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Data Mining by Smartphone and Big Data Analysis for Driver's Subconscious Behavior – *An Attempt to Recognize Driver's Characteristics and Realize Safe Driving Techniques*

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ABSTRACT

Last few years, some famous types of powerful smart phones have been revitalizing the market in the world and been coming available at every situation and environment. Data mining and Big Data Analysis seem to be very useful and attractive in the information processing domain. Combination of smartphones sensing technology and data mining approach can bring fruitful results to our recognition. This study has been treating with application for smartphones to acquire specific amount of data from the target, manipulation of data set, performance of data mining and visualization normally hidden data characteristics/ relationship through machine learning. Driving characteristics acquired by application of smartphone (iPhone) have been stored as data base. Machine learning (SVM) has been applied to the relevant data for generation of useful identification operator for pattern recognition. And Visualization of subconscious driver's behavior can be demonstrated through such identification operator.

KEYWORDS

Data acquisition, Smartphone application, Machine learning, Visualization of subconscious behavior.

1 INTRODUCTION

Day by day, the presence of car has become indispensable as shifting means of our everyday life due to highly motorized society. Although huge repetition of traffic accidents tends to decrease, major 40% of such accidents have occurred at the traffic intersections. Almost drivers have to be careful for such intersections because they are the very places where several kinds of driver's skill encounter one another nearly at the same time.

Drivers from beginners to proficiency must get a handle on their driving habits, tendencies and proclivities in order to avoid improperly-driving behavior, which may unfortunately but probably lead to traffic accidents. Therefore, they shall need to visualize and recognize their driving tendencies and proclivities as easily and correctly as possible.

Effective utilization of smartphones with its "software application" will be one of the most promising candidates to acquire adequate data for driving characteristics, simply and efficiently. A well-known article[1] presents "Mobile phones or smartphones are rapidly becoming the central computer and communication device in people's lives. Importantly, today's smartphones are programmable and come with a growing set of cheap powerful embedded sensors, such as an accelerometer, digital compass, gyroscope, GPS, microphone, and so on." And not only its authors but also almost all of us can "believe that sensor-equipped mobile phones will revolutionize many sectors of our economy, including business, healthcare, social networks, environmental monitoring, and transportation."

In this study, we have applied some smart devices such as Apple iPhone and Android-based smart phone to sensing or monitoring many kinds of data to imply driving characteristics, employed data mining approach in order to analyze driver's behavior, and demonstrated both of visualization and recognition of driving characteristics through machine learning such as k-Nearest Neighbors algorithm and/or Support Vector Machine.

This paper presents our study about data acquisition by "application" for smartphones, data mining for driver's behavior, pattern recognition through machine learning, and big data analysis to visualize driving characteristics. The next section introduces related work about application of smart phone-based data acquisition and analysis with machine learning. The third one illustrates system configuration and its data manipulation. The fourth one describes patterns for supervised learning and an experiment of practical data acquisition. The fifth one demonstrates classification of machine learning and consideration of recognized results. Finally the last one summarizes our conclusion.

2 RELATED WORK

This section introduces useful related works. Two papers are describing smartphones for driving, one is treating with human behavior, and three are reporting application of machine learning.

Mohamed Fazeen[2] of the University of North Texas and his colleagues pointed out, "Mobile smartphones today are equipped with numerous sensors that can help to aid in safety enhancements for drivers on the road." And in their paper, the three-axis accelerometer of an Android-based smartphone had been used to record and analyze various driver behaviors and external road conditions that could potentially be hazardous to the health of the driver, the neighboring public, and the automobile. They described, "Effective use of these data can educate a potentially dangerous driver on how to safely and efficiently operate a vehicle. With real-time analysis and auditory alerts of these factors, we can increase a driver's overall awareness to maximize safety."
Jin-Hyuk Hong[3] and his colleagues of Carnegie Mellon University reported, "In order to understand and model aggressive driving style, we construct an in-vehicle sensing platform that uses a smartphone instead of using heavyweight, expensive systems. Utilizing additional cheap sensors, our sensing platform can collect useful information about vehicle movement, maneuvering and steering wheel movement." They utilized such data and applied machine learning to build a driver model that evaluates drivers' driving styles based on a number of driving-related features. And they analyzed the characteristics of drivers who have an aggressive driving style."
Erez Shmueli[4] and his colleagues of MIT(Media Lab.) described, "The ability to understand social systems through the aid of computational tools is central to the emerging field of computational social systems. Such understanding can answer epistemological questions on human behavior in a data-driven manner, and provide prescriptive guidelines for persuading humans to undertake certain actions in real-world social scenarios. The growing number of works in this subfield has the potential to impact multiple walks of human life including health, wellness, productivity, mobility, transportation, education, shopping, and sustenance."

Thuy Nguyen and Grenville Armitage from Swinburne University of Technology, Melbourne[5] surveyed techniques for internet traffic classification using machine learning(ML). They discussed a number of key requirements for the employment of ML-based traffic classifiers in operational IP networks, and qualitatively critique the extent to which the reviewed works meet these requirements.
Harris Drucker of AT&T Labs and his colleagues[6] studied the use of support vector machines (SVM) in classifying e-mail as spam or non-spam by comparing it to three other classification algorithms. They reported, "Such four algorithms had been tested on two different data sets: one data set where the number of features were constrained to the 1000 best features and another data set where the dimensionality was over 7000. SVM performed best when using binary features. SVM had significantly less training time."
R.Burbidge and colleagues of University College London[7] showed that the support vector machine (SVM) classification algorithm had proved its potential for structure–activity relationship analysis. In their benchmark test, the SVM had been compared to several machine learning techniques frequently used in the field. The classification task involved predicting the inhibition of dihydrofolate reductase by pyrimidines, using data obtained from the UCI machine learning repository. SVM had been significantly better than all.

Thanks to the above researches, we have decided to apply smartphone to acquire several kinds of data during driving, to shape driver’s behaviors and to classify/ categorize/pattern-recognize their characteristics with machine learning. The next section illustrates our study based on smartphone, human behavior shaping and classification with machine learning.

3 SYSTEM CONFIGURATION AND DATA MANIPULATION

System configuration and data flow are described in this section. And practical manipulation of acquired data is also illustrated below.

3.1 System Configuration and its Dataflow

As known in the previous sections, smart devices can allow us to acquire several kinds of data obtained by the following sensors such as GPS, compass, gyroscope, accelerometer, and so on. For example, data from GPS facility can provide us with not only navigation but also position-located several useful information, which allows the phone to localize itself, enables new location-based applications such as local search, mobile social networks, and navigation. The information from compass, gyroscope and accelerometer can realize the other following location-based and/or movement-sensing applications such as detecting direction and orientation, characterizing behavior and habit of movements, and recognizing physical situation and environment.
So we have begun to acquire several kinds of data and information from smart devices by means of our original software application, transfer such data to the specified server through HTTP connectivity between smart device(s) and server, and cumulate them into our special Web server based on simple SQL database scheme. **Figure 1** shows our system configuration about data acquisition between smart device and Web server.

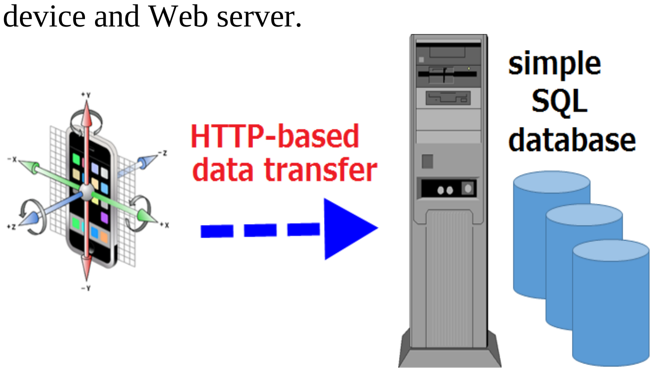

Figure 1. System Configuration about Data Acquisition and Transferring between Smart device and Web server.

At the above server, we can perform data mining by means of retrieving and extracting specified data from a series of data stream from the beginning to the end stored SQL database.

3.2 Data Manipulation with Sliding Windows

Well-known "static" *sliding window approach* uses fixed-length temporal areas called "windows" that shift to focus each window from left to right sequentially. Operation of shift is to move focused window, so it used to be called sliding window approach. Each window position produces one area, namely limited segment, which is used to isolate/extract a block of data, or a series of records for later processing.
It uses two parameters: the windows length (=***wl***) and the shift step (=***ss***). **Figure 2** shows our (static) sliding window approach to extract each block of data in order to detect a specific phenomenon and to recognize a characteristic behavior from left to right sequentially. Our approach defines 32 sampling size of data block for ***wl*** and half size of window, namely 16 size, for ***ss***.

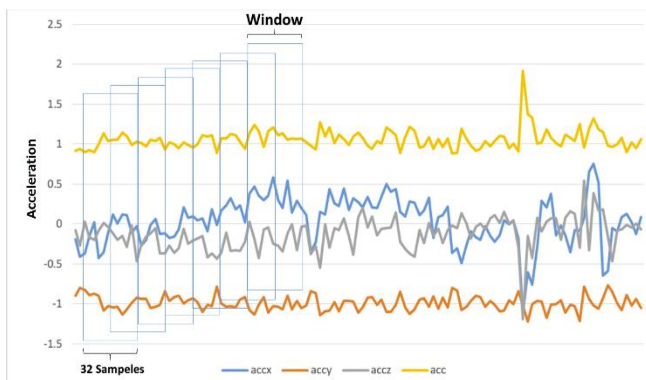

Figure 2. Employment of sliding window approach with half-size overlapping to extract focused data block and to recognize characteristic behavior.

We have employed half-size overlapping windows for sliding window approach because it is easy and efficient for us to find specific phenomenon in order to avoid misjudgment at the boundary point between the previous and the next windows, although it may pay approximately double computing costs.
We have plaid our attention to driving behaviors at the traffic intersections because many accidents or blood-freeze-feelings frequently occur at that places. Normally, drivers have decided to go straight through, make a right turn, or make a left

turn at the traffic intersection. In this study, we have focused on driving to make a left turn at the intersection. So, we must detect and recognize specific driving behavior of making a left turn automatically through scanning of acquired data files from smart devices. With sliding window approach, we can recognize driving behavior of "making a left turn" with more precision as well as efficiency.

Figure 3 shows how to recognize making a left turn with comparison between left and right halves in the Time Window using average **A1** and **A2** of azimuth direction values for left half and right one respectively.

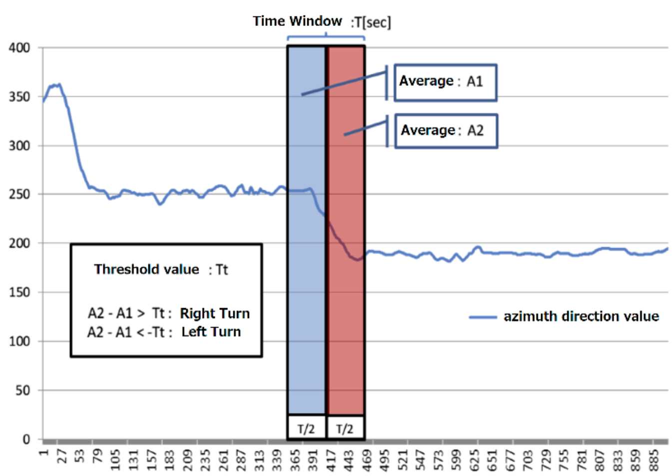

Figure 3. Comparison between left and right halves in the Time Window Using each average A1 and A2 of azimuth direction value(s).

We have defined some suitable value for threshold **Tr**. And we will be able to obtain computed result of recognition for a left turn at the case where **A2 - A1 < -Tr** or a right turn where **A2 - A1 > Tr**. So we can cast anchor at the suitable locations on the series of acquired data set just like specifying an effective time-stamp for each point when driver made "a left turn" for acquired data from smart device.

After that, we can utilize some anchored data set and perform data mining approach for recognize driving behavior in order to classify what a kind of making a left turn based on anchored position of several mounts of specific data or information obtained by a lot of kinds of sensors.

4 PATTERN FOR SUPERVISED LEARNING AND EXPERIMENT OF DATA ACQUISITION

This Section shows patterns for supervised learning and its experiment of practical data acquisition.

4.1 Four Patterns for Supervised Learning

Sotiris Kotsiantis from University of Peloponnese, Greece had described in his paper[8],"Supervised machine learning is the search for algorithms that reason from externally supplied instances to produce general hypotheses, which then make predictions about future instances. In other words, the goal of supervised learning is to build a concise model of the distribution of class labels in terms of predictor features. The resulting classifier is then used to assign class labels to the testing instances." In our case, we have acquired data from four kinds of patterns described below as the above ***instances*** in order to perform supervised machine learning

- Pattern No1 of Left turn: making a Left Turn at the traffic intersection with NO acceleration (Abbreviation: LtNo). **Figure 4** shows the pattern No1.
- Pattern No2 of Left turn: making a Left Turn at the traffic intersection with ACceleration (Abbreviation: LtAc). **Figure 5** shows the pattern No2.

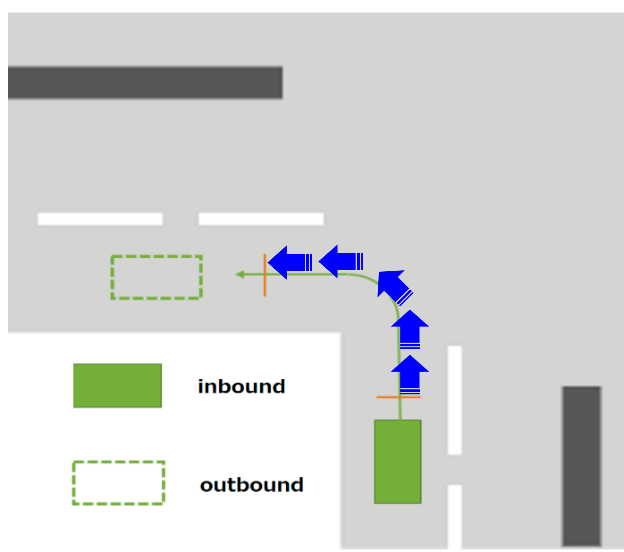

Figure 4. A Left Turn at the traffic intersection with No acceleration (Abbreviation: LtNo).

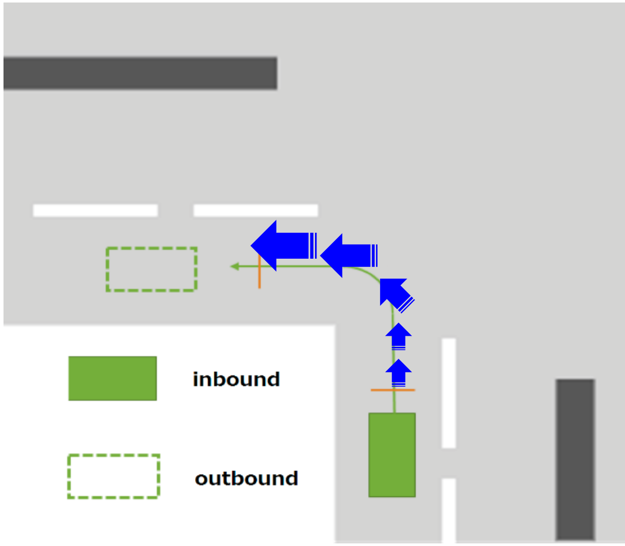

Figure 5. A Left Turn at the traffic intersection with Acceleration (Abbreviation: LtAc).

- Pattern No3 of Left turn: making a Left Turn at the traffic intersection with BRakeage (Abbreviation: LtBr). **Figure 6** shows the pattern No3.
- Pattern No4 of Left turn: making a Left Turn at the traffic intersection with OVerrunning (Abbreviation: LtOv). **Figure 7** shows the pattern No4.

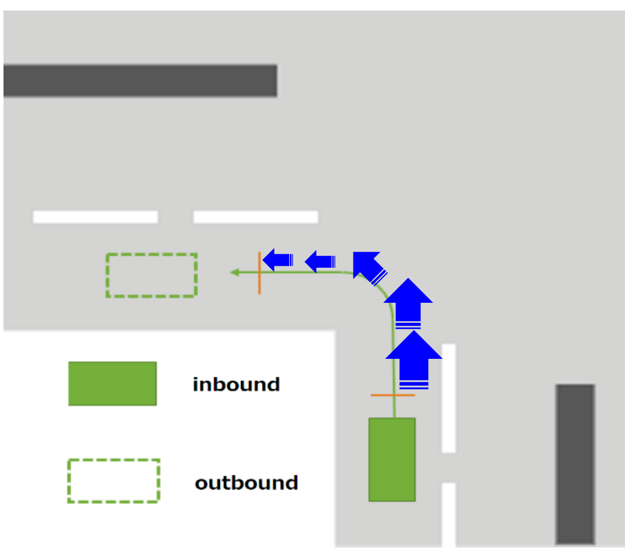

Figure 6. A Left Turn at the traffic intersection with BRakeage (Abbreviation: LtBr).

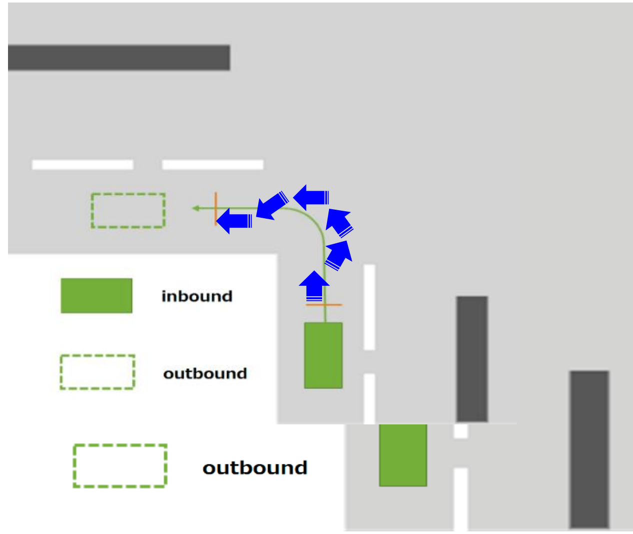

Figure 7. A Left Turn at the traffic intersection with OVerrunning (Abbreviation: LtOv).

We have defined the above four patterns of making a left turn at the intersection and illustrate such four kinds of patterns at Figure 4 - 7 in this sub-section, where Green-fill box specifies a starting position for inbound into left turn and green-frame box specifies an ending position for outbound from left turn. These are necessary to obtain several parameters in classification for supervised machine learning described below and with those instances, we will calculate our classifiers and predictors in the next section.

4.2 Experiment and Practical Data Acquisition

Figure 8 shows our experimental driving course, and we can have four times of necessary data sets from one-time drive on the circuit.

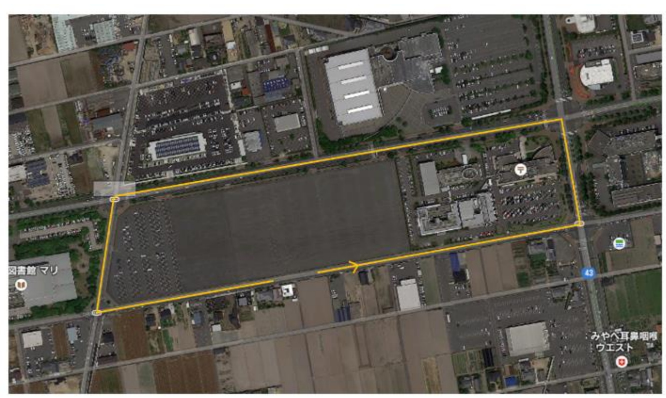

Figure 8. Our Experimental Driving Course.

It takes about 15 minutes to drive our experimental car along the yellow-lined square circuit. We used to drive our car at the speed approximately 40-50 Km/hour, which is a natural speed in the city.
From practical driving experiments, we have acquired several numbers of data described in **Table 1**.The number of experiments were 18 times, and we had four sets of data about making a left turn at the intersection from one time experiment.

Table 1. Detail of Acquired Data.

experiment	acquired data
numbers of experiments	18 times
acquired left-turn data file	72 (CSV files)
defective data	4 sets
unadapted data	4 sets
mismatch driving data	6 sets
usable data	58 sets

Table 1 includes 72 sets of acquired left-turn data files, but there were 4 sets of defective data, 6 sets of un-adapted data, and 6 sets of mismatch driving data in such 72 sets of files. So we must apply our data mining approach to the remaining 58 sets of data files and analyze them in order to recognize the relevant driving behavior about making a left turn at the intersection.

4.3 Parameters for Pattern Recognition

At first, we did not know which parameters were necessary or sufficient for our application of pattern recognition about driving behavior by means of Machine Learning (ML), so we had begun to perform classification by k-Nearest Neighbors algorithm and Support Vector Machines as ML with the following parameters;

1. Average of movement intensity: accelerations for x-, y-, and z-axis; ones for pitch, roll and yaw. -- (3+3 = 6 elements)
2. SD: standard deviations for x-, y-, and z-axis; ones for pitch, roll and yaw. -- (3+3 = 6 elements)
3. Maximal power spectra for x-, y-, and z-axis; maximal power spectra for pitch, roll and yaw. -- (3+3 = 6 elements)
4. Kinetic energies for x-, y-, and z-axis; ones for pitch, roll and yaw. -- (3+3 = 6 elements)
5. RMS: root-mean-square for x-, y-, and z-axis; RMS for pitch, roll and yaw. -- (3+3 = 6 elements)
6. Average intensity of 3-axis composite value and pitch/roll/yaw composite value. -- (1+1= 2 elements)
7. Dispersion intensity of 3-axis composite value and pitch/roll/yaw composite value.
8. SMA: Normalized Signal Magnitude Area[9][10] of 3-axis composite value and pitch/roll/yaw composite value. -- (1+1= 2 elements)

So we had begun to compute 36 dimensional elements of data set for initial pattern recognition for classification of driving behavior.

5 CLASSIFICATION AND RECOGNITION

This section demonstrates practical computation for classification by supervised machine learning about such remaining data to realize pattern recognition and visualize corresponding driver's behavior, namely the relevant driver's tendency or proclivity.

5.1 Classification by Machine Learning (I)

We have employed the k-Nearest Neighbors algorithm (or k-NN for short) and Support Vector Machines (or SVM for short) in order to perform pattern recognition or classification of driving behavior among the following four patterns: LtNO, LtAc, LtBr and LtOv, which are introduced in the previous section.
The former is a well-known non-parametric method used for classification in pattern recognition and the input consists of the (given value:) k closest training examples in the feature space. k-NN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification. The k-NN algorithm is among the simplest of all machine learning algorithms.
The latter is another well-known supervised learning model with associated learning algorithms. It can analyze data used for classification analysis-

Given a set of training examples, each marked for belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-probabilistic binary linear classifier - in machine learning.

In k-NN classification, the output is a class membership. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive, typically small integer.). If k = 1, then the object is simply assigned to the class of that single nearest neighbor. We had employed exhaustive cross-validation methods which learn and test on all possible ways to divide the original sample into a training and a validation set. And we had obtained good recognition rate(R=52.73%) with empirically optimal k=7 after choosing k to be an odd number from 1 to 19 via bootstrap (=counting up) method.

Table 2 is a result of average of rate for right answers from 8-fold cross-validation after every single subset is retained as the validation data for testing the model, and other remaining 7 subsets are used as training data consequently.

Table 2. Classification of Driving Behavior by k-NN.

	Driving Characteristics by k-NN			
	LtNo	LtAc	LtBr	LtOv
LtNo	43(48.9%)	13(17.6%)	13(18.6%)	10(12.7%)
LtAc	21(23.9%)	36(48.6%)	8(11.7%)	14(17.7%)
LtBr	12(13.6%)	14(18.9%)	39(55.7%)	10(12.7%)
LtOv	12(13.6%)	11(14.9%)	10(14.3%)	45(57.9%)

An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. We had employed SVM with Gaussian kernel and applied it to the usable dataset given in Table 1. And we had obtained good recognition rate (R=55.94%) with gamma value: γ = 0.05011872 and cost value: C=50.11872. **Table 3** is a result of average of rate for right answers based on the condition with the above good recognition rate (R=55.94%).

Table 3. Classification of Driving Behavior by SVM.

	Driving Characteristics by SVM			
	LtNo	LtAc	LtBr	LtOv
LtNo	76(96.2%)	2(2.9%)	5(6.7%)	2(2.6%)
LtAc	1(1.3%)	73(92.4%)	2(2.7%)	1(1.3%)
LtBr	1(1.3%)	1(1.3%)	62(82.7%)	4(5.1%)
LtOv	1(1.3%)	3(3.8%)	6(8.0%)	71(91.0%)

5.2 Principal Component Analysis–based Reduction of Dimensionality

Another effect of high dimensionality on distance functions concerns graphs constructed from a data set using a distance function. As the dimension increases, the degree of distribution of the k-NN digraph becomes skewed with a peak on the right because of the emergence of a disproportionate number of hubs, that is, data-points that appear in many more k-NN lists of other data-points than the average. This phenomenon - So-called "curse of dimensionality" refers to various phenomena that arise when analyzing and organizing data in high dimensional spaces - can have a considerable impact on various techniques for classification (including the k-NN classifier), semi-supervised learning, and clustering, and it also affects information retrieval.

Principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. Our PCA analysis has revealed that the top 5 components explains approximately 87.76% of the usable data set (shown in **Table 4**).

Table 4. Standard Deviation, Proportion of Variance, Cumulative Proportion of the top 5 components of the usable data set in Table1.

	the top 5 components of the usable data set				
	#1	#2	#3	#4	#5
SD	4.0883	2.2309	1.66807	1.22893	1.10492
PV	0.5392	0.1605	0.08976	0.04872	0.03938
CP	0.5392	0.6997	0.78948	0.83820	0.87758

(NB) SD: Standard Deviation, PV: Proportion of Variance, CP: Cumulative Proportion

It is sure that reduction of the total dimension can be carried out by elimination of non-contributed component(s) according to the above PCA, because

Table 4 shows analyzed results by our PCA and indicates that the score of Cumulative Proportion (CP) is more than 87% within the 5 components.
We have performed dimensionality reduction applying PCA and obtained the below results in order to classify factor loading over threshold limit within 5% significant level of test for correlation coefficient. The resulting classifier contains the following characteristic parameters:

- Average of movement intensity: accelerations for x-, y-, and z-axis (3 elements); accelerations for pitch, roll and yaw(3 elements).
- Maximal power spectra for x-, y-, and z-axis (3 elements); maximal power spectra for pitch and roll (2 elements).
- Root-Mean-Square (RMS) for y- and z-axis (2 elements); RMS for roll (1 element).

Consequently, we are now ready to compute the above 14(=3+3+3+2+2+1) dimensional elements of data set for improved pattern recognition for classification of driving characteristics.

5.3 Classification by Machine Learning (II)

At k-NN application to recognition of driving characteristics, at first, we have obtained good recognition rate (R = 58.16%) with empirically optimal k = 3 after choosing k to be an odd number from 1 to 19 via bootstrap method and **Table 5**, which is a result of average of rate for right answers from exhaustive cross-validation after every single subset is retained as the validation data for testing the model, and other remaining subsets are used as training data consequently.

Table 5. Improved Classification of Driving Behavior by k-NN.

	Driving Characteristics by k-NN			
	LtNo	LtAc	LtBr	LtOv
LtNo	43(55.1%)	14(18.9%)	16(19.5%)	6(8.1%)
LtAc	10(12.8%)	47(63.5%)	10(12.2%)	12(16.2%)
LtBr	13(16.7%)	6(8.1%)	48(58.5%)	8(10.8%)
LtOv	12(15.4%)	7(9.4%)	11(13.4%)	48(64.9%)

After comparison between Table 5 and Table 2, it is confirmed that recognition rate of Table 5 has been improved than one of Table 2 and PCA-based dimensionality reduction contributes to precision improvement of classification.
Secondarily, at SVM application to recognition of driving behavior, we have obtained good recognition rate (R = 60.13%) with gamma value: $\gamma = 0.2511886$ and cost value: $C = 3.981072$ and **Table 6**, which is a result of average of rate for right answers based on the condition with the above good recognition rate (R = 60.13%). Just like the case of k-NN application, it is confirmed that recognition rate of Table 6 has been improved than one of Table 3 and PCA-based dimensionality reduction contributes to precision improvement of this classification, too.

Table 6. Improved Classification of Driving Behavior by SVM.

	Driving Characteristics by SVM			
	LtNo	LtAc	LtBr	LtOv
LtNo	66(83.5%)	1(1.3%)	1(1.3%)	0(0.0%)
LtAc	0(0.0%)	74(93.7%)	6(8.0%)	6(7.7%)
LtBr	5(3.3%)	1(1.3%)	61(81.3%)	1(1.3%)
LtOv	8(10.1%)	3(3.8%)	7(9.3%)	71(91.0%)

5.4 Recognized Result of Driving Behavior

Although it is not so sufficiently re-cognitive rate for us to utilize for any case, we have applied our result (classifier from improved SVM recognition scheme) into recognition of driver's behavior at the normal situation. Recognized result shows **Table 7**. According to the red color fonts in Table 7, it is confirmed that our classifier can clearly recognize that driver's characteristic behavior, namely driving tendency/proclivity, is to make ***a left turn at the traffic intersection with acceleration***. This determination about recognition of driving behavior can be very reasonable and feasible because almost all drivers of middle age had been previously taught to make a left turn with acceleration in their driving school days.

Table 7. Recognized result of Driver’s Left Turn.

Pattern of Left Turn	Times (Percentage)
#1 Pattern of LtNo	13 (25.0%)
#2 Pattern of LtAc	39 (42.4%)
#3 Pattern of LtBr	12 (13.0%)
#4 Pattern of LtOv	18 (19.6%)

With analyzed results, drivers will be easily and efficiently able to recognize their habits, tendencies and proclivities in order to avoid improperly-driving behavior not only at the traffic intersections but also at other situations.

6 CONCLUSION

This paper describes our system configuration of data transmission between smart devices and Web server with SQL database facility, data mining application about driving characteristics recognition based on machine learning such k-NN and SVM, and practical recognition/classification results according to reduced/improved machine learning.

With application of PCA to dimensionality reduction, 36 dimensions of data set can be eliminated into 14 ones and rate of recognition can be improved from 52.73% to 58.16% at the case of k-NN as well as from 55.94% to 60.13% at SVM. Our classifier based on improved SVM machine learning can recognize that the relevant driver has characteristic tendency to make a left turn with acceleration at the traffic intersection.

Aim of this study is to visualize and recognize driver's characteristic behaviors for improvement of his/her driving techniques. With suitable application for smartphone and machine learning, it has been confirmed that we can obtain adequate data by smartphone during driving, perform data mining for pattern categorization of driving behavior, and recognize classification of driving characteristics. By means of such useful results, even beginners of driving will be able to improve their tendencies and/or proclivities for safe driving effectively and efficiently.

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REFERENCES

1. Lane,N., Miluzzo,E., Lu,H., Peebles,D., Choudhury,T., Campbell,A.: A Survey of Mobile Phone Sensing. IEEE Communications Magazine, Vol.48, No.9, pp.140--150 (Sep. 2010).
2. Fazeen,M., Gozick,B., Dantu,R., Bhukhiya,M., Gonzalez,M.C. : Safe Driving Using Mobile Phones. IEEE Transactions on Intelligent Transportation Systems, Vol.13, No.3, pp.1462--1468 (Sep. 2012).
3. Hong,J.-H., Margines,B., Dey,A.K. : A smartphone-based sensing platform to model aggressive driving behaviors. In: SIGCHI Conference on Human Factors in Computing Systems(CHI'14), pp.4047--4056 (2014).
4. Shmueli,E., Singh,V.K., Lepri,B., Pentland,A. : Sensing, Understanding, and Shaping Social Behavior. IEEE Transactions on Computational Social Systems, Vol.1, No.1, pp.22--34 (Mar. 2014).
5. Nguyen,T.T.T., Armitage,G. : A survey of techniques for internet traffic classification using machine learning. IEEE Communications Surveys & Tutorials, Vol.10, No.4, pp.56--76 (Fourth Quarter 2008).
6. Drucker,H., Wu, D., Vapnik,V.N. : Support vector machines for spam categorization. IEEE Transactions on Neural Networks, Vol.10, No.5, pp. 1048--1054 (Sep. 1999).
7. Lemma,S., Blankertza,B., Dickhausa,T., Mullera,K.-R. : Introduction to machine learning for brain imaging. NeuroImage, Vol.56, No.2, pp.387--399 (May 2011).
8. Kotsiantis, S.B. : Supervised Machine Learning: A Review of Classification Techniques. Informatica Vol. 31, pp.24--68 (July 2007). http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.95.9683&rep=rep1&type=pdf
9. Zhang,M., Sawchuk,A.A. : Motion primitive-based human activity recognition using a bag-of-features approach. In: the 2nd ACM SIGHIT International Health Informatics Symposium (IHI'12), pp.631--640 (2012).
10. Karantonis,D.M., Narayanan,M.R., Mathie,M., Lovell,N.H., Celler,B.G. : Implementation of a Real-Time Human Movement Classifier Using a Triaxial Accelerometer for Ambulatory Monitoring. IEEE Transactions on Information Technology in Biomedicine, Vol.10, No.1, pp.156--167 (Feb. 2006).