Artificial Proprioceptive Reflex Warning Using EMG in Advanced Driving Assistance System

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***Abstract*— A frequent cause of auto accidents is disregarding the proximal traffic of an ego-vehicle during lane changing. Presumably, in a split-second-decision situation we may prevent an accident by predicting the intention of a driver before her action onset using the neural signals data, meanwhile building the perception of surroundings of a vehicle using optical sensors. The prediction of an intended action fused with the perception can generate an instantaneous signal that may replenish the driver's ignorance about the surroundings. This study examines electromyography (EMG) signals to predict intention of a driver along perception building stack of an autonomous driving system (ADS) in building an advanced driving assistant system (ADAS). EMG are classified into left-turn and right-turn intended actions and lanes and object detection with camera and Lidar are used to detect vehicles approaching from behind. A warning issued before the action onset, can alert a driver and may save her from a fatal accident. The use of neural signals for intended action prediction is a novel addition to camera, radar and Lidar based ADAS systems. Furthermore, the study demonstrates efficacy of the proposed idea with experiments designed to classify online and offline EMG data in real-world settings with computation time and the latency of communicated warnings.**

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I. Introduction

WE SHIVER as emergency vehicles speed past us on the road to attend a crash. Our hearts miss a beat as we hear about a road accident on the news. – Tedros Adhanom Ghebreyesus. Road safety is an item point in United Nations (UN) sustainable development goals (SDG) and a target was set in 2015, to reduce the traffic deaths and injuries by 50% by the year, 2020. However, the percentage has increased by 8% as reported by the World Health Organization (WHO) [1].

Fig. 1 depicts a frequent driving situation that will assist to accentuate the nuisance value of traffic circumstances for a driver: The protagonist driver (driver-A) is in a grey car marked underneath with a green circle and a blue car (driver-B) is approaching from behind in the right lane. The approaching car is moving at 60 kilometers per hour(kph) and the grey car is close to stationary. A car is considered 5 meters (m) long (the average length of a family car) in this illustration. If driver-A decides to change lanes to her right without looking in the rearview mirrors, what would be the time margin to recover from her mistake? What would be the minimum distance from the blue car to save driver-A from a likely accident, if we could predict her intended action of turning right? Let's assume with 60 kph the blue car (driver-B) travels 17m in one second(sec) and with a break applied at this point we have one second to warn our driver about the situation before the following car comes in contact with an ego-vehicle. If a system takes 500 milliseconds (ms) to predict her intended action and the system is cognizant of the blue car, it cautions driver-A about her mistake. There is a possibility that with a prior prediction of driver-A's intended action, she may recover from the mistake and avoid a likely harmful accident.

Humans often drive with partial focus, varied attention, miscellaneous thoughts and influence of the conscious mind (Fig. 1). A large number of accident damages are caused by side sweeps and rear-end traffic collisions. The drivers, especially new drivers, often forget to look in the rearview mirrors or rely on precursive information and proceed with lane changing and turning of the steering wheel. Inevitably, with experience drivers finesse in certain emergencies like to avoid an approaching vehicle from the left or the right lane while turning left or right without looking in the rearview mirrors.

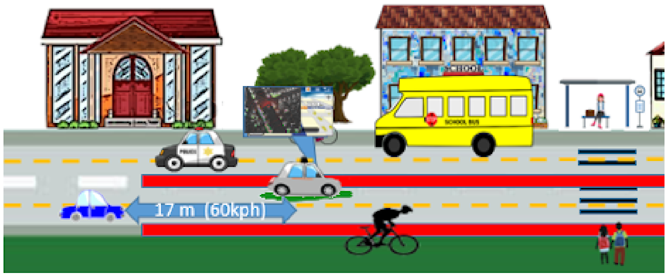


Fig. 1. Depiction of a common driving situation that shows circumstances for a driver in the car with a green marking underneath it. A blue car is approaching from behind supposedly at a speed of 60kph in the right lane. In this situation, common circumstances for the driver are to focus on the school bus, the cyclist, zebra crossing and children, traffic, school zone, and so on while driving.

Reflexes are often credited for saving humans from many unwanted situations, but the drivers' actions are voluntary actions that are initiated by the motor region with feedback from the sensory information processed by the pre-motor and prefrontal area. If the actions are performed without updated information collected from the surroundings, an unwanted situation may arise. An auxiliary system, acting as an artificial reflex by collecting the motor signals as sensory input to the system and responding with haptic feedback may neutralize the unwanted situation for an inattentive driver in autonomous vehicles (AV). Though AV is surmised to be on the verge of commercial launch, passengers have reservations about the machines and a recent survey [2] shows the acceptance of AVs decreases as the autonomy level increases. The ADAS is a safe and acceptable surrogate that may help to reduce unwanted situations, accidents, and collisions. Conventional ADAS are designed with inputs from the camera, ultrasonic sensors, radars, and they generally monitor the conditions of driving and a driver. This study explores the use of a proactive approach to warn drivers in case a critical situation is anticipated and uses electromyography (EMG) signals to predict the intended action of a driver and subsequently apprehends an unwanted situation with an ADAS.

Recent neuroscience research investigates the time between action planning and the initiation of neuron exaction for a certain movement action. Reference [3] examined an early awareness of the brain about an intended action and reported a prior awareness of as high as 0.5s (seconds). The time is reported to be approximately 10s in a later study [4], [5]. There are alternative theories which state other reasons behind the extended time reported in later studies about the prior known awareness of the brain about movement actions actions [6]. However, for this study, the alternative theories also support the experimentation setup as the driver is conscious about the activity of driving a vehicle. Presumably a prior intimation about the intended movement action of a driver when fused with perception building algorithms in autonomous driving software (ADS) and conditioned with simple heuristics can warn the driver about an apprehension.

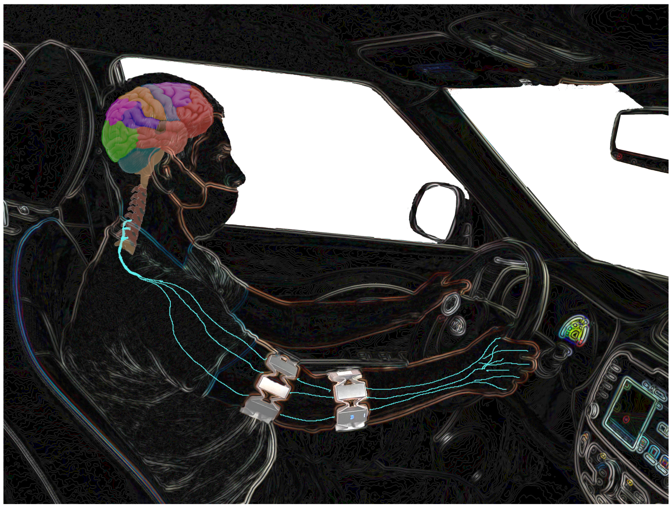
This study premises on findings in neuroscience and ADS and combines the proprioceptive(humans) and exteroceptive signals to develop an ADAS. The proposition in this work suggests that the accurate prediction of an intended movement action of a driver when fused with the perception building techniques in the ADS, effectively warns a driver about critical and unwanted situations. For example, side-sweep and rear-end collisions cause frequent fatal accidents and are caused by the drivers' ignorance about rear traffic while turning steering wheel. In the proposed work, the intended action of a driver is predicted from continuous stream of EMG data using a conventional support vector machine (SVM). The perception of surroundings of ego-vehicle is computed using camera and Lidar data. The camera images are used to detect lanes and vehicles in the rearview. The Lidar is calibrated with a rearview camera for measuring an accurate distance of the tailing vehicles. Here, lane change intention is the driver's thought of changing the lane, whereas the lane changing action is the driver's actions that she performs and can be noticed by the movement of the actuators. The study advocates the use of the proposed ADAS in intelligent transportation and safe vehicles. The rest of the manuscript is organized as follows: Section II presents the related literature and section III details the techniques adopted for each module of the proposed framework. The experimentation details and results are discussed in section IV and the conclusion is presented in section V.

II. Literature Review

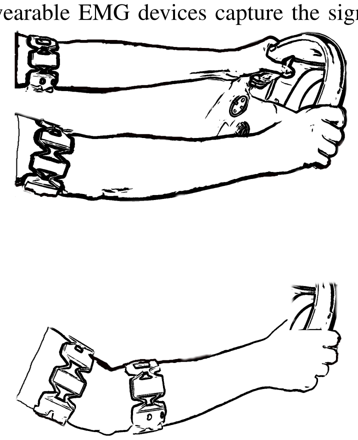
Consumer vehicles are equipped with basic safety features: lane departure warning, forward collision warning, and blindspot detection using ADAS [7]. New automobiles are stepping up a level and providing lane-centering assistants, rear-cross alert, and experimental self-park systems. This study introduces the use of biological clues for action prediction to device an ADAS which may act as an artificial reflex. In the following an overview of the relevant literature is presented in separate subsections.

A. Can We Really Predict the Intention?

The heading poses a pertinent question for the proposition that the proposed ADAS benefits from the prediction of the intended action of a driver. This study orients the proposition towards the computational design and framework of ADAS and introduces the literature for the premise that the intention of a driver is known using advancements in Neuroscience. Reference [6] details the decision-making and the freedom in choice juxtaposing the studies in favor of the argument to the rebuttals. The experiments favoring the arguments suggest that the brain knows at-least 0.5s prior to the actual realization of a decision of a human being [3]. Successively, the period is reported as up to 10s with new experimentation and the brain activity mapping techniques (functional magnetic resonance imaging - fMRI) [4], [5]. Whereas, [8] categorizes the distant intentions from the proximal intentions [9]: the former is the planning of activity later in time and the latter is a plan of action. It turns away the period suggested by the [3] for the proximal actions. Reference [10] supported the claims with experiments designed for predicting the decision from Electroencephalogram (EEG) signals and reported that the EEG signals are not different for two decisions: to move and not to move. However, the discussion is about the unconscious



(a) The motor electrical signals originate in the motor area in the cortex and innervate the nerves in pathway (not drawn to anatomical accuracy) as shown with the cyan color and carry out actions by innervating muscles. Two wearable EMG devices capture the signals.



(b) Wearable EMG devices are tested with two dressings. Top: One device on each upper arm. Bottom: Two devices on each arm.

Fig. 2. Nerves pathway and dressings of EMG wearable devices.

decision making and the readiness potential (RP) which is a prior signal observed in EEG for a limb's action [11]. However, the premise of this study is valid in the juxtaposition as a driver is involved in a limited set of driving actions and the conscious decision (RP) would be investigated for the prediction of intended actions.

B. Pathway of Nerves

The nerves carrying motor signals, from the brain to the upper limbs, travel from the spine to the upper limbs. Brachial plexus carries the motor signals to the arms and it leaves the spine (vertebral column) at Cervical C1-C8 and Thoracic T1 segments (vertebrae) in spine. A cartoon diagram in Fig. 2(a) (not drawn with anatomical precision) depicts the pathway of the nerves which carry the motor signals from the motor area of the brain to the limbs for fine movements. The Brachial plexus is branched into Medial, Ulnar, and Radial nerves. The radial nerve signals the movement of muscles to raise the hand, elbow, wrist, and fingers. The medial nerve innervates the forearm and hand, while the Ulnar nerve also stimulates the forearm and hand. This study uses the EMG wearable device which wraps around the arm and captures the electrical stimulation of the three nerves. The discussion of anatomy is briefly touched in this study and anatomy literature [12], [13], [14], [15] is referred for details.

C. Sensors

Sensors have categorised into Exteroceptive sensors and Proprioceptive sensors. In this study, the proprioceptive sensor definition is adjusted and it reveals the state of the driver. EEG is often used to capture electrical impulses generated during an activity in a driver's brain and a detailed review of EEG sensors used for this purpose is given in [16]. Whereas, a detailed review discusses deep learning algorithms applied on EEG data for various applications [17]. EMG is another sensing method that is lately used in ADAS for people with restricted mobility in upper limbs [18] and also for pedestrian collision avoidance [19]. Reference [20] details about the exteroceptive sensor technologies in use for ADAS and ADS. It reflects upon the capacity and challenges of the sensors and may help to choose the right sensor for further advancements in the proposed idea like event-based vision sensors [21] may help to reduce the crucial processing time. It also names the driver attention model but does not provide the sensors used in ADAS for the purpose. Reference [22] extends the discussion on the utility of various sensors in ADS and ADAS primarily focusing on their performance and limitations in various demanding situations.

D. Perception

ADAS aids human drivers by imitating an expert's response in a situation and it relies on the perception built with inputs from the exteroceptive sensors [23]. The pivotal role of the perception module is to perceive the surroundings and to become aware about the nearby objects and ego positioning. The perception is used to predict the objects' behavior in the immediate future. The state-of-the-art uses object-detection, segmentation, tracking, and depth-estimation to build the perception and often uses data fusion from heterogeneous sensors [24]. Reference [25] gives a detailed insight into the recent advancements in object detection and discusses the use of camera and Lidar data for 2D and 3D object detection in images and point cloud data. The perception module and its significance in a full stack of ADS is discussed in [26]. 3D object-detection is a protrusive research topic and ADS uses the data from Lidar and stereo-images to glean the interesting objects [27], [28]. Reference [29] uses knowledge distillation with a single shot detection neural network model and detects 3D objects in Lidar data. Stereo-images are used to detect 3D objects by generating a 3D feature volume from left-right stereo images and detecting the objects in 3D volume [30]. Nevertheless, 2D-object detection is a convenient and popular perception building technique and it is extensively pursued to develop economical ADAS and ADS [31], [32].

E. Prediction of Intention

Prediction in ADAS and ADS anticipates the behavior of objects in the surrounding. However, in this study, the prediction of intention is for the driver which is often termed as driver's behavior in ADAS. The topic impelled many researches and an earlier review paper [33] reflects on various behavior monitoring methods: visual features, physiological signals, and vehicle behavior. Reference [34] assess the driver monitoring techniques in relation to the levels of SAE automation. Vehicle's operational control by a driver suggests a lot about the state of a his behavior and it is used in [35] to predict the risky behavior from harsh braking, harsh steering wheel control, and aggressive acceleration. Vehicle steering angle and brake pressure help to predict a driver's intention to start a vehicle after stopping [36]. EEG is in frequent use with the experimentation in ADAS as the signals are captured from the core of human intelligence machinery and its communication [16]. More examples include, driver drowsiness detection using evaluation of EEG with convolutional neural network and episodic training [37]. Another study investigated the EEG signals to detect the fatigue-related performance declines for drivers [38]. However, an advance prediction of intention of a driver for an ADAS system using physiological signals is not found in literature, it has been studied intensively to infer the intention of a driver from his actions [39].

F. Use of EMG in ADAS

Advanced machine learning and signal processing techniques are effective in passable analysis of coarse EMG signals and their use in prediction of a sequence of actions. EMG wearable devices are used in experiments with prosthetic applications for people showing varying ability to use their upper limbs and [40] provides a detailed review of the applications. Reference [41] uses surface electromyography (sEMG) to design a steering control assistant's interface which servers drivers with limited movement of arms. The sEMG with an arm wearable EMG device is used in human driver trials to assist people who suffer upper limb amputation and shows effective aid to the driver to avoid pedestrian collision [19]. Another demonstration of the control of steering wheel using EMG signals is discussed in [18] and the authors advocate its utilization in ADAS for physically challenged drivers. This study propounds another utility of EMG signals which is homologous to steering action. The proposed framework predicts the intention of a driver and uses it to warn the driver anticipating a close contact with the approaching vehicle from behind. The framework apprehends using perception and prediction modules of ADAS and ADS. The perception module uses lane detection and object detection using a camera and object detection using Lidar. The detection in images is mapped to the detection in Lidar for accurate distance measurement. The driver's intention prediction is combined with the perception and a warning is generated if there are vehicles that are close enough and may cause an accident on turning of the steering wheel.

III. Methodology

The proposed framework is composed of four independent but synchronous data collection and prediction modules. First module performs EMG data collection and drivers' intended action prediction. Second is a lane detection module which uses the images from a camera mounted on the back of a vehicle for rearview. Third is an object detection system which also uses the images of the rearview camera. Fourth is a distance estimation modules which estimates the distance of objects approaching the ego-vehicle from behind. A block diagram in Fig. 3 depicts the flow of information among the four modules. Details of each module are given in the following subsections, whereas algorithm 1 gives a concise methodology adopted in this study.

Algorithm 1 Artificial Proprioceptive Reflex Warning ADAS

Require: Image I_t, PointCloud PC_t, EMG $E_{t-w,\dots,t}$ ▷ t is the time and w is the EMG signals window
▷ Image I captured at time t looking at backside, Point cloud data is the data captured by the Lidar, and EMG is captured using for a window of time w from the current time t

Ensure: $W_t, d_t \in \{W_L, W_R, W_n\}$ ▷ W is the warning if there is a vehicle on left or right, or no vehicle

while $True$ **do**
  $l \leftarrow Lane\_Detection(I_t)$ ▷ L is/are the points of the lane
  $v_{2D}, o \leftarrow object\_Detection(I_t)$ ▷ v, o are vehicles and objects
  $v_{3D}, d \leftarrow object\_Mapping(PC_t, v_{2D}, o)$ ▷ v_{3D} map the vehicle detected in 2D and their distance from vehicle
  $DI \leftarrow predict\_Intention(E_{t-w,\dots,t})$
  $C_v, C_d \leftarrow predict\_CriticalVehicles(DI, d, v_{2D})$
  if C_v in $\{l_l\}$ & DI_L **then**
    $W_t \leftarrow W_L$
    $d_t \leftarrow C_d$
  else if C_v in $\{l_r\}$ & DI_r **then**
    $W_t \leftarrow W_R$
    $d_t \leftarrow C_d$
  end if
  if $W_t \neq W_n$ **then**
    Show warning dialogue box for 5 sec
    $W_t \leftarrow W_n$
  end if
end while

A. Intended Action Detection Using Electromyography (ADE)

EMG sensors are used to capture and signal muscle activity in response to the stimulation of nerves. The sensors are attached to the surface of body muscles to detect neuromuscular activities. Seemingly, the muscles' movements initiate specific gestures and actions, and an early gleaning of the EMG signals provides an astute guess of the intended action. In this study, the EMG classification module predicts a driver's intended muscle movements of turning of the steering wheel in right or left direction. The driver wears EMG surface devices in two different dressings (Fig. 2(b)): one device on each arm and two devices on each arm. In the first dressing the signals are coarse and weak, whereas in the second dressing captures

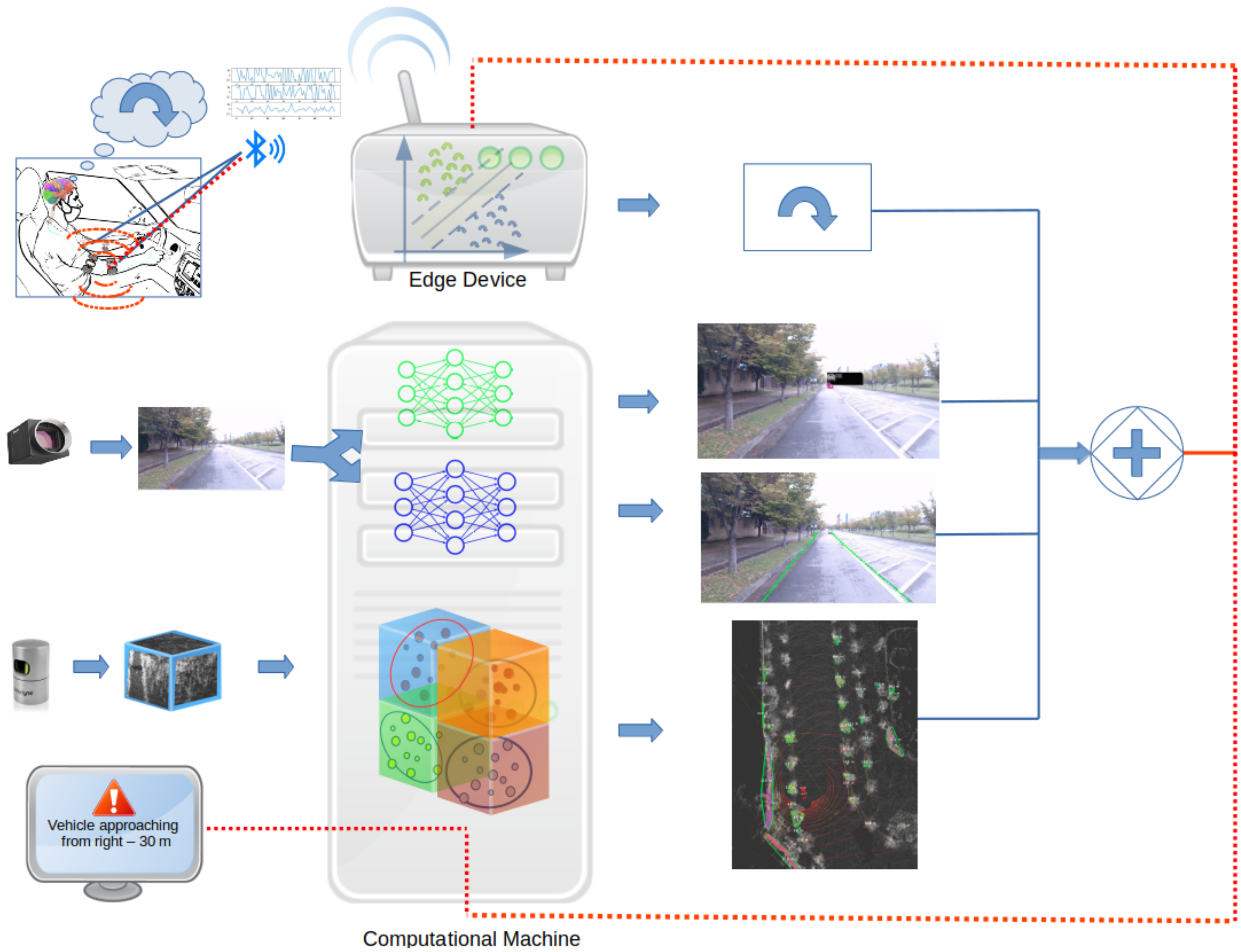


Fig. 3. System block diagram shows different modules. The EMG signals are communicated to the edge device on Bluetooth where it runs the classification algorithm and the red line on the driver shows the proprioceptive haptic signals in case of a warning detected by the system. The Computational system runs two Deep-learning networks (green for object detection and blue for lane detection), a matching algorithm on point cloud data, and data fusion from all modules including edge device data.

more differentiable signals. Each device has 16 sensors in a band which wraps around the arm and each sensor is supplemented by another two sensors which filter the noise. The wearable EMG band used in this study samples data at 200Hz. It is assumed that the driver puts both hands on the steering wheel while driving.

The two devices send signals synchronously to an edge device on a Bluetooth communication channel. The edge device predicts the intended action of the driver using a quick machine learning algorithm. This study experiments with conventional SVM. The training of SVM is performed with two different options: First, online training for every driver as it's not a tedious job and individual drivers have their own own EMG signatures. Second, the data is collected from various drivers and a pre-trained SVM is used to predict intended action of a driver. The SVMs are quick to train, update online and do not need abundant data which is a desideratum for state of the art. During driving, the EMG data is a continuous stream of signals $(x_1, x_2, \ldots x_N)$ which is input to the ADE module and a fixed stream $(x_{t-n}, \ldots, x_t)$ is used to predict the action. At time instance t the signal $x_{t-(n-1)}$ captured at time $t-1$ is dropped and the x_t is appended for the prediction. The predicted action is passed to the control module which fuses the information with the results of perception module that runs in parallel and nudges the driver about the situation of the traffic. A fundamental idea in this study is to predict the action in advance which may be implausible to test quantitatively with the used apparatus because the reported delay of muscle innervation and the action onset is little low. An alternative assessment is discussed in section IV-E.4. Purportedly, this is a pilot study and advocates for accurate and functional EMG sensors development for the specific tasks with passable results assessment tools.

B. Lane Detection

Lane detection is a widely targeted challenge in ADAS and ADS quests and often uses camera images for the detection. Earlier it was detected using conventional image processing and, later deep-learning techniques are employed for the detection. The latter gives rise to dataset collection and there are comprehensive dataset available with various imaging conditions. However, the lane annotations in the labeled dataset are available only for the front-view, whereas in this study the ADAS uses rearview. The models trained with the front-view annotated dataset are comparatively less accurate with rearview images. In this study, the same model is used to predict the lane in rearview images and sufficiently serve the purpose of identifying tailing vehicles in respective lanes. The lane detection information is separately computed in parallel to the vehicle detection with the object detection module.

A data augmentation technique to produce the automated annotation of rearview from the front-view is discussed briefly here for interested readership. The lanes are annotated in the image frame sampled from continuum of driving videos from a front-view camera, the same view is captured by the back-view camera after a certain number of frames. The conventional feature matching techniques in CV can be employed to compute the transformation parameters. The transformation parameters can be used to project the front-view annotations to the back-view annotations in a self-supervised manner. The deep-learning techniques with self-supervised learning can be applied using the computation of extrinsic parameters for the mapping.

C. Object Detection and Distance Computation

Human drivers exercise involuntary sensory-motor data fusion for vehicle control [42]. Quintessential object detection from different views supposedly includes the tailing vehicles using the rear and side mirrors involuntarily before a lane change. The detection is often observed in parallel to the voluntary control of the vehicle which may be ignored or masked in presence of other thoughts and actions. This study investigates the use of object detection in rearview images using state-of-the-art deep learning techniques. The rearview camera is used to detect the objects approaching from behind. A model trained with the general vehicle images suffices for this study as the object detection dataset are conveniently augmented to cater for the perceptive changes in rearview images.

The distance of the approaching vehicle is computed using a Lidar. The Lidar is calibrated with the rearview camera and the detection in images is mapped to the Lidar point-cloud data. The Lidar gives an accurate distance of the tailing vehicle. The objects are conveniently detected in the point-cloud data, but this study considers distant objects which lose resolution in point-cloud data. Another option is to use the monocular depth estimation and extract the distance information from the image only thus neutralizing the cost of an expensive Lidar sensor on the cost of computational latency.

D. Information Fusion

Human reflexes exhibit extraordinary skills in a certain situation and the instantaneous response meticulously benefits the requisite objectives. The reflexes often build the sensory-motor responses close in distance. In the case of driving the motor neurons engaged are the somatic nervous system and the sensors are distant from the actuators. Also, conscious movements are planned in response to particular perception that is built by the vision and auditory sensors. The information is continuously collected from vision(front, sides, rearview), hearing, and somatosensory signals, and the information is fused to build a perception of the surroundings. The fused information prompts future actions, and the following discussion about the proposed modules for data fusion is inspired by the spectacles of neuroscience.

The detection data from object detection and lane detection is fused to identify the lane of the tailing vehicle and spot the vehicles in immediate left, right, and following lanes as charging vehicles. The Lidar-camera transformation is fused to collect the distance of the charging vehicles and mark critical vehicles with a distance threshold. The intended action detected by ADE module is fused with the information of the critical vehicle and nudge the driver if the intended move apprehends a collision with the critical vehicles. A flow of information in Fig. 3 depicts the flow and fusion stages of the processed sensory information and the artificial haptic response.

IV. Experimentation

The experimentation to test the proposed framework is carried out with a model SAE level-2 experimental vehicle. The vehicle is mounted with a 32 channel Lidar, two cameras (front-view and rearview) and a radar for perception building. The vehicle is equipped with a custom-designed computational machine for vision and point-cloud data processing. The EMG sensors used in this study are two wearable Myo wraps[1] [40], one for each arm. Each wearable device has 16 sensors mounted on a round wrap of strips and each strip has two sensors.

A. Computational Environment

The computational setup for the experimentation is shown in Fig. 3. Camera images and Lidar point cloud data are transferred to a computational machine equipped with an Nvidia GTX1070 GPU. The experiments are performed on the ADS computational stack, which uses Robotics Operating System (ROS) as a data fusion middle-ware. ROS operates on a publisher and subscriber communication framework which supports the parallel computation demands of the proposed workflow of the ADAS. The EMG signals are captured on an edge device using a 1.3 GHz processor and 2 GB memory, and the EMG data is transmitted over Bluetooth. The EMG sensors used in this study are from ThalmicLab's Myo armband that records signals at 200 Hz and further details about the specification of EMG sensors are discussed in [40]. The same edge device runs the SVM for the prediction of the intended action. The device also runs a ROS node connected to the main computation machine running the ROS Master connected over LAN. The intended action and the EMG data are published on the edge device which is subscribed by the information fusion module running on the computation machine. The EMG data is also published on a separate channel to avoid the delays of communicating the prediction results. The data helps to examine and analyse the signals used for prediction.

[1]Thalmic labs (https://www.bynorth.com/)

B. Data Collection

There are three modules in the proposed framework that needed a dataset for their learning algorithms. First, object detection data set uses the Mscoco dataset [43] for detecting tailing vehicles. Mscoco object detection is a comprehensive dataset with 80 labeled categories of objects. The lane detection module uses the TUSimple[2] dataset which provides a labeled dataset for lane detection. The ADE uses a dataset of EMG signals collected with Myo wearable devices for experiments in this study.

C. EMG Dataset

The EMG dataset collected for this study uses the wearable Myo device worn by three different drivers performing two different actions and the third category is defined as no-turn. The actions are turning right, turning left, and third is otherwise. It is assumed in this pilot study that the driver is using both hands to drive and his hands are on the steering wheel during experiments. The data is collected with a stationary vehicle by turning the steering wheel only. The two wearable sensors are connected to an edge device and data is communicated over Bluetooth. Each device gives 64 readings (window size w) from each of the 8 sensors from the Myo device and the raw signal values from all the sensors and devices are concatenated to make one sample. The data is labeled manually into three classes for training. The data values are normalized and scaled between -10 and 10. The three classes are labeled as 0,1,2 for left, right, no-turn. This study is approved by the Gwangju Institute of Science and Technology (GIST), Institutional Review Board (IRB) approved this study under approval number (20230202-HR-70-06-02). Moreover, informed consent was obtained from all the subjects participated in data collection of the study.

The two wearable devices synchronously transfer the data which is collected at the edge device and stored as separate arm actions on the edge device. The synchronization of the two devices is a delicate part which is supported by the MyoConnect development library provided with the software. The synchronization is cross verified with the timestamps. In another experiment with two wearable devices wrapped on each arm (Fig. 2(b)) the data is collected separately for each arm and data for four devices is concatenated to emulate a single action. For each driver a around 100 ($\pm$6) samples for all three categories are collected and a 60 to 40 train-test split is used. In a second approach, the data is collected online before the start of the experiments for individual drivers. A similar procedure of data generation is adopted except that the data is not stored and fed live to the learning algorithm for N samples of window-size ($w = 64$) for each action. The details of the apparatus are given in section IV-A. EMG noise is filtered in the Myo armband. The resident noise however is considered a regularization of the EMG classification algorithm.

D. Lane Detection and Object Detection

The lane detection module discussed in section III uses a trained ANN UltraFast lane detection [44] algorithm for detecting lanes in rearview camera images. The images are resized to 416x416 for inference and then resized to original size for display. The algorithm uses a deep neural network which contextually divides a view into a grid. The features are extracted from an image and the grid is generated with row specific anchors. The grid structure of the image gives fast computational speed for lane detection as the grid contains spatially coarser data points than the competitive methods which use whole image pixels. The real time performance at 300 frames per second (fps) of the lane detection algorithm befits the requirements in the proposed study. The object detection module uses a state-of-the-art ANN Yolo3 [31]. Yolo3 is fast in detecting the objects in images at 23ms (60fps) and is optimal for suggested experiments. Yolo3 uses 53 convolution layers with 3x3 and 1x1 convolution kernel sizes and uses k-mean clustering for bound-box anchors. For further details, interested users are referred to the original manuscript [31]. The point cloud data is filtered using euclidean clustering algorithm to determine the object and maps it to the image from the camera using the calibration. It gives the accurate distance of the object detected in the image.

E. Results

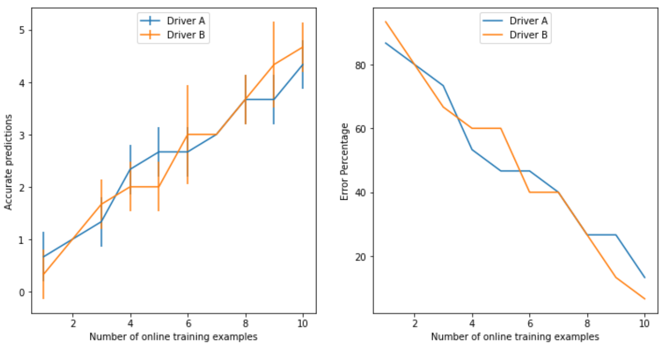
1) Accuracy of EMG Classification Offline: Primary focus of this study is anticipating the intended action of a driver and generating a warning for a driver using biological experiences. The EMG signals from three drivers are classified into three classes using the two different use of wearable sensors as discussed in section IV-C. The accuracy of the EMG classification is tested with the data collected from EMG wearable devices worn by the drivers and performing three actions with their hands on steering wheels. The vehicle was stationary for this experiment. In this section, the experiments are planned with two different variations based on the training and testing data. First, separate training data is prepared for each driver and tested for the same driver. The train to test split ratio is 60 to 40 for each driver(details about EMG dataset are discussed in IV-C). Second, a single training dataset is generated for all drivers and the test dataset is also combined for all drivers. Table I gives the results of two experiments. The correct prediction of the intention of the driver is in numerator and the denominator gives the total number of samples for a performed action. The accuracy increases as we increase the number of used EMG devices. The four devices data is collected separately by wearing two devices on each arm and concatenating the data later for training and testing. It is also noticed that the generalization causes more errors in prediction than person specific training and testing. The person specific testing will not decrease the effectiveness of the proposed idea as elaborated from an experiment in section IV-E.2. The reported prediction results in a cell where the numerator is greater than the denominator, it suggests bias towards the titled class in data collection.

2) EMG Classification Online: Another experiment was designed to test the efficacy of the system for a new driver on-the-spot. The training data was collected when the driver takes the wheel and with a minimal number of samples an SVM is

[2] https://github.com/TuSimple/tusimple-benchmark

TABLE I
EMG SIGNAL CLASSIFICATION FOR THREE DRIVERS

Driver	EMG Devices	Right Turn	Left Turn	No-Turns
A	2	10/12	9/10	21/18
	4	11/12	8/8	18/17
B	2	9/11	11/10	15/17
	4	12/12	10/12	16/14
C	2	6/9	8/7	13/11
Combined	2	27/32	25/27	41/34
	4	29/34	24/27	39/31



(a) Error bars

(b) Average Accuracy for Two Drivers

Fig. 4. (a) Error bars for on-the-spot training and testing for two drivers. (b) Accuracy in percentage for the two drivers after on-the-spot training.

trained and the learned parameters are used for instantaneous testing. The same EMG devices are used and the results are generated with a single device on each arm. w is 64 for each device. The samples are concatenated from both devices and used for training and prediction. The training dataset is composed of 6 examples and are considered sufficient to generate good predictions, as the system is tested for an individual. Fig. 4 depicts samples and prediction accuracy graph for two drivers. The number of examples proportionally increase the time for training but improve the result of predictions. The experiments suggest a minimal nuisance value for the whole process of training which may vary based on the real-world experience in a routine environment.

3) Warning Generation: A complete framework is tested in a setup prepared for the vehicle(called SDV). The test was performed on a major four lane in-campus road with two-way-traffic. The SDV was driven at a speed of $20kph$ for 5 minutes straight on the road with restricted traffic. The tailing vehicle was driven by a team member who was in continuous communication with the team in the SDV. The tailing vehicle was kept at a safe distance(30m-50m) during the experimentation. The driver in SDV wears the EMG devices and the camera and Lidar are calibrated using the ADS. The EMG signals were continuously streamed and w of 64 in one example was used for prediction. The continuous stream of signals was appended to a queue to generate a sample that strips the farthest signal and appends a recent signal for prediction with a continuous stream. A SVM was trained as discussed in section IV-E.2 and the prediction results are communicated to the ADS.

The ADS captures the stream of data from the camera capturing the rear view of the vehicle. The stream of data is passed to lane-detection and object detection algorithms. This

Fig. 5. A complete depiction of signals and computation results after processing. The left side shows the image data captured by the rearview camera, lane detection and object detection applied to the image. The right side shows the point cloud data at bottom and EMG data on top. The left side top image shows the fused results in one image that includes lane and object detection and the distance measured by the lidar. The red triangle in the EMG data shows the intention prediction in the continuous stream of EMG singals.

experiment used FLIR Blackfly-S camera for rearview with a frame rate of 522fps. Another experiment was performed with a Logitech c930 webcam rear view camera with a frame rate of 30fps. The lane detection and the object-detection work in real-time with more than 30fps. The experiments used Velodyne HDL-32E Lidar which gives a 360° field of view (FOV), a maximum of 1200 rotations per minute (RPM) that gives us 20fps, and covers 80m-100m distance. The Lidar settings for the experiments also used a 120° rear view range with 600RPM that reduce the frequency to 10fps. The calibration in the ADS and gave us the distance of the detected vehicle in the rearview.

Fig. 5 shows the results of all modules in the ADS, windows on the left shows the detected tailing vehicle. An image with lane-detection is shown on the left bottom separately. A calibrated 3D detection of the vehicle is visible on the right side in point cloud data which also shows the distance from the vehicle. Fig. 5 top right shows the classification and marking of the predicted intention in bounding boxes. A warning is generated with a dialogue box and a vibration of the wearable EMG device. It is visible in the point cloud data our vehicle is oriented a bit towards left at the time the warning was generated by the system.

4) Can She Recover From the Mistake?: A pertinent outcome to conclude this study is the computational time for prediction of the intended action considering the real-time computations in other modules. The intended movement action detection competes with the muscles' movement onset. The delays are often studied using the movement-related cortical potential (MRCP) [45], whereas the EMG is used to detect the onset movements in an experimental setup [46]. Moreover, electrochemical delays (ECD) and electromechanical delays (EMD) can be explored to assess the difference between intended action detection using EMG and the onset movement. This study pilots the utility of ADAS using EMG for movement intention detection and can not benefit from the discussed techniques to detect the exact latency using methods given in [46]. Therefore, this study relies on the computational time for each module of the proposed framework to answer the pertinent question.

The computations in this study are discussed as follows: The EMG wearable device is connected with an edge device using a Bluetooth device with a transmission latency of the low energy Bluetooth which is 46ms in worst case [47]. The computational time for prediction of EMG is 0.55ms ($\pm$ 0.1) and the communication from the edge device to the computational machine is on gigabit network which is insignificant. It does not add delay to final result transmitted to our computational machine and takes 100ms ($\pm$ 10). The computational machine computes the lane-detection, object-detection, and Lidar-to-camera mapping in real-time. All the computations are performed in parallel and a simple control logic accumulates the results from all modules and generates a warning in less than 2ms. The warning sends a signal back to the edge device which transmits a vibration command to the EMG wearable device to warn the driver. In all, the round-trip for the whole transmission takes less than 200ms.

If we hark back to our example from the section I, the system has 500ms to predict and warn the driver if the following vehicle is driving at a speed of 60kph and it is 17m away from our vehicle. The tested system's computation time is far less than the conjectured time. However, the pilot system uses the EMG signals which are captured from the upper limbs for intention prediction. The movement action is already initiated at the time the system starts its prediction, but a vehicle at a distance of more than 50m may provide a cushion to the driver to recover from an action which may lead to an undesirable situation. The experimentation details in section IV-E.2 are tangible evidence of timely prediction of a driver's intended action before the approaching vehicle reaches a close distance.

The related studies in [41] evaluate the later movement error for EMG guided steering control interface in a simulated environment and test three similar scenarios. However, a contrast in the objective makes it challenging to opt for the lateral moment error for a fair comparison. Whereas, [19] uses a time analysis of the pedestrian collision avoidance using the EMG Myo bands in a simulated game environment. A direct comparison of the response time for the collision avoidance is not possible, but the response time proposed strategy is generally quicker nonetheless. Moreover, the proposed study is tested in a real environment with the devised experimentation with veritable computational response times in real situations. We plan to introduce standard qualitative and quantitative evaluation metrics for comparisons in future studies.

F. Limitations

The proposed study uses a number of components and multi-modal heterogeneous data. A primary module, that predicts action of a driver in advance, uses EMG signals and it needs to be synchronized with video data which is used by lane detection module. EMG and videos are spatio-temporal data with different dimensions and modalities. As the proposed ADAS system operates in milliseconds granularity, a robust synchronization is required for accurate functioning of the system. Moreover, point-cloud data is used for accurate distance calculation, thus synchronization between camera and Lidar is highly recommended for the experimentation of a functional system. Moreover, Lidar and camera calibration affects accurate estimation of distance from a tailing vehicle. In this study, the experiment is carefully designed and all sensors are synchronized and calibrated for an effective demonstration of the proposed idea. An error in calibration and a drift in synchronization will definitely affect the performance of proposed system.

Overfitting can impact the framework in three modules EMG signal classification, Lane detection, and Object Detection. In EMG signal classification overfitting can impact in two different ways. First, with a general system trained offline with EMG signals of multiple users and inference for an individual. Second, a system is trained online with individual data. Both scenarios are tested and evaluated in this study and the impact is minimal in the results, but it cannot be ruled out in machine learning and should be evaluated with a large-scale test deployment. Lane detection and Object detection generalization are tested with the adopted networks trained on a public dataset and tested in a specified experimental setup. The performance is accurate for the experimentation without the tuning of the trained network on the experimental data.

V. Conclusion

This work presents a pilot study designed to assess the utility of biological neural activation for advanced driving assistance systems (ADAS). The electromyogram (EMG) is used to predict the intended movement of arms of a driver to turn the steering wheel in the left or right direction. The predicted information is combined with the object detection in images and Lidar point cloud data and feed to the control logic. The algorithms use rearview camera images and Lidar point cloud data to detect following vehicles, their locations, and distances from ego-vehicle. The results suggest that the warning generated by the proposed system can timely warns a driver about a tailing vehicle to recover from a movement onset and imitate a proprioceptive reflex with a haptic response. The system uses a simple EMG wearable device for inputs and a conventional SVM for the prediction of intended action. It can be extended to design an application-specific system with EEG and state-of-the-art machine learning algorithms. Moreover, task-specific EMG sensors can be designed to wear closer to the spine to sense electrical stimulation earlier and predict early. Another prospect is the use of EEG for the same purpose which will take it a step closer to the actual claims and will gain more time for the computations and generating warnings.

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