Human Inspired Control System

for an Unmanned Ground Vehicle

by

Alvaro Vargas-Clara

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Graduate Supervisory Committee:

Sangram Redkar, Chair
Ann McKenna
Nancy Cooke

ARIZONA STATE UNIVERSITY

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ABSTRACT

In this research work, a novel control system strategy for the robust control of an unmanned ground vehicle is proposed. This strategy is motivated by efforts to mitigate the problem for scenarios in which the human operator is unable to properly communicate with the vehicle. This novel control system strategy consisted of three major components: I.) Two independent intelligent controllers, II.) An intelligent navigation system, and III.) An intelligent controller tuning unit. The inner workings of the first two components are based off the Brain Emotional Learning (BEL), which is a mathematical model of the Amygdala-Orbitofrontal, a region in mammalians brain known to be responsible for emotional learning. Simulation results demonstrated the implementation of the BEL model to be very robust, efficient, and adaptable to dynamical changes in its application as controller and as a sensor fusion filter for an unmanned ground vehicle. These results were obtained with significantly less computational cost when compared to traditional methods for control and sensor fusion. For the intelligent controller tuning unit, the implementation of a human emotion recognition system was investigated. This system was utilized for the classification of driving behavior. Results from experiments showed that the affective states of the driver are accurately captured. However, the driver's affective state is not a good indicator of the driver's driving behavior. As a result, an alternative method for classifying driving behavior from the driver's brain activity was explored. This method proved to be successful at classifying the driver's behavior. It obtained results comparable to the common approach through vehicle parameters. This alternative approach has the advantage of directly classifying driving behavior from the driver, which is of particular

use in UGV domain because the operator's information is readily available. The classified driving mode was used tune the controllers' performance to a desired mode of operation. Such qualities are required for a contingency control system that would allow the vehicle to operate with no operator inputs.

DEDICATION

I dedicate this dissertation to Celina, my Mom, Dad, and Sisters who have made this possible with all their endless love, encouragement and support! I am motivated in making you proud. I am enormously grateful in having you all in my life. Thank you and I love you all very much!

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INTRODUCTION

1.1 Unmanned Vehicles

An Unmanned Vehicle (UV) is a vehicle that operates without any physical onboard human presence. In general, all UVs are equipped with multiple sensors to observe the environment. Depending on its level of autonomy, the UV will relay vehicle and environment information to human operators who will then provide commands at varying levels of supervisory control through teleoperation.

Understandably, there are numerous applications for which an onboard human operator is not feasible. Their applications vary across many domains: air, ground, sea, and space. As a result, there are various platforms of UVs, such as Unmanned Aerial Vehicles (UAVs), Unmanned Ground Vehicles (UGVs), and autonomous underwater vehicles. Currently, the capability to operate unmanned comes at the cost of increase in manpower, and high reliance of uninterrupted high-bandwidth communication links. The increase of manpower arises from the multiple human operators that are required to both operate and process the recorded data. The reliance of high bandwidth communication is due to the rich data required to safely operate the vehicle, and for the transmission of collected data. Thus, underlying goal is in making the vehicle autonomous.

It is important that we first clarify our definition of autonomous system used within the context of this work. An Autonomous System (AS) is self-directed in formulating its own set of actions to achieve a human-directed goal (Department of Defense, 2011). As previously mentioned, UVs can have varying levels of autonomy.

Common defined levels of autonomy are shown in Table 1.1 (Department of Defense, 2011).

Table 1.1

Autonomy Levels (Department of Defense, 2011)

Level	Name	Description
1	Human Operated	A human operator makes all decisions. The system has no autonomous control of its environment although it may have information-only responses to sensed data.
2	Human Delegated	The vehicle can perform many functions independently of human control when delegated to do so. This level encompasses automatic controls, engine controls, and other low-level automation that must be activated or deactivated by human input and must act in mutual exclusion of human operation.
3	Human Supervised	The system can perform a wide variety of activities when given top-level permissions or direction by a human. Both the human and the system can initiate behaviors based on sensed data, but the system can do so only if within the scope of its currently directed tasks.
4	Fully Autonomous	The system receives goals from humans and translates them into tasks to be performed without human interaction. A human could still enter the loop in an emergency or change the goals, although in practice there may be significant time delays before human intervention occurs.

As previously discussed, the ultimate goal in the field of UVs is toward developing fully autonomous UVs. So that in the near future, a single human is capable of commanding multiple UVs. Advances in computer processing techniques, miniaturization, image processing, and communication techniques have resulted in rapid progress towards developing fully autonomous UVs.

1.2 Problem Statement and Objectives

This research aims to address the current problem of robustly controlling a UGV. Particularly, for the challenges that arise in scenarios in which the available communication link exhibits high latency or a complete loss of communication. In such scenarios the vehicle will stop all operation, or worse, continue to operate without operator input. Therefore, there is a need for a CS that would provide contingency-based assurance of system safety in the absence of timely control of a UGV. Thus, for such an event the objective is to develop a CS that would give the UGV the capability to operate at an autonomy level of 3, in which the vehicle is able to perceive and maintain appropriate mode of operation, and thus continue to complete tasked objectives.

The objective of this research effort is to develop an intelligent, robust, and efficient CS for a UGV. This CS consist of three major components: I.) Two intelligent controllers. II.) An intelligent navigation system. III.) An intelligent controller tuning unit. The first component consists of two independent intelligent controllers implemented for the heading and path control of a UGV, capable of dealing with environment uncertainties and robust to plant parameter variations. The second component is an intelligent navigation system capable of integrating information from multiple sensors and providing accurate and precise data of the vehicle's states to the set of intelligent controllers. The inner workings of these three components will be based on the Brain Emotional Learning (BEL) model. The last component is a unit consisting of an emotion recognition system that utilizes an Electroencephalography (EEG) headset worn by operator. The data obtained from the headset will be utilized to capture the operator's affective state; this information will then be used for classifying operator's mode UGV of operation. Based on the classified mode of operation, the tuning unit will tune the controllers' performance to a desired mode of operation. It is anticipated that the proposed CS strategy, consisting of these three components, will ensure vehicle safety in the absence of timely operator inputs.

1.3 Relevance and Possible Applications

It is apparent that the direction for the field of CS for a UV is towards increasing the level of autonomy. UV autonomy translates to the intelligence of the vehicle, more precisely, its ability to function safely and robustly under external and internal disturbances, to be able to conform to fault conditions without significant degradation of its performance, to adapt to unforeseen events, and to be able to coordinate by itself to accomplish the mission objectives in the event of communication degradation between vehicle and operator. This requires that the components of CS to be intelligent, adaptable, robust, and easily implementable. As a result, the proposed research efforts can have direct impact on current and future UV designs.

Additionally, with the implementation of our proposed CS. The vehicle's ability to perceive operator's emotional state and utilize such perception classify driving behavior is not only useful for an UV, but can be applied to manned automobiles to alert the operator/driver of unsafe driving behavior and potentially correct for such behavior. Currently, there are a number of technologies that monitor human driver such as, the Driver Monitoring System by Toyota (Toyota, 2014), BMW's Active Driving Assist with Attention Assistant (BMW, 2014), and Mercedes-Benz's Attention Assist (Mercedes-Benz, 2014). These technologies monitor the driver's driving behavior and is triggered once driving behavior is consistent with signs of drowsiness, fatigue or inattention. Our proposed CS can potentially be an improvement for automotive technologies by monitoring the driver itself.

1.4 Research Questions

As mentioned in Section 1.2, the objective of this research effort is to develop an intelligent, robust, and efficient CS for a UGV. This CS consists of three major components: I.) Two intelligent controllers. II.) An intelligent navigation system. III.) An intelligent controller tuning unit. In which all these components work in conjunction with one another towards enabling the UGV to operate and maintain a desired mode of operation when no human operator inputs are available. This goal can be broken down into several research questions:

- *Which bio-inspired control methods can achieve improved controller performance in comparison to traditional control methods, while being easily implementable, and can be easily tuned to a desired performance?*
  The literature suggests that there are a number of bio-inspired algorithms that have been successfully utilized for control methods. However, we are primarily interest in an algorithm that best meets the above qualities, as this controller will have to be designed to work in conjunction with navigation and a tuning unit. In addition, the bio-inspired control method should still be able to have superior performance than traditional control strategies.
- *Is the utilization of a bio-inspired algorithm, as a filter, a feasible alternative for sensor fusion which can attain similar performance compare to traditional methods?*
  From the literature, a number of bio-inspired algorithms have been used for sensor fusion. However, the majority of these algorithms' configurations caused the navigation system to greatly increase in complexity and computational cost. We can design, and simulate a sensor fusion filter based on a bio-inspired algorithm which has been utilize in other applications, and shown to have desirable qualities applicable for

sensor fusion application. Additionally, this algorithm can potentially reduce the computational cost due to the simplicity of this algorithm.

- *By incorporating a human emotion recognition system through EEG measurement, is the utilization of these captured emotional states a viable alternative method for classifying vehicle mode operation in comparison to using vehicle parameters?*

  Literature shows that EEG measurement is successful at identifying distinct human emotional states. Additionally, literature has indicated that emotional states are motivational factors that guide driving behavior. However, very little work has been conducted in which affective states are used to categorize driving behavior.

If successful, it will be possible to develop a system that can use these affective states to classify vehicle mode operation and use this information to appropriately tune vehicle controllers to mimic human driving behavior in the absence of direct human input. More precisely, for the interaction of a human operator and a UGV, so that in the event of communication loss with operator the UGV can use the operator's affective state, and pass that information to tune controller parameters so that it can safely mimic the desired mode of operation.

1.5 Scope and Limitation

The scope of these research efforts are meant to provide the groundwork for potential implementation of the proposed CS strategy into a physical system. This research is meant to determine whether a CS consisting of these three major components is feasible in detecting and then using affective states to classify vehicle mode operation, and then finally used this information to appropriately tune vehicle controllers to mimic human driving behavior in absence of direct human input.

It is important that we note that this CS strategy has a number of limitations. First, this CS strategy is conceived under the assumption that the ‘trained’ operator’s affective state is a direct consequence of the current mission situation (ex: enemy is spotted, as a result mode of operation is aggressive or keen). Any previous affective states that an operator experienced before the mission are neglected (i.e. the operator was having a bad day). Steps can be taken to reduce the impact of these types of emotions, such as, the operator can be asked to relax and meditate prior to operating the UGV. Lastly, cognitive states are not considered. This is due to the fact that cognitive states are difficult to capture, identify, and respond to on-line.

1.6 Outline

Chapter 2 will provide a relevant literature review which discusses and analyzes the current research in the areas of: Bio-Inspired methods for control and navigation of UVs; Theory of emotion, methods of human emotion recognition and their utilization; Methods for classifying human driving behavior. Chapter 3 will explain the design and implementation of our intelligent UGV controller. In Chapter 4 we will address the implementation of the BEL model as filter for sensor integration for UGV navigation. Chapter 5 we will address the development of an intelligent controller tuning unit based on a human emotion recognition system through EEG measurement. Finally, the conclusions about our proposed CS strategy can be found in Chapter 6.

CHAPTER 2

LITERATURE REVIEW

In the field of CS for UVs, the progress has been towards developing an intelligent CS. However, advancement has been limited in large part to the traditional methods utilized. Fortunately, researchers in Artificial Intelligence (AI), and cognitive science fields have worked towards developing models that simulate the processes involved in human intelligence. This has led to the development of bio-inspired algorithms that try to produce human like intelligence (Department of Defense, 2011). However, there are key differences between the approaches used by researchers in the field of AI and cognitive science.

In the field of AI, research is focused on creating intelligent machines, and now intelligent computer programs. It follows a similar approach in using computers to understand human intelligence, however, AI is not limited to methods that are biologically observable. In this field, intelligence is defined as the computational aspect of the ability to achieve goals in the world (McCarthy, 2007). There are varying kinds and degrees of intelligence that are present in people, several animals, and now machines. In the field of AI, researchers have outlined the key processes involved in intelligence. These are: the ability to interact with the real world; reasoning and planning; learning and adaptation. These processes are implemented in machines or programs with the ultimate goal of making an intelligent system.

In contrast, in the field of cognitive science research is driven to the study of the mind and its processes. Across the many interdisciplinary fields that cognitive science encompasses, the objective is to understand how people behave, perceive, process cognitive information, and represent knowledge (Miller, 2003).

Researchers in the fields of control and navigation of UVs have taken an interest in utilizing bio-inspired algorithms to resolve complex control and navigation problems. This interest is driven by the advantages these algorithms have over the traditional strategies. Consequently, the focus of this literature review will be on the relevant and novel research pertaining to biologically inspired algorithms for control, and navigation of UVs. In addition, a review of research related to current methods for human affective state recognition through a variety of physiological measurements, and methods for categorizing human mode of vehicle operation will be discussed. This review is organized as follows; Section 2.1 introduces the background of the typical components within a CS. Section 2.2 reviews, discusses and analyzes the current research in UV control as well as the gaps in this area of research. Section 2.3 is a review of current research in navigation and outlines disconnects within this area of research. Section 2.4 reviews research methods for capturing human affective state, and the methods for categorizing human driving modes. Finally, Section 2.5 identifies a potential new direction for UV control, and navigation, along with a novel approach for capturing and utilizing human's affective state.

2.1 Control System

A CS consists of multiple devices with the objectives to control, regulate, guide, and manage the behavior of a system or another device (Guidance, navigation and control, 2012). For a UV, there are typically three major devices that perform these objectives i.e. guidance, navigation, and control (Seldon, 2009).

The guidance system directs the vehicle to a set trajectory. This trajectory can be specified by an operator or a Mission Planning System (MPS) depending on the level of autonomy of the vehicle. The objective of the guidance system is to convert the desired trajectory into low level orders that a controller can understand and implement (Seldon, 2009).

The navigation system gives the vehicle the ability to determine its current location, velocity, and direction; in other words determine the state of the vehicle (Seldon, 2009). This information is obtained from multiple sensors on the vehicle. The sensors are usually Global Positioning Systems (GPS), and Inertial Measurement Units (IMU). The navigation utilizes the signals from these sensors and combines them to obtain precise information about the vehicle’s state. The typical method that the navigation system integrates the signals from multiple sensors, is by a Kalman filter (Grewal, Weill, & Andrews, 2007). This process is commonly referred to as sensor fusion, which will be discussed in detail in the following sections.

The controller then takes the output signals from both the guidance and navigation systems and utilizes them to maintain/change heading and velocity to effectively follow the desired trajectory. In addition, the controller uses navigational output signals to stabilize the vehicle due to disturbances, and/or maintain stability due to unstable design of the vehicle (Seldon, 2009).

These components are essential parts of a CS. Additionally, each of these components can impact the level of autonomy of the UV. Therefore, the objective is to produce a well-rounded intelligent CS. We will first review relevant research on bio motivated algorithms for UV control.

2.2 UV Control

Researchers in AI, and cognitive science fields have developed and inspired algorithms that simulate the processes involved in human intelligence. Examples of these algorithms are fuzzy logic, which mimics human control logic (Bräunl, 2003); neural networks, which model the functional aspects of biological neural networks; brain emotional learning, which models the amygdala and the orbitofrontal cortex system (Balkenius & Moren, 2001). The advantages these algorithms have over traditional control strategies are: they are highly adaptable, robust, and require low computational costs (Bräunl, 2003; Huang, Zhen, & Wang, 2008; Chao, Cao, & Chen, 2010).

2.2.1 Fuzzy Logic for Control

The first to be reviewed of these bio inspired algorithms for control is fuzzy logic. This linguistic based algorithm was first introduced by Professor L. A. Zadeh (1975). Later on, the first actual Fuzzy Logic Control (FLC) was developed by Professor E. H. Mamdani (Ying, 2000). In essence, the fuzzy logic is made up of three important elements: a fuzzifier, a fuzzy inference engine, and defuzzifier. The fuzzy algorithm inner workings are described by Kurnaz et al. (2009):

> "*The fuzzifier maps a crisp input into some fuzzy sets. The fuzzy inference engine uses fuzzy IF-THEN rules from a rule base to reason for the fuzzy output. The output in fuzzy terms is converted back to a crisp value by the defuzzifier.*"

This logic is different than traditional binary logic in that it allows linguistic variables to be mapped to truth values in range between 0 and 1 (Bräunl, 2003). Please refer to the literature for detailed information on components/workings of fuzzy control (Ying, 2000). Applications of fuzzy logic have been utilized for various control applications; however this review will focus on UV control applications.

One such case was done by Kurnaz et al. (2009), where they developed a fuzzy logic based approach for the control of a UAV. They utilized the software configuration of MATLAB and Aerosim Aeronautical Simulation Block Set to obtain tools and UAV model to evaluate the fuzzy control performance during various simulated flight patterns (e.g. climb, cruise, loiter, and descent). The fuzzy control system consisted of three fuzzy controls for heading, altitude, and airspeed respectively. Each of the fuzzy controls was designed by first selecting simple Mamdani-type fuzzy rule tables that were selected by a specialist based on his/her knowledge and experience. The inputs for the throttle fuzzy control were the speed error and its rate of change. Similarly, the inputs for the altitude fuzzy control were altitude error and its derivative. Therefore, the selected fuzzy control for both throttle and altitude was a Proportional Integral (PI) type fuzzy controller, which produces an incremental control output. However, for the heading control the authors elected to use a Proportional Integral Derivative (PID) type fuzzy control. For each of the control inputs, a triangular membership function was created. For the inference process of the fuzzy control, the authors utilized product-sum inference. Lastly, for defuzzication process, the authors utilized the common centroid method. The results from this research were the following; the fuzzy controller was successful in maintaining the desired altitude and heading even while being under wind disturbance. In addition, the UAV was successful at reaching every waypoint within 01° (00’ 00’’ 010 in GPS definition) error range. However, larger throttle errors were seen while trying to maintain a specific speed throughout the flight trajectory. They comment that this was due in large part by the fact that speed was controlled only by the throttle controller and not with the angle of attack, therefore producing the errors during a climb and descent patterns. Lastly, the authors comment that there were some oscillations and errors with the addition of wind disturbances.

In latter research by the same authors, they were able to implement a similar fuzzy control strategy for the landing system of a UAV (Cetin, Kurnaz, & Kaynak, 2011). The authors recognized three important attributes for a successful UAV landing, these were: lateral position of UAV with respect to runway, altitude of UAV, and speed of the aircraft during the final approach. For those reasons the authors developed three fuzzy controls: lateral, vertical, and speed. Each of the fuzzy controllers had the goal to resolve lateral errors, resolve altitude errors and maintain desired speed under current conditions, respectively. Results for this research were that the fuzzy control system illustrated adequate overall performance for maintaining the UAV at correct frame during the final approach. However, these results were obtained by neglecting any disturbances.

In different research conducted by Lai & Hsiao (2010), the authors were able to implement a fuzzy logic controller in the autopilot of a UAV. In this work, the authors assumed the aircraft's dynamics to be decoupled into longitudinal and lateral motion, and therefore developed two independent control strategies. The longitudinal control strategy consisted of two fuzzy controllers for pitch and altitude, respectively. Likewise, the lateral control strategy consisted of two fuzzy controllers for roll and heading respectively. In similar fashion as in the previous works, the input variables for the pitch control, altitude control, and roll control are the error and change in error. However, for the heading control, the inputs were the heading error and the deviation distance from the line between the previous and next waypoints. Outputs for the controllers were elevator deflection, desired pitch angle, aileron deflection, and desired roll angle. The architecture for each of the fuzzy controllers were seven linguistic sets for each variable and seven triangular membership functions for each input and output variable. Both membership functions and fuzzy rules were obtained from the expert's knowledge and experience in UAV flight. The results during simulated waypoint navigation and trajectory following were obtained. The results were that the autopilot was able to control the aircraft close to the desired heading and also maintained the altitude of the aircraft within an error of 4.5 meters or less. Similar results were obtained when simulated under wind disturbances, but again some oscillations were noticeable.

In an attempt to reduce the unwanted behavior from the fuzzy control, Gomez & Jamshidi (2011), proposed the combination of a FLC and Model Reference Adaptive Control (MRAC). The design of the fuzzy control consisted of six variables: roll, pitch, airspeed, airspeed error, heading error, and altitude error. For each of the variables six fuzzy rules were selected. The ranges of the membership functions were selected to be small and were scaled in order to minimize the number of rules while still maintaining precision. These produce three fuzzy logic controllers for heading, altitude and throttle, which were able to smoothly control the UAV. In addition, the authors designed an additional fuzzy control utilizing three rules per control, and low precision for the combination of the FLC and MRAC. This low number and low precision FLC created a fast switching final control output. The FLC utilized for UAV control had a greater contribution to final control output when the plant error was large. However, when the error was small the MRAC controller had a greater contribution to the final control output. Results from a simulated waypoint following flight pattern were that the combination of the fuzzy control with the MRAC did have an effect on the final control output. Both controllers were successful in maintaining the aircraft stability and converged to the desired specifications. However, oscillations were still noticeable in roll.

From the literature, it is apparent that application of fuzzy logic for the control of a fixed-wing UAV has been demonstrated to be successful. It has demonstrated the qualities of a robust, easily implementable control requiring low computing cost. However, similar control qualities have been achieved by another bio-inspired algorithm, neural networks, which are discussed in the following section.

2.2.2 Neural Network for Control

Neural networks, commonly referred to as Artificial Neural Networks (ANN), are a computational representation of the biological neural networks. Neural networks consist of neurons working in parallel that are connected to other neurons by weighted connections. The connection between neurons primarily defines the network function. Neural networks are trained to perform a specific function by fine-tuning the weights of the connections between neurons. Normally, neural networks are tuned, or taught, so that an input is directed to a specific target output (Toolbox: Neural networks overview, 2012). For additional information on neural networks please refer to (Priddy & Keller, 2005).

Depending on the structure, neural nets are versatile and can be designed to execute several kinds of control strategies for various control applications. The following is a review of the research utilizing neural networks for UV control.

Suresh and Kannan (2008), implemented a direct adaptive neural flight control for an unstable unmanned aircraft. The goal of the neural network was to estimate the control law such that the aircraft response tracks the reference command. The architecture of the neural network consisted of current stick deflection as the input, elevator deflection as the output, and a hyperbolic tangent function for the activation function. The neural network consisted of eleven input neurons, thirty-five hidden neurons, and one output neuron. The neural network was trained with the objective to find the optimal weights so that squared error between the aircraft response and reference signal in finite time was minimized to less than 0.002. The adjustment of the weights was done through back propagations through time learning algorithm. However, since the aircraft analyzed in this research was unstable, the neural network was trained off-line and on-line. First, it was trained off-line using the reference signal so that the networks could approximate the control law within the finite sequence and stabilize the aircraft for various initial conditions. Then, it was trained on-line so that the weights were adapted for aerodynamic uncertainties and control fault conditions. Twenty data sets were used for off-line training in which it was able to converge to optimal value. The various performance measures of this control scheme were then compared with comparable indirect adaptive neural control. The direct adaptive control had better performance measures than the indirect adaptive control and had the least amount of control effort at different flight conditions. The authors evaluated the performance of this neural controller with wind gusts. It demonstrated that it was able to reject gust very well while maintaining control surface deflection within acceptable limits and accurately track the pitch rate command. These results illustrated the robustness of this control strategy.

Puttige et al. (2009), proposed a modified indirect adaptive control by utilizing Dual Neural Networks (DNN) for development of a low-cost UAV; in hopes of catering to commercial and defense applications. The control system for this research consisted of an identifier neural model and DNN controller both with the capability for on-line adaptations. The DNN consisted of an internal neural model (NN_m) and a neural controller (NN_c). This complex control system worked in the following method. First, the NN_m was pre-trained offline with actuator and steady state outputs from the nonlinear plant. This NN_m provided corrections to the NN_c at every training iteration. Then, once the NN_c had been trained its output was validated against the identifier neural model which was trained on-line. The identifier neural model predicts the plant behavior corresponding to the inputs from the DNN controller. Lastly, the predicted output was compared to the commanded reference input. Utilizing this comparison, suitable weights were adjusted to obtain desired plant outputs at every instant of time. In essence, this control strategy consists of two feedback loops for NN_c, one by the NN_m at every iteration and another by the trained identifier neural model at every sample time. Figure 2.1 shows the control system.

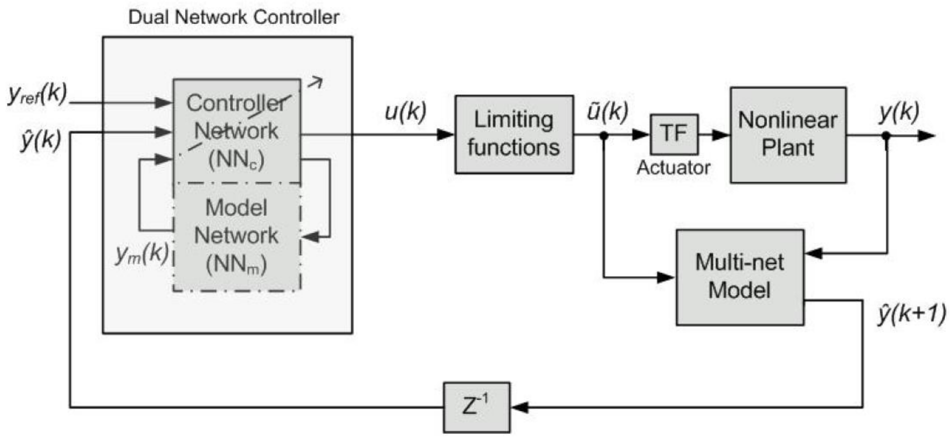

Figure 2.1. Overall Adaptive Control (Puttige, Anavatti, & Samal, 2009)

This DNN was implemented into a DNN velocity control, where NN_c had four hidden neurons and the NN_m had six neurons. DNN controller was trained with 25 iterations while minimizing the performance index below 10^{-7} threshold. Results from this control strategy were compared to that of a traditional PID controller. Both strategies were simulated for a varied flight condition while under the influence of external disturbances. The first disturbance test was simulated under sensor noise and the DNN control was able to track the commanded input. The next disturbances were wind gust and plant variations. The DNN controller was able to cancel out the majority of the wind effects, and it was able to adapt to the changes in the flight conditions unlike the PID controller.

These direct and indirect adaptive neural network controllers were the most prevalent in the field of fixed-wing control. This might be due to the fact that these neural control types were the best suitable control for fixed-wing aircraft. As mentioned in MATLAB Neural Network toolbox (2012), there is no single neural controller that is suitable for all applications.

The above neural network controls demonstrate the capability to learn, and if trained on-line, can adapt to variations in the plant and external disturbances (Dash, Panda, Lee, & Xu, 1997). These characteristics make them an enticing adaptive control strategy. However, there is one last of the bio-inspired control strategies with similar characteristics, which is discussed in the next section.

2.2.3 Brain Emotional Learning for Control

BEL model was developed by Balkenius and Moren (2001). It is a computational model of the amygdala, Orbitofrontal Cortex (OFC), thalamus, and sensory input cortex, which are known to be responsible for emotional learning and processing. This model originated under Mowrer's two-process theory of learning, and acquisition of a learned response. In this theory the first step is the association of a stimulus to an emotional consequence. The second step is an emotional evaluation that forms an association of the stimulus to a response (Mowrer, 1960). Researchers in control have taken interest in utilizing this BEL model as a controller. This is motivated by the fact that research in psychology, and cognitive science identify the reciprocal influences of emotion and cognition (Balkenius & Moren, 2001). Therefore, Lucas et al. (2004), introduced the Brain Emotional Learning Based Intelligent Controller (BELBIC) which consisted of the BEL model but utilized as direct adaptive feedback control. The inner working of BEL as described by Mehrabian et al. (2006) is an action generation system founded on sensory input and emotional signal (reward/punishment signal). Figure 2.2 illustrates the BEL model.

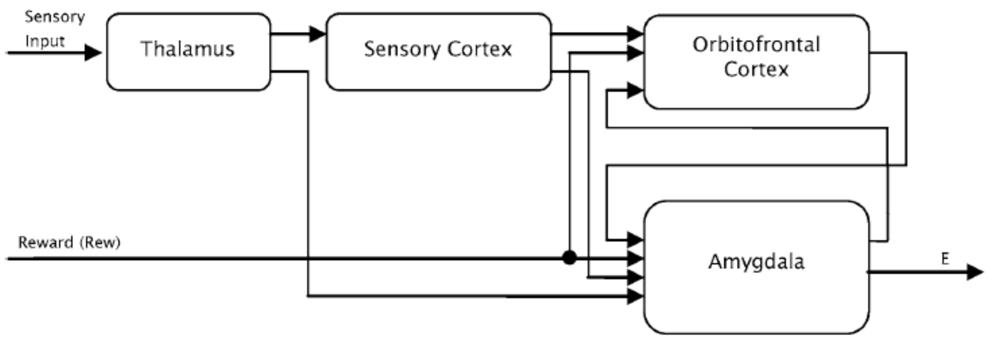

Figure 2.2. BEL Model (Mehrabian, Lucas, & Roshanian, 2006)

The amygdala learns to predict and react to give an emotional signal. While the OFC system detects the difference between the expected system's prediction and the actual received emotional signal (Mehrabian, Lucas, & Roshanian, 2008). For further details on BELBIC and BEL please refer to (Lucas, Shahmirzadi, & Sheikholeslami, 2004; Balkenius & Moren, 2001). Various complex control applications have been solved by applying BELBIC. However, we will review research pertaining to UV control.

Mehrabian et al. (2006), implemented BELBIC as an approach for aerospace launch vehicle autopilot design. This vehicle was expected to experience nonlinearities, disturbances and uncertainties through its flight. Therefore, the objective of this controller was to compensate for these effects. In the research they focused on the longitudinal control of the vehicle, as most guidance maneuvers were in the longitudinal plane. First, due to the nature of the BEL as an open-loop the designers chose to make the sensory input to be fed back from the system response, likewise the emotional signal was fed back, in accordance to the control engineer's requirements of the problem. Figure 2.3 illustrates the implementation of BEL as a control.

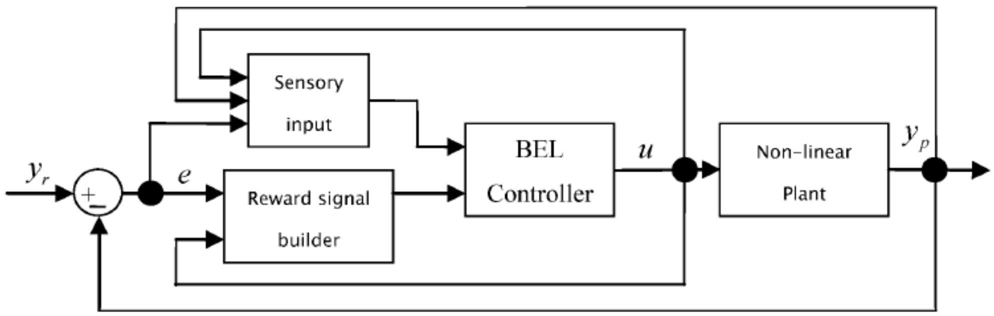

Figure 2.3. BELBIC and Plant Configuration (Mehrabian, Lucas, & Roshanian, 2006)

Next, since the sensory input and emotional signal can be arbitrary functions of reference output, controller output, and error signal, it was the designer's duty to find appropriate functions. The authors selected the sensory input and emotional signal functions based on experience utilizing BELBIC. The gains of these functions were selected through trial and error. The dynamics of the aerospace vehicle were linearized. The controller was then simulated to follow a desired pitch angle and pitch rate, where a Gain Schedule (GS) controller was also compared. BELBIC was able to follow very closely the desired command signals with minimal error. Additionally, BELBIC's response to powerful gust and severe uncertainties were simulated. BELBIC was able to show superior robustness to wind disturbances and severe uncertainties in comparison to GS control.

This exact research was further improved by the same authors by implementing a Genetic Algorithm (GA) to find the suitable gains for the functions of both the sensory input and emotional signal (Mehrabian, Lucas, & Roshanian, 2008).

In a different research by Huang et al. (2008), the authors were able to implement BELBIC to the nonlinear UAV dynamics for attitude control. The primary focus was on longitudinal attitude control system for the UAV utilizing BELBIC. The two inputs for this control system were the difference between desired pitch angle and real pitch angle output of the nonlinear plant and the difference between the desired pitch angle velocity and the real pitch angle velocity output pitch of the nonlinear plant. The output of this control scheme was the elevator deflection. In similar fashion as the previous studies, the authors had the freedom to select the functions for the sensory input and emotional signal, which were selected to be defined by the same equation. In addition, three different values of the learning rate coefficients for both amygdala and OFC were studied, in order to determine their impact on the control performance. The control strategy was simulated for level flight and under the influence of wind disturbance at an angle of 45 degrees from the horizontal plane. Three main observations were obtained. First, the implementation of BELBIC allowed the system to respond quickly to the desired pitch angle and pitch angular velocity, therefore illustrating its effectiveness at overcoming the system's nonlinear characteristics. Second, the greater learning rate coefficient of the amygdala extended the dynamic adjusting time of the UAV. Similarly, the larger OFC coefficient prolonged the adjusting time, therefore it is important that a suitable range for learning rate coefficients are selected for obtaining good stability control performance. Third, the decision to utilize the identical function for the sensory input and emotional signal had no negative effect on control performance, but it was able to reduce the number of unknown parameters.

BELBIC demonstrated its ability for on-line adaptability and allowed learning with relatively low computational cost. In addition, it is a robust nonlinear adaptive controller that is easily implementable. The next step is to analyze the literature in bio-inspired controls for UV and determine the most feasible bio-inspired control strategy for UV control.

In analyzing the literature of bio-inspired controls it is noticeable that all of these control strategies were successful at being robust, adaptive, and utilized relative low computational cost. However, there are some key differences which can be disadvantageous to their effectiveness as controllers.

Fuzzy controls have two major disadvantages. First, fuzzy controls are nonlinear variable structure type controls. Therefore, the first step would be developing their analytical structures for analytical study. However, this step is often not possible due to the use of fuzzy sets, fuzzy rules and multiple input variables. The lack of an accurate mathematical structure of a fuzzy controller prevents the precise analysis and design of a fuzzy control system (Ying, 2000). Second, fuzzy controls have substantial numbers of design parameters. As a result, more time in the design process is spent tuning through trial and error. Also, lacking the knowledge of how these parameters impact the control performance prevents fuzzy controls from fully guarantee stability (Ying, 2000).

Neural Networks encounter similar disadvantages as fuzzy controllers, such as, its "black box" nature, and the experimental nature of network development (Tu, 1996). Additionally, there are two more disadvantages. First, neural networks require training for it to function. This can be an additional computational load, and in cases where there is limited data that is available for training, validation and testing. Second, the internal representation that the network generates is often difficult to interpret. In ensuing situations the network might fixate on features that are artifacts of the training data which are not relevant to the objective at hand (Davis & Stentz, 1995).

Lastly, BELBIC encounters similar disadvantages in both fuzzy and neural controls in its empirical nature of the control design process. The performance of BELBIC is dependent on functions for sensory input and for emotional signal, which in all applications has been determined through the experience of the control engineer and the problem domain requirements (Mehrabian, Lucas, & Roshanian, 2008). Similarly, BELBIC is unable to fully guarantee stability (Jafarzadeh, Mirheidari, Motlagh, & Barkhordari, 2008). Table 2.1 summarizes the important characteristics of each of the controllers.

Table 2.1

Summary of Controllers

SUMMARY					
Controller Type	Assumption	Required User defined parameters	Inputs	Outputs	Limitations
Fuzzy	Uses linguistic descriptions to define the relationship between the input information and the output action	Fuzzy sets; Fuzzy rules; Membership Functions; Inference methods	1	1	Designed empirically can not guarantee stability; Performance is dependent on the quality of fuzzy rules
Neural Network	Computational representation of the biological neural networks. Network is trained to perform a specific function by fine-tuning the weights of the connections between neurons	Hidden Layers; Reference Signal; Plant Signal; Weights	2	1	Designed empirically can not guarantee stability; Needs data to be trained offline; Performance is dependent on the quality of the data trained
BELBIC	Is an action generation system founded on sensory input and emotional signal (reward/punishment signal)	Sensory Function; Reward Function	2	1	Designed empirically can not guarantee stability; Performance is dependent on the sensor and reward functions selected

In analyzing the literature, we have been able to contrast the disadvantages between the bio-inspired controllers. From this study, it seems that the most feasible controller for the CS of a UV to be a variant of BELBIC. It demonstrated all the characteristics of intelligent decision making controller that can stabilize nonlinearities, adaptable, and be robust against uncertainties or disturbances. The next component of CS to be discussed is the navigation aspect for a UV.

2.3 UV Navigation

Advancement in intelligent controls, as discussed in the above sections, can contribute to the level of autonomy for UVs. Additionally, uncertainty about the UV's location and vehicle's state relative to the environment, limits the level of autonomy (Matía & Jiménez, 1998). A particular navigation issue arises when multiple sensor inputs are utilized for vehicle navigation. The navigation system needs to have the reasoning ability to allow it to make an appropriate decision to select, fuse, and integrate multiple heterogeneous sensor inputs (Matía & Jiménez, 1998). Therefore, it is imperative that intelligent methods for navigation be implemented to increase the autonomy level of the UV. Methods for intelligent navigation have been investigated; these include the previously mentioned bio-inspired methods of fuzzy logic and neural networks. Applications of these methods for sensor fusion and navigation are reviewed in the next sections.

2.3.1 Fuzzy Logic for Navigation

Kreucher and Beauvais (1999), proposed the implementation of fuzzy logic for unmanned navigation. The UV was equipped with three sets of sensors: front main camera, lane cameras (left and right), and ultrasonic sensors. For the front main camera fuzzy set of prohibited directions were generated based on the growth of obstacles and lane pixels in front of the vehicle, weighted by the distance from the vehicle.

For the lane cameras two descriptions were obtained, the distance from lane and orientations of the lane. For the distance from the lane three membership functions were developed. For the orientation of the lane four membership functions were developed.

This was done for both left and right side cameras. 22 fuzzy rules (11 for each side) were used to perform the control action. The use of these rules for both lanes generated a fuzzy set of desired directions from the lane camera sensor data.

Eight ultrasonic sensors were first grouped into four groups of two. Then, for each group a set of prohibited direction was developed based on the fuzzy variable of object range. Sensor fusion was implemented by taking the desired direction (set by lane fuzzy output) and combining it with the maximum prohibited directions (set by fused prohibited direction from front camera and ultrasonic sensor) to obtain fused desired direction. The final step was defuzzification of the fused desired direction into a crisp steering angle command by utilizing centroid largest area method.

An experiment was conducted where an obstacle was placed near the left lane. The UV obtained sensor data from the front camera, which it detected that a large portion of left direction was prohibited due to the obstacle. It also detected that smaller portion of the right direction was prohibited due to boundaries of the right lane. Additionally, the UV obtained sensor data from the ultrasonic sensor, which obtained similar results as the front camera. However, with the side camera sensors, the vehicle detected that vehicle was closer to the right lane so the side camera data favored steering to the left. Figure 2.4 illustrates the experiment setup. Data from all sensors were fused.

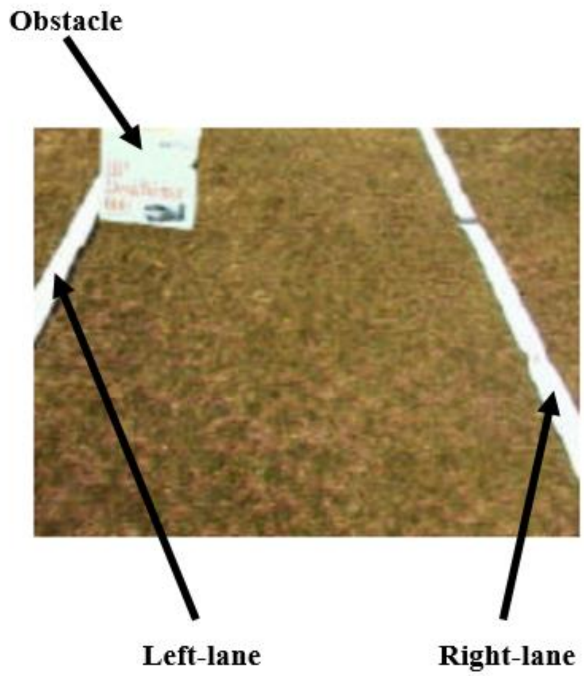

Figure 2.4. Obstacle and Lane Experiment Setup (Kreucher & Beauvais, 1999)

The defuzzification of the fused output resulted into a crisp 84° steering angle, which indicated a slight right turn. Favoring the data obtained from front camera and ultrasonic sensors to avoid obstacle. The result illustrated that fuzzy logic was able to robustly fuse heterogeneous sensor data and provide reliable navigation decisions.

In a more complex study, Subramanian et al. (2009) utilized a fuzzy logic enhanced Kalman filter for sensor fusion in an UV. The application consisted of the navigation of an UV through citrus grove alleyways. The sensors utilized in this vehicle were a machine vision, laser radar (ladar), an Inertial Measurement Unit (IMU), and an ultrasonic speed sensor. Very noisy sensor measurements were present, due to the specific application, so a Kalman filter was utilized to filter the noise and to perform fusion. However, Kalman filters tend to diverge and have a reliability issue where they have to be constantly updated, so the addition of a fuzzy logic was used to correct these issues. The approach taken by the authors was to construct two fuzzy logic systems.

The first fuzzy system was a fuzzy logic based supervisor that was used to decide which sensor was more reliable at different locations in the application and to update the measurement noise covariance matrix in the filter. The inputs were the horizontal distance of the vehicle centerline from the trees on either side for both machine vision and laser radar. The inputs were divided into linguistic variables: reasonable, unreasonable, and zero. A triangle-based fuzzification method was used. The defuzzification was done using center of gravity method. The crisp value of the decision was taken as the measurement noise covariance value for that sensor.

The second fuzzy system was used to correct for divergence by updating the process noise covariance matrix in the filter. Inputs for this fuzzy system were the lateral position error from vision, lateral position error from ladar, and required heading from vision. Various membership functions and fuzzy rules were constructed. Defuzzification was done by the center of gravity method. The crisp values obtained were the updated process noise covariance values.

Simulations were performed which confirmed the correct operation of the Kalman filter and of the fuzzy systems. Additionally, real life experiments were conducted. In a curvy test track the results obtained were that the fused navigation system produced max error of less than 4 cm, which the error was the deviation from the center line of the path. This error was only 1% of the path’s width. In a grove alleyway test where trees could be missing, the average error was less than 10 cm. The developed fusion navigation system was more accurate, versatile and reliable than individual sensor based navigation on both experiments.

The above research shows the successful implementation of fuzzy logic as a method for sensor fusion, and intelligent navigation system. One of the studies utilized only fuzzy logic to fuse and develop an intelligent navigation system. Whereas in the other study, it combined a traditional approach for fusion, Kalman Filter, with fuzzy logic to produce an intelligent navigation system. The latter approach has been the most popular method for fusion and intelligent navigation, due to its ability to solve complex problems utilizing inexact inputs from multiple heterogeneous sensors and thus provides a fairly accurate solution (Xu, Sutton, & Sharma, 2007). Similar characteristics for intelligent navigation can be achieved through the use of neural networks. In the next section we will review literature that utilizes neural networks as means for sensor fusion and intelligent navigation.

2.3.2 Neural Networks for Navigation

As discussed previously, it is difficult to create an accurate model for the navigation of UV because the plant can be nonlinear, and also, the environment information obtained by multi-sensors encompasses uncertainties. Coincidentally, neural networks, if properly trained, can ascertain and weigh the most significant features of an environment (Davis & Stentz, 1995). In this section, we will review various research in which neural networks were utilized for sensor fusion and intelligent navigation.

Davis and Stentz (1995), utilized neural networks for sensor fusion and successfully performed a simulated and real-world navigation task with multiple sensing modalities. In this research the vehicle consisted of a four-wheel-drive military vehicle equipped with a Charge Coupled Device (CCD) camera and laser range finder. Two neural networks were examined, a monolithic network and a modular network. The authors described a monolithic network as, a network in which all sensor data are given to it, and then it is allowed to develop an internal representation, which allows it to perform sufficiently within the context of the information that it was exposed to. The modular network was described as the integration of prior knowledge to the network. The authors utilized their own version of a modular network where it consisted of two levels, a feature level network and a task level network. The feature level network was trained to recognize specific features through any sensor modality. The task level network utilized feature level hidden layers as inputs to train the network to perform the navigation task. The two networks, monolithic and modular, are tested in a simulated world and real-world. The architecture for both monolithic network and their version of modular network was the following: three layer feed-forward network, five hidden units, and eleven output units with Gaussian form activation. In the simulated world the task was road following with stationary obstacles. First, the networks were trained via mouse steering of the vehicle as it followed the road several times in both directions. Additionally, several training sets of data were created in off-road driving, so the simulated vehicle could recover if it drove off the road. Performance for both networks was excellent; vehicle maintained desired speed and avoided obstacles. In real-world unmanned navigation the results were that the monolithic neural network was able to learn how to fuse the different modalities and navigate accordingly. However for their own version of modular neural network it allowed them to control how to utilize the information obtained from the various modalities, though this also meant more training had to be done in comparison to the monolithic.

In a different research study, Cordoba (2007) implemented digital neural network for the integration of 3 Micro-Electro-Mechanical System (MEMS) accelerometers, 3 MEMS rate-gyroscopes, and 3 magneto resistive transducers. The objective was to develop an intelligent attitude and heading reference system for a UAV. A digital neural network made the ideal technique for improving the aerial vehicle attitude calculation and estimation process. For that reason, a multilayer digital neural network was used as on-line learning estimator because of its high performance in multivariable and non-linear systems. The neural network for this application was back-propagation multi-input and multi-output network architecture. The sensors data were the inputs to the network. The digital neural network was simulated and validated. The results were an enhanced method for integrating sensor data from the accelerometers, gyros and magnetometers utilizing a digital neural network. This method was able to produce accurate attitude angle measurements.

The results from both studies were inherent capabilities of neural networks to intelligently fuse and navigate the UV by selecting and weighing the most significant information from the environment. Additionally, the ability of the neural networks to accurately approximate the plant's nonlinearity and sensor data uncertainty make it a good candidate for intelligent navigation and sensor fusion.

In analyzing the literature, fuzzy logic can be easily integrated with the Kalman filter for sensor fusion and work well together to produce an intelligent navigation system. However, the integration of Kalman filter with Fuzzy logic increases the complexity of the navigation system. In a stand-alone application of fuzzy logic as a navigation system it provided good results for simple cases. On the other hand, neural networks have been successfully applied to UAV sensor fusion and navigation. Yet, neural network performance as intelligent navigation system is sensitive to how they are trained, this was observed in one of the literatures discussed above. Another interesting gap is that BEL models have not been implemented for UV navigation, particularly for sensor fusion, even though they share similar characteristics as fuzzy logic and neural networks.

In analyzing the literature, we have been able to contrast the disadvantages between the bio-inspired algorithms for the sensor fusion in a navigation system. However, an interesting gap in the literature was found, in that there was no implementation of the BEL model for sensor fusion. Thus, it will be interesting to develop and implement the BEL model as a filter for sensor integration, because this algorithm was demonstrated to be adaptable, and be robust against uncertainties or disturbances. The next aspect of the literature review to be discussed is the research methods of capturing human's affective state and the utilization these states.

2.4 Human Emotion Recognition

As the autonomy level of an AS increases, the interaction between human-AS can be increasingly similar to that of human to human interactions. Human interactions can be characterized in to two forms of communication, explicit and implicit. The explicit form of communication transmits unconcealed information, while the implicit one transmits concealed information about the communicator's intention, attitude, and likes/dislikes. The ability to sense the implicit form of communication is one of the vital obligations associated with this form of interaction (Cowie, et al., 2001).

2.4.1 Emotions

Through implicit communication, emotions are predominantly exchanged. Emotions have been identified to be an important factor in cognition. As stated by Picard (Affective Computing, 2000), "emotions play an essential role in rational decision-making, perception, learning, and a variety of other cognitive functions”. Furthermore, emotions can be easily captured and implemented in computational models (Mowrer, 1960). However, an AS may never need all the emotional skills of humans. But by equipping them with the ability to perceive human emotions, can potentially make it behave more intelligent when interacting with humans (Picard, Vyzas, & Healey, 2001). Thus, by developing the AS’s capability of emotional intelligence should permit for a more efficient and natural human-AS interaction.

Emotions are spontaneous mental states produced by subjective experiences, physiological arousal, cognitive processes, and motivational tendencies (Kim & André, 2008). Being in an emotional state is commonly known as an affective state. Researchers most often characterize emotions based on two models, discrete and dimensional. The discrete model consists of six primary emotions (happiness, sadness, fear, surprise, disgust, anger). Other emotions are derived from combinations of the primary emotions. A widely used dimensional model developed by James Russell (1980), plots emotions on two continuous axes, valance and arousal. Valance measures the degree of how negative or positive the experience is. While arousal measures the intensity of the emotion. As a result, all emotions can be plotted on the valance-arousal model, shown in Figure 2.5.

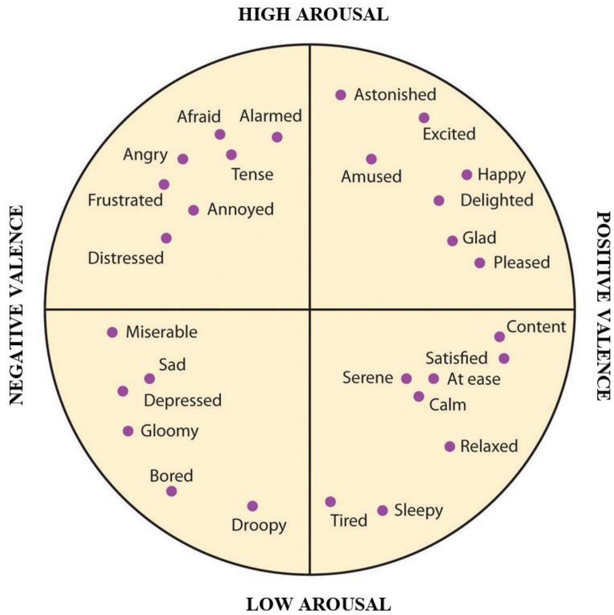

Figure 2.5. Valence-Arousal Model (Stangor, 2012)

2.4.2 Methods for Human Emotion Recognition

There are numerous methods that can be employed to determine a person’s affective state, such as, facial expression, gestures, postures, and physiological. However, in the instance of facial expression, literature shows that it is difficult to capture the affective state real-time, and for the AS to react to it (Bartlett, Littlewort, Fasel, & Movellan, 2003). Additionally, for gestures and postures the literature shows that the understanding of user emotions from gestures/postures is a much more complex task, and such work in the framework of human-AS interaction is not feasible (Firby, Kahn, Prokopowicz, & Swain, 1995). Conversely, physiology is a promising way of approximating the affective state of a person. It has been known that emotions and physiology (biological signals: heart activity, muscle tension, blood pressure, skin conductance etc.) are closely correlated, and that one affects the other. Research initiated by Picard exploits this relationship between emotions and physiology to detect human affective states (2001). These concepts have been applied to domains such as driving (Backs, Lenneman, Wetzel, & Green, 2003), flying (Hudlicka & Mcneese, 2002), and machine operation (Hayakawa & Sugano, 1998).

Several interesting studies were conducted by Rani et al. (2004; 2006), who empirically demonstrated the capabilities of a robot to detect and recognize the affective state of a human companion, and change its tasks sequence to accommodate a suitable response based on the human’s affective state. In these studies, the authors utilized several physiological signals (cardiac response, electrodermal response, and electromyographic response) and several biological sensors to recognize the human’s affective state. The affective state information along with other environment information were then relayed to a controller that instructed the robot to perform a suitable response. Figure 2.6 illustrates the physiological sensors utilized in this study.

Figure 2.6. Physiological Sensors (Rani, Sarkar, Smith, & Kirby, 2004)

However, in this study only one affective state (anxiety) was captured and utilized. In addition, the physiological sensors appear to be fairly intrusive, and thus potentially affecting the human performance in completing the task. A potential improvement can be made by using a single bio sensor, such as an EEG headset, which can be used to capture several affective states.

Several studies have been conducted in which emotional states were classified by analyzing EEG signals. One such study was performed by Natarajan et al. (2004) in which researchers performed nonlinear analysis of EEG signals at different mental states. They used nonlinear parameters like Correlation Dimension (CD), Largest Lyapunov Exponent (LLE), Hurst Exponent (H) and Approximate Entropy (ApEn) to analyze EEG signals. Participant's EEG signals were recorded at three mental stages: under normal resting stage; under music stimuli (classic and rock); under foot reflexologic stimulation. The results from this study showed statistical differences in each of the nonlinear parameters across the various mental states. Thus, they were able to distinguish differences among EEG signals from the nonlinear parameters at different mental states. The results further suggest that when the participants were under sound or reflexologic stimuli the brain went to a more relaxed state.

In a study performed by Chanel et al. (2006), researchers evaluated the arousal dimension of human emotion through two physiological methods: EEG signals and peripheral signals. Participant's EEG signals and peripheral signals were recorded while 50 images of high arousal and 50 images of low arousal were presented. These 100 images had uniform distribution of valence. In addition, all images were selected from the International Affective Picture System (IAPS) in which these images had been extensively evaluated in terms of valence/arousal values and with collective means and variances. Preprocessing of the EEG signal was done through band pass filter which kept frequencies in the 4 – 45 Hz range to remove power line noise. Six EEG frequency bands were selected ($\theta_1,\ \theta_2,\ \gamma,\ \alpha_2,\ \beta_1,\ \beta_3$), based on their correlation between arousal elicited by IAPS images (Aftanas, Reva, Varlamov, Pavlov, & Makhnev, 2004). The 6 features were extracted from EEG signals, which consisted of the average power of electrodes for each band. While 18 features were selected for the peripheral signals. Classification of both EEG features and peripheral features was accomplished by both naïve Bayes and Fisher Discriminant Analysis (FDA). Results showed that arousal recognition can be accomplished through the use of EEG signals. In addition, the fusion of peripheral features and EEG features improved classifier performance and was better with FDA.

In another study by Hosseini (2012), EEG signals were utilized to develop an emotion recognition system. This system consisted of four major processes: an EEG acquisition, preprocessing filter, feature extraction, and classification. This system would be able to recognize two emotional states of participants, calm-neutral and negatively excited. These emotions were based on the valence-arousal model. The targeted emotions were elicited by the stimuli of pictures. The preprocessing filter selected was a band pass filter to remove environmental noises and drift. Filtering was done through a MATLAB built in function “filtfilt” which allowed EEG signals of frequencies of 0.5 – 60 Hz. After preprocessing EEG signals, a Higher Order Spectra (HOS) was employed to extract the features for classifying human emotions. Due to dimensionality of the signals, the authors employed a Genetic Algorithm (GA) and Support Vector Machine (SVM) for feature selection method. This method would improve the computational speed of the feature selection process. Lastly, after extracting the features the authors utilized a Linear Discriminant Analysis (LDA) to classify them into the two emotional states. The researchers used 65% of EEG data from participants for training, 25% for testing, and 10% for validation. Results from this study were an average 82.32% accuracy for correctly recognizing the two emotional states of the participants.

In a more elaborate study conducted by Murugappan et al. (2010), researchers used EEG signals and wavelet transform for human emotion recognition. Participant’s EEG signals were recorded while inducing them into five emotional states (disgust, happy, surprise, fear and neutral) through audio-visual stimuli. The raw EEG signals were preprocessed through a Surface Laplacian (SL) filter method. The filtered EEG signals were then decomposed through Discrete Wavelet Transform (DWT) into three frequency bands ($\gamma, \ \alpha, \ \beta$). From the decomposed EEG signals features were extracted through the *Logarithmic Recoursing Energy Efficiency* (*LREE*) and *Absolute Logarithmic REE* (*ALREE*) methods. These methods for feature extraction are modified versions of their previously proposed method of *Recoursing Energy Efficiency* (*REE*) in which they previously used the Fuzzy C-Means (FCM) and Fuzzy K-Means (FKM) for grouping the human emotions (Murugappan, et al., 2008). Lastly, after extracting the features the authors utilized both a Linear Discriminant Analysis (LDA) and K Nearest Neighbor (KNN) to classify them into the five emotional states. A performance comparison between the two classifiers was analyzed. In addition, the researchers took the study further in analyzing their classifier accuracy with respect to number of channels/electrodes on the EEG headset (64, 24, and 8). Results from this study indicated that, KNN gives higher average classification accuracy than LDA on three different channel sets. The maximum classification accuracy of 83.26%, 79.93% and 72.68% was obtained using *ALREE* feature on 62 channels, 24 channels and 8 channels respectively. Additionally, among the three different feature extraction methods, *ALREE* performed better than the other proposed (*REE and LREE*).

2.4.3 Classification of Driving Behavior

In regards to research pertaining to the area of classifying human driving behavior it is apparent that there are three methods. One method used questionnaires in which drivers assessed their own driving behavior after completing a driving task (Taubman-Ben-Ari, Mikulincer, & Gillath, 2004; Chung & Wong, 2010). This approach categorized drivers into eight types: anxious, risky, angry, high-velocity, careful, dissociative, distress-reduction, and patient (Taubman-Ben-Ari, Mikulincer, & Gillath, 2004). Another method for categorizing driving styles is analyzing real-time vehicle parameters, such as throttle position, brake force, steering angle, and engine information (Bar, Nienhuser, Kohlhaas, & Zollner, 2011; Driving style evaluation, 2014; AMG, 2011; Squarell Tech, 2014; Scania Driver Support system, 2014). By using this method, researchers were able to successfully categorize distinct driving styles: anxious, economical, aggressive, keen, and sedate (Bar, Nienhuser, Kohlhaas, & Zollner, 2011). The last method is through driver mood. In this method the driver's mood is used to characterize the driving style. In a number of studies, it has been shown that the emotion that a driver is experiencing is associated with their driving behavior. Aggressive driving was associated with a driver in an angry, annoyed, or frustrated state (Dula & Geller, 2003; Ellison-Potter, Bell, & Deffenbacher, 2001; Tasca, 2000; Shinar, 1998). Another study, used boredom to classify drivers (Harvey, Heslop, & Thorpe, 2011). Vaa (2007) identified emotion as a motivational factor that guides driving behavior (Cacciabue, 2007). In addition, in the book *Modelling Driver Behaviour in Automotive Environments* a representation of driving moods in terms of the valence/arousal model was presented (Cacciabue, 2007). Figure 2.7 illustrates this representation.

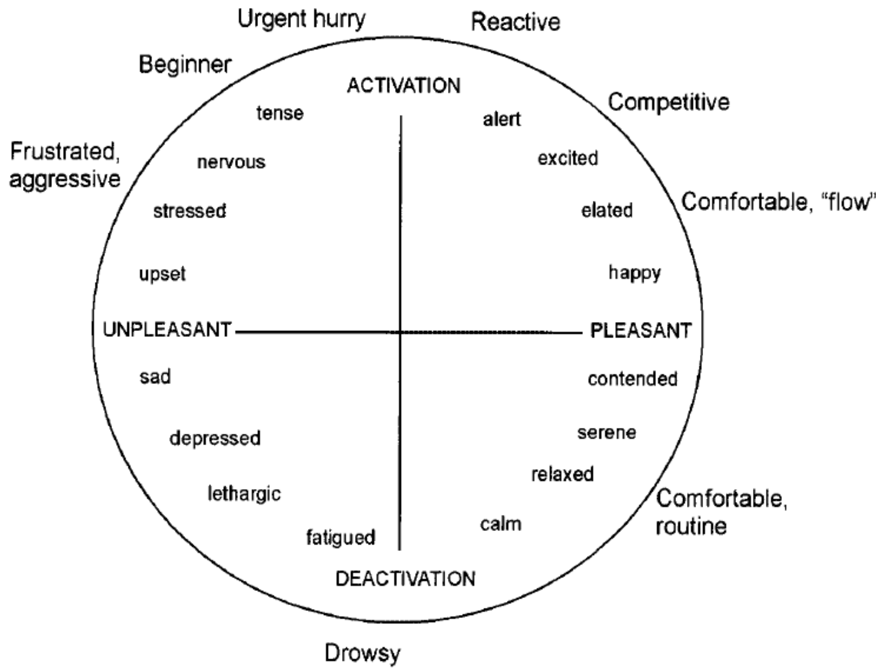

Figure 2.7. Driving Moods Representation in Terms of Valence-Arousal Model (Cacciabue, 2007)

In synthesizing the literature in this section, it is evident that further research can be conducted in the area of AS. Primarily, towards making the human-AS interaction more seamless and efficient. This was first attempted in Rani et al. (2004; 2006), in which a robot was able to implicitly sense a single emotional state through various intrusive physiological measurements. Based on these measurements the robot was able to detect if a human companion was in an anxious state and respond accordingly. However, this research can be further improved by using EEG technology. As discussed in the literature, there were numerous studies in which human EEG signals were used to accurately classify a number of distinct emotional states experienced by individuals. This method of human emotion recognition through EEG signals is a viable alternative to the more intrusive biological sensors previously used. Additionally, results from this research method can be extended for the classification of driving modes based on the affective states of human operator.

From the literature it was evident that emotions play an important role in decision-making, perception, and other cognitive functions. Thus, by determining a person’s affective state, one can characterize their behavior, more precisely, for the scenario of operating a vehicle. This can be done by employing a similar approach under taken by Cacciabue (2007) in which driving moods were characterized in terms of the valence-arousal model. Further research can be conducted to develop a method for the classification of driving mode based on the valence-arousal model. This new method can then be validated by comparing it to the more widely implemented method of using vehicle parameters for driving behavior classification.

Thus, by utilizing the method for human emotion recognition through EEG signals and by developing a method for classifying human driving modes based on perceived emotions it is anticipated that we can develop a system that would permit an AS to efficiently detect and respond accordingly to an operator’s affective state.

2.5 Research Direction

In reviewing the literature, the following things were apparent. First, in regard to the bio-inspired controllers discussed in the literature. All of the bio-inspired control methods (Fuzzy logic, neural networks, BELBIC) were shown to be robust, adaptable, and efficient controllers across many applications with superior performance to traditional control methods. Thus, for the controllers for a UV reviewed here, the control method that seems to be the most appropriate was BELBIC. It was developed under the principle that emotions and cognition are required for intelligent decision making. When utilized as a controller, it demonstrated all the characteristics of an intelligent controller in various applications that were complex, nonlinear and highly uncertain. More importantly, it was shown to be the method that required the least amount of user-defined parameters required during the controller design process. This important quality will facilitate the controller tuning process when used in conjunction with the proposed intelligent tuning unit. However, there are some further improvements that are required, such as, characterizations of the effects of these design parameters, like sensory and reward functions, and their impacts to controller performance. Therefore, the direction in bio-inspired controls we hope to take is to further improve BELBIC for UGV control.

Second, in regard to sensor integration for a navigation system in a UV, it is evident that utilization of bio-inspired methods for sensor fusion is a feasible alternatives. Fuzzy logic was successfully used as stand-alone for simple sensor fusion applications. It was also used in conjunction with a Kalman filter. However, this configuration caused the navigation system to greatly increase in complexity and with additional computational cost. Neural networks also proved to be an alternative, however, sensitivity issues to training data were noticeable. Interestingly, there was little progress in implementing BEL algorithm for sensor integration even though it has been shown to be adaptable, and robust to uncertainty, which are desirable qualities for a sensor integration filter. Hence, the direction we anticipate to take for UGV intelligent navigation is in developing and implementing a BEL filter for sensor fusion in a navigation system.

Lastly, in regards to methods for capturing and using a human affective state to determine mode of vehicle operation, it is noticeable that there are disconnects. In the study by Rani et al (2004; 2006), they were successful in developing a system for a robot that gave it the ability to detect and used a human companion's anxious state to change the robot's behavior. This was done by using a number of intrusive physiological measurements. However, little progress has been made to further improve and extend these studies. These studies can be further improved by incorporating the use of EEG signals to detect and classify a human's affective state. As mentioned earlier, there are numerous studies that have implemented EEG signals for human emotion recognition. In addition, these captured affective states can be utilized for determining human driving behavior. Very little work has been conducted in which affective states are used to categorize driving behavior.

CHAPTER 3

BELBIC UGV CONTROL

In this chapter we present a novel implementation of BELBIC for the control of a UGV. This is accomplished by developing two low hierarchy intelligent controllers to improve the navigation performance of a UGV. This improvement occurs regardless if the UGV is fully teleoperated, or it is operating at an autonomy level of 3. The UGV navigation aspect we are focusing is on the lateral control, in its ability to follow a set trajectory in terms of two different methods, heading and path control. As a result, two independent intelligent controllers are developed, one for the case of I.) Heading control II.) Path control.

A common approach for control is the implementation of a PID control, as it is the most commonly used feedback controller (Macia & Thale, 2005). PID controllers operate on an error, the difference between measured plant output and a desired plant output. The controller attempts to minimize the error by adjusting the plants control inputs. PID controllers are relatively easy to implement and operate. However, PID controllers are limited in being a linear control, and the derivative term amplifies high frequency measurement noise that produce large changes in the plant output. Researchers in the field of control have taken interest in utilizing bio-inspired algorithms to resolve complex control problems. This interest is driven by the advantages these algorithms have over traditional control strategies. One such algorithm example is BEL model. As discussed in the literature review, the BEL model has been used extensively in a variety of control applications (Mohammdi-Milasi, Lucas, & Najar-Arrabi, 2004; Mehrabian, Lucas, & Roshanian, 2006; Huang, Zhen, & Wang, 2008) in the form of

BELBIC (Lucas, Shahmirzadi, & Sheikholeslami, 2004), which consisted of the BEL model but utilized it as a direct adaptive feedback control. In all applications the BEL model demonstrated robustness to uncertainties, on-line adaptability, and small computational cost. However, there is no research in implementing BELBIC for heading and path control for a UGV. Therefore control strategy selected is in implementing BELBIC for both heading and path control.

This chapter is organized as follows. Heading and path models are discussed in section 3.1. In section 3.2 and 3.3 heading and path control are presented, respectively. The inner workings of BELBIC are discussed in section 3.4. Implementation of the BELBIC controllers for the two cases (I and II), and simulation results are discussed in section 3.5.

3.1 Heading and Path Models

In this section of the work we focus in modeling heading and path tracking motion of the UGV, as it navigates freely in uncertain environments. The modeling method used here is a two degree-of freedom bicycle model. This is a common approximation used for simple vehicle analysis and for deriving intuitive control algorithms (Hoblet, O'Brien, & Piepmeier, 2003; Massey, 2006). This is done by the assumption of combining the left and right wheels of a vehicle into a single in-line pair of wheels. The heading and path-tracking control of an autonomous vehicle is one of the most difficult automation tasks because of constraints in mobility, and speed of motion in undulating terrain. The vehicle control can be separated into lateral and longitudinal controls. As previously mentioned, we focus on the lateral control of a UGV in terms of two separate cases: I.) Heading, and II.) Path.

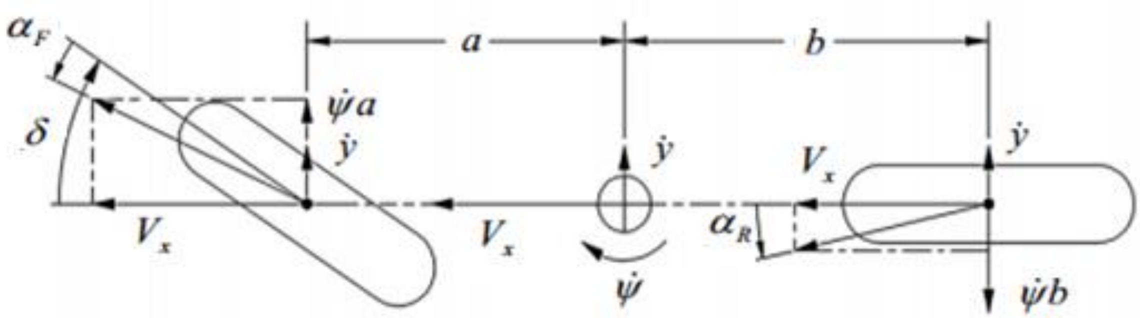

Figure 3.1. Bicycle Model (Massey, 2006)

Where:

m = Mass of the Vehicle
a = Distance from Center of Gravity (CG) to front axle
b = Distance from CG to rear axle
V_x = Longitudinal velocity
C_F & C_R = Front tire cornering stiffness & rear tire cornering stiffness, respectively
I_z = Yaw moment of Inertia
Ψ = Yaw
δ = Steering angle

3.2 Heading Control

For heading control, the objective is to move along a desired heading. The control variable is steering (δ) and output variable is heading (Ψ), which is controlled to steer towards a waypoint. Consider the heading control transfer function as follows (Velaskar, Vargas-Clara, Jameel, & Redkar, 2013):

$$\frac{\Psi}{\delta} = \frac{Fs + FA - CD}{s^3 + s^2(A+E) + s(AE - BD)} \tag{1}$$

Where the constants are defined by:

$$A = \frac{C_F + C_R}{mV_x};\; B = \frac{C_F a - C_R b}{mV_x} - V_x;\; C = \frac{C_F}{m}$$

$$D = \frac{C_F a - C_R b}{I_z V_x};\; E = \frac{C_F a^2 + C_R b^2}{I_z V_x};\; F = \frac{C_F a}{I_z}$$

3.3 Path Control

Path control is another control approach that is useful in minimizing the lateral displacement of the vehicle from the straight line path between two waypoints. The lateral displacement (Y_{earth}) is the path error, and is the output variable. Again the steering (δ) is control variable. Thus, the path control transfer function follows (Velaskar, Vargas-Clara, Jameel, & Redkar, 2013):

$$\frac{Y_{earth}}{\delta} = \frac{s^2 C + s(V_x F + CE - BF) + V_x(FA - CD)}{s^4 + s^3(A+E) + s^2(EA - BD)} \tag{2}$$

The implementation consist of two independent BELBIC controllers, one for Equation (1) and another for Equation (2). Thus, creating a heading BELBIC controller and a path BELBIC controller. Their implementation are discussed in greater detail in the following section.

3.4 BELBIC

The inner working of BELBIC is an action generation system founded on sensory input and reward signal (Mehrabian, Lucas, & Roshanian, 2008). The emotional learning occurs primarily in the amygdala. The learning of the amygdala is given in the following equation:

$$\Delta G_a = \alpha S_i \max(0, Rew - A) \tag{3}$$

where Ga is the amygdala gain, α is the amygdala learning rate, S_i is the sensory input, *Rew* is the reward signal, and *A* is the amygdala output. The *max* term is for making the learning in the amygdala monotonic, implying that learning in the amygdala should be permanent.

Similarly, the learning rule in OFC is shown in the following equation:

$$\Delta G_o = \beta S_i (MO - Rew) \tag{4}$$

where G_o is the OFC gain, β is the OFC learning rate, and *MO* is the model output, calculated as in Equation (5):

$$MO = A - O \tag{5}$$

In which, *O* is the output of the OFC. The model first receives the sensory input, S_i, then the model calculates the internal signals of the amygdala and OFC, these signals are calculated as in Equations (6) and (7):

$$A = G_a S_i \tag{6}$$
$$O = G_o S_i \tag{7}$$

The amygdala learns to predict and react to give an emotional signal. The OFC system detects the difference between the expected system's prediction and the actual received emotional signal (Mehrabian, Lucas, & Roshanian, 2008). However, for the implementation of BELBIC as a heading and path control, we use the continuous form of BELBIC. In continuous form, BELBIC states (3) and (4) are updated with continuous relations as follow:

$$\dot{G}_a = \alpha S_i (Rew - A) \tag{8}$$
$$\dot{G}_o = \beta S_i (Rew + S_i + O - A) \tag{9}$$

To utilize this version of the BELBIC as a controller, it is important to understand that BEL model in essence converts two sets of inputs (S_i and *Rew*) into a decision signal as its output (*MO*). Therefore, it is important to implement this BELBIC in an appropriate manner so that input signals and output signals have the proper interpretations for the problem at hand. For the implementation of the BELBIC in this study, we selected the sensory input function (S_i) to be of the form Equation (10):

$$\begin{aligned} S_i &= K_1(\Psi_d - \Psi) && \text{(Heading Control)} \\ S_i &= K_1(Y_{earth-d} - Y_{earth}) && \text{(Path Control)} \end{aligned} \tag{10}$$

where Ψ_d and $Y_{earth-d}$ are the *desired* heading and *desired* displacement, respectively. While, Ψ and Y_{earth} are the *measured* heading and *measured* lateral displacement, respectively. Lastly K_1 is a positive real number gain. Important note, the same K_1 variable name is used for both cases (Heading and Path), but it might have a different value for each of the cases.

The reward function (*Rew*) is selected with the objective of minimizing the difference between *desired* and *measured*. This function plays an important role in BELBIC. *Rew* function attempts to increase the reward while minimizing the sensory input. The implemented reward function is given in Equation (11):

$$Rew = -K_2\left|e\right| + K_3 \tag{11}$$

where K_2 and K_3 are positive real numbers gains. The same reward function (11) is used for both cases (Heading and Path), however, K_2 and K_3 might have different values for each of the two cases. From equation (11), it can be seen that the BELBIC obtains maximum reward when the sensory input is zero. Closely noticing equation (10), the sensory input is in essence, an error signal. The BELBIC tries to diminish the error. A schematic of BELBIC implementation for heading and path control are illustrated in Figure 3.2 and 3.3, respectively.

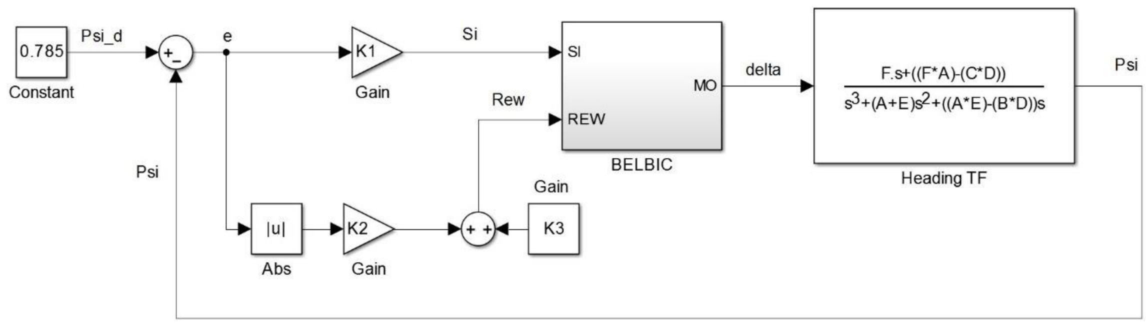

Figure 3.2. Heading Control Configuration Using BELBIC

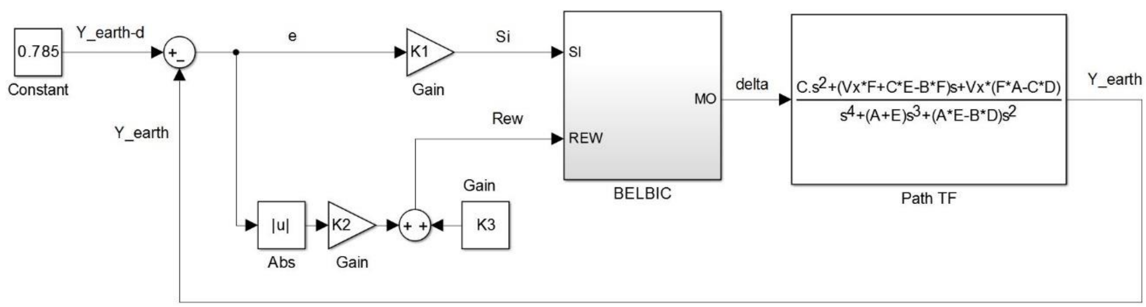

Figure 3.3. Path Control Configuration Using BELBIC

3.5 BELBIC Implementation and Simulation Results

To carry out the simulations a number of BELBIC parameters had to be selected. These parameters included the learning rates in Equations (8) and (9); the gains in Equation (10) and (11). Table 3.1 shows all BELBIC parameters selected. These parameters were selected through trial and error to improve BELBIC performance for the cases of heading and path control.

Table 3.1

BELBIC Controller Parameters

Case	**Learning Rates**		**Sensory Input Function (*Si*)**	**Reward Function (*Rew*)**	
	α	β	K_1	K_2	K_3
Heading Control	2	1	2	110	0.5
Path Control	2	1	2	173	0.2

To assess the performance of the BELBIC controllers, a comparison with PID controllers is conducted. The PID gains (KP, KI, and KD) are selected as in (Velaskar, Vargas-Clara, Jameel, & Redkar, 2013). Built in MATLAB Simulink PID block are utilized to create the PID heading and path controllers. To evaluate the performance of the two mentioned control strategies (BELBICs and PIDs), we have simulated the control systems in Simulink. The UGV should follow a desired heading and maintain a desired lateral displacement. A sinusoidal and step signal were selected as inputs for both desired heading and desired lateral displacement. In addition, plant parameters are varied. These variations include changes in the mass of vehicle (m), and longitudinal velocity (V_x).

First scenario simulated is a comparison of the heading controls with different inputs and varied longitudinal velocities. The following results were obtained, shown in following table.

Table 3.2

Heading Control Comparison: Varied Input Signal and Longitudinal Velocity

HEADING CONTROL				
Step Reference Input: Amplitude 0.785 rad				
Velocity	CPU Time [sec.]		RMS Error [rad.]	
[m/s]	PID	BELBIC	PID	BELBIC
1	0.585	0.377	0.0126	3.259E-04
3	0.597	0.375	7.700E-03	3.249E-04
5	0.607	0.375	6.900E-03	3.248E-04
7	0.589	0.378	6.500E-03	3.248E-04
10	0.586	0.383	6.400E-03	3.248E-04
Sine Reference Input: Amplitude 0.785 rad. and frequency 0.25 Hz				
Velocity	CPU Time [sec.]		RMS Error [rad.]	
[m/s]	PID	BELBIC	PID	BELBIC
1	0.593	0.520	0.0867	8.597E-05
3	0.589	0.537	0.0238	1.251E-04
5	0.588	0.527	0.0169	1.403E-04
7	0.600	0.533	0.0158	1.458E-04
10	0.607	0.530	0.0165	1.494E-04

It can be seen from the first scenario simulated that the performance of BELBIC controller for a step and sine reference input is better than a PID controller in having reduced RMS error from desired heading. In addition, variations in the velocity of the UGV have less impact on the performance of a BELBIC controller than in the PID controller. Also, the Central Processing Unit (CPU) time is less than in the PID for all input signal variations and velocity variations. To further demonstrate the superior BELBIC performance, Figure 3.4 demonstrates a comparison of both control strategies with a step input response when PID performs at its best, which is at V_x = 10 m/s. Figure 3.5 illustrates a comparison of both control strategies with a sine input response when PID performs at its best, which is at V_x = 7 m/s.

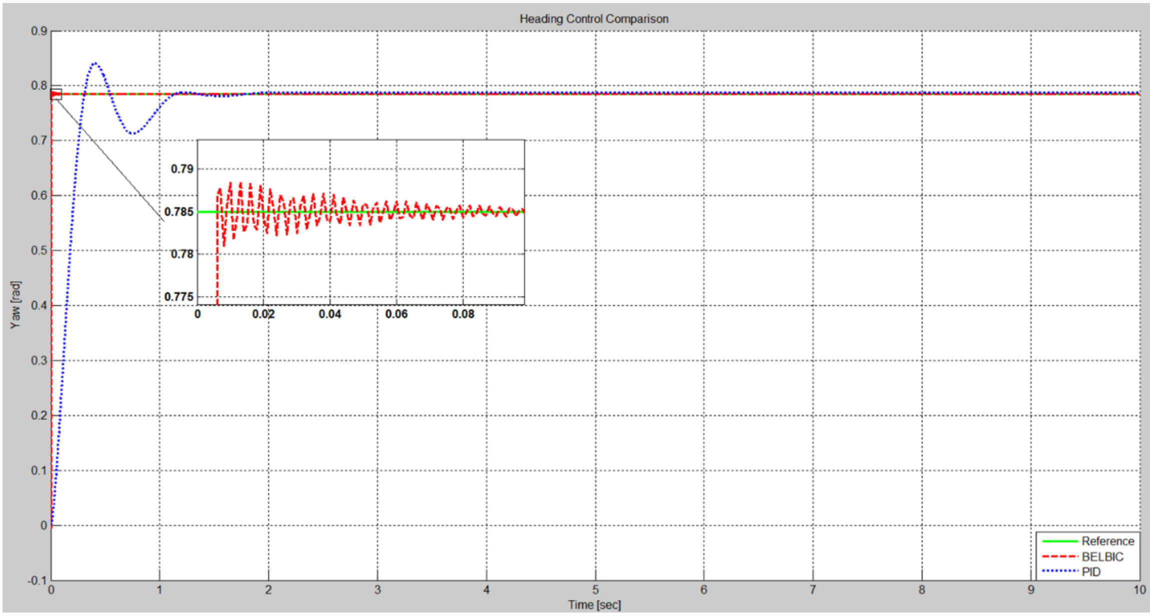

Figure 3.4. Heading Control Comparison: Step Input at V_x = 10 m/s

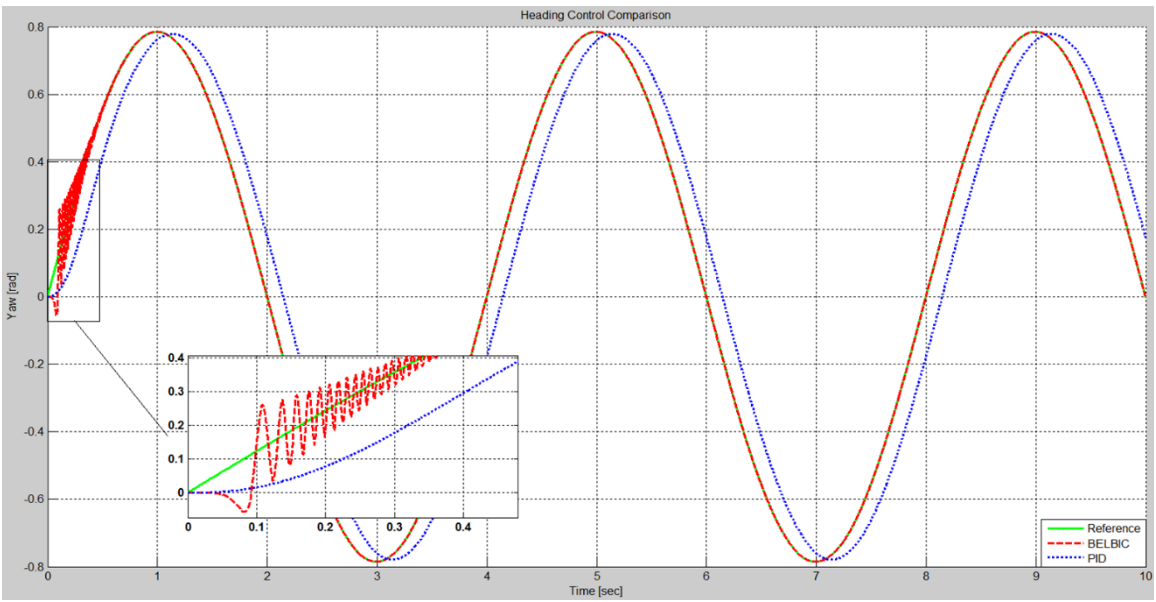

Figure 3.5. Heading Control Comparison: Sine Input at V_x = 7 m/s

The second scenario simulated is a comparison of the heading controls with again different inputs and varied mass. Note that V_x is kept constant at 1 m/s. The following results were obtained, shown in Table 3.3 below.

Table 3.3

Heading Control Comparison: Varied Input Signal and Vehicle Mass

HEADING CONTROL				
Step Reference Input: Amplitude 0.785 rad				
Mass	CPU Time [sec.]		RMS Error [rad.]	
	PID	BELBIC	PID	BELBIC
+10%	0.598	0.539	0.0126	3.258E-04
0.927 kg	0.585	0.377	0.0126	3.259E-04
-10%	0.643	0.513	0.0126	3.260E-04
Sine Reference Input: Amplitude 0.785 rad. and frequency 0.25 Hz				
Mass	CPU Time [sec.]		RMS Error [rad.]	
	PID	BELBIC	PID	BELBIC
+10%	0.606	0.542	0.0870	8.687E-05
0.927 kg	0.593	0.520	0.0867	8.597E-05
-10%	0.601	0.440	0.0865	8.504E-05

From the second scenario simulated it is again noticeable that the BELBIC controller performed better than the PID controller, and that changes in the mass had less effect in the BELBIC performance than in the PID controller.

The third scenario simulated is carried out in similar fashion as the first scenario, except that it is for path controls. The following results were obtained, shown in the following Table 3.4.

Table 3.4

Path Control Comparison: Varied Input Signal and Longitudinal Velocity

PATH CONTROL				
Step Reference Input: Amplitude - 0.785 m				
Velocity [m/s]	CPU Time [sec.]		RMS Error [m]	
	PID	BELBIC	PID	BELBIC
1	0.602	0.507	0.0825	3.242E-04
3	0.724	0.551	0.0406	3.251E-04
5	0.597	0.489	0.0240	3.273E-04
7	0.609	0.494	0.1101	3.300E-04
10	0.601	0.503	1.204E+07	3.326E-04
Sine Reference Input: Amplitude 0.785 m and frequency 0.25 Hz				
Velocity [m/s]	CPU Time [sec.]		RMS Error [m]	
	PID	BELBIC	PID	BELBIC
1	0.615	0.508	1.9883	6.895E-05
3	0.615	0.512	0.0177	1.207E-04
5	0.622	0.512	0.0035	1.604E-04
7	0.618	0.513	0.0050	1.719E-04
10	0.629	0.543	3.235E+05	1.823E-04

The results from this scenario again demonstrate that the performance, in terms of reducing RMS error and CPU time, of the BELBIC controller for a step and sine reference input is superior to the PID controller performance. In addition, variations in the velocity of the UGV have again less effect on the performance BELBIC controller than in the PID controller. More importantly, is that at the velocity of 1 m/s (sine input) and 10 m/s (step and sine input) the UGV plant becomes unstable, and the PID fails to stabilize the plant. In contrast, these velocity changes do not have detrimental effects on the performance of the BELBIC controller. Again to further illustrate the superior BELBIC performance, Figures 3.6 and Figure 3.7 demonstrate the step and sine input response of both control strategies when PID performs at its best, which are at V_x = 5 m/s for both step and sine inputs.

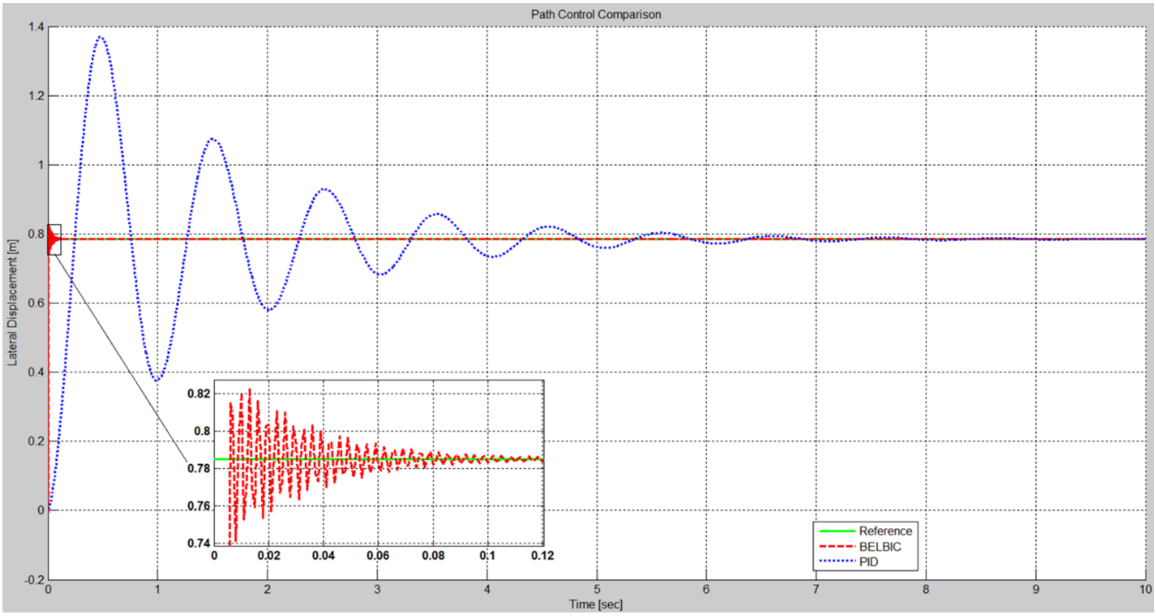

Figure 3.6. Path Control Comparison: Step Input at V_x = 5 m/s

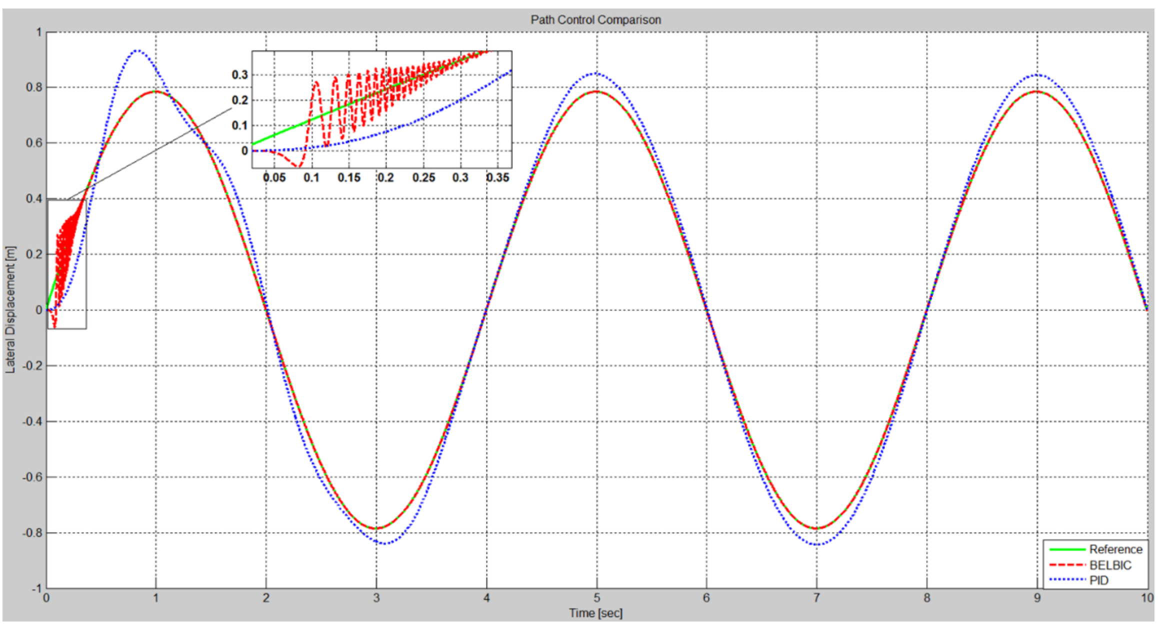

Figure 3.7. Path Control Comparison: Sine Input at V_x = 5 m/s

The last scenario simulated was conducted in similar fashion as the second scenario with the exception that it is for path control. Note that V_x is kept constant at 1 m/s. The following results were obtained, shown in Table 3.5.

Table 3.5

Path Control Comparison: Varied Input Signal and Vehicle Mass

PATH CONTROL				
Step Reference Input: Amplitude - 0.785 m				
Mass	**CPU Time [sec.]**		**RMS Error [m]**	
	PID	**BELBIC**	**PID**	**BELBIC**
+10%	0.613	0.496	0.0811	3.431E-04
0.927 kg	0.602	0.507	0.0825	3.242E-04
-10%	0.611	0.487	0.0839	3.262E-04
Sine Reference Input: Amplitude 0.785 m and frequency 0.25 Hz				
Mass	**CPU Time [sec.]**		**RMS Error [m]**	
	PID	**BELBIC**	**PID**	**BELBIC**
+10%	0.618	0.502	1.9524	7.050E-05
0.927 kg	0.615	0.508	1.9883	6.895E-05
-10%	0.616	0.508	2.0253	6.740E-05

From the above results it is again noticeable that the BELBIC controller performed better than the PID controller, and that changes in the mass had less effect in the BELBIC performance than in the PID controller. However, an interesting point mentioned before is that at velocity of 1 m/s with a sine reference input the UGV plant is unstable, but the BELBIC controllers were still able to stabilize it, unlike the PID controller.

CHAPTER 4

BEL UGV NAVIGATION

In this chapter, the analysis of a filter consisting of the BEL algorithm is presented. The BEL filter is implemented in simulation for the purpose of sensor fusion in a ground vehicle. In simulation, the signals from a GPS and an Inertial Navigation System (INS) are integrated, in order to accurately track the trajectory of a ground vehicle around a track.

To reiterate, the purpose of a navigation system in a vehicle is to determine its current location, velocity, and direction; in other words determine the state of the vehicle. This information is usually obtained from multiple sensors on the vehicle. The sensors commonly used are a GPS, and an INS.

Typically, GPS is a sensor that provides positioning data relative to an earth-centered coordinate system. It uses at least 4 or more satellites with an unobstructed line of sight to calculate position, time, and velocity. GPS receivers can obtain signals from GPS satellites under any weather conditions, and anywhere on Earth. GPS are available for civilian and military applications. They are highly accurate in three-dimensional positioning. GPS position errors are bounded and are dependent on the availability of GPS satellites (Grewal, Weill, & Andrews, 2007).

An INS sensor uses acceleration, and rotational sensors to continuously calculate position, orientation, and velocity, though, its primary output is position relative to an earth-centered coordinate system. In contrast to a GPS sensor, the INS position errors are not bounded, and grow with time. In addition, the errors are dependent on the quality of its inertial sensors (Grewal, Weill, & Andrews, 2007).

The integration of GPS and INS are in efforts to combat each of the sensing unit's weaknesses. For example, INS are initially given position and velocity information from another source, and subsequently it generates its own updated position and velocity by integrating information received from its inertial sensors. However, any small errors which arise in the measurement are integrated into gradually larger errors. By integrating the INS with a GPS, the GPS capability for online calibration and error estimation will help mitigate the INS integration drift. Conversely, in the event that there is an obstruction to the line of sight between vehicle and satellites, and the GPS is unable to perform. The INS can perform as the short-term backup when GPS signals are unavailable. Therefore, as GPS and INS have complementary characteristics, their implementation are considered in an integrated approach (Qi & Moore, 2002).

As a result, the navigation system utilizes the output signals from these sensors and integrates them to obtain a more precise information about the vehicle's state. This process of integration is commonly referred to as sensor fusion. There are numerous methods to fuse INS and GPS, such as, loosely coupled or tightly coupled integration. In the majority of these designs GPS and INS integration filter is usually some form of a Kalman filter (Grewal, Weill, & Andrews, 2007; Wei & Schwarz, 1990; Schwarz, Wei, & Gelderen, 1994; Guangrong, Hongshen, & Ninghui, 2013; Guo, 2013). In most cases, an extended Kalman filter is implemented with inertial errors as its state to obtain satisfactory performance. Kalman filter equations are optimal when sensor observations are unbiased with white noise. Also, there is a heavy computational cost in Kalman filter implementation, due to constant updating of Kalman gains.

In this chapter, we present a BEL filter integration approach to achieve lower computational effort but with competitive performance measures compared to the more commonly used Kalman filter.

The chapter is organized as follows. The sensor integration BEL filter is discussed in section 4.1. Simulation setup is discussed in section 4.2. Simulations results are presented in section 4.3.

4.1 BEL Filter

The implementation of this BEL filter follows similarly to the BELBIC implementation in section 3.4. However, there are several modifications that need to be addressed. First, a discrete version of the BEL model is utilized. In the discrete form, BEL states are updated with discrete relations as follow:

$$\Delta G_a = \alpha S_i \max(0, Rew - A) \tag{12}$$

$$\Delta G_o = \beta S_i (MO - Rew) \tag{13}$$

Equations (5 – 7) remain unchanged for the implementation of the BEL filter. However, it is important that for the sensor fusion filter application, the sensory input (S_i) and the reward function (*Rew*) are appropriately selected in a manner that the input signals and output signals have the proper interpretations for this filter application. In addition, the implementation of BEL model as a filter is chosen to be in similar manner as the Kalman filter implementation. This is done in efforts to draw an accurate performance comparison between BEL filter and Kalman filter. However, slight differences arise due to the fact that BEL model is originally designed for descriptive purpose with no engineering application in mind. Therefore, it is up-to the designer to appropriately select the sensory input signal and reward signal in accordance to engineering application.

Thus, we selected the sensory input function (S_i) to be of the form:

$$S_i = \mathbf{z} - \mathbf{x_1} \tag{14}$$

where $\mathbf{x_1}$ is the vehicle states obtained from the vehicle trajectory model, and $\mathbf{z}$ is measurement vector, which is composed of the computed position, velocity and clock errors from the GPS.

The reward function (*Rew*) is selected with objective of minimizing the difference between *GPS* and *Measured*. This function plays an important role in BEL filter. The filter attempts to increase the reward while minimizing the sensory input. The implemented reward function is given in Equation (15):

$$\mathrm{Re}\,w = -K_1 \left| S_i \right| + K_2 \tag{15}$$

where K_1 and K_2 are gains. The reward function gains are positive real numbers. From equation (15), it can be seen that BEL filter obtains maximum reward when the sensory input is zero. Closely noticing equation (14), the sensory input function is in essence, an error signal. The BEL filter tries to diminish this error.

4.2 Simulation Setup

In this study, a simulation of a ground vehicle around a track is utilized to draw performance comparison between Kalman Filter and the BEL filter. The performance of these two filter is based on their ability reduce noise from GPS as the vehicle trajectory is tracked. Two tracks are simulated, a circular and figure-8 track. The vehicle is modeled as traveling at a velocity of 5 m/s. The trajectory of the vehicle on the track is given by the following equation (Grewal, Weill, & Andrews, 2007):

$$\boldsymbol{\delta}_{pos} = \begin{bmatrix} Northing \\ Easting \\ -Down \end{bmatrix} = \begin{bmatrix} 3S\sin(\omega t + \phi) \\ 2S\sin(\omega t + \phi)\cos(\omega t + \phi) \\ -\frac{1}{2}h\cos(\omega t + \phi) \end{bmatrix} \tag{16}$$

where S is the track scaling parameter, h is the crossover height, ω is mean angular speed, and ϕ is an arbitrary phase angle. Implemented in MATLAB, this model calculates vehicle velocity, acceleration attitude, and attitude rates. The trajectories simulated can be seen in Figure 4.1. Both simulated tracks have changes in elevation of 10 meters.

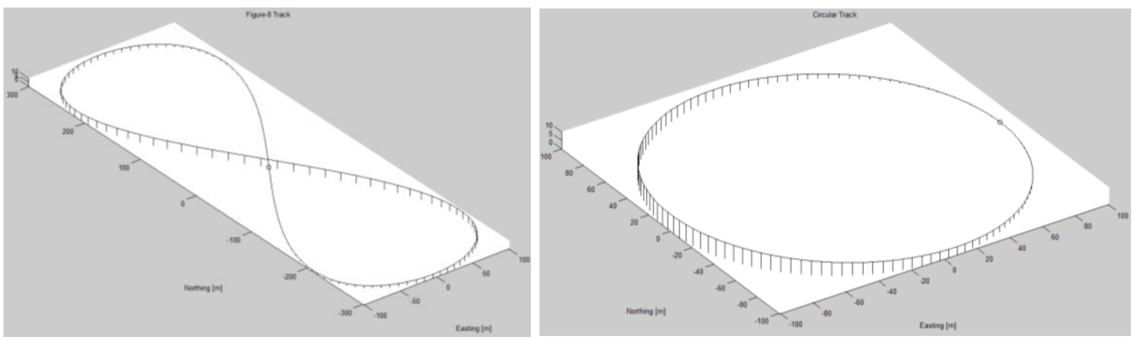

Figure 4.1. Figure-8 Track and Circular Track

The vehicle dynamic model consist of a Type2 Tracking Model. This tracking model can estimate position, velocity in three-dimensions, given the appropriate measurements. The tracker utilizes a host vehicle dynamic model with zero-mean white noise acceleration, unbounded steady-state mean squared velocity and unbounded steady-state mean squared position variations. The full tracking model is implemented, which include three position components and three velocity components. The necessary Kalman filter components for a three-dimension Type2 tracking filter are the following:

$$
\mathbf{P_0} = \begin{bmatrix} \sigma_N^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma_E^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma_D^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{v,N}^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_{v,E}^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_{v,D}^2 \end{bmatrix} \tag{17}
$$

$$
\mathbf{\Phi} = \begin{bmatrix} 1 & 0 & 0 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta t & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta t \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{18}
$$

$$
\mathbf{Q} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{acc}^2 \Delta t^2 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma_{acc}^2 \Delta t^2 & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma_{acc}^2 \Delta t^2 \end{bmatrix} \tag{19}
$$

where $\mathbf{P_0}$ is the estimation uncertainty covariance matrix, $\mathbf{\Phi}$ is the state-transition matrix, and $\mathbf{Q}$ is the covariance of dynamic disturbance noise.

The Kalman filter utilized for the performance comparison is of the following form:

$$
\mathbf{K} = \mathbf{PH}^{\mathrm{T}}[\mathbf{HPH}^{\mathrm{T}} + \mathbf{R}] \tag{20}
$$

where $\mathbf{K}$ is the Kalman gain, $\mathbf{H}$ is measurement sensitivity matrix, and $\mathbf{R}$ is the sensor noise covariance matrix.

$$
\mathbf{x}_1 = \mathbf{x}_1 + \mathbf{K}[\mathbf{z} - \mathbf{H}\mathbf{x}_1] \tag{21}
$$

where $\mathbf{z}$ is measurement vector, which is composed of the computed position, velocity and clock errors from the GPS.

$$\mathbf{P} = \mathbf{P} - \mathbf{KHP} \tag{22}$$

The implementation follows the above equations in chronological order. First, the Kalman gain is computed by equation (20). Followed by the corrected state estimation in equation (21). Lastly, the corrected covariance matrix is computed by equation (22). To finalize the Kalman filter implementation, the temporal updates are computed by the following equations:

$$\mathbf{x}_1 = \mathbf{\Phi}\mathbf{x}_1 \tag{23}$$

$$\mathbf{P} = \mathbf{\Phi}\mathbf{P}\mathbf{\Phi}^{\mathrm{T}} + \mathbf{Q} \tag{24}$$

To carry out the simulation a number of parameters had to be selected. First, the learning rates for the amygdala and OFC were selected to be $\alpha = 1e-6$, and $\beta = 1e-4$, respectively. The OFC learning rate was chosen to be slightly larger to make the OFC learn the error in the amygdala quicker than the amygdala itself to eliminate the error. The other parameters were the gains in the *Rew* function, which were selected to be K_1 = 0.001 and K_2 = 1. These parameters, and learning rates were selected through trial and error to improve BEL filter performance.

All simulations are carried out in MATLAB. The simulation time was selected to be 0.2 hours. The first 100 seconds of the simulation data was not sampled to allow settling time. The simulation was executed 100 iterations. The number of satellites for GPS were varied. In addition, GPS noise distributions were varied. Performance measures for both Kalman and BEL filter are average RMS error for positions, velocity, and average Central Processing Unit (CPU) time.

4.3 Simulation Results

The first scenario simulated is with a circular track. The number of satellites for this scenario is 29. The performance of Kalman filter and BEL filter were obtained, results are shown in the following table.

Table 4.1

Performance Comparison for Circular Track Simulation

Kalman Filter							
GPS Noise Distribution	Avg. CPU Time [sec]	Avg. RMS Error					
		Position N [m]	Position E [m]	Position D [m]	Velocity N [m/s]	Velocity E [m/s]	Velocity D [m/s]
N(0,2)	1.145	10.316	7.779	5.373	3.206	3.333	0.101
U(-1,1)	1.268	8.131	6.045	4.772	3.031	3.228	0.092
Exp(2)	1.165	10.819	8.305	8.245	3.192	3.335	0.157
Tri(-1,0,1)	1.133	7.854	5.721	4.749	3.027	3.212	0.089
Wei(1,2)	1.174	8.258	5.951	5.750	3.026	3.219	0.105
BEL Filter							
GPS Noise Distribution	Avg. CPU Time [sec]	Avg. RMS Error					
		Position N [m]	Position E [m]	Position D [m]	Velocity N [m/s]	Velocity E [m/s]	Velocity D [m/s]
N(0,2)	0.586	4.915	5.017	4.934	4.908	4.998	4.919
U(-1,1)	0.575	2.276	2.861	2.714	2.768	2.868	2.710
Exp(2)	0.593	4.925	4.885	4.894	4.927	4.935	4.911
Tri(-1,0,1)	0.540	1.937	2.010	1.907	1.944	2.014	1.907
Wei(1,2)	0.598	4.264	4.018	4.169	4.353	4.250	4.235

The above table demonstrates that BEL filter was superior in diminishing positional errors. This trend was maintained through all GPS noise distributions. In some cases, it even performed better than Kalman filter in reducing velocity errors. A significant result obtained is that BEL performed better in reducing the computational cost across all noise distribution cases. In the worst case, BEL CPU time was half of the Kalman filter best CPU time.

The second scenario simulated was with a figure-8 track. This simulation was conducted in similar fashion as the first scenario. The figure-8 track simulated a more demanding tracking trajectory. Table 4.2 illustrates the results obtained from the second simulation scenario.

Table 4.2

Performance Comparison for Figure-8 Track Simulation

Kalman Filter							
GPS Noise Distribution	Avg. CPU Time [sec]	Avg. RMS Error					
		Position N [m]	Position E [m]	Position D [m]	Velocity N [m/s]	Velocity E [m/s]	Velocity D [m/s]
N(0,2)	1.195	11.259	8.241	5.481	1.421	1.233	0.100
U(-1,1)	1.190	9.113	6.413	4.932	1.032	0.879	0.090
Exp(2)	1.198	11.429	8.451	8.470	1.458	1.211	0.152
Tri(-1,0,1)	1.158	8.674	6.196	5.034	1.002	0.858	0.089
Wei(1,2)	1.202	8.829	6.201	5.837	0.998	0.864	0.109
BEL Filter							
GPS Noise Distribution	Avg. CPU Time [sec]	Avg. RMS Error					
		Position N [m]	Position E [m]	Position D [m]	Velocity N [m/s]	Velocity E [m/s]	Velocity D [m/s]
N(0,2)	0.588	4.936	5.035	4.929	4.915	5.006	4.932
U(-1,1)	0.581	2.823	2.822	2.796	2.830	2.837	2.799
Exp(2)	0.591	4.939	4.928	4.905	4.957	4.943	4.854
Tri(-1,0,1)	0.543	2.006	1.972	1.992	2.009	1.995	1.992
Wei(1,2)	0.594	4.264	4.092	4.180	4.375	4.158	4.267

Results obtained from the figure-8 track simulation are similar to the ones obtained in the previous scenario, but with slightly higher CPU time and positional errors for both Kalman filter and BEL filter implementations. The figure-8 track appears to be no more rigorous than the circular track. For further performance comparison between the two filter implementations, a more interesting scenario is analyzed.

To conclude, the effects of the number of satellites available is analyzed. As previously discussed, the number of satellites is a detrimental factor for GPS to accurately calculate position and velocity of a vehicle. Therefore, for this last scenario the number of satellites is varied from 4 to 29. Their effects on the Kalman and BEL filter performance are obtained, shown in the table below:

Table 4.3

Effects of Number of GPS Satellites on Kalman and BEL Filter Performance

Kalman Filter: Normal Noise Distribution							
No. Sats	Avg. CPU Time [sec]	Avg. RMS Error					
		Position N [m]	Position E [m]	Position D [m]	Velocity N [m/s]	Velocity E [m/s]	Velocity D [m/s]
4	0.466	414.316	2694.149	258.880	2.096	6.439	0.075
9	0.620	29.285	30.007	29.869	1.831	1.695	0.129
14	0.767	14.058	8.515	6.582	1.712	1.258	0.106
19	0.920	12.259	8.546	6.077	1.527	1.258	0.105
24	1.011	12.051	8.294	5.774	1.519	1.242	0.104
29	1.195	11.259	8.241	5.481	1.421	1.233	0.100
BEL Filter: Normal Noise Distribution							
No. Sats	Avg. CPU Time [sec]	Avg. RMS Error					
		Position N [m]	Position E [m]	Position D [m]	Velocity N [m/s]	Velocity E [m/s]	Velocity D [m/s]
4	0.341	5.054	4.950	4.955	5.090	4.960	4.909
9	0.380	4.977	4.947	4.934	4.952	4.981	4.941
14	0.437	4.929	4.897	4.916	4.937	4.941	4.914
19	0.476	4.932	4.921	4.915	4.923	4.929	4.924
24	0.539	4.935	4.998	4.924	4.920	5.125	4.930
29	0.588	4.936	5.035	4.929	4.915	5.006	4.932

In the majority of the cases the RMS error for position and velocity increased as the number of satellites decreased for both filter implementations. However, the increments in the BEL implementation were small in comparison to the Kalman filter. In the Kalman filter implementation, the RMS error for position and velocity appear to grow exponentially when the satellites decreased from 14 to 4. The results demonstrate that the BEL filter is less sensitive to the effects of the number of satellites available. In addition, the CPU time increased as the number of satellites increased for both filter implementations. Although this effect was more noticeable for the Kalman filter implementation. Lastly, a similar trend was obtained in that the BEL filter was superior at diminishing positional errors, while the Kalman filter was superior at reducing the velocity errors. An important note about this scenario, the effects on the number of satellites was carried out with a Gaussian GPS noise distribution.

The results from this study demonstrated the BEL qualities as a filter. It successfully filtered the noise from GPS and was able to accurately follow the trajectory of a vehicle around a track. It demonstrated robustness to a variety of noise distributions, and all this with significantly less computational cost.

CHAPTER 5

INTELLIGENT CONTROLLER TUNING UNIT

As discussed in the literature review, Section 2.4.3, there are two widely used methods for classifying human driving behavior: questionnaires after a driving task and through data logging of vehicle parameters (steering angle, throttle position, brake position, etc.). Consequently, the purpose of this study is to develop, test, and compare the performance of an alternative method for classifying human driving behavior. The proposed alternative method in this study consist of two parts: I.) Capturing a human's affective states. II.) Classifying driving behavior based on captured affective states. Figure 5.1 illustrates the driving behavior classification through affective state methodology.

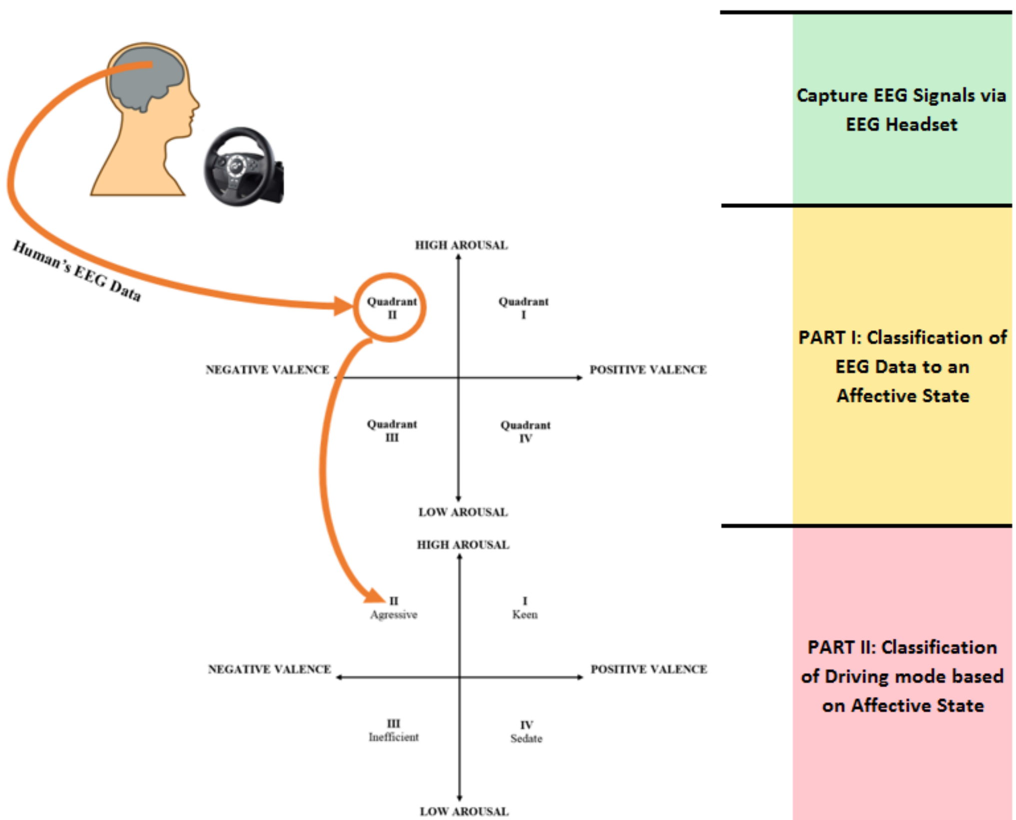

Figure 5.1. Proposed Driving Behavior Classification Approach

This driving behavior classification method can potentially have the advantages of being used in real-time, not dependent of driving terrain, and comparably accurate to current methods.

More importantly, findings from this study can be used in the development of an intelligent controller tuning unit. As previously mentioned, this unit is intended to be implemented for the purpose of giving the UGV the ability to sense and utilized the operator's affective state, then to tune BELBIC controller performance to mimic desired mode/tactic of operation. This unit along with the other proposed components will allow the CS to robustly control the UGV in the absence of timely control input from a human operator.

In this chapter an alternative method for driving behavior classification through human affective states is developed, and its implementation is proposed. The chapter is organized as follows. Section 5.1 outlines the objectives of this study. Section 5.2 explains the study design. Section 5.3 discusses Experiment I design and results. Section 5.4 presents Experiment II design and results. In section 5.5 driving behavior classification through EEG measurement is explored. Lastly, section 5.6 discusses implementation of a novel method for driving behavior classification as the intelligent controller tuning unit for the proposed CS.

5.1 Objectives

This study consists of two parts. The objective of Part I, is to capture and classify a human's affective state into one of the four emotional states (a quadrant) in the valence-arousal model, shown in Figure 5.1. The human's affective states is captured through an

EEG headset worn by the participant. The participant's emotion is elicited through the viewing of images. Affective state classification of raw EEG signals is done through a neural network technique.

Successively, the objective of Part II is to classify the human driving behavior based on the classified human affective state. This is accomplished by collecting EEG data of a person while driving a simulated automobile. Driving behavior is classified into one of four driving modes, shown in Figure 5.1.

5.2 Study Design

The proposed study consists of two experiments for each participant. The purpose of the first experiment (Experiment I) is to validate and test the effectiveness of the affective state classification through EEG measurement. Experiment I only consists of PART I, shown in Figure 5.1. Experiment I follows a simplistic manner of data collection in which the participant's EEG data is recorded while they are viewing an image (stimulus with varying levels of valence and arousal), and at a relaxed state (blank-white screen). In addition, a quick survey in between images is given to assess the participant's emotional state based on arousal/valence levels. This experiment only gathers data about the participant's EEG recordings, and their self-assessment of their emotional state.

The purpose of the second experiment (Experiment II) is to assess the performance of the proposed driving behavior classification method. Experiment II consists of all the processes depicted in Figure 5.1 (PART I and PART II). Similarly, this second experiment follows a simplistic manner of data collection in which the participant's EEG data is recorded while they are operating a simulated vehicle.

Concurrently, vehicle parameters such as vehicle speed, brake pedal position, throttle pedal position, and steering angle are recorded. The specific details of each experiment is discussed in the following sections.

5.3 Experiment I

5.3.1 Methods

Participants: The group of participants used in this study consisted of four healthy volunteers (two females and two males) with no previous history of epilepsy, and or seizures. Their age ranged from 18 – 35 years. This age range was selected to be similar to current United States Armed Forces enlistment age. Additionally, all participants met the following inclusion criteria:

1. Have a valid driver’s license
2. Full range limb motion including: arms, hands, legs, knees, and feet
3. Ability to follow simple instructions
4. Ability to wear EEG headset

This criteria was selected because these same participants are used for Experiment II, in which they drive an automobile in a driving simulator. Additionally, the effects of driving experience was reduced due to age range and driver’s license requirement. All the participants were given written consent prior to the recording. Every participant was given information about the design and purpose of the experiment.

Materials and Apparatus:

A PowerPoint presentation was used to display a blank-white screen for 5 seconds before each stimulus was displayed. A slide of the stimulus was then displayed on the monitor for 6 seconds. Lastly, a prompt was then displayed to instruct participants to conduct their self-assessment.

An EPOC EEG headset was used to record the participant's EEG signals. EPOC is a research-grade EEG headset aimed for the general consumer for the purposes of education, entertainment, health and research (EMOTIV, 2014). This headset has the capability to measure raw EEG signals from four brain waves (γ, θ, α, β), distinguish and measure four mental states (excitement, engagement/boredom, meditation, and frustration), and detect facial expressions. EPOC records from 14 channels with a 10-20 International electrode placement. It has a built in sinc filter allowing frequencies 0.2 – 45 Hz. Figure 5.2 demonstrates the EPOC EEG headset. In addition, Emotiv provides various toolkits to allow users to link the headset, record real-time raw EEG data, and process the data (Software Development Kit: User Manual , 2014). Before any experiment was conducted, the participant was provided with the opportunity to gain familiarity with EPOC EEG headset. In addition, correct placement of the EEG headset for each participant was ensured to obtain the most accurate EEG signal readings. EEG recordings were taken while the participant was viewing the blank-white screen, and while he/she was viewing the stimulus. The EEG recordings were sampled at fixed rate of 128 Hz for all the channels.

Figure 5.2. EPOC EEG Headset by Emotiv (EMOTIV, 2014)

After each stimulus, the participants were asked to take a paper survey of their self-assessment of their emotional state based on levels of valence and arousal. This survey consisted of a version of the Self-Assessment Manikin (SAM), which is a pictorial based assessment technique that directly measures the valence, and arousal associated with the participant’s affective reaction to a stimuli (Bradley & Lang, 1994; Chanel, Kronegg, Grandjean, & Pun, 2006). Figure 5.3 illustrates the self-assessment survey.

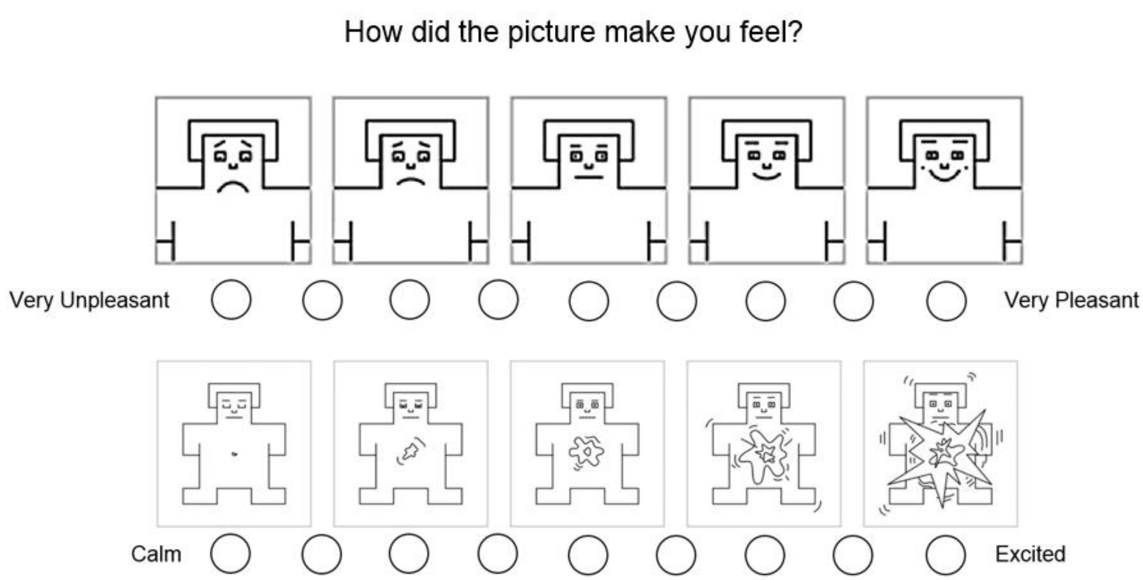

Figure 5.3. Self-Assessment Survey (Bradley & Lang, 1994)

Stimulus: The stimulus for this experiment consisted of several images. Emotions were elicited by showing images that have been selected from IAPS, in which these images have been extensively evaluated in terms of valence/arousal values and with collective means and variances. 10 images were selected from each quadrant in the valence-arousal model (40 total images). The images were selected by selecting the extremes from each quadrant in the valence/arousal model. This approach was taken so that the image would correctly elicit the emotion the image was intended for. The IAP images used in this experiment are listed in Appendix B. Each IAP image was shown to the participants for 6 seconds.

Procedure: The procedure for this experiment was as follows. Participants equipped with an EPOC EEG headset sat in front of a computer monitor in a bare room. They were instructed to relax and avoid movement. A blank-white screen was first displayed for 5 seconds to allow the participants to relax and prepare for the ensuing image. Successively, an IAP image was shown to the participants for 6 seconds. Participants were then instructed to take a self-assessment of their emotions based on level of valence and arousal. The self-assessment period was without any time constraint, to also allow them to rest and 'regroup'. Subsequently, the process was repeated for each image. This process is shown in Figure 5.4. The actual experiment duration was approximately 25 minutes per participant.

Blank Screen	IAP Image	Self Assessment
5 sec.	6 sec.	Approx. 20 sec.
Time --->		
EEG recording -------------------------------->|		

Figure 5.4. Experiment Procedure

Data Analysis:

Measured EEG signals contain valuable information about brain activity. However, majority of these signals consist of a lot of background noise. Therefore, in order to use these signals for emotion recognition, they have to be preprocessed in order to remove unwanted noise. Additionally, certain features are important for distinguishing human emotions. As a result, this EEG data analysis follows a similar approach as discussed in literature review, in that there will be preprocessing, feature extraction, and finally classification.

The raw EEG data was first preprocessed by a band pass filter to only allow frequencies of 4 – 45 Hz, in efforts to remove any noise and artifacts. Figure 5.5 illustrates the band pass filter. Secondly, the baseline from each electrode channel was removed. Lastly, only the EEG recordings in which the participant was viewing the image was selected, approximately 6 seconds per image. All the preprocessing steps were implemented through EEGLAB MATLAB Toolbox (EEGLAB, 2014).

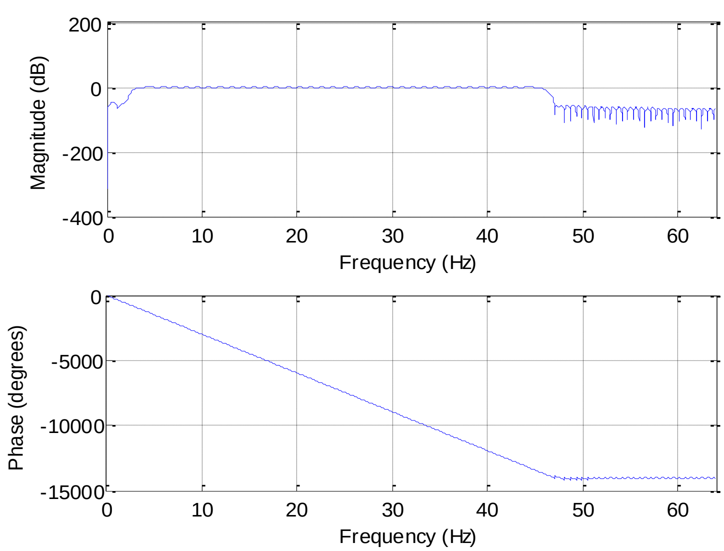

Figure 5.5. Band Pass Filter

After the preprocessing the EEG data, features were extracted from the EEG data to make more noticeable the differences between signals at each emotional state. The features that were extracted were the following:

- Amplitude and location of the highest 6 peaks of Welch’s Power Spectral Density function of each electrode channel (168 features)
- Amplitude of first peak, amplitude and location of the second peak in the Auto-correlation for each electrode channel (42 features)

These features were selected because this feature extraction approach typically produced the most distinguishable features of the signals at different emotions, as found in previous studies (Chanel, Kronegg, Grandjean, & Pun, 2006; Choppin, 2000; Musha, Terasaki, Haque, & Ivanitsky, 1997). The total number of features extracted from the EEG data when viewing an image was 210 features.

Lastly, for classification of EEG measurements an ANN was implemented using MATLAB Neural Network Toolbox. The network was trained, validated and tested to classify the participant’s affective state from their EEG data for each image. It is important to point out that a neural network was created for each participant. Each network was trained, validated and tested with the EEG data from one participant. Table 5.1 provides details of each neural network classifier.

Table 5.1

Affective State Classifiers using EEG Data from each Participant

Neural Network Classifiers: Structure						
Participant	No. of Inputs	Inputs	Samples	No. of Hidden Neurons	No. of Outputs	Outputs
1	210	Features from EEG Data	39 Images	20	4	Affective State
2	210	Features from EEG Data	37 Images	20	4	Affective State
3	210	Features from EEG Data	38 Images	20	4	Affective State
4	210	Features from EEG Data	40 Images	20	4	Affective State

The structure of the ANN consisted of 20 hidden neurons in the hidden layer. The EEG data was classified into one of the four distinct quadrants of the valence-arousal model. Each quadrant in the valence-arousal model encompasses a number of emotions, as shown in Figure 2.5. Depending on the degree of valence and arousal of the EEG data, the affective state was classified as one of the quadrants in the model. Figure 5.6 shows this model.

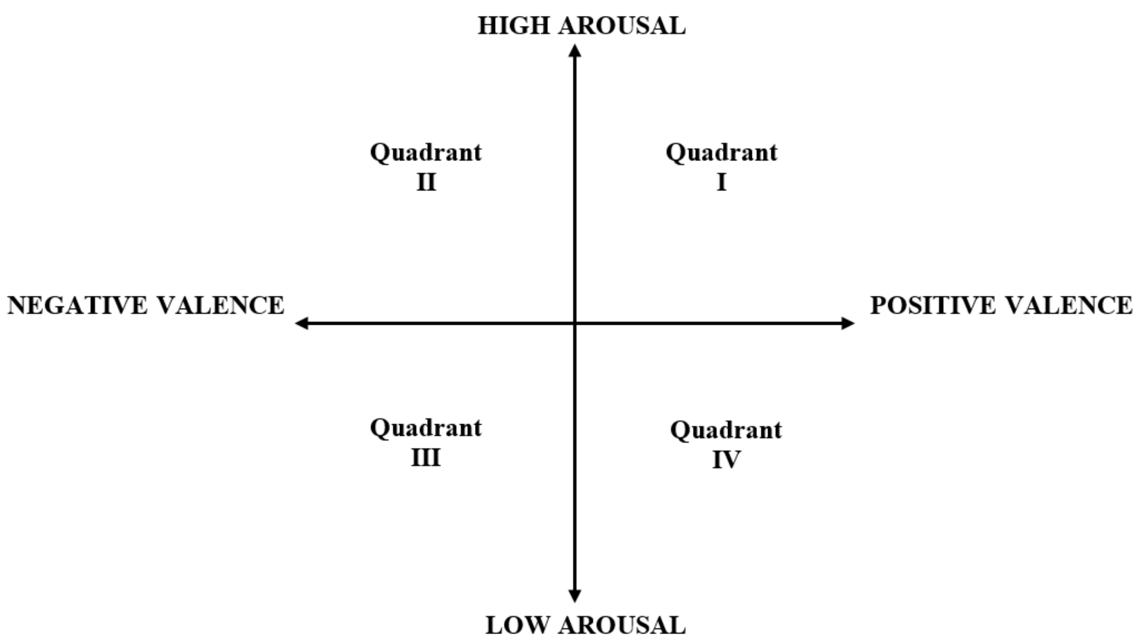

Figure 5.6. Affective State Classification Based on Valence-Arousal Model

5.3.2 Results

As mentioned before, the images used in this experiment sometimes do not evoke the emotion they are intended for. This is due to a number of reasons. First, the participant might have difficulty in assessing his/her emotions when filling in the self-assessment survey. Another reason can be that the images evoke other emotions than denoted in the IAPS list, due to the participant's life experience or other factors. To investigate this matter, the correspondence between the IAPS picture scores and the self-assessment survey scores are analyzed.

The Pearson correlation coefficient between the IAPS scores and survey scores from all participants were 0.93 for the valence dimension, and 0.91 for the arousal dimension. These coefficients indicate that there is very good correspondence between expected emotions and the experienced emotions in both dimensions. This fact is also obtained by the mean difference between the two scores. Figure 5.7 shows the distribution of the differences between the IAPS scores and their self-assessment scores for both dimensions.

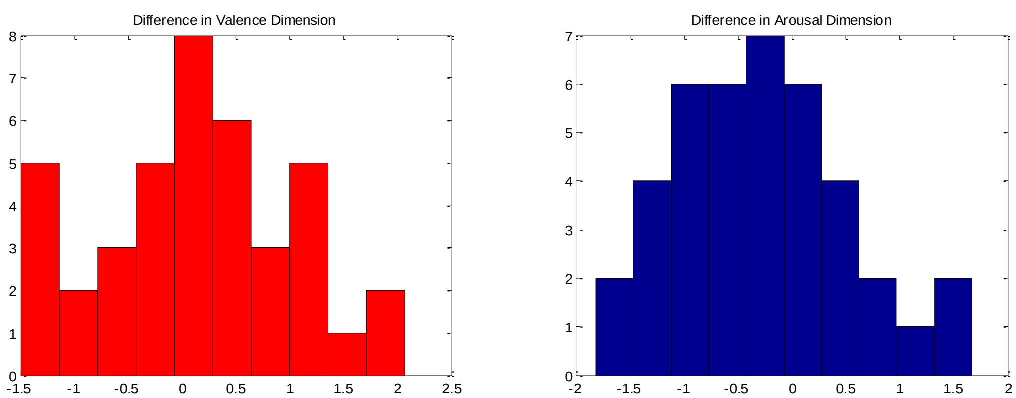

Figure 5.7. Distributions of the Differences between IAPS Scores and Self-Assessments Scores for All Participants for each Dimension

The differences in the both dimensions are more or less normally distributed (mean of zero), as expected. However, the arousal dimension is slightly less accurate.

In proceeding with the experiment's objective, the classification of the participants' affective state through EEG measurement, the following results were obtained. The neural network was able to correctly classify affective states of all the participants using their EEG data at an average accuracy of 88.35%. Table 5.2 shows this results.

Table 5.2

Neural Network Emotion Classification Accuracy for All Participants EEG

Correct Target Classification of Emotions					
Subject	**QI**	**QII**	**QIII**	**QIV**	**Total Accuracy**
S1	90.0%	88.9%	80.0%	90.0%	**87.2%**
S2	90.0%	77.8%	100.0%	88.9%	**89.2%**
S3	88.9%	90.0%	88.9%	90.0%	**89.5%**
S4	80.0%	100.0%	80.0%	90.0%	**87.5%**
Average	87.23%	89.18%	87.23%	89.73%	**88.35%**
STDEV	4.20%	7.86%	8.22%	0.48%	**1.17%**

Several interesting results were obtained. First, the results indicate that the features selected in the feature extraction process were successful at differentiating the EEG signals of different emotional states. Secondly, of the four quadrants in the valence-arousal model, quadrant IV had the highest average accuracy with the smallest standard deviation for all participants. In contrast, emotions in quadrant III had one of the lowest average accuracy with highest standard deviation. Interestingly, male participants (S2 and S3) had slightly higher total accuracy than female participants (S1 and S4).

An important note, is that for some of the participants EEG data was not usable, due to too much movement, or recording errors. Thus, some the participant's neural network classifier had less data to classify. Table 5.3 shows the samples that were removed. This could have affected their accuracy.

Table 5.3

Image Samples Removed

Subject	Number of Images removed from:				Total Images used
	QI	QII	QIII	QIV	
S1	0	1	0	0	**39**
S2	0	1	1	1	**37**
S3	1	0	1	0	**38**
S4	0	0	0	0	**40**

Nevertheless, results indicate high accuracy at distinguishing and classifying the participants' emotional state through EEG measurement.

5.4 Experiment II

For the second part in this study, the association of the human's affective state to driving behavior, it is anticipated that the human's affective state can be mapped into one of 4 distinct driving modes: keen, aggressive, inefficient, and sedate. Each of these driving behaviors can be characterized by a number of emotions. Therefore, each driving mode is mapped to the quadrant where the emotions that characterize them are located. This approach closely follows the method used for associating driving moods to affective states (Cacciabue, 2007). Figure 5.8 demonstrates the mapping of emotions to driving modes in a modified valence-arousal model.

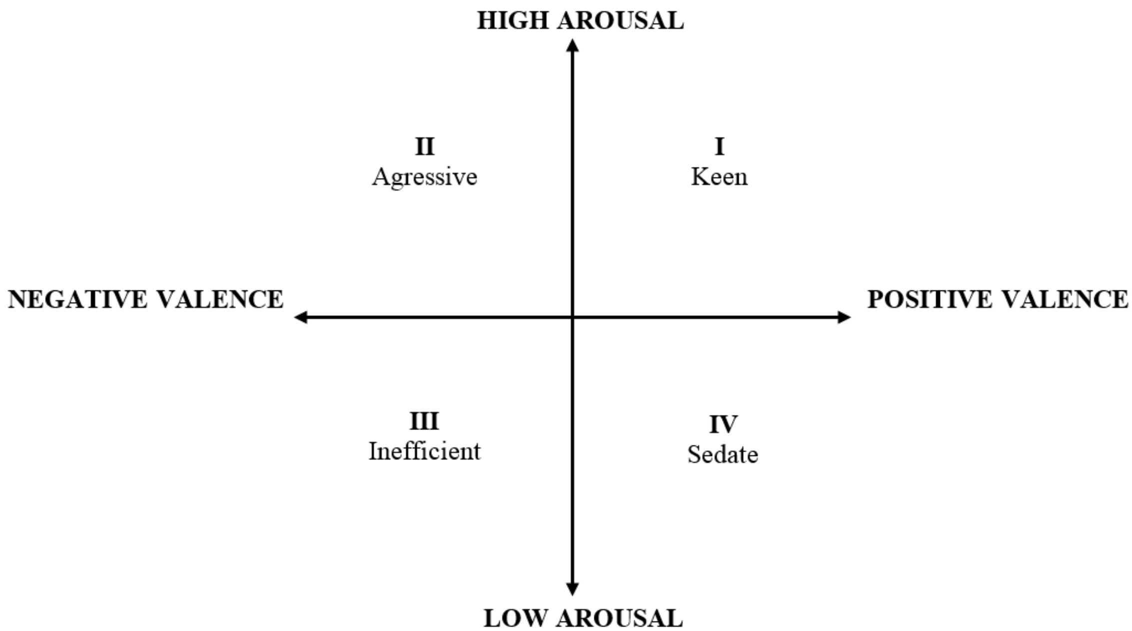

Figure 5.8. Mapping of Driving Mode to Affective States

Our definition of the driving behaviors are the following (Bar, Nienhuser, Kohlhaas, & Zollner, 2011):

Keen:

A keen operator is a person characterized as being in an eagerness or enthusiastic emotional state; that is in a high-arousal and with positive valence state (Summala, 2007). In terms of vehicle operation, the operator is well aware of the vehicle's characteristics and will utilized the full dynamics of the vehicle. Maneuvering of vehicle is quick and precise. Any deviations from the desired response is quickly corrected. Drives at or slightly above speed limit

Aggressive:

An aggressive operator is a person characterized in using forceful methods to succeed or to accomplish a goal; that is in a high-arousal state, but with a negative valence (Summala, 2007). Generally, taking high risks. In terms of vehicle operation, it is similar to keen, in being quick maneuvering, but irresponsible. Drives close to other vehicles, and driving at higher speeds and accelerations. Due to the reckless maneuvering, the response is less precise.

Inefficient:

An inefficient operator is characterized by the emotional state of fatigue, boredom; that is in a low-arousal and negative valence state (Summala, 2007). In terms of vehicle operation, the operator will tend to deviate from planned trajectory, speed of vehicle will greatly vary. Maneuvering is slow and imprecise.

Sedate:

A sedate operator is characterized as being in a relaxed, calm emotional state; that is in low-arousal and positive valence state (Summala, 2007). In terms of vehicle operation, it is in a constant, restrained and responsible manner. Maneuvering is very slow but precise.

To assess the accuracy of the association of human's emotional state to the driving behavior, a simulated driving experiment is performed

5.4.1 Methods

Participants: The same four participants that were used in Experiment I, because results of the previous experiment are used in this experiment.

Materials and Apparatus:

The apparatus required for this experiment were the following. The experiment was performed in RS-600 by DriveSafety (DriveSafety, 2015), which is a high performance, high fidelity driving simulation system designed for use in ground vehicle research, training and assessment applications. Figure 5.9 shows the driving simulator. This driving simulator is located in SIM building at ASU Polytechnic campus. The simulator has the capability to record various vehicle parameters: vehicle speed, brake pedal position, throttle pedal position, steering angle and other user-defined parameters. These parameters were recorded as participants operated the simulated vehicle around a planned driving route.

Figure 5.9. RS-600 Driving Simulator in SIM Building

An EPOC EEG headset was used to record the participant's EEG signals. Recordings were taken while the participants operated the simulated vehicle around a planned driving route.

Stimulus: The stimulus for this experiment was a planned driving route in a simulated environment. Figure 5.10 illustrates the layout of the simulated driving route. The planned route consisted of several curved roads, left/right turns, and with instances where the participants was required stop and go. In addition, the driving route had varying degrees of traffic. Additionally, the route had varying speed limit signs. More importantly, the planned route had several preplanned scenarios to evoke a number driving responses.

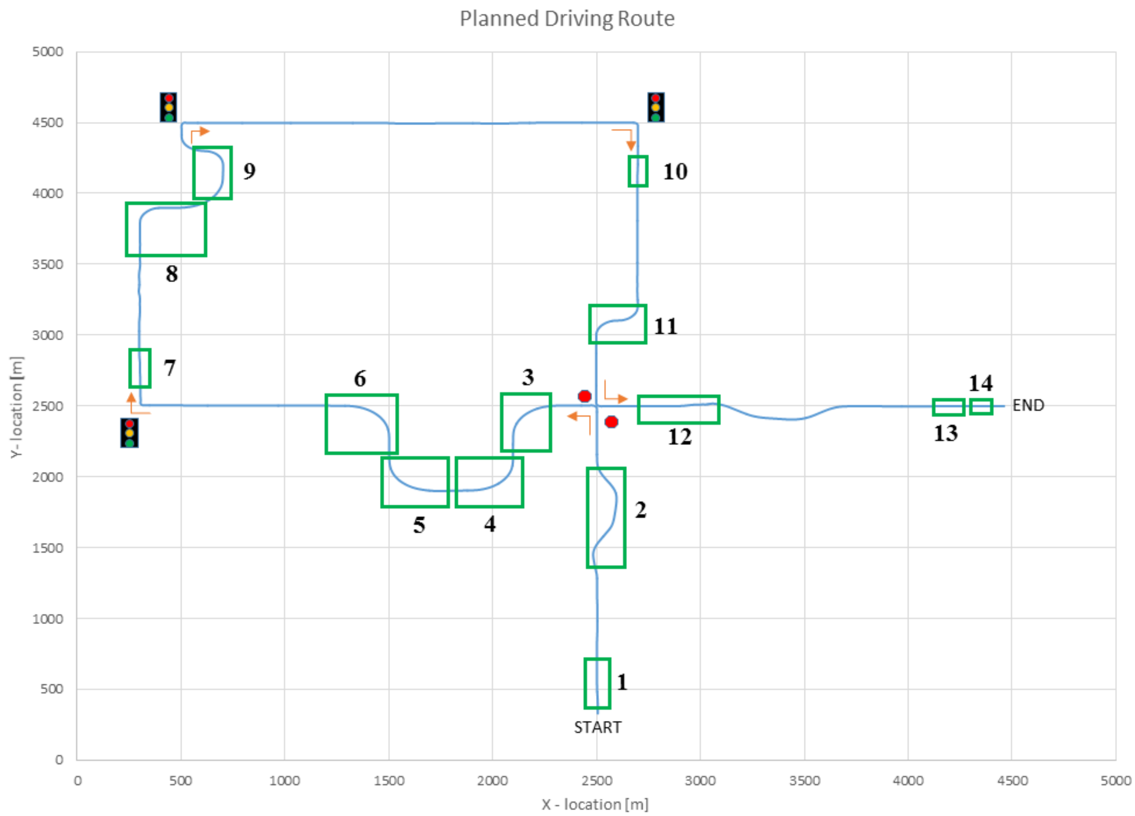

Figure 5.10. Planned Driving Route

The green boxes indicate the location of the different driving scenarios. There were a total of 14 driving scenarios. Details of each scenario are described in Table 5.4.

Table 5.4

Driving Scenarios Descriptions

Scenario	Details
1	School bus pulls over, no stopping lights, in a residential setting and speed limit at 35 mph
2	On coming police and emergency vehicles with sirens and lights on. Two lane road with winding hills, and speed limit at 50 mph
3	Encounter traffic behind a very slow vehicle in a two lane road, no passing, and speed limit at 50 mph
4	Behind very slow driver in a two lane curved road, no passing, and speed limit at 50 mph. Car directly in-front of the subject's vehicle illegally passes slow vehicle
5	Directly behind slow vehicle in a two lane curved road, no passing, and speed limit at 45 mph
6	Directly behind slow vehicle in a two lane road, passing is permitted, and speed limit at 55 mph.
7	Encounter another slow vehicle, but it quickly speeds up. Two lane road, passing is permitted and speed limit at 45 mph
8	Tight curves in a two lane road, no passing, and speed limit at 45 mph
9	Encounter police vehicles pull to the side of the road, and lights are on. Two lane road, tight curves, no passing, and speed limit at 45 mph
10	Urban setting, two lane road with parked cars, and speed limit at 40 mph. Parked car has turn signal on indicating it plans to merge into roadway. Car merges directly in-front of subject's vehicle
11	Tight curves in a two lane road, no passing, and speed limit at 45 mph
12	Encounter police vehicle parked on the side of the road. Once subject passes police, police vehicle turns on lights and sirens. Two lane road, passing is permitted, and speed limit 55 mph
13	Approach residential neighborhood. Two lane road, passing is permitted, and speed limit at 25 mph. There is a bicyclist
14	Residential setting, a dog crosses the roadway. Speed limit at 25 mph

These driving scenarios were selected to evaluate the driving behavior of the participants. In all the scenarios the following vehicle parameters were measured: vehicle speed, lane position, steering angle, brake pedal position, throttle pedal position, lateral acceleration, and longitudinal acceleration. These parameters have been successfully used to determine driving behaviors/styles (Bar, Nienhuser, Kohlhaas, & Zollner, 2011). In addition, headway distance was a user-defined parameter used for driving Scenario 1 and Scenario 3 – 6, which measures the distance between the participant's vehicle and the vehicle in-front.

Procedure: The procedure for this experiment was as follows. Each experimental session began with a 10 minutes practice trial, designed to allow the participants to become comfortable with driving in the virtual environment. During this session, participants drove on a roadway similar to the planned driving route.

For the actual experiment, participants were first instructed to drive as they would in real life, by following all road rules, and road signs that they encountered. In addition, the participants were asked to follow driving directions of the planned driving route. EEG recordings were taken throughout the entire driving simulation. Concurrently, vehicle parameters such as speed, brake pedal position, throttle pedal position, steering angle, etc. were recorded. The driving simulation lasted approximately 14 minutes.

Data Analysis:

First, neural network classifiers for each driving scenario were created. These classifiers were created by driving in each of the driving behaviors/styles through each driving scenario. A total of 14 neural network classifiers were created. Table 5.5 shows the classifiers structure and performance. These classifiers would be used to classify the participant's driving behavior using their vehicle data for each driving scenario.

Table 5.5

Driving Behavior Classifiers using Vehicle Data for each Driving Scenario

Neural Network Classifiers: Structure and Performance						
Scenario	No. of Inputs	Inputs	No. of Hidden Neurons	No. of Outputs	Outputs	Accuracy [%]
1	8	Vehicle parameters and headway distance	8	4	Driving Behavior	91.4
2	7	Vehicle parameters	7	4	Driving Behavior	92.5
3	8	Vehicle parameters and headway distance	8	4	Driving Behavior	98.7
4	8	Vehicle parameters and headway distance	8	4	Driving Behavior	100
5	8	Vehicle parameters and headway distance	8	4	Driving Behavior	100
6	8	Vehicle parameters and headway distance	8	4	Driving Behavior	98.5
7	7	Vehicle parameters	7	4	Driving Behavior	99.1
8	7	Vehicle parameters	7	4	Driving Behavior	99.2
9	7	Vehicle parameters	7	4	Driving Behavior	96.5
10	7	Vehicle parameters	7	4	Driving Behavior	86.3
11	7	Vehicle parameters	7	4	Driving Behavior	98.3
12	7	Vehicle parameters	7	4	Driving Behavior	95.5
13	7	Vehicle parameters	7	4	Driving Behavior	96.9
14	7	Vehicle parameters	7	4	Driving Behavior	100

Secondly, the participant's EEG data collected while driving would be used as inputs for the neural network used to classify their emotions in Experiment I. Their EEG data from this experiment would be treated as if it was the EEG data while viewing an image. Hence, the participant's EEG data at each driving scenario would be preprocessed, feature extracted and classified in the same manner as in Experiment I.

5.4.2 Results

Driving behavior classification through the use of vehicle parameters produced the following results, shown in Table 5.6.

Table 5.6

Driving Behavior Classification through Vehicle Parameters

Driving Behavior Classification using Vehicle Parameters				
Driving Scenario	Participants:			
	S1	S2	S3	S4
1	Inefficient	Inefficient	Inefficient	Keen
2	Sedate	Sedate	Keen	Keen
3	Keen	Inefficient	Keen	Keen
4	Inefficient	Inefficient	Sedate	Inefficient
5	Inefficient	Inefficient	Sedate	Inefficient
6	Keen	Inefficient	Keen	Inefficient
7	Aggressive	Inefficient	Inefficient	Keen
8	Sedate	Sedate	Aggressive	Inefficient
9	Sedate	Inefficient	Keen	Keen
10	Inefficient	Keen	Inefficient	Sedate
11	Inefficient	Sedate	Inefficient	Inefficient
12	-	Inefficient	Aggressive	Sedate
13	-	Keen	Inefficient	Keen
14	-	Keen	Keen	Sedate

Aggressive driving was the least classified driving mode, this could be due to a number of factors. One could be that the driving scenarios did not provoke such driving behavior. Another possibility is that since the participants know they are being monitored they might change their driving behavior. In contrast, inefficient was the most classified driving behavior. Again this could be due to a number of reasons, such as, the participants not having enough time get familiar with driving in a simulated environment.

However, several interesting results were noticeable. First, participant S2 was classified most often as inefficient. This participant in fact had the least amount of driving experience. Interestingly, for a majority of the instances that this participant was classified as inefficient occurred in scenarios that involved curved roads. In contrast, participant S4 was the participant most often classified as a keen driver, and this participant was the most experienced driver. Additionally, if keen and sedate are considered desirable driving behavior, while aggressive and inefficient as undesirable. Then the most experienced drivers, S3 and S4, were classified as driving in a desirable driving mode 64.2% and 50% of the time, respectively. In contrast, the less experienced drivers, S2 and S1, drove in desirable driving behavior 42.8% and 45.4% of the time, respectively.

Another interesting observation was that the participants that were classified as inefficient in driving scenarios 3 – 6, were the ones that were observed driving too close and then too far from the slow motorist. Lastly, an interesting event that was captured, was that participant S3 attempted to pass the vehicle in scenario 7, but when the vehicle sped up, the participant had to get back behind the vehicle, and thus this participant was classified as inefficient for this scenario.

An important note, is participant S1 started to feel motion sickness, so the experiment was immediately stopped. As result, the participant was unable to finish the entire driving simulation.

Now, in regards to driving behavior classification through the use of affective states, the following results were obtained.

Table 5.7

Driving Behavior Classification through Captured Affective States

Driving Behavior Classification using Participants' Affective State				
Driving Scenario	Participants:			
	S1	S2	S3	S4
1	Sedate	Inefficient	Keen	Keen
2	Sedate	Inefficient	Keen	Keen
3	Sedate	Aggressive	Aggressive	Keen
4	Sedate	Inefficient	Aggressive	Keen
5	Sedate	Inefficient	Aggressive	Keen
6	Sedate	Inefficient	Keen	Keen
7	Sedate	Aggressive	Inefficient	-
8	Sedate	Aggressive	Aggressive	-
9	Sedate	Inefficient	Keen	-
10	Sedate	Inefficient	Aggressive	Keen
11	Sedate	Aggressive	Keen	Keen
12	-	Aggressive	Keen	Keen
13	-	Aggressive	Aggressive	Keen
14	-	Sedate	Keen	Sedate

In analyzing the results obtained, it is easily noticeable that there is not a direct correspondence of driving behavior classification from vehicle parameters to classification using the participants' affective state. This could be due to a number of factors. One of them, can be that affective states are not a dominant factor in guiding driving behavior as anticipated. However, there was some consistency between both classification methods. The most inexperienced driver was again classified most often as inefficient, whereas one of the most experienced driver was classified as keen. In addition, several interesting things were observed. First, all of the female participants most often had a consistent emotional state throughout the entire driving experiment, and that emotional state was positive in valence. In contrast, male participants were the only ones to be classified in an aggressive emotional state, negative valence and high arousal. Furthermore, the scenarios in which participants S2 and S3 where behind the slow driver, were the scenarios where they were classified as aggressive.

An important note, is that participant S4's EEG headset momentarily lost signal during scenarios 7-9, as a result, driving behavior classification through affective states was not possible.

To investigate whether the emotional states felt while driving were consistent to the emotional states felt while viewing images, their auto-correlation was compared. For a positive valence and high arousal affective state, the researcher selected participant S4 because this participant had the most instances classified as keen through affective state methodology. S4's EEG data for driving scenario 7 was selected, because in this particular scenario the classification of keen was the most accurate. Lastly, S4's EEG data while viewing images in Quadrant I were selected. The auto-correlation was computed for both EEG data sets. Figure 5.11 shows this comparison.

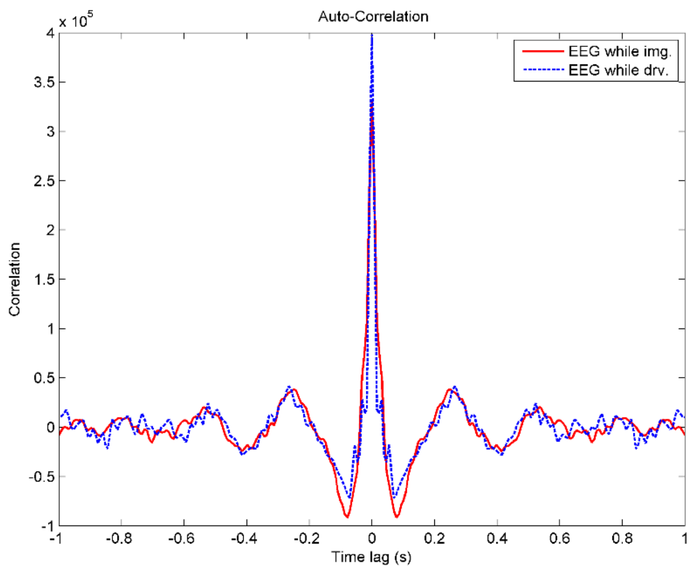

Figure 5.11. Quadrant I: Auto-Correlation of EEG while Viewing an Image vs. while Driving

The above results shows that there is good correlation between the participant's affective state while viewing an image and driving, even though the affective state occurred while doing very different tasks. Similar procedure was continued for the remaining three affective states.

However, for an affective state that was negative valence and high arousal, participant S3 was selected. Since this participant had the most instances classified as aggressive through affective state. While for an affective state that was negative valence and low arousal, participant S2 was selected. Since this participant had the most instances classified as inefficient through affective state. Lastly, for an affective state that was positive valence and low arousal, participant S1 was selected. Since this participant had the most instances classified as sedate through affective state.

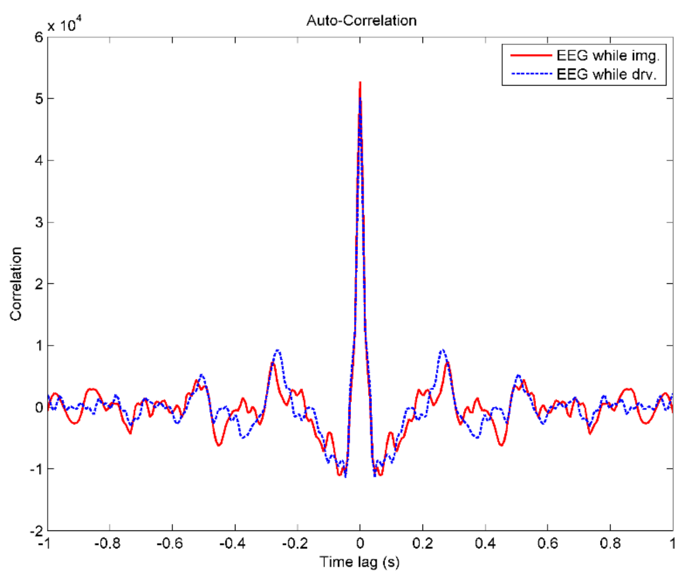

Figure 5.12. Quadrant II: Auto-Correlation of EEG while Viewing an Image vs. while Driving

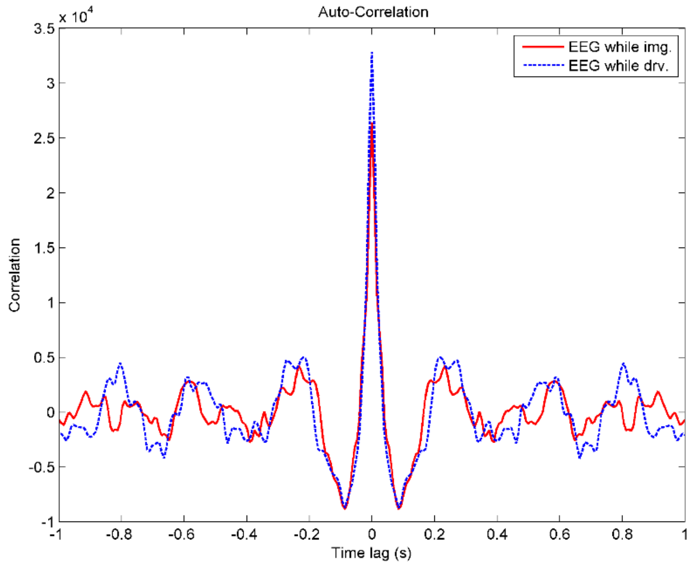

Figure 5.13. Quadrant III: Auto-Correlation of EEG while Viewing an Image vs. while Driving

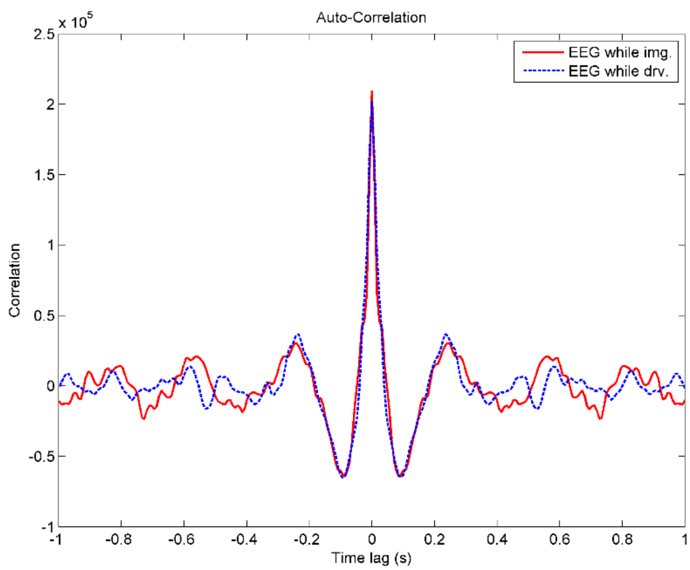

Figure 5.14. Quadrant IV: Auto-Correlation of EEG while Viewing an Image vs. while Driving

The results shown in Figures 5.11 – 5.14 all indicate that affective state the participants felt while driving were similar to the affective states felt while viewing images. Additionally, these results further illustrate that even though the participants were under a particular affective state while driving, this did not directly influence their driving behavior.

5.5 Driving Behavior Classification using Participants' EEG

Because a one-to-one correspondence was not obtained between participants' driving behavior and their affective state, an alternative method was explored in this section. This alternative method was intended for classification of driving behavior from the participants' EEG data as they are driving/operating a vehicle. It is important to point out that this is not the same as what was proposed and implemented in the above section. To reiterate, in the previous method the affective state classifier, obtained from Experiment I, was used to classify the participant's EEG data to an affective state while driving. This affective state was then associated to a driving behavior. Thus, the results on Table 5.7 were obtained.

The method explored here consists of the following. First, assuming that the participant's driving behavior obtained from vehicle parameters was entirely accurate for each driving scenario, the researcher created a neural network classifier for the participant's EEG data using their "known" driving behavior as a target. For example, participant S1 EEG data collected for driving scenario 1 was assigned the target class Inefficient. For driving scenario 2, participant S1 EEG data was assigned the target class Sedate. This process was repeated for all scenarios and for each participant. As a result four neural networks were constructed, one for each participant. The details of these neural networks are shown in Table 5.8.

Table 5.8

Driving Behavior Classifiers using EEG data from each Participant

Neural Network Classifiers: Structure						
Participant	No. of Inputs	Inputs	Samples	No. of Hidden Neurons	No. of Outputs	Outputs
1	210	Features from EEG Data	11 Driving Scenarios	20	4	Driving Behavior
2	210	Features from EEG Data	14 Driving Scenarios	20	4	Driving Behavior
3	210	Features from EEG Data	14 Driving Scenarios	20	4	Driving Behavior
4	210	Features from EEG Data	14 Driving Scenarios	20	4	Driving Behavior

The results obtained for each participant are shown in the following tables.

Table 5.9

Neural Network Confusion Matrix for each Participant

Table 5.10

Driving Behavior Classification through Participants EEG Data

Driving Behavior Classification using Participants' EEG				
Driving Scenario	**Participants:**			
	S1	**S2**	**S3**	**S4**
1	**Sedate**	Inefficient	Inefficient	Keen
2	Sedate	Sedate	Keen	Keen
3	Keen	Inefficient	Keen	Keen
4	Inefficient	Inefficient	Sedate	Inefficient
5	Inefficient	Inefficient	Sedate	Inefficient
6	Keen	Inefficient	Keen	Inefficient
7	Aggressive	Inefficient	Inefficient	-
8	Sedate	Sedate	Aggressive	-
9	Sedate	Inefficient	Keen	-
10	Inefficient	Keen	Inefficient	Sedate
11	Inefficient	Sedate	Inefficient	Inefficient
12	-	**Sedate**	Aggressive	Sedate
13	-	Keen	Inefficient	Keen
14	-	Keen	Keen	**Keen**

The results from Table 5.9 demonstrate that on average, for all participants, classification through EEG measurement and through vehicle parameters classified the same driving behavior 93.7% of the time. Results from Table 5.10 show the scenarios that were classified differently (bold text) in comparison to classification through vehicle parameters. Results indicate that driving behavior classification through driver's EEG measurements is feasible. This is of particular interest, since information about the driver/operator is readily available in comparison to vehicle parameters, which are less accessible in the UV domain. Thus, this driving behavior classification method is better suited for the application as an intelligent controller tuning unit in our proposed CS. Its implementation is discussed in the following section.

5.6 Intelligent Controller Tuning Unit

Lastly, in this section the development of an intelligent controller tuning unit is presented. As previously mentioned, this unit is implemented for the purpose of giving the UGV the ability to sense and utilized the operator's EEG data. This unit along with the other proposed components allows the CS to robustly control the UGV in the absence of timely control input from a human operator. This is accomplished by capturing the operator's EEG, and then used this to classify vehicle mode/tactic of operation (e.g. aggressive, sedate, keen, etc.), in a similar method as in the previous section. In the event of communication degradation, the classified driving mode along with the environmental inputs are utilized to decide the appropriate BELBIC controllers' configuration to mimic desired mode/tactic of operation. Figure 5.15 outlines the processes involved the intelligent controller tuning unit.

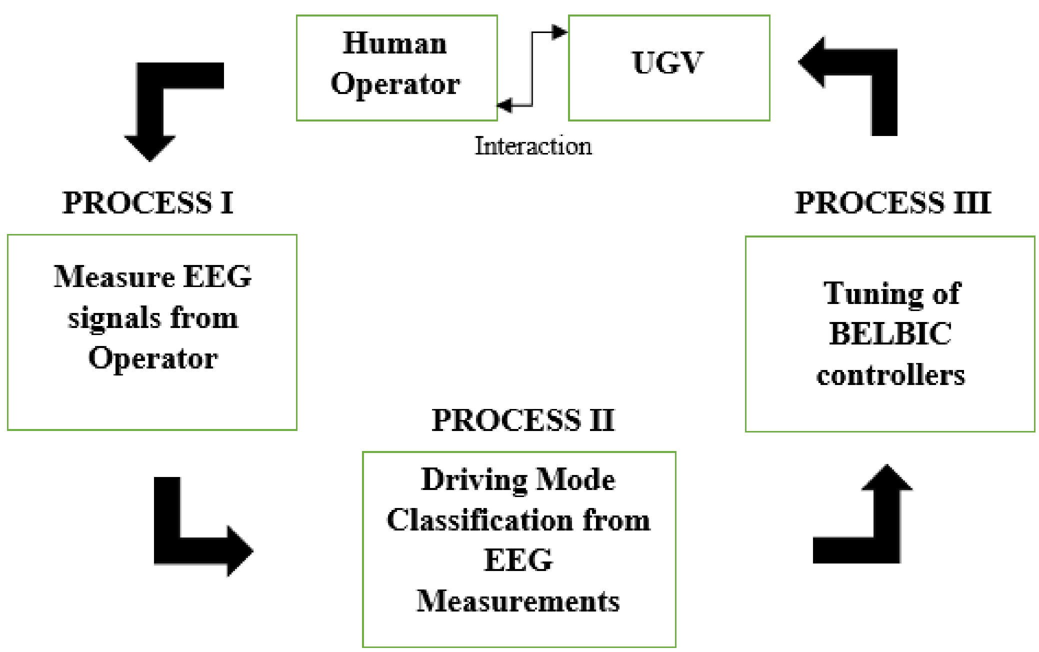

Figure 5.15. Processes in an Intelligent Controller Tuning Unit.

Process I: In this process the operator's EEG signals are continuously measured through an EEG headset.

Process II: In this process the EEG signals are classified to particular UGV driving mode. This is accomplished in a similar method as outlined in Section 5.5.

Process III: In this process, the classified mode of UGV operation is used to tune the BELBIC heading and path controls performance. This is done in efforts to maintain or adjust the mode of operation to safely control UGV in the event of communication degradation.

This is accomplished by adjusting the user-defined parameters: gains (sensory and reward functions), and learning rates (α and β). These parameters are tuned to attain a desired performance from the two BELBIC controllers; with the goal to mimic the driver's path following response. Figure 5.16 illustrates results obtained from tuning these parameters for path control to each UGV driving mode. For instance, an aggressive mode, which is characterized by risky, quick, and abrupt motions, was tuned so that transient response was quick but with large overshoot. This overshoot was assumed to be the greater risk, associated with this mode of operation, as the likelihood to deviate from path. For a keen mode, which is similar to an aggressive in that it is a quick response, was tuned to a quick transient response with little to no overshoot. Thus the vehicle was able to reduce the risk of losing control and able to closely follow the path. In the case of an inefficient mode, in which response is slower and varies greatly, was tuned to a slow transient response time with large overshoot constituting to large path deviations. Lastly, for the sedate mode, which is operation in a constant and precise manner, was tuned to a transient response that is slow but with no overshoot.

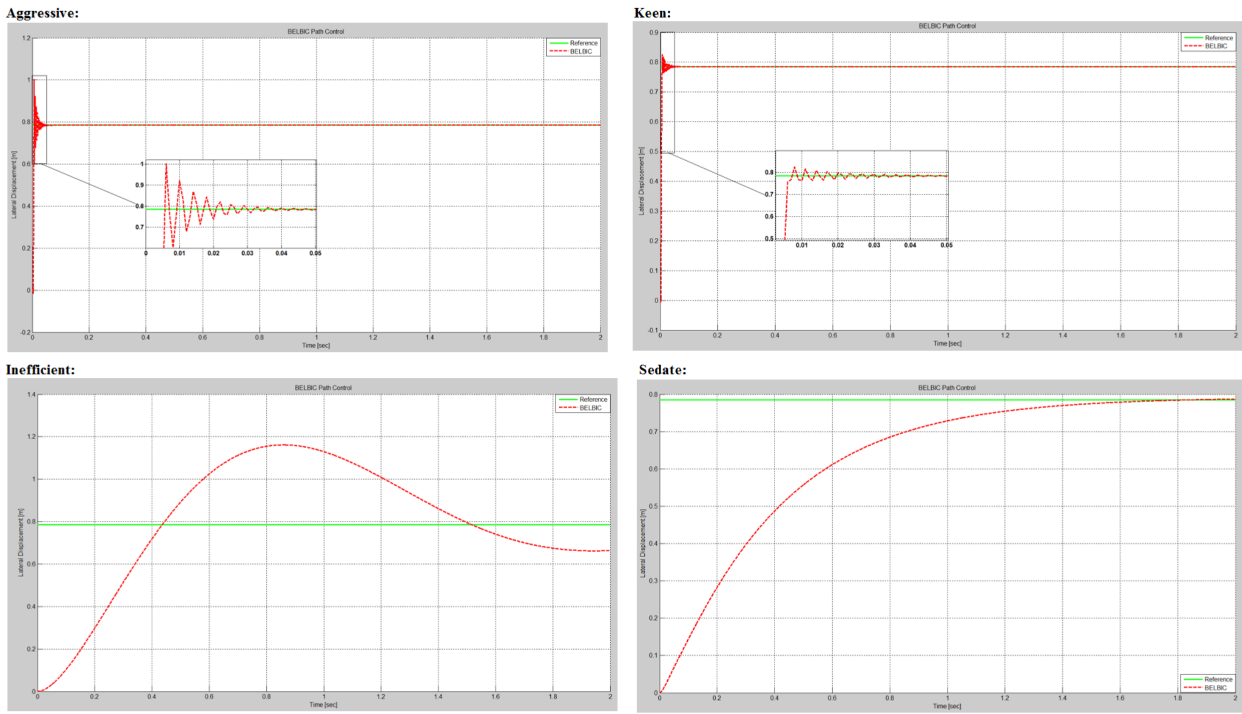

Figure 5.16. Tuning of BELBIC Parameters for each Mode of UGV Operation

It is anticipated that future work can be done to find ranges for values of K_1, K_2, K_3, α, and β for transition regions between UGV driving modes.

In conclusion, the utilization of the operator's affective states for driving behavior classification was investigated and shown not to be an appropriate method for correctly identifying driving behavior. However, an alternative method was explored and implement. This approach successfully classified driving behavior from the operator's EEG measurements. Lastly, the implementation of this method as the intelligent controller tuning unit was shown to be feasible.

CHAPTER 6

CONCLUSION

6.1 Summary and Conclusions

In the course of this dissertation research we have focused in developing an intelligent CS for a UGV for the particular scenario when communication between human operator and vehicle is hindered. Our proposed CS consisted of three major components, I) Two independent intelligent controllers, II.) An intelligent navigation system, III.) An intelligent controller tuning unit. All of these components working cohesively towards achieving the desired goal. In doing so, we have analyzed the literature in the areas of UV control, UV navigation, and human emotion recognition systems and identified key areas that can be further explored and utilized for our proposed CS.

First, in the area of UV control we identified that bio-inspired methods for control have been utilized, and shown to be an improvement over traditional methods for control. For our particular research objective, we selected BELBIC as the most appropriate method for UGV control. In simulation, we implement two independent BELBIC controllers, one for each case of I.) Heading, II.) Path control. We compared each of their performance against a PID controller, which is a common, practical, and efficient control approach. The transient and steady state response of the BELBIC controller was superior to the PID controller for both cases, by having significantly smaller RMS errors from desired trajectory. Additionally, the BELBIC controllers demonstrated robustness to variations in the plant parameters due to its on-line adaptability. They also demonstrated the capability to stabilize the plant when variations in plant parameters unstabilized vehicle dynamics. In addition, the BELBIC controllers were able to accomplish all these with little computational cost. More importantly, due to BELBIC's small number of user-define parameters we were able to easily tune the controller performance to any desired performance. Thus, when these BELBIC controllers are used in conjunction with the other components in our proposed CS, they can be tuned easily to mimic or change to a desired performance when no human input is available.

Secondly, in analyzing the literature for UV navigation we noticed that some bio-inspired methods (fuzzy logic and neural nets) have been explored for the purpose of sensor fusion, and in some instances they were shown to be feasible methods. Interestingly, we found that little work has been done in implementing BEL model for sensor fusion even though it shared similar qualities as the other algorithms, and due to the simplicity of this algorithm it can potentially reduce the computational cost. Therefore, we developed and implemented the BEL model as filter in efforts to reduce GPS sensor noise and to accurately acquire the vehicle's states as it traveled around a simulated track. The results from this part of the research demonstrated the BEL qualities as a filter. It performed better at reducing positional RMS error while having significantly less computational cost than the traditional Kalman filter implementation. In addition, results showed that BEL filter is less sensitive to the effects of the number of satellites available to obtain GPS data. However, the BEL filter performance is greatly affected by the selection of the sensory input and reward signal. Further research in the characterization of the sensory input and reward signal can further enhance the BEL filter performance. Furthermore, this BEL filter is an essential component in our proposed CS, by providing accurate information of the vehicle's state to the two independent intelligent controllers.

Lastly, for the area for human emotion recognition systems, and their applications, we identified some disconnects. First, emotions have been identified to be an important role in rational decision making, and for our particular research problem, a motivational factor in driving behavior. Moreover, there are many methods for recognizing human emotions, and the particular method that seems to be the most practical is through EEG measurements. Yet, there is very little research in which a human emotion system is utilized for the classification of human driving behavior. The utilization of such a system is appealing for our particular research question. As a result, we conducted two experiments to test the effectiveness of a human emotion recognition system for classifying modes of vehicle operation. In the first experiment, we were successful at eliciting particular emotions from participants for each quadrant of the valence-arousal model, and then classifying the participant's emotions through EEG measurements. Results showed an average of 88% correct emotion classification for all participants. In the second experiment, we were successful at classifying human driving behavior using vehicle parameters. However, when comparing driving behavior classification through the driver's emotional state to the approach of using vehicle parameters, the results were not similar. Results showed very little indication that the emotional state the driver is experiencing directly determines their driving behavior. Interestingly, we found that there is good correlation between the affective states captured while viewing an image compared to driving in that particular affective state. Even though the affective states were classified while performing two different tasks.

This further suggest that the emotional state does not necessarily influence driving behavior.

6.2 Contributions

In Chapter 1 we formulated a number of research questions to answer during this dissertation research.

1. *Which bio-inspired control methods can achieve improved controller performance in comparison to traditional control methods, while being easily implementable, and can be easily tuned to a desired performance?*
   The implementation of BELBIC for the two independent cases of heading and path control of a ground vehicle demonstrated the effectiveness at attaining superior performance in terms of reducing RMS errors from desired trajectory, while doing so with significantly less computational cost in comparison to the common PID control approach.
2. *Whether the utilization of a bio-inspired algorithm, as a filter, is a feasible alternative for sensor fusion which can attain similar performance compare to traditional methods?*
   The novel development and implementation of the BEL model as filter for fusion of GPS and INS proved to be successful in tracking the trajectory of a vehicle around various simulated tracks. It obtained reduced positional RMS errors, and it obtained comparable velocity RMS errors to the Kalman filter. Additionally, it demonstrated less sensitivity to the effects of different GPS noise distributions, and to the effects of the

number of GPS satellites available. More importantly, it performed all these with significantly less computational cost. This application of the BEL model as a filter for sensor fusion was successful for the particular sensor modalities fused. However, this might not be the case for other sensor fusion applications.

3. *By incorporating a human emotion recognition system through EEG measurement, is the utilization of these captured emotional states a viable alternative method for classifying vehicle mode operation in comparison to using vehicle parameters?*

   The results obtained from comparing classification of driving behavior using vehicle parameters compared to using the captured emotional states of the operator did not match, possibly indicating that emotions are not a major factor that contributes to a person's driving behavior. However, there was good correlation of the emotions evoked while driving and emotions evoked while viewing an image. Nonetheless, an alternative method for using the driver's/operator's EEG measurements was explored and successfully implemented for classifying driving behavior.

The implementation of all the above components in a CS for a UGV application was proposed. Results from all the studies conducted in this dissertation research indicate that the implementation of all these components as contingency control system for UGV is feasible. Therefore, a CS consisting of these components should be able to robustly control a UGV in the event of communication loss between operator and vehicle.

6.3 Future Work

The results from this research show several possibilities for further work. First, implementing various methods for feature extractions on the EEG measurements can potentially attain comparable classification of driving behavior through affective states to that through vehicle parameters. Another option is to evoke emotion in manner that is similar to how emotions are evoked while driving. Here, emotions were initially evoked by viewing images and then creating a classifier based on those emotions. But if emotions are evoked by viewing a movie in which a vehicle or driving is involved, this might result in better emotion classification of driving behavior. Also, further research can be conducted to investigate to identify specific factors that directly affect driving behavior. More importantly, further work can be conducted for the implementation of the proposed CS into a physical system.

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APPENDIX A

IRB APPROVAL

ASU Knowledge Enterprise Development

APPROVAL: EXPEDITED REVIEW

Sangram Redkar
Polytechnic School - EGR Programs
480/727-1129
Sangram.Redkar@asu.edu

Dear Sangram Redkar:

On 1/20/2015 the ASU IRB reviewed the following protocol:

Type of Review:	Initial Study
Title:	Driving Behavior Classification through Affective States
Investigator:	Sangram Redkar
IRB ID:	STUDY00002042
Category of review:	(4) Noninvasive procedures, (7)(b) Social science methods, (7)(a) Behavioral research
Funding:	None
Grant Title:	None
Grant ID:	None
Documents Reviewed:	• Verbal Script.docx, Category: Recruitment Materials; • IRB Submission Protocol.docx, Category: IRB Protocol; • Consent Form V2.docx, Category: Consent Form;

The IRB approved the protocol from 1/20/2015 to 1/19/2016 inclusive. Three weeks before 1/19/2016 you are to submit a completed "FORM: Continuing Review (HRP-212)" and required attachments to request continuing approval or closure.

If continuing review approval is not granted before the expiration date of 1/19/2016 approval of this protocol expires on that date. When consent is appropriate, you must use final, watermarked versions available under the "Documents" tab in ERA-IRB.

In conducting this protocol you are required to follow the requirements listed in the INVESTIGATOR MANUAL (HRP-103).

Sincerely,

IRB Administrator

cc:

Alvaro Vargas-Clara

APPENDIX B

LIST OF IAPS IMAGES USED

Images	IAPS	valmn	valsd	aromn	arosd	set\
Sailing	8080	7.73	1.34	6.65	2.2	2\
EroticFemale	4220	8.02	1.93	7.17	2.69	2\
Rafting	8370	7.77	1.29	6.73	2.24	5\
Skydivers	8185	7.57	1.52	7.27	2.08	12\
SkyDivers	5621	7.57	1.42	6.99	1.95	7\
Skier	8030	7.33	1.76	7.35	2.02	2\
Rollercoaster	8492	7.21	2.26	7.31	1.64	17\
RollerCoaster	8490	7.2	2.35	6.68	1.97	4\
Skysurfer	8186	7.01	1.57	6.84	2.01	14\
EroticCouple	4670	6.99	1.73	6.74	2.03	9\
Attack	6313	1.98	1.38	6.94	2.23	7\
Attack	6350	1.9	1.29	7.29	1.87	5\
Attack	3530	1.8	1.32	6.82	2.09	6\
Attack	6563	1.77	1.23	6.85	2.18	20\
Hanging	9413	1.76	1.08	6.81	2.09	19\
Explosion	9940	1.62	1.2	7.15	2.24	20\
DeadBody	3120	1.56	1.09	6.84	2.36	1\
Soldier	9410	1.51	1.15	7.07	2.06	4\
Mutilation	3071	1.88	1.39	6.86	2.05	6\
BabyTumor	3170	1.46	1.01	7.21	1.99	3\
Jail	6010	3.73	1.98	3.95	1.87	4\
HomelessMan	9331	2.87	1.28	3.85	2	10\
Cemetery	9001	3.1	2.02	3.67	2.3	5\
Jail	2722	3.47	1.65	3.52	2.05	9\
Woman	2039	3.65	1.44	3.46	1.94	18\
Bucket	7078	3.79	1.45	3.69	1.86	20\
ElderlyWoman	2590	3.26	1.92	3.93	1.94	5\
Man	2490	3.32	1.82	3.95	2	5\
Exhaust	9090	3.56	1.5	3.97	2.12	2\
Woman	2399	3.69	1.4	3.93	2.01	14\
Nature	5760	8.05	1.23	3.22	2.39	1\
Rabbit	1610	7.82	1.34	3.08	2.19	1\
Flowers	5200	7.36	1.52	3.2	2.16	3\
Flower	5010	7.14	1.5	3	2.25	1\
ThreeMen	2370	7.14	1.46	2.9	2.14	4\
Flower	5000	7.08	1.77	2.67	1.99	1\
Couple	2501	6.89	1.78	3.09	2.21	6\
Cow	1670	6.81	1.76	3.05	1.91	1\
Clouds	5870	6.78	1.76	3.1	2.22	3\
Field	5711	6.62	1.65	3.03	1.96	13\