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Driver Identification Using Variance of the Acceleration Data

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***Abstract*— This paper presents a novel methodology for driver identification using hidden characteristics in the variance of acceleration data of the target vehicles. The proposed method is based on the use of raw acceleration data of moving vehicles collected from mobile devices such as smartphone which provides an easy access solution in comparison to existing approaches based on bio-sensors, cameras and steering wheel movements. Results from the analysis showed that the proposed driver identification method can tell the relationship of the acceleration data of each driver and lead to guidelines to distinguish the driving habits of each motorist.**

***Keywords*— Driver Identification; Principal Component Analysis (PCA).**

I. INTRODUCTION

The problem of road safety is an important issue for all road users, including drivers as well as pedestrian. When the accident happened, what followed was a lot of damage, such as damage to property, loss of time, energy consumption and the most serious is the risk of life. So when the accident happened on the road, there must be a responsible for that. In order to find those responsible, there must be something that can indicate whether a person is the one who caused the accident. In this study, we chose to use a factor in driving behavior analysis to determine the difference of each driver and be able to identify the driver.

The driving habit of each person is different. This might be because the traffic, accidents, or even the weather each day. Making each one have a different kind of driving habits. In addition, the driving behavior may vary from day to day. We had to find the link or the relationship of the individual's driving habits and assess of each driver-behavior characteristics.

A number of existing approaches can be found in the literature regarding driver identification. Some approaches are based on driver behavior such as steering wheel control [1] [2] [3]. Driving assistance system and lane changing behavior have also been used to identify drivers [4] [5]. More complex approach based on bio-sensors, retina scan and fingerprint scan are found in [7] [8]. These existing approaches require additional hardware installation and expensive sensors to be used in the vehicle which makes it difficult for a universal implementation. This paper proposes an alternative approach to address that issue by using smartphone as a platform. It is easily accessible and low cost with no hardware installation required. This paper aims to study the driving behavior of the individual and analyze the difference in driving habits. The proposed approach uses data acceleration data collected from accelerometer sensor found in every smartphone available in the market today. Real-world data collection was carried out using Android based smartphone with five school buses each with its own dedicated driver over the period of three months. The data were calculated using the proposed algorithm which is based on Principal Component Analysis through statistical software called SPSS to seek variances or data relationships to be used for further analysis.

II. RELATED WORK

Okamoto M. et al. have developed a model to identify the driver using a basic behavior of driver in system design. Basic behaviors of driver such as driver check, alerts, built-in control and learning were used. The system will consider the behavior that occurs in conjunction with past behavior of the driver [1].

Keen S.D. and Cole D.J. presented research about predicting behavior by using the steering and using the linear model analysis of classified information. The results showed that the behavior of the steering has a different significance. In addition, driving test among drivers shows the diversity in steering behavior [2].

Diehm G. et al. the proposed a method of identifying the behavior of each driver using steering wheel online because the movement of steering wheel has changed the nerves and muscle all the time. And the steering wheel is also dependent on the environment or other routes. Therefore arm movements and steering are so different in each person. The results showed that the driving wheel of each is different. The driver and the steering wheel can be used to identify individuals [3].

del Campo I. et al. studied about the availability of Advanced Driver Assistance Systems (ADAS) to develop electronic tools. They embed the engine into the vehicle for storage the data then process and analyze to see the individual's driving style [4]. In a similar manner, Kusano K.D. and Gabler H.C. Education Pre-Collision System (PCS), and Lane Departure Warning system (LDW), the two systems are not only used in the event of unusual circumstances only but also includes the ability to tell the behavior of the driver as well [5].

Cheng Guo-zhu and Zhang Bao-nan offered research on comparing the ability of driving in daytime and nighttime on highway by dividing driving effect into speed, radius of curvature and slope. Their work analysis driver's ocular movements in day, night and also when it rains. They found that in the nighttime and raining, the drivers have low visibility conditions and the accuracy of image reduction [6].

Young-Min Jang et al. proposed eye movements as a feature in the analysis. To find an upcoming event, such as changing lanes, turning, or driving in various traffic conditions they analyze characteristics of the iris and cornea [7].

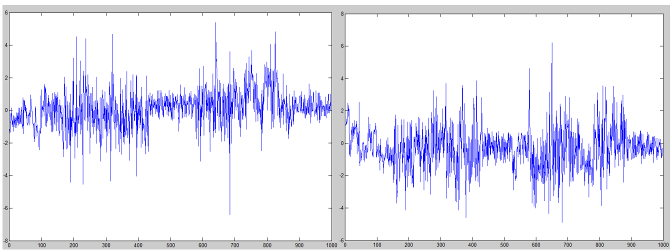
Tashk A. et al. proposed image processing of vehicle car license plate which is automatically linked to the fingerprint of the driver to indicate the car owner. This research has two features that link together to identify the drivers that are fingerprint and license plate [8].

Quintero M C.G. et al. proposed development of intelligent driving behaviors. It is security integrated using of GPS data such as position, velocity, acceleration and steering to analyze driving behavior and also uses statistical data for further analysis including steering history, accelerator pedal, the speed change lanes, etc. Moreover, they used the Neural Network to develop model by hoping that is going to identify the identity of the driver [9]. Next they added the environmental factors into the system and developed system using Neural Network model and Fuzzy logic in action on environmental factors. The result has identified locations where is the high risk of accidents. It also has a high ability to distinguish the riders reliably [10].

There are a variety of methods used to identify the driver, such as driving style, speed, acceleration, steering characteristics, eye movements, verification of fingerprints from the existing approaches. These existing approaches require additional hardware installation and expensive sensors to be used in the vehicle which makes it difficult for a universal implementation. This paper collected from smartphone in the analysis. It can reduce costs and save time in installation and data collection. In addition, it offers greater ease of use because using just smartphone, you can identify of the driver.

III. THE VARIABLES USED THE ANALYSIS

The information collected from the custom made Android application on mobile devices are as follows: data timestamp, the number of car, the acceleration of the X-axis, the acceleration of the Y-axis, the acceleration of Z-axis, and a sequence of moments on the record. Raw data was collected from placing a smartphone inside 5 vehicles using a sliding window of 5Hz or one sample every 200 millisecond. The acceleration of the X-axis which represent driving actions in side to side direction such as turn left (+) and turn right (-) and the acceleration of the Y-axis which represents driving actions forward and backward direction such as accelerating (+) and braking (-) are the primary feature used in the proposed algorithm. Raw acceleration data can be seen in Fig. 1.



(a) The acceleration in the X-axis (b) The acceleration in the Y-axis

Fig. 1. Graph show the acceleration in the X-axis (a) and the acceleration in the Y-axis (b).

For more features to be used in identification process, the following variables are deduced from the raw acceleration data.

The average variable of the acceleration in the X-axis and The average variable of the acceleration in the Y-axis: This is to reduce noise in the acceleration data of the X-axis and Y-axis and to calculate the average value of the variable is used simple moving average with a sliding window = 5 is the average of every 5 data points. (1 second = 5 data point).

The standard deviation variable of the acceleration in X-axis and the standard deviation variable of the acceleration in the Y-axis: The purpose is to check the variation in acceleration data in each moving window. In this process a sliding window = 5 is used. (1 second = 5 data point).

The difference variable of the acceleration in the X-axis and the difference variable of the acceleration in the Y-axis: They are the variables showing difference between the current accelerations and the past acceleration of each axis. If the difference value is high then the current acceleration value and the past acceleration value are very different. That means the car has sudden increase or sudden decrease in acceleration. But if the difference value is low, the current acceleration value and the past acceleration value has very little difference. It shows that the car gradually increases or gradually decreases acceleration.

The correlation variable of the acceleration in the X-axis relative to the acceleration in the Y-axis: Creation of the correlation variable between X-axis and Y-axis because need to know the relationship between the X-axis and Y-axis in 1 window. This will indicate whether X-axis and Y-axis are correlated in any direction such as one direction or opposite directions.

IV. PRINCIPAL COMPONENT ANALYSIS

Principal Component Analysis is statistical method that has been very popular. Most of Principal Component Analysis was used in the selection of the important features of the data and the key components required to process also known as The reduced dimensions (Dimension Reduction). Principal Components Analysis used to create a matrix of covariance (Covariance Matrix) and the Eigenvalue of the data in any dimension and cut out low-priority data. The data will be used in learning has decreased. Help make learning easier and faster.

Brought vectors of all the information provided in the form of a matrix as shown in Fig. 2.

$$A = \begin{vmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{vmatrix}$$

Fig. 2. Show forms metric for use to import data.

Matrix A used in the calculation for the principal components analysis.

By m refers to the number of features

n refers to the number of data

Fig. 2 is a major step forward in the process of principal components analysis were sequenced and the equations used in the processing.

Provide information in the form of a matrix and calculate the average of each row of the following (1):

$$\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \quad (1)$$

This matrix is a matrix of the calculation for the average value of each rows of X_i.

By i refers to the order of rows.

n refers to the number of rows.

Bring the average value of each dimension minus the data in each column (2):

$$\phi_i = X_i - \overline{X} \quad (2)$$

Create a matrix of covariance (Covariance Matrix) from the matrix.

$$A = [\phi_1 \phi_2 \phi_3 \ldots \phi_m]$$

Calculate the covariance matrix as (3):

$$C = \frac{1}{m}\sum_{n=1}^{m} \phi_n \phi_n^T = AA^T \quad (3)$$

Calculate the Eigenvalue of Covariance Matrix (4):

$$C : \lambda_1 \rangle \lambda_2 \rangle \lambda_3 \rangle \ldots \rangle \lambda_n \quad (4)$$

By λ_n refers to Eigenvalue of each column.

Calculate Eigenvectors of Covariance matrix (5):

$$C : \mu_1 \rangle \mu_2 \rangle \mu_3 \rangle \ldots \rangle \mu_n \quad (5)$$

By μ_n refers to Eigenvectors of each column.

The result is Eigenvalues and Eigenvectors. The two both have a value corresponding to each other. Then consider selecting the Eigenvalue is higher. And cut the Eigenvalue are lower. Because Eigenvalue is less, it means that information remains fragmented. The Eigenvectors corresponding to the Eigenvalue are selected. Multiplied by the original data, it will reduce the number of dimensional data. But the selection of data attributes should regardless the number of remaining data is critical. For each trial if the data is cut too much. Will have to be brought to trial is low and this may affect the efficiency of the data.

V. PROPOSED METHODOLOGY

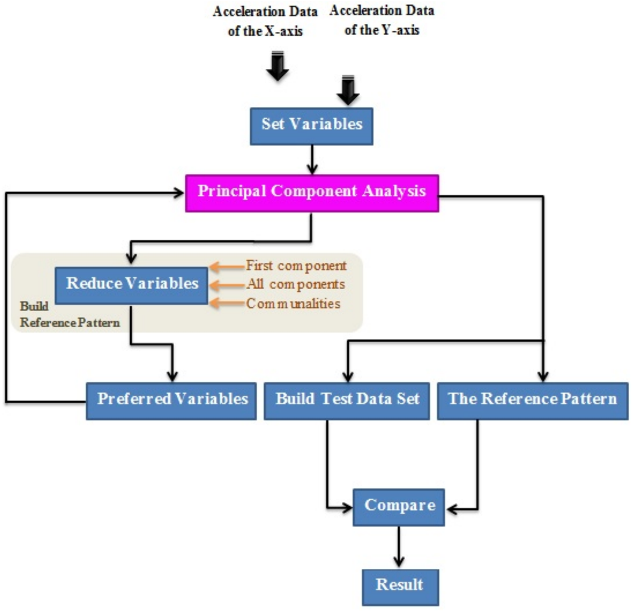


Fig. 3. Diagram analyses to find method.

Fig. 3 is a procedure performed to find out how to distinguish the behavior of acceleration since data were analyzed to determine characteristics. Then the data and attributes defined calculate the PCA to bring the results of PCA analysis criteria to distinguish the behavior of acceleration by creating a pattern to compare the dataset others and how to select the variables the most relationship with data used in the analysis. The steps are as follows:

A. Set Variables

Set variables are used for initial stage of driver identification. In this paper there are nine variables which are acceleration of the X-axis, acceleration of the Y-axis, the average of acceleration in the X-axis (averageX), the average of acceleration in the Y-axis (averageY), the standard deviation of acceleration in the X-axis (standardX), the standard deviation of acceleration in the Y-axis (standardY), the difference of acceleration in the X-axis (differenceX), the difference of acceleration in the Y-axis (differenceY) and the correlation of acceleration in the X-axis relative to acceleration in the Y-axis (correlationXY).

B. Build Reference Pattern

After the set variables stage, PCA is applied to the input data with all nine variables to calculate the Eigenvalue and Eigenvector. The table of Eigenvector is new components arise. That is the result of the calculation PCA and the new components that have a relationship of each variable were used as input for PCA. Therefore, the relationship of each variable with the new components were analyzed to determine the difference of behavior acceleration. To build a reference pattern the algorithm is run once. After initial trial run the findings from the outcome of analyzing Eigenvector and Eigenvalue revealed that using all nine variables, the Eigenvector of each car are quite similar. As a result it was not very likely distinguish the driving behavior of the individual because the calculation is the same for all the variables. In order to overcome that, therefore, it is logical to reduce the number of variable in each car resulting in each car to contain different characteristics. This makes the criteria for the classification more diverse. In selecting the variables of each car, the required criteria in selecting the appropriate variables are the reference pattern to indicate the characteristics of each car. In this paper, three criteria are used for variable selection to build the reference pattern for each vehicle. First criteria are the variance value of all components from the table of Eigenvector as seen in Fig. 4. The second criteria are the variance value of first component from the table of Eigenvector in Fig. 5. The third criteria are the table of communalities which are correlation coefficient value of all components to one variable in Fig. 6. In the table of communalities has initial column and extraction column. Initial column is the initial communality of each variable equal to 1. Extraction column is the communality after the extraction component. If communality equals to = 0, it means that the component cannot explain the variation of variables, but if communality equals to = 1, it means that the component can explain the variation at all.

Rotated Component Matrix[a]

	Component			
	1	2	3	4
x	1 .947	-.085	.018	-.010
averageX	5 .820	-.115	.044	-.247
differX	9 -.625	.009	.037	-.431
y	-.127	2 .901	-.276	.133
averageY	-.135	6 .786	-.362	.272
differY	-.015	8 -.636	-.273	.471
standardY	.006	-.132	3 .849	.057
standardX	.012	-.140	4 .845	.029
correlationXY	-.052	.130	.118	7 .712

Fig. 4. Show Eigenvector selection from the variance value of all components.

Criteria 1: The variance value of all components from the table of Eigenvector: The reference pattern is created by combining all collected driving data each car and using nine defined variables calculated through PCA. After that the table of Eigenvector in Fig. 4 is considered. Next reduce the number of variables by the all variance value from the table of Eigenvector with nine variables sorted from the highest coefficient value to the lowest as shown by the blue numbers in Fig. 4. Then cut variables with low variance. Only variables with high variance as coefficient which are circled in red are selected. In this particular instance, 6 variables are selected. The number of variables to be selected is not fixed but depends on the settings which would produce the best identification accuracy. This applies to all of the criteria to be discussed later in this section.

Criteria 2: The variance value of first components from the table of Eigenvector: Using this criterion, the reference pattern is created by reducing the number of variables from the variance value of first components from the table of Eigenvector because the first component is the most important component of the data. Therefore, the relationship of the first component to consider the selection of variables associated with the data. The first components from the table of Eigenvector with nine variables sorted from the highest coefficient value to the lowest as shown using blue numbers in Fig. 5. Then variables with low variance are removed. Only variables with high variance as coefficient value in red circle in Fig. 5 are selected.

Rotated Component Matrix[a]

	Component			
	1	2	3	4
x	1 .947	-.085	.018	-.010
averageX	2 .820	-.115	.044	-.247
differX	3 -.625	.009	.037	-.431
y	5 -.127	.901	-.276	.133
averageY	4 -.135	.786	-.362	.272
differY	7 -.015	-.636	-.273	.471
standardY	9 .006	-.132	.849	.057
standardX	8 .012	-.140	.845	.029
correlationXY	6 -.052	.130	.118	.712

Fig. 5. Show Eigenvector selection from the variance value of first components.

Criteria 3: The table of communalities: This criterion creates the reference pattern by reducing the number of variables from correlation coefficient value with nine variables sorted from the highest correlation coefficient value to the lowest shown with the blue numbers in Fig. 6. Variables with low coefficient value are removed. Only variables with high coefficient value as coefficient value in red circle in Fig. 6 are selected.

As mentioned earlier in the section, the number of variables to be selected is not fixed. It is dependent on the greatest variance in the table according to the required number. Should the number of variables that make up a good performance in the classification. So the comparison of the number of variables such as variables 7, variables 6, variables 5, and variables 4.

Communalities

	Initial	Extraction
x	1.000	2 .905
y	1.000	1 .922
averageX	1.000	4 .748
averageY	1.000	3 .841
standardX	1.000	6 .735
standardY	1.000	5 .742
differX	1.000	8 .577
differY	1.000	7 .701
correlationXY	1.000	9 .540

Fig. 6. Show selection from the table of communalities.

C. Prefered Variables

The example in Fig. 6 selected top six variables (the red circle) from sorting is prefered variables. This leads to six variables to calculate PCA again. Each times to calculate the PCA, takes only 1-2 seconds. The output is the reference pattern which is obtained as in Fig. 7. This reference pattern will signify one class of the classification process in the driver identification algorithm where each car will have its own distinct reference pattern. This is to be used for comparison with raw acceleration data produced from unknown driver.

Rotated Component Matrix[a]

	Component		
	1	2	3
y	.956	-.117	-.167
averageY	.951	-.118	-.192
x	-.081	.934	.014
averageX	-.133	.926	.019
standardY	-.154	.014	.877
standardX	-.165	.018	.874

Fig. 7. The refernce pattern.

D. Compare test data set and the refernce pattern

To identify an unknown car, its data set is computed and built according to the settings used for each reference pattern. After that the similarity of the data set of the unknown car is checked against the reference pattern. A perfect match would be the ranking of the selected variables are in exactly the same order. This will indicate a perfect match for the identification process. Other outcomes would indicate partial match or no match for the case that the rankings of the selected variables are completely different.

VI. RESULTS

This paper has an analysis of variance of each component in the Eigenvector. The variables were associated with each component, however. Driver identification is performed by looking at components of the car to be compared with components of the reference pattern. If components of that car has variables in each component and are in the same order as the reference pattern itself, then it means correct identification. An example is shown in Fig. 8.

Rotated Component Matrix[a]

	Component		
	1	2	3
averageY	.957	.057	.012
y	.954	.085	.009
x	.070	.914	.003
averageX	.065	.914	.005
standardX	-.044	-.021	.905
standardY	.065	.030	.903

(a) The reference pattern

Rotated Component Matrix[a]

	Component		
	1	2	3
y	.928	.082	.009
averageY	.928	-.009	.003
x	.088	.907	.012
averageX	-.017	.907	.031
standardX	-.012	.012	.891
standardY	.023	.031	.890

(b) The unknown car

Fig. 8. Show compare the reference pattern (a) with the unknow car (b) is correct identification.

Fig. 8 shows the reference pattern (a) to be compared with the unknown car (b). And using Criteria 3 in selecting variables and 6 variables in the analysis. The variables for each component of the unknown car (b) appear in the same component as the variables of reference pattern (a). For example, variable x and variable differX have a high impact on component 1 for both the unknown car (b) and the reference pattern (a), as indicated by high coefficient values in the table. Similar pattern is noted for component 2 and 3. This represents a match.

The reference pattern 2 forms are the table of Rotated Component Matrix (a) is Eigenvectors adjust plane and the table of Component Matrix (b) is Eigenvectors not adjust plane.

Fig. 9 shows the effect of applying PCA to the variables. It can be seen in Fig. 9 (b) that the coefficient values for variable y are not very distinct in all three components. In Component Matrix variable y (in red circle) the first component is the coefficient 0.669. The second component is the coefficient 0.637. The first component is the coefficient -0.096. When comparing the three components, see that the first component and the second component is the coefficient is same. So both components cannot be separated clearly that the variable y is any component. Or have the most relationship with any components. This means that it will be difficult to use for driver identification. And in Fig. 9 (a) Rotated Component Matrix variable y (in red circle) the first component is the coefficient -0.029. The second component is the coefficient 0.928. The first component is the coefficient -0.007. When comparing the three components, see that the coefficient of the second component has the most valuable clearly. By using the method of rotating component matrix, where the data set is rotated to be in the plane of the components based on the result of PCA, it can be seen that the values of coefficient in each component become more distinct. Thus, the variable y is organized in the second component.

Rotated Component Matrix[a]

	Component		
	1	2	3
x	.921	-.014	.003
differX	-.804	.040	.023
averageX	.701	-.003	.021
y	-.029	.928	-.007
differY	.036	-.761	.021
averageY	.007	.733	.016
standardY	.031	.036	.866
standardX	-.011	.023	.856
correlationXY	.007	.033	-.403

(a) Rotated Component Matrix

Component Matrix[a]

	Component		
	1	2	3
y	.669	.637	-.096
x	-.668	.631	-.059
differX	.603	-.528	.074
differY	-.557	-.512	.093
averageX	-.502	.488	-.027
averageY	.508	.526	-.056
standardY	.020	.149	.854
standardX	.041	.109	.849
correlationXY	.010	-.019	-.404

(b) Component Matrix.

Fig. 9. The impact of matrix rotation.

Following is a comparison of variables selection to determine the criteria for selecting the most appropriate variables. In the selection of variables should be choose the variables that are most closely associated with the data set. It can be effective in making driver identification. In this paper comparison is made between three criteria which are Criteria 1 Criteria 2 and Criteria 3.

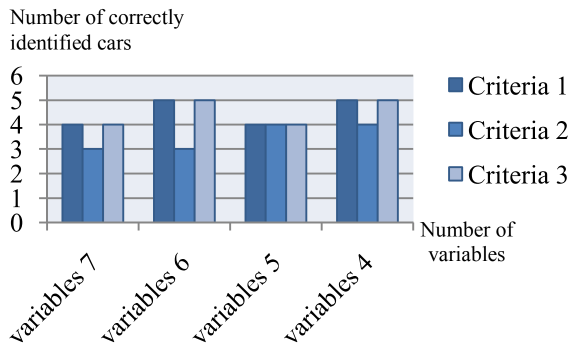


Fig. 10. Show the graph of the number of variables on the number of cars in each of select variables.

In Fig. 10 shows number of correctly identified cars in the vertical axis and number of variables in horizontal axis. From Fig. 10 it can be seen that using 4 variables provides the best solution with the most number of cars correctly identified. However, choosing the 4 variables might be too few variables and at the same time can create only a few numbers of distinct reference patterns. As a result, each car is indistinguishable from each other. On the other hand, if the number of variables is many variables (7-8), then the combination of creating reference pattern is too high. Therefore, the best is to the number of variables between 5-6. The graph shows comparison of the criteria for selecting variables and it found that Criteria 1 and Criteria 3, had a number of cars with almost the same classification because Criteria 1 showing the relationship of each component on each variable and Criteria 3 is showing the relationship of all the components on each variable, this two criteria are used relationship of all components. Thus, the criteria for selecting variables from Criteria 1 and Criteria 3 were the variable that correlated most in the series. This graph shows the number of cars that matched the reference pattern of the car itself, but does not show the number of cars that matched other the reference patterns.

		Pattern of First car	Pattern of2 Second car	Pattern of3 Third car	Pattern of4 Fourth car	Pattern of5 Fifth car
First car	Day 1	1	0	0	0	0
	Day 2	0	0	0.5	0	0.5
	Day 3	0.5	0	0	0	0
	Day 4	1	0	0	0	0
	Day 5	0.5	0	0	0	0
	Day 6	1	0	0	0	0
Second car	Day 1	0	0	0	0	0
	Day 2	0	0.5	0	0	0
	Day 3	0	0	0	0	0
	Day 4	0	0	0	0	0
	Day 5	0	0	0	0	0
	Day 6	0	0	0	0	0
Third car	Day 1	0.5	0.5	0	0.5	0
	Day 2	0	0	0.5	0	0.5
	Day 3	0	0	0.5	0	0.5
	Day 4	0	0	1	0	0.5
	Day 5	0	0	0.5	0	0.5
	Day 6	0	0	1	0	0.5
Fourth car	Day 1	0	1	0	1	0
	Day 2	0	0	0	0	0
	Day 3	0	0	0.5	0	0.5
	Day 4	0	0	0.5	0	0.5
	Day 5	0	1	0	1	0
	Day 6	0	0	0.5	0	0.5
Fifth car	Day 1	0	0	0	0	0
	Day 2	0	0	0	0	0
	Day 3	0	0	0.5	0	0.5
	Day 4	0	0	0.5	0	0.5
	Day 5	0	0	0	0	0
	Day 6	0	0	0.5	0	0.5

Fig. 11. Show the results of each the car with each the reference pattern in 6 days.

The following is using criteria to match the reference pattern with various cars in Fig. 11 shows the result of each car with each reference pattern in 6 days. Criteria 3 in selecting variables and 6 variables in the analysis. In the grid 1 refers to the same for all sequence of variables in the data set and any reference pattern. 0.5 refers to each variable in component of data set as any reference pattern, but the sequence of variance value is not the same, which can be seen in Fig. 8. 0 refers to the data set of the car and the reference pattern that are different. Results in red circle are the car and its matching the reference pattern. Therefore, between these selected cars with its the reference pattern found that the first car had the data set that matched the other pattern also, but most of number of data set matched with its own pattern. The second car matched the reference pattern itself. The third car matched the reference pattern of the third car and the reference pattern of the fifth car, but sequence of variables for some data set of the third car and its reference pattern are similar. So the reference pattern of the third car can be classified as the third car. The fourth car and the fifth car had the data set matched the reference pattern itself, but cannot be identified because that data set matched other patterns as well.

It can be concluded that some data sets for 5 cars matched its own reference pattern (Circled in red). However, there were 3 cars that the reference pattern can analyze the driver identification and 2 cars were unable to determine the driver identification.

VII. CONCLUSION

This paper analyzes and compares the methods for the effective identification of the driver using the variance of the occurred data. It can be seen that the variance of each driver is different. Thus, it is possible to analyze the identification methods for individual driving behavior. In this paper, there are comparisons of the criteria for selecting variables because the selection of the appropriate variable can identify the driver more efficiently, including variable reduction because the appropriate number of variables can classify information more efficiently.

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