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A driver fatigue recognition model based on information fusion and dynamic Bayesian network

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ABSTRACT

We propose a driver fatigue recognition model based on the dynamic Bayesian network, information fusion and multiple contextual and physiological features. We include features such as the contact physiological features (e.g., ECG and EEG), and apply the first-order Hidden Markov Model to compute the dynamics of the Bayesian network at different time slices. The experimental validation shows the effectiveness of the proposed system; also it indicates that the contact physiological features (especially ECG and EEG) are significant factors for inferring the fatigue state of a driver.

1. Introduction

The recent advances in cognitive science, psychology, and related fields have indicated that the human emotion (such as anger, fear, stress, distraction, and fatigue) plays a critical role in a person's behavior [28,21]. The behavior of drivers has been an active field of study for decades [23], and it has attracted considerable attention recently [34]. The driver fatigue remains to be one of the important factors that contribute to traffic accidents. The National Highway Traffic Safety Administration (NHTSA) of USA estimates that there are annually about 100,000 crashes in USA that are caused by fatigue and result in more than 1500 fatalities and 71,000 injuries [15]. Some studies have demonstrated that the driver drowsiness accounts for 16% of all crashes and over 20% of the crashes in the highways [8]. Thus, the driver fatigue assessment remains to be a big challenge to meet the demands of future intelligent transportation systems [3]. Developing a system that actively monitors the driver's fatigue level in real time (and produces alarm signals when necessary), is important for the prevention of accidents, and this is the main motivation of our paper.

One of the key steps towards developing a fatigue monitoring system is to consider the features that could be effectively used for fatigue recognition. We can classify these features into four general categories: (1) causal/contextual features, (2) physiological features, (3) performance features, and (4) multi-features. In the following paragraphs, we discuss these categories.

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1.1. Contextual features based method

The contextual features mainly include (i) the personality, sleeping quality, circadian rhythm, physical condition, (ii) the work conditions such as noise, driving hours [11,30], and the cab temperature; (iii) the environment such as monotony of road, density of cars, and number of lane. Such contextual features are collected mainly by questionnaires, and then the driver's fatigue is inferred from the collected data using some statistical methods or other means such as neural network or fuzzy set theory [10,11,33,35].

1.2. Physiological features based method

The drivers may exhibit some easily observable physiological features from which their fatigue can be inferred [15,28,32,39,41]. Physiological features may be classified into: *contact features*, including the brain activity, heart rate variability, and skin conductance – these can be easily detected by EEG (electroencephalogram), ECG (Electrocardiograph), and EMG (electromyogram); and *contactless features*, including the eye movements (EM), head movement, and facial expressions – these can be easily observed from the dynamic images provided by a CCD camera. Consequently, two approaches for research are feasible: the *contact feature based method* and the *contactless feature based method*.

The contact feature based method focuses on inferring the driver's fatigue from the contact features. Using the fact that the EEG can represent abundant information on the human cognitive states, an algorithm based on the changes in all the major EEG bands (delta, theta, alpha, and beta bands) during the fatigue was developed by Lal et al. [19] to detect different levels of fatigue. Combining the EEG power spectrum estimation, principal component analysis, and fuzzy neural network model, Jung et al. [17] designed a system to estimate and predict the drowsiness level of a driver. Taking the associated wavelet representations for the EEG at different scales as system inputs, Wilson and Bracewell [41] constructed a neural network to detect the onset of the driver's fatigue. Zhou et al. [46] proposed a new feature extraction method based on the bispectrum and applied it for the classification of the right and left motor imagery for developing EEG-based brain–computer interface systems. Budi et al. [2] assessed the four electroencephalography (EEG) activities, (delta (δ), theta (θ), alpha (α) and beta (β)) during a monotonous driving session for 52 subjects (36 males and 16 females), and got the results for conditions stable delta and theta activities over time, a slight decrease of alpha activity, and a significant decrease of beta activity.

The ECG is another contact feature, including the LF (low frequency), VFH (very low frequency), HF (high frequency), and the LF/HF ratio, that contains relevant information about fatigue [33]. By taking the Hermite polynomial coefficients of the ECG as inputs, [24] presented a neuro-fuzzy network approach that was used to recognize and classify the heart rate variation. It is noted that Picard et al. [28] also applied this to affective computing, and proposed a hybrid recognition algorithm combining the *Sequential Floating Forward Search* and the *Fisher Projection* for the emotion recognition, by selecting the means, the standard deviations, the first differences, and the second differences of the EMG, BVP (blood volume pulse), GSR (galvanic skin response), and respiration from the chest expansion as physiological features. In addition, the fast Fourier transforms (FFTs) and three other modeling techniques, namely, the autoregressive (AR) model, the moving average (MA) model and the autoregressive moving average (ARMA) model, are used to estimate the power spectral densities of the RR interval variability in Zachary et al. (2008). The spectral parameters obtained from the spectral analysis of the HRV signals are used as the input parameters to the artificial neural network (ANN) for the classification of the different cardiac classes.

The contactless feature-based method focuses on inferring the driver's fatigue from the contactless features [13,18,26,44,1. Experiments have demonstrated that the driver in fatigue should exhibit some visual cues Ji et al. [15]. Horng et al. [13] proposed a driver fatigue detection algorithm based on the eye tracking and dynamic template matching. Norimatsu et al. [26] investigated the detection of the gaze direction using the time-varying image processing in which the facial and the gaze directions, without considering the facial direction, were detected separately, and then they were integrated into the final gaze direction. Kim et al. [18] constructed a fuzzy neural network-based method for fatigue recognition by taking the openness degrees of the mouth and eyes respectively, and the vertical distance between the eyebrows and eyes as inputs.

1.3. Performance measurement based method

Driver's fatigue can contribute to the deterioration in the operational performance (such as the reaction time, lane position deviation, and hand movement of controlling the steering wheel). A fuzzy set-based method involving the small movement of controlling the steering wheel was put forward by Vysoký [38,37] to calibrate and predict the driver's fatigue.

1.4. Multi-feature fusion-based method

The three methods described above focus only on a certain specific aspect, and that may lead to inaccurate results because the driver's fatigue is not directly observable but can only be inferred from the information available. There are a number of reasons for the inaccuracies using the method mentioned above: (i) the driver's fatigue derived from the contextual features contains much subjectivity that can not always reflect the real objectivity; (ii) inferring the driver's fatigue from the facial expression is not always reliable because of the following two limitations: (a) the current techniques for image processing can not always ensure the recognition accuracy; (b) an introverted person might have a tendency to control his or her display of emotions, especially in the presence of people he/she is not well acquainted with [6], which leads to an inaccurate interpretation of the facial expression. Thus, to fuse as many as possible features from uncertain events is a better way to make an accurate inference [5]. Further, Picard et al. [28] pointed out that it was necessary to fuse the contextual and physiological features, and the driver's performance in order to make the fatigue recognition more reliable.

By considering the evidence and beliefs of the contextual information and the visual cues from a single time instant, Ji et al. [15] constructed a static Bayesian network (SBN) to infer and predict the fatigue of human beings, enhancing the reliability of fatigue recognition. However, such a network does not consider the physiological contact features and is not suited to systems that evolve over time [16,21,43,45]. The Dynamic Bayesian network (DBN) has been developed to overcome this limitation. Li and Ji [21] introduce a new probabilistic framework based on DBN to dynamically model and recognize the user's affective states and to provide the appropriate assistance in order to keep the users in a productive state. Considering the evidence and beliefs of contextual information and visual cues from multiple time stamps, a new probabilistic framework based on DBN has been introduced in Ji et al. [16] but it has excluded the contact physiological features.

Besides the contextual information and visual cues (the contactless features), the contact physiological features (such as the EEG, and the ECG) may also contribute significantly to the fatigue because a person usually has little control over these contact features and so they could provide reliable source of information on a person's emotion [6]. However, it is very difficult to apply these two physiological signals non-intrusively because usually the electrodes and wires are used to contact a driver intrusively in order to obtain the EEG and ECG signals. There have been some efforts in developing non-obtrusive EEG and ECG technologies, and there has been a certain degree of success related to the non-obtrusive instrument use in laboratory settings. It is thus expected that the non-obtrusive EEG and ECG technologies (e.g. wireless technology) will become feasible in the near future for applications to fatigue estimation for drivers. Therefore, it is useful to investigate fusing the ECG and EEG features with other features for getting reliable fatigue estimations, which lays a strong foundation for the real application of getting reliable fatigue estimation from multiple features.

Inspired by the research of Ji et al. [16], in particular by the inclusion of the contextual features with the contactless features (mainly the facial expression features), we have developed a DBN-based fatigue recognition model along with its inferring algorithm to make the fatigue recognition task more feasible. However, our approach differs from that of Ji et al. [16] in the following ways: (i) we have included the contact physiological features – in particular the ECG and EEG, and (ii) in the treatment of the dynamics of a Bayesian network from one time slice to another, we have used the first order HMM (Hidden Markov Model).

The rest of the paper is organized as follows. Section 2 presents the problem description and a general architecture of the proposed DBN-based fatigue recognition model. In Section 3, the proposed DBN-based fatigue recognition model using multiple contextual and physiological features is presented along with the inference method corresponding to the model. In Section 4, the validation of the model is presented. Section 5 concludes the paper with further discussions.

2. Problem description

Assume that $[Z_1,Z_2,\ldots,Z_t,\ldots]$ is the semi-infinite collection of random variables, $Z_t = (C_t, X_t, O_t)$ denotes the input, hidden and output variables of a state-space model at a certain time instant t. A DBN is used to model the probability distributions over the semi-infinite collection. A DBN can be considered as a collection of SBNs interconnected by sequential time slices, and the relationships between two neighboring time slices are modeled by an HMM (hidden Markov Model) [21,43]. In particular, without loss of generality, we took the first-order HMM. A DBN is defined as a pair of $(B, \vec{B})$, where B is a SBN which defines the prior $P(Z_1)$, and $\vec{B}$ is a two-slice Temporal Bayesian Network (2TBN) which defines $P(Z_t—Z_{t-1})$ in the following equation [25] by means of a DAG (directed acyclic graph):

$$P(Z_t|Z_{t-1}) = \prod_{i=1}^{N} P\left(Z_t^i \middle| Pa\left(Z_t^i\right)\right) \quad (1)$$

where N is the number of the nodes in the graph, Z_t^i is the ith node at time$t$, which could be a component of C_t, X_t or O_t, and $Pa\left(Z_t^i\right)$ are the parents of Z_t^i which can be either in the same time slice or in the previous time slice. In the following, we show how to construct a DBN for fatigue recognition in particular. The construction of a DBN has two tasks: (1) the determination of nodes and (2) the determination of their prior probability. The nodes are related to the features (i.e., the cues) of human drivers while the prior probability indicates the likelihood of a particular feature that contributes to the fatigue.

As remarked in Section 1, there are many contextual and physiological features related to driver fatigue. Among these features, some of them lead to more contributions to the fatigue while others have lesser contributions to the fatigue. For the sake of simplicity but without any loss of generality, we only select those contextual and physiological features that have immediate relations with the fatigue. In particular, the following features or variables are selected.

2.1. Sleeping quality (SQ) analysis

The SQ is an important contextual feature that has an immediate relation with the fatigue [33]. The driver's SQ is associated with such quantities such as: the duration of sleep (and the lack thereof), difficulty in falling asleep at night, the sleeping environment, and other social factors. Among them, the sleep time and the sleeping environment were taken as the key contributors to SQ because a certain minimum number sleep hours is necessary for everyone, especially to drivers, and whether the sleep is good or not mainly depends on the sleeping environment. Therefore, the SQ was taken as one of the contextual features corresponding to the nodes of the DBN graph.

2.2. Circadian rhythm (CR) analysis

The circadian rhythm (CR) is a cardinal contextual variable in recognizing the fatigue. Lal et al. [20] pointed out that the CR should be an important consideration in the study of the driver fatigue because it is found that there are two peaks of sleep each day (these peaks appear during 3–5 A.M. and 3–5 P.M. approximately), and sleep may come more easily and fatigue may reach the highest level during these periods. Vysoký [37] identified CR as a factor mainly influencing the driver's alertness. Therefore, the CR is also selected in this paper as one of the contextual variables corresponding to the nodes of the DBN graph.

2.3. Work environment (WE)

It is obvious that noise, the monotony of the road, the density of cars on a highway, the number of lanes, and the in-car temperature have strong relations with the driving environment that has contributions to the driver's fatigue. Among these features, the noise and temperature have immediate relations with the work environment. Therefore, the noise and temperature were taken as two contextual features corresponding to the nodes of the DBN graph.

2.4. Eye movement (EM) analysis

The eye gaze, eye blink, and eyelid closure are different manifestations of the EM [22]. When the EM is used to research the driver's fatigue, these manifestations are described as the PERCLOS (percentage of eyelid closure over the pupil in a given time) [40], which is a reliable and valid determination of a driver's fatigue [15]. Several studies [15,40] indicate that the driver is possibly in a state of fatigue if the eyes are at least 80% closed in the unit of time of a minute. Thus, the proportion of the eye-closed time was taken in this paper as one of the observable variables corresponding to the nodes of the DBN graph.

2.5. ECG analysis

The heart rate varies significantly for the same individual in different states such as alertness and fatigue. This is the main reason why the ECG is often used for detecting the driver's states. The ECG signal is first smoothed by a simple low-pass filter with a cut-off frequency of 100 Hz, and then transformed by the FFT algorithm into the frequency domain mainly including the LF, VLF, and HF. Among these frequency features is the LF/HF ratio that has strong relations to a driver's fatigue. Calcagnini et al. [4] pointed out that the LF/HF ratio would decrease progressively when passing from the awake state to the fatigue state. Therefore, the LF/HF ratio describing driver's states was taken as one of the observable variables corresponding to the nodes of the DBN graph. In this paper, the method presented by Yang et al. [9] is adapted to calculate the changes around the standard baseline of EEG.

2.6. EEG analysis

The frequency domain of EEG mainly includes the delta band (0.5–4 Hz) corresponding to the sleep activity, the theta band (4–7 Hz) related with drowsiness, the alpha band (8–13 Hz) corresponding to relaxation and creativity, and the beta band (13–25 Hz) corresponding to activity and alertness [17]. Note that only the alpha band has strong relations with fatigue study, and the variations in the EEG trace, such as a decrease in the alpha rhythms, is interpreted to indicate states of fatigue [20,31]. Further, the decrease in the alpha rhythms shows that a driver is at the fatigue state. During a stage of vigorous activity or stress, the driver's average magnitude of the signal within the alpha band is taken as the standard baseline. In the fatigue situation, obvious changes of the alpha signals around the standard baseline always take place. Therefore, the change around the standard baseline of the EEG spectrum was taken as one of the observable variables corresponding to the nodes of the DBN graph. In the present study, a simple low-pass filter with a cuto? frequency of 50 Hz and the independent component analysis are employed to smoothen the EEG signals, the smoothened signals are then transformed into the frequency domain by use of the fast Fourier transform (FFT) algorithm (for further details on calculating the change around the standard baseline of EEG, see Yang et al. [9]).

On the basis of the above analysis, the SQ, WE and CR are chosen as the key contextual variables corresponding to the component C_t of Z_t, while the EM, ECG, and EEG are the observable variables corresponding to the component O_t of Z_t. Given that the FAT representing the driver's fatigue has two states (fatigue and alertness) corresponding to the hidden variable X, the proposed generic DBN structure used to recognize driver's fatigue is illustrated in Fig. 1.

3. DBN-Based fatigue recognition model

A DBN can be applied to deal with either continuous or discrete stochastic processes. In this paper, we only consider the discrete stochastic process; i.e., the contextual, hidden and observable variables have finite random values, which form a

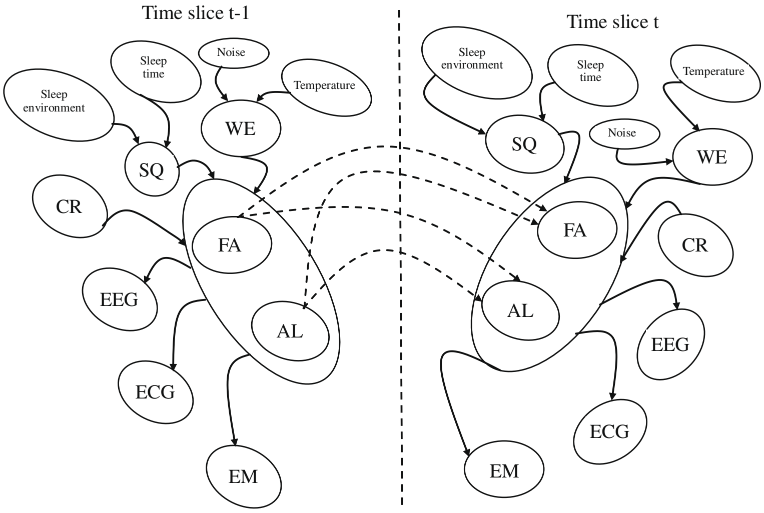

Fig. 1. The detailed DBN structure used to recognize driver's fatigue.

Table 1
SQ and its parent discrete variables and their states.

Sleep_time node (states)		Sleep environment node (states)		SQ node (states)	
sufficient	Deprived	Poor	Normal	Bad	Good

Table 2
WE and its parent discrete variables and their states.

Temperature node (states)		Noise node (states)		WE node (states)	
High	Normal	High	Normal	Bad	Good

Table 3
CR discrete variables and their states.

CR node (states)	
Low	High

discrete DBN. To set up a fatigue recognition model based on the discrete DBN, the first step is to specify the nodes of the discrete DBN. In other words, we need to specify the contextual, hidden and observable variables that are used to construct the discrete DBN network (where we take the SQ, WE and CR as the key contextual variables, the EM, ECG, and EEG as the observable variables, and the FAT including fatigue and alertness as the hidden variable, as explained in Section 2, see Fig. 1). The second step is to determine what values are used to represent the discrete variables. The third step is to configure the initial states of variables, i.e., to calculate the SBN (or B) at time $t = 1$. The last step is to calculate the conditional probability over time and to infer the fatigue of a driver. In the following, the last three steps are described in detail.

3.1. Step 1: Determining discrete values for each node (variable)

As for the contextual, hidden and observables selected in Section 2, the fuzzy method is used to determine the discrete values for each variable based on a set of heuristic knowledge rules [31]. Tables 1–4 summarize the discrete variables and their state values.

3.2. Step 2: Calculating SBN (B)

With reference to Eq. (1), it is necessary for calculating DBN to know the prior $P(Z_1)$ in advance, i.e., determining the SBN at time $t = 1$ given the initial conditions. We use capital letters to denote the variable (or node) names, and lowercase letters

Table 4
Hidden and observation discrete variables and states.

Component	Variable	State values		Description
Hidden variable	FAT	State1	Fatigue	The state of driver's fatigue
		State2	Alertness	
Observation variable	EM	State1	Large	Percentage of eyelid closure over time
		State2	Medium	
		State3	Small	
	ECG	State1	Decrease	LF/HF ratio of ECG wave
		State2	No-change	
		State3	Increase	
	EEG	State1	Decrease	The changes of average magnitude within alpha band of EEG spectrum
		State2	No-change	
		State3	Increase	

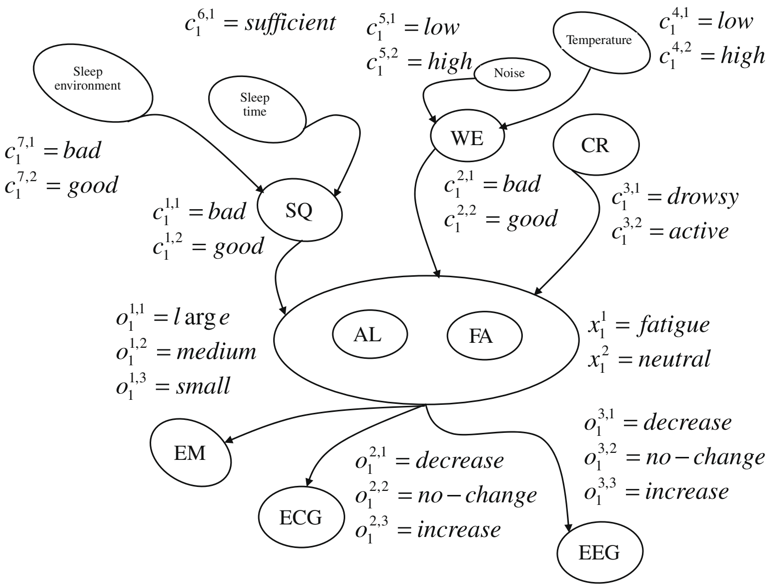

Fig. 2. The SBN structure at time $t = 1$.

to denote the specific values taken by the variables. Following such a notation, let X_t, C_t^j and O_t^i ($j = 1, 2$ or 3 be the *SQ, WE* or *CR* (where *SQ*and*WE* are represented in conditional probability by sleep time and sleep environment variables or temperature and noise variables), while $i = 1, 2$ or 3 can be the *EM*, *ECG* or *EEG*) be the hidden fatigue node, the contextual nodes, and the observable nodes at time t, respectively, and $x_t^k,\ c_t^{j,m}$ and $o_t^{j,n}(k, m = 1, 2\ and\ j, n = 1, 2, 3)$ denote the specific values taken by X, C^j and O^i, respectively. From Fig. 1, we can derive the SBN at time $t = 1$, shown as Fig. 2.

Assume that the evidences from the contextual nodes at time $t = 1$ are represented as $e_1^c = \left\{e_{c,1}^{i,j}\right\}$, where $e_{c,1}^{i,j}$ represents the evidence of the ith contextual node with the jth state value, and the evidences from the observable nodes at time $t = 1$ are represented as $e_1^o = \left\{e_{o,1}^{i,j}\right\}$, where $e_{o,1}^{i,j}$ represents the evidence of the ith observable node with the $j$thstate value. Denote $e_1 = \{e_1^c, e_1^o\}$ to be the evidences from the contextual and observable nodes at time $t = 1$, then the conditional probability of X given the occurrence of e_1^c can be written as [7]

$$P(X = x_1^k | e_1^c) \propto \sum_{i=1}^{2}\sum_{j=1}^{2}\sum_{l=1}^{2} P\left(X = x_1^k \middle| c_1^{1,i}, c_1^{2,j} c_1^{3,l}\right) P\left(c_1^{1,i}\right) P\left(c_1^{2,j}\right) P\left(c_1^{3,l}\right) \quad k = 1, 2 \tag{2}$$

and the conditional probability of e_1^o given the occurrence of node X can be written as [7]

$$\begin{aligned} P(e_1^o | X = x_1^k) &\propto P\left(e_{o,1}^{1,j} | X = x_1^k\right) P\left(e_{o,1}^{2,j} | X = x_1^k\right) P\left(e_{o,1}^{3,j} | X = x_1^k\right) \\ &= \left(\sum_{l=1}^{3} P\left(e_{o,1}^{1,j} \middle| o_1^{1,l}\right) P\left(o_1^{1,l} | X = x_1^k\right)\right) \times \left(\sum_{m=1}^{3} P\left(e_{o,1}^{2,j} | o_1^{2,m}\right) P\left(o_1^{2,m} | X = x_1^k\right)\right) \times \left(\sum_{n=1}^{3} P\left(e_{o,1}^{3,j} | o_1^{3,n}\right) P(o_1^{3,n} | X = x_1^k)\right) \\ & k = 1,\ 2 \text{ and } j = 1, 2, 3 \end{aligned} \tag{3}$$

According to Bayes' theorem, the conditional probability of node X given the occurrence evidence of e_1 at time $t = 1$ is obtained by combining Eqs. (2) and (3).

$$P(X = x_1^k|e_1) = \frac{P(X = x_1^k|e_1^c)P(e_1^o|X = x_1^k)}{\sum_{j=1}^{2} P\left(X = x_1^j|e_1^c\right)P\left(e_1^o\middle|X = x_1^j\right)} \quad k = 1,2 \tag{4}$$

Eqs. (2)–(4) indicate the initial case, i.e., the SBN at time $t = 1$.

3.3. Step 3: Calculating the conditional probability over time

Having specified the nodes of the discrete DBN and the initial state values of each node, and having configured the SBN (or B) at time $t = 1$, the next step is to calculate the conditional fatigue probability over time and to infer what we want about the driver, i.e., to calculate Eq. (1) (or$\vec{B}$). In this paper, a DBN is viewed as interconnected time slices of SBNs, and the relationships between two neighboring time slices are modeled by a first-order HMM. Following such a stipulation, we have considered that the random fatigue variable at the current time slice t is influenced by the contextual and observable variables at the current time slice t, as well as by the corresponding random fatigue variable at the previous time slice $t - 1$ only. Based on this principle and corresponding to Fig. 1, we draw the DBN structure at time t, as shown in Fig. 3.

Denote $P(x_{t-1}^k),\ where\ k = 1,2$ as the conditional probability of the node X with different state values at time slice $t - 1$. The conditional probability of X given the occurrence of e_t^c at time slice t can be obtained by using Eq. (2), see Fig. 3:

$$P(X = x_t^k|e_t^c) \propto \sum_{i=1}^{2}\sum_{j=1}^{2}\sum_{l=1}^{2}\sum_{m=1}^{2} P\left(X = x_1^k\middle|c_t^{1,i},c_t^{2,j}c_t^{3,k}x_{t-1}^m\right)P\left(c_1^{1,i}\right)P\left(c_1^{2,j}\right)P\left(c_1^{3,k}\right)P(x_{t-1}^m) \quad k = 1,2 \tag{5}$$

and the conditional probability of e_t^o given the occurrence of node X at time slice t can be calculated by using Eq. (3).

$$\begin{aligned} P(e_t^o|X = x_t^k) &\propto P\left(e_{o,t}^{1,j}|X = x_t^k\right)P\left(e_{o,t}^{2,j}|X = x_t^k\right)P\left(e_{0,t}^{3,j}|X = x_t^k\right) \\ &= \left(\sum_{l=1}^{3} P\left(e_{0,t}^{1,j}\middle|o_t^{1,l}\right)P\left(o_t^{1,l}|X = x_t^k\right)\right) \times \left(\sum_{m=1}^{3} P\left(e_{o,t}^{2,j}|o_t^{2,m}\right)P\left(o_t^{2,m}|X = x_t^k\right)\right) \times \left(\sum_{n=1}^{3} P\left(e_{o,t}^{3,j}|o_t^{3,n}\right)P\left(o_t^{3,n}|X = x_t^k\right)\right) \\ & k = 1,2\ j = 1,2,3 \end{aligned} \tag{6}$$

According to the Bayes' theorem, the conditional probability of node X given the occurrence evidence of $e_t = \{e_t^c, e_t^o\}$ at time slice t is obtained by combining Eqs. (5) and (6).

$$P(X = x_t^k|e_t) = \frac{P(X = x_t^k|e_t^c)P(e_t^o|X = x_t^k)}{\sum_{j=1}^{2} P\left(X = x_t^j|e_t^c\right)P\left(e_t^o\middle|X = x_t^j\right)} \quad k = 1,2 \tag{7}$$

Eqs. (5)–(7) indicate the conditional fatigue probability over time slice t.

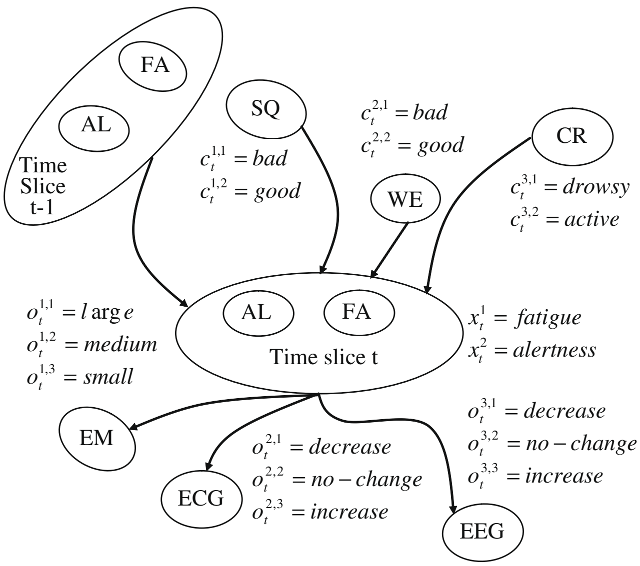

Fig. 3. The DBN structure at time t.

4. Validation

The validation of the proposed DBN model to predict the fatigue was conducted in a simulated driving environment. In the following, we first describe how the parameters of the proposed model are determined, and then we present the results of the experiments.

4.1. Construction of prior probability tables

The prior probabilities for the root nodes and the conditional probabilities for the links of the network need to be determined before the model can be useful. Usually, the probability is obtained from statistical analysis of a large amount of training data. In this study, we acquired information from several published papers [11,12,15,16,21,28,30,33,44]. However, not all the required data can be obtained; in this study we also obtained data through the computer generation following the noise-or principle (http://www.ai.mit.edu, Murphyk). Yet, some probabilities were still determined based on our experience. For example, the transitional probability between the same states of two slices, e.g., the positive to positive or the negative to the negative, is considered to be relatively high; on the other hand the transitional probability between the opposite states, the positive to negative, or the negative to positive, is much lower. With all these efforts, we obtained the probabilities used in our DBN model, which are shown in Tables 5–10.

In Table 5, the numbers represent the conditional probability for SQ as the different events of the sleep_time and sleep_environment take place simultaneously.

In Table 6, the numbers represent the conditional probability for WE as the different events of the temperature and noise take place simultaneously.

In Table 7, the numbers represent the conditional probability for CR as the event of the active time or drowsy time takes place.

In Table 8, the numbers represent the conditional probability for fatigue as the different events of SQ,WE and CR take place simultaneously.

In Table 9, the numbers represent the conditional probability for EM, ECG, and EEG respectively as the event of fatigue take place simultaneously.

In Table 10, the numbers represent the conditional probability for the current fatigue as the different events of SQ, WE, CR and the fatigue before the current fatigue take place simultaneously.

To get the data set of CR, we designed a questionnaire mainly concerning the time period in which the drowsy state is most likely to take place. The questionnaires were distributed among thirty computer science students of the Henan Univer-

Table 5
Conditional probability for SQ.

Sleep_time node	Sleep_environment node	SQ node (states)	
		Bad	Good
Sufficient	Poor	0.34	0.66
	Normal	0.05	0.95
Deprived	Poor	0.95	0.05
	Normal	0.73	0.27

Table 6
Conditional probability for WE.

Temperature node	Noise node	WE node (states)	
		Bad	Good
High	High	0.94	0.06
	normal	0.8	0.2
Normal	High	0.73	0.27
	Normal	0.10	0.9

Table 7
Probability for CR.

CR node (States = drowsy or awake)		
Drowsy time	0.94	0.06
Active time	0.8	0.2

Table 8
Conditional probability for fatigue node.

SQ	WE	CR	Fatigue node	
			Drowsy	Active
Bad	Bad	High	0.98	0.02
		Normal	0.89	0.11
	Good	High	0.88	0.12
		Normal	0.77	0.33
Good	Bad	High	0.51	0.49
		Normal	0.27	0.73
	Good	High	0.15	0.85
			0.05	0.95

Table 9
Conditional probabilities for EM, ECG and EEG given fatigue node.

Fatigue node	EM node			ECG node			EEG node		
	Large	Medium	Small	Decrease	No-change	Increase	Decrease	No-change	Increase
FA	0.94	0.05	0.01	0.93	0.06	0.01	0.91	0.08	0.01
AL	0.01	0.05	0.94	0.01	0.06	0.93	0.01	0.08	0.91

Table 10
Conditional probability for Fatigue node.

Fatigue (time $t-1$)	SQ	WE	CR	Fatigue (time t)	
				Drowsy	Active
FA	Bad	Bad	Drowsy	0.91	0.09
			Active	0.88	0.12
		Good	Drowsy	0.90	0.10
			Active	0.85	0.15
	Good	Bad	Drowsy	0.87	0.13
			Active	0.82	0.18
		Good	Drowsy	0.83	0.17
			Active	0.81	0.19
AL	Bad	Bad	Drowsy	0.20	0.80
			Active	o.17	0.83
		Good	Drowsy	0.18	0.82
			Active	0.13	0.87
	Good	Bad	Drowsy	0.15	0.85
			Active	0.1	0.9
		Good	Drowsy	0.12	0.88
			Active	0.09	0.91

sity, China who were asked to answer questions regarding their drowsiness statees from 2:30 P.M to 5:30 P.M in the recent days. The statistical analysis of the questionnaire results in the probability for CR, as shown in Table 11.

To get the data sets of SQ, EEG, ECG and WE, a driver simulator equipped with instruments such as the CCD camera, EEG and ECG was acquired with the help of the Multi-Media Lab and the Psychology Lab of the Henan University. Thirty students from the Computer Science Department of Henan University who do not have any kind of sleep disorder volunteered to participate in the experiments. They were deprived of good sleep during the previous night (e.g. the sleep time was less than 6 h) and were asked to participate in the simulation test when they came to the Lab after 2:30 P.M next day. With this scenario (the Lab environment was relatively good), each participant was asked to operate the driving simulator at the speed of 65 km/h, and no food or drink were permitted during the experiment. The probabilities of SQ and WE were determined and shown in Tables 12 and 13.

The simulation experiments lasted from 2:30 P.M to 5:30 during which, each participant was asked to operate the driving simulator at the speed of 65 km/h. The EEG and ECG signals of each participant were measured at the sampling rate of 250HZ, and his/her dynamical facial image was obtained at the sampling rate of 2 seconds. The EEG, ECG and dynamical facial image signals of each participant were collected at the same rate of 6 minutes. Signals were processed with the corresponding methods to form the evidence data sets which are needed to infer driver's fatigue estimation. For example, if the evidence coming from EM is that PERCLOS is equal to 85, then $P\left(e_{0,t}^{1,1}\right) = 0.89, P\left(e_{0,t}^{1,2}\right) = 0.42, P\left(e_{0,t}^{1,3}\right) = 0.18$; if the evidence coming from ECG is that the decrease of LF/HF is large, then $P\left(e_{0,t}^{2,1}\right) = 0.92, P\left(e_{0,t}^{2,2}\right) = 0.21, P(e_{0,t}^{2,3}) = 0.09$; if the evidence

Table 11
Probability for CR.

Drowsy	Active
0.89	0.11

Table 12
Probability for SQ.

Bad	Good
0.95	0.05

Table 13
Probability for WE.

Bad	Good
0.1	0.9

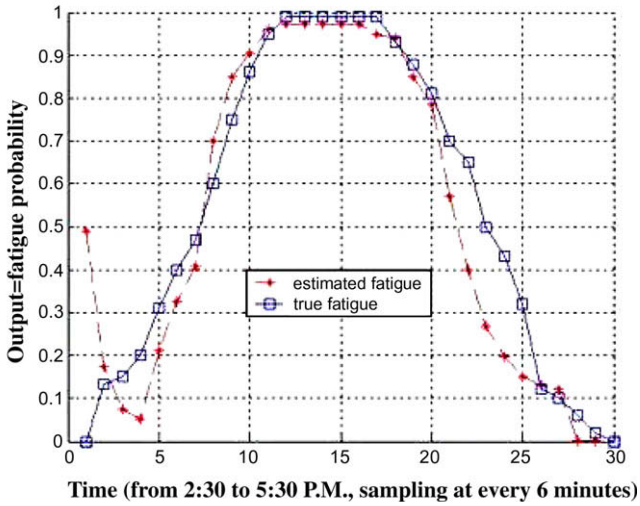

Fig. 4. Simulation result (Features: SQ, WE, CR, EM, EEG and ECG).

coming from EEG is that the decreases in alpha rhythms is large, then $P\left(e_{0,t}^{3,1}\right) = 0.91, P\left(e_{0,t}^{3,2}\right) = 0.19, P\left(e_{0,t}^{3,3}\right) = 0.10$. These probabilities were assigned according to the statistical properties of the data obtained from the participants.

4.2. Results and discussion

Under the constructed simulation scenarios, computer simulations were performed on the proposed fatigue recognition model by using the data described above. The simulation results are shown in Figs. 4–7. Fig. 4 is the simulation result with the features of SQ, WE, CR, EM, EEG and ECG. It can be observed from Fig. 4 that: (1) the time period in which the participants are in their completely drowsy state is about from 3 P.M to 3:45 P.M, which is consistent with the "true" fatigue; (2) when multiple features of SQ, WE, CR, EM, EEG and ECG are employed to infer the driver's fatigue, the estimation is almost completely approximating the "true" fatigue after 30 minutes, especially in the drowsy time period; and (3) the average square error is $1/30 * \sum(estimated\_fatigue - true\_fatigue)^2 = 0.5269$. These results have provided a good validation of the effectiveness of the proposed fatigue recognition model.

Fig. 5 is the simulation result with the features of SQ, WE, CR, EM and EEG but without ECG.

Fig. 6 is the simulation result with the features of SQ, WE, CR, EM and ECG but without EEG.

Fig. 7 is the simulation result with the features of SQ, WE, CR and EM but without ECG and EEG.

The following observations can be made from Figs. 5–7:

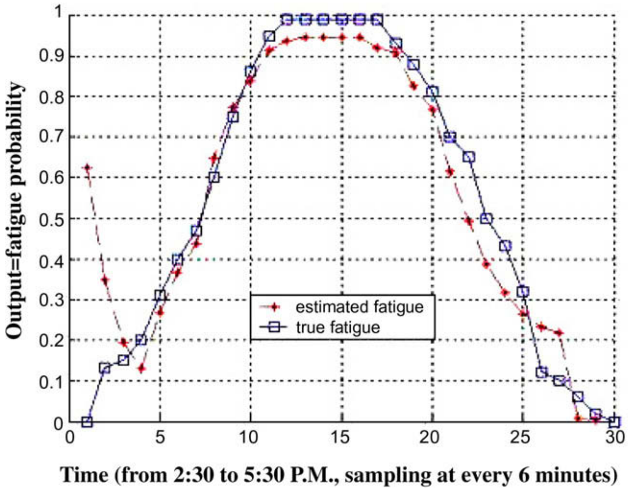

Fig. 5. Simulation result (Features: SQ, WE, CR, EM, and EEG, without ECG).

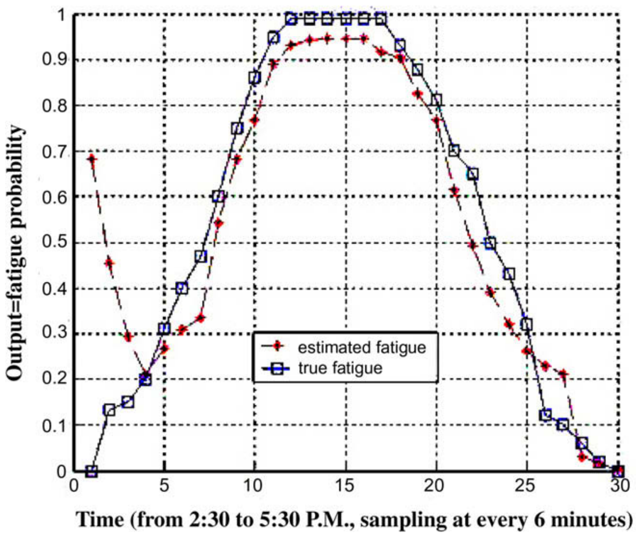

Fig. 6. Simulation result (Features: SQ, WE, CR, EM, and ECG, without EEG).

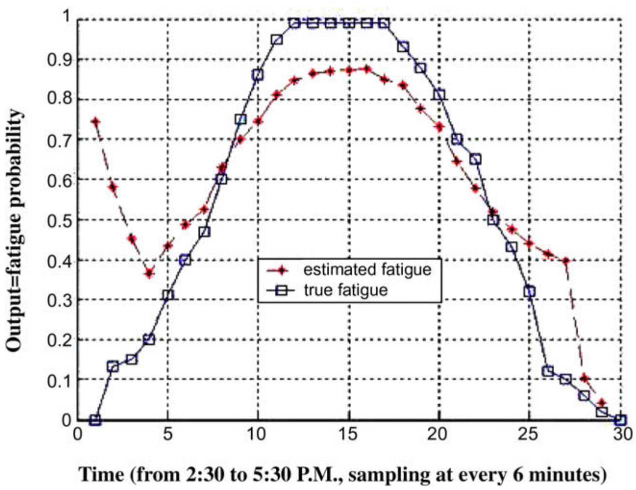

Fig. 7. Simulation result (Features: SQ, WE, CR and EM, without ECG and EEG).

(1) When the ECG or EEG features are removed from the feature set, the performance of the fatigue estimation becomes slightly worse than that of Fig. 4, as can be observed from Figs. 5 and 6. However, such a difference is not obvious, which can be highlighted by the fact that the average square error in Fig. 5 is 0.6723, while the average square error for Fig. 6 is 0.7488, both are a little bigger than the one (0.5269) in Fig. 4. This shows that the ECG or EEG feature has an immediate impact on the inferring driver's fatigue estimation.
(2) When both the ECG and EEG feature are removed from the feature set, an obvious difference exists between the estimated fatigue and the true fatigue, especially in the drowsy time period, which can be seen from Fig. 7. Thus, the performance of the fatigue estimation without ECG and EEG is much worse than that depected in Fig. 4, which can be explained by the fact that the average square error in Fig. 7 is 1.2629, while the average square error for Fig. 4 is 0.5269.

Comparing Fig. 4 with Fig. 7, the previous works such as Ji et al. [16] that can be considered as the one without ECG and EEG (see Fig. 7). Thus, the result based on the simulated experiment has implied that the proposed model may improve the accuracy of predictio.

5. Conclusion and future work

In this paper, a new method for inferring driver's fatigue estimation based on the dynamic Bayesian network was proposed. Multiple features, including contextual, contact physiological, and contactless physiological features were used, which have the widest coverage of the categories of features. The first-order Hidden Markov Model (HMM) has been employed to compute the dynamics of a Bayesian network at two different time slices. Simulation-based experiments were performed to demonstrate the validation of the proposed model. Two important conclusions can be drawn from this study: (i) more features, especially the contact physiological feature category, which covers more features implying driver fatigue recognition, are favorable for inferring the driver fatigue more reliably and accurately; (ii) the ECG and EEG are two important features for fatigue recognition, and they should not be absent from consideration in any driver fatigue detection system.

It would be of significant interest to extend the current model of a discrete random process to a continuous random process to handle more practical situations; and also to investigate how to decrease the subjectivity in determining the transition probability (i.e., learning the DBN structure and parameters from the samplings), which is very important for the problem discussed in this study. We hope that this work would generate further interest in this challenging research problem.

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