Driver Alertness Monitoring Using Fusion of Facial Features and Bio-Signals

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***Abstract*— Driver drowsiness is among the leading causal factors in traffic accidents occurring worldwide. This paper describes a method to monitor driver safety by analyzing information related to fatigue using two distinct methods: eye movement monitoring and bio-signal processing. A monitoring system is designed in Android-based smartphone where it receives sensory data via wireless sensor network and further processes the data to indicate the current driving aptitude of the driver. It is critical that several sensors are integrated and synchronized for a more realistic evaluation of the driver behavior. The sensors applied include a video sensor to capture the driver image and a bio-signal sensor to gather the driver photoplethysmograph signal. A dynamic Bayesian network framework is used for the driver fatigue evaluation. A warning alarm is sounded if driver fatigue is believed to reach a defined threshold. The manifold testing of the system demonstrates the practical use of multiple features, particularly with discrete methods, and their fusion enables a more authentic and ample fatigue detection.**

***Index Terms*— Android-based smartphone, dynamic Bayesian network, fatigue, features fusion, photoplethysmograph.**

I. Introduction

THE growth of sensor technology and network-based information technology has expanded the reach of wireless sensor networks into numerous areas such as healthcare, remote control, wildlife habitat monitoring, military explosive detection, intelligent home monitoring, and environment observation and forecasting system [1]–[2]. On the other hand, the recent increase in traffic accidents ispossibly caused by driver distraction and low attention during driving. Cooperative efforts between the government and private sectors have been attempted to reduce the number of traffic accidents by proposing numerous types of approaches. Intelligent transport systemsare promoted by integrating the sensor technology into the transport to measure the driver alertness level.

Lai *et al.* [3] developed a fuzzy-control massage seat to keep drowsy drivers awake. A nonintrusive prototype computer vision system has been proposed for monitoring driver's attentiveness in real-time (Luis *et al.* [4]). Kasukabe *et al.* [5] developed a system with visual, cognitive, and decision-making functions for elderly drivers to recognize various objects encountered during driving. Pauwelussen *et al.* [6] developed a traffic-simulation model in which a vehicle is equipped with an adaptive cruise-control (ACC) and lane-departure warning (LDW) system to monitor driver behavior in a real traffic environment. Moreover, Lee *et al.* [7] proposed a system with two fixed cameras to capture images of the driver and the road respectively, and then the images are mapped to global coordinates to monitor the driver sight line. The authors found four distinctive driving patterns through analysis by a hidden Markov model (HMM). Zhao *et al.* [8] studied the reliability of steering behavior to detect driver fatigue by multiwavelet packet energy spectrum using a support vector machine (SVM). Lee *et al.* [9] developed a video sensor-based eye-tracking and blink-detection system with Haar-like features and template matching for an automated drowsiness warning system. In addition, Yang *et al.* [10] demonstrated that drowsiness has a greater effect on rule-based driving tasks than on skill-based tasks using a Bayesian network (BN) paradigm through simulator-based human-in-the-loop experiments.

Wang *et al.* [11] proposed a latent variable to represent the attributes of individual drivers for recognizing the emotional state of drivers using four sensors, specifically for respiration, skin conductance, temperature, and blood pressure. Shin *et al.* [12] described the design of an electrocardiograph (ECG) and photoplethysmograph (PPG) sensor to measure the driver's metabolic condition. Bouchner *et al.* [13] presented an overall design of classification based on multiple features such as electroencephalography (EEG) signals, steering wheel correction movements, lateral position, average velocity change trends and weaving, position within the traffic lane and analysis results on recorded videos. Khushaba *et al.* [14] maximized the drowsiness-related information extracted from electrooculogram (EOG), EEG and ECG signals to classify driver attentiveness. Lin *et al.* [15] proposed a brain-computer interface (BCI) system that can analyze EEG signals in real-time to monitor a driver's physiological and cognitive states. A neural network approach to classify mental fatigue and drowsiness in driver was proposed by Bundele *et al.* [16], where they focused on skin conductance and pulse oximetry. Yang *et al.* [17] used a first-order HMM to compute the dynamics of BN for compiling information about multiple physiological characteristics such as ECG and EEG to infer the level of driver fatigue.

Meanwhile, Deshmukh *et al.* [18] developed a system to analyze a driver's eye-lid movement, jaw movement, and

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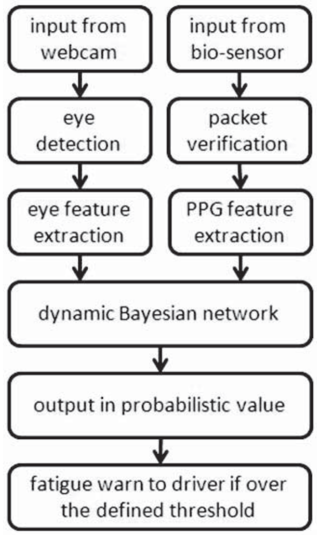


Fig. 1. Overview system flow chart.

variation in pulse. Giusti *et al.* [19] designed an intelligent system that compiled physiological data acquired from a sensor on the steering wheel, as well as mechanical data from a simulation platform to evaluate a driver's level of attentiveness. Additionally, Eskandarian *et al.* [20] proposed a method for detecting a driver's distraction and drowsiness levels by analyzing several parameters, including EEG signals, facial features, body posture, steering, braking, velocity, and lane position using an artificial neural network (ANN). Similar fusion approaches can be applied using SVM, which is a data-mining method for detecting cognitive distraction using driver eye movement. Such a driving performance data model has been proposed by Liang *et al.* [21]. Likewise, Liao *et al.* [22] used a DBN framework to model driver stress in term of physical appearance using a visual sensor, physiological conditions collected from emotional mouse, and behavioral data from user interaction activities using a driving simulation.

The fatigue monitoring system is implemented in Android-based smartphone for nonintrusive and portable flexibility. A webcam is placed on the dashboard in front of the driver to capture the driver image whereas a PPG sensor is installed at the steering wheel to collect the driver PPG signals through a finger underneath skin.The smartphone received the signals via connected wireless sensor. A Dynamic Bayesian network (DBN) paradigm is programmed in the smartphone to perform statistical analysis on driver fatigue level based on extracted received information as inputs.

II. System Structure

There are four significant modules consisting of hardware design and software implementation that build up the complete system for driver fatigue monitoring. Those modules are biomedical-sensor, video-sensor, information fusion, and smartphone programming in Android platform. An overview design of the system is displayed in Fig. 1. Initially, the smartphone system gathers the biomedical signals and image frames via RS232 serial port and USB port respectively. Information is extracted using the received data and further given as inputs to the DBN system. The DBN delivers the final output as the level of driver alertness in probabilistic value. The warning is sounded to the driver if the output reached defined threshold.

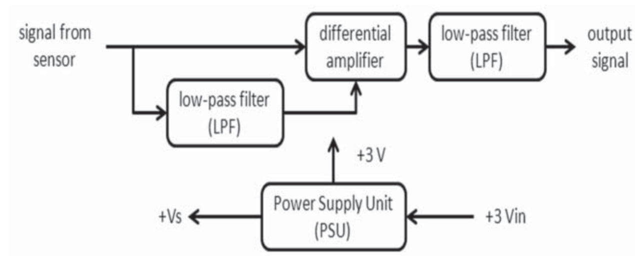


Fig. 2. PPG sensor analog conditioning circuit.

format	header							message			
name	length	fcf	dsn	dspan	daddr	type	group	saddr	count	chan	data
size	1	2	1	2	2	1	1	2	2	2	20

length: message length
fcf: IEEE 802.15.4 frame control field
dsn: IEEE 802.15.4 data sequence number
dspan: IEEE 802.15.4 destination identifier
daddr: destination address
type: active message number
group: group ID
saddr: source address
count: sample counter
chan: adc channel
data: adc readings data

Fig. 3. PPG sensor data packet format.

A. Biomedical Sensor Module

The driver PPG signal isobtained using a pulse oximeter that measures the changes in light absorption under a finger skin. The PPG sensor contains an infrared light-emitting diode (LED) in 940 nm wavelength and a PIN photodiode that measure the amount of light reflected from the LED. The analog signal acquired is filtered and amplified by an analog conditioning circuit which comprised of an amplifier, a low-pass filter (LPF), and a differential amplifier as depicted in Fig. 2. The circuit is connected to a CC2420 wireless transceiver operating in IEEE 802.15.4 ZigBee compliant with frequency band between 2.4 GHz and 2.485 GHz [23]. The CC2420 transceiver is controlled by a MSP430F1611 through the SP1 port and a series of digital I/O lines. The MSP430F1611 has a micro-controller with a 48 kb flash memory, 10 kb RAM, and 12-bit A/D converter operating on 3.3V power. The analog signal is converted to a digital signal and transmitted to the smartphone for analysis. The PPG data packet format is illustrated in Fig. 3.

Each packet contains a source address, source node ID, sequence number, channel number, data and etc. in hexadecimal format. A complete packet starts with a "7E" hexadecimal and ends with a "7E" hexadecimal. The data field size is 20 bytes with total 10 data in little-endian format.

B. Video-Sensor Module

A low-cost custom made webcam is placed on the driver seat dashboard to capture the driver image. The webcam is connected via USB port, with resolution up to

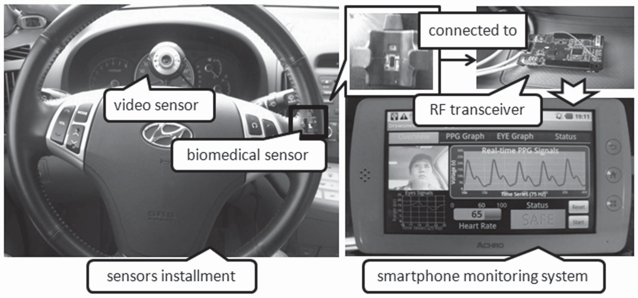


Fig. 4. Installment of video sensor and biomedical sensor and prototype of fatigue monitoring system in smartphone.

800 × 600 VGA, 30 frame per seconds (fps), built-in auto-white balance and auto electronic exposure functions. Several infrared LEDs are built at the left and right side near to the camera used to captured the driver image more clearly during night time. Fig. 4 demonstrates the installment of the biomedical sensor and video sensor on the steering wheel and dashboard respectively.

In order to avoid incorrect information interpretation, the data packet received is first validated by its length, channel number, and identification number before analysis take place. The CC2420 transceiver is coded in TinyOS operating system, which is a system designed specifically for low-power wireless devices. The video sensor is directly connected to the smartphone using USB port whereas the biomedical sensor transmits the data packets wirelessly to the smartphone through the transceiver connected by RS232 serial port. The webcam resolution is set to 320 × 240 as to reduce the computation tasks and time required for the processing.

C. Smartphone Programming Module

This module's principal function is to deal with the synchronization of the received data and information fusion analysis in DBN inference system. The whole system is programmed in Android platform. Briefly, Android is a software stack for mobile application devices consists of an operating system, middleware, and a set of key applications [24]. The system is coded using an Android development kit including a development platform (Achro HD [25]) and a development board (Achro PC100 [26]) designed by Huins Inc. in South Korea because the development board provides several common data transmission serial ports for development purposes. The ports are Ethernet, UART, Debug, and Debugging JTA. In addition, the development board supports Wi-Fi communication, GPS, and a three-axis accelerometer and is able to support the TinyOS operating system which gives us a huge advantage when designing the smartphone-based system. The development platform runs in Linux Kernel version 2.6.29 and SDK version 2.1 (Éclair).

The input image needed to be extracted to obtain the meaningful information related to fatigue measurement. First of all, an initial frame is grabbed to detect any facial featuresif any appeared. The face features detection approach is carried out by Active Shape Model (ASM) [27] method. The shape of a face is represented by a list of points. The shape model is matched with the input image. The model parametersare updated to find the best match in the image using the Procrustes algorithm. In the first step, the features points for eyes and nose are defined. The feature profiles are trained on the desktop computer and stored in the smartphone for the shape model matching. Aprofile points are initialized at the centroid of the image. Normally, RGB color model in which red, green, and blue colors are added together in various ways to reproduce an image in webcam. Mahalanobis distance measures the similarity between the profile points and the image points in for the RGB color spaces as in,

$$D(x_i) = \sqrt{(x_i - \mu_i)^T S^{-1} (x_i - \mu_i)} \tag{1}$$

where x is the x-axis multivariate vector $x = (x_1, x_2, \ldots, x_N)$ for $i = 0, 1, 2$ is defined as red, green, blue colors respectively whereas is the mean values for the each RGB colors.

Next, the transformation T is calculated using the Procrustes algorithm. The transformation T includes translation, uniform scaling, and orientation. The translation of the profile points-from the origin to new points is calculated as,

$$(\hat{x}, \hat{y}) = (x - \bar{x}, y - \bar{y}) \tag{2}$$

where $\hat{x}$ is the mean points calculated as $(1/N)\sum x_i$. The y-axis iscalculated similar to x-axis. Meanwhile, the scale δ is measured with root mean square methodas in (3) and new profile points are updated as shown in (4)

$$\delta = \sqrt{\frac{1}{N}\sum [(x_i - \bar{x}_l) + (y_i - \bar{y}_l)]} \tag{3}$$

$$(\hat{x}, \hat{y}) = \left(\frac{x_i - \bar{x}_l}{\delta}, \frac{y_i - \bar{y}_l}{\delta}\right). \tag{4}$$

On the other hand, the new profile points in orientation areupdated using (5) where the calculation is slightly more complex than the translation and scaling calculation. The value is ranges from $-15°$ to $+15°$.

$$(\hat{x}, \hat{y}) = (x_i \cos\theta - y_i \sin\theta, x_i \sin\theta - y_i \cos\theta). \tag{5}$$

A variable τ is used to update the threshold value during profile points matching processes. Here, τ is initialize as zero and computed as in (6) for the consecutive iteration. The value is set to π if the value is greater than $3 \times \sqrt{\pi}$. Lastly, the threshold value is updated by summing up $\bar{x}$ and (6). The process is repeated until the updated threshold value in is less than a convergence value.

$$\tau = (x - \bar{x})' \left[T^{-1} - \bar{x}\right]. \tag{6}$$

Once the best match is found,the sizes of left (ϑ_1) and right (ϑ_r) eyes are averaged and defined as $\vartheta_{\text{avg}} = 1/2(\vartheta_1 + \vartheta_r)$.

Biomedical signals can only be interpreted using a series of data unlike the image data [28]-[29]. Thus, a hundred bytessize of buffer is declared to store the incoming PPG data packet before any further extraction can be done. Fig. 5 illustrates the plotting of sample PPG signals obtained using our designed biomedical sensor. As shown in the Fig. 5, the value represents the peak of a PPG signals in one complete cycle. The peak value can be obtained by using first-order-derivation (FOD)where $dy/dx = 0$. Based on the peaks value,

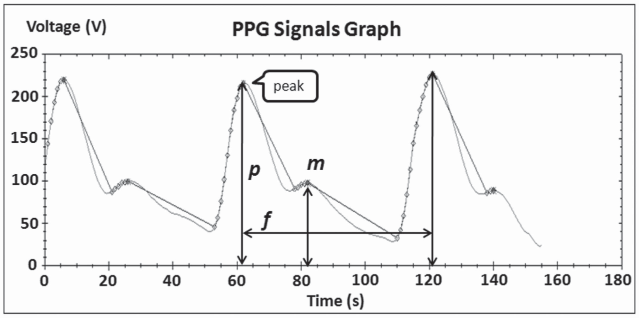


Fig. 5. Sample of the PPG signals and peak detection using a series of data inside the buffer.

f value is the interval between two peaks. In our studies, it showed that the 100 bytes buffer size is the optimum size with at least two peaks can acquired. If the buffer size is too big, a longer time is needed for analysis whereas if the buffer size is too small, there is no guarantee that more than one peak can be detected. Notice that there is a local maxima point beside the peak value which is represented by the value m. It is taken into consideration as a feature in fatigue analysis.

Another useful method in analyzing biomedical signals is to calculate its power spectral density (PSD), which defines how the signal power is distributed with frequency. The power is the actual voltage value output directly from the sensor without normalization. Using the Welch method, the Welch spectral estimator is defined as,

$$\widehat{P_l}(t) = \sum_{k=n_0}^{n_e} x(k) e^{j2\pi(kft)} \tag{7}$$

$$\widehat{P_w} = \frac{1}{N} \sum_{k=n_0}^{N} \widehat{P_l}(t) \tag{8}$$

where $\widehat{P_l}$ is the discrete Fourier transform between n_0 (first peak) and n_e (second peak) for series of signal points $x(k)$ whereas $\widehat{P_w}$ is the average Welch PSD for $\widehat{P_l}$ points. We only considered the average PSD computation on the interval between two peaks segment to signify the differences foreach complete cycle. For the next iteration, 20 bytes of the data in the buffer is removed and new data is inserted based on first in first out basis. The extraction process is repeated using the new buffer data.

D. Information Fusion Module

Various variables or parameters can be used to reflect the characteristic of the driver attentiveness level. Basically, those parameters are divided into two groups: image and bio-signal. In our implementation, a dynamic Bayesian network paradigm is applied for fatigue analysis. DBN paradigm [10] is a probabilistic graphical model that uses different mathematical techniques tomodel an object based on the given input data. The foremost reason of adapting DBN is that its ability to integrate distinct categories of parameters even the extraction methods, measurement techniques, and etc. of those parameters are different. Thus, few parameters are extracted based on the variables obtained in previous sections and given as input data to DBN paradigm.

TABLE I
Parameters for Fatigue-Level Analysis

Image	Bio-signal
BF	HV
BR	RM
PC	FD
AC	PD

BF: blink frequency HV: heart rate variability
BR: blink rate RM: root mean square
PC: percentage of eye closure FD: first-order-derivation
AC: average eye closure speed PD: power spectrum density

Firstly, ϑ_{avg} obtained from the image feature extraction can be utilized in blink frequency (BF). BF measures the number of blinks for eyes in a specified period. The distance between the local maxima and minima in ϑ_{avg} timeline is defined as bf. BF is simply how frequent bf appeared in a bounded time interval. A similar method, blink rate (BR) calculates the blinking speed for each eyes blink. Next, a well-known approach known as percentage of eye closure (PERCLOS)which described the amount of time the eyes are closed is considered as well. The value P60, P70 and P80 indicates the percentage of the eyes openness for a specific time. The details of the PERCLOS calculation can be referred to [30]. A method called Average Eye Closure/Open Speed (AECS) is another useful indicatorfor fatigue. As the name implies, it calculates the speed of opening or closing the eyes for a specific time.

In terms of bio-signals, the f values, also known as heart rate variability (HRV) can be noticeably categorizing the status of the driver for a particular time. HRV is defined as the time interval between heart beats and measured by the variation in the beat-to-beat interval, in other words, the p-to-p interval. The second parameter is root mean square (RMS) over a specific time calculated as $\text{RMS} = \sqrt{[\sum_n x^2(t)]/n}$, where n is the total number of points in the buffer. The FOD averaged value and $\widehat{P_w}$ are another two parameters to be included as DBN inputs. Table I illustrates the summary of the parameters considered as the DBN inputs for fatigue measurement.

DBN calculates its probability based on joint probability density function which is the product of the individual density functions, conditional on their parent variables. The joint probability density function can be written as,

$$P(Y_1 = y_1, \ldots, Y_N = y_N) = \prod_{u=1}^{N} P(Y_u = y_u | Y_v = y_v) \tag{9}$$

where each Y_v is a parent of Y_u. In this case, Y_v is the parent nodeswhich are the parameters declared in Table I whereas Y_u is the child node defined the status of the driver in probabilistic value. Next, the correlations for parameters are calculated to illustrate the dependencies relationships among them. Table II depicted the Pearson's correlation among the parameters, which is defined as (10).

$$\rho_{X,Y} = E[(X_{\mu_X})(Y - \mu_Y)]/(\sigma_X \sigma_Y) \tag{10}$$

TABLE II
MATRIX PEARSON CORRELATIONS

	BF	BR	PC	AC	HV	RM	FD	PD
BF	-	-	-	-	–	-	-	-
BR	0.81	-	-	-	-	-	-	-
PC	−0.14	0.12	-	-	-	-	-	-
AC	0.07	−0.11	−0.09	-	-	-	-	-
HV	0.03	−0.03	0.06	−0.09	-	-	-	-
RM	−0.69	−0.61	0.22	0.05	0.01	-	-	-
FD	0.58	0.54	0.29	−0.10	−0.02	−0.44	-	-
PD	0.02	0.19	−0.06	−0.19	0.05	0.07	−0.06	-

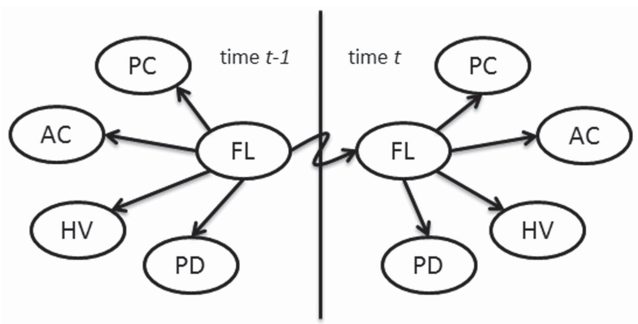


Fig. 6. Structure of a dynamic Bayesian network with four parameters as parent nodes and the final output as child node.

where μ_X and μ_Y is the mean of parameter X and Y respectively. Meanwhile, σ_X and σ_Y stand for the standard derivation for X and Y parameters. The correlation value is zero if the parameters are totally independent and the negative sign expresses the inverse relationship between the parameters. The BF and BR have the highest correlation value which means that BF and BR shows the most closet linear relationship. Increased value in BF will also demonstrated the increasing value in BR. This implied that by adapting either BF or BR is enough for categorizing the fatigue level. Thus, the high correlation parameters should be removed to reduce the repeated calculation since the different parameters may demonstrate the same pattern.The highest correlation of PC and AC with other parameters is 0.29 and −0.19 respectively. Meanwhile, HV shows their correlation with other parameters up to −0.09 whereas PD shows 0.19 or −0.19 for highest correlation. Lastly, we decided to select these foremost highly independent parameters: PC, AC, HV, and PD as inputs to the DBN paradigm.

Fig. 6 depicted the bipartite structure of the DBN with the four parameters mentioned above as parent nodes and FT is the child nodewhich is defined as Y_u in (9). Instead of performing the analysiswith the current available data, DBN also utilized the previous calculated results by averaging both the values as the final output.

III. EXPERIMENTS AND TESTS DISCUSSION

Experiments are carried out by 10 volunteers, aged between 24 to 40 years old. The volunteers consist of both male and female drivers from different countries including Korean, Malaysians, Chinese, and Indians. This should help us in better understanding of the variation in parameters for different person. In addition, each volunteer had submitted a health report indicate their health status. None of the volunteers had serious illness and are suitable for the experiments and tests. In this paper, we only considered the healthy volunteers as the experiments and tests are taken in real driving situation where the person with illness is believed that he/she can't control the vehicle well. Therefore, it is not wise and not considerable for an ill person to driver a vehicle even in real daily life. However, various types of illness detection will be included in our future work that the setting of parameters may vary depending on how serious the person's illness is.

Before the experiments are started, every volunteer is required to fill out a survey form for the results validation. The survey questions included sleeping hours, time since last awake, hunger state, current feeling, mental status, health condition, driving experiences, driving skills, injuries, pregnancy (for woman only), and etc. which could affect the driving performance during experiments. Each volunteer is given 15 minutes to get used to the environment before real experiments are conducted. The data is recorded as well during the experiments as references in the future. In addition, volunteers are requested to conduct the experiments in three different times as in early morning (7 a.m. to 8 a.m.), after lunch time between 1 p.m. to 2 p.m. and late night around 12 a.m. to 1 a.m. The main purpose of these experiments is to gather the data required for the analysis. System testingis being carried outafter a week of the experiments to inspect the validation and accuracy of the system. Experiments and tests took place in the areas near to university, where the volunteers are driving start from the university to the city and routed back to the university. Every experiment and test is lasted for 40 to 50 minutes depending on the traffic conditions. In order to ensure the safety of the volunteer, an experienced and skillful driver accompanies along during the experiments and teststo take over for the volunteer if the volunteer can't proceed with the tasks. The volunteers' conditions are recorded every 2 minutes.

In order for the DBN to perform analysis, a conditional probability table (CPT) is required for each parent node. Conditional probability is the probability of an event occurring given that another event has already occurred. This stated that FL is the conditional probability given the condition of its parent nodes and CPT describes the interaction of FL child node and its immediate predecessors. Experiments' data filtering for any incomplete or missing parts is necessary before a CPT can be constructed. During the experiments, some of the images captured are not able to process due to the sudden huge movement of driver or affected by the changes of light in the surrounding environment.Moreover, parts of the PPG signals are missing when the volunteer's finger is not attached on the sensor. Thus, only meaningful data is extracted and labeled when constructing the CPT. Table III displayed the CPT for the four parent nodes. The "AW" indicates the volunteer is awakes and "DW" illustrates the volunteer is actually drowsyat a specific time during the experiments. Besides that, "PS" is the estimated probability of partial-sleep whereas "NS" is the non-partial sleep estimated probability given the true and false conditions. The predicted probability of PC is approximately

TABLE III
CONDITIONAL PROBABILITY TABLE FOR DBN PARENT NODES

	PC		AC		HV		PD	
	AW	DW	AW	DW	AW	DW	AW	DW
NS	0.81	0.19	0.76	0.24	0.61	0.39	0.78	0.22
PS	0.36	0.64	0.22	0.78	0.34	0.66	0.21	0.79

AW: actual condition is awake
DW: actual condition is drowsy
NS: non-partial sleep probability
PS: partial-sleep probability

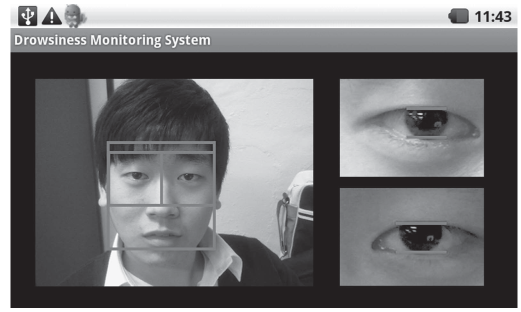
TABLE IV
ESTIMATED PROBABILITY BASED ON THE FUSION OF PARAMETERS

Parameters Fusion	T	F
P(FL|PC, AC)	0.8223	0.5494
P(FL|PC, HV)	0.8210	0.6078
P(FL|PC, PD)	0.8345	0.2194
P(FL|AC, HV)	0.8238	0.6866
P(FL|AC, PD)	0.8171	0.2843
P(FL|HV,PD)	0.8354	0.3354
P(FL|PC, AC, HV)	0.8877	0.4671
P(FL|PC, AC, PD)	0.8865	0.1372
P(FL|PC, HV, PD)	0.8762	0.1681
P(FL|AC, HV, PD)	0.8841	0.2221
P(FL|PC, AC, HV, PD)	0.9476	0.1026

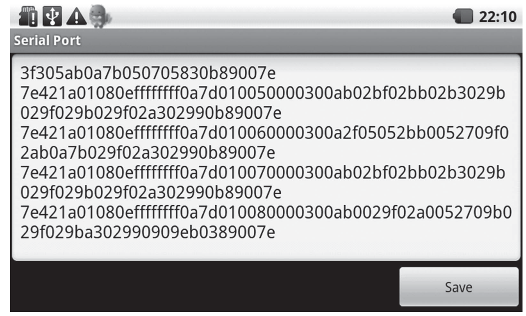
T: true case
F: false case

81% for true awake condition. However, the false awake condition is excessively high at 36% which is not an ideal probability. The same case applied to other parameters as well such as 22%, 34%, and 21% for AC, HV, and PD respectively. Moreover, the true detection is low in case of AW for AC, HV, and PD which is less than 80%in general. In term of DW true detection rate, PD has the highest estimated probability of 79% and AC in 78% whereas PC and HV only have the low probability around 66%. Based on this estimated probability, it is not a quintessential performance resultthat we are seeking.

Notably, instead of estimating the probability on a single parameter, an information fusion is surveyed. First, the fatigue probability is estimated based on fusion of two parameters as depicted in Table IV. Fusion of PC and PD yields the highest true detection rate and lowest false detection rate of 83% and 22% respectively. The rest of the parameters fusion performed an essential true detection rate, but unfortunately higher for false detection rate as well. High rate of false detection may trigger the false alarm more frequently. This will annoy the driver and surveys proved that most people are preferred to turn off the system to avoid the distraction during driving. Next, the fusion is increased to three parameters. It showed a superb improvement in the estimated probability especially for the false case. Nonetheless, it is still not the requirement to be achieved. Lastly, with the fusion of all four parameters, it revealed the best achievement with nearly 95% of true detection rate and 10% for false detection rate. The above results are performed using the data of 10 volunteers collected during the experiments.



(a)



(b)

Fig. 7. Screenshot for the fatigue monitoring prototype system: (a) face and eyes detection and (b) incoming packet data from the biomedical sensor in smartphone.

The CPTs is then used as the discrete function probability in the respective parent nodes for the system testing. Tests are carried out similar to the experiments but in slightly different ways. Volunteers are required to fill outa survey form and given exactly 15 minutes to familiarizewith the vehicle used for the testing. An extra alarm is set in the vehicle that will be triggered every minute. Each volunteer is requested to inform the inspector about their mental condition once the alarm is sounded. If volunteer doesn't inform the inspector, the inspector will check the volunteer condition personally, and noted as PS if volunteer attention level is indeed low. The tests are recorded for system validation. After volunteers finished the tests, they are requested to fill outa feedback form to write down their opinions on the system, and provide some suggestions for future improvement if any. The tests results revealed a promising true and false detection rate of 96% and 8% respectively. This stated that our fatigue monitoring system indeed has an impeccable performance under diverse conditions. This research focused on studying the benefit of parameters fusion to increase true fatigue detection rate and concurrently decrease false fatigue detection rate. Thus, when operating the fatigue monitoring system, if either the webcam data or biomedical signals are not present, itis not considered by us as it is out of the scope of this study. Fig. 7(a) depicted the screenshot of face and eyes detection. The upper right side is the left eye while the bottom right side represents the right eye. In Fig. 7(b), it shows the data packet received from the biomedical sensors.

IV. CONCLUSION

A fatigue monitoring system focused on information fusion is designed and implemented in Android-based smartphone.

The final output of the system defining the driver status at a specific time is estimated with a dynamic Bayesian network paradigm.The studies revealed that adoption of more information in fatigue detection; the higher degree of performance can be achieved instead of performing statistical analysis based on single information. In our studies, theinformation used is mainly the facial expression and physiological data of the driver. The future works may focus on the utilization of outer factors such as vehicle states, sleeping hours, weather conditions, mechanical data, and etc. for fatigue measurement. The feedback from the volunteers was promising and encouragementwas given for further improvement in the future. Signals changes for person in different conditions such as illness will be studied and considered in our future works as well.

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