The Use of Wavelet Analysis and the Nearest Neighbor Rule for the Prognosis of Failures in Electric Motors

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Abstract – The ability to give a prognosis for failure of a system is an invaluable tool and can be applied to electric motors. In this paper, two wavelet based methods have been developed that achieve this goal. Wavelet and filter bank theory is reviewed as well as the nearest neighbor rule. A framework for the development of a fault detection and classification algorithm based on the coefficients calculated from the discrete wavelet transform and using clustering is described. An experimental setup based on RT-Linux is described and results from testing are presented, verifying the analysis.

Index Items – Fault Prognosis, Wavelets, DC Motors

I. INTRODUCTION

In recent years, industry has focused much attention on analytical methods to determine the state of health of electrical systems. The state of health of a system can include information such as the existence and the type of imminent problems and an estimation of the remaining life expectancy. The ability to give a prognosis for the failure of a system is synonymous to detecting faults that lead to reduced performance and eventual failure of the system. With this prognosis, attention can be brought to any problems a system may exhibit before they cause the system to fail. The presence of small transient signals, superimposed on larger, perhaps noisy signals always present in the system, may indicate lack of health and a more or less imminent fault.

The electric motor is a prime example of a system, where failure occurring at an inopportune time can be inconvenient, expensive and possibly dangerous. The current through an unhealthy electric motor is a non-stationary signal and the minor transients it may contain makes Fourier methods unsuitable for analysis. Wavelets [1] on the other hand, are an excellent tool for the analysis of non-stationary signals. Using wavelet decomposition, information about the health of the system can be extracted from a signal over a wide band of frequencies and the analysis is localized in both the time and frequency domains.

In this work [2] we started with the assumption that specific conditions leading to faults produce short transients on the currents of electrical motors. We developed the analysis and computational tools to recognize these transients and applied them to two types of automotive motors. Two techniques are used in this work to discriminate between machine faults. One technique is deterministic in nature and used an *if-then-else* set of rules directly on results from the wavelet decomposition of the current through a machine to identify and distinguish between faults. The second technique focuses on mapping the wavelet decomposition of the current into a multi-dimensional space, clustering the resultant vectors, and using several variants of the nearest neighbor rule [3] to distinguish faults. In the remaining of this paper the term fault means a condition of the motor that allows its continuous operation, but may eventually lead to failure.

II. BACKGROUND

A. Wavelets and Filter Banks

Classical frequency domain analysis, such as Fourier series, is best suited for stationary signals which are periodic in nature. Fourier series analysis provides the ability to localize a signal in frequency. It can not, however, localize a signal in time, since its basis functions are sinusoids, which have an infinite amount of energy spreading out over all time.

Wavelets on the other hand, are a good tool for the analysis of non-stationary signals having transient behavior. The basis functions of a wavelet system, the scaling function $\varphi(t)$ and the wavelet function $\psi(t)$, have finite energy, which is concentrated around a point. This property gives a wavelet system the ability to localize any $L^2(\mathbf{R})$ signal in both time and frequency.

Both scaling and wavelet functions can be derived from a single scaling or wavelet function by scaling and translation. A scaling function, $\varphi_{j,k}(t)$, both scales and translates a function $\varphi(t)$, where j is the $\log_2$ of the scale and $2^{-j}k$ represents the translation in time (1).

$$\varphi_{j,k}(t) = 2^{j/2}\varphi(2^j(t - 2^{-j}k)) \quad j,k \in \mathbf{Z} \quad \varphi \in L^2 \quad (1)$$

The same is true in the case of a wavelet function (2).

$$\psi_{j,k}(t) = 2^{j/2}\psi(2^j(t - 2^{-j}k)) \quad j,k \in \mathbf{Z} \quad \psi \in L^2 \quad (2)$$

The wavelet function $\psi(t)$ for the case where j=k=0 is often referred to as the mother wavelet.

Any function in $L^2(\mathbf{R})$ can be written as an expansion of a scaling function and wavelets (3), where $c_{j_0}(k)$ are the scaling function coefficients, $\varphi_{j_0,k}(t)$ is the scaling function at the initial scale j_0, $d_j(k)$ are the wavelet function coefficients and $\psi_{j,k}(t)$ are the wavelet functions spanning the space between $\mathcal{V}_{j_0}$ and L^2.

$$f(t) = \sum_{k=-\infty}^{\infty} c_{j_0}(k)\varphi_{j_0,k}(t) + \sum_{k=-\infty}^{\infty}\sum_{j=j_0}^{\infty} d_j(k)\psi_{j,k}(t) \quad (3)$$

We implement the discrete wavelet transform on a computer by using only additions and multiplications to perform convolutions. The scaling and wavelet function coefficients are calculated using filter banks. We define the scaling function coefficients for a coarse scale from the scaling function coefficients at the next finer scale by convolving the coefficients at the finer scale with the recursion coefficients $h_0(n)$ and then down-sampling (4). $h_0(n)$ is often referred to as the decomposition low-pass filter. We can do the same in the case of the wavelet coefficients using the recursion coefficients $h_1(n)$ (5). $h_1(n)$ is often referred to as the decomposition high-pass filter.

$$c_j(k) = \sum_m h_0(m - 2k)c_{j+1}(m) \quad (4)$$

$$d_j(k) = \sum_m h_1(m - 2k)c_{j+1}(m) \quad (5)$$

B. Nearest Neighbor Rule

In order to categorize a sample point in d-dimensional space into a set of previously classified points, we use the nearest neighbor rule (1-NN). We assume that observations which are close to each other (in some appropriate metric) will have the same classification [4]. Using this technique we developed a method based on wavelet analysis to recognize the presence of a fault and two different methods to discriminate between faults. We applied these techniques to two sets of DC automotive motors, windshield wiper and fuel pump ones. The current signals for the first were derived for operation at wet and dry windshield at two speeds, and for the second operation at different fuel pressures.

III. ANALYSIS METHODS

In building the detection and classification algorithm, fifteen mother wavelets were used. Tables were built comparing the coefficient resulting from each mother wavelet over ten levels of decomposition. Tables I, II, and III give the wavelet coefficients at ten different levels, resulting from the analysis of the current in five motors, using a variety of mother wavelets, under the same operating conditions. The coefficients that exceeded the ones of 'healthy' motors by 5% are marked in black.

We used this observation at the detection phase of the algorithm; it was considered that a fault is present when one of the wavelet transform modulus maxima exceeded this threshold of 5% above the maximum of the modulus maxima observed on new good motors.

It can be noticed that for each fault there is a generally similar distribution of the coefficients exceeding the threshold values. This observation motivated the first approach, where a faulty motor is categorized based on a decision tree.

The second method is based on the observations that:

1. The same fault may manifest itself on different motors with relatively small variations in the coefficients that exceed the threshold corresponding to that fault,
2. the same fault, but of different degree of severity, will cause coefficients of neighboring levels to exceed the corresponding thresholds.

To determine which mother wavelet(s) are to be used in the analysis, we chose the one that produced the minimum number of maxima in the modulus of the wavelet coefficients (5) necessary to detect the desired irregularities in the signal [5] that resulted from a specific fault. In general the number of wavelet maxima increases proportionally to the number of irregularities in the signal. Also, the number of maxima at a given scale often increases linearly with the number of vanishing moments in the wavelet.

A. First Method of Classification

For the classification strategy an additional localization parameter, α, is defined in (6) if and only if the criterion for detection is met, i.e. for at least one level of decomposition, i, the coefficient of the test motor, d_i was higher than the threshold level $\hat{d}_i$, $d_i - \hat{d}_i > 0$.

$$\alpha = \frac{\sum_{i=1}^{10}(i \times (d_i - \hat{d}_i))}{\sum_{i=1}^{10}(d_i - \hat{d}_i)} \quad d_i - \hat{d}_i > 0 \quad (6)$$

Then the decomposition coefficients as well as the parameter α are used in a decision tree to categorize the fault.

TABLE I

Modulus maxima of the wavelet coefficients for motors with Fault D (shaded coefficients are above the corresponding threshold)

level	1	2	3	4	5	6	7	8	9	10
db1	0.717093	0.820063	0.752505	0.766853	0.900793	0.590006	0.879767	1.504751	4.140991	9.42641
db4	0.69268	0.707528	0.803055	0.653901	0.946526	0.526287	0.541581	0.493274	0.758289	5.921158
db7	0.569517	0.721924	0.651035	0.749868	0.998592	0.475737	0.589265	0.513786	0.655265	4.898857
db10	0.630688	0.582064	0.607427	0.688686	1.007181	0.527558	0.528321	0.705984	0.514883	3.75176
bior2.2	0.513474	0.939003	0.986833	0.899144	1.421663	0.717133	1.136949	0.986394	1.252359	5.20985
bior2.8	0.513474	0.941099	1.072152	0.862459	1.508311	0.509889	0.70256	0.749227	1.063549	5.566987
bior3.5	0.473636	1.033722	1.239877	0.873671	2.025743	1.012536	1.141763	0.938268	1.20116	4.07039
bior6.8	0.55704	0.83863	0.861185	0.732841	1.06151	0.45079	0.580475	0.551084	0.647608	4.844287
coif1	0.605858	0.905969	0.769876	0.71847	0.952749	0.560384	0.640424	0.709703	1.53381	7.227646
coif3	0.575787	0.843728	0.786734	0.725139	0.977852	0.446878	0.5685	0.508019	0.648964	5.39482
coif5	0.564062	0.812591	0.72297	0.736863	1.032048	0.435888	0.542352	0.480244	0.594193	4.681002
sym2	0.623361	0.800808	0.747439	0.724487	0.916117	0.547293	0.63882	0.756953	1.788106	6.331952
sym4	0.546735	0.832419	0.755916	0.679571	0.971832	0.575874	0.565442	0.48004	0.777677	5.795135
sym6	0.5443	0.823535	0.757493	0.733413	0.976857	0.511151	0.594311	0.50164	0.678997	5.235544
sym8	0.544479	0.815737	0.799806	0.731826	0.961435	0.445064	0.571001	0.492958	0.631554	5.053121

D2

level	1	2	3	4	5	6	7	8	9	10
db1	0.876447	0.826322	0.730372	0.691732	0.798983	0.456981	0.872021	1.587696	4.165889	10.028937
db4	0.73854	0.788259	0.711716	0.591608	0.851694	0.350834	0.429406	0.442357	0.904319	5.300098
db7	0.752271	0.701224	0.669457	0.628284	0.898655	0.31251	0.453662	0.402881	0.746629	5.274361
db10	0.702385	0.622199	0.587454	0.630435	0.910626	0.290563	0.41254	0.413045	0.66748	4.759
bior2.2	0.63299	0.834147	0.987662	0.819769	1.316728	0.560204	0.897954	0.85479	1.193269	5.900039
bior2.8	0.63299	0.876153	0.93891	0.729246	1.462225	0.359576	0.514715	0.670696	1.213433	6.107591
bior3.5	0.564379	1.055467	1.146244	0.760775	1.949106	0.609384	1.065876	0.964778	1.067884	2.854382
bior6.8	0.697716	0.779069	0.763416	0.5786	1.068783	0.287251	0.432271	0.446129	0.519302	4.79501
coif1	0.733525	0.818221	0.795788	0.668446	0.890702	0.412417	0.481984	0.620405	1.756283	7.518838
coif3	0.719335	0.772833	0.716835	0.595324	0.988765	0.326513	0.426861	0.424504	0.529224	5.277242
coif5	0.711795	0.743291	0.741355	0.613053	0.937002	0.264622	0.394169	0.413949	0.603606	3.721771
sym2	0.769987	0.852382	0.857762	0.653797	0.894325	0.339856	0.469755	0.53556	1.627138	7.73751
sym4	0.7547	0.851575	0.722007	0.583315	0.93874	0.438712	0.458667	0.473155	0.663723	5.862317
sym6	0.752505	0.784341	0.732509	0.576578	0.946864	0.374795	0.423302	0.416146	0.528854	5.056883
sym8	0.747705	0.796333	0.721757	0.579698	0.985539	0.289957	0.411865	0.413753	0.546052	4.895758

D3

level	1	2	3	4	5	6	7	8	9	10
db1	0.79677	0.851362	0.832182	0.873271	1.060147	0.622872	1.155317	1.550137	4.215688	9.854437
db4	0.728575	0.749646	0.690037	0.811524	1.116601	0.490156	0.631988	0.656383	0.906199	5.628133
db7	0.653634	0.658203	0.618599	0.754815	1.150876	0.460059	0.490921	0.567373	1.103164	4.392732
db10	0.668243	0.590935	0.559203	0.878686	1.120792	0.366046	0.513157	0.535771	0.615391	3.400422
bior2.2	0.610857	0.967173	1.01353	1.049923	1.45229	0.913676	1.490278	0.992435	1.788413	5.671198
bior2.8	0.610857	0.87755	0.968872	1.00073	1.596031	0.604099	0.655149	0.883687	1.422175	5.621316
bior3.5	0.542246	1.021978	1.176774	1.133381	2.34987	1.068038	1.433092	1.093838	1.073193	3.877563
bior6.8	0.654908	0.770512	0.76594	0.793075	1.209837	0.447794	0.522811	0.605361	0.725346	3.370112
coif1	0.729718	0.890472	0.80978	0.856566	1.015279	0.585558	0.681679	0.684572	1.861496	7.722182
coif3	0.681149	0.802548	0.754393	0.794596	1.126368	0.465887	0.528102	0.576031	0.712375	4.021609
coif5	0.665032	0.762823	0.706794	0.725734	1.102482	0.41286	0.506336	0.536795	0.754062	3.121422
sym2	0.76628	0.791867	0.820578	0.775866	1.076362	0.558434	0.645622	0.770003	2.162294	7.643172
sym4	0.658727	0.866242	0.79919	0.786391	1.062282	0.478361	0.527436	0.57286	1.057089	5.384972
sym6	0.652568	0.754969	0.759386	0.794017	1.080811	0.474069	0.534605	0.575611	0.762755	4.087421
sym8	0.64971	0.811722	0.720263	0.795805	1.134761	0.44812	0.515822	0.5589	0.690876	3.531158

TABLE II

Modulus maxima of the wavelet coefficients for a motor with Fault A (shaded coefficients are above the corresponding threshold)

level	1	2	3	4	5	6	7	8	9	10
db1	0.513474	0.582182	0.756932	1.145583	1.739614	1.508664	2.496546	3.807655	5.29686	9.715154
db4	0.422865	0.429809	0.603463	0.950324	2.300884	0.99721	1.914328	3.483603	3.241646	4.060825
db7	0.41593	0.394768	0.58911	1.0034	1.812486	0.890732	1.875576	3.363273	2.410555	4.484548
db10	0.369776	0.30445	0.461134	0.965922	1.98793	0.755256	1.649983	3.521698	2.382792	4.490138
bior2.2	0.393959	0.522712	0.913104	1.346343	2.437904	1.596848	2.363269	3.697593	5.597795	4.943661
bior2.8	0.393959	0.470764	0.825215	1.534214	2.535671	1.501542	2.234632	3.693707	4.861101	5.541678
bior3.5	0.336414	0.502464	1.095436	1.322298	3.437006	1.534607	2.884319	5.287654	8.946649	3.531382
bior6.8	0.42635	0.434695	0.606614	1.151904	1.939629	1.138326	1.740938	3.415566	2.961759	4.506663
coif1	0.472075	0.467598	0.904497	1.320279	1.93399	1.228725	2.565532	3.273147	3.837351	6.569654
coif3	0.444789	0.426173	0.544751	1.305831	1.902381	1.140047	1.940735	3.470469	2.594194	4.933213
coif5	0.437515	0.409235	0.69339	1.006335	1.812872	1.003593	1.617204	3.475818	2.381632	4.221958
sym2	0.443115	0.491402	0.836392	1.242546	1.761853	1.241268	2.305281	3.12097	3.830718	7.995317
sym4	0.443502	0.477825	0.73251	1.209615	1.910022	1.151371	2.403285	3.354932	2.930309	4.601186
sym6	0.43862	0.427136	0.617977	1.32771	1.880696	1.184823	2.107537	3.451377	2.77247	4.654624
sym8	0.435855	0.41157	0.614932	1.145949	1.890589	1.094035	1.803262	3.481211	2.562204	4.530842

TABLE III

Modulus maxima of the wavelet coefficients for a motor with Fault E (shaded coefficients are above the corresponding threshold)

level	1	2	3	4	5	6	7	8	9	10
db1	0.646269	0.663561	0.588724	0.791892	1.000389	0.885793	1.279259	2.953945	5.999567	12.556028
db4	0.561365	0.573707	0.505324	0.739772	1.090303	0.768941	0.71212	0.854309	1.321452	11.713396
db7	0.514442	0.491153	0.453078	0.689727	1.207884	0.342286	0.812168	0.804804	1.261869	8.997866
db10	0.541019	0.447667	0.435444	0.796316	1.203778	0.446171	0.57411	0.780158	1.010741	6.108969
bior2.2	0.482488	0.652607	0.739779	0.817128	1.523296	0.834381	1.411862	1.384348	2.180015	9.745206
bior2.8	0.482488	0.618056	0.715968	0.857362	1.756006	0.627119	0.973147	1.597413	2.320773	10.644165
bior3.5	0.451503	0.697576	0.834557	1.169104	2.305631	1.695044	1.740163	1.667718	1.541356	6.376933
bior6.8	0.534394	0.546305	0.559736	0.73252	1.270019	0.521261	0.788228	0.908929	0.932877	7.044127
coif1	0.566576	0.580389	0.574688	0.753122	1.115104	0.511131	0.845	1.349346	3.249909	13.206152
coif3	0.549131	0.549624	0.480131	0.745358	1.206512	0.456169	0.790675	0.809716	1.077559	8.327276
coif5	0.545279	0.534005	0.520833	0.810629	1.18016	0.464684	0.803008	0.826633	0.837175	6.223895
sym2	0.610369	0.666562	0.538594	0.747102	1.060233	0.556836	0.822889	1.153094	2.928657	13.212822
sym4	0.549269	0.61526	0.477629	0.731368	1.128973	0.367594	0.70255	0.880617	1.776192	10.617813
sym6	0.541391	0.557133	0.494215	0.770879	1.144058	0.441942	0.751476	0.819115	1.198038	8.818546
sym8	0.535454	0.563422	0.519535	0.748373	1.229421	0.465468	0.780527	0.80036	0.938683	7.440583

B. Second Method of Classification

The second approach to the detection and classification problem was implemented on both windshield wiper and fuel pump motors and represents a refinement of the first . When examining the modulus maxima of the wavelet coefficients from the motors with the same fault as in the first method, it can be seen that the coefficients are not exactly the same, however they follow the same general pattern. In this analysis, these coefficients were represented as a ten-dimensional vector.

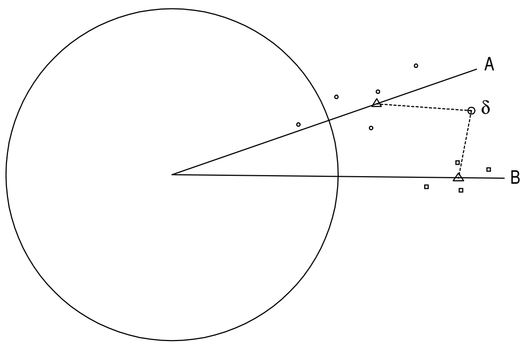

Fig. 1. Euclidean distance for a non-normalized set of points

The classification part of the algorithm involves two steps: During the training part of the algorithm the lengths of the vectors from each motor with known faults are normalized, and the coefficients of the normalized vectors from faults of the same type are averaged. The resultant vectors serve as the centers of each fault cluster. The radius of each fault cluster is also determined in this stage, to include all the motors with a known fault.

In the characterization stage of a motor that has been determined to have a fault, again the vector corresponding to the coefficients resulting from wavelet analysis is normalized. Through this normalization only the direction of the coefficient vector determines the type of fault. The classification strategy consists then of finding the center of an already identified fault cluster, on the 10-dimensional unit sphere, which has the minimum Euclidean distance from the vector of the normalized coefficients of the test motor. If the normalized coefficient vector representing a test motor does not fall into one of the fault clusters, it is said that the motor does not have any of the known faults.

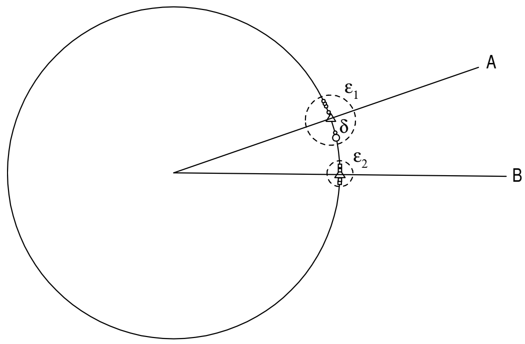

Fig. 2. Euclidean distance for a normalized set of points

A two-dimensional example of this technique is shown in Fig. 1 and 2. Here an attempt is made to classify the point δ (which corresponds to a motor with fault A) as corresponding to either fault A or B, and therefore belonging to the corresponding cluster. Points marked with a circle belong to cluster A and the points marked with squares belong to cluster B. The triangles represent the average of the vectors from each cluster. If δ is determined to belong to the cluster having the minimum Euclidean distance between δ and the cluster center, δ will be classified as part of cluster B rather than cluster A. This is similar to how the motor faults manifest themselves in the ten-dimensional space. Experimentation showed that the motor faults could be classified much more accurately by using a normalized Euclidean distance which is shown in Fig. 2. It is clear, after normalization that δ is closer to the center of cluster A.

If, however, δ were positioned slightly lower in the figure than it is, its normalized Euclidean distance would again classify it incorrectly as within B. This is due to the fact that cluster A has greater diameter than cluster B. To remedy this situation, a ball of radius ε was assigned to serve as a valid region for each cluster. This can be seen in Fig. 2 where ε_1 is the valid region for A and ε_2 is the valid region for B. Each test motor was therefore classified by finding its minimum normalized Euclidean distance within a radius ε from the center of each fault cluster. If the test motor did not fall within the radius ε_i from the center of any of the fault clusters i, it was classified as a good motor, or at least free of the faults which had been previously identified.

If the clusters on the unit sphere that correspond to each fault are small and distant from each other, then the algorithm discriminates accurately between faults. If, on the other hand, these clusters are large and the distance between their centers is small, that the algorithm is not as accurate. In the implementation of the second algorithm the quality of the clustering was measured by the ratio of the average cluster radius to the average distance between clusters. An illustration of this is shown in Fig. 3, where A and B are clusters, x and z are their radii , and y is the distance between the centers of clusters A and B. All measurements are made on the unit circle. This discriminating ratio, r, in this case is defined as in (7):

$$r = 1 : \frac{y}{\frac{x+z}{2}} \tag{7}$$

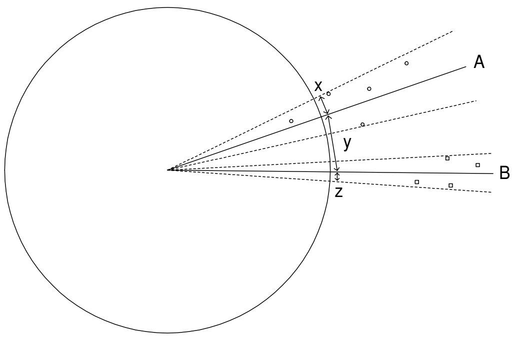

Fig. 3. Ratio of average cluster radius to average distance between clusters

The first approach to the detection and classification problem was implemented on DC windshield wiper motors. The algorithm uses an *if-then-else* set of rules on the modulus maxima of the wavelet coefficients from the first ten different levels of decomposition. Daubechies's D8 and the C18 Coiflet were used as mother wavelets for decomposition.

The only parameters required by the second algorithm were the modulus maxima of the coefficients from the decomposition, using the Biorthogonal 3.5 mother wavelet. For the windshield wiper motors, data was only required from low speed dry windshield testing and for the fuel pump motors, data was only used from testing at 250 kPa. This was one-fourth the amount of data that was required for the first approach.

IV. EXPERIMENTAL SETUP

A. *Wiper Motor Experimental Setup*

The experimental setup in the wiper motor testing is shown in Fig. 4. Torque profiles of the wiper system under different environmental conditions were applied. The torque profile for the wiper motor running in low speed mode on a dry windshield is shown in Fig. 5.

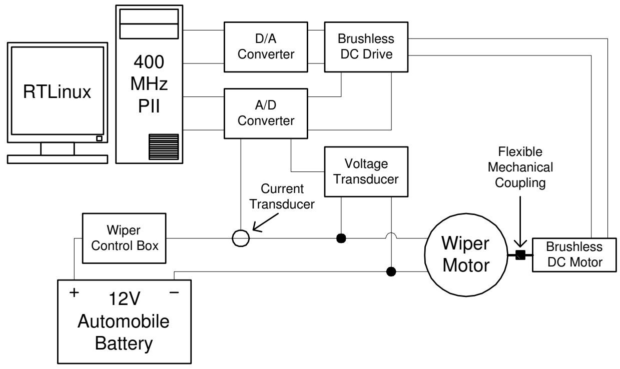

Fig. 4. Wiper motor experimental setup

Fig. 5. Wiper motor profile for low speed operation on dry glass

To develop and test the various detection and classification algorithms, both new windshield wiper motors, as well as motors that were manufactured to have specific faults known to significantly shorten their lives were analyzed. There were a variety of these faults; two due to poor brush contact, one the result of a faulty speed reduction mechanism, one due to shaft misalignment, three due to foreign materials, and one due to a faulty mechanism.

B. *Fuel Pump Experimental Setup*

The experimental setup for the fuel pump motor testing is shown in Fig. 6. As with the wiper motors, both new fuel pump motors as well as motors that were manufactured to have specific faults known to significantly shorten their lives were analyzed. Two of these faults were the result of increased resistance in one coil and one fault was due to an uneven commutation surface.

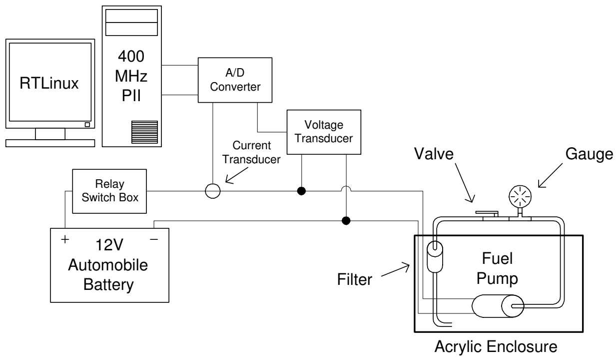

Fig. 6. Fuel pump experimental setup

V. EXPERIMENTAL RESULTS

Experiments were conducted on a number of wiper and fuel pump motors, both to determine the parameters needed and to categorize the motors. Of the wiper motors the first algorithm was able to detect and classify correctly 16 of the 19 motors used. The second algorithm on the other hand was able to detect the presence or absence of faults in 23 of the 24 motors tested, and to correctly classify 20 of 21 motors with faults. Of the fuel pump motors, the second algorithm was able to detect the presence or absence of faults in 27 of the 28 motors tested, and to correctly classify 21 of 22 motors with faults.

In the implementation of the first algorithm, it was observed that the modulus maxima of the coefficients of the wavelet transform for all of the motors having a given type of fault manifest themselves in a unique way. It was also observed that the localization parameter remained relatively constant for all motors with the same fault type. Motors having other faults showed similar behavior in that the modulus maxima of their wavelet coefficients manifested themselves in a similar way to each other but differently from motors with other faults.

For the wiper motor analysis, the discrimination ratio was $1 : 3.378$, and for the fuel pump motor analysis the ratio was $1 : 0.703$. In any case, a higher ratio indicates more closely spaced points and better separation between clusters.

VI. CONCLUSIONS

Two techniques have been developed and were used to detect and classify conditions in electric motors, defined as faults, that will result in a reduction in performance and eventual failure. The approaches developed would be useful in several situations, in particular as a system to monitor the health of electric motors either in a vehicle or at the end of an assembly line. By using these strategies, a prognosis for the failure of an electric motor can be made. Although both algorithms performed well, the second one was easier to implement and more accurate, as it could easily adapt to different types of faults, and fewer subjective decisions regarding its implementation were required. Measures of quality of performance were developed for the second method.

Both methods were implemented in the laboratory and experiments provided verification of their validity.

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