The Impact of the Diversity on Multiple Classifier System Performance

Identifying Changes in the Amount of Fuel in the Fleet Management System

Rafał Łysiak and Marek Kurzyński
Wroclaw University of Technology, Department of Systems and Computer Networks,
Wyb. Wyspiańskiego 27, 50-370 Wrocław, Poland

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Abstract: When it comes to the use of any recognition systems in the real world environment, it turns out that the reality differs from the theory. There is an assumption that the distribution of the incoming data will be at least similar to the distribution of the data, which were used during the learning process and that learning dataset represents the entire space of the problem. In fact, the incoming data differ from the training set and usually cover only a part of the feature space. Very often we have to deal with imbalanced datasets which leads to underfitting of classifiers in the final ensemble. In this paper we present the Multiple Classifier System based on Random Reference Classifier in the problem of fuel level change detection in the fleet management systems. The ensemble selection process uses probabilistic measures of competence and diversity at the same time. We compare different methods to determine the diversity within the ensemble.

1 INTRODUCTION

It's hard to imagine today's world without the information systems and decision support systems to monitor and support business processes. Each of us has contact with them every day. These systems are used in practically every area of industry, i.e.: supervision over the quality of production, automatic production lines, all kinds of security systems, power systems or mobile communication systems. They are also used in the transportation industry and automotive. The best known system that supports the automotive industry is GPS or any other types of the systems on the vehicle's board , which are designed to increase safety and comfort, and in recent years more often, to minimize the costs. The main component of the costs is generated by the fuel usage, which directly affects the financial balance of the transportation companies.

Due to the large amount of the information that is important for logistics companies within the regular working day, Fleet Management System (FMS) become a very important, popular and useful IT applications. FMS integrates in one place, all the information that is required to make key business decisions. As the most important, we should mention such data as current location of the vehicle, vehicle status, driver's working time, the status of transport, the current amount of the fuel, average fuel consumption or recently famous ecodriving, which analyzes the driving style to minimize fuel consumption. FMS provides this information with the clear and easy to understand user interface, and recently, more often, makes decisions based on those information. In this way, the FMS may be able to increase the profits. For the analysis of the fuel, we should not forget about environmental issues. Minimizing the fuel consumption, the CO2 emissions into the atmosphere is reduced as well.

In this paper we will focus on the issue of fuel analysis, and more specifically on the detection of the fuel level changes – if refuel or any loss of the fuel occurred. It should be noted that very often the fuel from the vehicle is stolen. This phenomenon is very common especially in the transport market, in the case of large trucks and tractors, where the amount of fuel in the tank exceed 1000 liters. The problem of analysis of changes in the amount of fuel in the tank becomes more complicated when we realize the conditions under which measurements are taken and with what kind of devices. More on this topic have been written in the *Section 2.*

Despite the fact that there are ongoing works to

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improve the quality of measurement devices, using the opportunity that we had to create the whole Fleet Management System, we decided to go one step further and focus on the analysis of the final data in order to decide whether there had been refueling, fuel theft or maybe the fuel level change was caused by the regular usage of the vehicle.

Intelligent decision support systems are able to classify an event based on the feature vector with a very good accuracy. Unfortunately, using those systems in the industry is still minor, especially in the areas where Quality of Service has crucial role, due to concerns that an unexpected error may be committed. Wrong decisions in the case of real systems are mainly due to the lack of appropriate datasets. Very often, we have to deal with imbalanced datasets, where the size of dataset that represents one class of the problem is much bigger than the other classes. The problem of analysis of the fuel level in the tank is also such example. It is very easy to get information about changes in the level of fuel in typical operating conditions of the vehicle, but it is difficult to gather learning data that represent different ways of fuel theft or extreme operating conditions. In this paper, in order to increase the accuracy of the decision, two techniques have been used. The first one is very well known Multiple Classifiers System idea (MCS) (*Dietterich, 2000*), (*Kuncheva, 2004*) that makes decisions based on the fusion of the outputs from all of the classifiers in the ensemble. MCS are very strongly developed, mostly because of the fact that committee, also known as an ensemble, can outperform its members (*Kittler, et al., 2006*). Due to the fact that we are dealing with imbalanced datasets, diversity measure was also used. Note that even the best MCS will not be able to outperform its members if classifiers in the team are identical. A very important issue is to increase the diversity between the members in case of wrong output, while maintaining high accuracy of individual classifiers in the pool. Furthermore, diversity measure doesn't bring any benefits if all of the members in the ensemble have a very good accuracy.

In this paper, it is shown that the MCS built with Random Reference Classifier (RRC) (*Woloszynski et al., 2010*) used in the analysis of the fuel level changes can provide very good results. In the first part of *Section 5*, it is shown that the RRC behaves as expected for imbalanced and balanced datasets (*Wang et al., 2013*). For this purpose artificially created datasets were used. The next step was to verify if the created MCS, constructed with RRC is able to identify the fuel level changes correctly based on the actual data. The different types of diversity measures have been used, both the pairwise and nonpairwise measures (*Kuncheva, 2004*) and the influence on the MCS performance was shown.

The paper is organized as follows. In the *section 2* methods of measuring fuel with their advantages and disadvantages are discussed. In the *section 3*, the whole architecture of the IT system that has been created in order to analyze the data was described. In the s*ection 4* the exact problem description is presented. The following sections discuss the experiments that have been carried out, we present the results and conclusions that may be noticed. We also present opportunities for the further research.

1.1 Motivation

It may not be clear why such comprehensive technique as MCS was used to answer relatively simple question. It has to be noted that identifying the typical fuel increase, especially when the fuel amount change is big, is not a problem. The most difficult task is to detect a small refueling or advanced method of fuel stealing. Small refueling may occur when the vehicle cannot reach the home station where the cost of the fuel is relatively low. In such circumstances it may be necessary to detect i.e. 40 liters change in 800 liter tank.

Detecting the fuel stealing is even more complicated. There are multiple ways to steal the fuel from the car. It has to be noted that the simplest method, where filler flap is opened and closed, and subsequently a fuel decrease is detected is rare. The very common method is to drain fuel from the fuel wire into external container, during the 8 hours stop. In this case the MCS is more like the decision support system. The system can analyse if the fuel was stolen or it was used by external fuel device, i.e. Webasto. This approach can improve the process of detecting the changes of the fuel, which in most cases is executed by the FMS system user.

2 FUEL LEVEL MEASUREMENT METHODS

There are several methods to measure the fuel level in the tank and its consumption by the vehicle. Depending on the operating conditions and type of the vehicle only some of them may be used. Below the overview of the most popular methods with information about their advantages and disadvantages is presented.

2.1 Flowmeter

The most accurate measurement of fuel consumption can be achieved by the flowmeter which, even with an accuracy of 1/1000 liter, measures the amount of fuel that was transported to the engine. Unfortunately, the flowmeter is not installed in the tank but in the fuel system, and hence it is not possible to detect whether refill or fuel theft occurred. Such decisions can be taken only after the deep analysis of the data from the long period of time and compare them to the list of invoices for the fuel. Installing the additional flowmeter in the vehicle where it is not pre-installed may be very complicated and needs a lot of changes in the vehicle's fuel system.

2.2 CAN based Analysis

To detect refill and possible loss of the fuel it is necessary to monitor the level of fuel in the tank. There are two possible methods to do it. The first one is the float, which is pre-installed, but the quality of the measurement is not accurate. A lot of false changes may occur during the normal operating of the vehicle. In addition, the float does not gather any data of the level of the fuel when the engine is turned off. The information about the fuel level using the float can be obtained in two ways. You can either use the CAN bus in the vehicle, which is not possible in some cases, or use the electrical wires from the float directly and hook them to the proper device to analyze the voltage. The undoubted advantage of the float is the fact that nowadays it is installed in almost every vehicle.

2.3 Fuel Probes

The alternative solution is to use the additional fuel probes which provide much more accurate results. The correct installation of the probe and a suitable choice of the type of probe allows to measure the amount of the fuel with high accuracy. Manufacturers of fuel probes assure measurement accuracy of 0.5% - 0.1%. However, such good results may be only obtained in the laboratory conditions. In the real world we have to deal with the situations and working conditions, which increase the error. The examples such as temperature changes (extra 1.5% - 2% error), natural movement of the fuel in the tank, because of the operation of the vehicle (0.5% - 1%) and the tank calibration error (0.5% to even 3% with the irregular shape of the tank) should be mentioned. Despite the above problems, which directly affect the accuracy of the measurements, fuel probes provide the most accurate measurements of the fuel level in the tank. Additionally, there is the possibility to change the sampling frequency, so it is possible to correct the signal from the fuel probes using the well-known signal processing mechanisms. Modification to the fuel system and vehicle's electronics during the installation of the fuel probe is very little. The only problem may be the limited physical access to the fuel tank. In case, when the vehicle has more tanks than one, each of them may be monitored separately.

3 FMS ARCHITECTURE DESCRIPTION

In this section the architecture of the Fleet Management System that was created is presented.

Figure 3.1: Fleet Management System Architecture.

The basic element of the system is the recorder installed in the vehicle. The recorder has multiple functions. First of all is the device that collects data from all peripheral devices in the vehicle: on-board computer, CAN bus, fuel probes, GPS and many others depends on the purpose of the installation. There is telemetry SIM card in each recorder, so that the device has constant access to the Internet using GPRS connection and is able to send all collected data to the server. There is a mechanism for receiving data from the device on the server side, which decodes the transmitted information and saves them in a database system. Thereafter there are numerous modules that are responsible for specific functionalities of the FMS and one of them is the analysis of the fuel level on which we focus in this work. Analysis of the fuel and its changes is divided into several small subtask to create the well optimized system that is working in a fast and efficient way.

It is important to understand that one vehicle generates on average one frame of data each minute so it is easy to calculate that the system has to gather 1440 frames per day for only one vehicle. With 100 vehicles in the system there are almost 4.5 million of records to analyze within a month. In the very

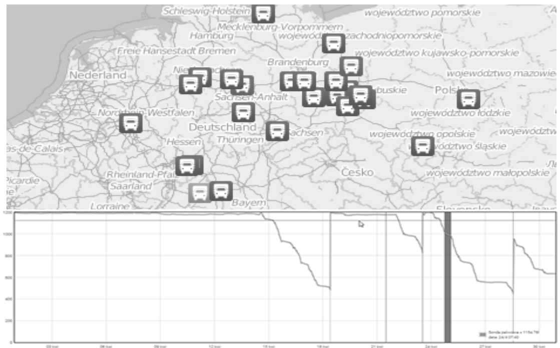

Figure 3.2: Screenshots from the Fleet Management System. The top image presents the current position of the vehicles on the OpenStreetMap. The bottom image presents the plot of the fuel level in one vehicle for the selected period of the time.

beginning the system rejects all incorrect frames. Incorrect frames may be created during collecting the data in the vehicle, because of the problem with GPS positioning or during transferring data through the GPRS tunnel. In the next step, all of the collected frames are aggregated in the events. There are three types of events: stop at the engine off, stop at the engine on and drive. For the purposes of this paper, we focus exclusively on the analysis of changes in fuel level during the standstill. This is the time when the vehicle is being refueled, but it is also the best opportunity for fuel theft. However, it should be noted, that it is also possible to analyze fuel changes while driving, so the incorrect operation of the engine or excessive fuel consumption may be noticed.

4 PROBLEM DESCRIPTION

In our study, the main problem that needs to be solved is to obtain the information if the fuel level change in the tank occurred due to refueling or fuel theft, or is the result of natural changes due to the operating condition of the vehicle. The above description of the problem can be used to define the binary classification problem. First Class C_1 represents the real fuel level change in the tank (refuel or fuel theft), second class C_2 means there were no change. It should be noted that MCS does not specify the type of the change - refuel or fuel theft - MCS only determines whether the change actually exists. The type of change is determined from the sign of the difference between the fuel amount at the end V_E and at the beginning V_B of the analyzed i-th event E_i. As previously was described, the single event should be understood as period of time in which the vehicle's state was constant.

With that being said, our problem can be described as follows. The set of events is given $E = \{E_1, E_2, E_3, \ldots, E_n\}$ and also the pool of the base classifiers is given $L = \{L_1, L_2, L_3, \ldots, L_m\}$. Each i-th event E_i in the set E is described by the given vector of features: event type, amount of the fuel at the beginning of the event - V_B, the amount of the fuel at the end of the event - V_E, the event duration in minutes - T, the difference in the fuel level F_{diff}, where:

$$F_{diff} = \frac{V_E - V_B}{V_{total}}, \tag{4.1}$$

the status of the fuel filler flap, where 0 means that the filler flap is closed, and 1 means that the filler flap is opened, the difference between the maximum and minimum temperatures during the event - T_A, and the state of digital inputs which may indicate the usage of external fuel device. There is the soft output of the MCS, with supports for both, C_1 and C_2 class which is the probability of the correct classification. It should be noted that the maximum duration of the event is 24 hours.

The base classifiers are Neural Networks. To determine the support for classes C_1 and C_2 the RRC was used. As it was stated in the work (*Lysiak et al., 2014*) supports for both classes will be determined in the validation points, then using the normalized Gaussian potential function will be extended to the entire feature space.

According to what has been written in the *section 1*, our datasets from the FMS are imbalanced datasets. The reason of such state was the fact that there were limited possibilities to verify that the fuel change was a result of fuel theft. *Table 4.1* provides the information about the datasets that were provided by the FMS.

Table 4.1: Properties of datasets used for teaching, validating and testing process in the Multiple Classifiers System.

Dataset name	# of examples	# C_1	# C_2
Car 1	1428	37	1391
Car 2	826	60	766
Car 3	568	46	522
Car 4	2415	131	2284
Car 5	576	65	511

It should be noted that each datasets provides the information about the specific vehicle, because of the unique character of the measurements. Each vehicle had other conditions of usage. It is obvious that the datasets are imbalanced in favor of class C_2.

5 EXPERIMENTS

The classification accuracies (the percentage of correctly classified objects) is the averaged accuracy over 20 runs (10 replications of two-fold cross validation) for both of the experiments. Statistical differences between the results were evaluated using Student's t-test (*Dietterich, 1988*). The level of $p < 0.05$ was considered as statistically significant. The problem of selecting the members of the ensemble for the MCS that made the decision by majority voting was solved with the Simulated Annealing Algorithm (*Lysiak et al., 2014*)., which proved to be a fast and providing good results algorithm. In the following experiments the modification of the DES-$CD_{d\text{-}opt}$ algorithm was used with several different measures of diversity. The threshold $\alpha = 1/2$ was used.

Multiple Classifier System with homogeneous ensemble consisted of 20 Neural Networks (NN) (2 layers with 8 neurons each) has been created. To prevent overlearning and obtaining diversity between classifiers, each classifier was trained using randomly selected 70% of objects from the training dataset.

5.1 Experiment 1

The first experiment was intended only to show that the behavior of the RRC, which statistically behaves as the corresponding base classifier is consistent with that shown in (*Wang, 2013*). For this purpose artificial balanced and imbalanced, two-class datasets were generated. *Table 5.1* provides the information about the generated datasets.

Table 5.1: Artificial datasets generated for the purpose of the experiment 1.

Dataset name	# of examples	# C_1	# C_2
400-50	450	400	50
400-400	800	400	400

For the experiment 1, the pairwise diversity measure from the original *DES-$CD_{d\text{-}opt}$* algorithm was used. Two different MCS algorithm were compared, the *DES-$CD_{d\text{-}opt}$* and *DES* (*Woloszynski et al., 2010*).

5.2 Experiment 2

In the first experiment the impact of taking into account the diversity measure for the dynamic classifiers ensemble selection for artificially generated imbalanced datasets is shown. In the second experiment, the accuracy of the MCS, which uses different methods of determining the diversity measure (pair- and non-pairwise) of classifiers in the ensemble was tested. The methods used for determining the diversity are presented in the *Table 5.2.1*. All simulations were performed on datasets that have been presented in the *Table 4.1*. The experiment schema was exactly the same as used in the experiment 1, which is consistent with the description in the introduction to *section 5*. In each test case the modified *DES-$CS_{d\text{-}opt}$* was used. The difference was only in the manner of determining the diversity measure.

Table 5.2.1: The information about the selected methods to determine the diversity measure used in Experiment 2.

Method name	Designation
DES-$CD_{d\text{-}opt}$ (*Lysiak et al., 2013*)	A
Correlation (*Kuncheva, 2004*)	B
The Q Statistic (*Kuncheva, 2004*)	C
Generalized Diversity (*Partridge et al., 1997*)	D

6 RESULTS AND DISCUSSION

In this section the results for experiment 1 and 2 are presented.

6.1 Experiment 1

Below in Table 6.1.1 the results for the experiment 1 are shown and the analysis of them is presented.

Table 6.1.1: Results for the experiment 1.

Dataset name	DES-CD	#1	DES-$CD_{d\text{-}opt}$	#2
400-50	58,4*	8	69,2*	4
400-400	92,8	16	90,6	7

Based on the results, it is easy to noticed that the inclusion of the diversity in the process of dynamic selection of classifiers has a significant impact on the quality of the output of the MCS when dealing with imbalanced dataset. It should be also noted that the improvement of the classification quality have been obtained with reduced number of classifiers in the ensemble. The values *#1* and *#2*, presented in the

Table 6.2.1: Results for the experiment 2.

	DES	A	B	C	D
Car 1	49,8	68,2*^{BCD}	62,9*^{AC}	53,3^{AB}	58,6*^{A}
Car 2	48,4	57,9*^{D}	55,1*	54,2	53,4^{A}
Car 3	52,9	54,8^{D}	56,2	55,9*^{D}	61,2*^{A}
Car 4	46,1	57,2*	55,3*	53,9*	58,6*
Car 5	58,3	65,1*^{D}	63,8	66,7*^{D}	59,9^{AC}

Table 6.1.1 are, respectively, the number of classifiers in the ensemble for *DES* and *DES-CD*$_{d\text{-}opt}$ algorithm. The sign * means that the difference between algorithms for specific dataset was statistically significant.

6.2 Experiment 2

Above in the *Table 6.2.1* the results for the experiment 1 are shown and the analysis of them is presented.

Similarly to the first experiment, also for datasets from the real-life Fleet Management System, the impact of the diversity for the quality of classification of the MCS for imbalanced datasets may be noticeable. The sign * means that the difference between the DES and the indicated algorithm was statistically significant.
The indexes A, B, C and D represent that the result is statistically different from those of the indicated modification of the CD-DES algorithm, which takes into account the method A, B, C or D in order to determine the diversity measure. 13 out of the 20 results of the modified *DES-CD* proved to be significantly better than *DES* algorithm for imbalanced datasets. 12 out of the 20 results turned out to be significantly different than the result of the other modification of *DES-CD* algorithm for the same dataset. Therefore it can be concluded that the method of calculating the diversity of the ensemble has a significant impact on the performance of the analyzed MCS.

7 CONCLUSIONS AND FURTHER WORK

In this paper, the actual implementation of the system that supports decision on the determination of the type of fuel change in vehicle's tank is presented. It has been shown that the MCS can be used in the analysis of such kind of changes. It has been shown that in the case of imbalanced datasets, the usage of the diversity measure for the dynamic ensemble selection process has a significant impact on the quality of the output of the MCS.

The issue described in this paper can be further investigated. In example, the presented method may be also used for analysis of the fuel level changes, based on the data provided by the CAN bus. There are a lot of other information in the database, therefore, another feature vector may be used. Our results also confirm that the various methods of determining the diversity of classifiers ensemble have the impact on the output of the MCS. Therefore, further work on methods for determining the measure is justified.

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