DATA MINING FOR VEHICLE TELEMETRY

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Abstract

This paper presents a data mining methodology for driving condition monitoring via CAN-bus data that is based on the general data mining process. The approach is applicable to many driving condition problems and the example of road type classification without the use of location information is investigated. Location information from Global Positioning Satellites and related map data are often not available (for business reasons), or cannot represent the full dynamics of road conditions. In this work, Controller Area Network (CAN)-bus signals are used instead as inputs to models produced by machine learning algorithms. Road type classification is formulated as two related labelling problems: Road Type (A, B, C and Motorway) and Carriageway Type (Single or Dual). An investigation is presented into preprocessing steps required prior to applying machine learning algorithms, namely, signal selection, feature extraction, and feature selection. The selection methods used include Principal Components Analysis (PCA) and Mutual Information (MI), which are used to determine the relevance and redundancy of extracted features, and are performed in various combinations. Finally, as there is an inherent bias towards certain road and carriageway labellings, the issue of class imbalance in classification is explained and investigated. A system is produced, which is demonstrated to successfully ascertain road type from CAN-bus data, and it is shown that the classification correlates well with input signals such as vehicle speed, steering wheel angle, and suspension height.

Keywords: Data mining, Driving condition monitoring, Feature selection, Road classification

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1 Introduction

Driving conditions monitoring aims to detect parameters about the road and a vehicle's surroundings (Huang et al., 2011), such as the road surface, level of congestion, or weather. Knowledge of the current driving conditions can have several benefits: user interface adaptation, engine power management, and driver monitoring (Huang et al., 2011; Langari and Won, 2005; Murphey et al., 2008; Park et al., 2008); all of which strive to improve driver safety and vehicle efficiency. In this paper we present a data mining methodology, based on the general data mining process, for driving condition monitoring via Controller Area Network (CAN)-bus data. Two related classification problems are considered, Road Type labelling (into types A, B, C and Motorway) and Carriageway Type labelling (into types Single or Dual). Road Type labelling aims to detect the state or governmental designation of roads from vehicle telemetry data. Using the same inputs, Carriageway Type labelling aims to detect whether the vehicle is being driven on a single or dual (or multi) track road.

In some instances, the road type can be determined with location and map data using Global Positioning Systems (GPS). However, although in principle it is an accurate system, it can be impractical or unsuitable because in many vehicles and locations, GPS signals are unavailable, or access to digital maps is costly and unreliable, and map data may be unavailable or outdated for a region. Another issue with digital map data with state road type designations is that these may not be reflective of the current driving conditions. In the UK, for example, class A roads can be fast dual carriageway roads in the countryside as well as restricted speed single track roads in congested urban areas. Furthermore, location information does not take into account changes in traffic flow, which may fluctuate throughout the day and is affected significantly by accidents and roadworks. For these reasons it can be preferable to make a business decision to exclude GPS data for certain driving conditions monitoring applications.

This paper, therefore, approaches the road type classification problem without recourse to GPS and maps, and instead relies on data mining of sensor data that is accessible via a vehicle's CAN-bus (Farsi et al., 1999). Vehicle sensors provide signal data including steering wheel angle, wheel speed, gear position, and suspension movement. The CAN-bus enables the communication between such sensors and actuators in the vehicle via a message-based protocol, without a central host. Messages sent between devices in the vehicle can be recorded and post-processed in order to sample sensor measurements at a certain frequency. Our proposed classification system uses machine learning, in a data mining framework, to correlate CAN-bus signals to pre-learned class labels, such as road types. With this approach, sudden and unexpected changes in driving conditions on a road can be taken into account, which is not possible when using location data without external data sources. If an accident significantly affects the driving conditions on a motorway, for example, a model based on speed and suspension measurements should be able to change its output appropriately.

CAN-bus data consists of thousands of signals sampled at high frequencies for hours at a time, generating very large datasets. Selecting which signals, and features of signals, to use is a challenging task, with engineers often hand picking model inputs from thousands of signals (Taylor et al., 2012). This manual selection, as well as being tedious, can introduce deficiencies into systems, as selection may be due more to an engineer's knowledge and preferences rather than the true usefulness of a signal. In this work, we also propose an automatic feature selection framework which might aid engineers in building better models for environment monitoring problems in general.

This paper makes the following key contributions:

- A methodology, based on the general data mining process (John, 1997), is presented for driving conditions monitoring problems such as road classification.
- Two related temporal classification problems are presented, using data collected from two cars with multiple drivers over 16 journeys. This provides a strong evaluation framework where models are tested on data from different journeys to those that were used to build them.
- An approach to the pre-processing of CAN-bus data is developed; including signal selection, feature extraction and feature selection.
- The methodology is applied to create a system that is able to successfully detect the current road type in real time, using only 2.5 seconds of historical data.

The remainder of this paper is structured as follows. In Section 2, literature on data mining of CAN-bus data and driving conditions monitoring is reviewed. Section 3 outlines a data mining methodology for problems of this kind. Details of the data and experimental process are described in Section 4, including the feature extraction and selection processes used. The results of our investigations are then presented in Section 5. Finally, in Sections 6 and 7, we discuss the results, draw conclusions and identify future steps.

2 Related work

Data mining of CAN-bus data has been used in several applications, including fault detection (Crossman et al., 2003; Guo et al., 2000), driver monitoring (Mehler et al., 2012; Taylor et al., 2013b), and driving conditions monitoring, which is surveyed by Wang and Lukic (2011) and is the focus of this paper. Fault detection aims to determine whether there is a vehicle failure and what may have caused the it. Whereas fault detection is usually performed offline in a workshop, driver monitoring and driving conditions monitoring operate while the vehicle is being driven. For instance, they aim to predict parameters about the driver and their surrounding environment, so that the driver interface can be adapted or the engine tuned.

In fault detection, both Guo et al. (2000) and Crossman et al. (2003) successfully apply wavelet analysis to split telemetry signals into segments, from which several features are extracted. The extracted features include the segment length, minimum and maximum values, as well as averages and fluctuations. A fuzzy rule classification algorithm is then used to determine whether the original signal was normal, or abnormal and indicative of a fault.

Driver monitoring aims to determine parameters of the driver, such as their attentiveness to the road or skill level. Detection of inattention is often performed from both CAN-bus data and other physiological measurements, such as heart rate or electrodermal activity (Mehler et al., 2012; Taylor et al., 2013b). In particular, when a driver is performing additional tasks unrelated to driving and is under higher workload, changes can be observed in features of the steering wheel angle (SWA) (Mehler et al., 2012). To determine the skill level of drivers, Zhang et al. (2010) use vehicle simulator telemetry data from typical and expert drivers as they performed several manoeuvres. As typical drivers were more numerous than experts, the data was re-sampled so that it included the same number of typical drivers as experts, although under-sampling of manoeuvres from all drivers may have been more appropriate. The Discrete Fourier Transform of the SWA was used in Artificial Neural Networks, Decision Drees, and Support Vector Machines, achieving comparable performances.

In this paper, we consider the driving conditions monitoring problem of road classification. Whereas driver monitoring focusses on driver state inside the vehicle, driving conditions problems relate to the outside environment, including the traffic levels, and road type (Huang et al., 2011; Langari and Won, 2005; Wang and Lukic, 2011). Driving conditions and road type can be defined in several ways, including level of service (Carlson and Austin, 1997; Langari and Won, 2005; Murphey et al., 2008), descriptive (Hauptmann et al., 1996; Huang et al., 2011; Qiao et al., 1995; Tang and Breckon, 2011; Taylor et al., 2012), and government classification (Taylor et al., 2012). Possibly the most used definition in research is that provided by Carlson and Austin (1997), based on level of service and driving cycles. Level of service and driving cycles are qualitative measures describing observed operational conditions (Langari and Won, 2005), and therefore may be subjective. Descriptive definitions are of most use, as they have a direct relationship to the current situation and environment. For example, Huang et al. (2011) use the labels highway, urban road (both congested and flowing), and country road. Hauptmann et al. (1996) use an even more direct classification structure, based upon current car behaviour. Their five labels range from very fast, straight line driving on flat roads, to very low speeds or stop. These are used to represent further driving situations, such as highway driving, and traffic lights or parking.

Wang and Lukic (2011) provide a survey for driving conditions prediction, with the focus on Hybrid Electric Vehicles. They recognise that many researchers use drive cycles for a road definition, and use only information from the vehicle speed in their models. For example, average velocity and acceleration, as well as peak accelerations and percentage of time in certain speed intervals are often used (Huang et al., 2011; Langari and Won, 2005; Murphey et al., 2008; Park et al., 2008). These features are also often extracted from 150 seconds of data in order to produce good classification performances (Wang and Lukic, 2011). These approaches have clear limitations in determining the current driving conditions. First, steering wheel behaviour is likely to differ in different situations, providing additional predictive information. Second, if features are extracted from large amounts of temporal history, the model is likely to be slow to react to changes in environment.

Other authors have used different features in addition to those extracted from speed cycles. Hauptmann et al. (1996), for example utilize engine speeds, accelerations, and gradient. Additionally, Qiao et al. (1995) extract features from the pedal positions, temperatures and selected gear. These features, however, although they contain different information from the vehicle speed, are all related to it. Engine speed, for example, has a Pearson correlation with vehicle speed of 0.96 on data we have collected, meaning that it is adding little new information into the system. Qiao et al. (1996) note that the length of the temporal window that features are extracted over is an important factor in the system's reaction time and they use a much smaller window length of 6.25 seconds. One shortfall in their work, however, is that automatic feature selection is not performed and features are selected based on the intuition of the researchers.

Examples of feature selection being used in this domain are mainly those that use features extracted from speed cycles. Murphey et al. (2008) and Park et al. (2008) proposed a selection procedure based on binary class separability of single features: if a feature is able to distinguish one class label from the others, then that feature is selected. Huang et al. (2011) also use a non-parametric, one-way analysis of variances to ensure that features used are relevant, and use cross correlation analysis to remove redundancy. They investigate 11 features in total, with only 4 being manually selected for classification. When dealing with CAN-bus data, however, the number of signals and features can be in the order of 1000 seconds, meaning automatic approaches are necessary (Taylor et al., 2013a).

A final approach to the problem of road classification is the use of visual inputs, e.g. from front mounted cameras, and applying image processing techniques (Jansen et al., 2005; Tang and Breckon, 2011). In their work, Tang and Breckon (2011) use color, texture and edge features from image sub-regions as inputs into a neural network, and using colour analysis, Jansen et al. (2005) identify the terrain type. Such systems are limited because they rely on non-standard sensors, generally need greater computational processing and are severely affected by poor lighting conditions, such as night-time driving.

3 Data mining methodology

The methodology we present is based on a general framework for data mining outlined by John (1997). As in (Huang et al., 2011; John, 1997), and others, we use the term *data mining* to refer to the process of collecting, processing, and learning from data as a whole. The methodology presented in this paper is of a similar form to those found in many temporal data mining applications, including (Constantinescu et al., 2010; Huang et al., 2011; Kargupta et al., 2004; Manimala et al., 2012; Sagheer et al., 2006; Shaikh et al., 2011; Wollmer et al., 2011) and others, and is split into stages of: data collection; feature extraction; feature selection; classification and evaluation. In this paper, we also consider selection of signals, prior to feature extraction. This has the advantage of saving computation, as only selected signals have to be processed later in the data mining process.

3.1 Data collection

The data collection must be planned carefully for data mining to be successful. First, the conditions under which data is to be collected, as well as what data should be recorded must be decided. It is important to control the acquisition conditions so that results become meaningful. Deciding on which data to record from vehicle telemetry is non-trivial, because of the thousands of signals available via the CAN-bus (Farsi et al., 1999). Recording and analysing all of them is an impossible task, so most researchers make educated guesses based on domain knowledge.

Second, the data representation should be in a form that is suitable for subsequent processing. For instance, the CAN-bus is an event based communications network where sensors broadcast data at varying rates (Farsi et al., 1999), so consequently, some data mining methods will not be directly applicable. It is typical therefore to re-sample the data at a common rate, e.g. between $10 - 100$Hz, producing M signals, $S_1, S_2, \ldots, S_M$, with samples of the same frequency.

Finally if the problem is to be posed as one of classification, the ground truth used to derive the labels must be assigned in a consistent and reliable way. Improper label assignment can lead to noise in the learning process leading to poorer classification results. Drive cycles can be generated for each label and treated as separate in order to simplify later processing (Huang et al., 2011). Treating the data in this way, however, ignores any transition periods where a label change occurs. This may cause an evaluation to prefer models that use large amounts of historical data, but have slow reactions to changes in environment. In this paper, we consider the more realistic scenario of journeys which contain several periods of differing labels. Although this introduces noise during label changes, we believe this approach will provide more accurate performance estimates that do not ignore these reaction times.

3.2 Feature extraction

In temporal data mining, it is advantageous to include historical information when performing classification (Antunes and Oliveira, 2001). Without this, an individual sample contains only information about the exact point that sensor measurements were made, which may be noise. This means that no trend or statistical information can be used in determining the classification. We refer to this process of incorporating historical information into the current sample as *temporal feature extraction*.

Consider a signal, S, of length T, such as the vehicle speed or SWA.

$$f(S(t), S(t-1), ..., S(t-l+1)) = f(S(t,l)),$$

where $f(S(t,l))$ is a temporal summary of the values between times t and $t-l+1$. If $t < l$, because it is at the beginning of the recorded signal, t samples are used. Features can generally be split into two categories, namely structural and statistical. Structural features describe the trend of the signals, whereas variations, peaks, and averages are represented by statistical features.

In each time instance, m signals, $S_1(t), S_2(t), ..., S_m(t)$ are sampled, from each of which k features, $f_1, f_2, ..., f_k$ are extracted. Therefore, after feature extraction, a sample, $x(t)$, at time t, is represented as,

$$\begin{aligned} x(t) = \{&f_1(S_1(t,l)), ..., f_1(S_m(t,l)); \\ &f_2(S_1(t,l)), ..., f_2(S_m(t,l)); \\ &...; \\ &f_k(S_1(t,l)), ..., f_k(S_m(t,l))\}. \end{aligned}$$

It should be noted here that in some cases, different features may be extracted over different temporal windows from each signal, meaning that the value of k and l may vary between signals and features in the same dataset. Finally, whereas Huang et al. (2011) extract features from windows with no overlap, in this paper features are extracted over sliding windows with an overlap of $l - 1$. This means that a temporal dataset of length T, is a sequence of samples,

$$X = x(1), x(2), ..., x(T-1), x(T).$$

This method both maximizes the number of samples and means their number is not dependent on window length. The overlap in windows does increase the autocorrelation in the data, however, which can be problematic for some data mining methods.

3.3 Signal and Feature selection

As previously stated, signals and features are often hand selected using domain knowledge. This is sub-optimal and time consuming, however, and may introduce biases toward the engineer's preferences. We therefore use automatic selection of both signals, prior to feature extraction, and features, after feature extraction. We consider two common feature selection methods, Principal Component Analysis (PCA), an unsupervised method for redundancy feature selection, and Mutual Information (MI), a supervised method for relevancy feature selection (Witten and Frank, 2005).

PCA transforms a dataset onto a set of orthogonal dimensions which are linearly uncorrelated, referred to as principal components (PCs) (Witten and Frank, 2005). This is done through computing Eigen values from the covariance matrix of the data. The idea is that because the dimensions produced are linearly uncorrelated, there is very little redundancy in the dataset. Also, if the PCs with the highest variance are selected (i.e. those associated with the largest Eigen values), they are also likely to contain the highest entropy and be good predictors.

Whereas PCA is an unsupervised method of feature selection, MI takes into account relationships between features and the class labels. MI is defined as,

$$MI(f_i, C) = \sum_{\substack{v_i \in vals(f_i), \\ v_c \in vals(C)}} p(v_i, v_c) \log_2 \frac{p(v_i, v_c)}{p(v_i)p(v_c)},$$

where f_i is a feature and C is the class labels. A high MI indicates that the feature is a good predictor of the class labels and that it should be included in a predictive model.

Both of these feature selection methods are able to provide a ranking of features. PCA ranks the PCs by their variance, where those with a larger variance are ranked higher. With MI, features are ranked by the closeness of their relationship with class labels.

3.4 Classification

In this paper, we employ three widely used machine learning algorithms: Naïve Bayes, Decision Tree, and Random Forest, that are all available in the Waikato Environment for Knowledge Analysis (WEKA) machine learning suite (Witten and Frank, 2005). The Naïve Bayes algorithm learns class conditional distributions from the data and uses Bayes rule to make inferences. For the Decision Tree classifier, we use the C4.5 algorithm which splits nodes based on MI. Once the full tree is built, pruning of nodes with few applicable samples is performed to prevent over-fitting. The Random Forest algorithm builds several Decision Trees, each on different sub-samples of the data and sub-sets of features. Each of these algorithms are chosen because of their wide-spread use and the ease with which models produced by them can be understood by a domain expert.

In road classification, there is an inherent class imbalance where one or more class labels dominate the training data. For example, there is a 5:1 ratio of single lane road examples to multiple lane roads, and a smaller number of motorways than other road types in our data. This imbalance can lead to biases in models, which tend to prefer to label instances that are a majority (He and Garcia, 2009). We consider two approaches to dealing with class imbalance, namely over-sampling and under-sampling. In over-sampling, samples of the minority class label are duplicated to increase their representation, while in under-sampling, some proportion of the majority class samples are decimated. Duplication and decimation is performed by selecting samples at random.

In the multi-class problem of road type classification, we adopt Error Correction Output Coding (ECOC) (Berger, 1999; Escalera et al., 2008; Soda and Iannello, 2010), which has been shown to have resilience to class imbalance (Berger, 1999; Escalera et al., 2008; Soda and Iannello, 2010). ECOC is an ensemble classification algorithm which splits a multi-class classification task into several binary-class problems. A unique binary code, C_i, is given to each of the classes as in Table 1. A classifier is built to predict each

Class	**Code**
A Road	1000111
B Road	0100100
C Road	0010010
Motorway	0001001

Table 1: Example exhaustive coding for Road classification.

of the bits in these codes, i.e. there will be as many models as there are bits in the codes. In this example, the classifier predicting the third digit of the codes would predict 1 for C roads, and 0 for the remainder. The true code with the smallest Hamming distance between itself and the predicted code is then output as the sample classification.

Some of the binary class models will have better performance than others, because of the difficulty of distinguishing the classes. A and B roads, for example, are much more closely related than C roads and Motorways, so we would expect a model distinguishing between A and B roads to have worse performance. Because of this, it is sometimes beneficial to take account of this in the Hamming distance calculation by weighting it with expected performance (Zhang et al., 2012). This is done by updating the Hamming distances by multiplying them by the expected performances and can be illustrated using the example in Table 1. Suppose, for example, that the expected success rate, estimated using the training data, for each of the dichotomies is $W = [0.75, 0.5, 1, 1, 1, 1, 0.5, 0.5]$. If the base models then output a bit string of 1100101, the weighted Hamming distances would be 1, 1.25, 4.25, 3.25 for A road, B road, C road and Motorway respectively. With these distances, the output the classification is of type A road.

3.5 Evaluation

For evaluation, we use random sub-set validation over sub-datasets, a variation on cross-folds validation. Each iteration consists of a training and a testing phase, where the model is built using data from a subset of the journeys and then used to label instances from unseen journeys. In each training phase the same number of datasets are used to select features and build a model, and the remainder of data is used as testing data.

This is repeated for several combinations of training and testing data, producing a large number of predictions made by the models. These predictions are then compared against the ground truth to produce a performance metric. Because it is possible to use some samples multiple times in an evaluation, the performance metrics exhibit Monte Carlo variation.

Unlike other work in environment classification, we choose to not use accuracy or error rates as a measure of performance. Instead, in this paper we use Area Under the ROC (Receiver Operating Characteristic) curve (AUC), as it is better suited in situations with a high class imbalance (Huang and Ling, 2005). This is because the imbalance may bias the output of a classifier, which is not accounted for by accuracy. Consider a model that outputs a probability distribution over the class labels and trained with an imbalanced binary classification dataset with numerous times more 0 labels than 1s. When using accuracy, an output of $p(0) = 0.7, p(1) = 0.3$ with a decision threshold of 0.5 would mean that the prediction is 0. In this case, a model that outputs $p(0) = 1$ for all inputs, always predicting 0, may provide a very high accuracy on the dataset due to this being correct for most of the samples. When used in the real world, however, predicting 0 regardless of the situation is not useful. The ROC curve accounts for any class biases by computing true positive and false positive rates over several thresholds, ranging from 0 to 1. A threshold of 1 for a class means that the class label is never predicted, producing no false negatives and no false positives. Conversely, a threshold of 0 would mean all instances are predicted as the class label, producing a false negative rate and false positive rate of 1. The true positives are then plotted on the y-axis against the false positives on the x-axis, with the ideal curve following the y-axis as close as possible, having an AUC of 1.

4 Experimental Setting

4.1 Data collection

We used a Video VBOX Pro for the data recording, which allowed for the recording of video streams synchronized with selected CAN-bus signals. In order to have the CAN-bus signals at a constant frequency, the VBOX interpolates signals by taking the last-seen value. This method ensured that nominal, integer or binary signals are not averaged outside of their domains. For instance, if a binary signal is only broadcast every second but sampled at 20Hz using linear interpolation, a value change would produce some samples between 0 and 1. Also, using the last broadcast value ensures that the signal is as up-to-date as possible, although it may mean it is more susceptible to noise.

The data used in this paper was collected over 16 drives across the Midlands, UK, in two cars. Each journey involves at least one driver, with a mean journey length of 51 minutes. Output from 15 CAN-bus sensors, listed with brief explanations in Table 2, were recorded each at 20Hz for a total of 49403 seconds, which is comparable to the length of data used in (Huang et al., 2011). Some sensors used are expected to have very little relevance in determining the road type, and others are highly redundant. As previously stated, these expectations may be incorrect, as is the case with the ambient temperature signal. Although it may initially be expected to be a poor predictor, it has one of the higher MI scores (0.197 for carriageway type) in data we have collected. On further inspection we find that its Pearson correlation with vehicle speed, which is expected to be a good predictor, is 0.774. This makes some intuitive sense, as the temperature near the engine will rise with vehicle speed as the engine works harder. With this insight we can say that ambient temperature is a good predictor of road type, but that it is somewhat redundant to other signals. After signal and feature selection, only the features which are useful for the problem should be used in classification.

The ground truth for the dataset was achieved using GPS and applied by hand using Google Earth. GPS coordinates are looked up in Google Earth and a label is decided, and assigned to samples. For the carriageway classification, the number of lanes is decided by looking at the satellite images provided. If there is more than one lane, the sample is *dual*, otherwise it is *single*. For road type, the road name is looked up on the map and the first letter taken. If no road name is provided, because it is a dirt track or car park, the label given is *C*. The distribution of labels is provided in Table 3.

4.2 Signal selection, feature extraction and feature selection

For temporal feature extraction, we use two statistical features, the mean,

$$f_\mu(s) = \frac{1}{|s|} \sum_{i=1}^{|s|} s_i,$$

Signal	**Description**
Ambient temperature	Outside temperature (measured behind grill).
Brake pressure	Pressure on brake pedal.
Gear position	(Automatically) selected gear.
Longitudinal/lateral accelerations	Forward and Side-to-side accelerations of the vehicle, measured by an accelerometer.
Suspension height (each wheel)	Heights of suspension (Front-Right, Front-Left, Rear-Right and Rear-Left).
SWA	Angle of steering wheel.
SWA speed	Rate of change of SWA.
Vehicle speed	Vehicle speed (measured from wheel speed).
Wiper status	Speed status of the front window wipers.

Table 2: List of signals recorded.

Label	**Percent (%)**	**Description**
Single carriageway	85	Single lane roads
Dual carriageway	15	Roads with multiple lanes
A road	48	Town road or non-highway arterial roads
B road	26	Smaller town or country roads
C road	21	Other types of road and car parks
Motorway	5	Highway with multiple lanes

Table 3: Label counts for the data.

and standard deviation,

$$f_\sigma(s) = \sqrt{\frac{1}{|s|-1}\sum_{i=1}^{|s|}(s_i - f_\mu(s))^2},$$

where s is a temporal window of the signal. We also use two structural features, the first and second derivatives, which are computed by taking the mean difference between each pair of points in the signal window,

$$\delta(s) = [s_2 - s_1, s_3 - s_2, \ldots, s_l - s_{l-1}].$$

The first derivative is then,

$$f_{\delta 1}(s) = f_\mu(\delta(s))$$

and second derivative is,

$$f_{\delta 2}(s) = f_\mu(\delta(\delta(s))).$$

The standard deviation provides a measure of signal variance, while the derivatives provide information on the gradient and shape of the signals. All four features are extracted from each signal with a window length of $l = 2.5$ seconds, or 50 samples. This length allows sufficient historical data for the features to be of use, while being small enough to be updated rapidly if the conditions change (Qiao et al., 1995). Also, in a previous study, we have shown that a window length of over 2.5 seconds can not provide much increase in performance without causing over-fitting (Taylor et al., 2012).

In many cases of learning from CAN-bus data (Huang et al., 2011; Murphey et al., 2008; Taylor et al., 2013a; Wollmer et al., 2011), feature selection is performed after feature extraction has taken place. However, because of their number, selecting from the full set of extracted features is computationally prohibitive. It is beneficial to perform selection on signals prior to feature extraction, because there are fewer signals than total features. Therefore, we investigate signal selection prior to feature extraction and explore the impact combination of redundant and relevant feature selection.

Figure 1 outlines the signal selection, feature extraction and feature selection methods investigated. The process starts at the top with the raw signal data, and moves downward through paths of feature extraction or selection. At the bottom, an evaluation of the resulting classification is performed to provide a measure of the quality of the feature set produced. As an example, in the left-most path the signals are ranked by MI prior

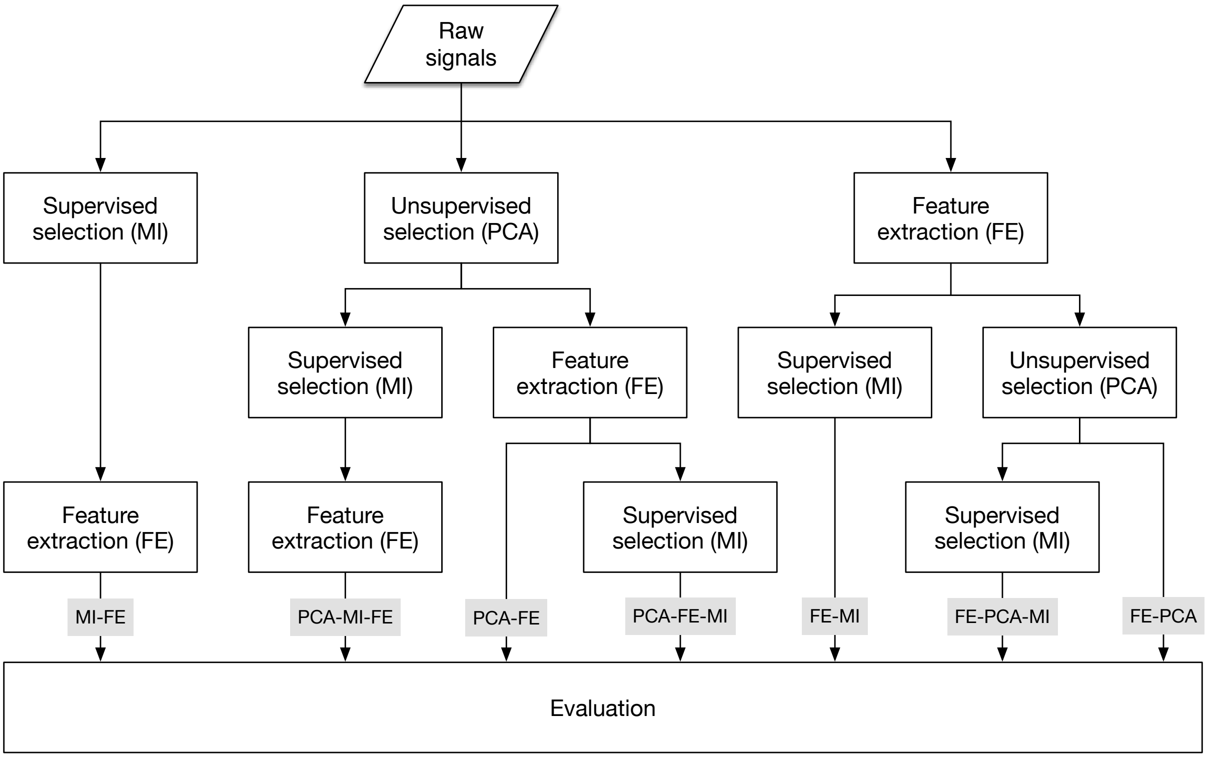


Figure 1: Processing methods for data, for Principal Components Analysis (PCA), Mutual Information (MI) and Feature Extraction (FE). Some selection is performed on signals, prior to feature extraction. In this diagram, for example, the leftmost path of MI-FE first performs signal selection with MI, and then extracts features on the selected signals.

to feature extraction, which are then all input into the evaluation procedure. We refer to this particular path as MI-FE. Some paths are equivalent and are therefore omitted from our investigations. For instance, any path that has an MI stage followed by PCA is equivalent to performing solely PCA.

4.3 Classification and evaluation

Features selected by a selection path are evaluated using a random sub-set validation over sub-datasets. In each iteration of the sub-set validation, a random half of the datasets are used as training data and the other half are used as testing data. There are a total of $\binom{16}{8} = 12870$ possible train-test iterations over the sub-datasets, of which a uniformly randomly selected 200 are performed. The feature selection process is performed on each training data set to rank the features. For computational reasons, the evaluation data is sub-sampled by a factor of 10 at this point. Thirty models are then built using different numbers of the ranked features, $(1, 2, \ldots, 30)$, and each are used to label the test dataset.

As previously stated, each repetition of the non-random sub-set validations provide AUC values as measures of performance. These AUC values are then plotted against the number of features used in the repetition. It is expected that the AUC values will increase as additional features are added, plateauing and then decreasing after a certain number (Kohavi and John, 1997). A good feature ranking will have a high peak or plateau which appears with a small number of features. In order to compare feature rankings therefore, both the magnitude and location of the peaks are inspected.

As discussed above, Naïve Bayes (Witten and Frank, 2005), Decision Tree (Witten and Frank, 2005), and Random Forest (Breiman, 2001) classification algorithms were used in this evaluation. The class imbalance problem was also tackled by using under-sampling and over-sampling for the binary classification task, and Weighted-ECOC for the multi-class classification task. For computational reasons, classifier parameters are not optimized, and the default options provided by WEKA are used (Witten and Frank, 2005). The results are discussed in the following section.

5 Results

In this section the results of the feature selection investigations are discussed, presenting AUC performances of the Naïve Bayes, Decision Tree, and Random Forest models, for:

- Carriageway and road classification with no class imbalance techniques being applied.
- Carriageway classification, having applied under-sampling and over-sampling to the training data.
- Road classification with Weighted-ECOC learning.

First, we provide evidence for why AUC is used as a performance measure instead of accuracy in this paper. Figure 2 shows accuracies for the Naïve Bayes classifier with features selected by the PCA-FE-MI path. The accuracies shown are over four decision thresholds, ranging from a threshold of 0 where the output is always *single*, to a threshold of 0.9. A threshold of 0.9 means that the output is *single* if the classifier reports that the

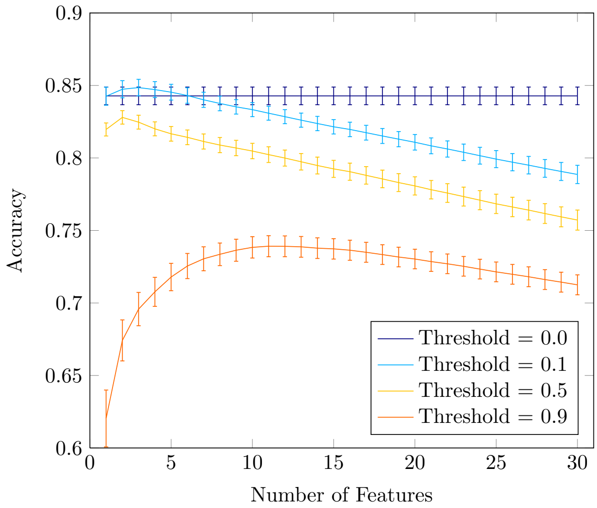
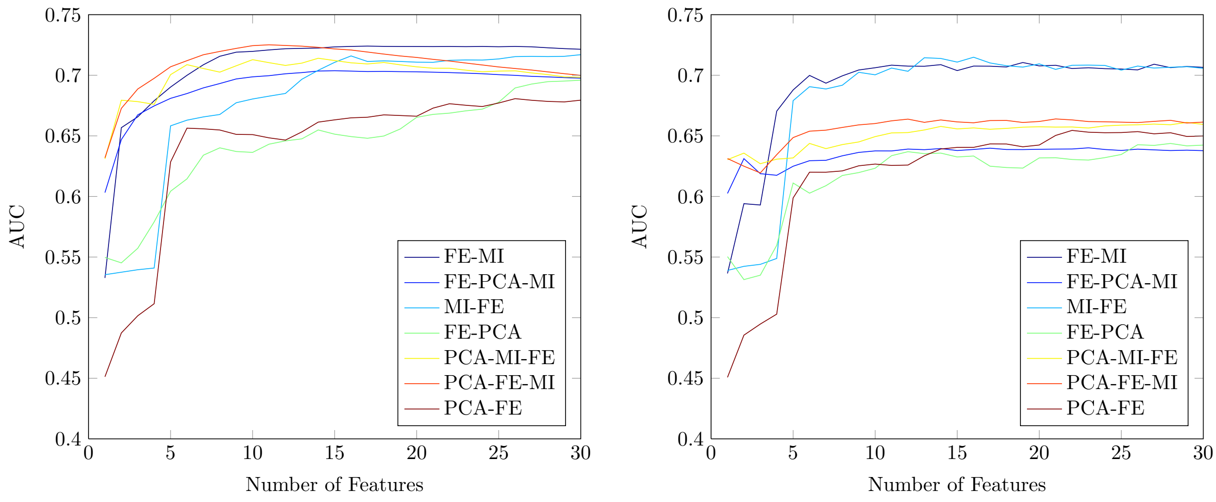


Figure 2: Plots showing mean accuracies of the 200 evaluation folds when using several decision thresholds for carriageway classification using Naïve Bayes without using class imbalance techniques and with features selected by PCA-FE-MI. The error bars are 95% confidence intervals computed using the standard deviation of accuracies of the 200 evaluation folds.

probability of a *single* is less than 0.9. The lines in this plot show the mean accuracies over the 200 folds performed in the evaluation, and the error bars for 95% confidence intervals computed on their standard deviation. In this example, a threshold of 0 provides a constant classification accuracy of 0.84, which is only bettered by using the threshold of 0.1. This 0 threshold means that the model will output *single* regardless of the input, which is not useful in the real world even though it achieves a high accuracy performance when compared to other thresholds. Therefore, when class imbalance is present, as is in our data, accuracy is not a good performance measure to use. ROC curves overcome this by computing error rates over many thresholds, and AUC then provides a measure of performance considering all thresholds.

The AUC performances for carriageway classification are shown in Figure 3, plotted against the number of selected features for the different selection paths. Overall, the Naïve Bayes classification algorithm has the best performance, with any selection path including an MI stage achieving at least 0.7 in AUC. The same performance is achieved by the Random Forest classifier, but only with the FE-MI and MI-FE selection paths. Other selection paths have a maximum AUC performance of around 0.65, with PCA-FE and FE-PCA again scoring lowest. The results of the Decision Tree classification algorithm



(a) Naïve Bayes (b) Random Forest

Figure 3: Carriageway classification AUC values against number of features used in the (a) Naïve Bayes and (b) Random Forest classifiers. Performance of the Naïve Bayes and Random Forest models are comparable when considering the FE-MI and MI-FE selection paths. Other selection paths perform less well using Random Forest, and any selection path containing a MI stage has good performance with Naïve Bayes.

are not presented because of its poor performance.

A similar pattern in the results is seen in the road classification AUC performances, shown in Figure 4. Again, the Naïve Bayes classifier has the highest AUC performance overall, with those feature sets produced by a selection path including an MI stage achieving at least 0.65 in AUC. One difference is that the FE-MI and MI-FE selection paths no longer produce the highest performing feature rankings. Instead, the highest AUC performance is given by performing an MI stage after a PCA stage, using either the PCA-FE-MI or PCA-MI-FE selection paths. The FE-PCA-MI selection path does not share this high performance, indicating that dealing with redundancy in the signals provides better features in this classification task.

Table 4 shows the peak performances of the Naïve Bayes, Decision Tree and Random Forest classification algorithms on the carriageway type and road type problems respectively. In both cases, the Naïve Bayes classifier built with features selected by the PCA-FE-MI selection path provides the highest peak AUC performance. The Decision Tree classifier has very poor performance in both classification tasks, and its peak performance is achieved with a small number of features in several cases. This shows that

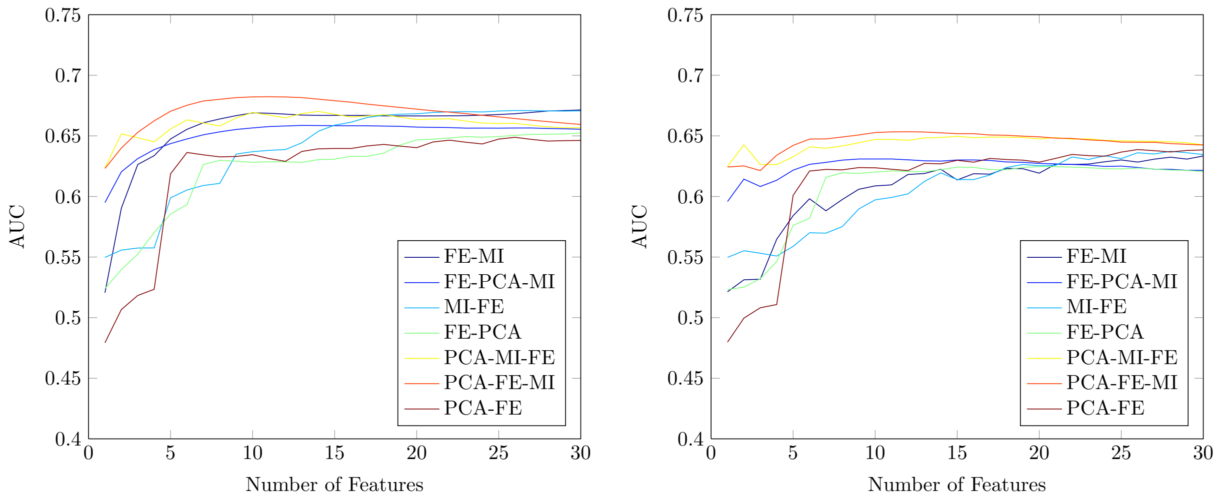
	Naïve Bayes	**Decision Tree**	**Random Forest**
FE-MI	0.724 (17)	0.571 (8)	0.711 (19)
FE-PCA-MI	0.704 (15)	0.608 (3)	0.640 (23)
MI-FE	0.717 (30)	0.571 (13)	**0.715 (16)**
FE-PCA	0.696 (30)	0.600 (28)	0.644 (28)
PCA-FE-MI	**0.725 (11)**	0.629 (1)	0.664 (21)
PCA-FE	0.681 (26)	0.625 (6)	0.655 (22)
PCA-MI-FE	0.714 (14)	**0.635 (2)**	0.661 (29)

(a) Carriageway Type

	Naïve Bayes	**Decision Tree**	**Random Forest**
FE-MI	0.671 (30)	0.552 (10)	0.633 (30)
FE-PCA-MI	0.659 (13)	0.607 (6)	0.631 (11)
MI-FE	0.671 (26)	0.554 (2)	0.637 (28)
FE-PCA	0.652 (30)	0.606 (19)	0.625 (20)
PCA-FE-MI	**0.682 (11)**	0.628 (7)	**0.653 (12)**
PCA-FE	0.649 (26)	0.631 (22)	0.639 (26)
PCA-MI-FE	0.670 (14)	**0.638 (2)**	0.650 (15)

(b) Road Type

Table 4: Peak AUC values for the Naïve Bayes, Decision Tree and Random Forest classification algorithms on (a) carriageway and (b) road types, with the number of features in braces. The highest AUC achieved for each model is highlighted in bold. These results show that Naïve Bayes trained using features produced by PCA-FE-MI, will produce the highest performance in both cases.



(a) Naïve Bayes (b) Random Forest

Figure 4: Road-type classification AUC values against number of features used in the (a) Naïve Bayes and (b) Random Forest classifiers. Naïve Bayes has highest AUC performance with features selected by the PCA-FE-MI, while Random Forest has slightly worse AUC performance for all selection paths.

the Decision Tree classification algorithm over-fits the data and often to the top ranked features, which is not generally rectified by pruning.

For the carriageway classification task, the FE-MI selection path provides a very similar AUC performance, but for road type classification it is lower. This again indicates that redundancy feature selection is a necessary step for the highest performance in the multi-class problem. Also from these results, there is some indication that the selection paths that contain both a relevancy and a redundancy stage require fewer features than those that only have one or the other. This can be clearly seen in the road classification peak scores, where 11 – 15 features are needed for those with both PCA and MI, and over 20 are commonly required for other selection paths.

Because the data collected for this study is imbalanced, we also tested techniques to rectify this. For the binary class carriageway type problem, we investigated both under-sampling and over-sampling. In Figure 5, AUC performance for the seven selection paths is shown against the number of features for under-sampling of the training data. The results for over-sampling are very similar to these and are therefore not presented in this paper. In general for carriageway classification, applying sampling to the data to mitigate class imbalance does not affect AUC performance by a large amount. Table 5 shows that

	Naïve Bayes	**Decision Tree**	**Random Forest**
FE-MI	**0.735 (17)**	0.581 (15)	**0.725 (27)**
FE-PCA-MI	0.712 (14)	0.660 (2)	0.681 (26)
MI-FE	0.730 (16)	0.581 (13)	0.718 (29)
FE-PCA	0.702 (30)	0.640 (5)	0.687 (27)
PCA-FE-MI	0.734 (11)	**0.677 (1)**	0.688 (28)
PCA-FE	0.687 (26)	0.655 (5)	0.685 (28)
PCA-MI-FE	0.724 (6)	0.676 (1)	0.689 (25)

(a) Under-sampling

	Naïve Bayes	**Decision Tree**	**Random Forest**
FE-MI	0.718 (26)	0.582 (4)	0.713 (25)
FE-PCA-MI	0.712 (14)	0.665 (2)	0.668 (2)
MI-FE	0.711 (30)	0.583 (6)	**0.715 (16)**
FE-PCA	0.701 (30)	0.634 (1)	0.655 (27)
PCA-FE-MI	**0.732 (11)**	**0.677 (1)**	0.678 (1)
PCA-FE	0.686 (26)	0.590 (23)	0.666 (24)
PCA-MI-FE	0.721 (6)	0.676 (1)	0.677 (1)

(b) Over-samplnig

Table 5: Peak AUC values when applying (a) under-sampling and (b) over-sampling to the data when using the Naïve Bayes, Decision Tree and Random Forest classification algorithms on carriageway type, with the number of features in braces. The highest AUC achieved for each model is highlighted in bold. Under-sampling shows higher performance the over-sampling, with features selected using FE-MI and the Naïve Bayes classifier performing the best overall.

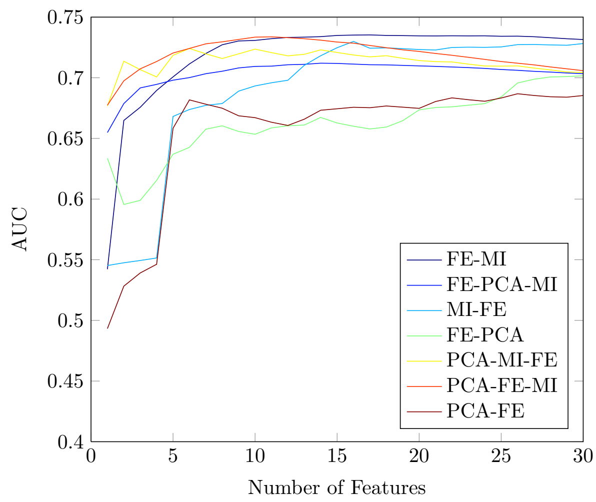


Figure 5: Carriageway classification with under-sampling AUC values against number of features used in the Naïve Bayes classifier. The performance is highest with features selected by the FE-MI or PCA-FE-MI selection paths.

the peak AUC performances increase in general by a small amount when under-sampling or over-sampling is applied. One effect of performing re-sampling on the data is that the peak AUC performances of the Decision Tree are now achieved with even fewer features in many cases, indicating that the over-fitting problem is intensified.

Finally, for the multi-class road type problem we evaluated ECOC, which has shown robustness to imbalance in other domains. Table 6 shows the peak AUC performances for the Weighted-ECOC approach described in (Zhang et al., 2012). For both Naïve Bayes and Random Forest classifiers the results are similar in distribution to when ECOC is not applied, with a small decrease in AUC values in general. The Decision Tree classifier now has a smaller peak AUC performance, but requires more features to achieve it.

6 Discussion

These results provide several insights into the best avenues for a data mining approach to environment monitoring problems from CAN-bus data. They show that considering both redundancy and relevancy in a feature selection process will generally provide the highest performance. In fact, both are necessary for the highest performance in the road type classification task. One exception to this is with the Random Forest model used for the carriageway classification task, which performs best with features selected

	Naïve Bayes	Decision Tree	Random Forest
FE-MI	**0.666 (30)**	0.563 (5)	0.604 (30)
FE-PCA-MI	0.658 (29)	0.603 (27)	0.607 (11)
MI-FE	0.662 (30)	0.561 (13)	0.607 (27)
FE-PCA	0.654 (30)	0.602 (27)	0.599 (15)
PCA-FE-MI	**0.666 (12)**	0.621 (11)	**0.627 (12)**
PCA-FE	0.647 (26)	**0.623 (30)**	0.607 (26)
PCA-MI-FE	0.657 (14)	0.621 (15)	0.624 (15)

Table 6: Peak AUC values when using Weighted-ECOC with the Naïve Bayes, Decision Tree and Random Forest classification algorithms on road type, with the number of features in braces. The highest AUC achieved for each model is highlighted in bold. These results show that Naïve Bayes trained using features produced by PCA-FE-MI will provide the highest performance with fewest features.

using only relevancy. Also, any redundancy analysis should be performed on the signals prior to feature extraction, and followed by a relevancy selection stage. Performing only redundancy feature selection does not provide a good feature ranking in any case, which is likely due to its unsupervised nature.

Also, the choice of methods may change depending on requirements of a system with respect to computing efficiency, rather than just predictive performance. For example, performing selection prior to feature extraction as in MI-FE is much less computationally expensive than selecting from the full feature set, while both methods will provide similar performance with 15 features. We find, however, that features selected using FE-MI or PCA-FE-MI provide higher AUC performances with fewer features than MI-FE or PCA-MI-FE. This result may be valuable where there is limit on the feasible number of signals that can be used in a model running on the vehicle's electronic control unit. In this case, it would also mean that any selection path including PCA is unlikely to be of use, because the principal components produced are a linear combination of all inputs.

In almost all cases, the Naïve Bayes classification algorithm achieves the highest AUC performance, followed closely by the Random Forest classifier. The Decision Tree classification algorithm does not have good AUC performance in any case. In order to mitigate

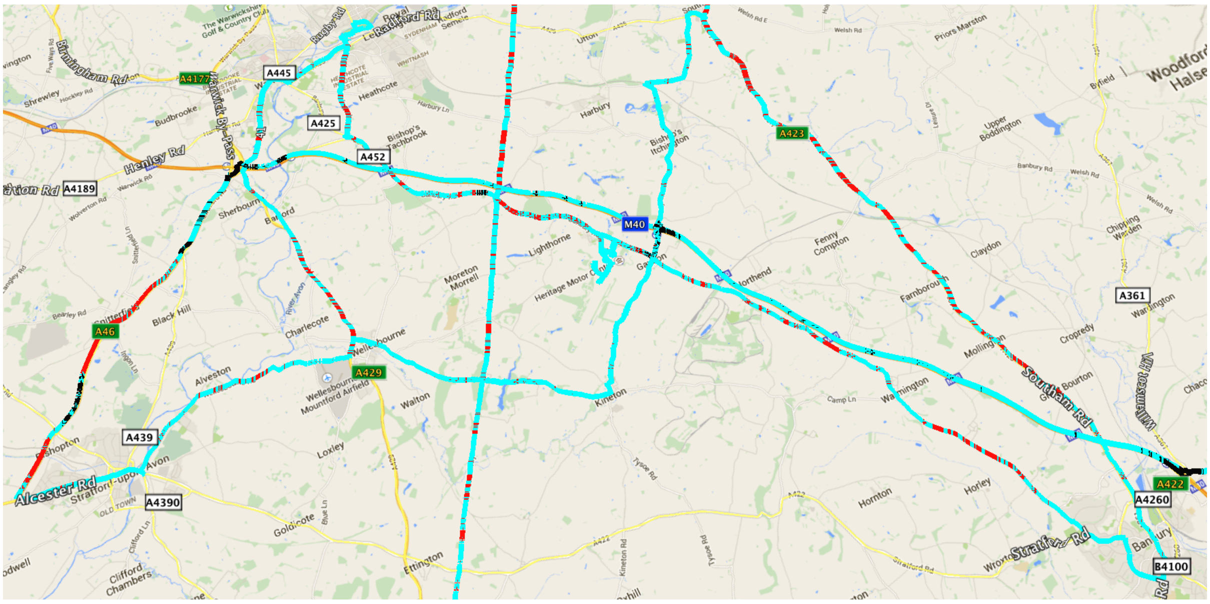


Figure 6: Road map showing correct predictions (Cyan), *single* roads incorrectly predicted as *dual* (Red) and *dual* roads predicted as *single* (Black) for carriageway classification. Naïve Bayes classifiers, trained with under-sampled training data and 10 features selected by the PCA-FE-MI selection path are used, with a decision threshold of 0.1. The yellow lines are other roads that are not recorded in our data.

class imbalance in the carriageway classification task, under-sampling or over-sampling the training data increases the AUC performance by a small amount. Although this increase in peak AUC performance is also seen in the with the Decision Tree classifier, any signs of over-fitting are exacerbated by under- or over-sampling. Using Weighted-ECOC to mitigate any class imbalance in the road type classification task decreases performance of all models. This may be because the class imbalance in this problem is less severe than in the binary classification task.

Taking into consideration these results, the highest performing model for carriageway classification by AUC is Naïve Bayes, trained with under-sampled data and features selected by FE-MI. This is only a small improvement on the same model built with no under-sampled training data, or with features selected by the PCA-FE-MI selection path. For road classification, the highest performing model is Naïve Bayes, trained with features selected by PCA-FE-MI. This is closely followed by the same model built with features from any of the selection paths containing both a PCA and MI stage.

Finally, an illustration of carriageway classification performance overlaid on a map is shown in Figure 6. The cyan regions show where predictions are correct, whereas *single* roads incorrectly labelled as *dual* roads are red and *dual* roads incorrectly labelled as *single* are black. The predictions were made by 16 Naïve Bayes classifiers, each trained using data from 15 journeys and tested on the remaining one. Data from each journey is used as testing data exactly once and a decision threshold of 0.1 is used to make a prediction for every sample in the dataset. The training data was under-sampled and 10 features selected by the PCA-FE-MI selection path are used in all the models. The image shows a majority predictions are correct, scattered with some short periods of incorrect classifications. These short periods might be labelled correctly if historical classifications are taken into account, such as taking the modal prediction over a temporal window. This, however, would introduce extra delay when the environment changes. The larger red section of road toward the left side of the map is classified incorrectly as *dual* because it is a straight road with wide lanes and a speed limit of 60mph. The cyan section of road next to this that is incorrectly labelled as *single* is actually a road with three lanes, where two are in the direction of travel. These are both examples of edge cases that are sufficiently similar to the other label. It may be possible to detect these cases and act appropriately if the classifier is unable to decide a label with sufficient confidence. One such action may be to assume a default label such as *dual* and activate a lane departure warning system.

7 Conclusions

In this paper we adapted and applied a data mining methodology to learning driving conditions from CAN-bus data, illustrating the approach with the road classification problem. We investigated signal selection, feature extraction and feature selection to produce a successful model for two sub-problems of this domain. Also, as the data collected was imbalanced, techniques to solve this were tested. The data mining methodology was then used to generate models that were capable of accurately predicting the carriageway type or road type using only 2.5 seconds of historical data.

Our investigations suggest how an automatic feature selection process for vehicle telemetry might be realised. We found that using both relevancy and redundancy is likely to produce the highest performance with the smallest number of model inputs. When PCA is used, however, inputs to the model are linear combinations of all signals or features, meaning that FE-MI or MI-FE may be preferable in deployment. Of these two selection paths, FE-MI provides the best feature set to build a model with. In future, however, we believe that relevancy and redundancy should be considered together (Kohavi and John, 1997). For both carriageway and road classification we found that Naïve Bayes is likely to provide the highest performance, which is improved upon by under-sampling the training data in carriageway classification. The models built for the road classification task were not improved by the Weighted-ECOC technique used to mitigate effects of class imbalance.

In this work the same window length of 2.5 seconds was used in all experiments and for all features, because we found this to be an appropriate size overall (Taylor et al., 2013a). Shorter window lengths caused a decrease in performance, while longer window lengths increased performance minimally and introduced errors shortly after label changes. This may not be the case in general, however, as features extracted using different window lengths capture different information. Two derivative features extracted using short and long windows, for example, would capture short and long term trends in the signal. Further, it may be the case that both of these features should be used in a model for the highest performance.

In this paper, we have considered the problem where location and map data are unavailable at any point (or their use is undesirable). However, if it is possible to obtain a ground truth during driving, even for short periods of time, it may be possible to develop an online learning system for road type classification. If this was the case, affects of concept drift could be investigated (Li et al., 2010). For instance, as a driver becomes more experienced over their lifetime, or tired during a journey, their driving patterns may change with respect to road type. Therefore, it may be essential to update on-line classification models with new information to maintain performance.

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