Distributed Multivariate Physiological Signal Analytics for Drivers' Mental State Monitoring

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Abstract. This paper presents a distributed data analytics approach for drivers' mental state monitoring using multivariate physiological signals. Driver's mental states such as cognitive distraction, sleepiness, stress, etc. can be fatal contributing factors and to prevent car crashes these factors need to be understood. Here, a cloud-based approach with heterogeneous sensor sources that generates extremely large data sets of physiological signals need to be handled and analysed in a big data scenario. In the proposed physiological big data analytics approach, for driver state monitoring, heterogeneous data coming from multiple sources i.e., multivariate physiological signals are used, processed and analyzed to aware impaired vehicle drivers. Here, in a distributed big data environment, multi-agent case-based reasoning facilitates parallel case similarity matching and handles data that are coming from single and multiple physiological signal sources.

Keywords: Physiological signals · Distributed analytics
Case-based reasoning

1 Introduction

While driving, cognitive distractions occur when a driver keeps his/her eye on the road and hands on the steering, yet takes the mind off from the driving task, such as hands-free cell phone calls, listening to the radio, and even having a conversation with fellow passenger. The concern of driving performance contemplating cognitively loading activities on traffic safety is addressed in [1, 2, 20]. Driving is a proactive task that requires anticipation and adaptation with respect to the road users' behaviours, and their actions are revolving all the time. This whole process of driving can be seen as a nearly automated, partially self-paced and satisficing task [3] and to anticipate safe travel plan and goal full attention is required from the driver. Hence, for the futuristic automated transportation and new theory of driver distraction it is important to determine the cognitive driving distraction and the contribution factors of inattention while driving, which can prevent happening bad things.

Physiological signals became reliable and most useful over the years in identifying driver's cognitive distraction. The advancement of wearable sensor technology makes it possible to collect tremendous amount of data with various variation which also

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becomes the part of big data biological process and it requires trade-off between resources, to handle the stream of sensor data [4]. Issues that arise in the big data biological process such as data are frequently reside in distributed data platforms, often data are too large to fit in a single memory, and single thread processing is not sufficient to regulate the growing computational volume and complexity [5, 6]. The big data biological process can be leveraged through distributed analytics using machine learning. However, currently there are few distributed platforms available for predictive analytics and most machine learning are not embarrassingly parallel. For example, case-based reasoning (CBR) is a reasoner that solves a new problem by remembering and using previously solved problems that are similar to the current problem, thus avoids the re-invent the wheel approach. However, CBR examines individual cases in a sequence to find the most similar cases, which constrains parallelization. In big data paradigm, multi-agent CBR architecture can be beneficial for organizing knowledge base within the system and processing knowledge by the system [7, 18, 19].

This paper presents a distributed analytics approach for drivers' mental state monitoring in terms of cognitive distraction using multivariate physiological signals. Physiological sensors signal used in the analytics are Electrooculogram (EOG), Pupil Diameter, Electroencephalogram (EEG), Electrogastrogram (EGG), respiration, and Skin Conductance. In the study, the Attention Selection Model (ASM) [8] is considered to detect the effect of cognitive distraction on traffic safety. The ASM is a conceptual model of attention selection and multitasking in everyday natural driving situations, where attention selection is acknowledged as a form of adaptive behavior, rather than consequence of limited capacity. Reflecting the ASM model a version of n-back task [9] is adapted as a cognitively loading secondary task.

2 Materials and Methods

The vehicle driver monitoring study was performed in an advanced moving-base simulator (SIM III[1]) at VTI in Linköping. This moving based simulator has the ability to simulate movements and forces that act upon natural driving by allowing motion in four degrees of freedom, and the platform can simulate vibrations and smaller movements. Data acquisition was performed using DeweSoft S-box 2[2] computer with analog terminals and in the simulation control computer. The physiological signals were recorded using g.tec system, where g.tec plugin was connected to the S-box. Physiological signals were recorded from 36 male participants with no known disease and medication; aged between 35 to 50 years and having driving license for more than 10 years. The scenarios in the simulator were design as rural road with one lane in each direction, some curves and slopes, and a speed limit of 80 km/h. For this cognitive distraction study, driving environment in the simulator was consisted of three reoccurring scenarios: four way crossing, a hidden exit on the right side of the road with a warning sign, and a strong side wind in open terrain [10]. A secondary task (auditory 1-back task) was deployed in two occasions in each scenario.

1 https://www.vti.se/en/research-areas/vtis-driving-simulators/.

2 www.dewesoft.com.

The sample size of the physiological signals was 256 Hz and six different physiological signals were recorded. Besides, 30 channels EEG system was used in the data collection. All these produce a large amount of data in long run and each of the signal has different characteristics for example, rapid changes of EEG, where ECG and skin conductance signals have slow fluctuation. Thus, the sample set requires consideration of 3 V's of big data: *Volume*, *Variety* and *Veracity*. Moreover, the data value from different signals often needs to handle differently. Again, considering real-time monitoring of cognitive distraction the *Velocity* of the data needs to be handled.

2.1 Distributed Analytics Approach

To handle and analyse such big data set for vehicle driver monitoring a cloud-based distributed analytics approach is proposed. A schematic diagram of the big data (i.e. distributed multivariate physiological signal) analytics for drivers' state monitoring is shown in Fig. 1. The approach is comprised of several cloud modules/nodes namely data storage, data processing and analytics platform. All forms of recorded data are transferred from the local computer to the data storage via Internet.

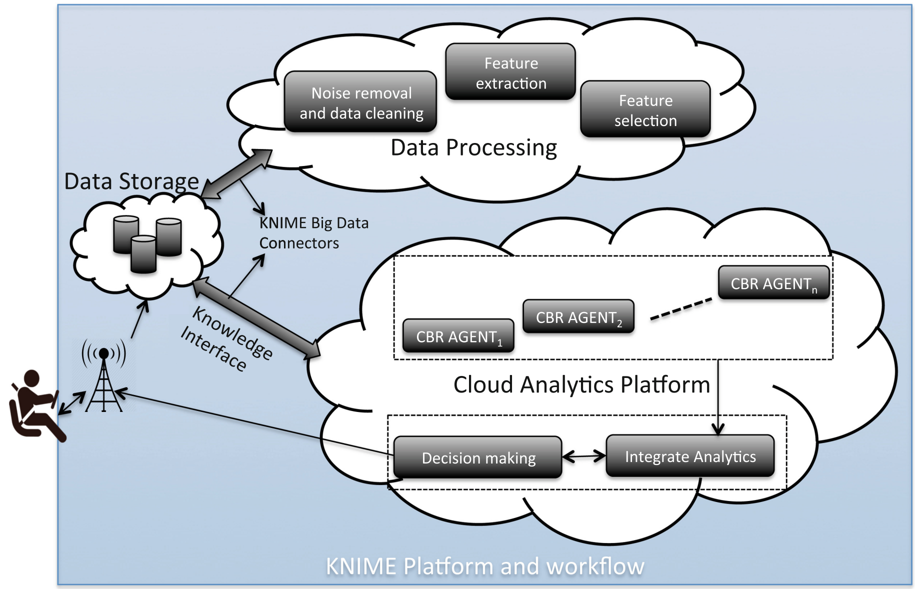

Fig. 1. Schematic diagram of the proposed distributed analytics system

The KNIME Platform and server[3] are used to develop the workflow and its big data extensions are used to connect the data storage and analytics platform. CBR agents, noise handling, feature extraction, and feature selections are done in Matlab scripting

[3] https://www.knime.com/.

and KNIME's community nodes were used to integrate them in the KNIME workflow. KNIME Big Data Connectors and KNIME Cluster Executor are two node libraries that enable to work within Hadoop ecosystem such as Hive and Impala. Data storage i.e., import and export of data and SQL are handled using the KNIME Big Data Connectors. The data distribution and analytics are distributed among the KNIME clusters through KNIME Cluster Executor, which provides a slim connection layer between KNIME Analytics Platform and computing cluster.

One of the important tasks in any data analytics is to ensure the quality of the data. Here, a cloud-based data processing module is considered, which mainly performs the noise handling and data cleaning. Since each physiological signal affects differently, it requires different algorithms for different analytics. In this study, for the EEG signals a fully automated EEG artifacts handling algorithm [11] has been developed. Other methods such as moving average filtering is used to remove noise from skin conductance and pupil diameter signals, EOG signal is filtered with a median filters, ECG can be cleaned using [12], etc. Another key component for analytics is the representations of data for specific problem domain. It requires a feature extraction and selection of sub-modules. Features are extracted from all kinds of signals, and stored for the data analytics. Table 1 represents the list of features extracted from the physiological signals.

The cloud analytics platform is comprised of multi-agent case-based reasoning (CBR). CBR system comprises of sub-tasks such as case base maintenance, cases retrieval, cases adaptation and retaining new cases [13], where distributed CBR can achieve maximum efficiency for big data. In distributed CBR research, multiple agent CBR systems are widely used and well establish for managing the CBR sub-tasks [14, 21].

Table 1. Features extracted from physiological signals.

Signals	Extracted features
EEG	**Frequency:** Power Spectral Density (PSD) of delta (0–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–50 Hz) [10] **Time:** Hurst Exponent, three Hjorth descriptors, kurtosis, auto mutual information, sample entropy, permutation entropy, and approximate entropy [10]
EOG	Number of blinks, blink time, standard deviation of amplitude [15]
Respiration	Respiration rate
Pupil diameter	Average pupil diameter [16]
Skin conductance	**Frequency:** average power of the signal under 1 Hz [16] **Time:** mean value, standard deviation, mean of normalised signal, standard deviation of normalised signal, means of absolute values of the first and second differences in normalised signal, sum of Peak magnitudes, peak duration, number of peaks, time to peak [16]
ECG	**Frequency:** Power spectral destiny of very low (≤ 0.04 Hz), low (0.04–0.15 Hz), high (0.15–0.4 Hz) and ratio low and high frequency power [17] **Time:** mean and standard deviation RR peak, mean heart rate, SDNN, RMSSD, NN50 Count, and pNN50 [17] **Nonlinear:** Dispersion of the points perpendicular and along to the axis of line of identity Alpha of total slop, short and long-range scaling exponent

In the proposed approach, each CBR agent can be called to perform the classification task either for individual signals or a combination of signals. This depends on how the case library is requested from the data storage. Thus, it reduces the feature vector size of the cases. Moreover, when a new case arrives distributed case libraries can append only that new case to them, which supports the parallel classification. Hence, knowledge bases are distributed across several nodes in clusters using the multiple agents. Then the only overhead is to integrate the results from the multiple agents using *Integrate Analytics* sub module. This provides the freedom to choose type of analytics i.e., using individualized knowledge or combination of knowledge for decision-making. Consequently, this approach tackles the sub-tasks require by CBR and other needs of the big data processing such as noise handling, anomaly detection condition monitoring etc.

3 Results

Case libraries reside in the data storage. Here the cases are labeled based on the 1-back task was performed or not. Each multi-agent CBR retrieves most similar cases that have similarity $\geq 90\%$, using a Euclidian distance-based similarity matching function. The *Integrate Analytics* sub module collects all the similar cases and then applies a majority voting to choose the most similar case. For the evaluation of the CBR classification a leave-one-out approach is used for selecting the query cases. The evaluation was performed considering individual scenario and combination of different scenarios and the results are presented in Table 2.

Table 2. Summary of CBR classification considering individual scenario and combined scenario. Here, HE = Hidden exit scenario, CR = Crossing scenario, SW = side wind scenario, and All = case library containing cases from all scenarios.

Scenarios	Criteria							
	Total cases	True positive (TP)	False positive (FP)	False negative (FN)	True negative (TN)	Sensitivity = TP/(TP + FN)	Specificity = TN/(FP + TN)	Accuracy = (TP + TN)/(P + N)
	EEG signals							
All	396	146	52	64	134	≈ 0.70	≈ 0.72	≈ 0.71
HE + CR	264	104	28	43	89	≈ 0.71	≈ 0.76	≈ 0.73
CR	132	49	17	19	47	≈ 0.72	≈ 0.73	≈ 0.73
HE	132	51	15	30	36	≈ 0.63	≈ 0.71	≈ 0.66
SW	132	53	13	19	47	≈ 0.71	≈ 0.78	≈ 0.76
	Combined other signals							
All	396	141	57	62	136	≈ 0.69	≈ 0.70	≈ 0.70
HE + CR	264	86	46	43	89	≈ 0.66	≈ 0.67	≈ 0.66
CR	132	49	17	26	40	≈ 0.65	≈ 0.70	≈ 0.67
HE	132	41	25	22	44	≈ 0.65	≈ 0.64	≈ 0.64
SW	132	47	19	16	50	≈ 0.75	≈ 0.72	≈ 0.75

It can be observed from Table 2 that for CBR classification, two case libraries were built one using the EEG signals and other using the combination of signals. The results show that for both EEG signals and combination of signals side wind scenario achieved better classification accuracy that is 76% and 75% respectively. Compare to the other signals, EEG signals based classification shows better performance, which suggests cognitive distraction may influence EEG signals better than other signals. The overall classification results is less than 80% and the reason might be that the 1-back task is easy for these drivers to perform and thus the differences are not sufficient enough to classify the load and normal states. However, it shows a preliminary investigation result using multi-agent CBR, which illustrates that distributed CBR classification has a good potential in big data context. However, further development is ongoing in terms of feature selection and decision fusion in the *Integrate Analytics* module to improve the classification results.

4 Summary

Cognitive distraction while driving is an important research area of traffic safety. Today, because of the wearable sensors availability, cloud computing, and IoT, datasets become huge in volume, with high velocity and also consist of large variety in characteristics. In this paper, we have considered a distributed data analytics approach to classify cognitive distraction using multivariate physiological signals in the cloud. Here, not only the data but also the analytical services are distributed in several modules in the cloud. The main CBR classification scheme is developed considering multi-agent technology. Multi-agent based distributed CBR has been long using, and in big data paradigm it can leverage over the increasing data volume and competence and contextualisation. The proposed multi-agent CBR approach can achieve parallelism in terms of running the same or different similarity function in parallel for large distributed case libraries. In this work only multi-agent based case retrieval is proposed, yet it opens several future directions such as the distributed adaptation for CBR, interface between case libraries and agents for distributed data.

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