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Comparison of Machine Learning Techniques for Vehicle Classification using Road Side Sensors

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Abstract—The main contribution of this paper is a comparison of different machine learning algorithms for vehicle classification according to the “Nordic system for intelligent classification of vehicles” standard using measurements of road surface vibrations and magnetic field disturbances caused by vehicles. The considered algorithms are logistic regression, neural networks, and support vector machines. They were evaluated on a large dataset consisting of 3074 samples. Hence, a good estimate of the actual classification rate was obtained. The results show that for the considered classification problem the logistic regression is the best choice with the overall classification rate of 93.4%.

I. INTRODUCTION

Vehicle classification is an important task in traffic monitoring and analysis. Rich information about the traffic composition provided by a classification analysis is commonly used for different purposes such as urban planning, road maintenance, traffic light scheduling, etc. For a long time, this kind of information has been obtained based on inductive loop detectors for permanent installations or pressure tubes for temporary installations [2], [3]. During the last decade, with the advance of cheaply available sensors, wireless communication, and electronics hardware, sensor networks have started to replace those traditional systems [4], [5]. Some advantages of these novel approaches include the possibility of on-demand or real-time access to the data due to their connectivity, and less wear due to the possibility of non-invasive installations.

Therefore, the Nordic Research and Development cooperation (NordFoU) has started to formulate the “Nordic system for intelligent classification of vehicles” (NorSIKT) standard, a new vehicle classification standard. The purpose of the standard is to “establish a Nordic standard for classification of vehicles and thereby to be able to exchange and compare traffic data between the different countries” [6]. This development also requires adaption of the existing as well as the development of new classification methods to fit both the newly available sensor hardware and classification standards.

Traffic monitoring using wireless sensor nodes as a such is a rather mature field. In [5], it was shown that magnetometers can be used to count traffic, to estimate vehicles’ speed, and even to classify vehicles. Furthermore, in [7] it was shown how to use a road-surface mounted micro accelerometer and a neural networks-based algorithm to distinguish between diesel, gasoline, and heavy diesel engine vehicles using the vehicle’s frequency spectrum as a feature. The works in [8], [9]

also used accelerometer-based vehicle detection. The authors developed a peak detection algorithm to detect individual vehicle axles followed by a table lookup. Finally, a setup using vibration measurements from under the roadway combined with a neural network classifier for perimeter surveillance was introduced in [10].

The main contribution of this paper is a comparison of three different machine learning algorithms (linear regression, neural networks, and support vector machines) for vehicle classification according to the NorSIKT classification standard. The sensors used are an accelerometer and a magnetometer, both mounted in a single sensor node on the road side. The algorithms are evaluated on a large dataset, consisting of 3074 samples, hence, a good estimate of the actual classification rate is obtained. The data sets were aggregated during evaluation trials which were conducted by the Swedish Traffic Administration.

The remainder of this article is structured as follows. The NorSIKT classification standard is described in Section II followed by a description of the measurement setup used for data collection in Section III. Section IV presents the features used for classification. The machine learning algorithms including their parameters used during the classification are described in Section V. The main contribution of the paper, the performance comparison, is presented in Section VI. We conclude the article in Section VII.

II. NORSIKT CLASSIFICATION SCHEME

A. Classification Scheme

The “Nordic system for intelligent classification of vehicles” (NorSIKT) vehicle classification scheme [11] is based on four different classification levels as illustrated in Table I. Here, a higher classification level, represents a more fine-grained classification of the vehicles. For example, level one represents the most coarse classification that essentially corresponds to a detection of a vehicle only. Level four is on the other end of the scale, i.e. the most detailed level with a total of 14 classes for light and heavy vehicles including with and without trailers and distinguishing between, for example, motorcycles and mopeds.

This newly developed standard will help national transportation authorities to easily compare different traffic counting

TABLE I
THE NORSIKT CLASSIFICATION SCHEME AND CLASSIFICATION OF THE MEASURED VEHICLES.

| Level 1 | Level 2 | Level 3 | Level 4 |
|----------------------------|---|-----------------------------------|---|
| Motor Vehicle (MV) 3074 | Light Motor Vehicles + Motorcycle (LMV) 2845 | Motorcycles (LMV1): 53 | Motorcycle (MC): 50 Moped (MP): 3 |
| | | Light Motor Vehicles (LMV2): 2792 | Passenger car without coupled vehicle (PC WOC): 2466 |
| | | | Passenger car with coupled vehicle (PC WC) |
| | | | Light goods road motor vehicle without coupled vehicle (LGV WOC): 326 |
| | | | Light goods road motor vehicle with coupled vehicle (LGV WC) |
| | | | Light bus (LB) |
| | Other light road motor vehicle (LV) | | |
| | Heavy Motor Vehicles (HMV) 229 | Heavy Motor Vehicles (HMV1): 229 | Heavy goods road motor vehicle without coupled vehicle (HGV WOC): 86 |
| | | | Heavy goods road motor vehicle with coupled vehicle (HGV WC): 118 |
| | | | Heavy bus (HB): 27 |
| | | | Road tractor without coupled vehicle (RT WOC): 2 |
| | | | Road tractor with coupled vehicle (RT WC) |
| | | | Other heavy road motor vehicle (HV) |

equipments under consideration. Furthermore, it also provides a mean for certification of equipment in the future.

B. Performance Metrics

The main performance metric is the classification rate of the classifier. It basically indicates how well the classifier is able to assign a vehicle to the correct class and is defined as

$$\hat{r} = \frac{1}{N} \sum_{n=1}^N I_n(\hat{c}_n) \quad (1)$$

where N is the number of classified vehicles and $I(\hat{c}_n)$ is the indicator function indicating whether the estimated class \hat{c}_n is the true class c_n^* or not. It is defined as

$$I(\hat{c}_n) = \begin{cases} 1 & \hat{c}_n = c_n^* \\ 0 & \hat{c}_n \neq c_n^* \end{cases} \quad (2)$$

The variance of the classification rate can be used as a measure of how accurate the classification rate is. It is estimated as

$$\hat{\sigma}_r^2 \triangleq \widehat{\text{Var}\{r\}} = \frac{1}{N^2} \sum_{n=1}^N (I(\hat{c}_n) - \hat{r})^2. \quad (3)$$

Furthermore, in order to evaluate different measurement equipment, NordFoU has also defined different performance metrics in the form of error types [12]. Specifically, two types of errors in individual vehicle categories are specified:

- Type A: For class c_j , a vehicle of class c_j^* is assigned to a class $\hat{c}_i \neq c_j^*$ or missed completely (vehicles leaving the class);
- Type B: For class c_i , a vehicle of class c_j^* is incorrectly assigned to class \hat{c}_i (vehicles entering the class).

In the scope of this paper, missed vehicles are not present in the dataset used for classification. From the point of view of the traffic monitoring it is more important to correctly classify the number of vehicles in a particular class rather than correctly classify a category of a particular vehicle. Thus, the error rate of classification for vehicles classes is the difference between type A and type B errors related to the number of vehicles in the class. According to the NorSIKT standard, this error rate should be less than 10% for all vehicle classes where the sample size is larger than 50 [12].

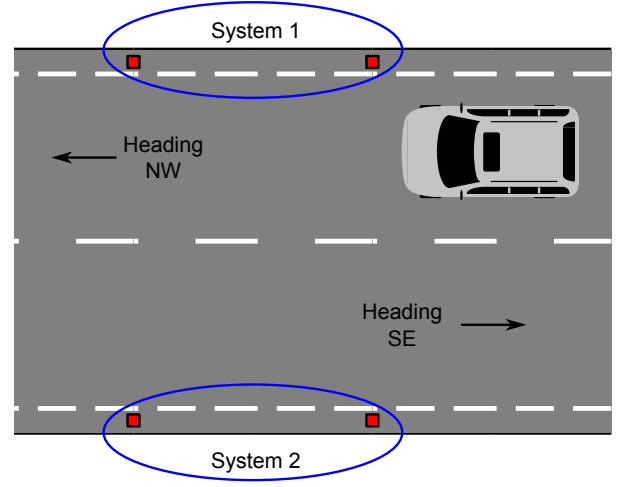


Fig. 1. Measurement setup used for the Amsberg tests.

III. TESTBED DESCRIPTION

The results reported in this paper are based on the measurements at the Amsberg test site conducted in August 2013 in Amsberg, Sweden. These trials were arranged by the Swedish Traffic Administration who also provided ground truth assessment of the traffic. Beside the system which is discussed in this paper, several other systems were evaluated in the tests. The outcome of the tests, including the assessment criterions are discussed [12].

The measurement setup is illustrated in Fig. 1. A pair of sensor nodes of the type as described in [13] was deployed on both sides of the two-lane, two-way highway. The two sensors on the same side were separated by 6 m and worked in pairs for the detection and the estimation. Each node is equipped with an accelerometer measuring the road surface vibrations (normal to the road surface) and a magnetometer measuring the x- and y-components of the magnetic field disturbances. The signal from the accelerometer was preprocessed (filtered and down-sampled) such that only the signal magnitude (envelope) is stored. The resulting signals are both sampled at 256 Hz.

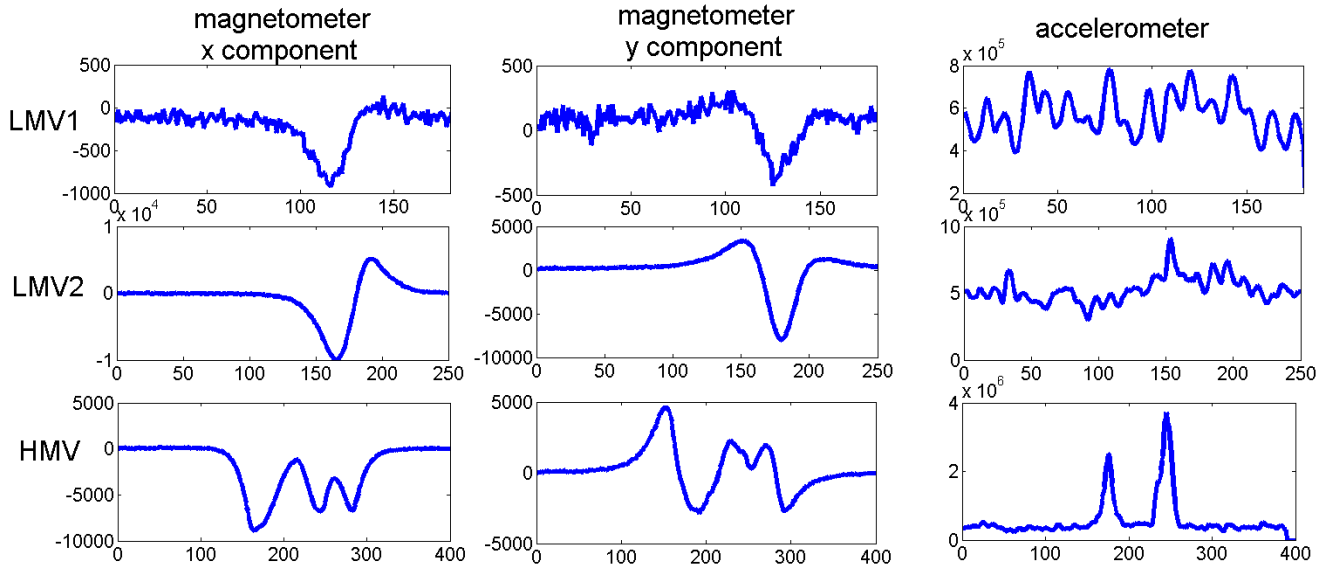


Fig. 2. Examples of magnetometer and accelerometer signals for each class at level three in the NorSIKT standard.

From the three day trial, an four hour period was chosen and a ground truth for that period was established. In total, 3399 vehicles were registered. Out of these, 175 were not correctly detected by the sensor nodes, hence, they are excluded from the dataset. Additionally 150 vehicles were not used during evaluation. Thus, 3074 passages were available for the evaluation in total. Table I illustrates the classification of the ground truth according to the NorSIKT standard introduced in Section II.

Unfortunately, the dataset is heavily biased toward light motor vehicles in general and passenger cars in particular. This makes it difficult to evaluate classifiers that target level 4 classification with high confidence, especially since some classes are heavily underrepresented. Thus, we focus on level 3 classification only in this paper. Examples of measured signals for classes in level 3 are presented in Fig. 2.

IV. CLASSIFICATION FEATURES

Machine learning based classification is a three stage process: First, a set of distinctive features is extracted from the raw measurement data; then, the classification algorithm of choice is trained using a subset of the data, the training set; finally, the trained classifier is validated using the remaining available data, the testing set. This section presents the features chosen for the classification. The applied classification algorithms, namely logistic regression (LR), artificial neural networks (NN), and support vector machines (SVM) [14] are described in the next section.

As mentioned earlier, machine learning techniques require a set of features that will be used for distinguishing between different classes. Naturally, the features should be chosen such that they differ significantly for the different classes in order to obtain a good class separation. The features can be completely non-parametric, for example obtained by transforming the

measurement data or parameters obtained from a fitted model. Non-parametric features have the advantage that there is no intermediate estimation step required but they might not yield a good enough separation of the classes. The number of features is usually preferred to be small since a small number of features can make it easier to interpret and understand the classification model. Furthermore, extraction of good features from raw data is an engineering art on its own and requires good understanding of the problem at hand. A good choice of features may significantly improve the accuracy of the classifier.

In total, there are three raw signals available from the sensors: The x- and y-components of the magnetometer ($y_m^x[n]$ and $y_m^y[n]$, respectively) and the z-component of the accelerometer ($y_a^z[n]$), see Fig. 2 for examples. In total, we derive five non-parametric features, one based on the magnetometer signals and four based on the accelerometer measurements. Each of the features is described in details in turn below.

A. Magnetometer Magnitude Integral

The first feature is the discrete-time integral of the magnetometer magnitude calculated as

$$F_1 = vT_s \sum_{n=0}^{N_m} \sqrt{(y_m^x[n])^2 + (y_m^y[n])^2}. \quad (4)$$

where N_m is the number of samples, v is the vehicle speed, and T_s is the sampling time of the signal. The scaling factor vT_s transforms the integral from a discrete-time integral to a discrete-space integral such that the passages are comparable and independent of both sampling time and vehicle speed.

The magnetometer integral is based on the fact that larger vehicles create more complex magnetic disturbances while small vehicles create small ones (see Fig. 2 and [15]). Hence,

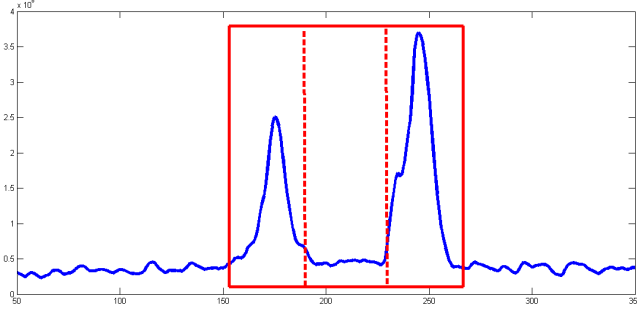


Fig. 3. An example of the extraction of a relevant part from an accelerometer signal.

the integral tries to capture the overall magnetic variance caused by a vehicle passing the sensor.

B. Accelerometer Magnitude Integral

The remaining features are based on the vibration data measured by the accelerometer. First, the measurement data of the passage is narrowed to a N_a sample window around the signal center where the signal magnitude exceeds 3 standard deviations of the noise and a possible noise-offset is subtracted (the outer, solid box in Fig. 3). Then, the second feature is the integral of the windowed signal

$$F_2 = vT_s \sum_{n=0}^{N_a} y_a^z[n]. \quad (5)$$

Again, this feature tries to capture the fact that the intensities of the seismic signatures measured for light vehicles differ heavily from the ones measured for heavy vehicles. Since the integral is taken over the whole measurement window, the overall vibration energy is considered.

C. Accelerometer Magnitude Distribution Integrals

In order to calculate features three to five, the accelerometer window is further split into three sub-windows, each of size $N_{a,s} = N_a/3$ (Fig. 3, dashed lines). Then, the integrals of these three windows are calculated according to (5) but with the reduced number of samples.

These features capture the fact that different vehicles have different axle configurations, that is, instead of trying to detect individual axles, these features provide an indication of how the axles and the load are distributed relatively to the measurement window.

V. MACHINE LEARNING ALGORITHMS

In this section, the three machine learning algorithms considered in this paper together with their parameters are briefly introduced. The algorithms themselves are described and discussed more thoroughly in, for example, [14]. Furthermore, a the naïve classifier for unbalanced datasets is discussed.

Note that since this is a three-class classification problem (LMV1, LMV2, and HMV), all the algorithms use a one-vs-all approach. This means that three models are fitted to the training data; one model for every class. When fitting the

model for the k th class, the labels of the training dataset are changed. The k th class gets label '1' for its samples while the rest of the samples are labeled '0'. Thus the model is fitted to classify between two classes. During the validation with the test dataset, three individual scores are estimated; one for every model. Then, the class with the highest score is chosen as the predicted class.

A. Logistic Regression

For logistic regression (LR), the sigmoid function (6) is used as the hypothesis function. Let $\mathbf{F} = [F_1 \ F_2 \ \dots \ F_5]^T$ be the vector of features. Then, LR fits the model

$$h_{\Theta}(\mathbf{F}) = \frac{1}{1 + e^{-\Theta^T \mathbf{F}}} \quad (6)$$

to the data. The vector $\Theta = [\Theta_0 \ \Theta_1 \ \dots \ \Theta_5]^T$ contains the linear coefficients of the exponent in the denominator. The coefficient Θ_0 is the intercept term while the other five terms determine the contribution of every feature.

For training, the cost function (7) is used. It includes scoring of the result of the sigmoid function (the first term) as well as a regularization part (the second term).

$$J(\Theta) = \frac{1}{M} \sum_{m=1}^M [-c_m^* \log(h_{\Theta}(\mathbf{F}_m)) - (1 - c_m^*) \log(1 - h_{\Theta}(\mathbf{F}_m))] + \frac{\lambda}{2M} \sum_{n=1}^N \Theta_n^2. \quad (7)$$

Here, M is the number of samples in the training set, N is the number of features, and λ is the regularization parameter (set to 3).

B. Neural Networks

In the neural network (NN) classifier, the same sigmoid function (6) is used. The network itself has three layers. The input layer has six units (five features and the intercept term). The output layer has three units (LMV1, LMV2, HMV). The hidden layer has 25 units. The neuron weights were initialized randomly and the back-propagation algorithm was used to calculate gradient values for every learning iteration. As for the LR, the cost function (7) was used for the NN classifier as well.

C. Support Vector Machine

For the support vector machine (SVM), a linear kernel was used (see [14] for details). Furthermore, the following cost function was used for training:

$$J(\Theta) = C \sum_{m=1}^M \left[c_m^* \text{cost}_1(\Theta^T \mathbf{F}_m) + (1 - c_m^*) \text{cost}_0(\Theta^T \mathbf{F}_m) \right] + \frac{1}{2} \sum_{n=1}^N \Theta_n^2, \quad (8)$$

where $\text{cost}_1(\Theta^T \mathbf{F}_m)$ and $\text{cost}_0(\Theta^T \mathbf{F}_m)$ are costs for positive and negative cases respectively [14]. Again, this cost function includes a regularization term in addition to the measure of fit.

TABLE II
CONTINGENCY TABLE FOR THE CLASSIFICATION RESULTS BY LOGISTIC REGRESSION.

| | | Ground truth | | |
|----------|------|--------------|--------|-------|
| | | LMV1 | LMV2 | HMV |
| Forecast | LMV1 | 20.0 | 23.3 | 0.3 |
| | LMV2 | 0.9 | 2528.9 | 10.2 |
| | HMV | 0.1 | 155.8 | 149.5 |

TABLE III
CONTINGENCY TABLE FOR THE CLASSIFICATION RESULTS BY NEURAL NETWORK.

| | | Ground truth | | |
|----------|------|--------------|--------|-------|
| | | LMV1 | LMV2 | HMV |
| Forecast | LMV1 | 20.0 | 41.2 | 1.0 |
| | LMV2 | 1.0 | 2510.4 | 12.0 |
| | HMV | 0.0 | 156.4 | 147.0 |

Furthermore, C is a regularization parameter and was chosen to be 10.

D. Naïve Classifier

In many real situations the distribution of classes of vehicles can be unbalanced, for example due to seasonal variations (e.g. less LMV1 during winter) or specific traffic restrictions (e.g. signs forbidding HMV). In this case, vehicles of a specific class start to dominate. A naïve classification approach would be to assign all vehicles to the dominating class. While this approach could appear as counterintuitive it may, in fact, achieve a very high classification rate. However, the classification rate in individual classes would be obviously extremely poor. Since our dataset is an example of such an unbalanced dataset (LMV2 dominates) we use this classification approach for discussion purposes in Section VI.

VI. RESULTS AND DISCUSSION

A. Test and Validation Datasets

Recall from Table I that the dataset consists of 53 passages in the class LMV1, 2792 passages of LMV2 and 229 passages of HMV1. As practice suggests, approximately 60% (32 passages) of the available LMV1 passages were used to form the training dataset. The rest (21 passages) was used for the test dataset to validate the trained models. In order to keep the training dataset more balanced, the presence of LMV2 and HMV classes was restricted to 69 and 84 passages respectively. Thus the size of the testing dataset is bigger than the training dataset and consists of 2889 passages being highly biased toward LMV2 class. To minimize the influence of passages chosen for the training dataset and get the averaged performance of the classifiers, the training and testing datasets were randomly generated 10 times from the initial dataset. LR, NN and SVM were then applied to the training dataset. The performance of the trained models was assessed by estimating the classes for passages in the test dataset and comparing them with the ground truth.

TABLE IV
CONTINGENCY TABLE FOR THE CLASSIFICATION RESULTS BY SUPPORT VECTOR MACHINE.

| | | Ground truth | | |
|----------|------|--------------|--------|-------|
| | | LMV1 | LMV2 | HMV |
| Forecast | LMV1 | 16.6 | 26.6 | 7.5 |
| | LMV2 | 4.1 | 2549.6 | 27.3 |
| | HMV | 0.3 | 131.8 | 125.2 |

TABLE V
CLASSIFICATION RATES.

| | LMV1 | LMV2 | HMV | Overall |
|-----|-------|-------|-------|---------|
| LR | 95.2% | 93.4% | 93.4% | 93.4% |
| NN | 95.2% | 92.7% | 91.9% | 92.7% |
| SVM | 79.0% | 94.2% | 78.3% | 93.2% |

B. Results

The performance of the different classifiers are presented in Table II, Table III, and Table IV in the form of contingency tables for LR, NN and SVM, respectively. The values in the diagonals of the tables suggest that LR classification achieves the highest number of correct classifications for LMV1 and HMV while SVM is best in recognizing LMV2. The values outside the diagonals indicate which classes that get confused with which. It is particularly interesting that for all classifiers, the largest mistakes occur around LMV2s that either get classified as LMV1s or HMVs (middle columns). This indicates that the features for LMV2 can be quite diverse ranging from the boundary to very small vehicles to large vehicles.

Table V shows the classification rates for each algorithm for the different classes in the dataset as well as the overall classification rates. The resulting classification rates are basically a reflection of the diagonals of Tables II-IV and hence, the same results are obtained for the different algorithms. Additionally, the last column in Table V shows the overall performance of each algorithm. Note, however, that while the overall performance of all algorithms is similar, the classification rates of the individual classes might be significantly lower. The fact that the overall classification rate is similar is due to the test dataset that is dominated by LMV2 which in turn heavily influences the classification rate.

Finally, Table VI shows the error rates for both type A and B errors are according to NordFoU for every class.

C. Discussion and Future Work

As the results in the previous section show, logistic regression achieved the best overall classification rate of the methods applied. However, the results have to be interpreted very carefully. First, note that the available dataset is heavily biased towards the LMV2 class. With a naïve classifier with respect to LMV2 as discussed in Section V-D, a classification rate of 94.1% would be obtained. At first this would actually be close to the performance of all classification algorithms considered here. Thus, it is important to consider not only the overall classification rate but also the classification rates for

TABLE VI
ERROR RATES FOR TYPE A AND B ERRORS DEFINED BY NORDFOU.

| | LMV1 | | LMV2 | | HMV | |
|-----|--------|--------|--------|--------|--------|--------|
| | Type A | Type B | Type A | Type B | Type A | Type B |
| LR | 4.8% | 1.0% | 6.6% | 10.7% | 6.6% | 6.2% |
| NN | 4.8% | 2.1% | 7.3% | 12.2% | 8.1% | 5.8% |
| SVM | 21.0% | 5.7% | 5.8% | 36.5% | 21.7% | 6.3% |

the individual classes which show the inferiority of the naïve classifier.

Furthermore, the worse performance of the NN and SMV classifiers could probably be due to the overfit caused by the size of the training dataset, which is in turn restricted by the number of LMV1 passages. Additionally, the regularization parameters for the algorithms were chosen based on qualified knowledge. Clearly, cross-validation should be used instead, in order to optimize the parameter choice, for example using Monte Carlo simulations. However, due to the low number of samples in the LMV1 class a further split of the dataset is problematic.

Studying the effects of the different features on the classification rate is out of scope of this paper. However, the design of good features is an important component for successful classification. Therefore it is an important direction for future work.

Finally, the presented work performs classification at the third level of the NorSIKT classification scheme, which consists of only three classes. An ultimate goal is to be able to classify vehicles at the most detailed, fourth level with 14 classes. This task would require a significant improvement in the diversity of the dataset (new measurements and a labeled dataset which is generally expensive to obtain would be required), experimentation with extraction of different features from raw data, and possibly considering other machine learning methods.

VII. CONCLUSION

This paper presented a comparison of three different machine learning techniques for the task of vehicle classification based on magnetometer and accelerometer measurements from road side sensors. The considered techniques were logistic regression, neural networks and support vector machines. The algorithms were evaluated on a large dataset, consisting of 3074 vehicle passages in total. Five features were extracted from the measurements and then used as input data for the algorithms. Contingency tables, classification rates, and two error rates were used to assess the performance of the algorithms.

It was found that logistic regression showed the best performance with the average classification rate on the validation

dataset of 93.4 % and maximum 4.1% error in a particular class. The main limitation found in this study is the dataset: Even though it consists of a large number of samples, it is heavily biased towards one of the classes which makes it difficult to properly split the data into training, validation, and testing data.

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