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Neural response based behavioral profiling of vehicle drivers to personalize alarm sequences, warn safety systems and trigger non-driver-in-loop control

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***Abstract*---**Quantitative measurement of vehicle driver alertness and response readiness to on-road emergency cues could add more response time to driver assistance and safety features. Exogenous Electroencephalogram (EEG) potentials generated in Beta frequencies can imply driver's attention to the situation, the absence of which may be associated with distraction or drowsiness. Detection of specific Alpha potentials during action-soliciting events may further indicate risk of violating response-trigger thresholds beyond which physical and vehicular response periods may become too short to avoid collision. Specific Event-Related Potentials (ERP) associated with early automatic cognitive process of consciousness to obstacles, emotional reaction to visual cues, risk evaluation, drier's emotional intensity, anticipation and motor preparation can be identified, isolated and processed to create a model that predicts driver's intension/capability to respond to obstacles within a derived time threshold. Isolating signals that indicate driver in-activity (extreme fatigue, sleep, visual or auditory distraction) during near-obstacle situations could further be used to preempt user-in-loop drive, in semi-autonomous vehicles, even if the driver is inhibiting normal transition to self-drive mode.

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Existing safety components, like airbags, could be issued pre-warnings about possible crash situations (currently they are actuated only upon impact), giving them critical additional time to get pre-actuation sequences triggered.

***Keywords*---**BCI (brain-computer-interface), B2V (brain-to-vehicle), collision avoidance, ERP (event-related-potentials), feature extraction.

Introduction

Driver and passenger safety has been a prime consideration over all generations of automotive technology. While the quantity of vehicular traffic keeps increasing, in-vehicle feature advancements including dashboard electronics and connectivity functions share a significant bandwidth of the driver's attention (Li et al., 2013). Consequently, current ADAS technologies that leverage state-of-the-art sensor and Machine Learning software innovations evolve around betterment of vehicle safety systems. One critical aspect of safety that directly contributes to obstacle detection and collision avoidance is the earliest indication of risk identification. Since this earliest cognitive notification of hazard happens at a sub-conscious neural state, even before a conscious assessment by the driver pitches in, tapping this response and reacting based on it would extend the chance of avoiding injury, fatality or property damage to the maximum possible extent.

The human brain

The human body is a highly organized bilaterally symmetrical physical structure composed of billions of cells and extracellular material that combine to form tissues, organs, and systems each performing tasks vital for our existence and survival. This multifaceted system has evolved over 6 million years since humans became an independent species within the primate group gradually adding several distinct capabilities including bipedalism, creation of sophisticated tools and usage of languages. Most aspects of evolutionary progression including basic and advanced traits like abstract thought, reasoning, expression were all characterized by significant development in the size and intricacy of one of the most complex organs namely the human Brain. Anatomically the human body is divided into several biological organ systems that carry out specific functions. The brain along with the spinal cord forms the Central Nervous System while nerves that connect this system with other parts of the body form the Peripheral Nervous System. Put together, the Nervous System controls all other systems in the body. The brain, specifically, controls most body functions including emotions, thoughts, movements, breathing, heart rate and body temperature (Tan & Nijholt, 2010).

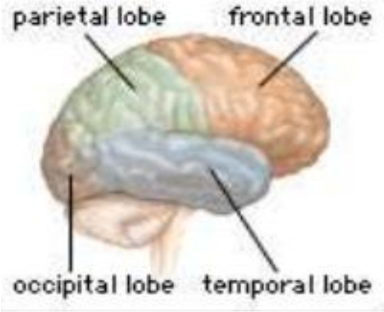


Figure 1: The Human Brain. It has 4 sections or lobes: Temporal lobe (handles sensory inputs, emotional reactions, long-time memory and language processing), Occipital lobe (visual processing), Parietal lobe (integrates sensory information, spatial awareness, navigation), Frontal lobe (attention, reward, short-term memory, motivation, planning).

Each section of the brain is made up of nerve cells called neurons. There are an estimated 100 billion neurons in the brain, each communicating with thousands of other neurons to execute neural functions. Neurons communicate either by sending electrical signals to other neurons through physical connections or by exchanging chemicals called neurotransmitters.

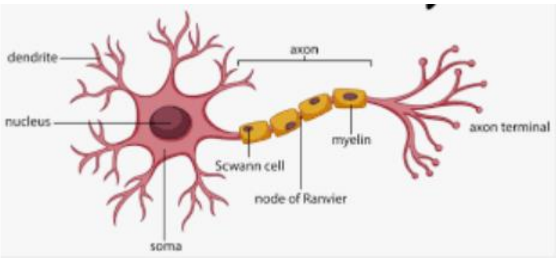


Figure 2: Neuron Anatomy. A neuron has three main parts: axon (transmitting part), soma (cell body) and dendrites (receiving part).

When a neuron is not communicating, the inside of it has a negative charge relative to the positive charge outside the cell (by around 70 millivolts). While a need to communicate develops in the neuron (to process an action needed by the body) positive sodium cells enter it, increasing its potential. Once a threshold is reached an “Action potential” is triggered as an electrical pulse along the axon of the neuron cell. This activity is termed as Neuronal Firing. Neuron are connected to each other over junctions called synapses. Action potential from one neuron ends in an excitatory synapse and an excitatory postsynaptic potential (EPSP) occurs in the following neuron connected to it. The synaptic current that flows during these excitations generate a secondary electric field over the scalp measurable by an Electroencephalogram (EEG) system. Detection and analysis of these neural potentials would add information to vehicles supporting moderate to advanced levels of automation for improving reaction times of drivers or self-drive algorithms. Studies have shown that Event-Related Potentials that are direct measures of perpetual and cognitive response processes to stimuli have high temporal resolution to be effectually used in real time scenarios (Ma et al., 2010).

Synopsis of concept

Real time detection and processing of brain waves is used in B2V (Brain to Vehicle) communication systems for applications that aid autonomous drive algorithms in aligning to the drivers' intensions by inferring data from motor-preparation and error-related neural potentials. This study is pioneered in part by Nissan Motor Corporation (nissan-global.com, 2018). These potentials can be detected 100s of milli seconds before actual motor activity of the driver or during user's abstract assessment of decisions taken by the self-drive system. These applications aim at improving user experience mostly in vehicles equipped with automation levels of three and above.

In order to apply neural signal interfaces to safety critical situations like collision avoidance, neural activity that may become dominant during or immediately following obstacle detection and brain waves that may suggest driver inactivity or inability to react within the required timeline threshold may need to be identified and isolated. Information generated by processing such neural potentials may assist self-drive vehicles on decisions to take control or lesser equipped vehicles to alert the driver, passengers and traditional physical safety systems about an impending crash scenario. Existing safety systems may initiate self-check routines or priority allocations based on this added time.

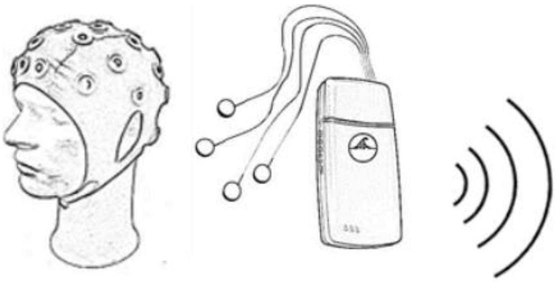
This data could further be used to derive response patterns specific to each driver in order to create a behavioral model. The historic data generated by this model would be used to normalize decisions derived on initiating and personalizing warning systems and in triggering intimations to other modules. This data would also serve as a driver assessment record in case of chauffer driven or shared mobility scenarios, enabling customers to choose services based on a driver "score".

Materials and Methods

Studies have shown that Contingent Negative Variation (CNV) is seen developing as a slow negative EEG variation in frontal-central areas after a warning cue (Chavarriaga et al., 2018; Walter et al., 1964). Further they suggest that Event-Related Potentials P200, N300, P300 and Late Positive Potential (LPP) are prevalent and measurable during various stages of cognitive information processing (Ma et al., 2018). P200 is an early positive ERP component with a peak latency from 100 to 200ms that seems to be an attention bias occurring automatically (Huang & Luo, 2006). It can be associated with early detection of threatening stimuli (Correll et al., 2006). N300 component of the ERP that occurs as large amplitudes at parietal sites can be viewed as the emotional reaction to visual stimuli (Carretié et al., 2001; Carretié et al., 1997). P300 is a positive ERP component with a peak latency between 300 and 400ms after a stimulus, and is found widely scattered over all brain areas with amplitudes increasing from front to back. It is associated with the cognitive evaluation of the meaning of a stimulus (Huang & Luo, 2006; Ito et al., 1998) and differentiates emotional or threatening stimuli from neutral stimuli during active evaluation (Correll et al., 2006; Munoz & Martin-Loeches, 2015). Late positive potential (LPP) component of ERP that manifests mainly in the central-parietal regions between 300 and 700ms after the onset of a cue signifies the emotional intensity of the stimulus (Brown et al., 2012).

In driving scenarios sudden changes in road conditions, especially ones that require user action (acceleration/brake/steering position change) would serve as warning cues or stimuli and development of CNV and ERPs in the driver can be inferred as probable indications of the driver's recognition and assessment of these cues. Studies further have shown that a state of high fatigue or rest (lack of situational attention) can be detected by increased amplitudes in the alpha frequencies of brain waves that occur in parietal and occipital regions (Gharagozlou et al., 2015; Liu et al., 2013). The initial phase of this study would focus on recording, isolating and processing these neural signals from multiple subjects in a vehicle or vehicle-like setting.

Driver safety and comfort would be the dominating parameters in selection of the EEG recording system. It should be dry, reliable and efficient in handling high noise situations prevalent in vehicle cabin environments. It also needs to be portable for this application and should minimize any physical stress levied on the driver. A skull cap type EEG recorder with up to 20 electrodes would be most suitable for driving positions.



Source: www.biopac.com

Figure 3: A WiFi Enabled Portable EEG Cap. Though this would reduce wiring related artifacts, its impact on temporal and spatial resolutions needs to be evaluated

Since electrode positioning needs to be precise the cap should be easily re-sizable to be used by multiple subjects. Locations of the scalp electrode would be as defined by the International 10-20 system. The right montage (positioning of required electrodes based on 10-20 system) would be selected based on EEG waves identified to be processed and studied for the current application.

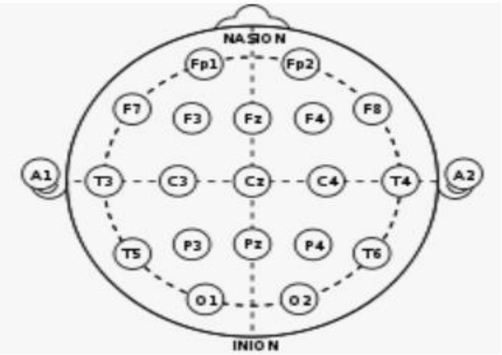


Figure 4: 10-20 EEG Electrode System. Electrodes are placed above the pre-frontal (Fp), frontal (F), temporal (T), parietal (P), occipital (O) and central (C) areas of the brain. The distances between adjacent electrodes are either 10% or 20% of the total front–to-back or right–to-left measurement of the skull.

Figure 5 captures high level blocks of the proposed system. Filtered and processed signals would be mapped to the driver and stored in a signal-in queue. This data would be used by a behavioral pattern generation logic as well as a real time Decision box. Aided by real time and historic inputs related to the current driver and current environmental situation the Decision box would generate inputs to an Alarm system and to existing safety and self-drive components in the vehicle.

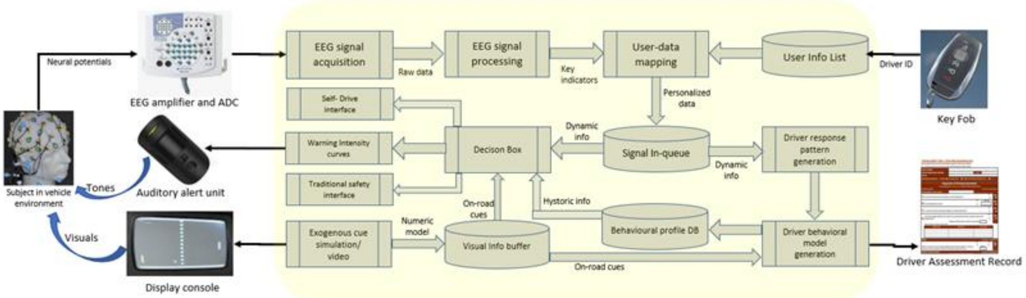


Figure 5: High Level Blocks. The highlighted section including EEG acquisition, processing, driver mapping, decision, behavioral profile, cue simulation and decision-sink interfaces are software modules. The EEG recording system and driver Key FOB are external inputs to the software block. Display console serves as the visual cue input to the user. Auditory alert unit and driver assessment record are key outputs of the system along with callbacks to self-drive and traditional safety interface modules.

Signal processing tools should meet derived artifact removal KPIs to ensure isolated signals would have required information to enable calculation of response patterns and personalization of behavioral aspects with minimal deviation. Identifying and tuning optimal techniques for each step in EEG signal processing (Figure 6) for driver response application would be a core area of focus in this research segment.

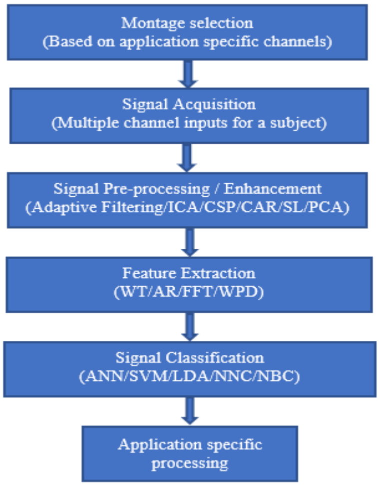


Figure 6: Flow Diagram. Once montage is designed, inputs from the selected channels are acquired through an EEG recorder. Pre-processing to remove noise and artifacts is followed by feature extraction logic. Signal are further classified and fed into the application module.

Frequently used options for signal pre-processing (also termed as Signal Enhancement) include Adaptive Filtering, Independent Component Analysis (ICA), Common Spatial Patterns (CSP), Common Average Referencing (CAR), Surface Laplacian (SL) and Principal Component Analysis (PCA). Feature Extraction techniques that would be analyzed for a best fit include Wavelet Transformations (WT), Auto Regressive parameters (AR), Fast Fourier Transforms (FFT) and Wavelet Packet Decomposition (WPD). Signal classification methods to be reviewed for use are Artificial Neural Networks (ANN), Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Nearest Neighbor Classifiers (NNC) and Nonlinear Bayesian Classifiers (NBC) (Lotte et al., 2018).

Design and implementation of a learning algorithm that would consume processed neural potential values of selected neural signals and numeric representations of on-road cues to generate serviceable profiling variables that can normalize the system's feedback would be another core area of focus.

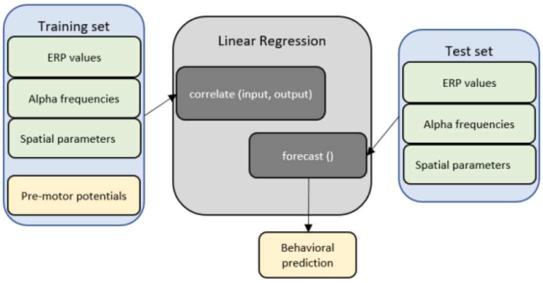


Figure 7: The Learning Model. This model based on linear regression predicts behavior of the driver in terms of response turn-around times to on-road stimuli.

A multiple-linear regression based model would be most suitable to get trained with continuously varying spatial coordinates of the obstacle, ERP measurements and amplitudes of alpha frequencies as inputs and pre-motor potentials as output (actual motor action trigger time can also be measured from other inputs like sensors attached to the driver's arms and legs though these may not be suitable for practical applications unless wireless and convenient devices that can withstand high levels of vibration and noise are used). Training set would involve historic inputs from actual driver behavior over a period of time (measured response turn-around values for different obstacle coordinates and varying neural conditions/feedback).

The Decision box would use dynamic neural inputs of the driver, historic response patterns and parameters from the on-road situation to generate inputs to a warning system, self-drive component (if available) and controlling software of traditional safety assets like airbags.

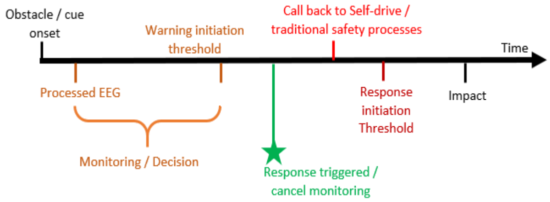


Figure 8: Milestones from Obstacle Onset Until Impact. The Decision box would iteratively monitor neural response. Lack/delay of driver attention, driver's historic behavioral profile and detection of driver inactive state would be criteria to initiate warning sequences and intimations to self-drive and traditional safety processes.

Based on user-wise input, the Warning system would support personalized intensity curves to avoid counter distractions and panic and to improve user experience.

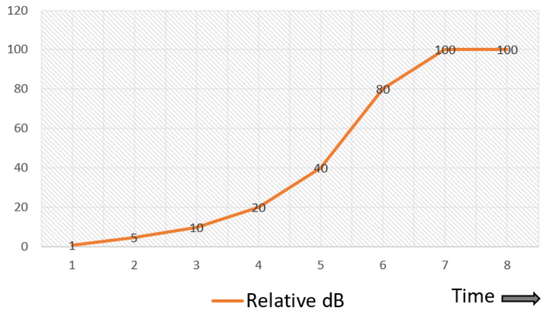


Figure 9: Output DB curve of a Sample Warning System. Relative amplitude is a function of time and decision confidence score of the current driver.

Results

Effectiveness of identified neural signals in consistently yielding recordable patterns across human subjects and under in-vehicle scenarios would be critical for the viability of various planned outputs. Isolating and processing these potentials could be challenging due to increased artifacts generated by multiple sources of noise in vehicle environments and due to physical movements and associated vibrations. Selection of efficient feature extraction techniques is essential to generate usable data that can estimate driver's neural condition with high accuracy. Efficacy of the profiling module would depend on the quality of extracted data and also on the learning time that each subject could spend in training the system.

Significant improvement in reaction time based on feedback from this system would be a factor of several variables including human behavioral differences, neural signal measurement, filtering, processing limitations and test simulation approximations. Quantitative assessment of this improvement would be realized by measuring driver responses and outcome of collision avoidance exercises with and without the help of feedback from the proposed system.

Discussions

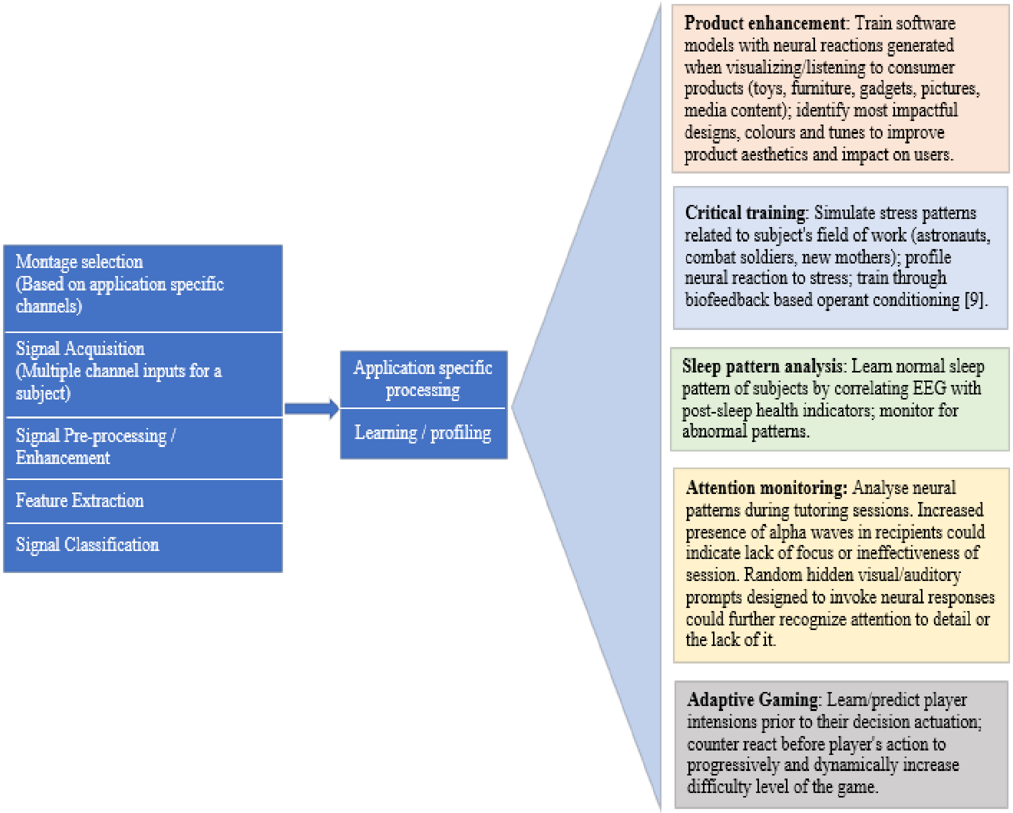
BCI in automotive applications can play a critical role in enhancing driver and passenger safety until a near complete penetration of driver-less vehicles is accomplished. Most industries contributing to the automotive world are rapidly shifting focus towards increasing and improving autonomous features of vehicles spanning from privately owned and shared low-to-mid segment cars to commercial heavy-duty transportation. Specific and mature requirements have been defined for each level of automation (J3016 Standard/SAE). Several advantages of automated vehicles including reduced emissions and fuel economy have been discussed in multiple forums and studies (Igliński & Babiak, 2017; Stern et al., 2019). However, while progress in technology has been significant in the last few decades, implementation of an autonomous driving environment is still far away owing to challenges in defining legal regulations and policies (Rozhkova et al., 2020; Ilková & Ilka, 2017), traffic administration methods and in providing safe infrastructure in all types of roads (freeways, streets, alleys, etc), all these factoring in the 'human' factor. Hence Auto OEMs do not expect to launch driver-less vehicles in the near future (Martínez & Soriguera, 2018). Further a recent survey (J.D.Power press release – Oct2020) shows that around 31% of automotive industry experts believe that gaining consumer trust and increase in consumers' comfort level over using self-driven cars is a bigger challenge than technical feasibility. Another study based on inputs from a group of diverse experts found that not more than 11% of the vehicles on road would be conditionally automated by 2030 and not more than 61% vehicles would be fully automated by 2050 (Milakis et al., 2017).

Though instantaneous transition to fully automated vehicles is practically feasible in geo-fenced surroundings, it might take a few decades for this transition to happen in open environments. During this transition, human drivers would have to compete with autonomous vehicles which would attract much more legal and ethical complications (Pattinson et al., 2020). A BCI solution aiding driver reaction times in this scenario could become a life-saving addition.

Alternate applications

The BCI and profiling system suggested in this proposal can, in principle, be used for several applications that need a platform similar to that needed for automotive safety. The BCI module can use one or a combination of several neural signal acquisition techniques including MEG (Magneto Encephalography), fMRI (functional Magnetic Resonance Imaging), NIRS (Near-Infrared Spectroscopy) and EEG (Electroencephalogram). Owing to its high temporal resolution, portability, safety, lower cost and ease of use EEG would be the most practical and preferred choice.

Selection of specific neural potentials for a targeted time-critical or soft real-time application depends on the effectiveness of the signals in real time scenarios and their intensity over high noise conditions. A learning algorithm, that works with feedback-based training sets, used in addition to the extracted signals helps in tuning their interpretation and usage to further expand this application space. Figure 10 lists some use cases, similar in requirements to automotive safety, that can benefit from real time monitoring of neural activity and user profiling.



Product enhancement: Train software models with neural reactions generated when visualizing/listening to consumer products (toys, furniture, gadgets, pictures, media content); identify most impactful designs, colours and tunes to improve product aesthetics and impact on users.

Critical training: Simulate stress patterns related to subject's field of work (astronauts, combat soldiers, new mothers); profile neural reaction to stress; train through biofeedback based operant conditioning [9].

Sleep pattern analysis: Learn normal sleep pattern of subjects by correlating EEG with post-sleep health indicators; monitor for abnormal patterns.

Attention monitoring: Analyse neural patterns during tutoring sessions. Increased presence of alpha waves in recipients could indicate lack of focus or ineffectiveness of session. Random hidden visual/auditory prompts designed to invoke neural responses could further recognize attention to detail or the lack of it.

Adaptive Gaming: Learn/predict player intensions prior to their decision actuation; counter react before player's action to progressively and dynamically increase difficulty level of the game.

Figure 10: Alternate Applications of Behavioral Profiling Model Trained Using EEG. These targeted applications would involve exogenous EEG potentials generated in response to real-world obstacles or subconscious emotional cues and a need to normalize real time interpretations by continuous assessment of reactions generated in human subjects.

Conclusion

The scope of this concept would be limited to conceptual feasibility of a hardware-software model that can utilize information in neural feedback to assist vehicle drivers and driver assistance safety systems. Practical challenges and commodification are not discussed, although several leading technology organizations are already pursuing productization of basic EEG based features within the vehicular cockpit. Apart from implementation of the proposed design, future work would focus on two distinct evaluations of the proposed model:

A. Would ERPs and alpha potentials have enough content, accuracy and measurable amplitudes (after employing competent feature extraction techniques) to consistently enable calculation of human reaction times with an accuracy level required to be used for safety critical applications?
B. Can a continuously trained prediction model add significant value by normalizing response patterns calculated with real time samples given that human responses can vary considerably within the same subject with time, and across subjects with experience, attitude, emotional situation and non-visual or non-auditory distractions that cannot be detected or measured?

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