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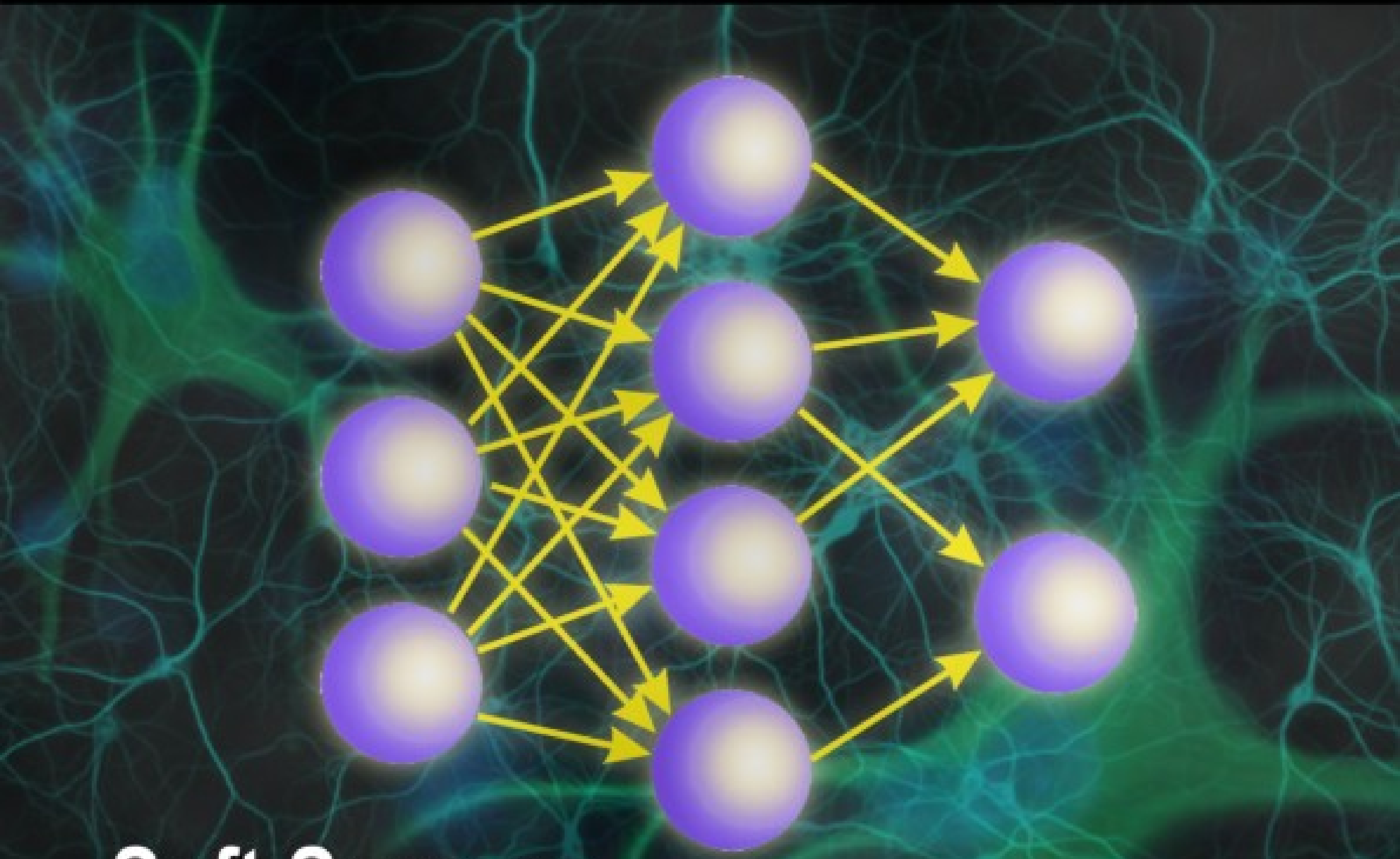

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Accurate Fluid Level Measurement in Dynamic Environment Using Ultrasonic Sensor and ν-SVM

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Abstract: A fluid level measurement system based on a single Ultrasonic Sensor and Support Vector Machines (SVM) based signal processing and classification system has been developed to determine the fluid level in automotive fuel tanks. The novel approach based on the ν-SVM classification method uses the Radial Basis Function (RBF) to compensate for the measurement error induced by the sloshing effects in the tank caused by vehicle motion. A broad investigation on selected pre-processing filters, namely, Moving Mean, Moving Median, and Wavelet filter, has also been presented. Field drive trials were performed under normal driving conditions at various fuel volumes ranging from 5 L to 50 L to acquire sample data from the ultrasonic sensor for the training of SVM model. Further drive trials were conducted to obtain data to verify the SVM results. A comparison of the accuracy of the predicted fluid level obtained using SVM and the pre-processing filters is provided. It is demonstrated that the ν-SVM model using the RBF kernel function and the Moving Median filter has produced the most accurate outcome compared with the other signal filtration methods in terms of fluid level measurement. *Copyright © 2009 IFSA.*

Keywords: Intelligent level measurement, Liquid slosh, Radial basis function, Support vector machine

1. Introduction

Modern automotive vehicles are equipped with digital gauges as well as with additional functionalities that inform drivers about their vehicle's fuel consumption and the remaining distance that the vehicle can travel without refuelling. However, the high precision digital displays and these additional utilities have to rely on the accuracy of the level sensor itself. The reliability and accuracy of the fluid level measurement system in a dynamic environment, which primarily depends on the level sensor, is increasingly becoming a concern for automotive industries as well as the everyday vehicle user.

Conventional fluid level measurement systems determine the fluid level with the use of float that is linked with a variable resistor whose resistance is a function of the fluid level. These conventional mechanical level sensors need to occupy a large space and suffer from the frictional wear-out over a period of time. The importance of level sensor reliability in hostile environments over long periods of time has lead to the introduction of various forms of motionless level sensors. The ultrasonic sensor is one such example of a compact as well as contact-less proximity sensor that is being investigated to determine the fluid level in automotive fuel tanks. The ultrasonic sensor determines the fluid level by transmitting echo pulses and measuring the return time of the reflected echoes. If the speed of sound in the medium is known then the fluid level can be calculated using the following equation.

$$level = level_{ref} - \frac{1}{2} v.\tau \, , \qquad (1)$$

where, $level_{ref}$ is the height of the tank, v is the speed of the sound and τ is the time-of-flight of the ultrasonic echo.

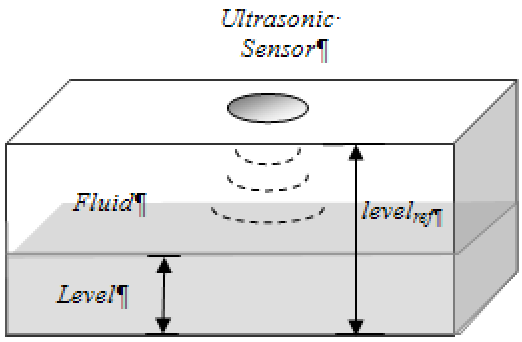

Fig. 1. Fluid level measurement using ultrasonic transducer.

However, the speed of sound is influenced by the temperature of the medium through which it travels [1]. Therefore, changes in the ambient temperature will create incorrect fluid level readings. The speed of sound in terms of temperature can be approximated as:

$$v(T) = 331.3 + kT \text{ m/s}, \qquad (2)$$

where, T is the ambient temperature in degree Celsius, k is the rate at which the speed changes with respect to the temperature, which is approximately 0.607 m/s at every change of 1 °C in temperature.

Ultrasonic sensors are normally combined with a temperature sensor to compensate for the effects of temperature variations [2-5]. Apart from the accuracy of the level sensor itself, the fluid level measurement system in dynamic environments, (i.e. automotive fuel tank) is influenced by the sloshing effects caused by acceleration. In automotive fuel tanks, vehicle acceleration induces slosh waves having natural frequencies whose wave pattern is dependent on the magnitude of the acceleration, geometry of the tank and the amount of fluid contained in the tank. Theoretical studies and numerical analysis have been carried out in the past to describe various sloshing phenomenon [6-10].

To compensate for the effects of sloshing in fluid level measurement systems, various mechanical dampening methods consisting of baffles, electrical dampening techniques, and statistical averaging methods have been used in the past. However, all these methods follow approaches that lead to higher production cost. The accuracy of these measurement systems under sloshing conditions is also very limited. The electrical dampening techniques and the statistical averaging methods primarily perform averaging on the raw sensor signals over some period of time. Averaging over a variable time frame has also been used in the past [11-13] to improve the level sensor accuracy under sloshing conditions by determining the running state of the vehicle using the vehicle speed data from the speed sensor. The fluid measurement systems described by Kobayashi et al [12] employ a vehicle speed sensor to determine the running state of the vehicle. When the vehicle is operating at low speed (i.e. near static condition), the averaging period is reduced to small values typically in the range from 5 to 25 seconds, and when the vehicle is operating at a higher speed, the averaging period is prolonged up to 90 seconds. Despite the dependence of the measurement system on the speed sensor, after analyzing the raw sensor data from a resistive type fuel level sensor in a moving vehicle, it can be observed that the averaging method still produces significant errors after averaging the raw sensor signal over a longer period of time. Fig. 2 illustrates the raw volume signal obtained from a driven vehicle, and two averaged signals calculated after averaging the raw signal over twenty seconds, which is the typical averaging time used in an automotive instrument cluster; and the second is averaged signal averaged over ninety seconds, which is a reasonably long period of time.

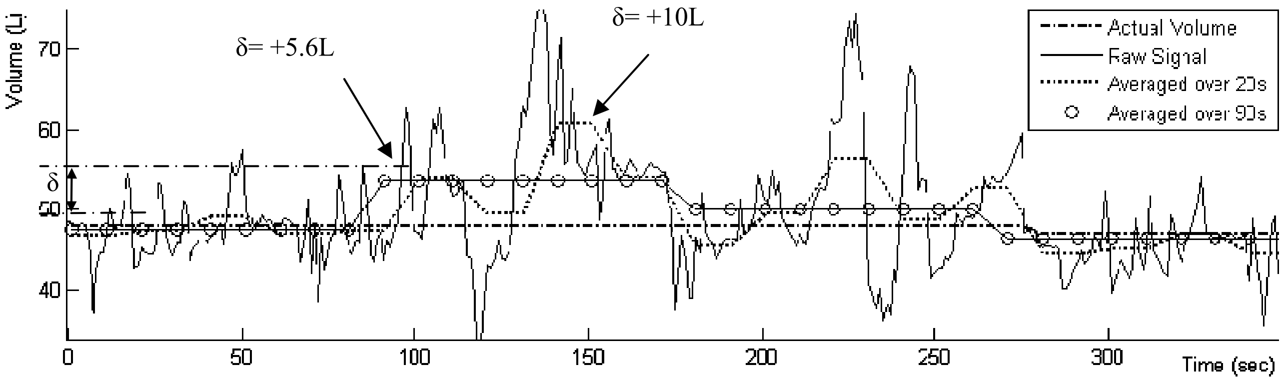

Fig. 2. Fuel level signal observed by the level sensor and the calculated average signal in a sample drive trial.

Support Vector Machine (SVM) is a newly developed machine learning algorithm [14]. SVM is based on Statistical Learning Theory and has the ability to recognise patterns [15]. SVM has been successfully used in various applications for solving classification, regression, time series prediction and function estimation problems [16]. SVM has quickly found its place in many applications of pattern recognition such as handwritten character recognition [17], image classification [18], face detection [19] and signal processing [20], etc.

SVM can also be used to predict the fluid level in a dynamic environment, especially considering the variations in temperature and the vehicle movement creating slosh waves. This paper describes an SVM approach developed to determine the fluid level within a dynamic environment without compromising accuracy. The approach described here is also applicable to non-acoustic sensors such as capacitive and hall-effect sensors. The existing statistical slosh compensation methods are compared with the results obtained using the SVM approach.

2. SVM Based Measurement System

2.1. Measurement System Design

The observation and analysis of the slosh pattern, produced under the effects of acceleration in a closed container, instigated an approach that can eliminate the sloshing effects, whereby accurate fluid level measurements would be possible in dynamic environments. If the fluid quantity in a storage container remains constant, the instantaneous fluid level in a dynamic environment can be defined as:

$$L(t) = L_0 . f \ , \tag{3}$$

where, L_0 is the tank level at static condition, and f is the unknown sloshing function that depends on the acceleration exhibited on the tank, the existing fluid level, and the tank geometry. The goal is focused on determining the actual level L_0 using the sensor output $L(t)$ and the function f. The output of the level sensor was observed to have direct relationship with the vehicle acceleration when observed in a running vehicle, as shown in Fig. 3.

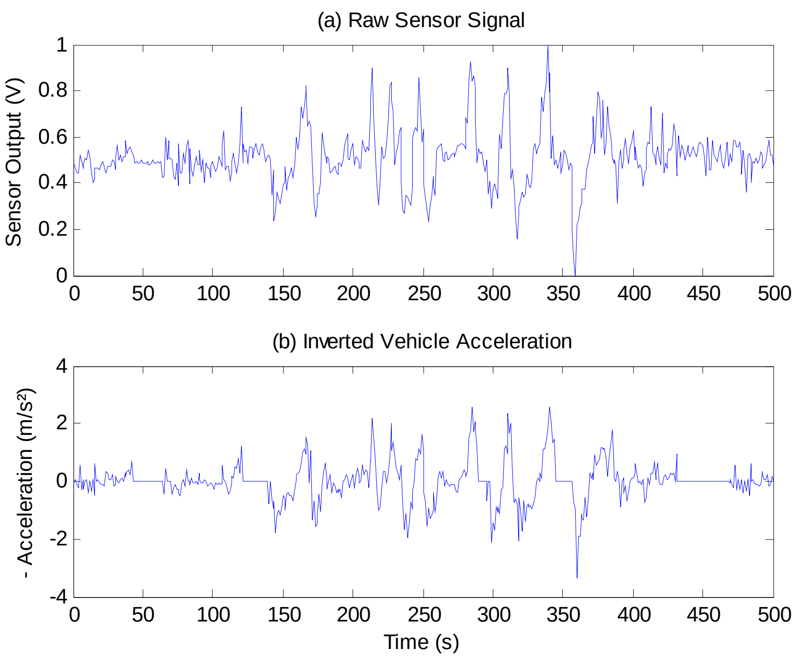

Fig. 3. Vehicle acceleration and the raw sensor signal.

The knowledge of the relationship between acceleration and the output *L(t)* can eliminate the sloshing effects, however with the knowledge of the sloshing function *f*.

$$L_0 = \frac{L(t)}{f} = constant \tag{4}$$

The unknown function *f* is solved by experimentation with the aid of an SVM based approach. An SVM model was constructed and trained with the actual driving data obtained through the field trials. Fig. 4 demonstrates the method adopted to develop the accurate fluid level measurement system.

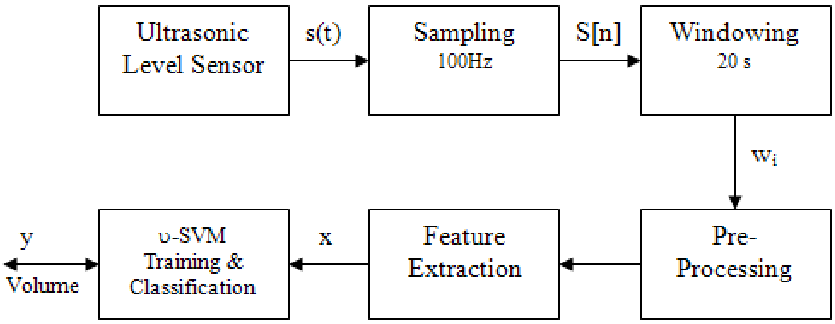

Fig. 4. Block diagram of the proposed system.

For the ultrasonic transducer mounted at height $level_{ref}$ on top of the tank, the instantaneous output of the ultrasonic level sensor at time t and temperature T can be calculated as:

$$Level(t,T) = level_{ref} - \frac{\tau(t)}{2} v(T), \tag{5}$$

where, $\tau(t)$ is the time-of-flight at instant t of the ultrasonic echo, and $v(T)$ is the speed of ultrasonic echo at temperature T. The expression $v(T)$ can be obtained using equation (2).

In a dynamic environment, the term $\tau(t)$ will exhibit variation that reflects an inverted image of the slosh wave produced in the liquid tank. The term $\tau(t)$ will be inverted since the ultrasonic sensor is facing down measuring time-of-flight of ultrasonic echo from the top of the tank. The expression $\frac{\Delta\tau}{\Delta t}$ will vary over time in a dynamic environment, however, under during static conditions, the expression $\frac{\Delta\tau}{\Delta t}$ will be equal to zero. Fig. 5 shows the variation in $\tau(t)$ and the actual slosh wave produced in the liquid tank along with its illustrative frequency spectrum.

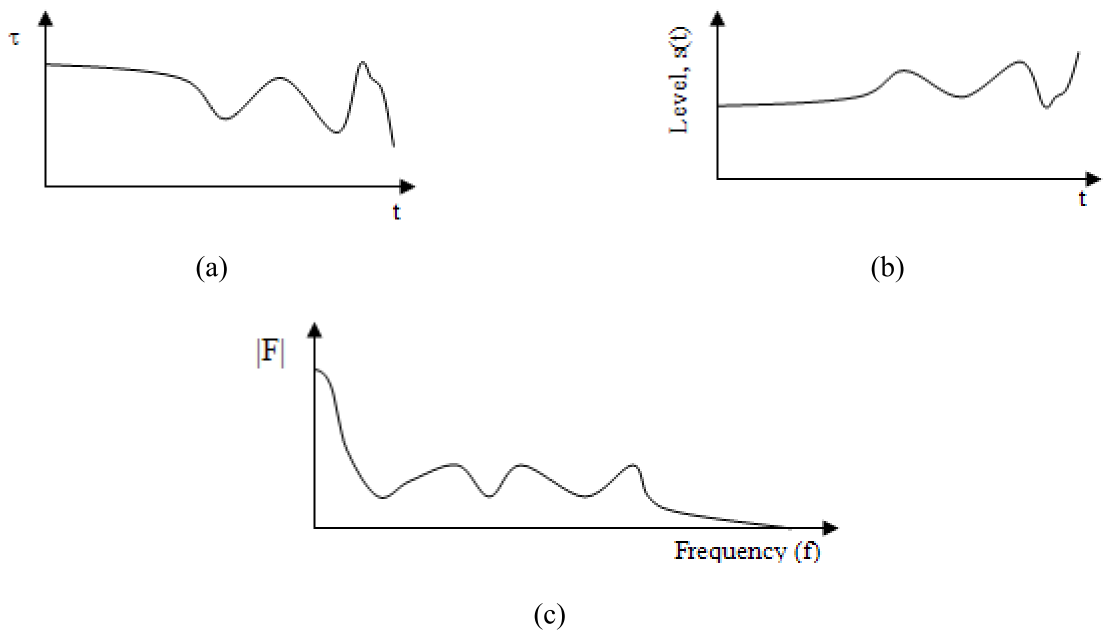

Fig. 5. Illustration of (a) the time-of-flight signal, (b) the exhibited slosh wave and (c) the frequency spectrum of the level signal.

Fig. 6 shows the overview block diagram of the fluid level measurement system.

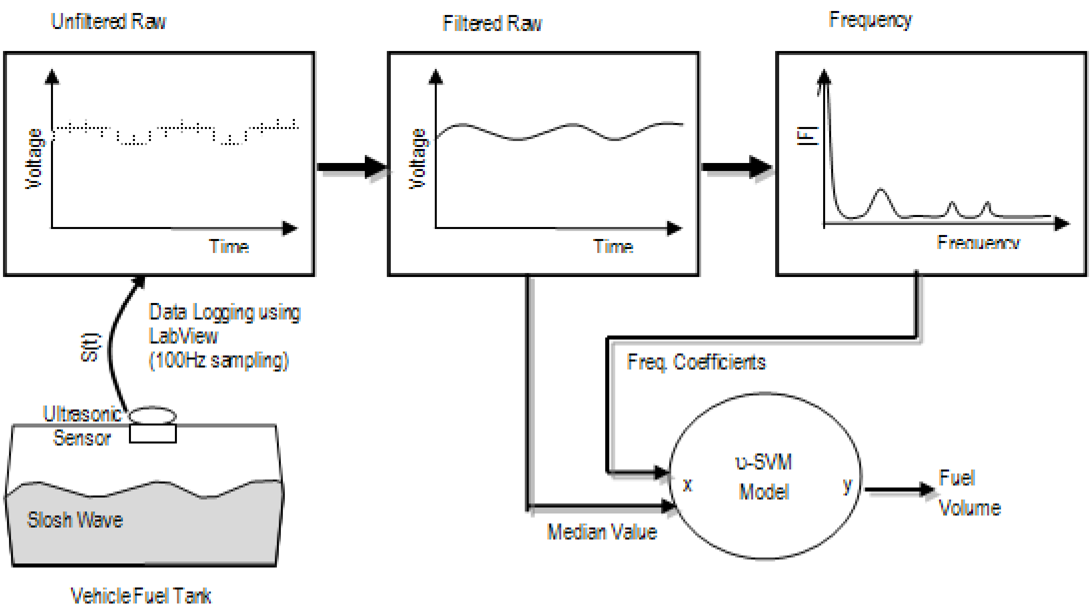

Fig. 6. Overview of the fluid measurement system.

The ultrasonic level sensor signal, denoted as s(t), is the voltage signal in the range from 0.5 – 4.5 V, which represents the minimum and maximum of the level range respectively. The sensor signal s(t) is sampled at 100 Hz. The sampled signal is accumulated in a 20 second window frame (w_i). After collecting the sensor data over 20 seconds, the 20-second data is filtered using the investigated filters. Then the signal features are extracted using FFT. The frequency coefficients (*coef*) and the median value (*med*) of the 20-second data are all directed into the SVM model for training and classification. The SVM input vector *x* can be expressed as:

$$x = [coef_1, coef_2, ..., coef_n, med], \text{ where } x_1 = coef_1 \tag{6}$$

2.2. SVM Model Description

Support Vector Machines (SVMs) consist of supervised learning methods for data classification and regression. Both linearly separable and non-linearly separable data can be classified using this technique [21]. The idea behind the SVM is to create distinction between two or more data classes. The decision boundary between two classes of data is known as a *hyper-plane*. The goal in SVM is to maximize the separation distance or margin between the hyper-plane and the nearest point of each class.

Considering the input data (x_i, y_i) consisting of l number of pairs, where x_i is the *p*-dimensional vector (sample data) and y_i is its associated class such that $i = 1,2,3,...,l$; $x_i \in R^n$. A hyper-plane can be stated as a set of points x satisfying:

$$w \bullet x - b = 0, \tag{7}$$

where, w is a normal vector that is perpendicular to the hyper-plane, and b is the offset parameter.

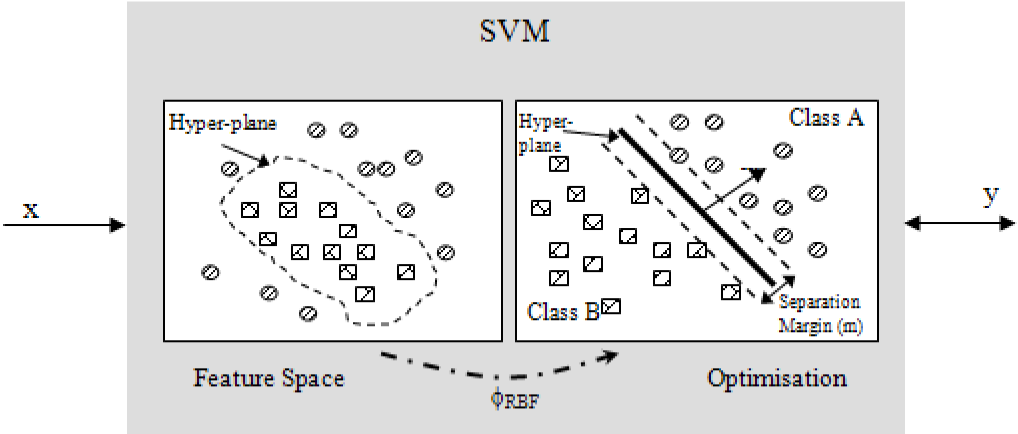

Fig. 7. Illustration of SVM classification.

For linearly separable data set, classification can be performed by creating a margin distance between two hyper-planes satisfying the following equations such that there is no sample data in between them:

$$w \bullet x - b \geq 1, \text{ if } y_i = +1 \text{ and}$$
$$w \bullet x - b \leq -1, \text{ if } y_i = -1 \tag{8}$$

The maximum separation distance or *optimal hyper-plane* can be linearly solved by considering:

$$\min_{w,b,\xi,\rho} \quad \frac{1}{2}\|w\|^2 - \upsilon\rho + \frac{1}{l}\sum_{i=1}^{l}\xi_i \tag{9}$$

$$\text{subject to} \quad y_i(k(w,x_i)+b) \geq \rho - \xi_i, \tag{10}$$

$$\xi_i \geq 0, \quad 1 \leq i \leq l, \quad \rho \geq 0$$

where, ξ is slack variables that measures the degree of misclassification of the vector x_i.

A mapping function ϕ is included in *(8)* to map the samples x_i to a higher dimensional feature space, where the samples could then be separated by a linear hyper-plane [21]. The non-linear optimization problem can be written as:

$$y_i(w \bullet \phi(x_i) - b) \geq 1 - \xi_i, \tag{11}$$

Non-linear kernel functions are used for classification of the non-linearly separable samples. A kernel function can be defined as:

$$\kappa(x_i, x_j) = \phi(x_i) \bullet \phi(x_j) \tag{12}$$

The Gaussian Radial Basis Function (RBF) [22] used in the experiment is given as:

$$\kappa(x_i, x_j) = \exp\left(-\gamma\left\|(x_i - x_j)\right\|^2\right), \quad where \quad \gamma > 0 \tag{13}$$

The SVM decision function $f(x)$ can be generally expressed by using the kernel function as:

$$f(x) = sign\left(\sum_{i=1}^{l} \lambda_i^* y_i \kappa(x_i, x_j) + b^*\right) \tag{14}$$

2.3. Signal Filtration

In the signal filtration process, the raw signal is filtered to remove the signal noise by smoothening it with the three investigated methods: Moving Mean, Moving Median and Wavelet Transform. A raw signal over twenty seconds is passed through the investigated filters. The moving mean and moving median filters slide across the raw signal and calculate the mean/median values in the neighbouring sampled points. If x is the sampled raw signal of N length, and w is size of the moving window, then the filtered output y using mean and median can be obtained using equations (15) and (16), respectively. The width of the moving window w is set to 20. Therefore, the sliding window takes 20 sampled values (or 0.2 second values) of the raw signal and produces a mean or median value at the output.

$$\begin{gathered} y[i] = mean(x[i-1], x[i-2], ..., x[i-w]), \quad for\ \ w \le i \le N \\ y[i] = mean(x[1], x[2], ..., x[i]), \quad for\ \ 1 \le i < w \end{gathered} \tag{15}$$

$$\begin{gathered} y[i] = median(x[i-1], x[i-2], ..., x[i-w]), \quad w \le i \le N \\ y[i] = median(x[1], x[2], ..., x[i]), \quad for\ \ 1 \le i < w \end{gathered} \tag{16}$$

The value of N for the twenty second signal at 100 Hz is calculated as (6):

$$N = 100 \ \text{samples/s} \times 20s = 2000\,\text{samples} \tag{17}$$

Another filter investigated is the Wavelet Transform (WT) filter that analyses signals at different frequency bands by de-composing them into coarse information and detailed information sets. The coarse information set contains the low-frequencies, whereas, the detailed information set contains the high-frequencies of the input signal. Only low frequency components, which reflect a smoothened version of the raw signal, are used and the high frequency components of the raw signal, which usually contain noise, are eliminated.

Fig. 8 shows the high frequency signal (b) and the low-pass filtered signal (c) when the raw sensor signal (a) was processed with the Discrete Wavelet Transform (DWT) function. The Wavelet Transformation was processed through the MATLAB Wavelet Toolbox using the *dwt* function, which used *db1* wavelet.

All filtered signals using the investigate filtration methods were then transformed into the frequency domain and the frequency coefficients were obtained, which were then fed into the SVM model.

3. Experimental Setup

A fuel tank was fitted with an ultrasonic sensor near the top center of the tank. The tank can be approximated as a rounded edge rectangle with dimensions 34 × 34 × 81 cm. The fuel tank was filled with fuel levels ranging from 5 – 50 L in the experiment, which corresponds to 6 % - 70 % of the tank capacity. The fuel tank was mounted in latitudinal direction, where the longest length of the tank was in parallel to the direction of the vehicle. Table 1 lists all the fuel levels investigated in the experiment.

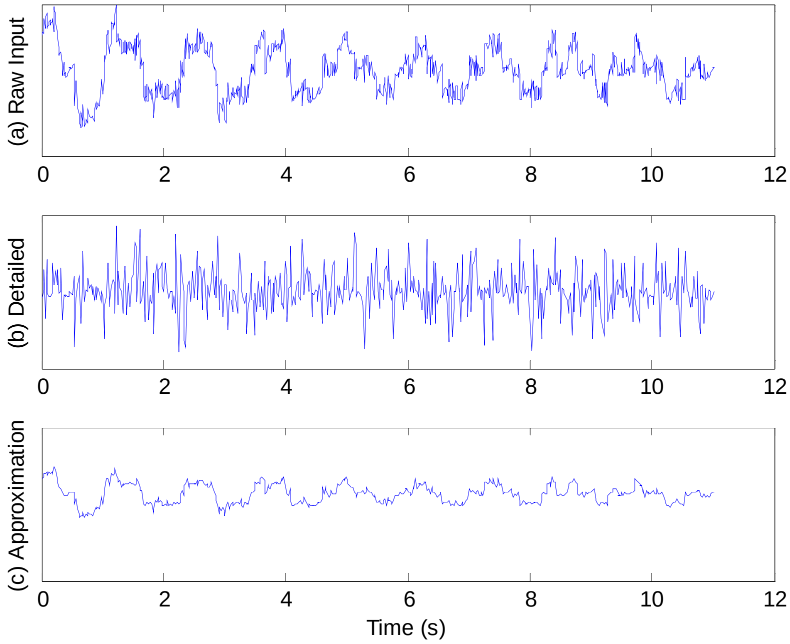

Fig. 8. Wavelet Filter applied on the Raw Signal.

Table 1. List of tank volumes investigated in the experiment.

Investigated Tank Levels
5L, 6L, 7L, 8L, 9L,
15L, 20L, 25L, 30L,
35L, 36L, 37L, 38L, 39L, 40L,
45L, 46L, 47L, 48L, 49L, 50L

Table 2. Details of the ultrasonic transducer used in the experiment

Ultrasonic Sensor Specifications	
Accuracy	± 0.32 cm
Output	0.5 – 4.5 V (min to max)
Resolution	0.18 cm
Operating Temperature	-40 … +80 °C
Designed for gasoline and diesel liquids	

The level signal from the ultrasonic sensor was acquired using the LabVIEW software and a Data Acquisition Card, which was connected to the ultrasonic sensor in the vehicle. The ultrasonic sensor signal indicating the fuel level was sampled and recorded at 100 Hz. Each experiment was conducted by driving a vehicle containing the instrumented fuel tank for 3 km in a suburban residential area, where occasional stops were made at some road intersections.

Fig. 9 shows a graph of typical acceleration and speed of the vehicle that was observed while running the drive trials.

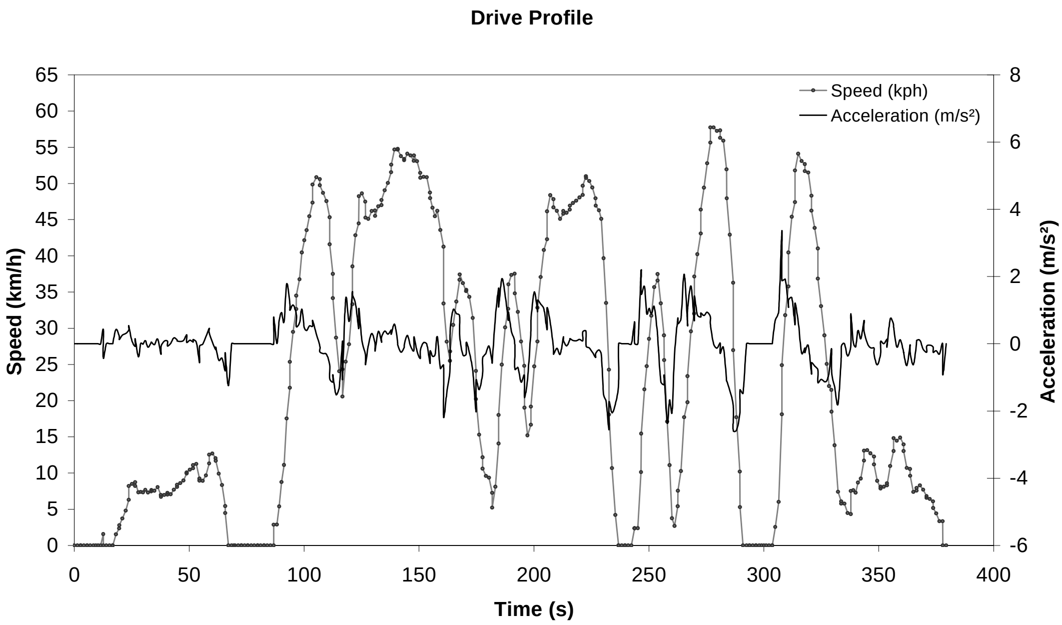

Fig. 9. Plot of typical speed and acceleration observed during the experiments.

4. Simulation Results

Each investigated filter was applied on a separate SVM model, where the SVM parameters for each SVM model were the same. One half of the data from the first field trial was used to train the SVM model, and half of the second field trial samples were used for verification of the network performance. The training and simulation process is shown in Fig. 10, which was carried out using MATLAB and LIBSVM [23]. LIBSVM is integrated software for support vector classification, regression and distribution estimation. It supports multi-class classification, which is required for training the ultrasonic signals at multiple volume levels. The signal features were scaled between an optimum range (0 – 1) using LIBSVM *train* tool. Fig. 10. SVM Training and Validation Flowchart.

Table 3. lists the LIBSVM training parameters used in the classification.

Fig. 11 shows the frequency coefficients of the unfiltered signals obtained using the MATLAB built in *fft* function. To increase the network training speed without incurring performance penalty, only the first sixty-three frequency coefficients that approximately correspond to the slosh frequency 0 – 6.5 Hz, were used to train the SVM model.

Table 3. SVM training parameters.

Parameter	**Value**
SVM Type	= 1 (υ-SVM)
Kernel Function	= 2 (RBF)
Gamma (γ)	= 0.105
Nu (υ)	= 0.1
Coef0	= -0.3
Tolerance (ξ)	= 10^{-5}

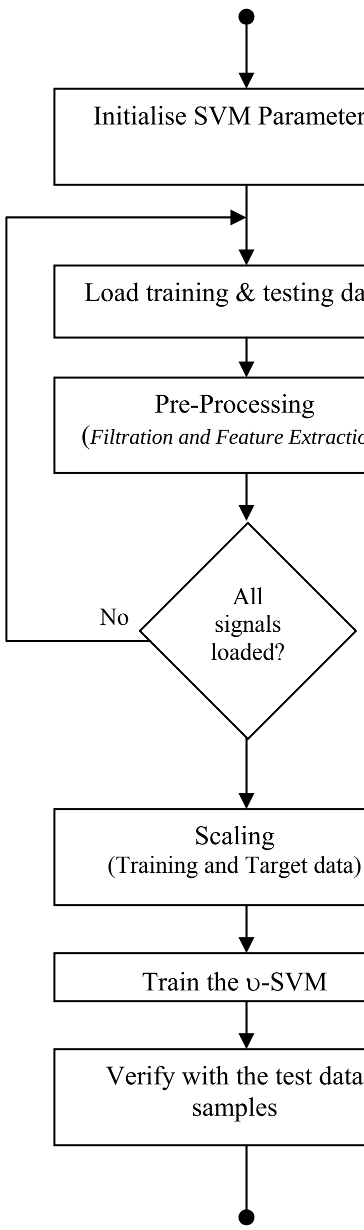

Fig. 10. SVM Training and Validation Flowchart.

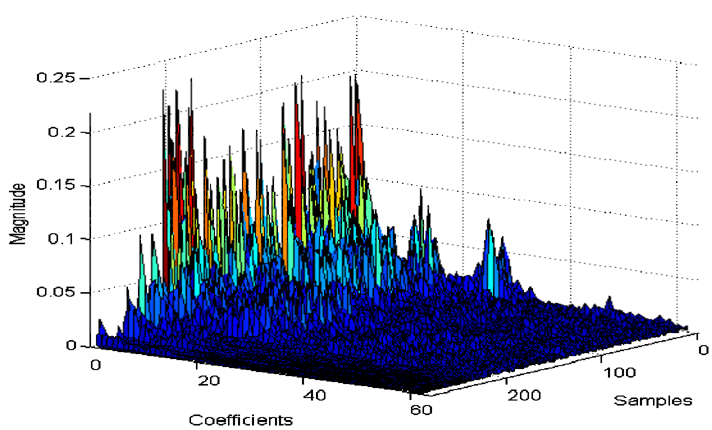

Fig. 11. FFT coefficients obtained using the training data.

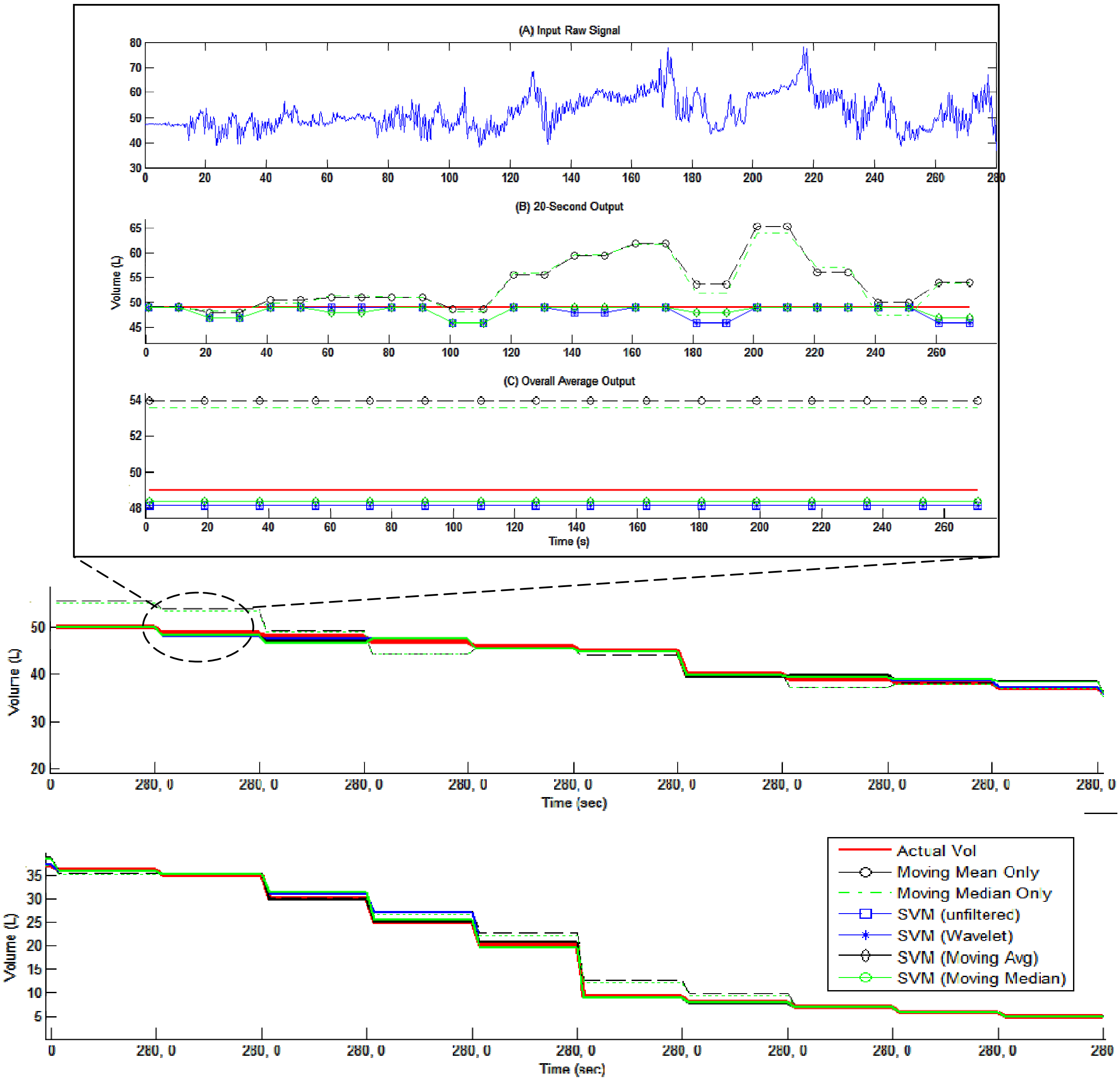

Fig. 12. Network verification data generated after training the SVM.

After training the SVM model, the model was validated using the test samples obtained from the second field trial.

Fig. 12 shows the output results obtained using different processing methods. The output volume was calculated as the overall average of each investigated tank volume. Field trial results for each investigated tank volume are placed adjacent to each other. The time length of each trial is indicated as 280 seconds. A closer look at the 49 litre trial is also shown in Fig.12. The raw signal illustrated in Fig. 12 (a) was divided into twenty-second long signals, as shown in Fig.12 (b), which were then filtered and processed through the SVM. The overall averaged volume Fig.12 (c) was calculated by averaging the SVM model outputs for each trial over 280 seconds.

Table 4 shows the volume figures obtained using the statistical mean and median functions, and the SVM predicted results using different pre-processing filters. Average error values at a particular investigated tank volume are shown in Table 5. All values listed in Table 4 and Table 5 are in litres.

Table 4. Overview of the results obtained using the statistical methods and the SVM approach with different pre-processing filters.

Actual Volume	Statistical Averaging		Support Vector Machine			
	Moving Mean* (without SVM)	Moving Median* (without SVM)	SVM (Unfiltered)	SVM (Moving Mean)	SVM (Moving Median)	SVM (Wavelet filter)
50	55.77	55.19	50.12	50.07	50.02	50.09
49	53.94	53.57	48.14	48.36	48.36	48.14
48	49.29	49.12	47.50	47.07	46.79	47.50
47	44.51	44.50	47.64	47.50	47.50	47.64
46	45.66	45.57	45.64	45.50	45.57	45.64
45	44.10	43.83	44.93	44.86	44.79	44.93
40	40.04	39.96	39.79	39.36	39.79	39.79
39	37.26	37.20	39.36	39.93	39.36	39.36
38	38.18	37.74	38.43	39.04	38.93	38.43
37	37.34	37.02	37.21	38.50	38.36	37.21
36	35.27	35.11	35.71	35.71	35.79	35.71
35	35.37	35.04	35.14	35.14	35.07	35.14
30	30.13	29.82	30.79	29.64	31.29	30.79
25	27.23	26.51	27.07	25.00	25.36	27.07
20	22.91	22.12	20.64	20.64	19.50	20.64
9	12.65	12.19	8.93	8.93	8.93	8.93
8	9.87	9.38	7.86	7.82	7.90	7.88
7	7.35	7.06	7.02	7.04	7.05	7.04
6	6.06	5.94	6.03	6.02	6.02	6.04
5	5.36	5.09	5.07	5.08	5.10	5.07

* Averaged filter values without using SVM

Table 5. Obtained errors using different statistical averaging and SVM methods.

Actual Volume	Statistical Averaging		Support Vector Machines			
	Moving Mean* (without SVM)	Moving Median* (without SVM)	SVM (Unfiltered)	SVM (Moving Mean)	SVM (Moving Median)	SVM (Wavelet filter)
50	5.77	5.19	0.12	0.07	0.02	0.09
49	4.94	4.57	0.86	0.64	0.64	0.86
48	1.29	1.12	0.50	0.93	1.21	0.50
47	2.49	2.50	0.64	0.50	0.50	0.64
46	0.34	0.43	0.36	0.50	0.43	0.36
45	0.90	1.17	0.07	0.14	0.21	0.07
40	0.03	0.04	0.21	0.64	0.21	0.21
39	1.74	1.81	0.36	0.93	0.36	0.36
38	0.18	0.26	0.43	1.04	0.93	0.43
37	0.34	0.02	0.21	1.50	1.36	0.21
36	0.73	0.89	0.29	0.29	0.21	0.29
35	0.37	0.04	0.14	0.14	0.07	0.14
30	0.13	0.18	0.79	0.36	1.29	0.79
25	2.23	1.51	2.07	0.00	0.36	2.07
20	2.91	2.12	0.64	0.64	0.50	0.64
9	3.65	3.19	0.07	0.07	0.07	0.07
8	1.87	1.38	0.14	0.18	0.10	0.12
7	0.35	0.06	0.02	0.04	0.05	0.04
6	0.06	0.06	0.03	0.02	0.02	0.04
5	0.36	0.09	0.07	0.08	0.10	0.07
Absolute Average Error	1.60	1.40	0.42	0.45	0.45	0.42
Max. Error	5.77	5.19	2.07	1.50	1.36	2.07

* Averaged filter values without using SVM

Fig. 13 shows the overall average error plots using the investigated filters at different tank volumes. It shows that the SVM models with applied Moving Mean, Unfiltered, and Wavelet filters produced little error, especially near the lower and higher tank volumes, when compared with the simple statistical methods.

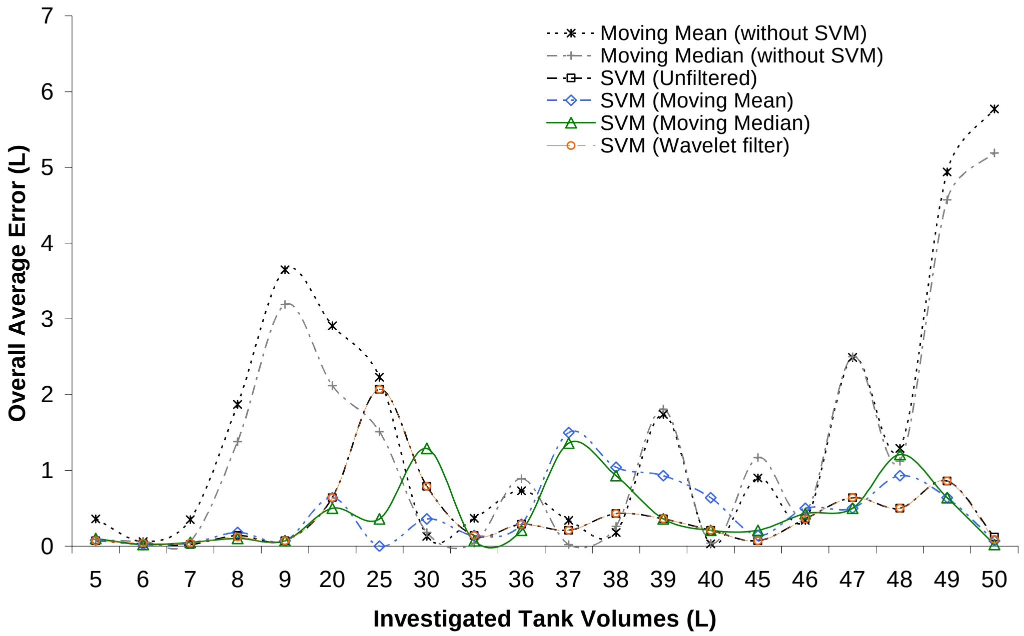

Fig. 13. Graph of the average error produced at different investigated tank volumes.

Fig. 14 summarizes the errors obtained using the averaging method and the three investigated pre-processing techniques.

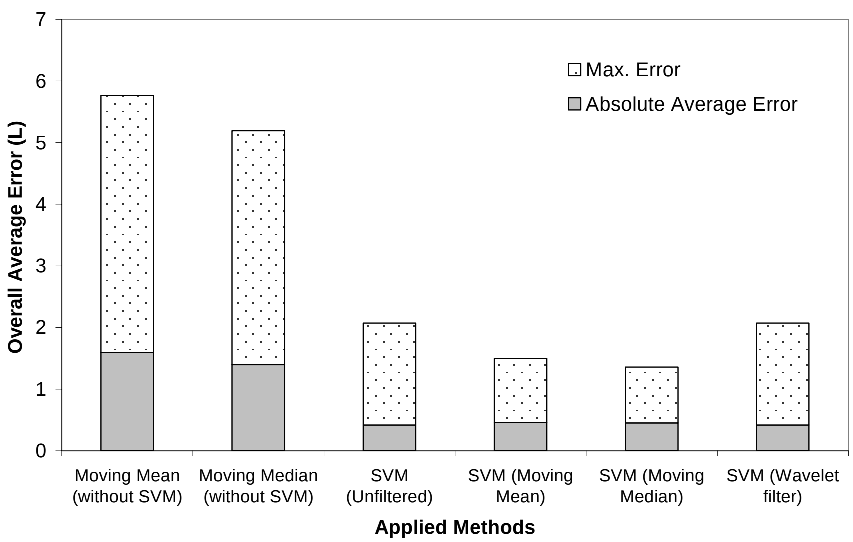

Fig. 14. Summary of the investigation showing the maximum error obtained using signal different processing methods.

5. Summary

The Support Vector Machines based signal processing and classification approach coupled with a signal ultrasonic sensor has been used to accurately determine the fuel level in an automotive fuel tank under dynamic conditions. Four identical SVM models were developed and an investigation was carried out by applying three filtration methods and keeping one unfiltered raw signal to analyze the performance of the υ-SVM model in improving the accuracy of the level sensor in the presence of liquid slosh. The SVM model applied with the Moving Median filter produced a maximum averaged error of 1.4 litres, which is significantly better than the results obtained using the statistical and non-SVM network Moving Mean, and Moving Median functions that produced a maximum averaged error of 5.8 litres and 5.2 litres, respectively.

6. Future Work

An Ultrasonic Sensor coupled with the Support Vector Machine (SVM) approach to signal processing will be used to address other influencing factors such as atmospheric pressure and the tilt that causes liquid to shift to one side. With the rapid improvements in microprocessor technology, it will be possible to automatically train the SVM model in real time, which will further increase the effectiveness of the measurement system in dynamic environments.

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Guide for Contributors

Aims and Scope

Sensors & Transducers Journal (ISSN 1726-5479) provides an advanced forum for the science and technology of physical, chemical sensors and biosensors. It publishes state-of-the-art reviews, regular research and application specific papers, short notes, letters to Editor and sensors related books reviews as well as academic, practical and commercial information of interest to its readership. Because it is an open access, peer review international journal, papers rapidly published in *Sensors & Transducers Journal* will receive a very high publicity. The journal is published monthly as twelve issues per annual by International Frequency Association (IFSA). In additional, some special sponsored and conference issues published annually. *Sensors & Transducers Journal* is indexed and abstracted very quickly by Chemical Abstracts, IndexCopernicus Journals Master List, Open J-Gate, Google Scholar, etc.

Topics Covered

Contributions are invited on all aspects of research, development and application of the science and technology of sensors, transducers and sensor instrumentations. Topics include, but are not restricted to:

- Physical, chemical and biosensors;
- Digital, frequency, period, duty-cycle, time interval, PWM, pulse number output sensors and transducers;
- Theory, principles, effects, design, standardization and modeling;
- Smart sensors and systems;
- Sensor instrumentation;
- Virtual instruments;
- Sensors interfaces, buses and networks;
- Signal processing;
- Frequency (period, duty-cycle)-to-digital converters, ADC;
- Technologies and materials;
- Nanosensors;
- Microsystems;
- Applications.

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