Riding Pattern Identification by Machine Learning for Electric Motorcycles

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***Abstract*- Identification of riding patterns is one of the key enablers to update energy consumption strategy, optimise the energy management system and increase the range of electric motorcycles despite their weight and space limits. Considering the varying driving conditions in real applications, improving accuracy of the riding pattern recognition without significant complexity is the main challenge. In this paper a simple and efficient online classification method is introduced based on features extracted only from the motorcycle speed. The recognition mechanism is firstly developed using support vector machine technique. The effect of validation method for removing the optimism in classification and the contribution of features to the accuracy of model is then investigated. Evaluation of the method on the real riding conditions in simulation environment shows the effectiveness of the approach.**

Keywords-Ride Cycle Classification, Electric Motorcycles, Machine Learning

I. INTRODUCTION

During the last few years, the electric and hybrid transportation systems have gained an increasing attention as powerful candidates to deal with the environmental issues and challenges such as global warming and air pollution [1, 2, 3]. Considering the small size, economical affordability, energy system efficiency and zero emission of the electric motorcycles, they are starting to substitute the traditional motorcycles in the growing market. With the recent improvements in the Li-ion battery technology as the main energy source for the electric vehicles, the electric and hybrid motorcycle industry is moving forward very rapidly [4].

The performance and range of battery powered motorcycles are highly dependent on their energy-power management, which interprets the energy and power demands to the battery pack. To increase the battery pack usage as well as durability an optimal management strategy is necessary and that's why developing advanced control frameworks for electric/hybrid motorcycles have become an emerging research topic in the recent years [5]. Yet compared to the considerable number of the research dedicated to energy management of the 4-wheel electric/hybrid vehicles [6, 7], the 2-wheelers have not been investigated comprehensively [8, 9, 10]. Energy/power management strategies for electric/hybrid vehicles, including motorcycles, are usually built upon one of the two following approaches: i) rule-based control and ii) the optimization-based control [8]. The first category includes predefined rules, and the energy management algorithms are usually designed following fuzzy logic [10] or heuristic rules [9]. These methods are usually simple, but not quite capable of ensuring an optimized or real-time energy management. The second category aims at optimizing the performance via minimizing a cost function. This approach can be implemented by applying optimization techniques such as dynamic programming [11] if the ride conditions are already known. In order to extend this kind of management strategies for real-time and online implementations, the time-varying nature of the riding conditions should be well addressed. The drive cycles and riding conditions directly affect the energy consumption and so the battery pack performance in hybrid/electric vehicle to a high degree [12, 13]. Good examples are high-performance vehicles with specific requirements for battery electrical and thermal management systems [14]. Obviously, to achieve a desired performance under variable driving scenarios, online identification of driving patterns is very crucial in developing optimal energy-power management strategies. For electric vehicle applications, the State-of-Art indicates that this research challenge has been addressed via different approaches. For instance, in [15], a fuzzy classifier is built to recognize the driving pattern. Meanwhile, in [8], Markov models are utilized to identify the working conditions and in [16], a hybrid approach based on Markov predictors and Fuzzy classifiers is developed. Gaussian mixture models are built to recognize driving conditions by using the historical data in [7] and wavelet-Markov models are designed to identify the high and low demand loads in [6]. Most of these existing approaches are built upon and tested on drive cycle data associated with electric four-wheelers.

Different from four-wheelers, identifying riding patterns of an electric motorcycle is even more difficult due to its highly transient dynamics during operation which are heavily dependent on the riding conditions and rider behaviors. From the best of the authors' knowledge, there is limited study of riding pattern recognition for motorcycles so far. As an attempt to fill this research gap, the present study focuses on building and evaluating a simple and effective ride cycle classifier for high-performance electric motorcycles. In this study, support vector machine is selected as the classification algorithm and optimized to maximize the accuracy of recognition. The classifier here is based on a selection of features that requires only motorcycle speed information. Furthermore, this study investigates how the validation technique could affect the accuracy of the classification and what is the contribution of each feature to that accuracy. It is worth mentioning that while the riding patterns are the same for the conventional, electric, and hybrid motorcycles. The energy management strategy update by riding pattern is more important for the latter two due to the effect of charge and discharge currents on the battery lifetime and performance.

The structure of this paper is as follows: in Section II the classification algorithm is explained. In Section III, the results are obtained and discussed, comparison and validation analysis are also provided. Finally, section IV is dedicated to the conclusions and remarks.

II. CLASSIFICATION ALGORITHM

A. Support Vector Machine

For building the classification model, the support vector machine (SVM) has been chosen. SVM is one of the most powerful and robust classification algorithms and a black box modeling technique. This algorithm suggests a hyperplane (or a set of them) for separating the data in a high dimensional space. It is aimed at finding the hyperplane that has the largest distance to the nearest training data points of various classes [17]. This algorithm has several advantages. It not only minimizes the classification error, but also minimizes the misclassification risk. It is taking advantage of kernel tricks in order to map the original space of variables to a new space in which the input data are easier to be separated and classified [18].

The SVM algorithm maps the n-dimensional input patterns $X \in \mathbb{R}^n$ into the high dimensional feature space $\mathcal{F}$ and finds a decision surface f in $\mathcal{F}$ as a classifier, where Φ is the $\mathbb{R}^n \rightarrow \mathcal{F}$ project, w is the normal vector to hyperplane and b is its bias term.

$$f(x) = W^T \Phi(X) + b \tag{1}$$

The classifier in (1) can be rewritten in the following form,

$$f(x) = \sum_{i=1}^{N} \alpha_i y_i k(x_i, X) + b \tag{2}$$

By defining a kernel function k as

$$k(x_i, X) = \Phi(x_i)\Phi(X) \tag{3}$$

And a quadratic optimization in the form of (4) with $\{\alpha_i\}_{i=1}^{N}$ are Lagrange multipliers,

$$\max_{\alpha_{i=1}^{N}} \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{N} \alpha_i \alpha_j y_i y_j k(x_i, X) \tag{4}$$

subject to conditions of (5).

$$\begin{gathered} \sum_{i=1}^{N} \alpha_i y_i = 0 \\ 0 \le \alpha_i \le C, \quad i = 1, \ldots, N. \end{gathered} \tag{5}$$

Here $\{(x_i, y_i)\}_{i=1}^{N}$ includes the training data x_i and the class labels, y_i, For SVM, kernel functions facilitate mapping data into a higher dimensional space, the kernel space, to better represent data with nonlinear interconnections. C is the constant penalising the data points crossing the boundaries between the classes. Further details of the derivation of model equations can be found in [19].

B. Design of Riding Pattern Classifier using SVM

In this section, details of building the riding pattern classifier are provided. Ride cycles are made up of a large number of sample points and in order to successfully classify them, it is necessary to reduce their dimension. For this purpose, the feature extraction approach is utilised. Based on the motorcycle speed information, ten features have been defined as depicted in Table 1. The table includes a selection of common features in the concept of ride cycle characterization according to the experts view and literature [11].

The SVM technique is the applied to construct the classification model. For this study the linear kernel is preferred. The reason is that it is simple and requires less computational effort. Considering the nature of this classification that should be performed in real-time for an on-road electric motorcycle the computational cost is a significant factor when selecting the model parameters. The effect of other kernels on the model's accuracy will be discussed in future works.

Table 1: Feature sets for ride cycle recognition

	Feature	Description of Feature	Unit
1	MeanV	Average velocity over the time window	m/s
2	MaxV	Maximum velocity over the time window	m/s
3	MinV	Minimum velocity over the time window	m/s
4	StartV	Start velocity	m/s
5	EndV	End velocity	m/s
6	MeanACC	Average Acceleration over the time window	m/s^2
7	MaxACC	Maximum Acceleration over the time window	m/s^2
8	MinACC	Minimum Acceleration over the time window	m/s^2
9	StartACC	Start Acceleration	m/s^2
10	EndACC	End Acceleration	m/s^2

To extract the features of the ride cycles for SVM classification, the time-windows with 10 sample lengths are used. The number of samples is selected as a compromise between the complexity of calculations and the amount of information to get the features, its effect is further investigated in the next section. Starting from the first sample, the ride cycle data are divided into a number of non-overlapping windows. After the model is built and validated via the features developed by these data, the same approach, but with overlapping windows (or time-moving windows) are used to extract features of the ride cycles and build a dataset for the purpose of the testing the validated model. Data from the non-overlapping and overlapping windows are separated to provide different data points for training and testing. The methodology for data preparation is described in Figure 1.

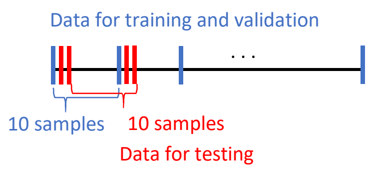


Fig 1. Data preparation for training, validation, and test

III. RESULTS AND DISCUSSSIONS

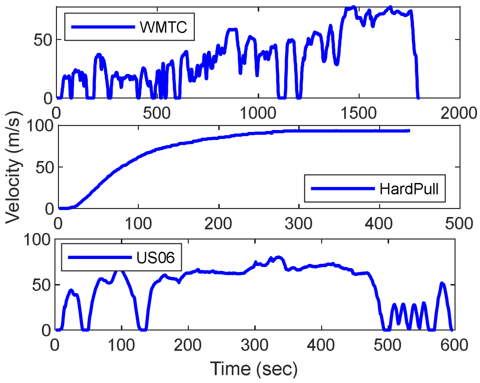
A. Case Study Defintion

In this study, three drive cycles have been selected as a case study to evaluate the capability of the proposed classifier. Without loss of generality the ride cycles can be replaced with other examples.

The data of this study are a combination of three benchmark ride cycles, including WMTC (The World Motorcycle Test Cycle) and Hard pull [20]. The ride cycles are also mixed with the drive cycle US06 to make the training dataset richer, Figure 2. The three cases are examples of three different riding patterns that are recognized to have different energy consumption and requirements.

In order to build the classifiers, the following steps are taken:

1. Select the ride cycle for training, normalize the data and segment the ride cycle, according to the methodology in Figure 2.
2. For each *C*
   2.1. Split the train and test, or cross validate
   2.2. Train the SVM
   2.3. Store the success rate
3. For cross validation average the success rates
4. Update *C* and go back to 2 for optimization



5. Fig 2: Ride cycles of this study

The success rate metric here is the confusion matrix. The confusion matrices of the built classifier show the performance of the model. The output of this reach could act as a guide for the design and implementation of an optimized energy management system for a hybrid motorcycle, same as an effective battery management system for an electric motorcycle.

B. Simulation Results

In this section the classification results are reported and discussed. As SVM has a stochastic framework for handling the data, the analysis is performed for 10 runs and the average of the results is reported. The number of runs is selected based on the design experience and a tradeoff between the run time and the variance of the results for this particular application. For classification the models are developed in MATLAB 2021, and Python 3. Figure 3 shows the classification accuracy of the SVM model with the features calculated at each 10-sample time of the three ride cycle profiles.

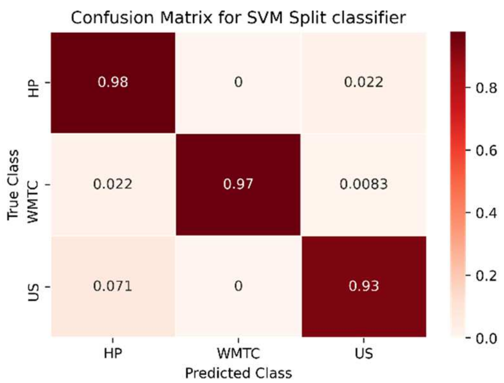


Fig 3: Confusion matrix for non-overlapping windows ride cycle classification with train and test split approach

In each run only 80% of the data are used for training and 20% is left for testing. The accuracy indices are calculated only for the test data. It is worth mentioning that the data of each time window used for feature extraction is not overlapping with the data of the next time window. The results indicate that the three classes of HP, WMTS and US06 ride cycles have been identified with higher than 98, 97 and 93 percent accuracy respectively and the misclassification rate is below 4%.

For a more comprehensive analysis, the trained modeled is tested on the whole ride cycle dataset, but with the overlapping windows used for feature extraction. This gives a larger data set of features and labels (HP, WMTS and Us06) that have not been used for the training directly. This approach can highlight the capability of the model in predicting the labels of the unseen data. The confusion matrix of this scenario is obtained as depicted in Figure 4. According to this confusion matrix, the US06 profile has been identified with the highest accuracy of 99%. This is due to the fact that the US06 is the longest ride cycle with large number of data points, so the training and testing has been very well performed on that basis. The accuracy of classification for the other two load profiles is higher than 95% which is very desirable.

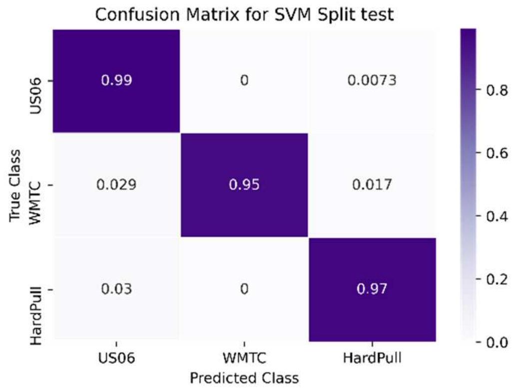


Fig 4: Confusion matrix for overlapping windows ride cycle classification with train and test split approach

Figure 5 highlights the effect of the volume of data that is used for training the model. The analysis considers features of data in windows of 5 to 150 sample points. For getting a reliable result the same window size has been used to evaluate and classify the unseen data. The window size is selected to make sure the training process is still computationally manageable, and enough data is left for validation and test.

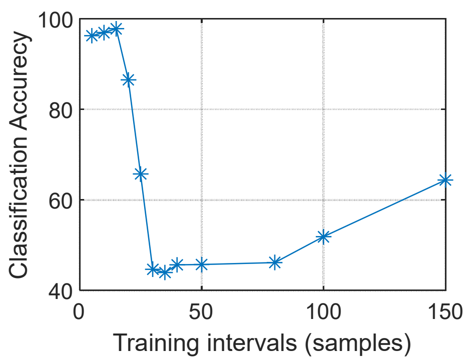


Fig 5: Average accuracy of classification in relation to the size of the window including training samples

According to Figure 5, the size of the window, including the samples of the ride cycle that is used to extract features could affect the accuracy of the model for classification unseen data. For the ride cycles of this study, the length of 15 sample points is giving the highest accuracy about 99%. As the size of the window increases more samples are compressed into a single feature and this is the reason that the model performs poorly in the range of 30 to 80. It is worth mentioning that for windows larger than 80, the model faces the danger of being overfitted as it would have very limited amount of data for the training purposes.

Designing the classifier using the train-test split approach for validation is usually the first choice. It is simple to be implemented and serves as a benchmark to other validation methods. Here we have compared the results with the cross-validation approach. In cross validation, the data set is randomly split up into a limited number of groups, *k*. The groups are usually called folds. *k*-1 folds are used to train the model, and the remain fold is used for testing. The process is then repeated k times so that each fold is used for testing purposes at least once.

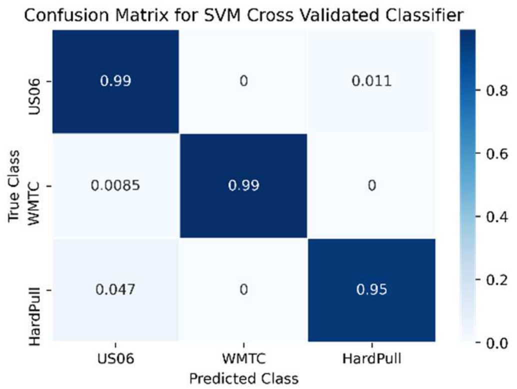


Fig 6: Confusion matrix for non-overlapping windows ride cycle classification with cross validation

The confusion matrix of the classification with the cross-validation approach is given in Figure 6 and Figure 7 for overlapping and non-overlapping time-windows respectively.

According to these figures, the accuracy score for the cross-validation method is higher than the scores of the train and test split approach as shown on Figure 3 compared to Figure 6, for train and test mix and on Figure 4 compared to Figure 7 for the testing. This confirms that the cross validation is providing a more reliable model for recognition and classification of the ride cycles. Furthermore, it does not overfit the data during training so is able to give better results on unseen data (non-overlapping windows).

Results of the classifier using the cross validation then is depicted in Figure 8. The trend is very similar to what is witnessed for the train-test-split approach. The best classification performance (98.28% accuracy) can be achieved by using 15 data points.

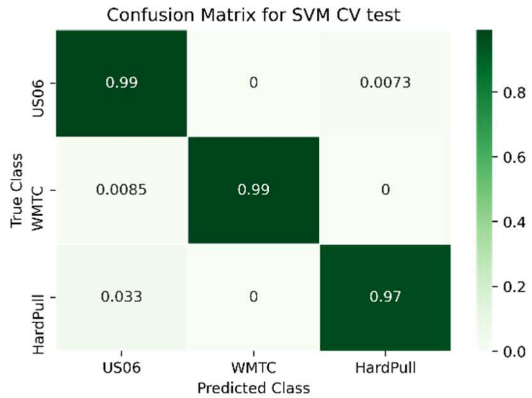


Fig 7: Confusion matrix for overlapping windows ride cycle classification with cross validation

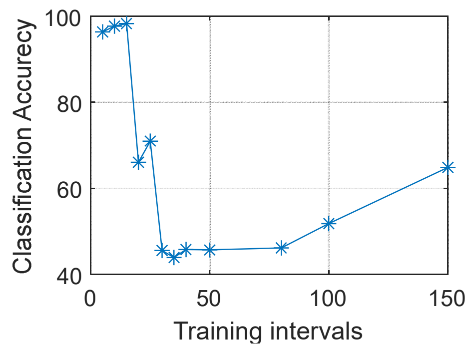


Fig 8: Average accuracy of classification with cross validation in relation with the size of the window including training samples

C. Real-time Applicability

In this section, the ability to implement the designed classifier is investigated. Firstly, utilizing the design presented in Section III.*B*, the classifier is constructed within the MATLAB/Simulink environment as shown in Figure 9.

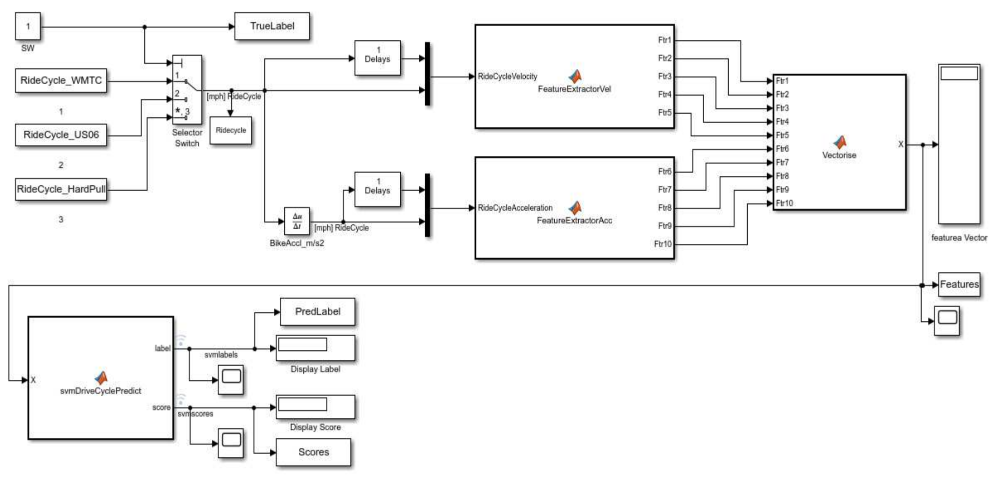


Fig 9: Real-time Simulation of the classifier in Simulink

After building the SVM-based classifiers, it is useful to represent the relationship between each feature and the model output, evaluate and quantify the importance of those. Considering the classifier designed in Section II, the coefficients of the linear model are given in Figure 10.

Here, the coefficients of the defined features are either positive or negative. Larger values show stronger correlations between features and the output, and the sign highlights if the correlation is direct or inverse.

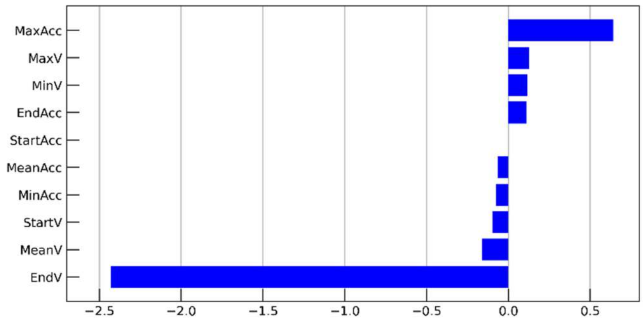


Fig 10: Feature contribution for SVM classifier

The analytical result indicates that there are 7 features with the correlation coefficients less than 0.2.

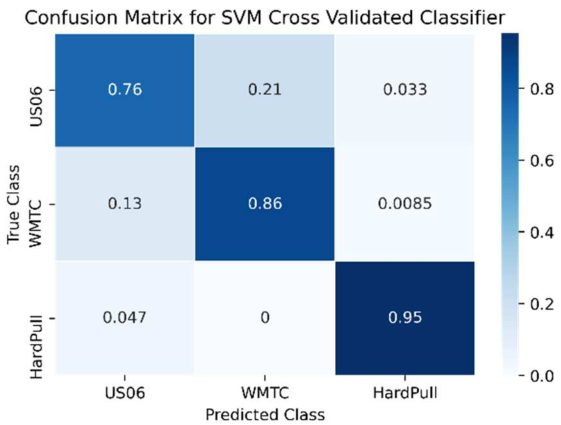


Fig 11: Classification accuracy with reduced features

When the 3 least correlated features are removed from the feature set, the classification performance with respect to the three ride cycles is updated as demonstrated in Figure 11 and Figure 12.

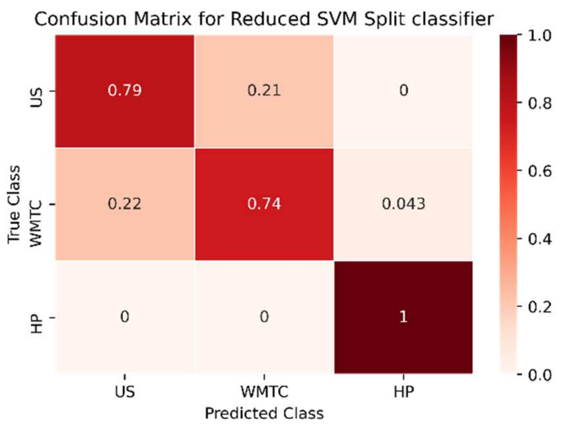


Fig 12: Classification accuracy with reduced features and cross validation

According to the confusion matrices, although some of the features are having smaller correlation weights and are less important compared to the others in the classification problem, but when those are removed, the accuracy drops significantly. This shows that the 10 features extracted from the motorcycle speed as defined in Table 1 are necessary in this application for a high-accuracy ride cycle recognition.

IV. Conclusions

This paper presents a machine learning approach combined with the real-world ride cycle data to identify the ride patterns of an electric motorcycle. Considering the nature of the problems, this is a supervised model based on 10 distinctive features derived from the motorcycle speed. The data for this study has been extracted from sections of the whole profile and it is shown that the performance of the classifiers is acceptable on that basis.

For validation based on splitting the train and test data, the accuracy is 96% for non-overlapping and 97% for overlapping windows of data (test data). The accuracy for the cross-validation method increases to 97.66% for non-overlapping and 98.33% for overlapping windows. Furthermore, the feature importance analysis confirms that the contribution of each feature is quite different and yet removing less contributed features can reduce the accuracy to 86.66% and 84.33% for cross validation and train-test split approaches of validation. This shows that further investigations on optimizing the number of features for an accurate pattern recognition is still required. The ride cycle recognition of this study is the steppingstone for building an optimized energy/battery management system for hybrid/electric motorcycles. Feature identification helps to riding pattern recognition, and the energy consumption strategy can accordingly get updated for each riding pattern. This update is shown to have an impact on the final energy consumption according to the references and will be further investigated in future work by authors.

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