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"Fitting Data": A Case Study on Effective Driver Distraction State Classification

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Abstract

The goal of this project was to investigate how to make driver distraction state classification more efficient by applying selected machine learning techniques to existing datasets. The data set used in this project included both overt driver behavior measures (e.g., lane keeping and headway measures) and indices of internal cognitive processes (e.g., driver situation awareness responses) collected under four distraction conditions, including no-distraction, visual-manual distraction only, cognitive distraction only, and dual distraction conditions. The baseline classification method that we employed was a support vector machine (SVM) to first identify driver states of visual-manual distraction and then to identify any cognitive-related distraction among the visual-manual distraction cases and other non-visual manual distraction cases. The new aspect of this research is optimization of the classification effort, which involved cardinality constraints on 16 overt driver behavior measures. A spline transformation was also implemented to achieve better classification performance. In addition to testing our optimization approach with the SVM, we also explored logistic regression. Results revealed the spline-transformed variables to produce a good "out-of-sample" performance for both the SVM and logistic regression. Beyond this, the cardinality constraints were important for selection of the most influential variables in driver state classification accuracy and preventing data overfitting. Regarding the objective of efficiency in distraction classification, with only two input variables our optimized approach achieved state classification accuracies similar to accuracies achieved with "brute-force" application of SVM with all 16 overt driver behavior measures as inputs. Interestingly, with splined- transformed variables, reducing the number of input variables to 2 only led to a marginal decrease in classification accuracy (75.38% to 74.16%). The optimization methods explored in this paper could be applied to other in-vehicle real-time data to reduce computational demands in using machine learning methods for driver state classification.

Introduction

The automotive sector is always looking for solutions to optimize driver safety and driving experiences. With the abundance of sensors in today's vehicle, more data has become available to support advanced driver assistant features such as fatigue detection [1], emotion detection [2], distraction detection [3, 4] and future maneuver/intention prediction [5, 6, 7]. Various streams of data are captured from the vehicle, driver, and surrounding objects equipped with connected components (e.g., DSRC or 5G). These data create many new opportunities for automotive engineers.

On the other hand, real-time processing of large volumes of data is challenging and resource demanding [8, 9]. In general, it is challenging to host "big data" processing in a car, due to competition for computational resources among numerous vehicle functions. Consequently, reducing the data footprint while extracting critical state information become essential steps for successful automotive data analysis applications. Selecting signature variables from available inputs is a common way to reduce data complexity. We have previously used 0-1 integer programming methodologies to select important variables in regression problems (see [10] for theoretical background). Although these methods have been used in other fields, they have been rarely applied to automotive applications, particularly to driver status monitoring features. To assess the value of these methods in automotive applications, this paper investigates how to improve the efficiency of a driver distraction classification method by applying some selected machine learning techniques on an existing data set.

Data Source

Data used in this case study were first reported by Rogers et al. in 2011 [11]. They conducted a driving simulation study to collect performance and behavioral observations on 20 volunteers. The study followed a within-subject design with two levels of visual-manual distraction (with and without), two levels of cognitive distraction (with and without), and two types of driving tasks (following and passing). Each volunteer completed 8 simulation runs with each featuring a unique combination of four distraction states and driving tasks. Each run embodied one unique combination of the three major experiment manipulations, implemented on a four-lane interstate highway. Curves and changes in speed limits (between 55 mph and 65 mph) were used to increase driver vulnerability to errors.

The visual-manual distraction task was implemented on a table computer positioned to the right side of the simulator steering wheel. The display included three arrows pointing in different directions. Among them, a yellow upward arrow was the target while gray arrows were distractors. Volunteers were asked to touch the target whenever it appeared. The display refreshed every 10 seconds or after a target was pressed. The cognitive distraction task involved mental rotation based on audio messages. Each message described a path of a virtual car traveling on an octagonal highway loop with an exit at each segment of the loop. Messages identified the start poison (e.g., "North"), direction of travel (clockwise or counterclockwise), and the number of exits passed by the virtual car. Volunteers were asked to identify the end position of the car (e.g., "east") verbally.

The two driving tasks involved different levels of vehicle control. The following task involved only operational control (steering and braking). Volunteers followed a lead vehicle at a safe distance and changed lanes when the lead vehicle changed lanes. The passing task consisted of both operational and tactical control. This task also involved lead vehicles. Volunteers would follow a lead vehicle, pass the lead vehicle when it decelerated to 10 mph below the posted speed limit, and then follow another lead vehicle.

Rogers et al. reported both overt behavior measures and internal process indices [11, 12, 13]. Overt behaviors were summarized for two phases of driving, including: (1) when drivers were following a lead vehicle within a lane; and (2) when drivers were making lane changes or passes. There were two major groups of overt behavior measures, including: (1) eye movement metrics (off-road glance frequency, off-road glance duration, percentage of off-road glance, and 95th percentile glance durations); and (2) vehicle dynamic measures (speed variance, speeding percentage, steering entropy, lane deviation, headway and headway time). Internal process indices included response time and accuracy in addressing situation awareness queries as well as NASA Task Load indeX (NASA TLX) scores. Each observation in the data set included experiment condition labels and all overt behavior measures and internal process indices. There were three labels for each experimental condition, including the types of primary driving task, the visual distraction state and the cognitive distraction state. The results of the machine learning algorithm were compared with distraction states, as noted in the experiment condition labels.

Baseline Methods

Zhang et al. [3] applied a Supportive Vector Machine (SVM) analysis to the data set described above to classify driver distraction states, including none, visual-manual, cognitive, and combined distraction states. They showed near perfect prediction accuracies with both overt behavior measures and internal process indices used as SVM inputs. However, in today's production vehicles, internal process indices, such as response accuracies to situation awareness queries, may hardly be available. Engineers need to utilize external behavior measures that can be captured with various sensors to create applications for assisting drivers in addressing today's roadway challenges. Therefore, we decided to apply dimension optimization techniques on only the external measures. It should, however, be noted that the internal process indices made a significant contribution to the cognitive distraction classifications accuracies reported in [3, 14]. Excluding internal process indices could result in lower overall classification accuracy when cognitive distraction is part of a driving scenario.

Conceptually, SVMs apply an implicit mapping function $\mathbf{\Phi}$ to project single-dimension vectors to a high-dimension feature space $\mathbf{Z}$. Data in this space Z are separated by hyper-planes as different classes. The SVM approach optimizes the hyper-plane function and the mapping function to maximize the separation among classes while minimizing classification errors on a training dataset [15]. The core of the mapping function $\mathbf{\Phi}$ is a kernel function $\boldsymbol{\kappa}(\mathbf{x}, \mathbf{x}')$. Zhang et al. adopted the radial basis function (RBF) kernel proposed by Hsu, Chang and Lin [16]. This RBF kernel uses one hyper-parameter $\boldsymbol{\gamma}$ and one penalty coefficient $\boldsymbol{C}$. These two parameters are tuned to construct SVM models for greater class prediction accuracy. Zhang et al. implemented a "grid search" procedure to find the best pair of $\boldsymbol{\gamma}$ and $\boldsymbol{C}$. This "grid search" procedure involves estimating the performance of different pairs of $\boldsymbol{\gamma}$ and $\boldsymbol{C}$ by using a k-fold cross-validation (CV) method. In particular, they implemented ten repetitions of a 10-fold CV. With the 10-fold CV, the training data set is divided into ten mutually exclusive subsets of equal size. The SVM models were trained on data in 9 subsets and tested on the remaining subset. In this way, each subset represented the "test" data in a repetition of the CV and returned an estimation of the model accuracy. Subsequently, the average of the ten estimates of model accuracy was used to estimate the "true" model accuracy. To avoid attributes with wider numeric ranges dictating model construction, Zhang et al. also applied a linear scaling of all model inputs to the range of [-1, 1].

Zhang et al. adopted several model evaluation criteria. For the overall performance of models, they calculated overall accuracy (the number of data entries correctly classified divided by the total number of entries) and Cohen's κ (Kappa) statistics (the difference between overall classification accuracy and the chance agreement divided by the overall error rate). For each distraction state, performance of models was estimated based on the four potential outcomes of signal detection theory (SDT). The four outcomes include a "hit" (the presence of a distraction state is correctly identified), a "miss" (the presence of a distraction state is not identified), a "false alarm" (a distraction state is absent but is identified as present), and a "correct rejection" (a distraction state is absent and is not identified as present). Zhang et al.'s evaluated a "two-stage" strategy to classify distraction states. In the "two-stage" approach, visual-manual distraction states were identified. Subsequently, cognitive distraction states were identified within the visual-manual distraction cases and non-visual-manual distraction cases. This approach was first reported in

Liang's study [4]. She achieved 75% accuracy with only overt behavior measures. In the present study, we also used the "two-stage" strategy as a vehicle for testing new data dimension optimization methods. Applying SDT to this "two-stage" strategy yields 17 evaluation items, including: (1) hits of visual-manual only distraction states as visual-manual only distraction states; (2) hits of dual distraction states as visual-manual only distraction states, (3) hits of visual-manual distraction states in total, 4) misses of visual-manual distraction states in total, (5) misses of dual distraction states in total, (6) false alarms of visual-manual related distraction states (i.e., the proportion of no visual-manual distraction related distraction states were misclassfied as visual-manual related distraction states), (7) correct rejections of visual distraction states, (8) misses of cognitive distraction states as visual-manual states, (9) hits of cognitive distraction states for all remaining data, (10) misses of cognitive distraction states for all remaining data, (11) hits of dual distraction states as cognitive distraction states, (12) false alarms for all distraction states, (13) false alarms as visual-manual distraction states within the no-distraction states (i.e., the proportion of no distraction states were classified as visual-manual distraction related states), (14) false alarm as cognitive distraction states within the no-distraction states (i.e., the proportion of no distraction states were classified as cognitive distraction states), (15) misses for all distraction states, (16) misses for cognitive distraction states in total, and (17) correct rejections for all distraction states. Results of that data dimension reduction methods will be reported for all these evaluation criteria.

Dimension Reduction Techniques

Similar to SVMs, logistic regression is another popular for addressing classification problems due to its simplicity and robustness. With logistic regression, classification is done by maximizing a logarithmic likelihood function. In this study, we applied data dimension reduction techniques in conjunction with application of both SVM and logistic regression to driver distraction data in order to test algorithm efficiency.

For this case study, we used the Portfolio Safeguard software (PSG) (see [17]), which supports advanced analysis capabilities, as compared to standard statistical analysis packages. In particular, the PSG can execute nonlinear spline transformation of model coefficients and impose cardinality constraints on inputs. The PSG includes the following relevant analytic functions, which can be directly used in optimization code:

- *log_exp*: maximum likelihood function for logistic regression;
- *spline_sum*: spline transformation of variables; and
- *card*: cardinality function counting of non-zero optimization variables.

These analytic functions can be combined in simple and transparent code (only a few lines for addressing the present classification problem). The code can also be used in four programming environments: Text, MATLAB, R, C++. The nonlinear transformation of variables (see Problem 1 below) and cardinality constraints (see Problem 2 below) were expected to improve "out-of-sample" (test) performance of the algorithms. The selection of an optimal number of model input variables is done based on the out-of-sample test results (akin to Chen et al. [18] application of feed-forward neural networks for optimizing network classification accuracy for test data). In this paper we followed the approach of another case study conducted for selection of variables for characterizing a medical dataset (see [19]). In particular, we have considered the following optimization problems.

Problem 1. Maximizing the log-likelihood for spline construction of every independent variable:

$$\max_{\vec{a}} \operatorname{logexp\_sum}\left(\operatorname{spline\_sum}\left(D,K,S,\vec{x},\vec{a}\right)\right)$$

where (D,K,S) denotes the degree, piece number, and smoothness of the spline respectively. $\vec{x}$ represents a variable in the target dataset, and $\vec{a}$ denotes a spline coefficient.

Problem 2. Maximizing the log-likelihood with constraints on the number of independent variables for estimation of logistic regression coefficients:

$$\max_{\vec{a}}\left(\operatorname{logexp\_sum}\left(\vec{f},\vec{a}\right)\right)$$

subject to:

$$\operatorname{cardn}\left(\vec{f}\right) \le N$$

where $\vec{f}$ is a set of splined independent variables, $\vec{a}$ is a vector of coefficients of as part of a logistic regression model, and N is the number selected non-zero independent variables in the optimal solution (upper bound in the cardinality constraint).

Note, that splined-transformed variables obtained in *Problem 1* (hereafter referred to as splined factors) can be used as inputs to various classification algorithms, including SVM and logistic regression classification.

Results

We applied the data dimension optimization techniques to the overt behavior data from Rogers et al. following the "two-stage" strategy for driver distraction state classification based on Zhang et al. work. We applied both the SVM and the logistic regression approaches as base algorithms. Table 1 shows the performance of the base algorithms on the 16 external behavior measures. As expected, the overall accuracy of this classification is significantly lower than Zhang et al.'s report for both external behavior measures and internal process indices (74.94% ± 2.87% vs. 94.38%±3.62%). However, it is similar to Liang's report with only overt behavior measures (75%).

On the basis of these results, we attempted to limit the number of model input variables while maintaining predictive accuracy. We used *Problem 2* to select the two most important

TABLE 1 Results of the two-stage approach to classification of visual-manual and cognitive distraction states with 16 overt behavior measures.

Evaluation items	Mean ± SD
Hit visual-manual distraction as visual-manual distraction	96.6% ± 2.4%
Hit dual distraction as visual-manual distraction	96.2% ± 3.5%
Hit visual-manual distraction for all data	97.4% ± 2.8%
Miss visual-manual distraction for all data	2.7% ± 2.1%
Miss dual distraction	3.4% ± 3.3%
False alarm for visual-manual related distraction	2.4% ± 3%
Correct rejection for visual-manual distraction	97.6% ± 3%
Miss cognitive distraction as visual-manual	1.3% ± 1.9%
Hit cognitive distraction in non-visual-manual data	47.4% ± 11.9%
Miss cognitive distraction in non-visual-manual data	52.6% ± 11.9%
Hit dual distraction as cognitive distraction	62% ± 32.3%
False alarm for all distractions	37.4% ± 15.6%
False alarm as visual-manual distractions	3.5% ± 5.6%
False alarm as cognitive distractions	33.9% ± 16.9%
Miss distractions in all data	19.2% ± 6.9%
Miss cognitive distraction in all data	52.6% ± 11.9%
Correct rejection for all data	62.6% ± 15.6%
Total accuracy	74.9% ± 2.9%

variables from the 16 overt behavior measures collected by Rogers et al. as inputs to SVM approach. Table 2 presents the results when the cardinality constraint is set to 2. In this case, visual-manual distractions were first identified with two selected independent variables. Cognitive distraction states were classified within no-visual-manual distraction conditions, by using another two selected independent variables.

In our second optimization approach, we used *Problem 1* to apply the spline transformation to the input variables before using *Problem 2* to select the two most important variables. As in the first optimization approach, visual-manual distractions were first identified. Cognitive distraction states were also classified within no-visual-manual distraction conditions. Table 3 presents the results of this approach. The overall accuracy increased from 68.7% to 73.8%.

In the third optimization approach, we continued to use the spline-transformed variables as in *Problem 1* but without the cardinality constraints. We implemented logistic regression instead of SVM to classify visual-manual distractions first and classify cognitive distraction states within no-visual-manual distraction conditions (see Table 4). It is important to note that with the same settings as used for the SVM model, the logistic regression achieved 68.88% total accuracy while the SVMs achieved 73.82% total accuracy. The logistic regression appeared to be less robust for classifying false alarms in general, as compared to the SVM (60.19% vs. 35.17%) and less accurate in terms of correct rejections (39.81% vs. 64.83%).

In the fourth optimization approach, we implemented Zhang's "two-stage" classification approach with logistic regression. That is, visual-manual distraction related states were identified. Subsequently, the cognitive distraction states

TABLE 2 Results of using SVM with a cardinality constraint of 2 for the two problems of first classifying visual-manual or no-visual-manual distraction and then classifying cognitive or no-cognitive distraction within the no-visual-manual condition.

Evaluation items	Mean ± SD
Hit visual-manual distraction as visual-manual distraction	91.9% ± 4.8%
Hit dual distraction as visual-manual distraction	91.2% ± 4.3%
Hit visual-manual distraction for all data	92.8% ± 6.5%
Miss visual-manual distraction for all data	4.4% ± 3.9%
Miss dual distraction	4.4% ± 3.4%
False alarm for visual-manual related distraction	4.3% ± 3.6%
Correct rejection for visual-manual distraction	95.7% ± 3.6%
Miss cognitive distraction as visual-manual	5.1% ± 5%
Hit cognitive distraction in non-visual-manual data	44.1% ± 30%
Miss cognitive distraction in non-visual-manual data	55.9% ± 30%
Hit dual distraction as cognitive distraction	70% ± 58%
False alarm for all distractions	43.2% ± 27.7%
False alarm as visual-manual distractions	4.2% ± 5.3%
False alarm as cognitive distractions	39.1% ± 27.6%
Miss distractions in all data	22.4% ± 13.9%
Miss cognitive distraction in all data	55.9% ± 30%
Correct rejection for all data	56.8% ± 27.7%
Total accuracy	68.7% ± 5.9%

TABLE 3 Results of using SVM with spline-transformed variables and a cardinality constraint of 2 for the two problems of first classifying visual-manual or no-visual-manual distraction and then classifying cognitive or no-cognitive distraction within the no-visual-manual condition.

Evaluation items	Mean ± SD
Hit visual-manual distraction as visual-manual distraction	97.6% ± 2.4%
Hit dual distraction as visual-manual distraction	97.3% ± 3.2%
Hit visual-manual distraction for all data	98.3% ± 2.4%
Miss visual-manual distraction for all data	1.5% ± 2.1%
Miss dual distraction	1.9% ± 2.8%
False alarm for visual-manual related distraction	5% ± 2.7%
Correct rejection for visual-manual distraction	95% ± 2.7%
Miss cognitive distraction as visual-manual	3.5% ± 3.2%
Hit cognitive distraction in non-visual-manual data	37.9% ± 15.1%
Miss cognitive distraction in non-visual-manual data	62.1% ± 15.1%
Hit dual distraction as cognitive distraction	70.8% ± 34.6%
False alarm for all distractions	35.2% ± 15%
False alarm as visual-manual distractions	6.8% ± 4.2%
False alarm as cognitive distractions	28.4% ± 15.1%
Miss distractions in all data	21.2% ± 7.1%
Miss cognitive distraction in all data	62.1% ± 15.1%
Correct rejection for all data	64.8% ± 15%
Total accuracy	73.8% ± 2.5%

TABLE 4 Results of the logistic regression model with spline-transformed variables to address the two problems of first classifying visual-manual or no-visual-manual distraction and then classifying cognitive or no-cognitive distraction within the no-visual-manual condition.

Evaluation items	Mean ± SD
Hit visual-manual distraction as visual-manual distraction	95.5% ± 2.5%
Hit dual distraction as visual-manual distraction	93.6% ± 3.8%
Hit visual-manual distraction for all data	97.4% ± 3.1%
Miss visual-manual distraction for all data	2.5% ± 1.9%
Miss dual distraction	4.1% ± 3.5%
False alarm for visual-manual related distraction	5.1% ± 3.1%
Correct rejection for visual-manual distraction	94.9% ± 3.1%
Miss cognitive distraction as visual-manual	5.2% ± 4.4%
Hit cognitive distraction in non-visual-manual data	46% ± 9.3%
Miss cognitive distraction in non-visual-manual data	54% ± 9.3%
Hit dual distraction as cognitive distraction	59.6% ± 15.2%
False alarm for all distractions	60.2% ± 9.4%
False alarm as visual-manual distractions	4.7% ± 4.7%
False alarm as cognitive distractions	55.5% ± 9.6%
Miss distractions in all data	18.7% ± 3.7%
Miss cognitive distraction in all data	54% ± 9.3%
Correct rejection for all data	39.8% ± 9.4%
Total accuracy	68.9% ± 3.2%

were identified within the visual-manual distraction states as well as the non-visual-manual distraction states. In this case, we still used the spline-transformed variables as in *Problem 1* without the cardinality constraints. As shown in Table 5, even with the full implementation of the "two-stage" approach, the total accuracy of this approach was only 67.7 %.

In the fifth optimization approach, we used the SVM to implement the "two-stage" classification approach with the spline-transformed variables as in *Problem 1* without the cardinality constraint. As shown in Table 6, the SVM produced greater total accuracy than the logistic regression model (75.4% vs. 74.16%).

In the final optimization approach, we once again applied the SVM to implement the "two-stage" classification strategy with the spline-transformed variables as in *Problem 1* and cardinality constraint of 2 as in *Problem 2*. As shown in Table 7, by reducing the number of input variables from all 16 inputs to the two most important variables, the total accuracy of the SVM only decreased marginally (75.38% to 74.16%).

Discussion and Conclusion

From this research, we found that the use of spline-transformed variables as inputs to both SVM and logistic regression models supports good out-of-sample model classification performance (see Appendix A). Comparison of all tested methods). The utility of the spline transformation of variables

TABLE 5 Results of logistic regression with spline-transformed variables for the three problems of first classifying visual-manual or no-visual-manual distraction and then classifying cognitive or no-cognitive distraction within the visual-manual and no-visual-manual conditions.

Evaluation items	Mean ± SD
Hit visual-manual distraction as visual-manual distraction	97.7% ± 2.5%
Hit dual distraction as visual-manual distraction	97.1% ± 3.2%
Hit visual-manual distraction for all data	98.4% ± 2.3%
Miss visual-manual distraction for all data	1.5% ± 1.8%
Miss dual distraction	1.6% ± 2.3%
False alarm for visual-manual related distraction	3.1% ± 2.9%
Correct rejection for visual-manual distraction	96.9% ± 2.9%
Miss cognitive distraction as visual-manual	1.9% ± 2.8%
Hit cognitive distraction in non-visual-manual data	31.3% ± 15.4%
Miss cognitive distraction in non-visual-manual data	68.7% ± 15.4%
Hit dual distraction as cognitive distraction	51.8% ± 18.4%
False alarm for all distractions	53.8% ± 19.3%
False alarm as visual-manual distractions	4.4% ± 5.3%
False alarm as cognitive distractions	49.4% ± 19.1%
Miss distractions in all data	24.3% ± 6.4%
Miss cognitive distraction in all data	70.9% ± 15%
Correct rejection for all data	46.2% ± 19.3%
Total accuracy	67.7% ± 6.1%

TABLE 6 Results of the SVM approach with spline-transformed variables for the three problems of first classifying visual-manual or no-visual-manual distraction and then classifying cognitive or no-cognitive distraction within the visual-manual and no-visual-manual conditions.

Evaluation items	Mean ± SD
Hit visual-manual distraction as visual-manual distraction	99.2% ± 1.2%
Hit dual distraction as visual-manual distraction	99% ± 2%
Hit visual-manual distraction for all data	99.7% ± 1%
Miss visual-manual distraction for all data	0.6% ± 1.1%
Miss dual distraction	0.6% ± 1.8%
False alarm for visual-manual related distraction	2.7% ± 3.4%
Correct rejection for visual-manual distraction	97.3% ± 3.4%
Miss cognitive distraction as visual-manual	2.3% ± 2.9%
Hit cognitive distraction in non-visual-manual data	48.9% ± 7%
Miss cognitive distraction in non-visual-manual data	51.1% ± 7%
Hit dual distraction as cognitive distraction	58.6% ± 30%
False alarm for all distractions	41.7% ± 9.9%
False alarm as visual-manual distractions	3.1% ± 5.7%
False alarm as cognitive distractions	38.7% ± 10.1%
Miss distractions in all data	17.5% ± 5.9%
Miss cognitive distraction in all data	51.1% ± 7%
Correct rejection for all data	58.3% ± 9.9%
Total accuracy	75.4% ± 3.2%

TABLE 7 Results of the SVM approach with spline-transformed variables and cardinality constraint of 2 for the three problems of first classifying visual-manual or no-visual-manual distraction and then classifying cognitive or no-cognitive distraction within the visual-manual and no-visual-manual conditions.

Evaluation items	Mean ± SD
Hit visual-manual distraction as visual-manual distraction	97.7% ± 2.5%
Hit dual distraction as visual-manual distraction	97.1% ± 3.2%
Hit visual-manual distraction for all data	98.4% ± 2.3%
Miss visual-manual distraction for all data	1.7% ± 1.8%
Miss dual distraction	2.3% ± 3.3%
False alarm for visual-manual related distraction	3.1% ± 2.9%
Correct rejection for visual-manual distraction	96.9% ± 2.9%
Miss cognitive distraction as visual-manual	1.9% ± 2.8%
Hit cognitive distraction in non-visual-manual data	50.4% ± 8.8%
Miss cognitive distraction in non-visual-manual data	49.6% ± 8.8%
Hit dual distraction as cognitive distraction	51.8% ± 18.4%
False alarm for all distractions	38.5% ± 17%
False alarm as visual-manual distractions	4.4% ± 5.3%
False alarm as cognitive distractions	34% ± 19.4%
Miss distractions in all data	20.2% ± 7.7%
Miss cognitive distraction in all data	57.7% ± 16.3%
Correct rejection for all data	61.5% ± 17%
Total accuracy	74.2% ± 2.4%

also appears to be greater when cardinality constraints are implemented (return to Table 2 and Table 3). Additionally, the SVM method shows greater accuracy as compared to the logistic regression approach, based on the selected data set.

In addition, the implementation of cardinality constraints in attempting to increase the efficiency of classification approaches did not appear to substantially degrade model performance. With the SVM method, reducing inputs from a set of 16 to only two of the most important variables (with spline-transformation) only marginally reduced the total model classification accuracy (75.38% to 74.16%) for the target dataset. This result may be due, in part, to the overt behavior measures being highly correlated with each other. For example, visual distractions usually led to higher steering entropy and slower reaction time [6]. Therefore, using cardinality constraints to select the best two representative features still allowed for a high degree of model accuracy. It is important to apply the cardinality constraints in order to select the most important input variables and prevent potential training data set overfitting.

Based on this optimization study, we recommend implementing the use of spline-transformed variables coupled with cardinality constraints for efficient algorithm application in driver distraction state classification. In the case of distinguishing between driver distraction states, the SVM method may be a preferred learning method as compared to logistic regression.

A limitation of this study is that we only tested our optimization methods with one data set. The generalizability of the results to other in-vehicle big data classification problems may be limited. However, the general optimization approach of reducing input variables while applying transforms to achieve equivalent classification algorithm performance should be considered in any in-vehicle data application design process. Our study successfully demonstrated two promising techniques to achieve the balance of driver distraction state classification efficiency and effectiveness. The present approach should be applied to additional datasets for further validation. A future study could extend this effort by introducing other machine learning techniques and variable transformations to produce "lightweight" and reliable in-vehicle data analysis applications.

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Definitions/Abbreviations

SVM - Supportive Vector Machine

CV - Cross-validation

SDT - Signal detection theory

SD - Standard Deviation

PSG - Portfolio Safeguard software

Appendix

Appendix A. Comparison of All Tested Methods

Evaluation items	SVM [Baseline] No transformation No Cardinality constrain Three problems	SVM No transformation Cardinality constraint =2 Two problems	SVM Spline-transformed Cardinality constraint =2 Two problems	Logistic regression Spline-transformed No Cardinality constrain Two problems	Logistic regression Spline-transformed No Cardinality constrain Three problems	SVM Spline-transformed No Cardinality constrain Three problems	SVM Spline-transformed variables Cardinality constraint =2 Three problems
Hit: visual-manual distraction as visual-manual distraction	96.6% ± 2.4%	91.9% ± 4.8%	97.6% ± 2.4%	95.5% ± 2.5%	97.7% ± 2.5%	99.2% ± 1.2%	97.7% ± 2.5%
Hit: dual distraction as visual-manual distraction	96.2% ± 3.5%	91.2% ± 4.3%	97.3% ± 3.2%	93.6% ± 3.8%	97.1% ± 3.2%	99% ± 2%	97.1% ± 3.2%
Hit: visual-manual distraction for all data	97.4% ± 2.8%	92.8% ± 6.5%	98.3% ± 2.4%	97.4% ± 3.1%	98.4% ± 2.3%	99.7% ± 1%	98.4% ± 2.3%
Miss: visual-manual distraction for all data	2.7% ± 2.1%	4.4% ± 3.9%	1.5% ± 2.1%	2.5% ± 1.9%	1.5% ± 1.8%	0.6% ± 1.1%	1.7% ± 1.8%
Miss: dual distraction	3.4% ± 3.3%	4.4% ± 3.4%	1.9% ± 2.8%	4.1% ± 3.5%	1.6% ± 2.3%	0.6% ± 1.8%	2.3% ± 3.3%
False alarm: visual-manual related distraction	2.4% ± 3%	4.3% ± 3.6%	5% ± 2.7%	5.1% ± 3.1%	3.1% ± 2.9%	2.7% ± 3.4%	3.1% ± 2.9%
Correct rejection: visual-manual distraction	97.6% ± 3%	95.7% ± 3.6%	95% ± 2.7%	94.9% ± 3.1%	96.9% ± 2.9%	97.3% ± 3.4%	96.9% ± 2.9%
Miss: cognitive distraction as visual-manual	1.3% ± 1.9%	5.1% ± 5%	3.5% ± 3.2%	5.2% ± 4.4%	1.9% ± 2.8%	2.3% ± 2.9%	1.9% ± 2.8%
Hit: cognitive distraction in non-visual-manual data	47.4% ± 11.9%	44.1% ± 30%	37.9% ± 15.1%	46% ± 9.3%	31.3% ± 15.4%	48.9% ± 7%	50.4% ± 8.8%
Miss: cognitive distraction in non-visual-manual data	52.6% ± 11.9%	55.9% ± 30%	62.1% ± 15.1%	54% ± 9.3%	68.7% ± 15.4%	51.1% ± 7%	49.6% ± 8.8%
Hit: dual distraction as cognitive distraction	62% ± 32.3%	70% ± 58%	70.8% ± 34.6%	59.6% ± 15.2%	51.8% ± 18.4%	58.6% ± 30%	51.8% ± 18.4%
False alarm: all distractions	37.4% ± 15.6%	43.2% ± 27.7%	35.2% ± 15%	60.2% ± 9.4%	53.8% ± 19.3%	41.7% ± 9.9%	38.5% ± 17%
False alarm: visual-manual distractions	3.5% ± 5.6%	4.2% ± 5.3%	6.8% ± 4.2%	4.7% ± 4.7%	4.4% ± 5.3%	3.1% ± 5.7%	4.4% ± 5.3%
False alarm: cognitive distractions	33.9% ± 16.9%	39.1% ± 27.6%	28.4% ± 15.1%	55.5% ± 9.6%	49.4% ± 19.1%	38.7% ± 10.1%	34% ± 19.4%
Miss: distractions in all data	19.2% ± 6.9%	22.4% ± 13.9%	21.2% ± 7.1%	18.7% ± 3.7%	24.3% ± 6.4%	17.5% ± 5.9%	20.2% ± 7.7%
Miss: cognitive distraction in all data	52.6% ± 11.9%	55.9% ± 30%	62.1% ± 15.1%	54% ± 9.3%	70.9% ± 15%	51.1% ± 7%	57.7% ± 16.3%
Correct rejection: all data	62.6% ± 15.6%	56.8% ± 27.7%	64.8% ± 15%	39.8% ± 9.4%	46.2% ± 19.3%	58.3% ± 9.9%	61.5% ± 17%
Total accuracy	74.9% ± 2.9%	68.7% ± 5.9%	73.8% ± 2.5%	68.9% ± 3.2%	67.7% ± 6.1%	75.4% ± 3.2%	74.2% ± 2.4%

Note: Two problems: first classifying visual-manual or no-visual-manual distraction and then classifying cognitive or no-cognitive distraction within the no-visual-manual condition. Three problems: first classifying visual-manual or no-visual-manual distraction and then classifying cognitive or no-cognitive distraction within the visual-manual and no-visual-manual conditions.

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