Understanding Driver Behavior Using Multi-Dimensional CMAC

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Abstract—In this paper, detailed studies have been conducted to model individual driving behavior in order to identify features that may be efficiently and effectively used to profile each driver. The brake and gas pedal pressure are used to identify uniqueness in driving maneuver o0f each driver. These differences in the driving habits could be due to 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. 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 driver behavior under difference environment. Experimental results from the CMAC profiles show the potential of extracting features of drivers' behavior for identification, verification, emotion recognition, stress and many other behavioral conditions.

Keywords—Cerebellar Model Articulation Controller (CMAC), driver profiling, brake pedal signal, gas pedal signal,

I. 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 robotic control, signal processing, pattern recognition, speech enhancement and diagnosis [2,3,4] and for this paper it will be used for driver behavior profiling. In order to effectively utilize the full advantage of CMAC and achieve reasonable accuracy, there is a need for careful consideration in selecting the size/resolution of the CMAC. The size of CMAC will not only determine the amount of time and computation cost, but also effectiveness in exploiting CMAC neighborhood properties. Too large the CMAC size selected might cause low space utilization and an ineffective use of the CMAC neighborhood property. While too small the size of CMAC will cause the output result to be inaccurate. Before determining the size of a CMAC it is important that the data to be profiled must first be analyzed such that the length between the two adjacent data is minimized. In addition the distribution of the data to be profiled can also affect the accuracy of the local and global recall process which in tern will determine the complexity of the basis function used. Mapping function will eventually determine how the data will be profiled by defining its coordinates and weight values.

The CMAC memory can 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 in the Kohonen's neural networks framework, CMAC learning is a competitive learning process and follows self organizing feature map (SOFM) learning rules. However, since the weights of the cluster of neurons that represent the indices to the CMAC memory are fixed, learning only occurs at the output neuron. To achieve this 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 [5] equation (1).

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

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).

A. Accuracy in CMAC Outputs

Some preliminary experiment carried out on a multi-dimensional CMAC has shown that a random distribution of values will result in poor accuracy. This is because the neighboring values of the CMAC can have large differences. Thus CMAC is unable to produce a repeatable and accurate output. But by re-organizing the output data to be trained such that their neighboring values differ by a relatively small amount, its accuracy improves significantly. In some cases the

1-4244-0983-7/07/$25.00 ©2007 IEEE ICICS 2007

improvement can be as much as 40% from randomly stored values. 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 of the output data to be profiled. In this paper the input data is first analyze using frequency domain for profiling the distribution. Two factors that largely influence the profiling is the selection of input variables and their axes basis function in the CMAC.

Firstly, 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.

Secondly, 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 selected 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 the CMAC neighborhood property.

Besides being a 3-D CMAC, the CMAC applied here uses the initial idea first initiated by J.S Albus. There is no physical storage of the actual outputs of the defined size, but instead only the 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 axes and values from the represented CMAC to the weight tables.

Once the resolution of the CMAC is decided, the size of the weight tables needs to be estimated to ensure an optimum values and coverage of the output weights. Thus the maximum and minimum values of the output need to be known. Pairs consisting of coordinates and its respective values for the axes can now be entered into the CMAC. The weights stored in the CMAC memory are updated based on the initial weights stored and the sum of the neighboring values. The differences between the stored and desired values will constitute to the error. CMAC memory will now 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 all the CMAC memories have been updated and trained with the new output the retrieval process would only consist of summing the neighboring CMAC weight stored in the CMAC memory. Usually all the values will be retrieved, unless specific set of coordinates are defined.

II. Driving Profiling

The driving data utilized in this research are from the In-car Signal Corpus hosted in Center for Integrated Acoustic Information Research (CIAIR), Nagoya University, Japan [6]. The In-car Signal Corpus is one of several databases hosted by CIAIR. 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 2 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 (gas 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 with the objectives of increasing traffic safety or improving the performance of intelligent vehicle systems [7]. 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. Figure 1 and 2 show the diagrams of the recorded driving signals and their derived signals (gas and brake dynamics) belonging to one particular female driver over the duration of one stop-go region.

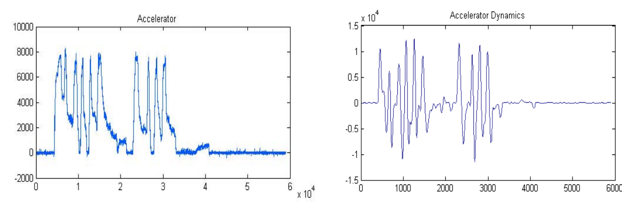


Figure 1 Gas signal and its Dynamics Signal

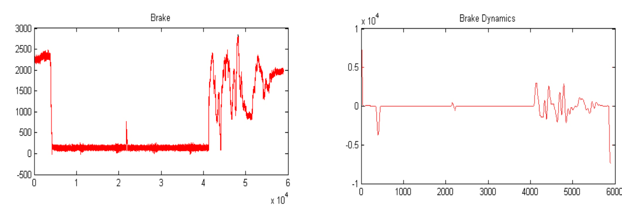


Figure 2 Brake signal and its Dynamics Signal

III. Experiment

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. The power spectral density (PSD) of each dataset is used instead to analyze the gas and brake pedal pressure and it's dynamic. The dynamic of the gas and brake pedal pressure is the first derivative of its pressure signal.

From previously work, it was shown that using the gas and brake pedal signals allows for the best training and identification of the driver's identity [8]. Furthermore, experiments also indicate higher accuracy of driver identification when combined with the derivative of the gas and brake pedal signals are used instead of solely relying on the original gas and brake pedal signals collected. In this paper we use both the original gas and brake pedal signal and it's' derivative.

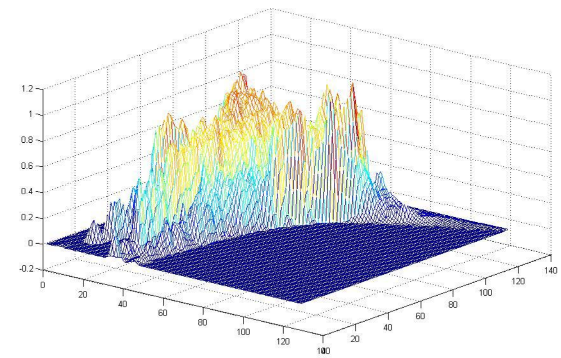
B. Experimental setup

In this experiment a 3-Layered CMAC initially proposed by J.S Albus was used to derive a 3-D CMAC as a profile for each of the drivers. From gas and brake pedal signals, and their first derivative, there are a total of four signals available for the 3-D driver behavior profile. All the four signals are first transform to frequency domain by deriving the PSD. In the first experiment we store the gas and brake pedal pressure together as a 3-D CMAC in frequency domain. Both the amplitude of the gas and brake pedal pressure forms the x and y axes of the CMAC memory respectively while the Z axis forms the common Z axis. Notice how the frequency, which is common between the two signals, is used as the Z-axis. Since the gas and brake pedal pressures and its derivative do not have the same values they are normalized to ease in our computation. In addition all signals are transformed to ensure no negative values thus all amplitudes of the signals will be normalized to values with respect to the desired CMAC resolution.

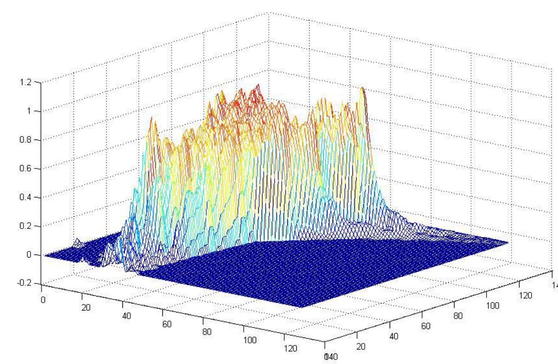
Four possible signals combination of the CMAC can be derived for a single driver. Figure 3 shows the 3-D mesh plot of two drivers' behavior profile for the derivative of the gas and brake pedal pressure. The z-axis is the frequency with maximum frequency of 100Hz since all the signals have been down sample to 200samples per second. The y-axis and the x-axis are the derivative gas and derivative brake pedal pressure signal respectively. Thus 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.

If only a single set value is 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 data set or event and classify their occurrences or recognize their identity will be bias and would not be conclusive. Thus the CMAC memory stores up to 10 different datasets collected for each of driver, such an approximation has the ability to not only allow small variations, but will also be able to capture occasional abnormalities. Although such abnormalities may seem to 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 surface.

After the creation of the CMAC memory, a possible combination of all the CMAC for all drivers may be stored in one CMAC to allow analyzing of the driver behavior under different environmental condition. Such studies could be useful in understanding if driver is under stress or the characteristic of drivers and its habits. This can thus lead to a possible correct prediction of the driver's identity or its behavioral state. Such a combination of CMAC memory created can be used to allow iterative learning of the CMAC memory to derive a common driver profile for culture characteristic. Besides making a large number of iterations to ensure a good approximation of the CMAC profiling, ideally the order of CMAC used and the learning/training algorithm can also help to avoid biasing in the combination of CMAC for all drivers.



(m1)



(m2)

Figure 3 3-D mesh plot of one driver of the derivative brake signal against the derivative gas pedal signal for two drivers' m1 and m2.

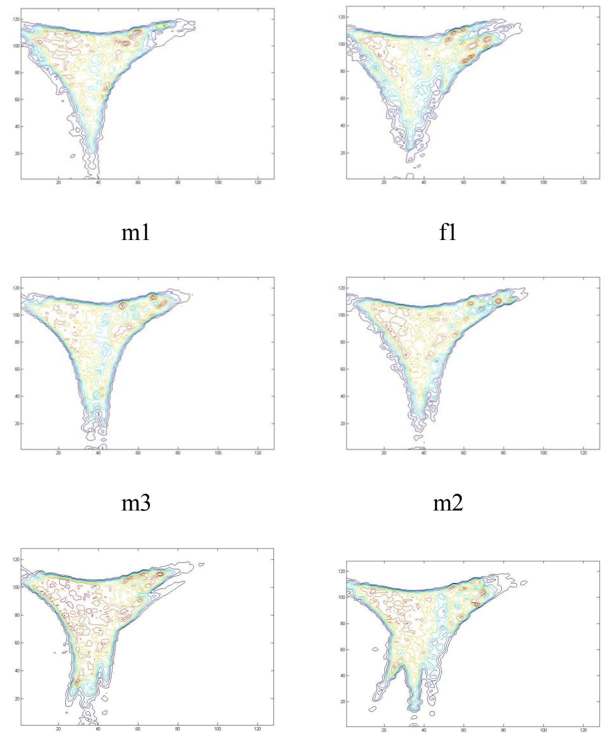
IV. DISCUSSION

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

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.

Besides carrying out the experiment with frequency values to be used as the pre-determined set of values to be mapped, variances for the x and y axes are amplitudes of the power spectral densities. Due to the lost of information created by small variance in a large number of amplitudes, it was not applicable for driver identification at this point of time. Instead of frequency values, the variance can also be used, which are able to highlight the features that vary the most among drivers. Such plots are able to highlight information and feature in the frequency domain and can have values that previously show unsuccessful driver identification. In the previous papers [8] the Gaussian mixture models (GMM) were used to analyze the brake and gas pedal pressure plots to identify the drivers. In our earlier study we also make use of the Mel Cepstral frequency coefficient MFCC to identify drivers with some degree of accuracy but still the performance of the GMM prove to be far better which will not be discussed in this paper.

Analyzing the mesh plots of figure 3 prove to be difficult and meaningless. Thus we have the contour plot of the CMAC memory shown by figure 4 for sets of 2 female drivers and 4 male drivers. These plots also show the contour of the gas and pedal pressure signals with respect to a common frequency in the z axis. The x and y axes are the brake and gas pedal respectively. Just analyzing the bottom portion of the CMAC driver profile for the gas and brake pedal shows different characteristics of the driver which is obvious using the naked eyes. Notice also this areas are the areas when the driver are just applying their gas pedal pressure by putting their right leg on to the gas pedal slightly for smooth driving condition. The way the driver applies the right leg to adjust the constant speed of the vehicle shows each of our driving characteristics. Notice how male drivers in general have the tendency to apply wider range of the gas pedal as compared to the other four male drivers.



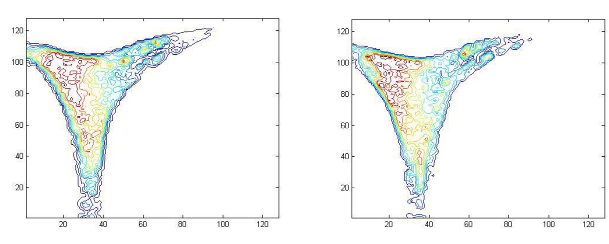
m1 f1

m3 m2

f2 m4

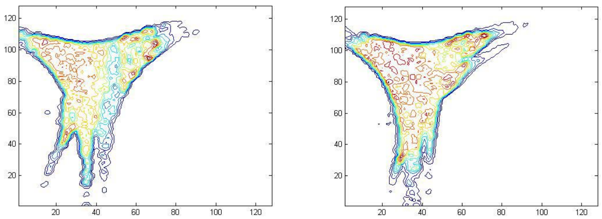
Figure 4 Contour plot of six different driver of the brake pedal versus the gas pedal

Let's now analyze the top right hand corner of figure 4. Again it shows distinct differences they way driver applies brake and gas pedal pressure. This region indicates how the driver applies the maximum gas and brake pedal pressure. This region also shows how frequent the driver would apply maximum pressure to the gas and brake pedal. Feature relating to the maximum gas and brake pedal pressure could in this case be used as features for driver identification in addition to the way driver applies the gas pedal for constant speed driving. This is an interesting observation thus we could also identify drivers not just based on the stop-go region but also the constant speed driving. It is highly probable the critical characteristic in which we are able to identify drivers will be the rate of increase in accelerator and brake pedal pressures. Thus figure 5, 6 and 7 shows the derivative of the brake pedal vs. the derivative of the gas pedal, derivative of gas pedal vs. gas pedal and derivative and brake pedal vs. brake pedal respectively.



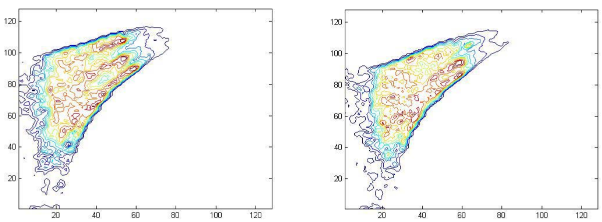
(m1) (m2)

Figure 5 Contour plot of one driver of the derivative brake signal against the derivative gas pedal signal.



(m1) (m2)

Figure 6 Contour plot of one driver of the brake pedal signal against the derivative brake pedal signal.



(m1) (m2)

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

V. CONCLUSION AND FUTURE WORKS

Each and every plots of the CMAC output memory shows the potential of using the 3-D CMAC driver behavior profile to be used for driver identification purposes. Such observations also indicate a driver's feature is highly influenced by his or her emotions and his subconscious mind. As a human being we make judgment based on our experienced and exposure. It may be possible to extract features from the driver behavior profile that determine the driver state of emotion. This emotion also reflects the activation of the cerebellum thus the movements of the leg muscles. This translation could have been hidden in the CMAC driver behavior profile that is not easily observed by the naked eyes. Further effort can be focused on optimizing the values to be mapped, it will have a high possibility of being able to not only identify the driver's accurately but may eventually be used to predict the emotions state of the driver at large.

Finally, to successfully identify the drivers and their emotions, critical or differentiating features may be required and extracted from the CMAC memories by some simple classification algorithms. As can be seen human inspection can provide some initial guess but a detail analysis of the feature extraction and selection methods are required to ensure the degree of confident.

While the 3-D classification is required to successfully recognize and identify the driver emotions and identity it can be seen that a multi-dimensional CMAC could help view the driver profile in a better and more wholesome perspective. Once features have been selected via the CMAC memory the next effort should be done towards testing and refining the techniques of feature extraction and selection from the CMAC or improve the feature during the process of storing. Further improvements can be made by augmenting the storing process to the CMAC or/and the feature extraction process from CMAC to compliment one another. Only after continual and thorough tests can refinement is done to the algorithm to achieve a higher degree of confident.

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