Chapter 13
Pre- and Postaccident Emotion Analysis on Driving Behavior

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Abstract There are many contributing factors that result in high number of traffic accidents on the roads and highways today. Globally, the human (operator) error is observed to be the leading cause. These errors may be transpired by the driver's emotional state that leads to his/her uncontrolled driving behavior. It has been reported in a number of recent studies that emotion has direct influence on the driver behavior. In this chapter, the pre- and postaccident emotion of the driver is studied in order to better understand the behavior of the driver. A two-dimensional Affective Space Model (ASM) is used to determine the correlation between the driver behavior and the driver emotion. A 2-D ASM developed in this study consists of the valance and arousal values extracted from electroencephalogram (EEG) signals of ten subjects while driving a simulator under three different conditions consisting of initialization, pre-accident, and postaccident. The initialization condition refers to the subject's brain signals during the initial period where he/she is asked to open and close his/her eyes. In order to elicit appropriate precursor emotion for the driver, the selected picture stimuli for three basic emotions, namely, happiness, fear, and sadness are used. The brain signals of the drivers are captured and labeled as the EEG reference signals for each driver. The Mel frequency cepstral coefficient (MFCC) feature extraction method is then

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employed to extract relevant features to be used by the multilayer perceptron (MLP) classifier to verify emotion. Experimental results show an acceptable accuracy for emotion verification and subject identification. Subsequently, a two-dimensional Affective Space Model (ASM) is employed to determine the correlation between the emotion and the behavior of drivers. The analysis using the 2-D ASM provides a visualization tool to facilitate better understanding of the pre- and postaccident driver emotion.

Keywords Driver behavior • Valance • Arousal • Pre- and postaccident emotion • Mel frequency cepstral coefficients (MFCC) • Multilayer perceptron (MLP)

13.1 Introduction

Driving requires making critical decisions in very short period of time, and oftentimes, such decision is needed under extraneous circumstances. To make an informed maneuvering decision, drivers rely on input from a number of sources including the road condition, traffic volume, other road users, the condition of the vehicle, duration of the trip, and the environment [1]. Drivers are observed to lack prudent decision-making ability (a) if their secondary tasks like mobile phone usage and texting and/or (b) if they are under the influence of alcohol, drugs, stress, fatigue, and excessive emotion. These are known to distract drivers' concentration and often cause accidents [2]. Hence, the understanding of drivers' emotion, in particular, on the pre- and postaccident instances is important to give us cues the way emotion impacts the driving activity. The following three conjectures are prevalent in the research community:

1. Emotion influences driver's behavior.
2. Individual emotional brain signal can be measured.
3. There are variations among brain signals of people for a particular emotion, and it could even be unique for each person.

Emotion is a very important factor in human life to interact and even to control his/her own behavior. Moreover, the uncontrolled emotion—i.e., negative emotion—during driving is observed to result in poor judgment calls and causing accidents with serious consequences.

It is often observed that anger impairs the driver's decision-making ability leading him/her to drive dangerously, taking unnecessary risks, or even force other drives to slow down or swerve, i.e., road rage.

Fear is observed to introduce overconscious behavior that makes drivers to hesitate or act in a non-confident way. For instance, if a driver has fear of speed (tachophobia syndrome), he/she does not want to drive higher than the speed that he/she is comfortable with, which poses concerns and even results in accidents at roads with a minimum speed limit. These drivers are observed to suffer from breathlessness, palpitations, and even full-blown anxiety attack.

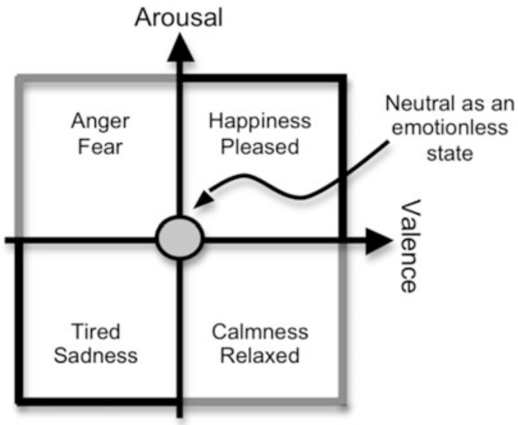

Fig. 13.1 Affective space model with axis valance (*vertical*) and arousal (*horizontal*)

Sadness can also influence driver behavior by making him/her lose concentration and long delays in reacting. This condition poses high risks in congested traffic and highways.

On the other hand, positive emotion can as well distract drivers. Often, drivers are observed to focus on his/her happiness and ignore the world around him/her. He/she could miss critical driving cues, such as, indication of empty fuel tank, blinking warning signs in the vehicle, and even road signs on construction and activities on the shoulder of the highway.

In a number studies~~,~~ the emotional effect has been conceptualized in terms of emotion primitives of valance and arousal values [3, 4]. Valance (v) refers to the impact of the emotion on oneself ranging from a positive to a negative effect, i.e., the extent of pleasure or sadness. It can be described as a bipolar continuum of positive and negative value of hedonic level [5]. The arousal (A) ranges from calm to excited. These two values can be used to generate an Affective Space Model (ASM) to illustrate different emotion boundaries. Figure 13.1 shows the affective space model with several labeled emotions and neutral as a black dot in the middle of the model according to Russel [6].

13.2 Related Work

In recent years a number of research teams have focused on capturing emotions from EEG recordings [7]. Chanel et al. have tried to recognize only the arousal dimension of emotion from their EEG database and other physiological measures [8]. Classification rates were around 60 % when using two emotional classes, and if an additional class is added, that number dropped to 50 %. Most studies in the literature are based on a two-dimensional model of emotions, valance (positive–negative) and arousal (calm–exciting). Emotions are then thought to be a point in a two-dimensional plane of valance vs. arousal as depicted in Fig. 13.1.

In a study at Israel Institute of Technology (Technion), the driving data has been collected by an in-vehicle data recorder (IVDR) called Drive Diagnostics. This IVDR has been designed to monitor and analyze driver behavior not only in crash or pre-crash events, but also in normal driving situations. It records the movement of the vehicle and uses this information to indicate overall trip safety. Their findings show strong correlations between the two datasets, suggesting that the driving risk indices can be used as indicators of the risk involvement in car crashes [9]. This connection has enabled our study on the potential impact of the system on driving behavior and on safety. Access to the feedback provided by the system has further impact on driver performance.

13.3 Methodology

13.3.1 Electrode Positions and Preprocessing

Five EEG electrodes were pasted on the scalp of subjects (C3, C4, T3, and T4) according to the "International 10–20" Standards and a Cz as reference. Figure 13.2 shows the block diagram of the procedure that was used to analyze the brain signals and their spectrum from the subjects under investigation (drivers).

Brain waves obtained from each channel are then decimated in order to decrease the sampling rate and to filter the data. As expected, the decimation process filters the input data with a low-pass filter and then resamples the resulting smoothed signal at a lower rate. The matlab code below reduces the sampling rate by a factor of 3:

input = decimate (input, 3).

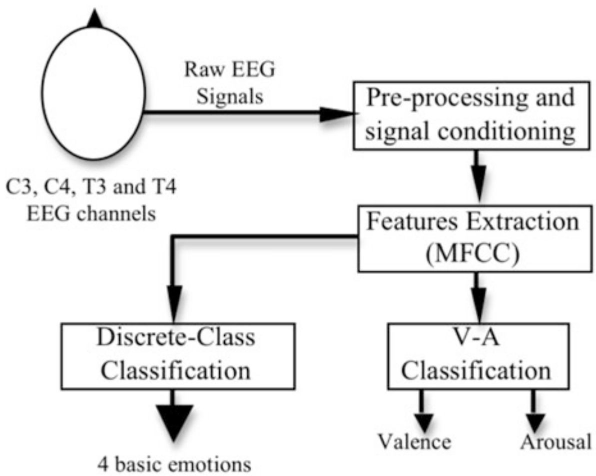

Fig. 13.2 Proposed procedure for analysis

13.3.2 Feature Extraction

Mel frequency cepstral coefficients (MFCC) were used as features in this study, which is used frequently in dimension reduction applications for waveforms. *melcepst* tool is utilized to calculate the cepstrum of the signal. We have used ten MFCC coefficients for capturing the relevant feature of the EEG. The final combined dataset from four channels gives a total of 40 features for classification. *enframe*, *rfft*, *melbankm*, and *rdct* are also utilized during processing.

13.3.3 Classification

The last step in this process is the classification of the features with a meaningful and yet computationally efficient classifier. Multilayer perceptron (MLP) method has been chosen to classify the extracted features so that it can derive the pre-emotion of the driver which relates to the driving behavior. Multilayer perceptron with a feedforward artificial neural network architecture maps sets of input data onto a set of appropriate output. Optimal model selection for the number of layers and the neurons needed for the best MLP architecture is essential to ensure a respectable performance. Data fed into the input layer are the 40 features obtained from the previous MFCC stage. Each of the data is processed by the network by multiplying it with assigned weights in the hidden layers synapses. In this research study, the mean square error (mse) goal was set to 0.1 with a single hidden layer consisting of ten neurons. In addition, we have used *tan-sig* as the activation function for the hidden layer and *purelin* as the output layer with 0.01 learning rate.

In experiments, *eyes open* data was used for the *calm emotion* since the subjects have not been burdened by any task at this stage. The data obtained from the subjects (drivers) are tested against the emotion data of affective state of *happy*, *calm*, *fear,* and *sad*.

In order to get reliable results with a high percentage of accuracy, we have used the k-fold cross-validation for our global validation. K-fold cross-validation builds on the idea of holdout testing in a clever way by rotating data through the process 0. Data is again divided randomly into groups, but now k equal-sized groups are used. The train-test process is repeated k times, each time leaving a different segment of the data out as the test set. The dataset and its desired result are randomized and sliced into fivefolds which mean that the process is repeated five times. This is required to eliminate any biases towards the data [10]. The slicing process enables to have different training and testing datasets. Each dataset consists of 440 instances by which 352 (80 %) instances are used for training and the remaining 88 (20 %) for testing.

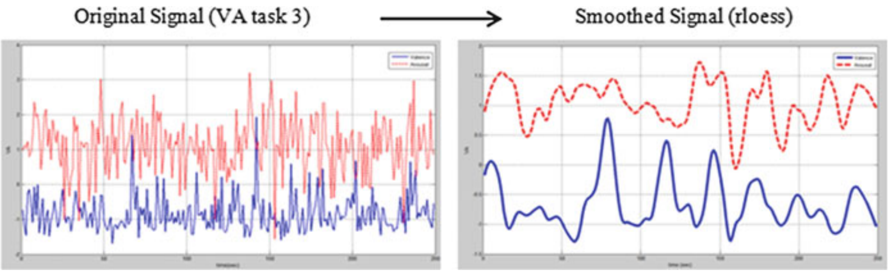

Fig. 13.3 Signal smoothing

13.3.4 Smoothing

This function basically smoothens the original data that has been selected. The process of smoothing the original dataset produces a new dataset containing smoothed response values. The smoothed signal is displayed in Fig. 13.3.

13.4 Experiment Design and Stimuli

Subjects are briefed on the experimental procedures and were asked to sign an informed consent form for participating in experiments. Then, subjects are seated in a lighted, quiet, and temperature-controlled room. Before the data collection, each subject is made familiar with the driving simulators. Next, the electrodes are placed on the scalp of each subject. The acquisition of signals is achieved by a module called BMC Acquisition. Initially, subjects are instructed to open their eyes for 1 min and then close for 1 min. Afterwards, the movie clips with three basic emotions are shown to them for 1 min per movie clip. Finally, they were asked to drive according to the three tasks given to them, and the recorded brain waves are then saved for offline processing.

13.4.1 Stimuli

In this study, we have used the movie clips with scenarios depicting emotions to obtain emotional responses and a driving simulator platform to simulate the driving framework. The drivers were exposed to three basic emotions by using (1) the International Affective Picture (IAPS), (2) Bernard Bouchard's synthesized musical clips, and (3) movie clips of Gross and Levenson which can be used to elicit emotional responses [8]. Then, they were asked to drive in three different types of conditions: Task 1—easy driving, where they were subject to noisy sounds that could disturb them while driving. Task 2—bulked driving, where they were interviewed by the experimenter deliberately to see their behavior while answering cognitive questions. Finally, Task 3—heavy driving, subjects had to deal with traffic congestion where their driving skills were challenged at this stage.

13.5 Results and Discussions

Since the correlation between the pre-emotional state of the subject and driving behavior is the primary interest, the accuracy of the acquired data gains importance to demonstrate that the results will be more robust from the proposed valance analysis (VA). To achieve that a memory test was performed for all subjects to see the level of accuracy, either it can be accepted or rejected. Next, we have performed a fivefold validation test to obtain the intensity of the selected emotions for each subject.

13.5.1 Pre-emotion (Memory Test and Fivefold)

Here, the accuracy is calculated from the valance analysis instead of directly getting the accuracy from MLP. There are two VA analyses in the identification of a particular; first: the memory test which consists of 100 % test data (Fig. 13.4) and second: the fivefold validation (Fig. 13.5). As it is clearly seen, four basic emotions can be identified, and higher than 80 % of accuracy can be achieved. The best accuracy value was at 0.1 of mean square error goal. Consequently, the emotions data can be used as the base for the subsequent driving task analysis. Furthermore, the highest intensity of emotion for each subject is shown in Fig. 13.5. Here the plots are according to the average k-fold percentage for each subject.

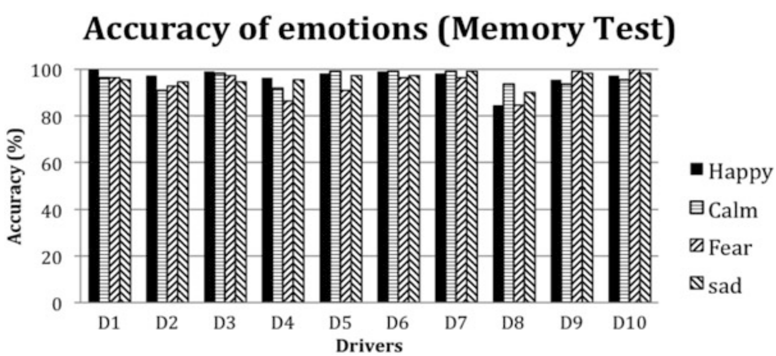

Fig. 13.4 Accuracy of emotion based on the memory test

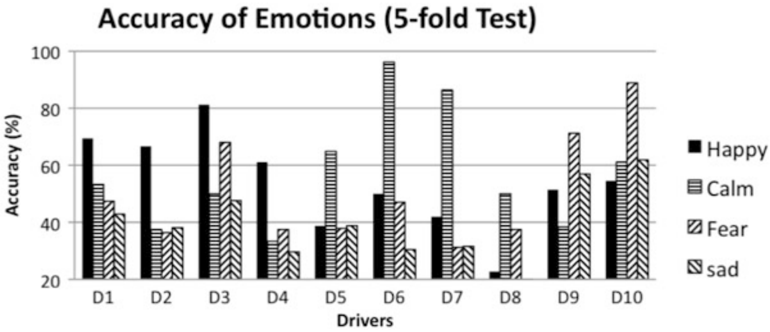

Fig. 13.5 Emotion intensity based on the average accuracy of k-fold test

Table 13.1 Confusion matrix, average emotion accuracy (memory test), subject 1 (happy)

		Expected emotion (%)			
		Happy	Calm	Fear	Sad
Output emotion (%)	Happy	100	0	3.6	0
	Calm	0	96.3	0	1.8
	Fear	0	0	96.3	2.7
	Sad	0	3.6	0	95.4

It is worth noting that when the emotion that gains the highest intensity in the k-fold yields the same result in the memory tests. In addition, there are four subjects with *happy* as the highest intensity of emotions, another four subjects fall into *calm*, and two subjects has *fear* as their pre-emotion. None of them is *sad*. The results indicate that each subject has their own pre-emotion which may affect their driving behavior.

13.5.2 Valance (V) and Arousal (A) Analysis

The results above point to four critical emotions relevant to driving, which are *happy*, *calm*, *fear,* and *sad*. With these findings, we extend the analysis to the valance and arousal analysis where emotions for three subjects studied in detail. The subjects have been chosen randomly based on the memory test results, and they show the emotion which exhibits the highest accuracy in the k-fold analysis. Here, we would like to see the relationship between pre-emotions and the driving tasks. Table 13.1 shows the accuracy of the memory test for subject 1, whereas Table 13.2 shows the average accuracy of emotions for the k-fold test. We observe that subject 1 has exhibited the highest accuracy for *happy* followed by *calm*, *fear,* and *sad*.

In Fig. 13.6, the emotion clusters for subject 1 have been plotted from the memory test experiment in order to see if each emotion falls into its own quadrant based on valance and arousal. As it is clearly seen that none of the *happy* emotion clusters falls into other three quadrants, whereas the other three emotions have reciprocally spread to each other.

Table 13.2 Confusion matrix, average emotion accuracy (VA), subject 1 (happy)

		Expected emotion (%)			
		Happy	Calm	Fear	Sad
Output emotion (%)	Happy	69.45	14.83	6.53	5.71
	Calm	23.71	53.29	8.44	9.76
	Fear	5.59	13.93	47.40	41.67
	Sad	1.25	17.95	37.63	42.86

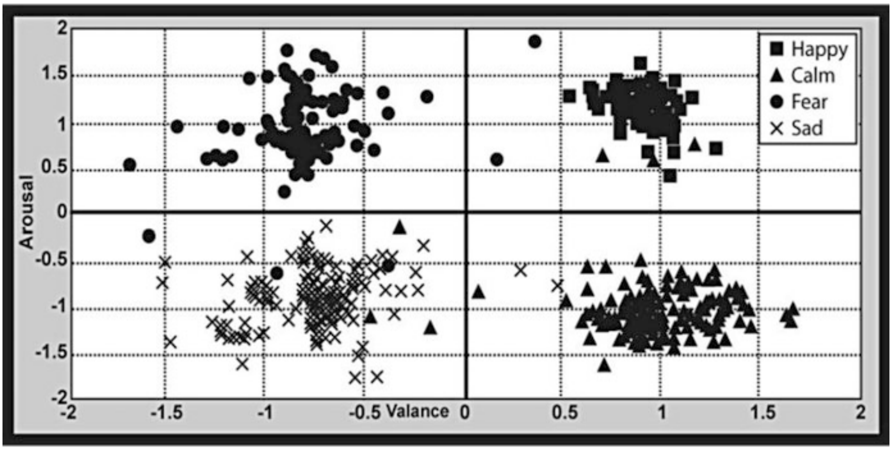

Fig. 13.6 Emotion clustering for subject 1

Table 13.3 Confusion matrix, average emotion accuracy (VA) for fivefold test, subject 5 (calm)

		Expected emotion (%)			
		Happy	Calm	Fear	Sad
Output emotion (%)	Happy	38.7	18.5	29.1	19.1
	Calm	9.6	64.9	7.3	12.6
	Fear	30.9	1.6	37.9	29.5
	Sad	20.7	15.1	25.7	38.8

Table 13.4 Confusion matrix, average emotion accuracy (VA), subject 9 (fear)

		Expected emotion (%)			
		Happy	Calm	Fear	Sad
Output emotion (%)	Happy	51.4	31.5	4.0	9.2
	Calm	27.2	38.4	5.7	9.3
	Fear	12.1	12.3	71.2	24.6
	Sad	9.2	17.8	19.0	57.0

Table 13.3 shows the emotion accuracy for subject 5 with the highest being *calm*. Finally for this VA analysis, subject 9 exhibits *fear* as the highest intensity of emotion as shown in Table 13.4.

For these three subjects, we can conclude that each subject has their own highest intensity for the pre-emotion, which could be due to their different backgrounds, cultures, or experiences of having positive or negative emotions that already exist in each subject, i.e., preexisting conditions.

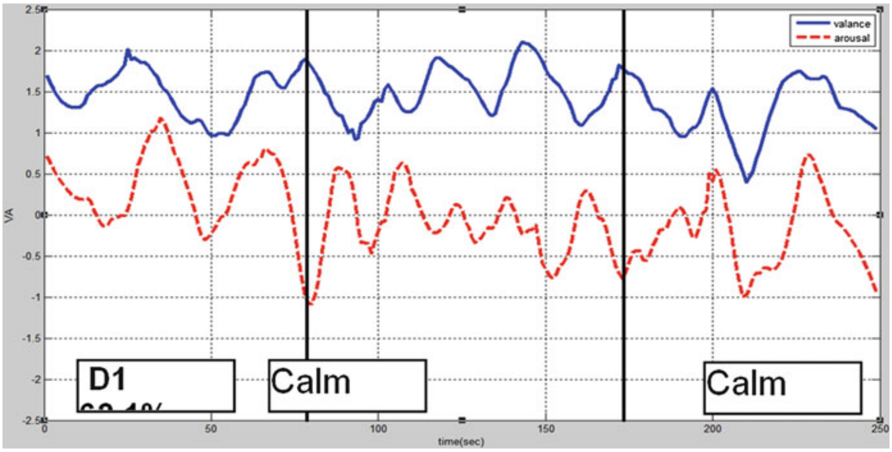

Fig. 13.7 Dynamic movement task 1, subject 1 (driving and sounds)

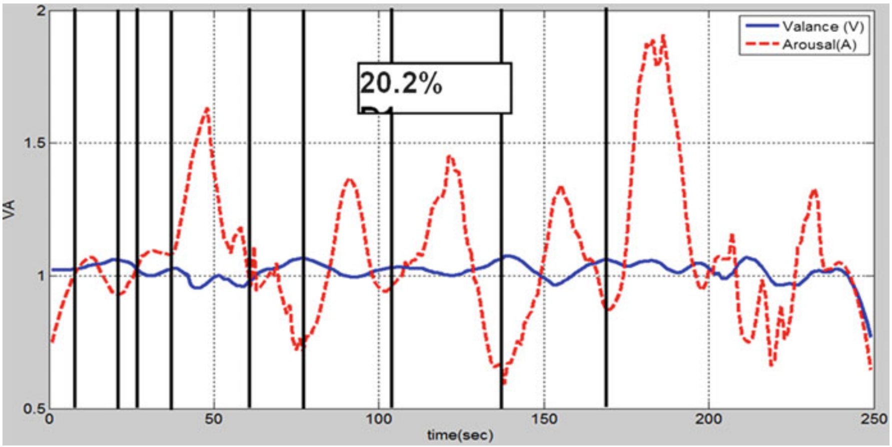

Fig. 13.8 Trajectory task 2, subject 1 (driving and interview)

13.5.3 Trajectory of the Driving Task

Each task that was given to the driver is expected to invoke some stress during driving, so we can observe the driver behavior while under duress. From these experiments, we see that each driver has a diverse driving behavior. For subject 1, who has not been affected by an accident, the emotions remain positive beginning with the first task until the one as they can be seen in Figs. 13.7, 13.8, and 13.9. Besides, this particular driver (female) has changed her emotion from *happy* to *calm* when the accident occurred during the first task. This result implies that this driver has a very high intensity of *happy* emotion.

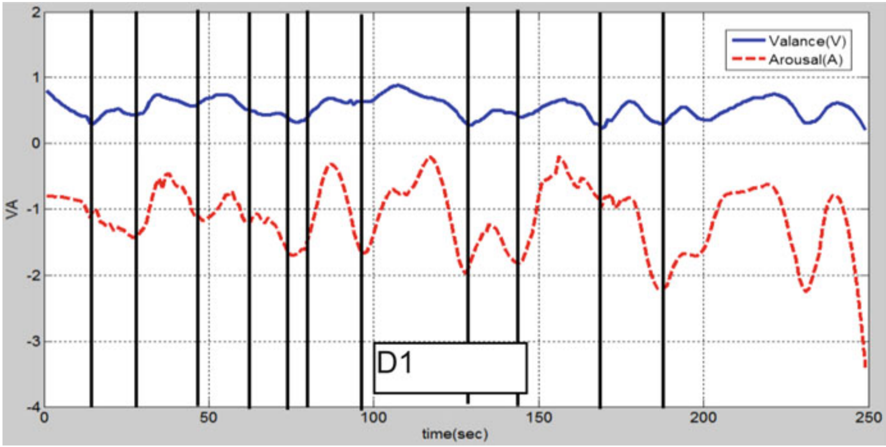

Fig. 13.9 Dynamic movement task 3, subject 1 (driving and congested traffic)

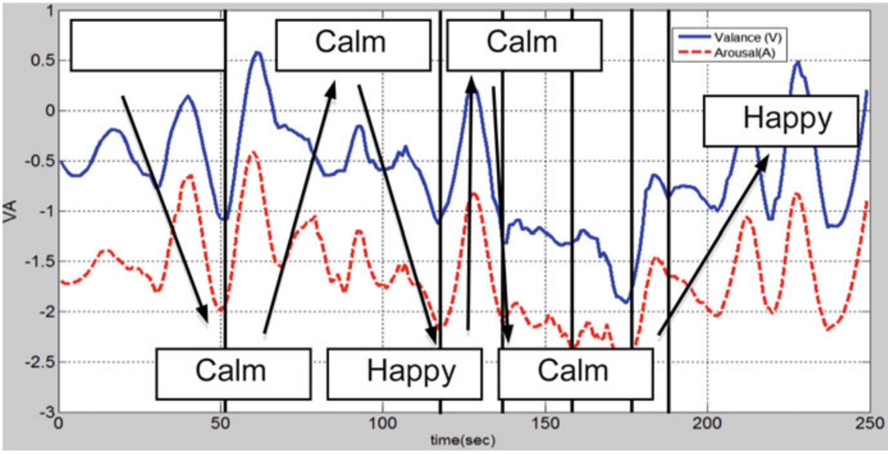

Fig. 13.10 Dynamic movement task 1, subject 5 (driving and sounds)

In contrast to subject 1, subject 5 has the same pre-emotion since the beginning, but his emotional state has changed when the accident occurred. However, he has managed to complete the driving task with *calm* emotion. Furthermore, this driver took some time to get back to the pre-emotion that he had. As we can see from Figs. 13.10, 13.11, and 13.12, the vertical solid black lines represent that accidents occurred while the subject was driving the vehicle. The trajectory of task 1 and 3 (Figs. 13.10 and 13.12, respectively) is mostly from *calm* to *sad* and vice versa, whereas for task 2 (Fig. 13.11), he was *sad* for the whole task. This is the indicator of giving up, as he had sighed a lot in order to maneuver the car while answering the question from the experimenter.

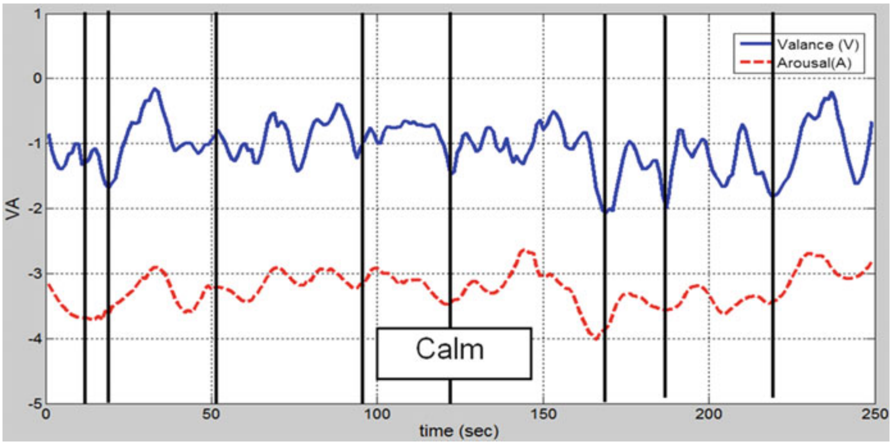

Fig. 13.11 Trajectory task 2, subject 5 (driving and interview)

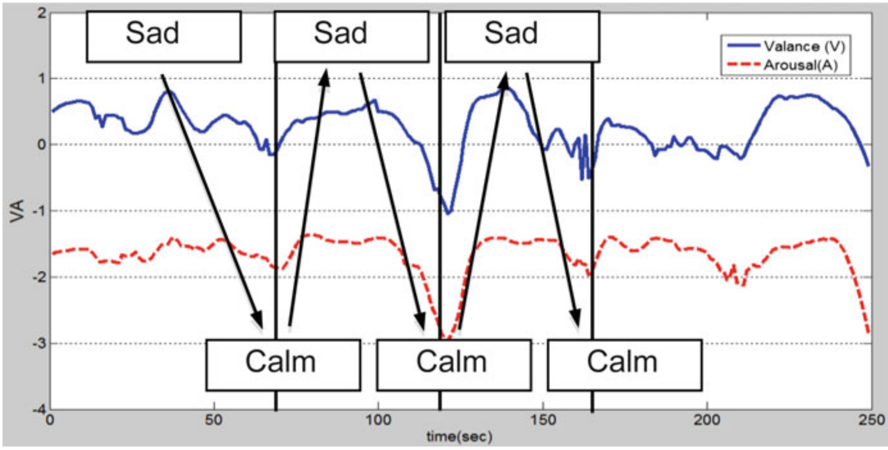

Fig. 13.12 Dynamic movement task 3, subject 5 (driving and congested traffic)

Finally, we include Figs. 13.13, 13.14, and 13.15 to illustrate the trajectories for subject 9. As we can see from Fig. 13.13, the trajectory has turned from *fear* to *sad* for task 1, whereas for task 2, he has just stayed *sad*. This could be interpreted as this subject was nervous behind the wheel at the beginning of the first task given to him, but after several accidents, he had just given up and became *sad* as it is obvious from Fig. 13.14. Finally, he has started with *happy* emotion for task 3 and turned to *fear* when accident occurred. After the accident he became *happy* again. Therefore, he demonstrated willingness to drive after a long period of driving but still manages to come back to the pre-emotion state even if there is an accident. This could be interpreted as the subject fears easily regardless of his pre-emotion state, i.e., before driving tasks.

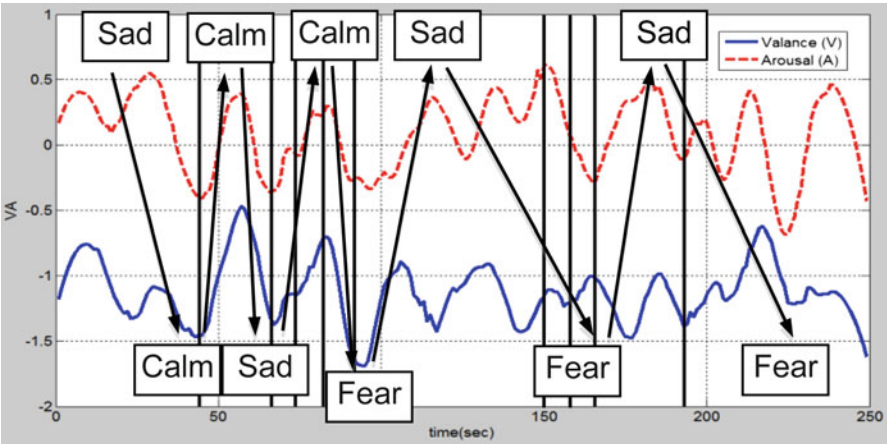

Fig. 13.13 Dynamic movement task 1, subject 5 (driving and sounds)

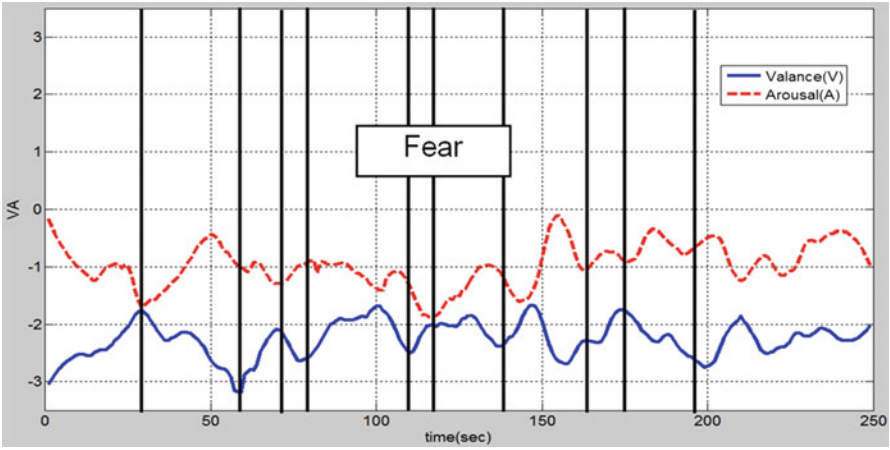

Fig. 13.14 Dynamic movement task 2, subject 5 (driving and interview)

From these results, we can conclude that each subject has his/her own pre-emotion state and a precursor emotion that impacts the driving behavior. The pre-emotion is the emotional state that the subject was in before coming for the experiment; while precursor is the emotion that was already in the mind of the subject caused by previous experiences or emotions that he/she already has experienced in the past. Therefore, these two emotional states have a strong relationship between each other since they affect the subject during the driving tasks.

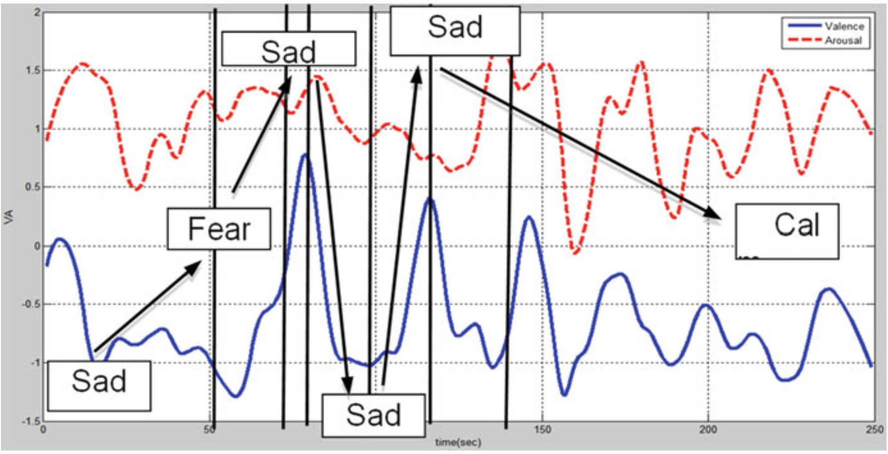

Fig. 13.15 Dynamic movement task 3 (driving and congested traffic)

13.6 Conclusion and Future Work

From these findings it can be deduced that there is a strong correlation between the pre-emotional state of drivers and their driving behavior. In addition, unstable emotion could potentially lead to accidents, and the drivers could easily change their positive emotion to a negative one. We also see that each driver has their own pre-emotion that could impact their driving behavior since the beginning.

In future work, we are planning to enlarge the driver database and to explore the behavior of a larger number of subjects from the same background and the driving culture to better understand the driving experience under different road, traffic, and environmental conditions. In addition, we would like to study the performance with a number of other classifiers including Adaptive Neuro-Fuzzy Inference Systems (*ANFIS*), Evolving Fuzzy Neural Networks (*eFuNN*), and *Support Vector Machines (SVM).*

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