3-D Driver Profiling Using CMAC

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Abstract

The influence of a person's nature and environment makes us unique. Especially in driving each of us behave differently when responding to situation. These differences could be the way our subconscious mind works and respond. In addition the switching between the subconscious to conscious mind will also produce unique respond on how the brain perform each switching. Since the activation of movements are controlled by the cerebellum we propose the use of cerebellum model articulation controller (CMAC), introduced by Albus, to model each driver behavior. In this paper we only focus on using the gas pedal and brake pedal pressure of the driver to understand the translation of the driver behavior to difference environment. Experimental results from the CMAC profiling show the potential of extracting features of drivers for identification, emotion and other behavioral conditions.

1. Introduction

The cerebellar model articulation controller (CMAC), developed by Albus, is a simple network architecture, which provides the advantages of fast learning and a high convergence rate [1]. The CMAC model has been successfully applied to various fields, such as robot control, signal processing, pattern recognition, and diagnosis. And now for this experiment it will be applied for driver profiling. In order to effectively utilize its advantages and achieve reasonable accuracy, there is a need for careful consideration in selection of the size/resolution of the CMAC as well as the method of profiling.

The CMAC size will not only determine the amount of time and computation cost, but also effectiveness in exploiting CMAC neighborhood properties. Therefore too large or too small a size selected might cause low space utilization and lost of neighborhood property advantage as well as the lost overlapping of values respectively. But even before a size is implemented, proper profiling must be examined. Profiling indicates the need for selection or augmentation of available variables in the problem domain and one or few mapping functions. Mapping function will eventually determine how the data will be profiled by defining its coordinates and weight values.

The CMAC memory can also be visualized as a neural network consisting of a cluster of two-dimensional *self-organizing neural network* (SOFM). However, instead of a random initialization of the neural net weights, they are fixed such that they form a two dimensional grid as shown in Figure 1.

The winning neuron in the CMAC memory at time step k is identified as the neuron with weights $Q(y_{\mathrm{ref}}(kT))$ and $Q(y_p(kT-T))$ given the inputs $y_{\mathrm{ref}}(kT)$ and $y_p(kT-T)$. The weights are effectively the coordinates i,j of the location of the neuron in the SOFM. The output of the winning neuron can be directly obtained from the weight $w_{i,j}$ of the output neuron.

As in the Kohonen's neural networks framework, CMAC learning is a competitive learning process and follows SOFM learning rules. However, since the weights of the cluster of neurons that represent indices to the CMAC memory are fixed, learning only occurs at the output neuron. To achieve this the CMAC learning rule is based on the Grossberg competitive learning rule and is applied only to the output layer and no competitive Kohonen learning rule is applied to the input layer. Therefore, the CMAC learning rule can be represented by [2]:

$$\begin{aligned} &i = Q(y_{ref}(kT)),\ j = Q(y_p(kT-T));\ i, j \in \mathrm{N} \\ &w_{i,j}^{(k+1)} = w_{i,j}^{(k)} + \lambda(x(kT) - w_{i,j}^{(k)}) \end{aligned} \tag{1}$$

where λ = learning constant ,
$x(kT)$ = plant input at discrete step k ,
$y_{\mathrm{ref}}(kT)$ = reference input at discrete step k ,
$y_p(kT\text{-}T)$ = plant output at discrete step k-1 ,
$w_{i,j}^{(k)}$ = contents of CMAC cell with coordinates i, j at discrete step k, and
$Q(\cdot)$ = the quantization function defined in equation (1).

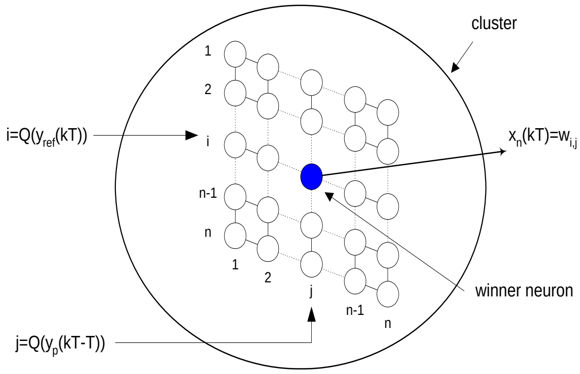


Figure 1. CMAC memory Architecture

2. CMAC Profiling

From previous tests carried out on a 3-D CMAC, it is observed that random distribution of values will result in poor accuracy in results. But when the values are organized such that their neighboring values differ by a relatively small amount, its accuracy is very high. Here the neighboring values are defined as a single unit distance in all dimensions. Thus the factor affecting the accuracy of a CMAC is the distribution or organization of values. And the specific area of distribution this paper tries to optimized is known as profiling. And the two factors that largely influence the profiling is the selection of variable values and their respective coordinates in the CMAC.

First, the variables must be of significant purpose and ideally should have large amount of distinct possible values it can take. These variables maybe further processed or augmented to enhance their distinctive properties or reduce noise. The result will then allow for a wide variety of combination and rich expression of the variables. Next, after the variables are identified, there is a need to express these variables on the CMAC. For a 3-D CMAC, there are three dimensions. Therefore three values must be identified, besides the large number of features collected; there is another important aspect as how these features will play a role in profiling. Furthermore, distribution should be created to reduce or remove overlapping values that will cause lost of information and take advantage of neighborhood property of the CMAC.

As in simpler versions, there is no physical storage of the actual entire 3-D CMAC of the defined size, but instead for this experiment three weight tables are used to store the values that will be combined to re-construct the entire CMAC. Therefore, a series of mapping are done to the coordinates and values from the represented CMAC to the weight tables. After the resolution of the CMAC is decided, there will be a function to calculate the size of the weight tables. Then after pairs consisting of coordinates and its respective values may be entered into the CMAC, upon attempting to store the values into the CMAC, a function will be used to derive its coordinates in the three weight tables. From there, the initial weights stored in the tables will be retrieved and compared with one third of the desired value to be stored and three differences between the stored and desired values will constitute to the error. Then the CMAC will alter its values in the weight table with respect to the error calculated. This process maybe iterated many times to reduce the error and thus achieve a closer estimation of the desired values in its respective coordinates.

After completion of its storing phrase, retrieval would only consist of the getting its actual coordinates and deriving the coordinates in the three weight tables and sum together. Usually all the values will be retrieved, unless specific set of coordinates are defined. Through the iterating the storing phrase, the result retrieved will be an estimation of the numerous different values.

3. Driving Profiling

The driving data utilized in this research are from the In-car Signal Corpus hosted at Nagoya University, Japan [3]. The In-car Signal Corpus is one of several databases available. This database contains multi-dimensional data collected in a vehicle under both driving and idling conditions. The purpose of setting up the database was to deal with both issues, namely noise robustness of speech and continual change of the vehicular environment. To date, the number of subjects involved in the data collection amounts to about 800 with a total recording time of over 600 hours. The multimedia data consists of speech, image, control (driving) and location signals, all synchronized with the speech recording. For this research, only the driving signals (accelerator pedal pressure & brake pedal pressure) were utilized.

Modeling and studies of driving behaviors began as early as in the 1950s. Many of the studies have been conducted to improve traffic safety or the performance of intelligent vehicle systems [4]. However, the utilization of driving behavior for personal identification is still not widely explored.

Segments known as stop-go regions were extracted from the original collected driving signals for the experiments. The motivation for using just the stop-go regions instead of the entire signals is instinctive since little or no information pertaining to driving behaviors is present when the vehicle is not in motion. Also, with the exception of engine and vehicle speed, the other signals are all driver-dependent and can be used in our analysis. The dynamics of the pedal pressure is defined as the rate of change in pressure applied on the pedal by the driver. These dynamics signals offer additional information on the “hardness” of the drivers’ pressure on the pedals. Below are the diagrams of the five recorded driving signals and two derived signals (accelerator and brake dynamics) belonging to one particular female driver over the duration of one stop-go region.

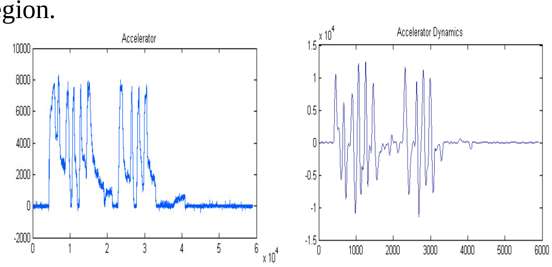


Figure 2. Accelerator signal and its Differential

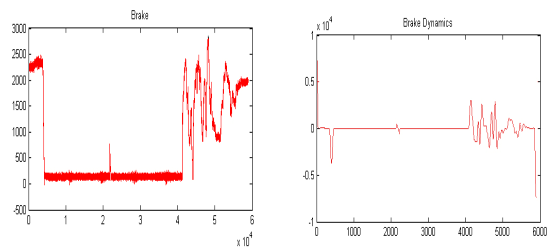


Figure 3. Brake signal and its Differential

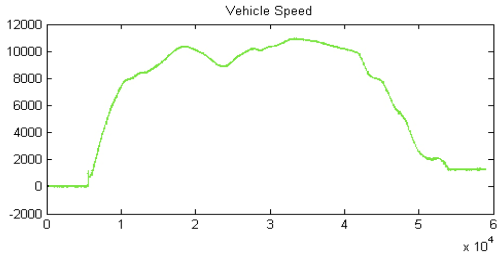


Figure 4. Vehicle Speed

4. Experiments

Initially the drivers' data were in time domain. But because there is no fixed amount of time for the datasets, therefore it would be unsuitable to carry out experiments on the datasets. Therefore the power spectral density of each dataset is used instead.

In earlier experiments, it was observed that using the acceleration and brake pedal signals allows for the best training and identification of the driver's identity. Furthermore, the previous experiments also showed a higher accuracy of driver identification when a combination of the first derivation of the acceleration and brake pedal signals are used instead of solely relying on the collected signals. Therefore in this experiment, both the initially collected acceleration and brake pedal signals and their first derivatives are used.

In the next set of experiments, a 3-Layered CMAC was employed to derive a 3-D plot as a profile for each driver. From the acceleration and brake pedal pressure signals and their first derivatives, a total of four signals are available to derive a 3-D profile. After the conversion of the signals from time domain to frequency domain, all signal will the same dimension length for the frequency, but varying amplitude values. And since both acceleration and brake signals together with their first derivation share a common set of values, their frequency values, therefore it would be sensible to use this common property to link two sets of signals together. But unlike the frequency values, amplitudes values are not common; therefore, amplitudes of these two signals will be normalized to values with respect to the desired CMAC resolution. Therefore essentially, this problem is map a fixed set of values (frequency range) into different points (coordinates derived from their amplitudes) on a 2-D plane and the result is a 3-D plot in CMAC.

Since four possible signals can be derived for a single driver, therefore it is possible to create a combination of four different pairs of values to be used coordinates to allocate coordinates for the frequency values in the CMAC.

But if only a single set values were to be used to map into a CMAC, then it would fail to utilize the approximation capability of the CMAC, and a simple 3-D plot might be suitable. Furthermore, taking a single experiment or event and classify their occurrences or recognize their identity will be bias and would fail. Thus the CMAC is applied to approximate average of 10 different datasets collected for each of the drivers, such an approximation has the ability to not only to allow small variations, but will also be able to capture occasional abnormalities. Although such abnormalities may seem distract the ability to correctly identify the driver's most likely behavior, but such abnormalities can be limited and controlled by specifying the learning rate of the CMAC. A large learning rate will have a higher probability of allowing such abnormalities to appear, while smaller probability of the appearance of the abnormalities appearing for a small learning rate.

After the creation of the CMAC plots, a possible average CMAC for all the drivers may be done to allow comparisons with the average thus leading to a possible correct prediction of the driver's identify. Such an average CMAC is created can be created by allowing a CMAC to iteratively learn the set of CMAC profiles derived from the drivers. Besides making a large number of iterations to ensure a good approximation of their average, ideally the order in which the CMAC profiles are presented to the learning average CMAC should be random, so as to avoid a bias average CMAC.

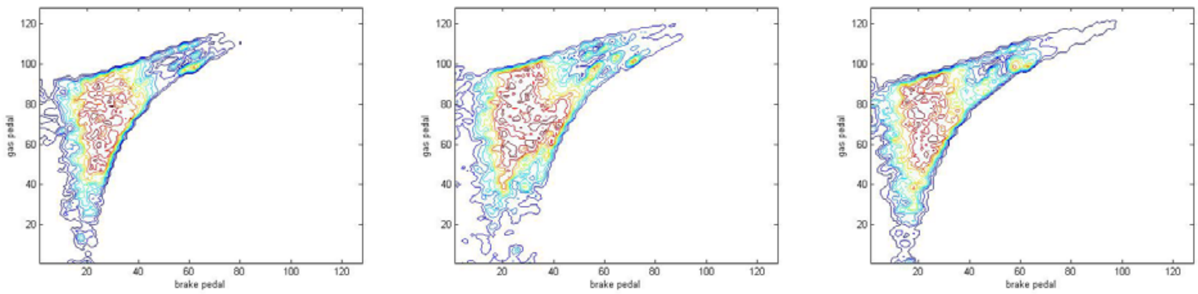
5. Discussions

From the mesh and contour plots for the drivers, besides being able to visually differentiate the one driver profile from another, it is also possible to identify driver features.

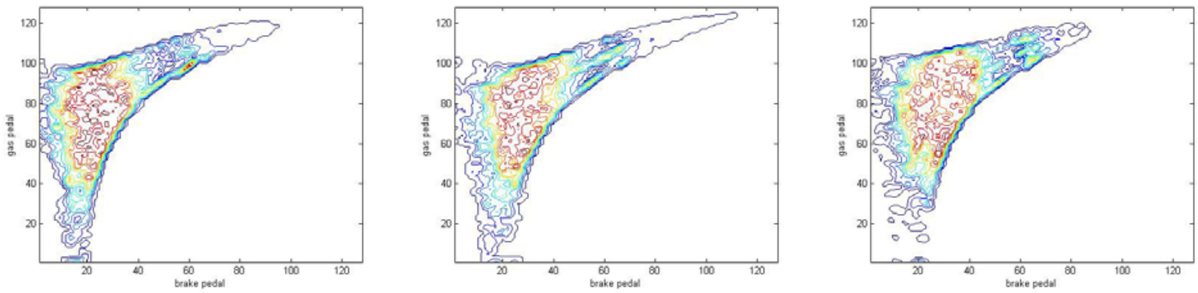
Since it is observed from the plot that for large values of derivate for brake reflected by the increasing number of peaks for larger values belonging to the derivative of brake axis, then by interpreting from the plots, it shows that most drivers then to create huge change of brake pedal pressure very often.

But with respect to the plots, the change in acceleration pressure would be milder, as peaks tend to be at the lower values for the derivative of acceleration axis. But these observations can only be considered estimation, considering the CMAC averaging properties among neighbors and the possibility of overlapping coordinates.

But on an average due to combining the frequencies of two different signals to represent their features, there is larger possibility and capability of differentiating the origin of the features, and for this case the identity of the drivers. This is because it maybe highly possible for some drivers to share certain characteristics of handling the accelerator and brake pedal, but sharing the characteristics over 2 features decreases the probability of a similar profile for different drivers. Furthermore, frequencies are measured and 10 samples are collected, therefore rare characteristics of the drivers will have less influence on the profile to prevent similar representations for different profiles.

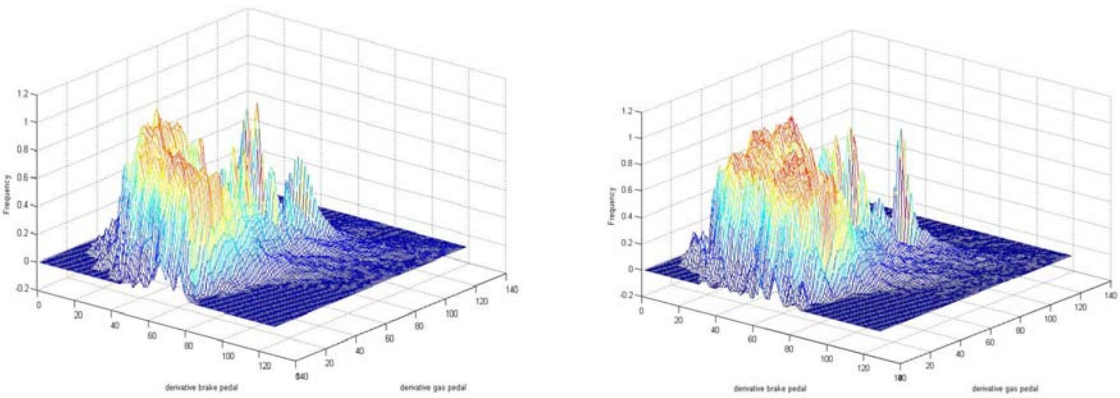


m1 f1 m3



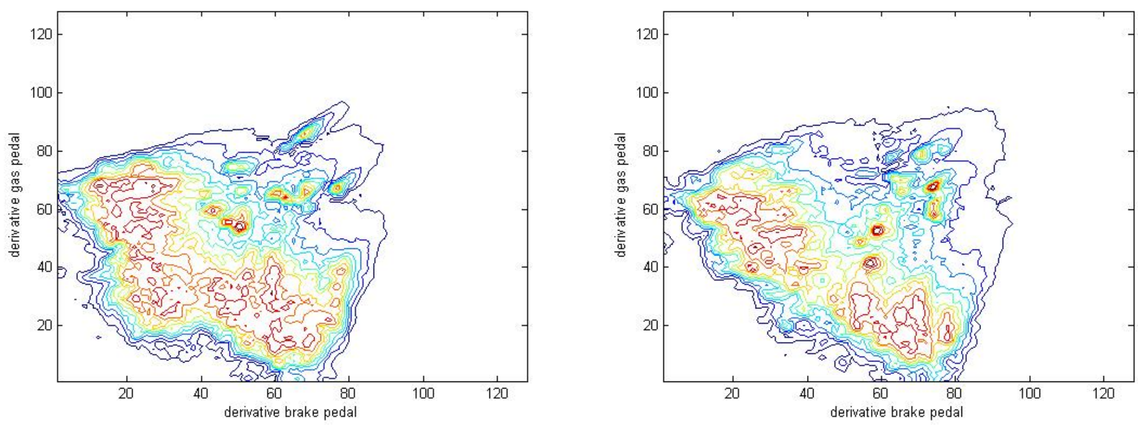
m2 f2 m4

Figure 5 Contour plot of six different driver of the brake pedal versus the gas pedal



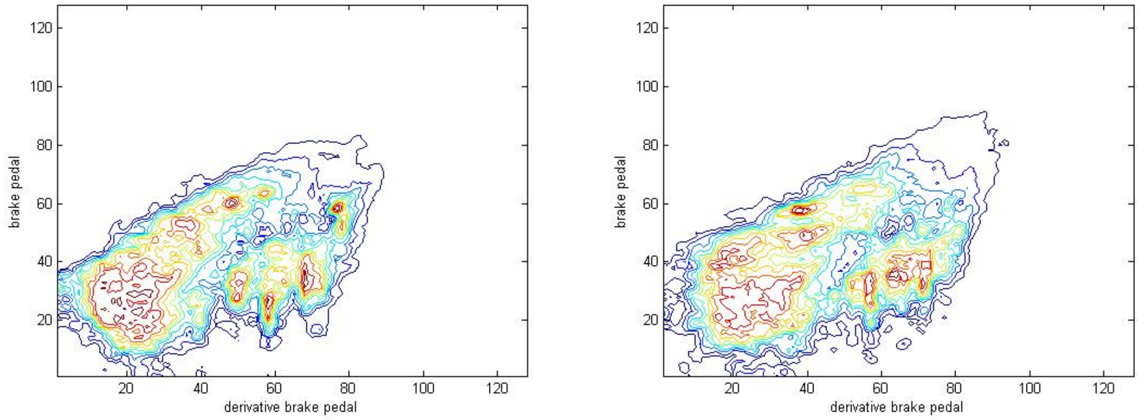
m2 f2

Figure 6 3-D mesh plot of one driver of the derivative brake signal against the derivative gas pedal signal.



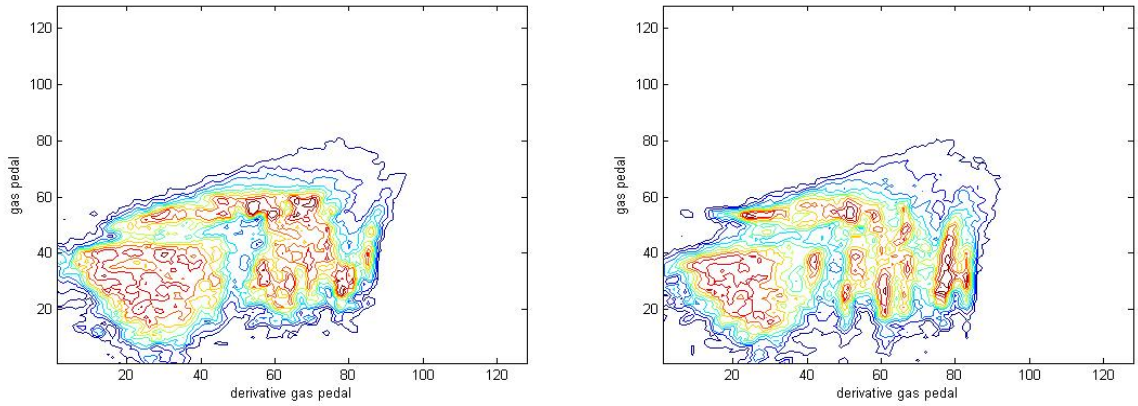
m1 f1

Figure 7 Contour plot of one driver of the derivative brake signal against the derivative gas pedal signal.



m1 f1

Figure 8 Contour plot of one driver of the brake pedal signal against the derivative brake pedal signal.



m1 f1

Figure 9 Contour plot of one driver of the gas pedal signal against the derivative gas pedal signal.

For Figures 5 to 9, the values for the 2-D points are taken from their common normalized frequency values and their coordinates are normalized from amplitude values of psd with respect to their own features defining its axis.

From Figure 6, it shows the 3-D mesh plots of a male (m2) and female (f2) driver. Generally the plot for f2 has a larger number of high frequency distribution compared to m2. Besides containing higher frequencies, there is a exceptionally steep peak around the normalized values of derivative brake pedal pressure from 65 to 75 and derivative of gas pedal pressure from 70 to 80. Furthermore, there is a reasonable amount of small frequencies observed in the area where derivative of brake pedal ranges from 0 to 20 and derivative of gas pedal ranges from 15 to 35.

Continuing, Figure 7 provides a contour plot of another pair male and female of derivative of both the brake and gas pedal pressure. The contour plot provides a different representation of the same information. It provides a more definite view of the points compared to the 3-D mesh that may tend to focus on both frequency values which is represented by the peaks. Here another different pair of drivers is discussed, but the areas of differences observed are very similar to the mesh plot.

Therefore for the rest of the discussion, the paper will focus on contour plots only.

Starting with Figure 5, it provides gas and brake pedal pressure plots for six different drivers. Overall, there is an clear difference in the distribution of frequency values in the these plots compared to when their derivatives are applied to at least one axis. There are mainly two extremely different areas for these six plots. The first area is defined by brake pedal pressure from 60 to 100 and gas pedal pressure from 90 to 110. In this area, there is not definite distinction between female and males drivers, but each driver has a different distribution of frequency values among one another. While another area is defined with values of brake pedal pressure ranges from 0 to 30 and gas pedal pressure ranging from 0 to 40. Among the six contour plots, the second area provides a more distinctive distribution of values compared to the first area identified. Example would be for m4 to have relatively less amount of points compared to m1, m2, m3 and f2, except for f1 contain also a small number of points, but still significantly more than m4. And among m1, m2, m3 and f2, m1 and m2 contained more higher frequency values, but still differ in their shape, while m3 and f2 although contain lower frequency values, but between them also differ in their shape in distribution of frequency values.

Figure 8 shows the contour plot of the brake and derivative of brake pressures. There are three main areas that differ between the plots. Firstly, for the area defined by derivative of brake in the range of 70 to 90 with brake also in the range 70 to 90, there is a larger distribution of small frequency in f1 compared to m1. Secondly, the area with derivative brake pedal ranging from 50 to 80 and brake ranging from 0 to 35, f1 has a larger spread of small frequency, while m1 has higher frequencies observed around the point derivative brake pedal = 60 and brake = 20. Thirdly, the area with derivative brake ranging from 0 to 40 and brake ranging from 40 to 60, f1 again has a larger spread of variety of different frequencies compared to m1 which contained a smaller set of values in that area.

Generally the areas of difference for Figure 8 and Figure 9 are very similar. The main exception would be that the area of derivative gas and gas between defined by the square of both axes ranging from 70 to 90. Both f1 and m1 do have almost the same amount of distribution of points, but shapes of arrangement for frequency values for both drivers are slightly different.

6. Conclusion

Besides carrying out with experiment with frequency values to be used as the pre-determined set of values to be mapped, variances in the amplitudes of the power spectral densities were applied. But due to the lost of information created by small variance in a large number of amplitudes, it was not applicable for driver identification. But because instead of the frequency values, the variance is used, the plot was able to highlight the characteristics that vary the most among drivers.

From such a plot it is able to highlight information that using the frequency values have failed to identified. In plots made by frequency values, there is usually weak or even no significant indication of the driver's characteristic of applying large increase in the accelerator and brake pedals. And the plot had peaks at the far right corner or largest increase in the accelerator and brake pressure, therefore it is highly probable the critical characteristic in which will be able to identify drivers will be the rate of increase in accelerator and brake pedal pressures.

From such an observation, if we assume that a driver's feature is highly influenced by his or her emotions, then it maybe possible to extract features that will have the capability to assist in determining the state of emotion of the driver. Thus if further effort were to focused on optimizing the values to be mapped, it will have a high possibility of being able to not only accurately identify the driver's identity, but may even eventually predict the emotions and emotional behavior when compared with the average driver's profile.

Finally, to successfully identify the drivers' identity and emotions, critical or differentiating features maybe extracted from the CMAC plots by either human inspection or clustering methods. Human inspection will include a visual observation of the plots of at least a majority of drivers to derive a certain distribution of values in the CMAC.

While the clustering methods would require a 3-D clustering method that will eventually be able to construct effective rules that assist direct or indirect application towards accurate classifications and predictions. After defining features in the CMAC, further effort should be done towards testing and refining the techniques of feature extraction from the CMAC or even improve the feature during the process of storing. Further improvisations maybe done by augmenting the storing process to the CMAC or/and the feature extraction process from the CMAC to compliment one another. Only after continual and thorough tests and refining, then it would be possible to achieve a reasonable and effective method of driver and emotion identification.

7. References

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