Chapter 14
Affective Driving

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Abstract In this chapter, we discuss how emotion may play important role in driving especially in terms of driving safety. Vehicle driving is a life-critical process and is pervasive in our daily life. Emotion is, however, often considered to be not particularly relevant to vehicle driving, with the arguments: (1) safety takes precedence over any emotional needs, so any driver assistance systems (DAS) should only look at the driver's performance and *not* emotion, and (2) emotion does not significantly change driving performance. However, several studies conducted by us reveal that emotion can be as important as fatigue in driving applications, and research on how DAS may help to regulate drivers' emotions is highly needed. This chapter gives an overview of our research, leading to the view that future DAS need to consider emotion. At the end, there is an outline of the existing issues and future research directions on incorporating emotion in the design and management of vehicle and transportation systems.

14.1 Introduction

Emotion is a well-known term but lacks a universal agreement on how it works. There appear to be two views of emotion in literature: the first is that emotion is the experience of involuntary physiological changes [1] (*e.g.*, anger accompanied by increased heart rate), while the second is that emotion is the outcome of cognitive evaluation (*e.g.*, whether one's goals are met in the interaction with the environment) [2, 3]. In our view, these two views are inter-related, and involve four processes (see Figure 14.1). First, a human must perform a cognitive task or

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a mixed cognitive and physical task. Second, the performance on the task is evaluated, which is a cognitive process. Third, the result of the evaluation induces changes in psychophysiology. Fourth, the changes in psychophysiology further affect the performance of the task alongside the experiences of these changes, which are transformative to different categories of semantics of the experiences, namely the different labels of these experiences (anger, happiness, *etc.*). These four processes happen in a cycle as shown in Figure 14.1. For the convenience of later discussions, let's put the four cyclic processes together as a model and call it "TCPE" (T: task; C: cognitive evaluation; P: psychophysiological; E: emotion) hereafter.

The discussion thus far suggests that all such notions as changes in psychophysiology, emotion, cognition, and bodily action are inter-related, as further depicted in Figure 14.2, where we also show that the brain serves as an ultimate center to manage the body, cognition, emotion, and their interaction. In addition, emotion is a semantic variable that is dependent on the psychophysiological states and their changes. The usefulness of emotion is such that particular emotional states represent mental states that are both related to human health and task performance. Though task performance depends on the psychophysiological states – which makes it sound that as far as task performance is concerned emotion is a redundant concept – the relationship between emotion and task performance is still useful. This is because (1) we do not know how many types of psychophysiological signals are needed to uniquely determine a particular type of emotion and task performance and (2) the use of psychophysiological states as independent variables to determine task performance can never be achieved because of (1). Therefore, if a subjective or a combined subjective and objective manner can tell one's emotion, this helps. These two reasons suggest that studies to establish the relationship between emotion and task performance will be useful.

Emotional state is a short-term state that usually lasts minutes and hours rather than days [4], compared with other human attributes such as mood, trait, and temperament [5]. Therefore, the interactions between emotion and cognition and between emotion and body are also short-term. Emotion changes can be further classified into transient and steady states; the former being defined as ahead of task performance and the latter being defined as along with task performance. In our study, we consider the steady state of emotion, which was ensured by a proper design of the experiments.

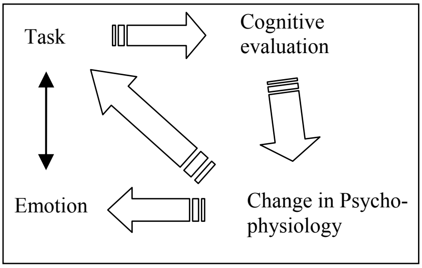


Figure 14.1 A unified view of emotion, task, and change in psychophysiology

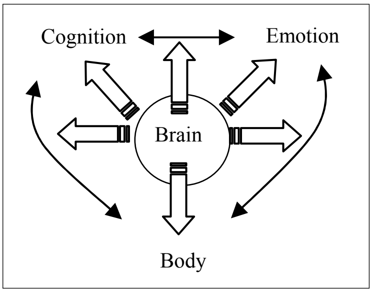


Figure 14.2 Brain, cognition, body, emotion and their conceptual relationship

Incorporating emotion into designing artifacts, especially dynamic systems or machines, is the last task for artificial intelligence research. This view appears to be similar to a view widely agreed among AI researchers in the discipline of computer science and engineering [6], *i.e.*, affective computing or incorporating emotion into computer systems is the last task for AI research. However, these two views are not exactly the same. The major difference is the difference of the target system: machine and computer. For a machine such as robot, it has its physical and chemical state that determines the machine task performance, while for a computer, it is the software running on it that interests us, so the state of the computer is not a determinant factor in the performance of the software. We will use the term "*affective machine*" in this chapter. Our study is on affective machines rather than affective computing.

There are two general questions that need to be answered in designing affective machines. The first question is how the machine knows human emotion (or emotional state) and emotional behavior. Here, emotional behavior means (1) the causes of emotions and (2) the emotional effects on cognition and action. The second question is how the machine responds to humans' emotional cognition and action. The first question can be divided into two sub-questions: how to get cues from humans and how to infer humans' emotion and emotional behavior. The second question can be further divided into two sub-questions: what should be the best response from the machine and how is the best response best expressed or acted in effect on the human? Nevertheless, the ultimate goal of the design is to improve the performance of such human–machine collaborative systems; in the case of vehicle driving it is to make DAS both a safeguard and of high usability.

In this chapter, we provide an overview of our research on "*affective vehicles*", with a focus on our studies towards an answer to the first question above. Therefore, Section 14.2 has an overview of our work on the development of sensors that acquire cues from the driver non-intrusively and in real-time. Section 14.3 has an overview of our work on the development of an algorithm that infers the driver's emotion. Section 14.4 looks at our work on understanding drivers' emotions versus cognition and action (or task performance). Section 14.5 discusses the existing issues and future research directions. Section 14.6 gives a conclusion.

14.2 Natural-contact Biosensor Method

There are generally two methods for sensors to acquire cues from humans: non-contact sensors and wearable sensors. The disadvantage of non-contact sensors is the limited types of cues that they can acquire. The shortcoming of wearable sensors is that they are still intrusive to the human, as they require the human to "wear" the sensor, which is not necessary to an activity per se. For instance, when a human driver drives, the driver has to wear something that is in fact a transducer, according to the wearable sensor method, in order to measure his or her physiological signal (otherwise, the wearing is not a part of human and machine interactive activities).

We proposed a new biosensor method called a natural-contact (NC) biosensor [7]. The idea of the NC biosensor is based on the observation that in any human–machine system there must be some contacts between humans and machines. Sensors can then be designed to be placed on the contact surface of the machine. This is very much like the machine wearing something. Therefore, there is no intrusiveness in philosophy to the human. Based on this idea, we decided on the fundamental problems of the NC biosensor method [7]. In particular, there are four fundamental problems: (1) the transducer elements must be designed to be sufficiently small, being a part of the machine system; (2) the transducer elements must be designed and constructed to cover the contact surface as much as possible to cope with uncertainty in the instant contact location on the contact surface; (3) the signal-to-noise (SNR) ratio must be sufficiently high to cope with noises owing to the varying nature of the human; and (4) multi-signals need to be decoupled as the promise of the NC biosensor is to have all signals measured at one site.

The first proof of the NC biosensor was completed at our research laboratory in 2005 [8, 9], which was to measure the gripping force (GF) and blood volume pulse (BVP) of a driver holding a steering wheel. The second proof was to have more signals measured from the steering wheel, including skin conductance (SC) and skin temperature (ST) [10]. In this design, the second fundamental problem of the NC biosensor was dealt with by two steps. The first step is to analyze the human palm and the contact behavior of the driver, and the second step is to determine the distribution of the NC biosensors over the wheel surface.

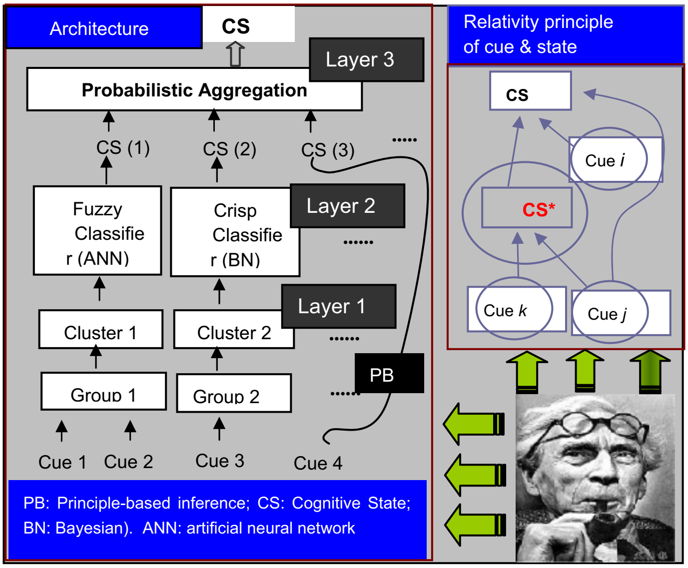
In summary, the NC biosensor has more distinct features than the wearable sensor and is more promising than the wearable sensor in terms of non-intrusiveness, acquisition of multi-signals, and acquisition of more types of physiological signals. Since human skin contains a rich set of information with a pathological connection to the human body and mind, the NC biosensor is a promising method for sensors to acquire physiological signals.

14.3 Inference of Human Emotion

The inference of human emotion is to determine human emotional state given a set of pscychophysiological cues and contexts. Contextual information includes information about the task, pre-conditioning of the human operator, and the task-performing environment itself (see again Figure 14.1). This understanding is slightly different from that of others, such as Lisetti and Nasoz [11] and Picard [6], who did not pay attention to contextual information. According to our research contextual information is quite important [12].

Machine learning techniques seem to be most applicable to the problem of inference. These techniques can be further classified into generative learning and discriminative learning. Most approaches are generative learning Bayesian or Markov chain network techniques. Another popular category of techniques is the artificial neural network, which are typically based on the discriminative learning technique [11]. On top of these machine learning techniques, fuzzy logic can be employed to represent a type of imprecise information – vagueness [12, 13]. There are two ideas of how to apply fuzzy logic for inference of emotion (or mental state in a more general sense). The first is that the word becomes the final outcome of the inference, with a typical outcome statement being "the level of anger is very high"; see the work of Mandryk and Atkins [13]. The second is that a number is used for the outcome of the inference, with a typical outcome statement being "the level of anger is 0.7" (out of 1, where 1 = very angry and 0 = not angry at all); see our work [12, 14].

In parallel with the research into cognitive state inference – in particular, a finding described in [15] that no approach is powerful enough to infer cognitive state for all situations and therefore an integrated approach is needed – we stated that this finding can be equally applied to the inference of emotion. Following this line of thinking, we proposed the architecture of an integrated algorithm as shown in Figure 14.3. This architecture has three layers. The *first layer* is a grouping and clustering process (Figure 14.3 (a)). The *Grouping of cues* is based on the "proximity" in their relevance to an inferred target. The *Clustering of cues* is based on the number of instances of the cues in a group. One can observe that grouping is semantic-oriented and clustering is value-oriented. The *second layer* is a classification layer in which algorithms based on various machine learning formalisms (*e.g.*, artificial neural network, Bayesian network, *etc.*) and principle-based knowledge for inference (PB in Figure 14.3 (a)) are integrated. The *third layer* of the architecture is a probability distribution aggregation process. Each classifier (*i.e.*, the second layer) comes up with a crisp value for the inferred cognitive state (CS for short), CS (1), CS (2)*, etc.* The CS takes on a value ranging from 0 to 1, which represents the degree of confidence in an inferred target (*e.g.*, fatigue of an operator, tank in a terrain field, *etc.*) with 1 representing the highest and 0 the lowest degree of confidence. The aggregation process integrates all CS (i) ($i = 1, 2, \ldots, n$, where n is the total number of classifiers or inference mappings) to an "agreed" inferred state or target. The aggregation process is built upon a probabilistic uncertainty (the deterministic case is viewed as a special case of the non-deterministic case). Methodologies in the fields of decision-making [16, 17] and expert opinion elicitation [18] are employed for this aggregation process. It is noted that in expert opinion elicitation [18], the problem can often be defined as a weighted average problem, in which each expert is associated with a weight that represents the expertise level of the expert with respect to a decision target. This can be applied to the cognitive inference problem here so that a group of cues corresponds to an expert, and a weight associated with the group represents the degree of inference power of the group with respect to an inferred CS. The notion of inference power makes sense; for example, heart rate variability is more sensitive than blood pressure to a driver's fatigue, and therefore the weight of the heart rate variability cue or its group should be higher than that of the blood pressure cue or its group in the aggregation process for the inferred driver's fatigue. The notion of the weight of the cue in the context of cognitive inference has not been discussed in the literature.



(a) (b)

Figure 14.3 Integrated multi-modality cognitive state inference: (a) overall architecture, and (b) cue–state network [16]

Finally, the architecture can simulate an important human inference behavior – that is, a particular state in one context may be viewed as a cue in another context with its relevant inference process (Figure 14.3 (b)). In Figure 14.3 (b), CS* serves as a cue together with other cues (i, j), some of which may infer CS* in one context, to infer CS. The structure as shown in Figure 14.3 (b) is in its nature a network structure, which further means that the general architecture as proposed here views the cue-state relationship as a network, which is the nature of the human cognitive system. It is noted that the notion of the network relationship among cues and states appears not to be discussed in the current literature.

We applied a simplified version of this architecture to the inference of the fatigue state of the driver. This takes a machine learning model which integrates the first two layers, and the integrated model is simply the TSK (Takagi–Sugeno–Kang) model developed in the ANN literature for control. The approach model of the probability distribution aggregation, *i.e.*, layer 3, is the OWA. In the fatigue state inference, we used the following cues: eye movement (EM); driving hour (DH); sleeping quality (SQ); EEG; and ECG. The EEG and ECG fall into the category of physiological cue. The EM falls into the category of non-contact cue, and the DH and SQ fall into the contextual category of cue. Tables 14.1 and 14.2 show the result of the fatigue state inference for two drivers [19]. The accuracy to infer the fatigue state achieved about 90%.

Table 14.1 Features and simulation result for the first driver

Input features	SQ	DH	ECG	EEG		EM
	0.25	0.5	0.83	0.81	0.85	0.82
TSK output	y_1	y_2	y_3	y_4		y_5
	0.9046	0.5907	0.8925	0.849		0.89
	Overall average: 0.8258					

Table 14.2 Features and simulation result for the second driver

Input features	SQ	DH	ECG	EEG		EM
	0.875	0. 167	0.33	0.38	0.41	0.43
TSK output	y_1	y_2	y_3	y_4		y_5
	0.075	0.21	0.29	0.33		0.41
	Overall average: 0.8258					

We further designed a simplified version of the architecture in the sense that we only include a fuzzy knowledge-based inference engine from the cue to emotion state [20]. In this case, we only considered the following psychophysiological signals: heart rate, skin conductance, skin temperature, and respiration rate, due to their highly relevant to emotional states. Table 14.3 shows an example of a driver's steady emotional state over a relatively long time period, and Figure 14.4 shows an example of driver's transient emotion state over a relatively short time period. The accuracy of inference achieved is about 86% (for anger) and 87% (for disgust).

From our study, emotion is a factor that cannot be ignored in vehicle driving. The inference of the driver's emotional states as well as other mental states such as fatigue, drowsiness, and attention can reach a level of accuracy of just over 85% with the physiological cues that are non-intrusively obtained. The next section will show the state of knowledge about how the emotional states affect the driver's driving performance.

Table 14.3 Emotion rating by self-reporting, expert rating, and fuzzy emotion analyzer

Emotion	Self-reporting	Expert-rating	Emotion analyzer (CF)	Meaning
Calm			–0.61	Unlikely
Joy				
Pleasure			0.19	Unknown
Anger	0.7	0.7	0.61	Probably
Sadness			0.4	Maybe
Excitement			–	–
Surprise			–	–
Fear	0.3		0.40	Maybe
Anxiety			–	–
Frustration			0.48	Probably
Disgust		0.3	0.34	Maybe
Nervousness			–	–

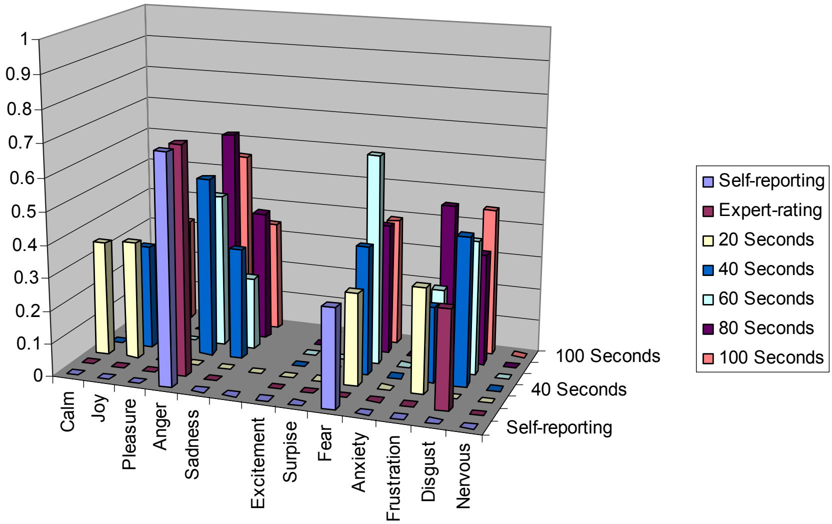


Figure 14.4 An example of emotion transition estimated by the emotion analyzer

14.4 Emotion Versus Performance in Driving

There are two methods of studying the relationship between emotion and task performance: experimental and theoretical. The experimental approach demands a sufficient number of samples and proper generalization. The theoretical approach demands accurate modeling of cues, emotions, tasks, and task performance according to the TCPE model as mentioned before. In this chapter, we give an overview of a study we conducted in an attempt to find a model of the general relationship between a driver's emotions and his/her performance, following the experimental approach.

In the literature, Russell [21] proposed an emotion model based on the two dimensions of arousal and valence (see Figure 14.5). Further, there is a well-known model of the relationship between performance and arousal, called the inverted U-shape model [22] (see Figure 14.6). Further, Brookhuis and De Waard [23] investigated the relationship between drivers' mental workload and driving performance in different situations. They concluded that mental workload has an inverted U-shape relationship with driving performance. This finding is, however, not a surprise, as mental workload has a close association with arousal [24].

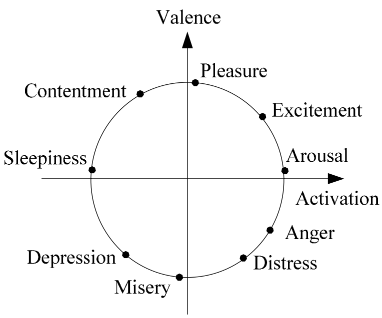


Figure 14.5 2D emotion model [21]

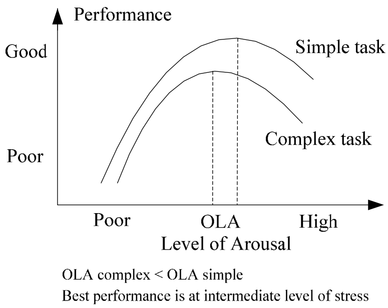


Figure 14.6 Yerkes–Dodson law [22]

It should be noted that the Yerkes–Dodson model is descriptive, so it cannot be used for any quantitative use. Mental workload is viewed as a single variable or attribute, while emotion is considered as a function of two variables according to the two-dimensional model (valence, arousal). Therefore, we investigated the quantitative relationship between emotion and task performance in the context of vehicle driving, which is a pioneer study. In particular, we proposed the following relationship between emotion and task performance [25]:

$$P_A = a\mathrm{Ar}^2 + b\mathrm{Ar} + c \text{, where } a < 0,\ -1 < \mathrm{Ar} < 1, \quad (14.1)$$

$$P_V = d\mathrm{Va} + e \text{, where } d > 0,\ -1 < \mathrm{Va} < 1, \quad (14.2)$$

$$P_{AV} = P_A \times P_V, \quad (14.3)$$

where Ar and Va are variables that indicate the level of valance and arousal; P_A is the task performance associated with the change in arousal and P_V is the task performance associated with the change in valence. Specifically, $a < 0$ indicates that the curve P_A opens downward, $d > 0$ indicates that the curve P_V increases with Va; and b, c, e are parameters relevant to a particular task.

The experiment was designed as follows. Fifty-three samples were taken from 15 participants. The participants saw a movie to stimulate their emotions, and then used a driving simulator. They did multi-tasks: primary driving task and secondary visual search task.

The result confirms that the model is adequate to represent the emotion and task performance relation. In the case of vehicle driving, the parameters in the model were determined through the experiment. This experimental study further concluded: (1) there is a downward U-shape relationship between arousal and task performance; (2) the optimal task performance occurred at the medium arousal range from $0.0 < \mathrm{Ar} < 0.4$; (3) there is a linear increase relationship between task performance and valence when $\mathrm{Va} < 0.5$, but this relationship stops at a positive valence ($\mathrm{Va} < 0.5$) or at high arousal ($\mathrm{Ar} \geq 0.6$); (4) arousal and valence were not perfectly independent in the whole 2D emotion plane; (5) the spaces of the emotion plane such as the planes $\mathrm{Va} > 0.5$ and $\mathrm{Ar} < 0$, and $\mathrm{Va} < -0.5$ and $\mathrm{Ar} < -0.5$ are not occupied at all, which may be due to the slight correlation between arousal and valence; (6) the effect of arousal and valence on the worst driving performance was significant ($p < 0.05$); and (6) the average driving performances at four emotion zones were also significantly different ($p < 0.05$).

In summary, the steady state period of emotion can have a significant effect on task performance in driving. The usefulness of the emotion–performance relationship model can help to predict drivers' task performance degradation and therefore assist drivers in managing emotion to avoid any safety-threatening performance.

14.5 Issues and Future Research Directions

The first issue is to improve the accuracy, robustness, and resilience of the biosensor system with the real-time and non-intrusive measurement capability. This requires an approach that integrates design, fabrication, and signal processing to look into finding a global optimum. The second issue is how to make "soft" or "flexible" biosensors in the context of the NC biosensor method; in particular a large array of transducer elements grown on a soft material. This will enable the biosensor to be more easily worn on the body of the machine that interacts with humans and will therefore be able to cope with any contact uncertainty. The third issue is the relationship between the internal state of the machine and its emotion (emotion engine and emotion expression). This issue is important when DAS is deciding how to express the machine's state to the driver in order to influence the driver's emotion and task performance, which in turn will affect the overall performance of the driver–vehicle system. The fourth issue is the decision-making of the DAS in order to assist the driver in achieving the primary goal of driving safely, along with the secondary goal of being of high usability to the driver.

14.6 Conclusions

This chapter gives an overview of the studies conducted by us on the subject of affective vehicles or affective machines in general. The overview concentrates on how machines can understand humans' emotion and the effect of emotion on their task performance. The following conclusions are made: first, drivers' emotional states have significant effects on their driving performance; second, drivers' emotional states can be inferred through cues that include both contextual and psycho-physiological elements. The results demonstrated in this chapter support the above two conclusions.

Finally, research towards such affective or emotional machines is highly important, especially with the development of more and more intelligent machines and/or human–machine interactions in modern society.

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