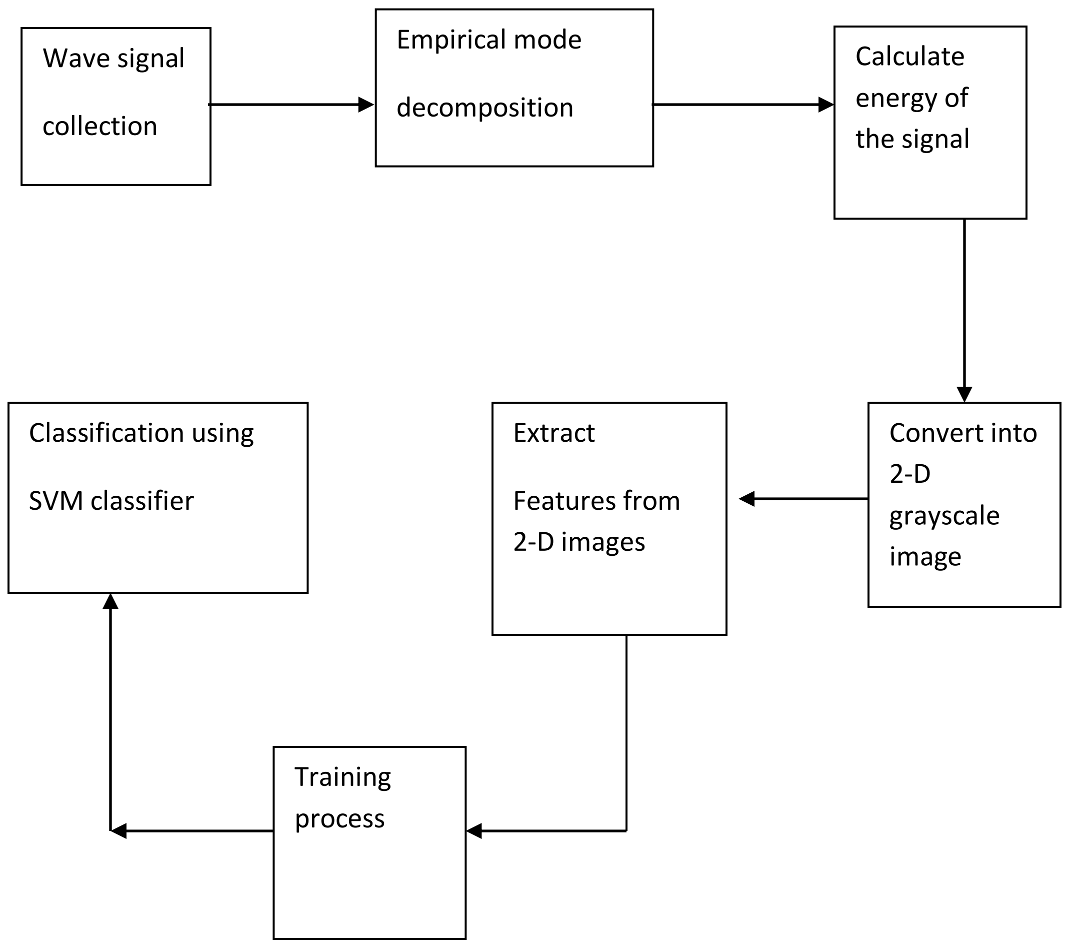



Figure 3.1 Diagram of proposed methodology

## 3.2 Wave signal dataset

In our experiment we have mainly collected wave signal of the faulty of the industrial motors. Motors are used to simulate the fault condition such as Broken Rotor Bar Fault (BRBF), Rotor Imbalance Fault(RIF), Bowed Shaft Fault(BSF), Bearing Fault(BF), Phase Imbalance Fault(PIF), Angular misalignment Fault(AMF), Parallel Misalignment Fault(PMF) [4].From these conditions wave signals were collected which depicts different nature of the signal. The signal were samples at 8kz frequencies and one second long in duration. The different fault conditions were as below:

Table 3.1 Fault conditions of dataset [12]

| Fault condition | Properties |
|---|---|
| The Broken Rotor Fault | These 12 of 34 rotor bars have been broken. |
| Rotor Imbalance Fault | These masses (8.4g) were added into one side of rotor. |
| Bowed Shaft Fault | The shaft has been bowed 0.075mm. |
| Bearing Fault | The out raceway has been damaged. |
| Phase Imbalance Fault | One phase has been adjusted by adding 4.3 Ohm resistor. |
| Angular Misalignment Fault | The bearing pedestal has been adjusted 0.48Ohm. |
| Parallel Misalignment fault | The offset between two centerlines of the motor and load has been changed 0.1mm. |

## 3.3 Empirical mode decomposition (EMD)

After we have collected the wave signals data for different kind of condition we applied empirical mode decomposition algorithm on those signals.EMD algorithm basically decomposed signals into a series frequency ordered IMF's(Intrinsic mode function) [6]. Each successive IMF contains lower frequency oscillations than the preceding one. After performing EMD algorithm having found out different IMF for an input signal we ignored few of the lowest frequency IMF's of the signal and created a refined signal having only higher frequencies as Characteristics of signal. Mainly consists in higher frequencies. This step of work helped us to improve the quality of the input signal and thus give advantages in the later process of the experiment [15].

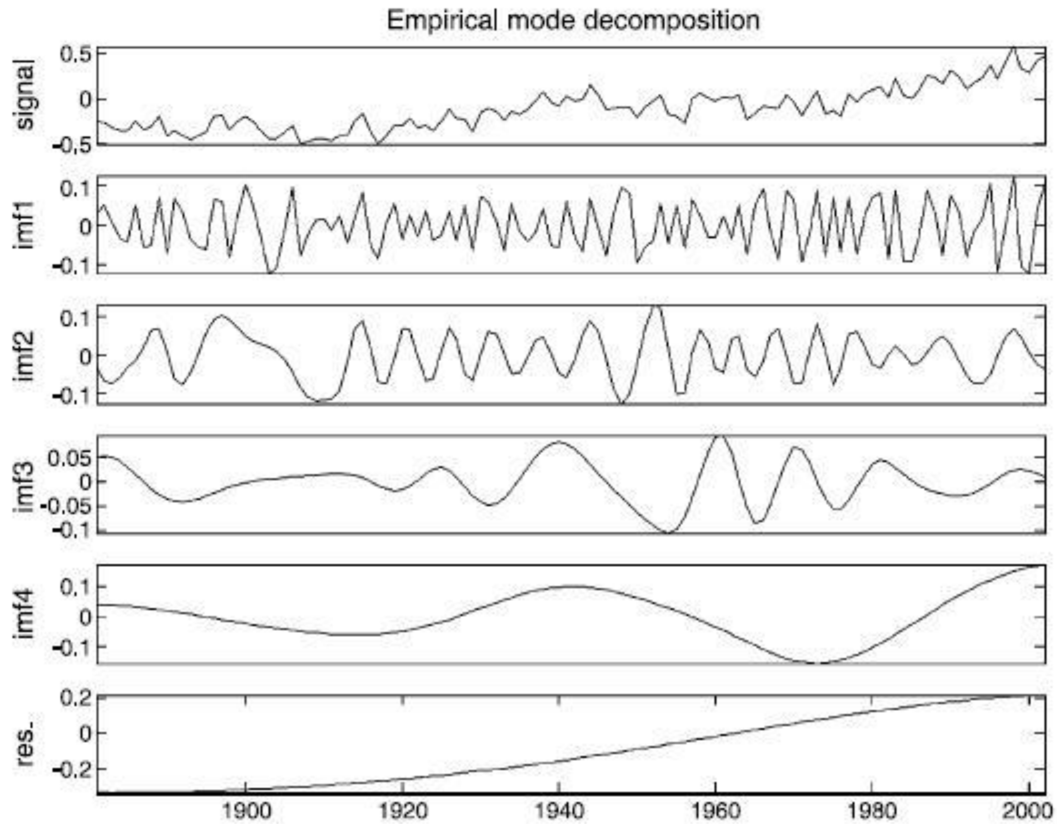



Figure 3.2 Decomposition of signal into series of IMF's [6].

The figure above shows that the successive IMF's frequencies are lower than the previous one. The lowest one is known as residue. We removed few lower IMF's along with the residue to improve the quality of our input signal.

Calculate energy of the signal:

Energy is one of the important features of a signal. In our experiment we calculated energy of the signal using the following formula:

$$E=\int_{-\infty}^{\infty}|x(t)|^2\,dt \qquad (1)$$

Instead of using the numerical values of the time domain of the signal we have used the energy of the wave signal which help use to depict the nature of the signal more efficiently. Using the energy values of the signal in the next stage we have converted the signal into 2-D image.

## 3.4 Convert into 2-D gray-scale image

In this process the vibration signals which are in time domain have been converted into 2-D dimension using the energy values. At the beginning, the signals are segmented into equal subparts each known as a frame. The size of the frame is calculated as the multiplication of the frame duration and frequency rate of the signal. After segmenting the signal we got a definite number of frames which along with the frame size helped to define the height and width of the matrix. The height of the matrix is equal to the size of the frame size and the width of the matrix is equal to the number of the frames [4].For instance, if our frame size is M and number of the frame is N then our size of the desired matrix is MxN. Later, the energy values of the frames are put into the cells of the matrix. The value of each frame is transferred into the matrix vertically. The energy values of first frame is put into the first column of the matrix as the first value goes into the first cell of the first row, second energy value goes into the first cell of the second row and so on. As a result, the last value of the first frame will be put into the first cell of the last column as the height of the matrix is equal to the size of the frame thus every value fits into the column. Similarly all other frame energy values are put into the matrix sequentially one by one. As the width of the matrix is equal to the number of frames all the frames can be fit in the matrix. After all the values have been set into the matrix we now normalized the values of the frames in the range of 0-255.The lowest numerical value of the matrix is considered as 0 and the highest value is considered as 255.Considering this range all the numerical values are calculated as per their ratios. These new values then replace the old values in the matrix. Normalization step helps to decrease the resolution of the original signal. This also helps to minimize noise on the acquired signals.2-D representation maintains features of signal in time domain and also texture feature of the signal in 2-D could be extracted to detect the signal [12].

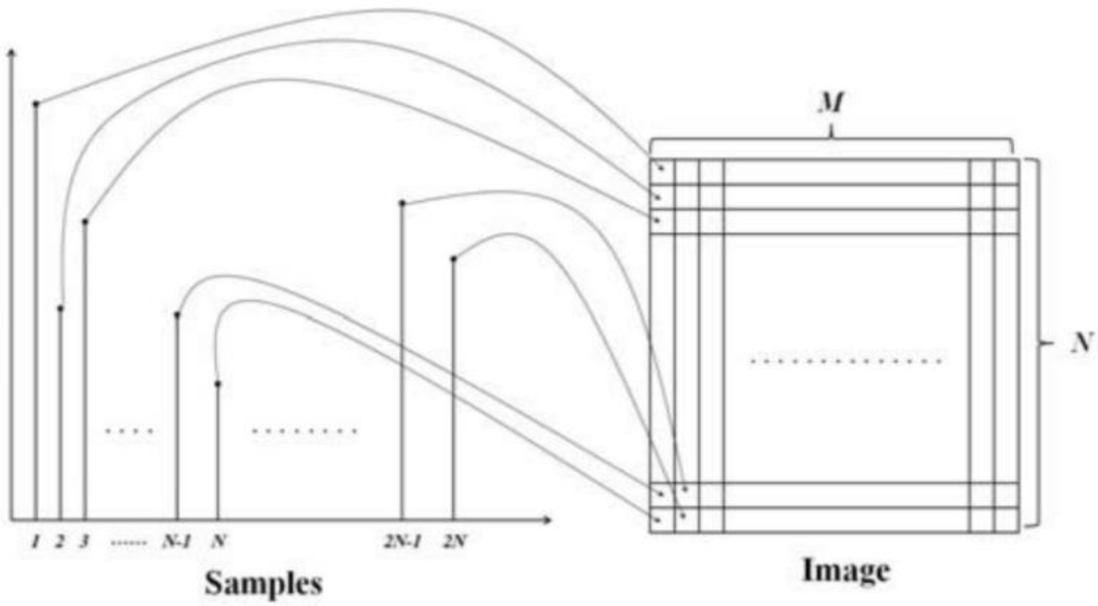



Figure 3.3 Conversion into 2-D matrix using the energy values of the sample [5].

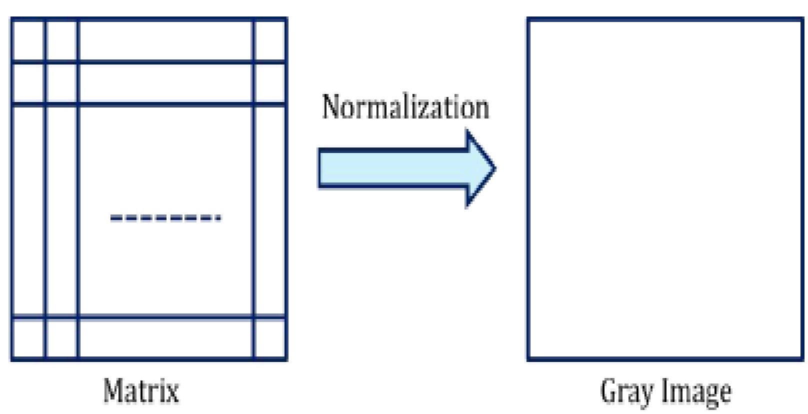



Figure 3.4 Producing 2-D gray scale image from matrix [5]

We have also used Frequency domain of signal which is representing the signal as a pair of amplitude and phase values at each component frequency. By using the frequency domain of the signal we also converted it into 2-D.Before that the vibration signal is changed into frequency domain by applying Fourier Transform. As we created 2-D representation using time domain coefficients similarly we created 2-D representation using frequency domain coefficients and followed similar process like the previous one. After that we normalized the values of the signal in the range of 0-255.However frequency domain 2-D representation did not produce any significant texture for different kinds of signals as almost all signal's efficient pattern converges in the low frequency band. As for this case the 2-D representation is not useful for efficient feature extraction method.

## 3.5 Extract features from 2-D image

As conversion of input signal into 2-D image is completed, then we will extract feature vectors from the converted images using SFTA algorithm. SFTA algorithm is one of the finest feature extracting algorithms from images. In this step we are going to segment our 2-D image into a set of binary images using the two threshold binary decomposition algorithm. From the binary images the SFTA [8] feature vector will be computed by finding the values of the image size, mean gray level and boundaries fractal dimension. The feature vector's size will be 3 times of the number of the binary images as we have 3 components for each binary images which are image size, mean gray level and boundaries fractal dimension. In our experiment we have used 7 binary images for each input image, as a result the size of our feature row vector is 21.

## 3.6 Training classifier

We have used SVM classifier in mat lab for training the classifier. After we have extracted features from converted 2-D images, we used the feature vectors our training data to train the classifier. We have taken 20 signals and as we have a feature row vector of size 21 therefore our feature matrix has size of  20x21.We have used approximately 20% of our dataset for training purpose of the classifier and rest of the data set was used for classifying classes. In the training process we have trained the classifier by using label true for bearing fault signals and label false for bowed shaft faults which helped us finding our result after the experiment was done [12].

## 3.7 Classification using SVM classifier

After completion of training the classifier, we tested rest of the dataset for classifying the classes of the signal. The feature vector of the input files' 2-D images were used to classify classes comparing to the training sets feature vectors. After classifying the SVM classifier gave output as 'True' if it detected the signal as bearing shaft fault or 'False' if it detected the signal as bowed shaft fault. After we got result for testing dataset we have used confusion matrix for measuring accuracy of our experiment to ensure the efficiency of the above mentioned approach [19].

# CHAPTER 4

# Experimental analysis

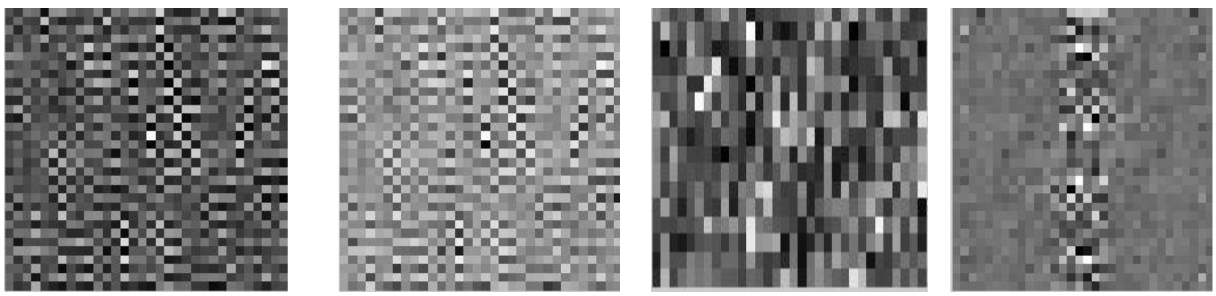
In our experiment we have collected faulty signals from industrial motor. Empirical mode decomposition is applied on the signals to improve the quality of the signals. Prior to that we have calculated the energy values of the signals and used to convert into 2-D gray-scale image. Then we used the gray scale image to extract features using SFTA algorithm. The training data features are being used to train classifier. Finally following a similar process and extracted feature from testing dataset which was used to classify. We have used confusion matrix to measure our classification accuracy.

In our experiment we have mainly collected wave signal of the faulty condition of the industrial motors. Motors are used to simulate the fault conditions such as Broken Rotor Bar Fault(BRBF),Rotor Imbalance Fault(RIF),Bowed Shaft Fault(BSF),Bearing Fault(BF),Phase Imbalance fault(PIF),Angular Misalignment Fault(AMF),Parallel Misalignment Fault(PMF).From these conditions wave signals were collected which depicts different nature of the signal. The signal were samples at 8kz frequencies and one second long in duration.

Now, EMD algorithm is applied on the signals to improve the quality of the signals by decomposing the signal into different IMF's. Each successive IMF has lower frequency level than the previous one. We have removed few of the lower IMF's to make the signal smoother and healthy to show different pattern for different type of signals.

After performing EMD algorithm we have calculated the energy values of the signals by using energy formula equation. Using the energy values we have converted the signal into 2-D gray-scale image. We have used mat lab for our conversion method of signal to 2-D gray-scale image. We divided the signal into a number of frames. Each frame's energy value was put into matrix vertically sequentially. The matrix height was defined by the size of the frame and matrix width was defined by the number of the frame. After all the values were put into the matrix mat lab function was used to plot the 2-D image of the input signals energy. We have also converted the signal's numerical value, mean grayscale value of neighbor pixels and fast fourier transform to create the 2-D image and compared the image with energy value signal's image. In the following figures the comparison can be observed:

Sample signal of bearing fault:



a) 2-D image using energy values

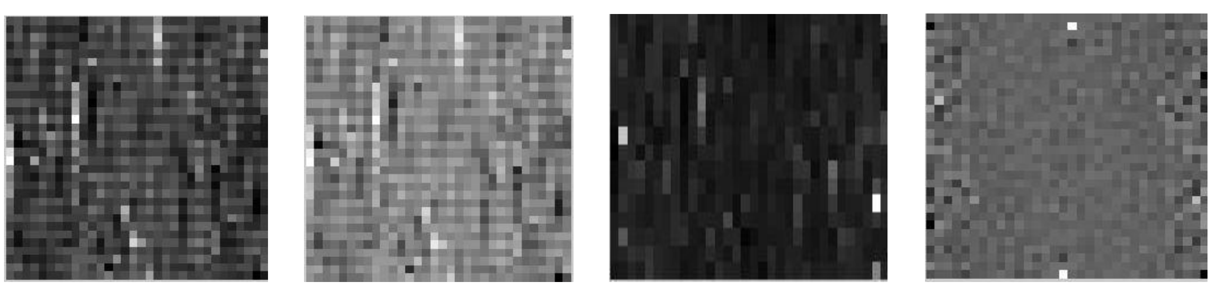
b) 2-D image using numerical value

c) 2-D image using mean value of the gray scale value

d) 2-D image using fourier transform

Figure 4.1 Comparison of 2-D gray scale image of bearing fault sig. using different approach

Sample signal of bowed shaft fault:



a) 2-D image using energy values

b) 2-D image using numerical value

c) 2-D image using mean value of the gray scale value

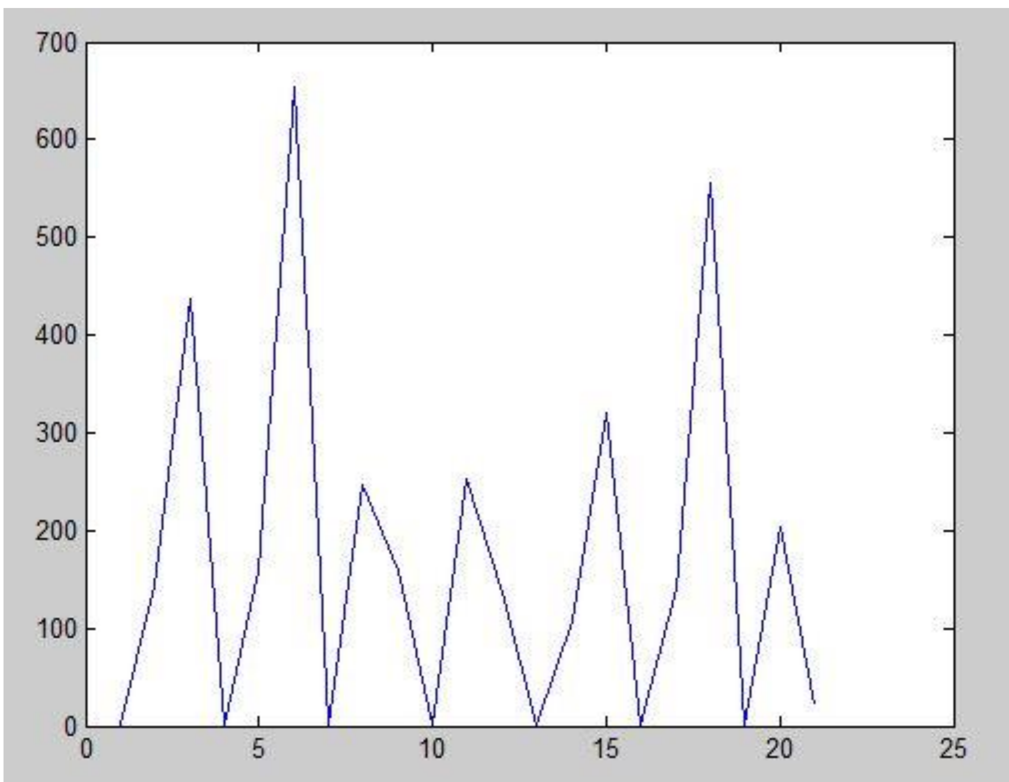
d) 2-D image using fourier transform

Figure 4.2 Comparison of 2-D gray scale imageof bowed rotor fault sig. using different approach

In Figure 4.1 comparison among 2-D images of bearing fault signal can be observed which were obtained by energy values, signal numerical values, mean pixel values and fast fourier transform. In figure 4.2 comparison among 2-D images of bowed shaft fault signal can be observed which were obtained by similar process. The images were quite different in each approach. The best image texture pattern was found using energy values of the signal.

After the acquisition of gray-scale image we extracted feature from the images using SFTA algorithm. We segmented our images into 7 binary images and for each images we calculated 3 features which are mean gray level, image size and boundaries fractal dimension. As we have 7 binary images our feature row vector size was 21.

value




feature vector size

Figure 4.3 Diagram of feature vector obtained from gray scale image.

Using the feature vector of the training images we have trained the binary SVM classifier. We have used the images of bearing fault and bowed shaft fault to train the SVM classifier. After training the SVM classifier we have produced images for the test dataset of the bearing fault and bowed shaft fault. Then we used the test images for SVM to classify the image and label the class as ‘true’ or ‘false’

In the experiment, we assumed

Bearing fault=true

Bowed shaft fault=false

After the classification process we have used confusion matrix to measure our classification accuracy to prove the efficiency of our approach for 2-D image feature extraction.

Table 4.1 Confusion matrix for measuring accuracy

| N=105 | Predicted: False | Predicted: True | Total number of actual false and true data |
|---|---|---|---|
| Actual: False | 40 | 5 | 45 |
| Actual: True | 7 | 53 | 60 |
| Sum | 47 | 58 | 105 |

Accuracy= (40+53)/(40+5+7+53) *100

=88.57%

The 88.57% accuracy shows that the SVM classifier was able to classify the test image class efficiently using the experiments approach of using energy values of the signal.

# CHAPTER 5

# Conclusions and Future work

In this thesis, we are proposing an efficient way to convert 1D signal to 2D digital image using energy. Our proposed approach is to take the energy of every pixel and put it on the matrix. Earlier we have seen that, in all the research paper of the signal processing techniques, the signal is always processed in one dimension (1D) representation; therefore, there is a lost of huge relationship information between time and frequency coefficients. To solve these problems, two dimensions representation of the signal energy values is considered to be the efficient one in this thesis. Signal acquisition, signal reprocessing and then extract features from the 2D gray-level image and finally the classification part is the workflow of our thesis and being done with these steps we are finding out the accuracy with a new efficient algorithm by which we created the 2D digital image.

We have a vision to take this research into another level and make it useful and profitable in business sectors, to recognize each and every given signal by which the 2D image is created.. Our another goal is to bring out the perfect accuracy of the image. Most importantly sometimes it is difficult to work on 1D signals so our goal is to make such a way by which we don't need to convert the 1D signals to 2D image, we will be rather using the 2D images for industrial works. Also in this thesis we are taking the motor signals as 1D signals but after finishing our thesis we want to take voice signals as input and try to convert it into 2D gray-level image just to differentiate the accuracy of different input signals. We also want do music general classification, to take music signals as input and to convert them to 2D gray level image and finally classify them by SVM and thus we will know which genre of music is taken as input signal.

At last it can be said that this work will ensure an efficient approach to get 2D gray-level image from 1D signal with more accurate result. By processing the features lots of work can be done in different applications. Beside texture information can be studied for various purposes in future.

Finally, the performance was compared to other approaches and we found out that it gives an efficient result than many of the approaches, not best yet but still an efficient approach for 2D digital gray-level image.

# References

[1] D.V. Tuan, U.P. Chong (2011). Signal Model-Based Fault Detection and Diagnosis for Induction Motors Using Features of Vibration Signal in Two-Dimension Domain. J.Mech. Eng., Vol. 57(9), pp. 655-666.

[2] Zhou, R. (2006). Feature extraction of musical content for automatic music transcription.

[3] F. M. Khellah (2011, Nov.). Texture Classification using Dominant Neighborhood Structure. IEEE Trans. Image Process. Vol. 20 (11), pp. 3270-3279

[4] Chang, T., &Kuo, C. C. (1993). Texture analysis and classification with tree-structured wavelet transform. *IEEE Transactions on image processing*, *2*(4), 429-441.

[5] Dinh Nguyen Van, "Two Dimension Representation Approach for Developing the Fault Diagnosing System based on Vibration Signal". University of Ulsan, Republic of Korea, 2013.

[6] Lei, Y., Lin, J., He, Z., &Zuo, M. J. (2013). A review on empirical mode decomposition in fault diagnosis of rotating machinery. Mechanical Systems and Signal Processing, 35(1-2), 108-126.

[7] P. Liao, T. Chen, and P. Chung, “A Fast Algorithm for MultilevelThresholding,” Journal of Information Science and Engineering, vol. 17,no. 5, pp. 713–727, 2001

[8] Costa, A. F., Humpire-Mamani, G., &Traina, A. J. M. (2012, August). An efficient algorithm for fractal analysis of textures. In Graphics, Patterns and Images (SIBGRAPI), 2012 25th SIBGRAPI Conference on (pp. 39-46). IEEE.

[9] Balan, A. G., Traina, A. J., Traina, C., &Azevedo-Marques, P. M. (2005, June). Fractal analysis of image textures for indexing and retrieval by content. In Computer-Based Medical Systems, 2005. Proceedings. 18th IEEE Symposium on (pp. 581-586). IEEE.

[10] X. Wu, V. Kumar, J.R. Quinlan, J. Ghosh, Q. Yang, H. Motoda, G.J. McLachlan, N. Angus, B. Liu, P.S. Yu, Z.H. Zhou, M. Steinbach, D.J. Hand, D. Steinberg (2007, Dec.). Top 10 algorithms in data mining. J. Know. Info. Syst., Vol. 14 (1), pp. 1-37.

[11] V. N. Vapnik. Statistica 0 ml learning theory. John Wiley& Sons, New York, 1998.

[12] Uddin, J., Kang, M., Nguyen, D. V., & Kim, J. M. (2014). Reliable fault classification of induction motors using texture feature extraction and a multiclass support vector machine. Mathematical Problems in Engineering, 2014.

[13] R. M. Haralick, K. Shanmugam, and I. H. Dinstein, "Textural Features for Image Classification," IEEE Transactions on Systems, Man and Cybernetics, vol. 3, no. 6, pp. 610–621, 1973.

[14] Huang, N. E., Shen, Z., Long, S. R., Wu, M. C., Shih, H. H., Zheng, Q., ... & Liu, H. H. (1998, March). The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. In Proceedings of the Royal Society of London A: mathematical, physical and engineering sciences (Vol. 454, No. 1971, pp. 903-995). The Royal Society.

[15] Rilling, G., Flandrin, P., &Goncalves, P. (2003, June). On empirical mode decomposition and its algorithms. In IEEE-EURASIP workshop on nonlinear signal and image processing (Vol. 3, pp. 8-11). NSIP-03, Grado (I).

[16] Phinyomark, A., Phukpattaranont, P., &Limsakul, C. (2012). Feature reduction and selection for EMG signal classification. *Expert Systems with Applications*, *39*(8), 7420-7431.

[17] Liu, Z., Wang, Y., & Chen, T. (1998). Audio feature extraction and analysis for scene segmentation and classification. *Journal of VLSI signal processing systems for signal, image and video technology*, *20*(1-2), 61-79.

[18] Jung, K., Kim, K. I., & Jain, A. K. (2004). Text information extraction in images and video: a survey. *Pattern recognition*, *37*(5), 977-997.

[19] Deng, X., Liu, Q., Deng, Y., &Mahadevan, S. (2016). An improved method to construct basic probability assignment based on the confusion matrix for classification problem. *Information Sciences*, *340*, 250-261.