IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received October 9, 2019, accepted November 15, 2019, date of publication December 18, 2019, date of current version December 31, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2960567

Inferring Drivers' Visual Focus Attention Through Head-Mounted Inertial Sensors

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This work was supported in part by the National Council of Science and Technology (CONACyT, México) through the Fondo Sectorial de Investigación para la Educación under Grant 288670.

ABSTRACT Driver distraction is one of the major causes of accidents. Most methods for inferring distracted driving behaviors are vision-based systems that determine the head's orientation. One of the significant challenges of this approach is to develop robust algorithms that detect face and eye features under various lighting conditions. Our approach is based on inferring the vehicle's cabin spot drawing the driver's attention through head-mounted inertial sensors. To achieve this aim, we collected accelerometer, gyroscope, and magnetometer data from ten participants who drove under semi-naturalistic conditions. We generated classifiers by using the Support Vector Machine (SVM linear and RBF), k-nearest neighbor (k-NN), and Random Forest (RF) machine learning techniques. These techniques, except SVM linear, produced an accuracy, precision and recall higher than 96%. Our results demonstrate that raw signals collected from the inertial sensors provide enough information about the head posture associated with the car's cabin spot.

INDEX TERMS Machine learning, vehicle driving, sensor systems and applications, distraction.

I. INTRODUCTION

Driver's inattention, in its various forms, is considered an essential factor in road crashes [1]. It refers to drivers' status in which their alertness diminishes due to drowsiness caused by fatigue or distractions caused by the lack of continuous attention for engaging in other tasks while driving. These tasks can be any diversion of attention like cognitive (e.g., being lost in thought), physical (e.g., adjusting the infotainment system), and visual distractions (e.g., looking away from the road) [2]. Additionally, the increasing use of in-vehicle information systems (IVISs) and the prevalence of mobile devices may affect driving performance in different ways by inducing visual and cognitive distractions [3]. Distractions are estimated to cause 23% of accidents or near-accidents [4] and could be reduced by 10-20% through systems that monitor and predict driving behaviors [5], [6]. Drowsy driving is a significant public health and safety problem around the world [7]. Thus, different methods for detecting driver distraction and drowsiness have been explored [3], [6], [8], [9].

The associate editor coordinating the review of this manuscript and approving it for publication was Utku Kose.

The head position is a reliable cue of the visual field and the current focus of the attention of drivers [8], [9]. Based on this, inferring the head position is considered essential to monitor the level of alertness of drivers. Most of these methods rely on the analysis of extracted characteristics from video images, which are subsequently used to infer the orientation of the head and the behavior of the gaze point [6]. In contrast, our work aims at inferring the car's cabin spot upon which drivers focus their visual attention based on raw signals from head-mounted inertial sensors. They included the accelerometer, magnetometer, and gyroscope sensors integrated into smart glasses.

In this paper, we first characterize the inertial sensors. Then, we carried out experiments to train classifiers using the sensing data collected from ten participants who drove in semi-naturalistic conditions. Finally, we compared the performances of Support Vector Machine (SVM), k-Nearest Neighbor (k-NN), and Random Forest (RF) learning-methods.

Before presenting the experiments, we first highlight the novelty of our approach through a mapping review of related works. Then we describe the design of the experiments conducted to train the classifiers. We discuss the implications of our results for implementing applications related to driving,

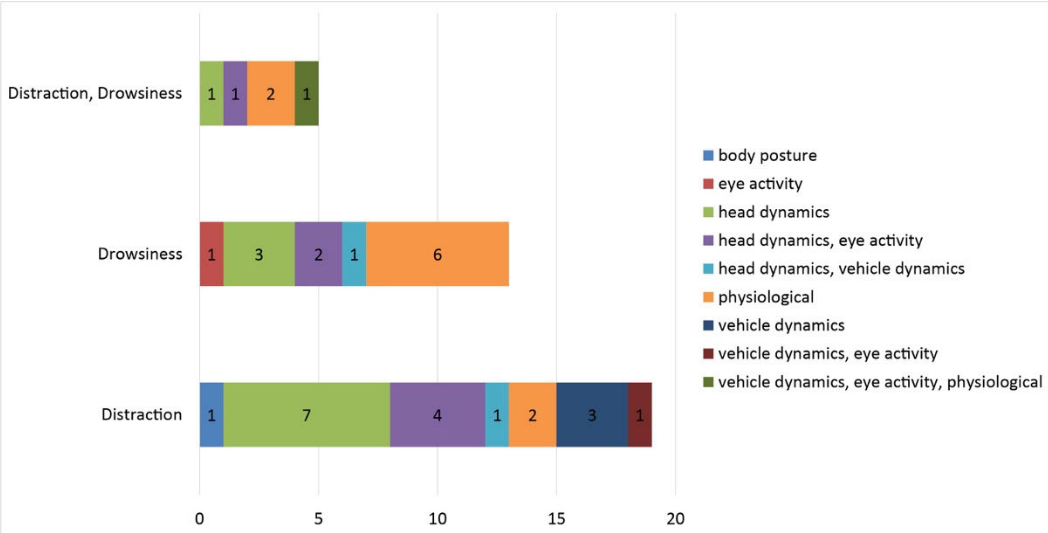

FIGURE 1. Number of papers (X axis) focused on detecting inattention behaviors (Y axis) by using different cues.

and the potential of our approach to be used in other application domains. Finally, we conclude and explain possible future directions for this work.

II. RELATED RESEARCH

We conducted a mapping review of relevant literature reporting similar approaches to ours in the last decade.

A. SEARCH AND SELECTION OF STUDIES

Our search process was by no means exhaustive. We opted for defining a conventional search strategy and complemented it with other techniques [10]. We searched on Scopus since it is one of the most extensive databases that index high-quality literature in different areas. We formulated a query string with the words: driver, inattention, distraction and drowsy; and applied search filters to retrieve papers related to the engineering and technology area. We complemented the search with the ''Snowballing'' technique [10], for which we decided to scan the references list of related literature review papers, i.e., [11], [12]. From these reference lists, we selected papers highly related to our work, except those reporting using a camera-based approach, since it was the most found from our search in Scopus.

To incorporate consolidated research, we selected papers written in English, published in journals, conferences and book chapters, and reporting experimental results about using sensing technologies that contribute to the development of monitoring systems of driver inattention. To this end, we first removed duplicate references to papers. The first selection stage was a binary rating of papers' abstracts (0: exclude; 1: consider for inclusion) by one of the authors. Afterward, three authors carried out a full-text review of the included papers to identify the technological approaches used for inferring inattention.

B. ANALYSIS OF STUDIES

We retrieved 1983 papers, from which 1659 were identified as not relevant when screening their titles and abstracts (first selection stage). From the resulting papers, we excluded 263 because they estimate head pose but not in the driving context, resulting in 61 included papers [9], [13]–[71]. As depicted in Fig. 1, most of the studies are on distraction behavior [9], [13]–[52], for which the cue most studied is head dynamics and motion. On the other hand, most of the papers that focus on inferring drowsiness use physiological cues, such as signals from electroencephalogram (EEG) [20], [53], electrocardiogram (ECG) [54]–[56], electro-oculography (EOG) [57], and surface electromyogram (sEMG) [56]. Besides, few works have studied hand [35] and body postures [47] through camera-based techniques to infer secondary tasks such as eating and talking on a mobile phone. Monitoring more than one cue is a strategy used to improve the inference of inattention behaviors. For instance, head pose and vehicle dynamics were used to predict distraction in [23] and were used to predict drowsiness in [58].

Each kind of sensor has pros and cons for detecting driving behaviors. As shown in Fig. 2, most of the technological approaches for monitoring distraction require instrumenting the vehicle with one or more sensors, mainly cameras, in-vehicle devices such as on-board diagnostics (OBD) devices, and infrared sensors.

Electrode-based sensors are mainly used to predict drowsiness since physiological signals such as the EEG are reliable predictors [72]. However, these sensors can be uncomfortable to wear and therefore perceived as intrusive. In this sense, cameras are less invasive than electrodes but require developing sophisticated and robust computer vision algorithms for detecting face and eyes features under various lighting conditions. For instance, changes in light intensity when entering or leaving a tunnel or non-uniformity of light sources cause asymmetric shades on the driver's face [12], making the detection process complex. On the other hand, wearable computing has been becoming mainstream, as evidenced by the large-scale market uptake of smartwatches and smart glasses [73]. These devices embed motion sensors that can

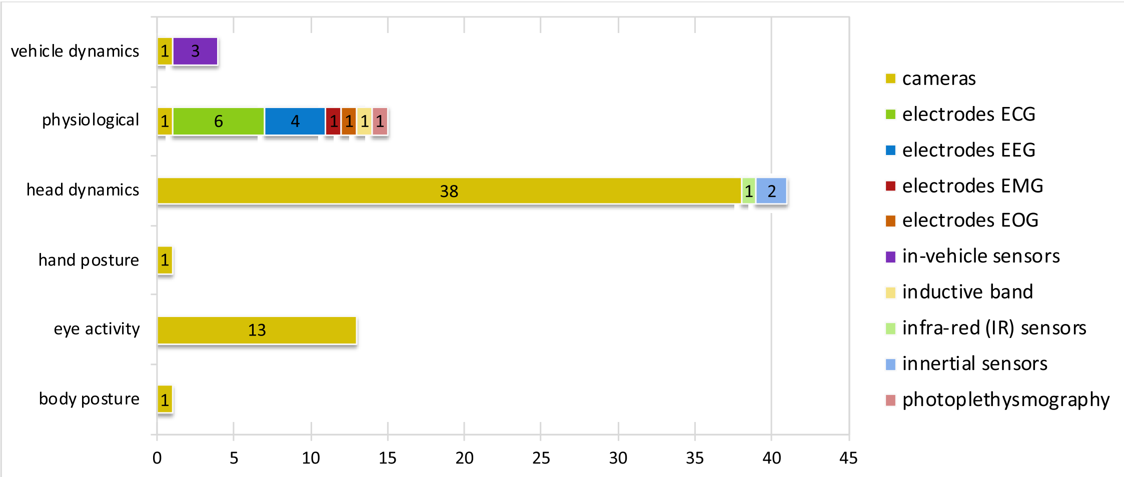

FIGURE 2. Number of papers (X axis) studying how to detect the cues (Y axis) associated to inattention through different sensors.

make the detection of driving behaviors more feasible and affordable in real-world settings.

Based on our search, we identified only two works that made use of the inertial sensors of smart glasses [23], [42], both from the same research group. In [23], the authors focus on detecting drivers head motion through a dual compass-based system that estimates the angular velocity from a head-mounted compass (magnetometer) and then subtract the angular velocity from a vehicle-end compass. In [42], they used raw data from the accelerometer, gyroscope, and magnetometer of smart glasses to estimate seven specific head postures based on rotation angles of yaw, pitch, and roll (e.g., 'yaw right', 'yaw left', 'pitch right', and 'pitch left') [42]. Thus, in the abovementioned approach, additional processing is required to infer the drivers' visual focus of attention. On the contrary, our work aims to generate classifiers that infer the cabin spot drawing the driver's visual focus of attention. To reach this end, we conducted experiments with several machine learning techniques. We next describe the methods used.

III. METHODS

A. CLASSIFICATION PROBLEM SCOPE

As explained in [74], not only secondary tasks are risky, but also those tasks highly related to driving, which demand glances away from the road. There are four types of driver inattention: *i) secondary task distraction*, which refers to the diverting of the driver's attention away from the driving task, for instance, handling a CD, and reaching for an object on the back seat; *ii) driving-related inattention from the road;* it is directly related to the driving task such as checking the speedometer and mirrors; *iii) drowsiness,* which includes eyes closures and repeated yawing; and *iv) non-specific eye-glance away from the road;* it involves glances at no discernible object, person, or unknown location outside the car and away from the road [75]. Our work aims at the two first categories in which drivers conduct activities that may involve glancing at spots of the car's cabin.

Thus, our classification problem can be described as inferring a set of spots based on the drivers' head postures. We hypothesize that the unprocessed signals, collected from the inertial sensors mounted on the driver's head, provide enough information about the head posture associated with the car's cabin spot. The scope of our study is limited to inferring the eleven spots depicted in Fig. 3 (S0-S10), which are the classes for our classification problem.

B. CLASSIFICATION ALGORITHMS AND TUNING PARAMETERS

We selected some of the most popular classification techniques. We chose SVM and RF over artificial neural networks (ANN) since the former is insensitive to noise and handle unbalanced data well [76]. Moreover, SVM, k-NN, and RF generally outperform other traditional supervised classifiers in several application contexts, such as for recognizing human activities from wearable inertial sensors data [77], and remote sensing images applications [78]. In this section, we briefly describe the supervised classification techniques used in this study and the parameters that were tuned to find the best classification performance for each of the algorithms.

1) SUPPORT VECTOR MACHINE

A classification task usually involves separating data into training and testing sets. Each instance in the training dataset contains one target value (i.e., the class labels) and several features (i.e., the observed variables) [79]. The Support Vector Machine (SVM) is a classifier derived from statistical learning theory, which produces a mapping function or model from the training dataset. The model can predict to which class each of the instances of the test dataset belongs [80]. SVM finds the linear hyperplane that provides the most significant separation margin between two classes. However, pairwise classifications can be used to address multi-class classification problems, which can be time-consuming when the training dataset is large. Another alternative for

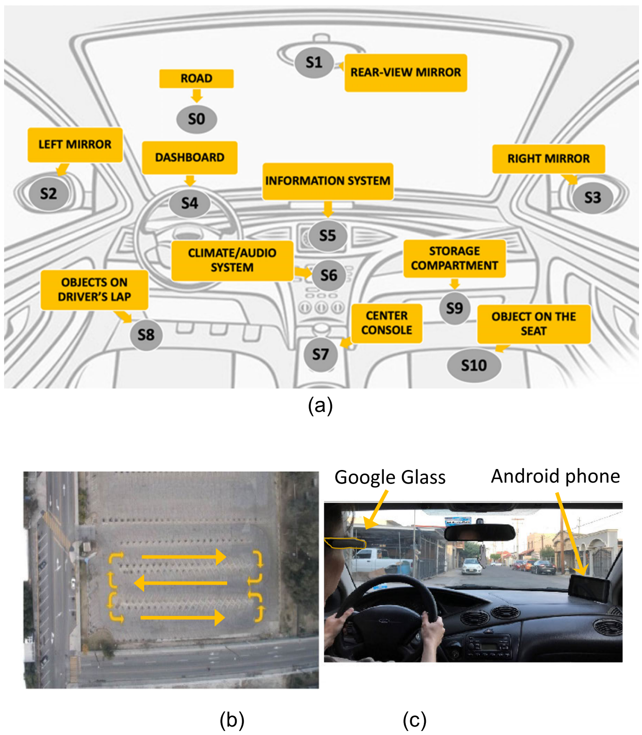

FIGURE 3. Setting for collecting data: (a) cabin's spots of the car used for collecting data, (b) route followed during the driving sessions in a private parking lot, (c) instruments used to collect data.

multi-class problems is to apply kernel-based methods, and one of the suggested is the RBF kernel [79]. Nevertheless, when the number of features is considerable, this kernel may not be suitable. The effectiveness of SVM relies on the selection of the kernel and the soft margin parameter c.

For the kernel RBF, two parameters need to be tested c, in addition to the kernel width parameter, namely γ. The c parameter decides the size of misclassification allowed for non-separable training data, and γ parameter affects the smoothing of the shape of the class-dividing hyperplane. Given the uncertainty about whether the size of our dataset can be considered small or large, we decided to assess the SVM by comparing its performance when applying the linear and the RBF kernels, in addition to varying the c parameter. Following the recommended values for these parameters given in [79], in this study, we tested the SVM performance for our dataset with 15 values of c ($2^{-3}, 2^{-2}, 2^{-1}, 2^{0}, 2^{1}, 2^{2}, 2^{3}, 2^{4}, 2^{5}, 2^{6}, 2^{7}, 2^{8}, 2^{9}, 2^{10}, 2^{11}$) for the linear SVM. And for the RBF we made 15 pairs of these c values with the following values of γ: $2^{-6}, 2^{-5}, 2^{-4}, 2^{-3}, 2^{-2}, 2^{-1}, 2^{0}, 2^{1}, 2^{2}, 2^{3}, 2^{4}, 2^{5}, 2^{6}, 2^{7}, 2^{8}$.

2) K-NEAREST NEIGHBOR

The k-NN algorithm [81] is a direct classification method because, unlike other supervised learning algorithms, such as SVM, it does not produce a mapping function from a training stage. It merely uses the training dataset at the test time to make predictions. Thus, k-NN requires the storage of the whole dataset. For classifying a new observation, k-NN uses the principle of similarity (Euclidean distance) between the training dataset and the observation to classify. Then, it is assigned to the most common class through a majority vote of its k nearest neighbors. With our experiment, we varied the value of k (from 1 to 20) to find a satisfactory algorithm performance.

3) RANDOM FOREST

Random Forests (RF) consists of building a combination of decision trees at the time of training [76]. RF improves the classification performance of a single-tree classifier by combining the bootstrap aggregating (bagging) method and the random assignment in the selection of partition data nodes in the construction of the decision tree. The assignment of a new observation to a class is based on the majority vote obtained from the trees that constitute the forest. RF needs a large training dataset to achieve good performance. For our dataset, we decided to assess the RF performance by varying the number of trees: 1,50, 80, 100, 200, 300, 400,…,1200, and 1300.

C. DATA COLLECTION AND INSTRUMENTS

We collected data from ten recruited participants (P1-P10), six males and four females, with a mean age of M = 31.50 and SD = 9.05 years. Each participant drove approximately 10-15 minutes in an empty parking lot of our university for safety reasons (see Fig. 3). Also, the following conditions were controlled to collect a balanced and representative dataset. Thus, everyone drove down the same low-speed road and were asked to see each cabin's spot while driving in a straight direction. Participants worn a Google Glass V3 (XE-C model) with a Java-based app implemented with GDK (Glass Development Kit). The app provides functionalities that facilitated the data collection and their labeling (see Fig. 4). This app requires selecting the spot to record through a sliding gesture, and a tap gesture to control the recording of the data collected.

The researcher (first author) accompanied each of the participants. He instructed them to fix their gaze on each of the cabin spots for approximately 2-3 seconds. Participants used the java-based app of Fig. 4 to record the data, which was labeled with the selected class. That is, the first dataset gathered was labeled as spot S0; then the drivers stop the recording, and select the next spot with a sliding gesture to start recording data labeled as S1, and so on. This process was repeated three times. By using the Google Glass screencast function, the researcher monitored the information recorded from his Android phone (see Fig. 3c). This allowed him to provide instructions to the participants on when to start and stop the recording of each spot through the interaction gestures depicted in Fig. 4. For all sessions, the sampling rate was set at 50 Hz.

D. DATASET DESCRIPTION

The dataset consisted of tuples (see Fig. 5). Each of them containing the x, y, and z values of the accelerometer (Accx,

TABLE 1. Instances captured for each participant (P1-P10) and labeled as spots classes (S0-S10).

Participant/Cabin spot	S0	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	Sub-total
P1	164	146	165	168	200	164	178	170	154	230	173	1912
P2	158	151	187	182	157	208	178	203	179	183	227	2013
P3	213	165	172	151	151	174	165	148	177	161	205	1882
P4	161	177	143	144	147	198	160	166	168	171	163	1798
P5	217	211	200	172	207	179	166	177	194	177	173	2073
P6	173	188	188	237	172	230	238	225	207	250	248	2356
P7	164	154	177	154	179	158	196	195	184	189	173	1923
P8	186	172	164	168	151	171	170	159	193	243	170	1947
P9	190	222	173	126	151	187	180	163	170	168	185	1915
P10	143	153	167	150	152	155	143	173	160	145	161	1702
TOTAL	**1769**	**1739**	**1736**	**1652**	**1667**	**1824**	**1774**	**1779**	**1786**	**1917**	**1878**	**19521**

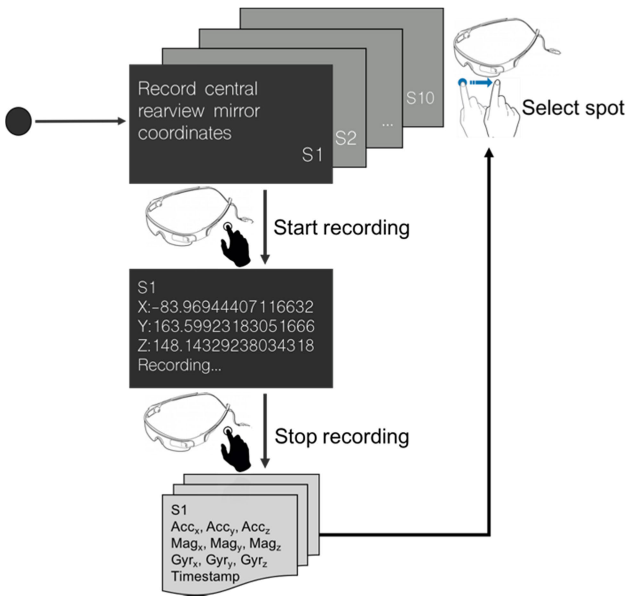

FIGURE 4. Interaction with the Java-based application implemented for the Google Glass, which requires selecting the spot to record through a sliding gesture, and a tap gesture to control the recording of the data collected.

Accelerometer			Magnetometer			Gyroscope				
Accx	Accy	Accz	Gyrx	Gyry	Gyrz	Magx	Magy	Magz	Time	Class
-6.924	6.213	1.666	-0.016	0.195	0.151	11.7	-11.64	23.46	1.5+E12	S0
-6.539	5.753	1.228	-0.011	0.197	0.107	11.88	-11.4	22.92	1.5+E12	S0
...	...	...	...	...	...	...	...	...	...	...
-7.295	6.285	1.262	0.015	0.215	0.015	13.02	-10.74	23.28	20+E12	S5
...	...	...	...	...	...	...	...	...	...	...
-7.791	6.745	1.391	0.02	0.207	0.006	13.26	-10.98	22.62	40+E12	S10

FIGURE 5. Structure of the collected dataset.

Accy, Accz), gyroscope (Gyrx, Gyry, Gyrz), and magnetometer (Magx, Magy, Magz); in addition to the timestamp in which they were collected. Each tuple was labeled with the spot class (S0-S10) through the Java app. As shown in Table 1, we collected 19,521 readings from the inertial sensors.

E. DATA TRAINING AND TESTING

The platform used to train and test the performances of SVM, k-NN, and RF was WEKA (Waikato Environment for Knowledge Analysis, version 3.8.2) [82]. WEKA offers a collection of automatic learning algorithms for data mining tasks and contains tools for pre-processing data classification, clustering, association, and visualization rules. Additionally, WEKA allows normalizing the data before the training. We used the 10-fold cross-validation training technique. It consists of dividing the dataset into n partitions ($n = 10$ in this case), where we used n-1 partitions for training the classifier, and the remaining one for testing. This process is done n times, in which the testing set is shifted in every iteration.

F. DATA ANALYSIS

We used accuracy, precision and recall as performance metrics of the classifiers [83]:

- Precision is the proportion of elements classified as positive that are true positives (tp) and false positives (fp).

$$Precision = tp/(tp + fp) \tag{1}$$

- Recall is the proportion between positive elements or correctly classified (tp), and false negatives elements (fn) [76].

$$Recall = tp/(tp + fn) \tag{2}$$

- Accuracy is a measure of general efficiency to evaluate the performance of a classifier, and refers to instances classified correctly, where tn are the true negatives [76].

$$Accuracy = (tp + tn)/(tp + tn + fp + fn) \tag{3}$$

IV. RESULTS

A. ANALYSIS OF THE BEHAVIOR OF THE SENSORS

Figures 6a-c present plots of data collected from one of the participants of our study. It is noticeable how the

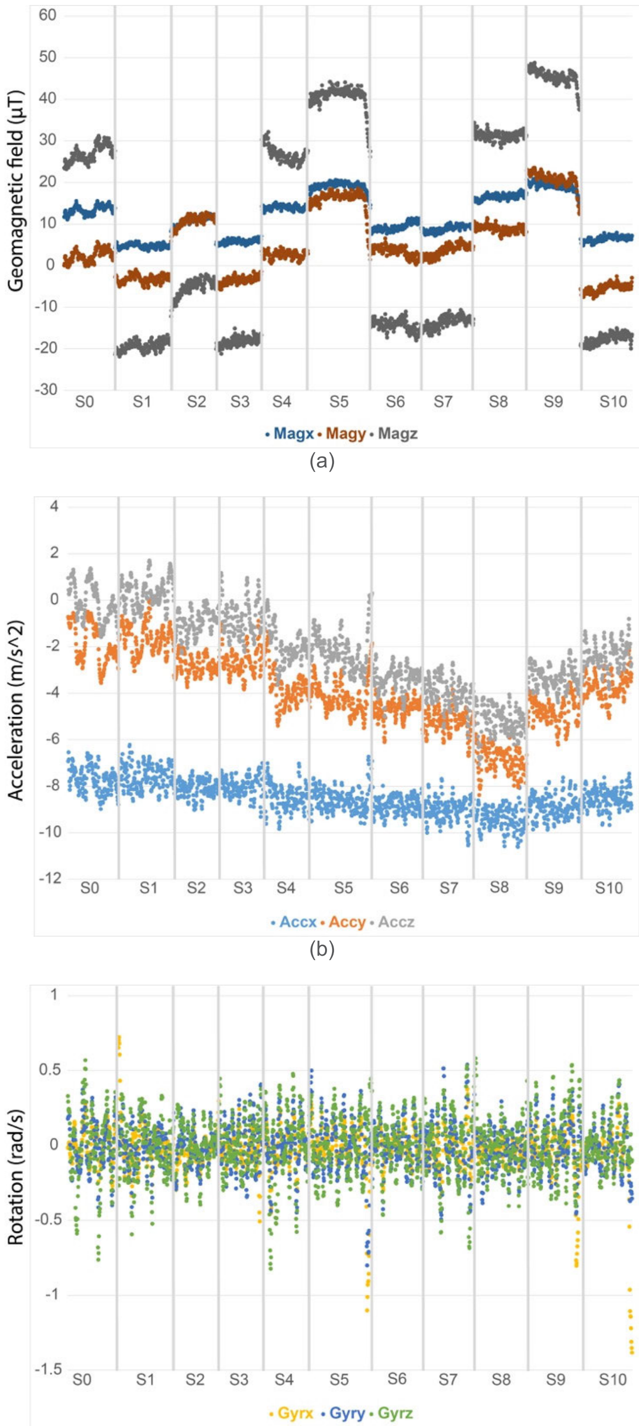

FIGURE 6. Raw data collected from the (a) accelerometer, (b) magnetometer, and (c) gyroscope, corresponding the cabin's spots depicted in Fig. 3a.

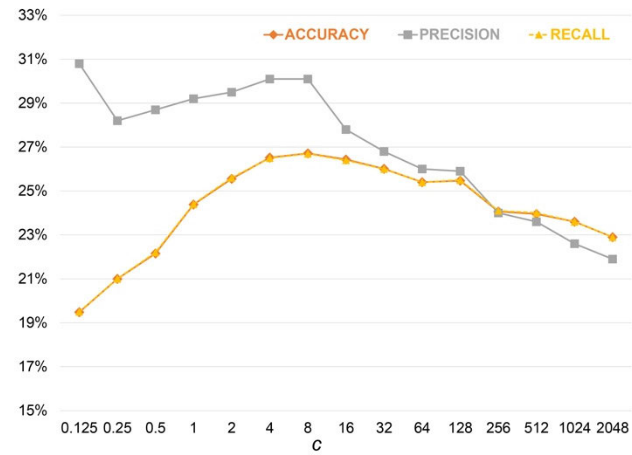

FIGURE 7. Performance results of linear SVM.

accelerometer and magnetometer signals (Fig. 6a and 6b) change their magnitude based on the head's orientation, unlike the gyroscope signal (Fig. 6c). However, the tree signals provide relevant information [84].

Kunze and Lukowicz [84] suggest using an accelerometer for identifying changes in the orientation of an object if the movement of translation dominates the movement of the object. And they suggest utilizing a gyroscope when dominated by rotational motion. Additionally, knowing the orientation of the phone's magnetic sensor axis concerning the user's body can be used to determine the direction to which the user is facing [84]. However, our problem is characterized by monitoring an object (driver's head) inside another moving object (a vehicle). Therefore, the rotational and translational motion might arbitrarily dominate [84]; therefore, the three inertial sensors provide relevant information about the head pose.

B. EFFECTS OF TUNING PARAMETER ON CLASSIFICATION PERFORMANCE

In this section, we review the performances obtained for each classifier.

1) SUPPORT VECTOR MACHINE

As depicted in Fig. 7, the linear SVM produces the best result for $c = 8$, with an accuracy of 26.71%. We found that the SVM with the RBF kernel shows that the accuracy improves when the c value increases (see Fig. 8). We obtained the best accuracy (98.82%) when c = 128 and $\gamma = 16$. Therefore, the SVM with the RBF kernel method shows better accuracy than the linear SVM.

2) K-NEAREST NEIGHBOR

In the case of the k-NN algorithm, the best accuracy (96.90%) was gotten for $k = 1$ (see Fig. 9). We found that as the value of k increases, the accuracy decreases.

3) RANDOM FOREST

As presented in Fig. 10, all the tests with RF resulted in an accuracy greater than 90%. The best performance was obtained for 1200 trees with an accuracy of 98.64%.

C. CLASSIFIERS COMPARISON

Table 2 compares the results obtained from each classifier based on the performance metrics used for this study.

TABLE 2. Best performance obtained from each classifier.

Metric	SVM (RBF)	SVM (LINEAR)	k-NN	RF
Accuracy (%)	98.82	26.71	96.90	98.64
Precision (%)	98.80	30.10	96.90	98.70
Recall (%)	98.80	26.70	96.90	98.60
Training/classification time (sec)	779.3	360.2	0.1	693

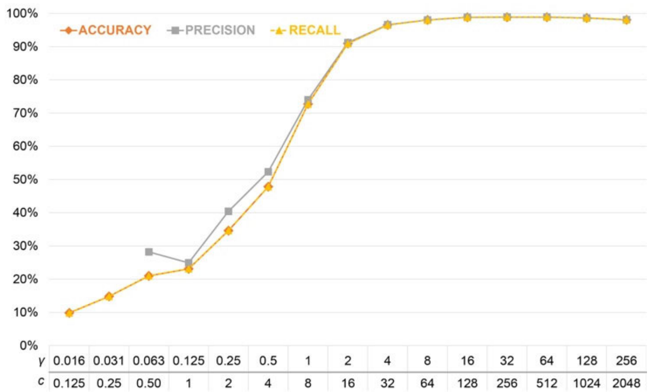

FIGURE 8. Performance results of SVM with RBF kernel.

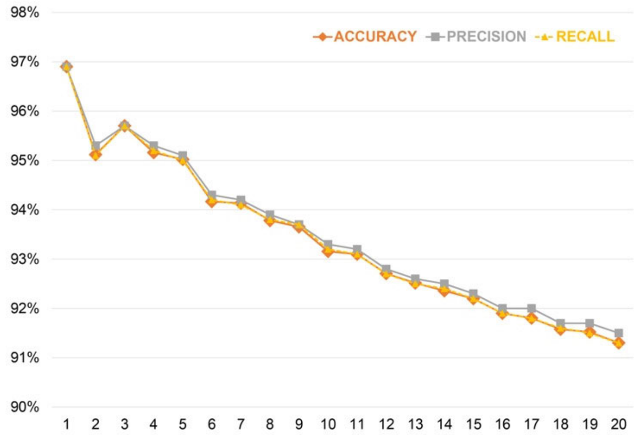

FIGURE 9. Performance results of k-NN.

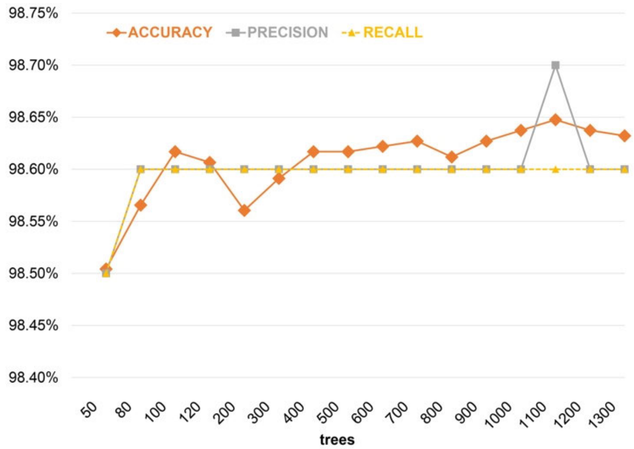

FIGURE 10. Performance results of RF.

We conclude that all the classifiers, except the linear SVM, show an accuracy, precision and recall higher than 96%. Additionally, the classifiers behave similarly according to the confusion matrixes presented in Fig. 11. They tended to confuse instances of the same spot classes; i.e., S0 with S4 (dashboard), S9 (storage compartment) with S10 (passenger seat), and S6 (climate/audio system) with S7 (center console). SVM (RBF) provides the best accuracy; however, it required the highest training time (see Table 2) and we consider that this is the algorithm most complex to implement to be executed in real-time. On the other hand, to implement the RF model, it is crucial to consider that fewer number of decision trees (e.g., 50 and 80) obtained a similar accuracy to that obtained with 1200 decision trees (see Fig. 9). In this case, a further analysis is needed to determine whether there is an optimal number of trees, that is, a threshold from which increasing the number of trees would bring no significant performance gain and would only increase the computational cost.

V. DISCUSSION

This study provides evidence that enables us to conclude that the raw signals, collected from the inertial sensors mounted on drivers' heads, provide enough information about the head posture associated with the car's cabin spot. However, one limitation of this study is that it was conducted in a semi-naturalistic setting. It was semi-naturalistic since the participants drove under controlled conditions, which included driving on the same low-speed and in a straight direction while staring the cabin's spots. Therefore, more studies have to be conducted to understand how different road and driving conditions must be taken into account since they affect the signals of the inertial sensors. For example, potholes and vehicle acceleration affect accelerometer signals. From the aforementioned, we identify as a research opportunity to develop new computing-based mechanisms to recognize these conditions and counteract their effect on the inertial sensors mounted on the head.

Our approach could be useful to develop not only applications that help identify distracted driving, but also that help research communities analyze driving behaviors. For instance, assessing seniors' driving performance decline for detecting effects of preclinical Alzheimer's disease [85], or analyzing the attention and behavior of older adults with cognitive impairment for assessing their autonomy for driving [86], [87]. Driving has been identified as an activity that could be safely performed in the early stages of dementia. However, to monitor older adults' fitness to drive, a set of tests should be used to assess different cognitive functions such as visual-spatial skills and attention-processing speed [86], [87].

SVM (RBF)											
S0	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	<-- CLASSIFIED AS
1754	3	0	0	12	0	0	0	0	0	0	S0
7	1728	0	0	1	2	1	0	0	0	0	S1
0	0	1736	0	0	0	0	0	0	0	0	S2
0	1	0	1642	0	1	0	4	0	4	0	S3
36	0	0	0	1630	0	0	0	0	0	1	S4
1	6	0	0	0	1801	15	0	1	0	0	S5
0	3	0	0	0	9	1741	12	6	3	0	S6
0	0	0	1	0	0	21	1753	1	3	0	S7
0	0	0	0	1	1	6	0	1772	6	0	S8
0	1	0	2	0	1	1	1	1	1890	20	S9
0	0	0	0	0	0	0	0	0	34	1844	S10

SVM (LINEAR)											
S0	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	<-- CLASSIFIED AS
1025	129	135	2	27	173	9	57	189	9	14	S0
457	396	95	152	29	74	12	321	152	47	4	S1
436	108	67	178	107	176	5	258	168	204	29	S2
484	65	5	424	14	146	2	19	151	340	2	S3
550	139	26	2	177	248	8	153	150	192	22	S4
171	239	8	126	63	298	113	334	116	344	12	S5
191	146	35	3	8	94	319	733	62	165	18	S6
80	32	11	0	75	14	80	978	301	196	12	S7
31	51	27	0	11	160	109	438	849	44	66	S8
113	73	27	166	86	139	21	774	52	466	0	S9
186	35	21	23	64	323	15	475	162	358	216	S10

RANDOM FOREST											
S0	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	<-- CLASSIFIED AS
1749	0	0	0	20	0	0	0	0	0	0	S0
9	1712	1	3	4	7	3	0	0	0	0	S1
0	0	1736	0	0	0	0	0	0	0	0	S2
0	0	0	1638	0	3	0	8	0	3	0	S3
44	0	0	0	1621	0	0	0	2	0	0	S4
1	7	0	0	0	1796	19	0	1	0	0	S5
0	2	0	0	0	13	1737	14	5	3	0	S6
0	0	0	1	0	0	16	1758	0	4	0	S7
0	1	0	0	0	1	6	0	1776	0	2	S8
0	2	0	5	0	5	7	5	4	1873	16	S9
0	0	0	1	0	0	0	0	0	16	1861	S10

k-NN											
S0	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	<-- CLASSIFIED AS
1741	2	0	0	26	0	0	0	0	0	0	S0
18	1688	0	9	8	11	5	0	0	0	0	S1
0	0	1735	1	0	0	0	0	0	0	0	S2
4	3	0	1621	0	4	0	9	0	11	0	S3
37	1	0	1	1619	0	3	0	6	0	0	S4
0	13	0	1	1	1735	69	0	3	2	0	S5
0	3	0	0	0	60	1670	17	12	10	2	S6
0	2	0	0	0	2	14	1728	1	25	7	S7
0	1	0	0	7	10	8	0	1750	10	0	S8
0	0	0	8	0	10	7	13	3	1833	43	S9
0	0	0	1	0	0	6	10	1	64	1796	S10

FIGURE 11. Confusion matrix obtained from each classifier.

In this sense, our approach may help to collect data to understand seniors' attentional behavior during driving.

Another potential application of our approach is in scenarios in which head-pose is used to deduce user's interaction intention and interest in displayed information items. For instance, this model could be used to analyze how the user looks at information items distributed in different regions of a large public display [88]. Similarly, the interaction of users with head-worn Augmented Reality (AR) devices can be improved through multimodal techniques that combine the tracking of head pointing and eye gaze [89]. To the best of our knowledge, these works have explored vision-based techniques [89]. A research opportunity can be to study how the conditions of the setting affect the models' performance, such as the user mobility in an AR environment or the distance between the user and a public screen.

Finally, we consider that our approach could be more prone to be accepted by users when it is used in controlled sessions conducted to assess driving behaviors than during daily driving scenarios. However, from our literature review, we identified that none of the studies had evaluated the acceptability of their approaches. Therefore, we conclude that further studies are needed to know the users' acceptance of applications that monitor daily driving behaviors.

VI. CONCLUSION

Thus far, our results provide evidence that using the raw data collected from the head-mounted inertial sensors are accurate predictors of visual focus of attention under controlled driving conditions. As future work, we plan to implement the SVM and Random Forest classifiers to evaluate their performance to predict in real-time during driving sessions. We will analyze how to incorporate strategies to handle the uncertainty that the classifiers could generate to use the predictions to determine if drivers are fixing their attention at a spot or staring at it frequently. Both of these behaviors are highly related to distractions, such as secondary tasks. Also, to reduce the computation time and complexity through reducing the size of a training dataset of classification models, we consider exploring classical dimension reduction algorithms. Finally, we plan to compare our results with those obtained through other prediction approaches, such as the Extreme Learning Machine (ELM), which is characterized by reducing the training time. Thus, it will let us understand how EML improves not only the time to generate the prediction models, but the accuracy.

ACKNOWLEDGMENT

The authors gratefully thank their participants and to UABC for the support provided to acquire the equipment used for the experiments.

REFERENCES

[1] J. Stutts, J. Feaganes, D. Reinfurt, E. Rodgman, C. Hamlett, K. Gish, and L. Staplin, "Driver's exposure to distractions in their natural driving environment," *Accident Anal. Prevention*, vol. 37, no. 6, pp. 1093–1101, 2005.

[2] A. Bennakhi and M. Safar, "Technology in vehicles: The benefits and risks," in *Proc. 7th Int. Conf. Ambient Syst., Netw. Technol. (ANT) Affiliated Workshops*, vol. 83, Madrid, Spain, May 2016, pp. 1056–1063.

[3] Sajan S and G. G. Ray, "Human factors in safe driving—A review of literature on systems perspective, distractions and errors," in *Proc. IEEE Global Humanitarian Technol. Conf.*, Seattle, WA, USA, Oct. 2012, pp. 83–88.

[4] S. G. Klauer, F. Guo, B. G. Simons-Morton, M. C. Ouimet, S. E. Lee, and T. A. Dingus, "Distracted driving and risk of road crashes among novice and experienced drivers," *New England J. Med.*, vol. 370, no. 1, pp. 54–59, 2014.

[5] M. Bayly, B. Fildes, M. Regan, and K. Young, "Review of crash effectiveness of intelligent transport systems," ARRB Group, Port Melbourne, VIC, Australia, Tech. Rep. 027763, 2007. Available:. [Online]. Available: http://www.trace-project.org/publication/archives/trace-wp4-wp6-d4-1-1-d6-2.pdf

[6] H.-B. Kang, "Various approaches for driver and driving behavior monitoring: A review," in *Proc. IEEE Int. Conf. Comput. Vis. Workshops*, Sydney, NSW, Australia, Dec. 2013, pp. 616–623.

[7] M. Gonçalves, R. Amici, R. Lucas, T. Åkerstedt, F. Cirignotta, J. Horne, D. Léger, W. T. Mcnicholas, M. Partinen, J. Téran-Santos, P. Peigneux, and L. Grote, "Sleepiness at the wheel across Europe: A survey of 19 countries," *J. Sleep Res.*, vol. 24, no. 3, pp. 242–253, 2015.

[8] L. Zhang, F. Liu, and J. Tang, "Real-time system for driver fatigue detection by RGB-D camera," *ACM Trans. Intell. Syst. Technol.*, vol. 6, no. 2, pp. 1–17, 2015.

[9] E. Murphy-Chutorian and M. M. Trivedi, "Head pose estimation and augmented reality tracking: An integrated system and evaluation for monitoring driver awareness," *IEEE Trans. Intell. Transp. Syst.*, vol. 11, no. 2, pp. 300–311, Jun. 2010.

[10] T. Greenhalgh and R. Peacock, "Effectiveness and efficiency of search methods in systematic reviews of complex evidence: Audit of primary sources," *Brit. Med. J.*, vol. 331, no. 7524, pp. 1064–1065, 2015.

[11] Y. Dong, Z. Hu, K. Uchimura, and N. Murayama, "Driver inattention monitoring system for intelligent vehicles: A review," *IEEE Trans. Intell. Transp. Syst.*, vol. 12, no. 2, pp. 596–614, Jun. 2011.

[12] A. Fernández, R. Usamentiaga, J. Carús, and R. Casado, "Driver distraction using visual-based sensors and algorithms," *Sensors*, vol. 16, no. 11, p. 1805, 2016.

[13] H. Kubota, M. Takeshi, and H. Saito, "3D head pose tracking using a particle filter with nose template matching," *Electron Commun Jpn.*, vol. 94, no. 1, pp. 34–42, 2011.

[14] M. R. Othman, Z. Zhang, and T. Imamura, "A novel method for driver inattention detection using driver operation signals," *Int. J. Innov. Comput. Inf. Control*, vol. 8, no. 4, pp. 2625–2636, 2012.

[15] Y. Dong, Z. Hu, K. Uchimura, and N. Murayama, "A robust and efficient face tracking kernel for driver inattention monitoring system," in *Proc. IEEE Intell. Vehicles Symp.*, San Diego, CA, USA, Jun. 2010, pp. 929–934.

[16] M. Breidt, H. H. Bulthoff, and C. Curio, "Accurate 3D head pose estimation under real-world driving conditions: A pilot study," in *Proc. 19th Int. Conf. Intell. Transp. Syst. (ITSC)*, Rio de Janeiro, Brazil, Nov. 2016, pp. 1261–1268.

[17] M. Ito, M. Fukumi, and K. Sato, "Analysis of safety verification behavior and classification of driver's head posture;," in *Proc. Int. Conf. Mechatronics Autom.*, Takamatsu, Japan, Aug. 2013, pp. 884–889.

[18] K. Liu, Y. Luo, G. Tei, and S. Yang, "Attention recognition of drivers based on head pose estimation," in *Proc. IEEE Vehicle Power Propuls. Conf.*, Harbin, China, Sep. 2008, pp. 1–5.

[19] J. Paone, D. Bolme, R. Ferrell, D. Aykac, and T. Karnowski, "Baseline face detection, head pose estimation, and coarse direction detection for facial data in the SHRP2 naturalistic driving study," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Seoul, South Korea, Jun./Jul. 2015, pp. 174–179.

[20] C.-T. Lin, L.-W. Ko, and T.-K. Shen, "Computational intelligent brain computer interaction and its applications on driving cognition," *IEEE Comput. Intell. Mag.*, vol. 4, no. 4, pp. 32–46, Nov. 2009.

[21] A. Tawari, S. Martin, and M. Trivedi, "Continuous head movement estimator for driver assistance: Issues, algorithms, and on-road evaluations," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 2, pp. 818–830, Apr. 2014.

[22] M. Othman, Z. Zhang, T. Akiduki, H. Suzuki, T. Imamura, and T. Miyake, "Development of a driver inattention detection system using dynamic relational network," *Int. J. Innov. Comput. Inf. Control*, vol. 10, no. 3, pp. 1189–1205, 2014.

[23] W.-Y. Chou, C.-H. Yang, H.-C. Tasi, Y.-C. Lin. C.-F. Chuang, and K.-H. Chen, "Driver distraction recognition based on dual compass motion sensoring," in *Proc. 17th IEEE Int. Conf. Intell. Transp. Syst. (ITSC)*, Qingdao, China, Oct. 2014, pp. 1375–1380.

[24] F. Vicente, Z. Huang, X. Xiong, F. D. L. Torre, W. Zhang, and D. Levi, "Driver gaze tracking and eyes off the road detection system," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 4, pp. 2014–2027, Aug. 2015.

[25] T. Bär, J. F. Reuter, and J. M. Zöllner, "Driver head pose and gaze estimation based on multi-template ICP 3-D point cloud alignment," in *Proc. IEEE Int. Conf. Intell. Transp. Syst.*, Anchorage, AK, USA, Sep. 2012, pp. 1797–1802.

[26] S. Bole, C. Fournier, C. Lavergne, G. Druart, and T. Lépine, "Driver head pose tracking with thermal camera," *Proc. SPIE*, vol. 9974, Sep. 2016, Art. no. 99740P.

[27] K. Torkkola, N. Massey, and C. Wood, "Driver inattention detection through intelligent analysis of readily available sensors," in *Proc. Int. Conf. Intell. Transp. Syst.*, Washington, DC, USA, Oct. 2004, pp. 326–331.

[28] G. A. Peláez C, F. García, A. de la Escalera, and J. M. Armingol, "Driver monitoring based on low-cost 3-D sensors," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 4, pp. 1855–1860, Aug. 2014.

[29] W. Won, M. Kim, and J. Son, "Driver's head detection model in color image for driver's status monitoring," in *Proc. Int. Conf. Intell. Transp. Syst.*, Beijing, China, Oct. 2008, pp. 1161–1166.

[30] T. Matsui, N. Suganuma, and N. Fujiwara, "Driver's head pose measurement and corner center detection," in *Proc. Int. Joint Conf. (SICE-ICASE)*, Busan, South Korea, Oct. 2006, pp. 2834–2839.

[31] K. Huang, M. Trivedi, and T. Gandhi, "Driver's view and vehicle surround estimation using omnidirectional video stream," in *Proc. Intell. Vehicles Symp.*, Columbus, OH, USA, Jun. 2003, pp. 444–449.

[32] A. Ghaffari, M. Rezvan, A. Khodayari, H. Sadati, and A. Vahidi-Shams, "Driver's head pose estimation using a hierarchical classification on an effective feature space," *Proc. Inst. Mech. Eng., D, J. Automobile Eng.*, vol. 229, no. 6, pp. 1233–1242, 2012.

[33] S. Noridomi, A. Utsumi, M. Tada, N. Yamamoto, T. Kondo, N. Hagita, and K. Takahashi, "Driving behavior analysis using vision-based head pose estimation for enhanced communication among traffic participants," in *Proc. IEEE Int. Conf. Connected Vehicles Expo (ICCVE)*, Las Vegas, NV, USA, Dec. 2013, pp. 26–31.

[34] L. Yu, X. Sun, and K. Zhang, "Driving distraction analysis by ECG signals: An entropy analysis," in *Proc. Int. Conf. Internationalization Design Global Develop.(IDGD)*, Berlin, Germany, 2011, pp. 258–264.

[35] F. Coenen, B. Zhang, and C. Yan, "Driving posture recognition by convolutional neural networks," *IET Comput. Vis.*, vol. 1, no. 2, pp. 103–114, 2016.

[36] H. S. Almahasneh, N. Kamel, A. S. Malik, N. Wlater, and W. T. Chooi, "EEG based driver cognitive distraction assessment," in *Proc. IEEE 5th Int. Conf. Intell. Adv. Syst. (ICIAS)*, Kuala Lumpur, Malaysia, Jun. 2014, pp. 1–4.

[37] D. Slieter, M. Gebhard, and P. Levi, "Evaluation of robust pose estimation methods within automotive environments," in *Proc. IEEE Int. Conf. Veh. Electron. Saf. (ICVES)*, Istanbul, Turkey, Jul. 2012, pp. 241–246.

[38] L. Zhang, D. Zhang, Y. Su, and C. Wang, "Head pose estimation based on feature extraction, fuzzy C-means and neural network for driver assistance system," in *Proc. IEEE 11th Int. Conf. Control Autom. (ICCA)*, Taichung, Taiwan, Jun. 2014, pp. 677–682.

[39] E. Murphy-Chutorian, A. Doshi, and M. M. Trivedi, "Head pose estimation for driver assistance systems: A robust algorithm and experimental evaluation," in *Proc. IEEE Intell. Transp. Syst. Conf.*, Seattle, WA, USA, Sep./Oct. 2007, pp. 709–714.

[40] Z. Youding and K. Fujimura, "Head pose estimation for driver monitoring," in *Proc. IEEE Intell. Vehicles Symp.*, Parma, Italy, Jun. 2004, pp. 501–506.

[41] X. Zhang, N. Zheng, F. Mu, and Y. He, "Head pose estimation using isophote features for driver assistance systems," in *Proc. IEEE Intell. Vehicles Symp.*, Xi'an, China, Jun. 2009, pp. 568–572.

[42] C. Chuang, C. Yang, and Y. Lin, "HMM-based driving behavior recognition for in-car control service," in *Proc. IEEE Int. Conf. Consum. Electron.*, Taipei, Taiwan, Jun. 2015, pp. 258–259.

[43] E. Murphy-Chutorian and M. Trivedi, "HyHOPE: Hybrid head orientation and position estimation for vision-based driver head tracking," in *Proc. IEEE Intell. Vehicles Symp.*, Eindhoven, The Netherlands, Jun. 2008, pp. 512–517.

[44] K. Yuen, S. Martin, and M. M. Trivedi, "Looking at faces in a vehicle: A deep CNN based approach and evaluation," in *Proc. IEEE 19th Int. Conf. Intell. Transp. Syst. (ITSC)*, Rio de Janeiro, Brazil, Nov. 2016, pp. 649–654.

[45] S. Martin, A. Tawari, E. Murphy-Chutorian, S. Cheng, and M. Trivedi, "On the design and evaluation of robust head pose for visual user interfaces: Algorithms, databases, and comparisons," in *Proc. ACM 4th Int. Conf. Automot. User Inter. Interact. Veh. Appl. (AutomotiveUI)*, Portsmouth, U.k., Oct. 2012, pp. 149–154.

[46] L. Xia, Z. Youding, and K. Fujimura, "Real-time pose classification for driver monitoring," in *Proc. IEEE 5th Int. Conf. Intell. Transp. Syst.*, Singapore, Sep. 2002, pp. 174–178.

[47] C. H. Zhao, B. L. Zhang, J. He, and J. Lian, "Recognition of driving postures by contourlet transform and random forests," *IET Intell. Transport Syst.*, vol. 6, no. 2, pp. 161–168, Jun. 2012.

[48] A. Tawari and M. M. Trivedi, "Robust and continuous estimation of driver gaze zone by dynamic analysis of multiple face videos," in *Proc. IEEE Intell. Vehicles Symp.*, Dearborn, MI, USA, Jun. 2014, pp. 344–349.

[49] M. Höffken, E. Tarayan, U. Kreßel, and K. Dietmayer, "Stereo vision-based driver head pose estimation," in *Proc. IEEE Intell. Vehicles Symp.*, Dearborn, MI, USA, Jul. 2014, pp. 253–260.

[50] W. Wang, X. Zhang, Y. Wen, and F. Wang, "Study of cognitive distraction detection based on GMA analysis," in *Proc. IEEE Int. Conf. Veh. Electron. Saf. (ICVES)*, Beijing, China, Jul. 2016, pp. 1–6.

[51] N. Ziraknejad, P. D. Lawrence, and D. P. Romilly, "The effect of time-of-flight camera integration time on vehicle driver head pose tracking accuracy," in *Proc. IEEE Int. Conf. Veh. Electron. Saf. (ICVES)*, Istanbul, Turkey, Jul. 2012, pp. 247–254.

[52] N. Hernández, P. Jiménez, L. Bergasa, B. Delgado, and M. Sevillano, "Vision-based distraction analysis tested on a realistic driving simulator," in *Proc. IEEE 13th Int. Conf. Intell. Transp. Syst.*, Funchal, Portugal, Nov. 2010, pp. 895–902.

[53] F. Rohit, V. Kulathumani, R. Kavi, I. Elwarfalli, V. Kecojevic, and A. Nimbarte, "Real-time drowsiness detection using wearable, lightweight brain sensing headbands," *IET Intell. Transp. Syst.*, vol. 11, no. 5, pp. 255–263, 2017.

[54] I. Takahashi and K. Yokoyama, "Development of a feedback stimulation for drowsy driver using heartbeat rhythms," in *Proc. IEEE Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Boston, MA, USA, Aug./Sep. 2011, pp. 4153–4158.

[55] E. Abe, K. Fujiwara, T. Hiraoka, T. Yamakawa, and M. Kano, "Development of drowsy driving accident prediction by heart rate variability analysis," in *Proc. IEEE Signal Inf. Process. Assoc. Annu. Summit Conf. (APSIPA), Asia–Pacific*, Siem Reap, Cambodia, Dec. 2014, pp. 1–4.

[56] A. Sahayadhas, K. Sundaraj, M. Murugappan, and R. Palaniappan, "Physiological signal based detection of driver hypovigilance using higher order spectra," *Expert Syst. Appl.*, vol. 42, no. 22, pp. 8669–8677, Dec. 2015.

[57] B. Roman, S. Pavel, P. Miroslav, V. Petr, and P. Lubomír, "Fatigue indicators of drowsy drivers based on analysis of physiological signals," in *Proc. Int. Symp. Med. Data Anal.*, Madrid, Spain, Oct. 2001, pp. 62–68.

[58] J. H. Yang and H. B. Jeong, "Validity analysis of vehicle and physiological data for detecting driver drowsiness, distraction, and workload," in *Proc. IEEE Int. Conf. Syst., Man, Cybern.*, Kowloon, China, Oct. 2015, pp. 1238–1243.

[59] G. Sun, Y. Jin, Z. Li, F. Zhang, and L. Jia, "A vision-based head status judging algorithm for driving fatigue detection system," *Adv. Transp. Stud.*, no. 37, pp. 51–64, Nov. 2015.

[60] J. Liu, "Detection of driver's low vigilance using vehicle steering information and facial inattention features," in *Proc. 20th ITS World Congr.*, Tokyo, Japan, Oct. 2013, pp. 1–10.

[61] N. Alioua, A. Amine, A. Rogozan, A. Bensrhair, and M. Rziza, "Driver head pose estimation using efficient descriptor fusion," *EURSIP J. Image Video Process*, no. 2, pp. 1–14, Jan. 2016.

[62] N. Rodríguez-Ibáñez, M. A. García-González, M. Fernández-Chimeno, and J. Ramos-Castro, "Drowsiness detection by thoracic effort signal analysis in real driving environments," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Boston, MA, USA, Aug./Sep. 2011, pp. 6055–6058.

[63] H. Park, S. Oh, and M. Hahn, "Drowsy driving detection based on human pulse wave by photoplethysmography signal processing," in *Proc. 3rd IEEE Int. Universal Commun. Symp. (IUCS)*, Tokyo, Japan, Dec. 2009, pp. 89–92.

[64] D. Lee, S. Oh, S. Heo, and M. Hahn, "Drowsy driving detection based on the driver's head movement using infrared sensors," in *Proc. 2nd IEEE Int. Symp. Universal Commun.*, Osaka, Japan, Dec. 2008, pp. 231–236.

[65] D. Morris, J. Pilcher, and F. Switzer, III, "Lane heading difference: An innovative model for drowsy driving detection using retrospective analysis around curve," *Accid. Anal. Prev*, vol. 80, pp. 117–124, Jul. 2015.

[66] L. Morency, J. Whitehill, and J. J. Movellan, "Monocular head pose estimation using generalized adaptive view-based appearance model," *Image Vis. Comput*, vol. 28, no. 5, pp. 754–761, 2010.

[67] J. Wang, S. Sun, S. Fang, T. Fu, and J. Stipancic, "Predicting drowsy driving in real-time situations: Using an advanced driving simulator, accelerated failure time model, and virtual location-based services," *Accident Anal. Prevention*, vol. 99, pp. 321–329, Feb. 2017.

[68] H. Matsuo and A. Khiat, "Prediction of drowsy driving by monitoring driver's behavior," in *Proc. IEEE Int. Conf. Pattern Recognit. (ICPR)*, Tsukuba, Japan, Nov. 2012, pp. 3390–3393.

[69] Q. Ji and X. Yang, "Real-time eye, gaze, and face pose tracking for monitoring driver vigilance," *Real-Time Imag.*, vol. 8, no. 5, pp. 357–377, 2002.

[70] I.-H. Choi, C.-H. Jeong, and Y.-G. Kim, "Robust facial states estimation against occlusion and inference of driver's drowsiness using hidden Markov model," in *Advanced Multimedia and Ubiquitous Engineering* (Lecture Notes in Electrical Engineering), J. Park, H. C. Chao, H. Arabnia, and N. Yen, Eds. Berlin, Germany: Springer, 2015, pp. 45–51.

[71] W. Junwen and M. M. Trivedi, "Visual modules for head gesture analysis in intelligent vehicle systems," in *Proc. IEEE Intell. Vehicles Symp.*, Tokyo, Japan, Jun. 2006, pp. 13–18.

[72] J. He, "Drowsiness detection and management," *J. Ergonom.*, vol. 3, no. 2, pp. 1–2, 2013.

[73] T. Ploetz and J. Healey, "ISWC 2017: Riding the waves of wearables," *IEEE Pervasive Comput.*, vol. 17, no. 2, pp. 78–83, Apr./Jun. 2018.

[74] J. K. Caird, K. A. Johnston, C. R. Willness, and M. Asbridge, "The use of meta-analysis or research synthesis to combine driving simulation or naturalistic study results on driver distraction," *J. Saf. Res*, vol. 49, pp. 49–91, Jun. 2014.

[75] T. A. Dingus, S. G. Klauer, V. L. Neapel, and A. Petersen, "The 100-car naturalistic driving study, phase II—Results of the 100-car field experiment," Virginia Tech. Transp. Inst. Nat. Highway Traffic Saf. Admin., Blacksburg, VA, USA, Tech. Rep. 01026409, 2006. [Online]. Available: http://www.nhtsa.gov/DOT/NHTSA/NRD/Multimedia/PDFs/Crash%20Avoidance/Driver

[76] L. Breiman, "Random forest," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001.

[77] F. Attal, S. Mohammed, M. Dedabrishvili, F. Chamroukhi, L. Oukhellou, and Y. Amirat, "Physical human activity recognition using wearable sensors," *Sensors*, vol. 15, no. 12, pp. 31314–31338, 2015.

[78] N. Thanh and M. Kappas, "Comparison of random forest, k-nearest neighbor, and support vector machine classifiers for land cover classification using Sentinel-2 imagery," *Sensors*, vol. 18, no. 1, pp. 1–20, 2017.

[79] C.-W. HSu, C.-C. Chang, and C.-J. Lin, "A practical guide to support vector classification," Dept. Comput. Sci., National Taiwan Univ., Taipei, Taiwan, Tech. Rep., 2016, p. 16. [Online]. Available: https://www.csie.ntu.edu.tw/~cjlin/papers/guide/guide.pdf

[80] C. Cortes and V. Vapnik, "Support-vector networks," *Mach. Learn.*, vol. 20, no. 3, pp. 273–297, 1995.

[81] N. S. Altman, "An introduction to kernel and nearest-neighbor nonparametric regression," *Amer. Statist.*, vol. 46, no. 3, pp. 175–185, 1992.

[82] *Weka 3: Data Mining Software in Java*. [Online]. Available: https://www.cs.waikato.ac.nz/ml/weka/

[83] I. H. Witten, E. Frank, and M. Hall, *Data Mining: Practical Machine Learning Tools and Techniques*, 4th ed. Amsterdam, The Netherlands: Elsevier, 2017.

[84] K. Kunze and P. Lukowicz, "Sensor placement variations in wearable activity recognition," *IEEE Pervasive Comput.*, vol. 13, no. 4, pp. 32–41, Oct. 2014.

[85] C. M. Roe, G. M. Babulal, and D. M. Head, "Preclinical Alzheimer's disease and longitudinal driving decline," *Alzheimer's Dementia, Transl. Res. Clin. Intervent.*, vol. 3, no. 1, pp. 74–82, 2017.

[86] L. B. Brown and B. R. Ott, "Driving and dementia: A review of the literature," *J. Geriatric Psychiatry Neurol.*, vol. 17, no. 4, pp. 232–240, 2004.

[87] J. M. Bennett, H. E. Chekaluk, and J. Batchelor, "Cognitive tests and determining fitness to drive in dementia: A systematic review," *J. Amer. Geriatrics Soc.*, vol. 64, no. 9, pp. 1904–1917, Jun. 2016.

[88] A. Riener and A. Sippl, "Head-pose-based attention recognition on large public displays," *IEEE Comput. Graph. Appl.*, vol. 34, no. 1, pp. 32–41, Jan. 2014.

[89] M. Kytö, B. Ens, T. Piumsomboon, G. Lee, and M. Billinghurst, "Pinpointing: Precise head- and eye-based target selection for augmented reality," in *Proc. Hum. Factors Comput. Syst. (CHI)*, Montreal, QC, Canada, Apr. 2018, pp. 1–13.

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