生体信号および環境信号を統合した知的安全運転支援システム

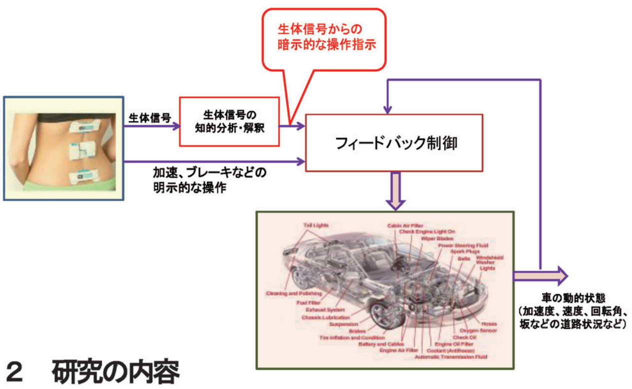
ゴウタム・チャクラボルティ（ソフトウェア情報学部、教授）
バサビ・チャクラボルティ（ソフトウェア情報学部、教授）
澤本潤（研究・地域連携本部 コーディネーター）

＜要旨＞
　ドライバーの高齢化に伴い、安全運転支援が重要になってきている。車外の障害物接触防止やプリクラッシュセーフティシステムなどの支援システムが既に存在する。また、自動運転技術の実用化も近いといわれている。しかし、高齢者の場合は突然死しても気がつかずに自動運転で走り続けるなど笑えない状況が想定される。車自体の安全は確保されても、ドライバーにとっては手遅れになる可能性もある。体調が変化し易い高齢者にとって、運転中に生体信号を監視することは大きな意味を持つと考える。車と人間を対象としたより総合的なシステムを提案する。そこでは、ドライバーからの明示的な操作指示のみでなく、ドライバーからの生体信号を取得・解釈することにより、車の制御に利用することを目標とする。

1　研究の概要

The outline of this research project was to detect anomaly, both from bio-signals generated from the driver's body, as well as that from the car are collected in real-time, processed to find any abnormal situation and used to create necessary signals for safe driving. Bio-signals can tell us about physical as well as emotional state of the driver. In the present state, Bio-signals like ECG, EMG, pulse rate, GSR data are collected continuously by sensor and transmitted to a system module which is connected to a tablet or a smart-phone to analyze the data. Signals from car, like gas-pedal pressure, brake-pressure, steering angle are collected simultaneously. Multivariate signals, collected as the driver's bio-signals and car-status signals are simultaneously analyzed to check whether the driver's decision is correct, or not. Depending on the situation, the system needs to override driver's decision for his/her own safety.

The main difference of this system, compared to existing safety procedures and that, existing safety measures are mostly external, like distance with nearby objects. This type of external safety equipment are important too, and they can co-exist with the proposed system. Two important aspects of the proposed systems are: (1) It learns the driving style of the particular driver and knows when it is beyond this driver's control; (2) It also monitors the bio-signals from which the health status of the driver could be decided and hopefully predicted. The overall operation of the system is shown below.



2　研究の内容

Up till now, we were able to collect ECG and pulse data. The aim of the project is to analyze multi-variate data to find any anomaly, a discord. In addition, most of the bio-signals are quasi-periodic, but not all. Signals sensing the state of the car (gas, brake or steering) are not quasi periodic as well. Analyzing all these signals together to identify different discords, and take proper decision is the main motivation of this project. As the car signals were not available, we just analyzed bio-signals to find discords. The rest of this report describes the methodology and results obtained. Our main motivation is to build an algorithm, which is light to run on platforms like smart phone, and identify discord in real-time. Results achieved are reported in Section 3.

There are many mobile applications to record bio-signals. The recorded data is uploaded on a PC for off-line analysis. There are studies on anomaly detection, both on periodic and non-periodic signals. Various techniques are used, such as HMM [1] based, prediction based [2], similarity based [3], window based [4] and segmentation based [5]. Depending on the algorithm used, anomaly location and the length of anomaly would vary. Bio-signals shape and period varies to some extent, even when normal. Ground truth is understood and could be identified correctly only by domain experts, in case of bio-signals by a health professional. We will identify anomaly on the basis of algorithmic analysis, and compare with true results.

Previous related works have some pitfalls. They are computationally heavy, and are not able to identify all anomaly locations, if there are more than one, as they are designed to find maximum deviation from other subsequences. As we assume weak computational platform, the proposed algorithm has to be light in computation and memory requirement. In addition, we need to be able to locate multiple anomalies (i.e., discords), if they are present in the signal.

Time series discords are subsequences of a longer time series that are maximally different from all the rest of the subsequences of the whole sequence. Discords could be detected by comparing every pair of sub-sequences (also called windows) and detect the ones with largest distances from their

nearest (least distant) neighbors. We can find such a discord using brute force method which is computationally heavy with time complexity of $\mathcal{O}(n^2)$, where n is the total number of possible subsequences out of the whole time series. Brute force method can list such subsequences in order of distances, and thus is able to detect all discords. Let us consider a discrete time series consisting of T time-slots. Let us also consider subsequences of length m time-slots where $m \ll T$. Thus, the original signal consists of $n = (T - m + 1)$ subsequences. $i^{th.}$ Sub-sequence starts at $i^{th.}$ slot, where $0 \le i \le (T - m)$. In previous works, the length of the subsequence was user defined [4]. In our work, we set the length m equal the fundamental period of time series. Thus, our method is applicable only to periodic signals. As $m \ll T$, $m \ll n$. We propose a new concept we called "mother signal". We consider only periodic signals and m is set equal to the fundamental period. Physically, mother signal is the average of subsequences of length m, which are normal (not discords) and therefore their number is overwhelmingly large compared to discords. Once mother signal is created, discords are detected more efficiently. Even by exhaustive comparison with mother signal, the complexity is $\mathcal{O}(m \times n)$,, and $\mathcal{O}(n^2) \gg \mathcal{O}(m \times n)$. The largest discord is the one whose distance is highest from the mother signal.
We can detect multiple discords, which are defined as subsequences whose distances with mother signal exceed a pre-defined threshold. Otherwise, we can identify and list the discords according to their distances from the mother signal.

In addition, we collect eye-tracking data of the driver. To do that, we performed the whole experiment on a diving simulator, where eye-tracking data collection was possible. As different situation create different emotions, especially a sudden dangerous situation will create strong emotion, it will be reflected in some bio-signals. Our aim is to correlate the visual stimuli with emotion. This experiment is not completed. An overview is shown below:

3　これまで得られた研究の成果

In this work, we detected discords from ECG data, which is periodic, but the period differs slightly. We need to find the period for every such sub-sequences. For that, we find the tip of the pulse and the distance between tips determine the period. This is explained in Fig. 1.

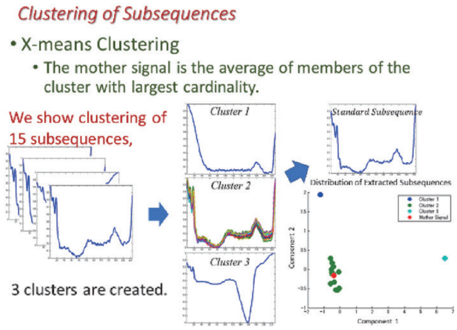


Fig. 1 Finding sub-sequence time-durations

Next, the sub-sequences with slightly different lengths are clustered. For distance measurement, because the time-durations are different, DTW would have worked fine. But, because DTW is computationally heavy, we abandoned that. Instead, we converted the signals to equal length using Lanczos2 algorithm which is very fast. The clustering result is shown in Fig. 2

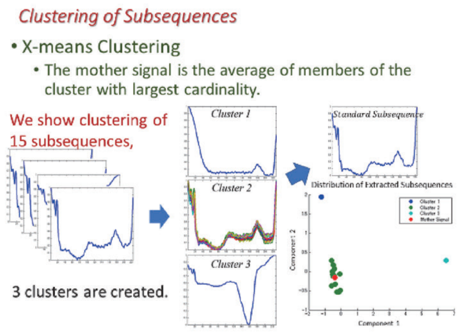


Fig. 2 Average of the cluster with largest cardinality is the mother signal

For very long sequence, to mitigate the drift (due to jogging or other physical activities), we used sliding window to find the mother signal suitable for the present situation. This is explained in Fig. 3 below.

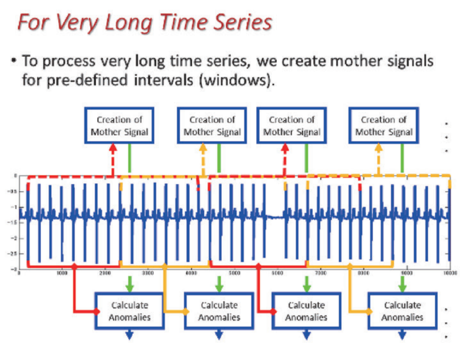
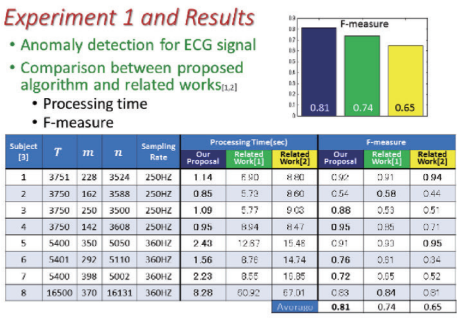


Fig. 3 The sliding window to mitigate drift

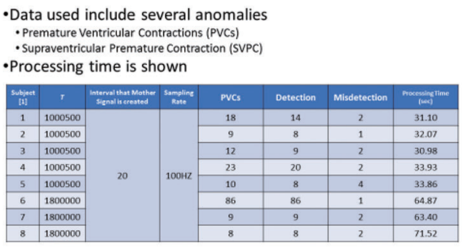
The results of the experiment, is shown in Fig. 4. We can see that the computation is more than 8 times faster. In addition, the F-measure is either better or very near to recently published works. In fact, the overall F-measure is much better as shown on top-right of Fig. 4.



Subject [3]	T	m	n	Sampling Rate	Processing Time(sec)			F-measure		
					Our Proposal	Related Work[1]	Related Work[2]	Our Proposal	Related Work[1]	Related Work[2]
1	3751	228	3524	250HZ	1.14	6.90	8.80	0.92	0.91	0.94
2	3750	162	3588	250HZ	0.85	5.73	8.60	0.54	0.58	0.44
3	3750	250	3500	250HZ	1.09	5.77	9.03	0.88	0.53	0.51
4	3750	142	3608	250HZ	0.95	8.94	8.47	0.95	0.85	0.71
5	5400	350	5050	360HZ	2.43	12.67	15.46	0.91	0.93	0.95
6	5401	292	5110	360HZ	1.56	8.76	14.74	0.76	0.61	0.34
7	5400	398	5002	360HZ	2.23	8.55	16.85	0.72	0.65	0.52
8	16500	370	16131	360HZ	8.28	60.92	67.01	0.83	0.84	0.81
							Average	0.81	0.74	0.65

Fig. 4 Experimental results, the computation time as well as correct identification accuracy

In ECG signals, there are two types of discords knows as Premature Ventricular Contraction (PVC) and SupraVenticular Premature Contraction (SVPC). In Table. 1, we show the results of correct detection as well as mis-detection. The processing time for the whole signal is shown in the last column. As we use a window size of 20 sub-sequences, which translates to T=20,000, the detection takes around 0.6 seconds, which is almost instantaneous. It ensures possibility of real-time application.



Subject [1]	T	Interval that Mother Signal is created	Sampling Rate	PVCs	Detection	Misdetection	Processing Time (sec)
1	1000500	20	100HZ	18	14	2	31.10
2	1000500			9	8	1	32.07
3	1000500			12	9	2	30.98
4	1000500			23	20	2	33.93
5	1000500			10	8	4	33.86
6	1800000			86	86	1	64.87
7	1800000			9	9	2	63.40
8	1800000			8	8	2	71.52

Table.1 The correct detection ratio and time needed

The proposed algorithm, though can detect most of the PVC discords, it can not detect SVPC discords. The distance measurement is not sufficient to detect the subtle shape distortion in case of SVPC. This is shown below in Fig. 5. This is the data of subject 6, with 86 PVC discords, all of which could be detected. There is 1 mis-detection, of false-positive type.

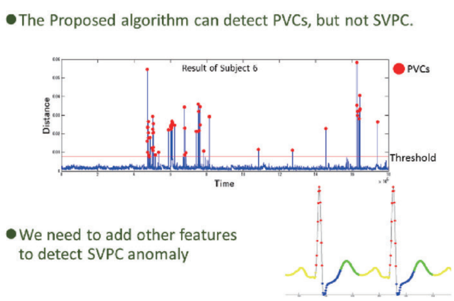


Fig. 5 PVC discords are detected, though SVPC are not

4　今後の具体的な展開

In the present work, we analyzed only bio-signals. The most important one, ECG is reported here.To understand the emotional state of the driver, we need multivariate analysis of several bio-signals, like ECG, pulse, GSR etc. In addition, we need to correlate them with driving state, like curve on the road, or alarming situation. For that, we need to take data while driving the simulator. We need wireless sensors to keep the driver free to move the steering, or maneuvering brake and gas. We will perform those experiments in the near future.

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６ 受賞・特許

None.

７ 参考文献

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