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SUPPORT VECTOR MACHINE BASED MULTIPLE FAULT DETECTION IN AN AUTOMOBILE ENGINE USING SOUND SIGNAL

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Abstract- This paper focuses the multiple fault detection techniques in an automobile engine using a single sensor. Fault detection is increasingly important for vehicle safety and reliability. One of the issues in vehicle fault detection is the difficulty of correctly diagnose the real root cause [1]. This paper presents the innovative technique to detect the multiple faults using single sensor [2]. We have made an attempt to detect the air filter fault, spark plug fault and insufficient lubricant fault in an automobile engine using a single sensor. The simple microphone is used as sensor to detect fault [3]. The detail analyses of the faults is carried out using all neural networks for individual fault and then combine three faults. The Classification Accuracy of all types of neural networks is compared. Finally optimal neural network is designed for the best performance.
Key words- Automobile Engine, Air Filter, Spark Plug, Insufficient Lubricants, Artificial Neural Network and Fault Detection.

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Introduction

In the recent years, a lot of technological advances are going on in motor vehicular systems, pertaining to improve driving safety and comfort. But this leads to making the vehicular systems more and more complex. At the same time, increase in road traffic is a major problem in big metropolitans' cities. There is also a scarcity of skilled mechanics in all over the world [4]. It is therefore difficult to maintain the vehicle in the rural areas. Determination of fault at an early stage and repairing them before it leads to larger fault is important, because it reduces the other damages, repairing cost and also reduces down time of the engine [5]. In this paper, analysis of Air filter fault, Spark Plug fault and Insufficient Lubricants has been carried out and the details of that are given as under.

A. Air Filter

The air filter is connected on the intake system of automotive engines. The function of air filter is to provide the clean air to an automobile engine [6]. Otherwise impurities like dust in the air cause a very rapid wear of the engine, particularly of the cylinders, pistons, & piston-rings. Further, if the dirty air enters in the crankcase, it contaminates the lubricating oil and ultimately damages the bearings and decreases the service period of the lubrication system. It is, therefore necessary to have good quality air filter on the intake system of automotive engines [7].

Besides filtering the air, air filters also perform other functions, like

- It acts as a silencer for the carburetor system. i.e., it reduces the engine induction noise to an acceptable level.
- In case, the engine back-fires, the air filter also acts as a flame arrester.

The air filters offer a resistance to air flow, which is increased as the air filters get clogged with dirt. Consequently, air flow would get decreased, resulting in sluggish engine performance and higher consumption of fuel [8].

B. Spark Plug

A spark plug is an electrical device that fits into the cylinder head of some internal combustion engines and ignites compressed petrol by means of an electric spark. Spark plugs have an insulated center electrode which is connected by a heavily insulated wire to an ignition coil circuit on the outside, forming, with a grounded terminal on the base of the plug, a spark gap inside the cylinder.

As the electrons flow from the coil, a voltage difference is developed between the center electrode and side electrode. No current can flow because the fuel and air in the gap is an insulator, but as the voltage rises further, it begins to change the structure of the gases between the electrodes. Once the voltage exceeds the dielectric strength of the gases, the gases become ionized. The ionized gas becomes a conductor and allows electrons to flow across the gap. Spark plugs usually require voltage in excess of 20,000 volts to 'fire' properly. Because the spark plug is inside the engine and is the only easily removable part it can be used as an indicator to the Faults in Spark Plug.

i. Normal Spark Plug

Combustion deposits are slight and not heavy enough to cause any negative effect on engine performance. Brown to grayish tan color and minimal amount of electrode erosion which clearly indicates the plug is in the correct heat range and has been operating in a "healthy" engine.

ii. Inappropriate Plug Gap

In appropriate plug gap is developed because of routine damage like mechanical damage caused by a foreign object that has accidentally entered the combustion chamber. This condition may also be due to inappropriate reach spark plugs that permit the piston to contact or collide with the firing end. The gap may also because the plug has served its useful life and should be replaced. The voltage required to fire the plug has approximately doubled and will continue to increase with additional miles of travel. Even higher voltage requirements, as much as 100% above normal, may occur when the engine is quickly accelerated. Poor engine performance and a loss in fuel economy are qualities of a worn or spoiled spark plug. The inappropriate gap is shown in Fig.1.

Fig.1- Inappropriate Gap Spark Plug.

The main cause of inappropriate gap is because of rough materials that accumulate on the side electrode may melt to bridge the gap when the engine is suddenly put under a heavy load. If the Air filter and spark plug are found faulty, it can be easily replaced or repaired. Thus maintaining a high level of engine reliability by efficient fault diagnosis is thus important for several reasons.

- The down time of the engine is expensive.
- Certain malfunctioning conditions can be threat to the safety of both human being and environment.

With the rapid development of the signal processing techniques, the sound emission and vibration signals can be used in condition monitoring and fault diagnosis because they always carry the dynamic information of the mechanical system [2, 5].

C. Insufficient Lubricant

A lubricant is a substance introduced to reduce friction between moving surfaces. It may also have the function of transporting foreign particles. The property of reducing friction is known as lubricity.

A good lubricant possesses the following characteristics:

- High boiling point.
- Low freezing point.
- High viscosity index
- Corrosion prevention.
- High resistance to oxygen

One of the single largest applications of lubricants, in the form of motor oil is protecting the internal combustion engine of motor vehicles and powered equipment.

D. Artificial Neural Networks

In this paper we have tested the performance of all the types of neural networks for fault detection in an automobile engine. The brief introduction of all neural networks is as follows.

MLP: Multilayer perceptrons (MLPs) are layered feedforward networks typically trained with static backpropagation. The main advantage is that they are easy to use, and that they can approximate any input/output map. The key disadvantages are that they train slowly, and require lots of training data.

GFF: Generalized feedforward networks are a generalization of the MLP such that connections can jump over one or more layers. In theory, a MLP can solve any problem that a generalized feedfoward network can solve. In practice, however, generalized feedforward networks often solve the problem much more efficiently.

MNN: Modular feed forward networks are a special class of MLP. These networks process their input using several parallel MLPs, and then recombine the results. In contrast to the MLP, modular networks do not have full interconnectivity between their layers. Therefore, a smaller number of weights are required for the same size network (i.e. the same number of PEs). This tends to speed up training times and reduce the number of required training exemplars.

JEN: Jordan and Elman networks extend the multilayer perceptron with context units, which are processing elements (PEs) that remember past activity. Context units provide the network with the ability to extract temporal information from the data. In the Elman network, the activity of the first hidden PEs are copied to the context units, while the Jordan network copies the output of the network.

PCAs: Principal component analysis networks combine unsupervised and supervised learning in the same topology. Principal component analysis is an unsupervised linear procedure that finds a set of uncorrelated features, principal components, from the input. A MLP is supervised to perform the nonlinear classification from these components.

RBF: Radial basis function (RBF) networks are nonlinear hybrid networks typically containing a single hidden layer of processing elements (PEs). This layer uses gaussian transfer functions, rather than the standard sigmoidal functions employed by MLPs. The centers and widths of the gaussians are set by unsupervised learning rules, and supervised learning is applied to the output layer. These networks tend to learn much faster than MLPs.

SOFM: Self-organizing feature maps transform the input of arbitrary dimension into a one or two dimensional discrete map subject to a topological constraint. The feature maps are computed using Kohonen unsupervised learning. The output of the SOFM can be used as input to a supervised classification neural network such as the MLP. The key advantage of this network is the clustering produced by the SOFM which reduces the input space into representative features using a self-organizing process.

TLRN: Time lagged recurrent networks are MLPs extended with short term memory structures. Most real-world data contains information in its time structure, i.e. how the data changes with time. Yet, most neural networks are purely static classifiers. TLRNs are the state of the art in nonlinear time series prediction, system identification and temporal pattern classification.

RN: Fully recurrent networks feed back the hidden layer to itself. Partially recurrent networks start with a fully recurrent net and add a feedforward connection that bypasses the recurrency, effectively treating the recurrent part as a state memory. These recurrent networks can have an infinite memory depth and thus find relationships through time as well as through the instantaneous input space. Most real-world data contains information in its time structure. Recurrent networks are the state of the art in nonlinear time series prediction, system identification, and temporal pattern classification.

SVM: The Support Vector Machine is implemented using the kernel Adatron algorithm. The kernel Adatron maps inputs to a high-dimensional feature space, and then optimally separates data into their respective classes by isolating those inputs which fall close to the data boundaries. Therefore, the kernel Adatron is especially effective in separating sets of data which share complex boundaries. SVMs can only be used for classification, not for function approximation

Block Diagram of the Systems

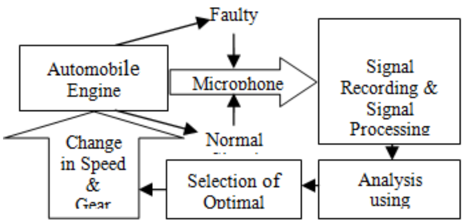


Fig. 2- Block diagram of the system

It will be acceptable for vehicular system that it must have vehicle information system. To develop such system, detail analysis of the fault is required. The working of the system is shown in the block diagram Fig 2. The MP3 sound recorder has been used to record the sound signals along with the carbon microphone. The parameters of recorded sound signals are extracted using the MATLAB software. The detailed analysis is carried out using neural networks and finally the optimal neural network is designed.

Experimental Set Up

The major components of a two-stroke spark ignition engine are the:

- **Cylinder:** A cylindrical vessel in which a piston makes an up and down motion.
- **Piston:** A cylindrical component making an up and down movement in the cylinder.
- **Combustion Chamber:** A portion above the cylinder in which the combustion of the fuel-air mixture takes place.
- **Intake and exhaust ports:** An intake port allows the fresh fuel -air mixture to enter the combustion chamber and an exhaust port discharges the products of combustion.
- **Crankshaft:** A shaft which converts the reciprocating motion of the piston into a rotary motion.
- **Connection Rod:** A rod which connects the piston with the crankshaft.
- **Spark Plug:** An ignition-source located at the cylinder head that is used to initiate the combustion process.

The experimental set up is shown in Fig. 3. It consists of an automobile engine along with the microphone and signal recording and signal processing system. The microphone is mounted closer to the engine. As sound variation carries the dynamic information of the engine, the recording system records sound variations in normal and faulty conditions of the engine. The engine was started in normal condition and signals were recorded for different speeds and the different gear positions. After that the normal air filter was replaced by faulty air filter and again the signals were recorded for the same speeds and the same gear positions. The same procedure was repeated for normal and faulty spark plug. Further the signals were also recorded for with lubricants and with fewer lubricants. The Engine used for experimentation is comprised of a 5-port single cylinder, 2-stroke, four speed gear and 150 cc engine & the detailed specifications are as shown in Table 1

Fig. 3- Experimental Setup

Table 1- Engine Specification

Performance		
Peak power	8.0 hp at 5500 rpm	Highest power amongst 2-stroke scooters
Peak torque	1.35 Kg-m at 3500 rpm	Instantaneous pick-up
Engine		
Type	5-port single cylinder, 2-stroke with reed valve induction	Advanced engine for superior performance
Transmission	4-speed gear box	Smooth easy shifting
Clutch	Wet multi-disc type	
Operating cycle	Two-stroke spark ignition, 150 cc engine	
Compression ratio	6-10	
Bore	0.05-0.085 m	
Stroke/bore ratio	1.2-0.9	
Max rated BMEP	3.17 bar	
Wt/power ratio	5.5-2.5	
Appr. Best Bsfc	350 (gm/kw hr)	

Result an Observations

Signal plot

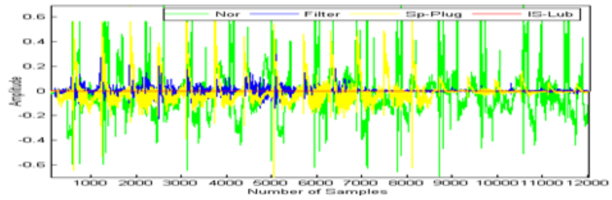
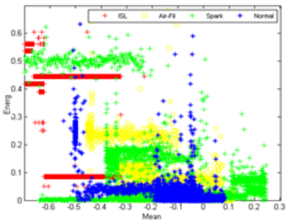


Fig. 4- Signal plot for normal and faulty condition.
(Nor- Normal Signal, Filter- Filter Fault signal, Sp-Plug- Spark Plug Fault signal, IS-Lub- Insufficient Lubricants signal.)

The recorded signals are plotted as shown in Fig.4. It is found that the signals are overlapped and the amplitude of the normal signals and faulty spark plug signals are found to be greater than the amplitude of filter faulty signal. It is also observed that the signal with fewer lubricants having very less amplitude as compared to other signal. Further it is found that the signals are overlapped and peaks are repeated after certain intervals.

Scatter Plot

The parameters of normal and faulty signals are extracted by using the MATLAB software. The parameter extraction is done for single frame consisting of 150000 samples in it. Then 150000 samples are divided into two parts i.e. in two frames. Now each frame is consisting of 75000 samples. This process of decomposition is continued up to 256 frames. After making the frame size smaller and smaller the parameters are extracted for each and every frame. The extracted parameters for 256 frames are plotted as shown in Fig. 5A and Fig 5B.



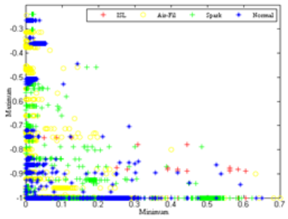


Fig. 5A- Mean Vs Energy **Fig. 5B-** Minimum Vs. Maximum
(Normal- Normal Signal, Air Fil- Air Filter Fault, Spark- Spark Plug Fault, ISL- Insufficient Lubricants signal)

It is clearly seen that at some places the parameter for insufficient lubricant are found separated than other parameters. But in most of the places the parameters ore not linearly separable. Therefore neural network has been employed to separate out the faults.

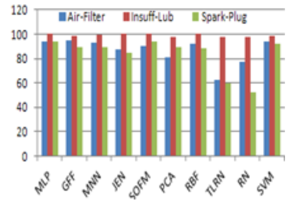
Table 2- Performance of Neural Networks for separate faults.

Neural Networks	Average Classification Accuracy (ACA)					
	Air Filter Fault		In. Lubricant		Spark Plug Fault	
	F - 16	F - 32	F - 16	F - 32	F -16	F - 32
MLP	93.88	97.5	100	100	93.65	94.93
GFF	95.11	98.36	98.73	100	89.38	90.31
MNN	92.61	96.89	99.36	100	89.46	89.05
JEN	87.59	95.29	100	98.76	84.85	87.49
PCA	90.23	94.19	100	99.69	94.32	91.89
RBF	80.57	94.68	98.13	99.69	89.69	89.34
SOFM	92.37	77.71	100	100	88.76	87.57
TLRN	62.41	75.84	97.3	98.44	60.13	76.59
RN	76.88	87.8	98.13	98.76	52.16	71.51
SVM	94.2	97.75	98.63	98.76	91.88	92.71

(In. Lubricant - Insufficient Lubricant fault)

The analysis has been carried out for separate fault and also after combining the faults. The performances of each network were observed on the basis of classification accuracy. The ACA for test data for 16 frames and 32 frames has been given in table 2. The classification accuracy for insufficient lubricant is found to be maximum.

The classification accuracy for test data for three separate faults is also shown in Bar chart Fig 6A and Fig 6B.



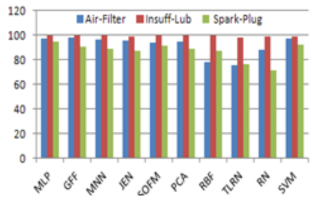


Fig. 6A- Bar chart for ACA for 16 frame of signal **Fig. 6B-** Bar chart for ACA for 32 frame of signal

(Air Filter - Air Filter Fault, Spark Plug - Spark Plug Fault, In. Lubricant - Insufficient Lubricant Fault.)

It observed that the insufficient lubricant faults have maximum classification accuracy than other two faults.

The table 3 shows the classification accuracy for combined three different faults from single frame to 256 frames. It is observed that the SVM performance is found to be improved as the number of frames increased. It is to be noted that as we increased in the frame number means to reduce the frame size and which increased the classification accuracy.

Table 3- ACA for three combined Faults.

ANN	Signal Samples Frames								
	1	2	4	8	16	32	64	128	256
MLP	51.1	67.6	81	77.1	77.2	76.6	77.4	76.2	72.7
GFF	51.1	73.9	81.1	82.1	73.2	72.1	72.2	74.3	75.1
MNN	47.5	61.4	77.6	73.4	71.6	69.3	73.2	74.5	76.8
JEN	47.5	57.7	79.2	72.8	72.8	70.9	72.7	71.9	69.2
PCA	56.8	68.2	80.6	76.3	70.9	69.6	72.1	71.4	65
RBF	49.6	66.9	75.7	78.5	73.7	76.2	76.9	75	73.8
SOFM	59.6	66.9	80.5	79.2	78.8	77.5	81.6	78.8	76.7
TLRN	40.4	48.8	45.6	53.5	56.3	59.9	65.6	65.4	64.9
RN	53.3	61.4	62.5	60.9	66.6	64.9	62.5	61.8	62.1
SVM	54.6	72.9	86.4	90.9	90	92.7	95.6	97	97.3

Fig 7. Shows the plot of performance of all neural network for three combine faults from one frame to 256 frame of signal.

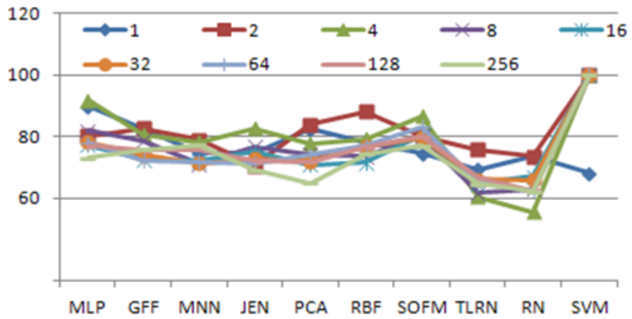


Fig. 7- Average Classification accuracy for three combine faults.

It is found that the SVM performance is found to be 100 % for 256 frames of the signal.

Performance of Support Vector Machine

The detail analysis of SVM is carried out. The maximum classification accuracy was found for the Processing Element (PE) 20, as shown in table 4.

Table 4- Classification Accuracy for SVM

SVM	Test Data	Cross Validation Data	Training Data
PE-02	94.515	94.857	99.794
PE-05	96.399	96.427	99.852
PE-06	96.477	96.698	99.852
PE-08	96.942	96.97	99.862
PE-10	97.06	97.008	99.902
PE-12	97.06	97.008	99.902
PE-14	97.217	97.219	99.931
PE-16	97.198	97.22	99.931
PE-18	97.198	97.24	99.931
PE-20	97.237	97.24	99.941
PE-22	97.218	97.317	99.941
PE-24	97.218	97.375	99.951
PE-26	97.199	97.316	99.951
PE-28	97.199	97.316	99.951
PE-30	97.199	97.316	99.951
PE-40	97.199	97.316	99.951
PE-50	97.199	97.316	99.951
PE-100	97.199	97.316	99.951
PE-200	97.199	97.316	99.951

The classification accuracy is plotted as shown in Fig 8.

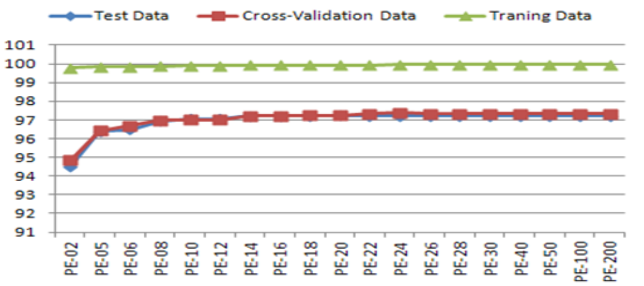


Fig. 8- Plot of ACA for SVM.

Table 5- Result of SVM for three combine fault

Performance	SYM(AF)	SYM(SP)	SYM(ISL)	SYM(NOR)
MSE	0.06784	0.06896	0.06534	0.06459
NMSE	0.36326	0.37216	0.35014	0.33770
MAE	0.23278	0.22763	0.21785	0.22338
Min Abs Error	0.00041	0.00001	0.00001	0.00041
Max Abs Error	0.73013	0.71120	0.59972	0.67732
r	0.92289	0.91137	0.87893	0.93076
Percent Correct	99.88212	99.64215	100.00000	99.92418

(MSE- Mean square error, NMSE- Normalise mean square error, MAE - mean absolute error, r- correlatrion coefficient. AF-Airfilter Fault, SP-Spark Plug Fault, ISL- Isufficient Lubricant and NOR-Normal Signal.)

The result obained is shown in table 5. It is found that the classification accuracy for insufficient lubricant is found to be maximum than the other two fault. The ACA for Air ilter fault is found to be 99.88212%, for Spark Plug Fault is 99.64215%, for Isufficient Lubericnt is 100 % and for Normal it is 99.92418. The correleation coefficient is found to be greater than 0.9 except in insufficient lubricants in that it is found to be 0.8789.

Conclusion

In this paper Multiple Fault Detection in an Automobile Engine Using Sound Signal is proposed. It is not a complete automotive fault detection system. But the main advantage of this system is that its simplicity and single sensor system. Using single sensor multiple fault detection is employed.

The comparative analysis of Artificial Neural Networks depicts that the frame size of 256 frames yields the best Classification Accuracy for all the classifiers. Amongst ten neural network classifiers used for the analysis, the classification accuracy obtained for single fault is greater than the simultaneously occurring three faults. The performance of SVM is found to be the better than any neural network and for 256 frame it is the best. The Processing Element is found to be 20 for the maximum classification accuracy. It is found that SVM can be used as a best classifier for fault detection in an automobile engine.

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