Pipeline Defect Classification by Using Non-Destructive Testing and Improved Support Vector Machine Classification

Muhsin Hassan, Rajprasad Rajkumar, Dino Isa, Roselina Arelhi
Department of Electrical and Electronic Engineering, Faculty of Engineering
University of Nottingham, Malaysia Campus, Jalan Broga 43500, Semenyih Selangor

Abstract—This paper deals with the efforts to improve classification accuracy of non-destructive testing (NDT) techniques by implementing hybrid of Kalman Filter (KF) and Support Vector Machine (SVM) in classifying corrosion depth. The main emphasis is on the improvement of accuracy for SVM classification in noisy environment with the help of Kalman Filter. Long range ultrasonic testing will be employed, where a ring of piezoelectric transducers are used to generate torsional guided waves. Various defects such as cracks as well as corrosion under insulation (CUI) will be simulated on test pipe. The machine learning algorithm known as the SVM will be used to classify transducer. The classification performance of SVM was exceptional, showing a facility to detect defects at different depths as well as for distinguishing closed spaced defects however this does not perform well with noisy data. This paper proposes the idea of using Kalman filter to filter out the noise and improves the classification accuracy of SVM classification on noisy data. A Discrete Wavelet Transform (DWT) with SVM application will be used as benchmark for comparison purposes.

Index Terms—Index Terms— Non-Destructive Testing (NDT), Corrosion Under Insulation (CUI), Artificial Intelligence, Support Vector Machine (SVM), Kalman Filter (KF).

I. INTRODUCTION

Research in Ultrasonic has started to use Artificial Intelligence in their signal processing step [1]. This paper describes the improvement of Support Vector Machine (SVM) classification accuracy in noisy environment by implementing Kalman Filter (KF). Support Vector Machine has been proven as an alternative option to Artificial Neural Networks (ANN) where SVM has been identified as much better classifier compared to the latter [2][3]. The difference between Structural Risk Minimization (SRM) which minimizes an upper bound on the expected risk and Empirical Risk Minimization (ERM) which minimizes the error on training data give SVM advantages over ANN due to SRM ability to have better generalization which is the objective in statistical learning [2]. SVM is a well known method to detect and classify defects. It has been extensively used for classification and detection of defects such as line weld defects [4], defect recognition in SonicIR using 2D heat diffusion features [5], defect characterization in infrared non-destructing testing with learning machines [6], and many more classification problems. In certain cases, SVM classification has a decline in accuracy due to noise that can contaminate datasets [7]. In practical scenario, datasets obtained from the field are susceptible to noise from an uncontrollable environment. This noise can greatly degrade the accuracy of SVM classification. To maintain the high level of SVM classification accuracy, a hybrid combination of KF and SVM has been proposed to counter this problem. Kalman Filter will be used as a pre-processing technique to de-noise the datasets which are then classified using SVM. A popular de-noising technique used with Support Vector Machine to filter out noise, the Discrete Wavelet Transform (DWT) is included in this study as a benchmark for comparison to the KF+SVM technique. Discrete Wavelet Transform is widely used as SVM noise filtering technique [8][9]. DWT has become a tool of choice due to its time-space frequency analysis which is particularly useful for pattern recognition [3]. In this paper, KF+SVM combination shows promising results in improving SVM accuracy. Even though Kalman Filter is not widely used for de-noising in SVM compared to DWT, it has the potential to perform as a de-noising technique for SVM. KF+SVM perform well in noisy environment and maintained a better classification accuracy than SVM and DWT+SVM as shown in Section IV.

II. BACKGROUND

A. Pipeline

Corrosion is a major problem in offshore oil and gas pipelines which can result in catastrophic pollution and wastage of raw material [10]. Frequent leaks of gas and oil due to ruptured pipes around the world calls for the need of better and more efficient methods of pipelines monitoring [11]. Currently, pipeline inspection is done at predetermined intervals using techniques such as pigging [12]. Other non-destructive testing techniques are also done at predetermined intervals where operators must be physically present to perform measurements and make judgments on the integrity of the pipelines. The condition of the pipe between these testing periods, which can be for several months, can go unmonitored. The use of a continuous monitoring system is needed. Non-Destructive Testing (NDT) techniques using ultrasonic sensors are ideal for monitoring pipelines as it does not interrupt media flow and can give precise information on the condition of the pipe wall. Long Range Ultrasonic Testing
(LRUT) utilizes guided waves to inspect long distances from a single location [13]. LRUT was specifically designed for inspection of corrosion under insulation (CUI) and has many advantages over other NDT techniques which have seen its widespread use in many other applications [14]. It is also able to detect both internal and external corrosion which makes it a more efficient and cost-saving alternative [15]. With recent developments in permanent mounting system using a special compound, the ability to perform a continuous monitoring system has now become a reality [16]. An LRUT system was developed in the laboratory for 6-inch diameter pipes using a ring of 8 piezo-electric transducers [17]. A ring transducer was chosen because of its ability that efficiently generates and detects an ultrasonic wave propagating in the air [18]. Signals were acquired from the pipe using a high speed data acquisition system. The developed LRUT system was tested out using a section of a carbon steel pipe which is 140mm in diameter and 5mm thick. A 1.5m pipe section was cut out and various defects were simulated as shown in Table 1.

**B. Support Vector Machine**

Guided wave signals have been used by many researchers as a means of identifying different types and depths of defects by utilizing different signal processing techniques. Advanced signal processing techniques such as neural networks have also been used to quantify and classify defects from the guided wave signals [19] [20]. Since neural networks are a supervised learning algorithm, the data required for its training phase from are obtained from simulation methods. Simulation is performed by modeling the damage based on reflection coefficients or finite elements [21]. The trained neural network model is then tested from data obtained experimentally and have shown to obtain very good accuracy in classifying defects in pipes, bars and plates [22]. Support vector machines, founded by V. Vapnik, is increasingly being used for classification problems due to its promising empirical performance and excellent generalization ability for small sample sizes with high dimensions. The SVM formulation uses the Structural Risk Minimization (SRM) principle, which has been shown to be superior to traditional Empirical Risk Minimization (ERM) principle used by conventional neural networks. SRM minimizes an upper bound on the expected risk, while ERM minimizes the error on the training data. It is this difference which equips SVM with a greater ability to generalize [23]. Given a set of independent and identically distributed (iid) training samples, \( S=\{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\} \), where \( x_i \in \mathbb{R}^N \) and \( y_i \in \{-1,1\} \) denotes the input and the output of the classification, SVM functions by creating a hyperplane that separates the dataset into two classes. According to the SRM principle, there will just be one optimal hyperplane, which has the maximum distance (called maximum margin) to the closest data points of each class as shown in Figure 1. These points, closest to the optimal hyperplane, are called Support Vectors (SV). The hyperplane is defined by the equation \( w.x+b=0 \) (1), and therefore the maximal margin can be found by minimizing \( \frac{1}{2} ||w||^2 \) (2) [23].

The Optimal Separating Hyperplane can thus be found by minimizing (2) under the constraint (3) that the training data is correctly separated [25].

\[
y_j (x_j, w + b) = \begin{cases} 1, & \text{if } y_j = 1, \\ -1, & \text{if } y_j = -1 \end{cases}
\]

The concept of the Optimal Separating Hyperplane can be generalized for the non-separable case by introducing a cost for violating the separation constraints (3). This can be done by introducing positive slack variables \( \xi_i \) in constraints (3), which then becomes,

\[
y_j (x_j, w + b) \geq 1 - \xi_i, \forall i
\]

If an error occurs, the corresponding \( \xi_i \) will exceed unity, so \( \sum \xi_i \) is an upper bound for the number of classification errors. Hence a logical way to assign an extra cost for errors is to change the objective function (2) to be minimized into:

\[
\min \frac{1}{2} ||w||^2 + C (\sum_i \xi_i )
\]

Where \( C \) is a chosen parameter. A larger \( C \) corresponds to assigning a higher penalty to classification errors. Minimizing (5) under constraint (4) gives the Generalized Optimal Separating Hyperplane. This is a Quadratic Programming (QP) problem which can be solved here using the method of Lagrange multipliers [26]. After performing the required calculations [23,25], the QP problem can be solved by finding the Lagrange multipliers, that maximizes the objective function in (6),

\[
W(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j (x_i^T x_j)
\]

Subject to the constraints,

\[
0 \leq \alpha_i \leq C, i = 1, \ldots, n, \text{and} \sum_{i=1}^{n} \alpha_i y_i = 0
\]

The new objective function is in terms of the Lagrange multipliers, \( \alpha_i \) only. It is known as the dual problem: if we know \( w \), we know all \( \alpha_i \); if we know all \( \alpha_i \), we know \( w \). Many of the \( \alpha_i \) are zero and so \( w \) is a linear combination of a small number of data points. \( x_i \) with non-zero \( \alpha_i \) are called the support vectors [24]. The decision boundary is determined only by the SV. Let \( t_j (j=1, \ldots, s) \) be the indices of the \( s \) support vectors. We can write,

\[
w = \sum_{j=1}^{s} \alpha_j t_j x_j
\]

So far we used a linear separating decision surface. In the case where decision function is not a linear function of the data, the
data will be mapped from the input space (i.e. space in which the data lives) into a high dimensional space (feature space) through a non-linear transformation function $\Phi (\cdot)$. In this (high dimensional) feature space, the (Generalized) Optimal Separating Hyperplane is constructed. This is illustrated on Fig. 2 [28].

$$K(x_i, x_j) = \langle \Phi(x_i), \Phi(x_j) \rangle.$$ (9)

It is not necessary to explicitly know $\Phi (\cdot)$. So that the optimization problem (6) can be translated directly to the more general kernel version [28],

$$W(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1, i \neq j}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j),$$ (10)

subject to $C \geq \alpha_i \geq 0$, $\sum_{i=1}^{n} \alpha_i y_i = 0$

After the $\alpha_i$ variables are calculated, the equation of the hyperplane, $d(x)$ is determined by,

$$d(x) = \sum_{i=1}^{l} y_i \alpha_i K(x, x_i) + b \quad (11)$$

The equation for the indicator function, used to classify test data (from sensors) is given below where the new data $z$ is classified as class 1 if $i > 0$, and as class 2 if $i < 0$ [29].

$$i_{F(x)} = \text{sign}[d(x)] = \text{sign} \left[ \sum_{i=1}^{l} y_i \alpha_i K(x, x_i) + b \right]$$ (12)

Note that the summation is not actually performed over all training data but rather over the support vectors, because only for them do the Lagrange multipliers differ from zero. As such, using the support vector machine we will have good generalization and this will enable an efficient and accurate classification of the sensor signals. It is this excellent generalization that we look for when analyzing sensor signals due to the small samples of actual defect data obtainable from field studies. In this work, we simulate the abnormal condition and therefore introduce an artificial condition not found in real life applications.

### C. Discrete Wavelet Transform

A discrete wavelet transform (DWT) is basically a wavelet transform for which the wavelets are sampled in discrete time. The DWT of a signal $x$ is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response $g$, resulting in a convolution of the two (13). The signal is then decomposed simultaneously using a high-pass filter $h$ (14).

$$y_{low}[n] = \sum_{k=\infty}^{-\infty} x[k] g[2n - k] \quad (13)$$

$$y_{high}[n] = \sum_{k=\infty}^{-\infty} x[k] h[2n - k] \quad (14)$$

The outputs of equations (13) and (14) give the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass). It is important that the two filters are related to each other for efficient computation and they are known as a quadrature mirror filter [30]. However, since half the frequencies of the signal have now been removed, half the samples can be discarded according to Nyquist’s rule. The filter outputs are then down sampled by 2 as illustrated in Figure. 3. This decomposition has halved the time resolution since only half of each filter output characterizes the signal. However, each output has half the frequency band of the input so the frequency resolution has been doubled. The coefficients are used as inputs to the SVM [31].

### D. Kalman Filter

Kalman Filter is named after Rudolf E. Kalman who invented this algorithm in 1960. In the past, Kalman Filters have been a vital implementation in military technology navigation systems for missiles (navigation system for nuclear ballistic missile submarines, guidance and navigation systems of cruise missiles such as U.S Navy’s Tomahawk missile and the U.S Air Force’s Air Launched Cruise Missile and guidance for NASA Space shuttle [32][32][33][34]. Even though Kalman Filter is not widely used for de-noising in SVM compared to DWT, it has the potential to perform as de-noising technique for SVM as shown by Huang in online option price forecasting for stocks market experiment [35] and by Lucie Daubigney and Oliver Pietquin in single trial p300 detection assessment [36]. In both paper, Kalman filter show a promising results in de-noising the noise before it being fed into SVM. G. Welch and G. Bishop [37] define Kalman Filter as “set of mathematical equations that provides
an efficient computational (recursive) means to estimate the state of a process, in a way that minimizes the mean of the squared error. According to Grewal and Andrews [38], “Theoretically Kalman Filter is an estimator for what is called the linear-quadratic problem, which is the problem of estimating the instantaneous “state” of a linear dynamic system perturbed by white noise – by using measurements linearly related to the state but corrupted by white noise. The resulting estimator is statistically optimal with respect to any quadratic function of estimation error.” In layman term, “To control a dynamic system, it is not always possible or desirable to measure every variable that you want to control, and the Kalman Filter provides a means for inferring the missing information from indirect (and noisy) measurements. The Kalman filter is also used for predicting the likely future courses of dynamic system that people are not likely to control” [38]. Equation for a simple Kalman Filter given below [39]: For a linear system and process model from time k to time k+1 is describe as:

\[ x_{k+1} = Fx_k + Gu_k + w_k \]  

Where \( x_k, x_{k+1} \) are the system state (vector) at time k, k+1. F is the system transition matrix, G is the gain of control \( u_k \), and \( w_k \) is the zero-mean Gaussian process noise, \( w_k \sim N(0, Q) \).

Huang suggested that for state estimation problem where the true system state is not available and needs to be estimated [37]. The initial \( x_0 \) is assumed to follow a known Gaussian distribution \( x_0 \sim N(\tilde{x}_0, P_0) \). The objective is to estimate the state at each time step by the process model and the observations. The observation model at time k+1 is given by.

\[ z_{k+1} = Hx_{k+1} + v_{k+1} \]  

Where \( H \) is the observation matrix and \( v_{k+1} \) is the zero-mean Gaussian observation noise \( v_{k+1} \sim N(0, R) \).

Suppose the knowledge on \( x_k \) at time k is

\[ x_k \sim N(\tilde{x}_k, P_k) \]  

Then \( x_{k+1} \) at time k+1 follow

\[ x_{k+1} \sim N(\tilde{x}_{k+1}, P_{k+1}) \]  

where \( \tilde{x}_{k+1}, P_{k+1} \) can be computed by the following Kalman filter formula.

Predict using process model:

\[ \tilde{x}_{k+1} = F\tilde{x}_k + Gu_k \]  

\[ F_{k+1} = FP_k F^T + Q \]  

Update using observation:

\[ \tilde{x}_{k+1} = \tilde{x}_{k+1} + K(Z_{k+1} - H\tilde{x}_{k+1}) \]  

Where the innovation covariance \( S \) (here \( z_{k+1} - H\tilde{x}_{k+1} \) is called innovation) and the Kalman gain, \( K \) are given by

\[ S = HP_{k+1}HT + R \]  

\[ K = P_{k+1}HTS^{-1} \]  

III. METHODOLOGY

A. 3.1 LRUT system implementation

Many systems that can perform LRUT using guided waves are commercially available [16]. These systems use sophisticated equipments and software to efficiently generate and analyze ultrasonic guided waves. The LRUT system used in this paper will be designed, simulated and constructed using standard laboratory equipments and components. Figure 4 shows the block diagram of the LRUT system to be implemented which has been derived from several published work in this field [40]. The piezoelectric transducers and inflatable collar are purchased from Plant Integrity Ltd. [16]. The transducers are highly specialized and are capable of specifically exciting torsional guided waves by manipulating their orientation. Tone burst signals are used to excite the transducers and the low bandwidth nature of these signals makes the generation of torsional mode much easier.

Fig 4: LRUT System Block Diagram [17]

Five cycle tone burst signals was created using Agilent’s 33220A arbitrary waveform generator. The waveforms were created in a computer using the waveform editor software and downloaded onto the waveform generator’s non-volatile memory location. The burst frequency is chosen as 10Hz which is the recommended maximum rating specified by the manufacturers of the transducers (Teletest®). The transducers also require a high voltage excitation signal in order to create waves with sufficient amplitude to propagate long distances. The tone burst signals are therefore amplified to a voltage of 200 V peak-to-peaks using a power amplifier. 16 piezoelectric transducers, arranged axially in a ring, are used for the LRUT system [17].

B. 3.2 Corrossion Simulation

The developed LRUT system was tested on a 1.5m section of a carbon steel pipe which is 140mm in diameter and 5mm thick. The frequency of the tone burst signals required to
excite the transducers for this pipe is experimentally determined as 20 kHz as this gives the highest back wall echo signal strength. Ideally the best form of corrosion simulation would be to gradually corrode a section of the pipe over a long period of time and take periodic measurement. However such an experiment would require considerable effort, first in fabricating a corrosion simulation rig, and second to simulate corrosion at sufficiently high rates. Hence in order to prove the concepts in this paper, a standard corrosion defect, full circumferential defect will be performed at different depths. Several measurements will be taken at each depth and all signals will be arranged sequentially in order to simulate a natural corrosion process. A full circumferential corrosion defect with 3mm axial length was created using a lathe machine. Depths of 1mm, 2mm, 3mm and 4mm were created with the LRUT system in place and measurements taken after each depth was machined. Figure 5 shows the location of defects on the pipe section. The Teletest inflatable collar is not designed for permanent installation hence a minor modification was performed. An airtight valve and pressure gauge assembly was added to the air inlet section and an air pressure of 30 psi was continuously maintained. To enable easy interpretation, the transducer collar is placed at one end of the pipe to limit backward wave propagation. Ideally more than one ring of sensors would be needed to limit backward waves and produce only unidirectional wave propagation.

Fig 5: Full Circumferential Corrosion Defect (I) Position (II) Actual Picture [17]

C. 3.3 Adaptive machine learning algorithm

The guided wave signals were sampled at a rate of 100 kHz and stored in the computer for processing. All data processing, including data acquisition, were performed using MATLAB®. The different components of the system will be integrated together in the form of a single MATLAB graphical user interface (GUI). Figure 6 shows the output waveform of the transducer response from the initial point of excitation to the arrival of the back well echo (BWE). The data sampled from the transducer signals must first be gated to remove all redundant information as well as significantly reducing data size. The critical information of the pipe’s condition was stored in the time frame between the excitation of the tone burst pulse and the arrival of the BWE. The gating technique first detects the excitation pulse and the arrival time of the (BWE) can be easily determined by knowing the speed of the torsional T(0,1) mode and the length of the pipe [41]. The critical signal to be processed can now be gated out and in this process, the redundant excitation pulse and BWE signals are removed.

Fig 6: Sampled Transducer Signal Showing Position Of Initial Pulse, BWE And Critical Analysis Area.

After gating, the guided wave signals are passed to a digital bandpass filter. The purpose of the filter is to remove any noisy components due to the electronic switch. A rectangular window bandpass filter is used with a center frequency of 20 kHz. The bandwidth of the filter is set as 10 kHz although this can be varied depending on the level of unwanted noise components. Datasets used for this test are 36x2500, 46x2500, 56x2500, 66x2500 and 76x2500 matrices which from now onwards will be known as dataset 36, dataset 46, dataset 56, dataset 66, and dataset 76 respectively which were obtained from the pipeline experiment in the Pipeline Laboratory [17]. Figure 7 shows a basic way to implement SVM classification (Red dash arrow line). This method works well for SVM classification, however a problem arises when noise is added into the data to mimic noise in real application show that noise can greatly affect SVM accuracy. In MATLAB tests, AWGN values used are from 5dB to -10dB. In this proposed solution, additive white Gaussian noise (AWGN) has been added using a function in MATLAB. AWGN is widely used to mimic noise because of its simplicity and traceable mathematical models which are useful to understand system behavior [42] [43]. Data contaminated with noise greatly affected the performance of SVM [42] show that LS-SVM accuracy is decreasing with higher no of noise dB). That is why Kalman Filter has been proposed as a solution to filter out this noise and maintain a high level of accuracy for SVM. This ensures a highly reliable and accurate classification from SVM. Figure 7 shows a proposed system to improve SVM accuracy by implementing Kalman Filter before SVM (blue straight arrow line)
IV. RESULTS AND DISCUSSIONS

This section discusses the results of SVM classification accuracy for SVM-only, DWT+SVM, and KF+SVM. Since data for natural corrosion progression over time is difficult to achieve and time consuming, the data at different corrosion defect depths will be arranged sequentially to simulate a continuous time signal for this test purpose. Five hundred guided wave measurements were taken on the original pipe and at each defect depth. Table 1 below shows the arrangement of the data points whereby every data point is labelled with a defect level.

Table 1: Arrangement of Data Points for Simulation of a Continuous Signal.

<table>
<thead>
<tr>
<th>Depth of defect</th>
<th>Assigned Defect level</th>
<th>Sample number</th>
</tr>
</thead>
<tbody>
<tr>
<td>0mm</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>1mm</td>
<td>1</td>
<td>501</td>
</tr>
<tr>
<td>2mm</td>
<td>2</td>
<td>1001</td>
</tr>
<tr>
<td>3mm</td>
<td>3</td>
<td>1501</td>
</tr>
<tr>
<td>4mm</td>
<td>4</td>
<td>2001</td>
</tr>
</tbody>
</table>

The test can be divided into two main parts:
1. Noiseless dataset: First test was done on the datasets with no noise added.
2. Noisy dataset: Second test was done with the datasets contaminated with Additive White Gaussian Noise.

A. 4.1 Noiseless Datasets Results:

For noiseless datasets classification accuracy, DWT+SVM performed slightly better than SVM alone and KF+SVM. DWT+SVM have 0.04%-0.20% better classification accuracy than the worst performer which in this case KF+SVM as shown in the graph above. However KF+SVM performed very well in noisy condition and maintained a high level of accuracy (above 90%) even with the high noise condition which brings down SVM and DWT+SVM results to merely 20% of accuracy as shown in the next experiments results below:

B. 4.2 Noisy Datasets Results:

These datasets are contaminated with Additive White Gaussian Noise using the function that is available in MATLAB. As mentioned in previous section, AWGN values used are from 5dB to -10dB. Figures 9, 10, 11, 12 and 13 compare SVM accuracy results between KF+SVM, DWT+SVM and SVM for different datasets. For all datasets tests, KF+SVM shows higher and consistent accuracy results compared to DWT+SVM and SVM.

Fig 8: The Difference in Accuracy Results between SVM, DWT+SVM and KF+SVM for Noiseless Datasets.

For noiseless datasets classification accuracy, DWT+SVM performed slightly better than SVM alone and KF+SVM. DWT+SVM have 0.04%-0.20% better classification accuracy than the worst performer which in this case KF+SVM as shown in the graph above. However KF+SVM performed very well in noisy condition and maintained a high level of accuracy (above 90%) even with the high noise condition which brings down SVM and DWT+SVM results to merely 20% of accuracy as shown in the next experiments results below:

Fig 9: Comparison Results between SVM, DWT+SVM and KF+SVM for Dataset 36.

Fig 10: Comparison Results between SVM, DWT+SVM and KF+SVM for Dataset 46.
As shown in Figure 9 to Figure 13, Kalman Filter application as a pre-processing technique improves Support Vector Machine classification accuracy greatly for noisy datasets. In the graphs above, as the additive white Gaussian noise level increases, SVM only and DWT+SVM classification accuracy decline to around 20% classification accuracy at -10dB AWGN noise. While classification accuracy decline for SVM and DWT+SVM, KF+SVM technique managed to maintain the classification accuracy above 90% of even at -10dB AWGN noise level.

V. CONCLUSION

A system consisting of Kalman Filter and SVM can achieve a much better classification accuracy results compared to a basic system application of DWT with SVM or SVM alone. As shown in Figure 9 – 13, techniques for combining Kalman Filter and SVM consistently produce a high SVM training accuracy (more than 90% accuracy) compared to basic system which SVM training accuracy depreciate with increasing signal to noise ratio. This shows that KF perform well as a de-noising element for SVM. However in noiseless environment, DWT+SVM proved to be a better classification technique compared to KF+SVM. This might be due to the Kalman Filter process transforming the noiseless datasets into a Kalman Filter output that might have decrease SVM classification accuracy due to the changes. For noiseless environment, KF+SVM have comparable performance to DWT+SVM and SVM in noiseless datasets. Taking this into consideration, it is safe to say that a hybrid Kalman Filter and Support Vector Machine is a good technique that proved to help SVM classification to maintain its accuracy above 90% in noiseless and noisy environment alike.

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