A Probabilistic Framework for Modeling and Real-Time Monitoring Human Fatigue

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***Abstract*—A probabilistic framework based on the Bayesian networks for modeling and real-time inferring human fatigue by integrating information from various sensory data and certain relevant contextual information is introduced. A static fatigue model that captures the static relationships between fatigue, significant factors that cause fatigue, and various sensory observations that typically result from fatigue is first presented. Such a model provides mathematically coherent and sound basis for systematically aggregating uncertain evidences from different sources, augmented with relevant contextual information. The static model, however, fails to capture the dynamic aspect of fatigue. Fatigue is a cognitive state that is developed over time. To account for the temporal aspect of human fatigue, the static fatigue model is extended based on dynamic Bayesian networks. The dynamic fatigue model allows to integrate fatigue evidences not only spatially but also temporally, therefore, leading to a more robust and accurate fatigue modeling and inference. A real-time nonintrusive fatigue monitor was built based on integrating the proposed fatigue model with a computer vision system developed for extracting various visual cues typically related to fatigue. Performance evaluation of the fatigue monitor using both synthetic and real data demonstrates the validity of the proposed fatigue model in both modeling and real-time inference of fatigue.**

***Index Terms*—Bayesian networks (BNs), dynamic Bayesian networks (DBNs), human fatigue monitoring, information fusion, vigilance test.**

I. Introduction

FATIGUE HAS been widely accepted as a significant factor in a variety of transportation accidents [1]. Although it is difficult to determine the exact number of accidents due to fatigue, it is much likely to be underestimated. In aviation, the Federal Aviation Administration (FAA) revealed that 21% of the reports in the Aviation Safety Reporting System (ASRS) were related to general issues of fatigue and 3.8% of them were directly related to fatigue [1]. A survey from 1488 corporate crew members in U.S. corporate/executive aviation operation discovered that about 61% of these crew members acknowledged the common occurrence of fatigue during operation. Furthermore, 71% of these pilots had "nodded off" during some flights [2]. In highway, the National Highway Traffic Safety Administration (NHTSA) estimates that 100 000 crashes are caused by drowsy drivers, which results in more than 1500 fatalities and 71 000 injuries each year in the U.S. This amounts to about 1.6% of all crashes and about 3.6% of fatal crashes [1]. In marine, a 1996 U.S. Coast Guard (USCG) analysis of 279 incidents showed that fatigue contributed to 16% of critical vessel casualties and 33% of personal injuries [1]. In railroad, an analysis from the Safety Board of Federal Railroad Administration (FRA) reported that there were also 18 cases that were coded "operator fell asleep" as a causal or contributing factor from January 1990 to February 1999 [1]. Therefore, it is hard to overstate that human fatigue detection and prevention is very essential to improving transportation safety.

Over the past several decades, much research has been conducted on human fatigue prevention, focusing on two main thrusts. The first one is to understand the physiological mechanism of human fatigue and how to measure fatigue level [3]–[5]. The second thrust focuses on developing human fatigue monitors for commercial transportation based on the achievements from the first effort [3], [6]. So far, these fatigue monitoring systems can be classified into two categories [7], which are: 1) measuring the extent and time-course of loss of driver alertness and 2) developing real-time in-vehicle drowsy driver detection and alerting systems. However, human fatigue results from a very complicated mechanism, and many factors affect fatigue in interacting ways [2], [3], [8], [9]. Up to now, the fatigue mechanism is still not well understood, and few of these existing fatigue monitors are effectively used in the real world. The main drawback of them is that most of the present safety systems only acquire information from limited sources (often just one). Therefore, as pointed by some researchers [10], many more efforts are still needed to develop systems for fatigue prevention in commercial transportation.

In previous studies [6], [11], [12], a noninvasive computer vision system for extracting various visual parameters that typically characterize human fatigue was developed. The systematic integration of these visual parameters, however, requires a fatigue model that models the fatigue generation process and that is able to systematically predict fatigue based on the available visual observations and the contextual information. In this paper, based on the modern research achievements of fatigue studies [2], [3], [7]–[9] and the authors' previous successful studies [6], [11], a probabilistic and dynamic framework based on dynamic Bayesian networks (DBNs) for human fatigue modeling and monitoring is presented. The framework

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combines different information sources spatially and temporally to monitor and infer human fatigue under uncertainty.

II. Literature Review

A. Significant Causes for Fatigue

From the physiological view, it is widely accepted that fatigue, alertness, and performance are physiologically determined [2], [4], [8], [9]. Two physiological factors—sleep and circadian—are thought fundamental to the determination of fatigue and alertness. Therefore, all the factors that affect sleep and circadian system have the potential to contribute to fatigue.

Modern scientific research has proved that sleep is a vital physiological human need like food, water, and air [2]. The difference between sleep and other physiological needs is that sleepiness is such a powerful biological signal that you will fall asleep in an uncontrolled and spontaneous way regardless of your situation [4]. The average sleep time of a person required is about 8 h every day regardless of the change of seasons [2], [4], [8], [9]. A sleep loss results in essentially degradation of all aspects of functioning, including cognitive processes, vigilance, physical coordination, judgment and decision making, communication, outlook, and numerous other parameters [2], [8].

Sleep is a very complicated physiological process. Its quantity and quality are influenced by many factors, including wakefulness, time of day, age, environment, psycho-physiological state, and the individual's innate and learned ability to sleep. The more complicated aspect is that these factors often interact with each other [2], [4], [8]. A survey [2] from the corporate flight crew members in U.S. corporate/executive aviation operations by the Ames Research Center, NASA revealed that the most often identified factors that interfere with their home sleep are the following: anxiety/worry (19%); heat/high temperature (17%); high humidity (15%); random noise events (9%); and background light (8%). The surveys of sleep quantity and quality in the on-board crew rest facility by the Ames Research Center at NASA [3], [9] reported more detailed but similar information on the factors that affect the sleep at home and bunk.

The circadian rhythm has been found to virtually control all physiological functions of the body, including sleep/wake, digestion, and immune function. The circadian system is very difficult to adjust to the need of work/rest schedule or time zone changes in a short time. Circadian disruption can cause sleep loss and finally results in fatigue [2], [5], [8]. The circadian rhythm is regulated by the circadian clock that has been found at a certain place in the brain [2], [4], [5], [8]. Generally, sleep is programmed at night and awake is programmed during daytime. In addition, it is found that there are two peaks of sleepiness and alertness each day [2], [5]. The two sleepiness peaks appear at approximately 3–5 A.M. and 3–5 P.M., respectively. During the sleepiness periods, sleep may come more easily and fatigue may reach the highest level. The two alertness peaks come about at 9–11 A.M. and 9–11 P.M. During this period, human may have difficulty falling sleep even if his sleep was deprived in the previous night [2], [4], [5], [8]. These concepts are soundly supported by the fact that there was a 16-fold increase of the risk of single vehicle truck accidents during the time between 3 and 6 A.M. [5], [13]. This is further verified by a large-scale study of fatigue factors in the North American commercial truck transportation [7], [14]. which also showed that the strongest and most consistent factor influencing driver fatigue and alertness was time of day. Even the hours of driving was not a strong or consistent predictor of observed fatigue compared with time of day.

Besides sleep and circadian, there are many environmental or contextual factors that may contribute/cause human fatigue. In recent years, a series of large-scale survey of fatigue factors in aviation and land transportation [2], [3], [7]–[9] identified some important fatigue-causing factors. In aviation, the survey from 1488 corporate flight crew members in U.S. corporate/executive aviation operations by the Ames Research Center at NASA [2] showed that besides sleep loss and time of day of operation, the most often cited factors that affect their fatigue in flight are as follows: greater than seven flying segments in the same duty; severe turbulence; illness; heavy workload; late arrival; four to six flight legs; high temperature; early morning departure; and no auto-pilot. The study also discovered that besides sleeping or napping (73%), the most often mentioned pretrip strategies to prevent fatigue were as follows: healthy diet (41%); exercise (28%); flight planning activities (26%); and caffeine (16%). Another survey of fatigue factors from 1424 crew members in U.S. regional airline operation by the Ames Research Center at NASA [8] obtained similar results. A large over-the-road study [7] showed that the main factors that affected the pilot's fatigue in aviation also contributed to the fatigue of drivers in commercial truck transportation.

In addition to the above factors, some clinical studies [3] found that about one third of the population suffers from several different types of clinical disturbances of sleep, which meet various diagnostic criteria for certain sleep disorders and significantly affect fatigue and alertness. These disturbances are insomnia, which refers to too little sleep, hypersomnia, which refers to too much sleep, and parasomnias, which refers to a deviation from normal sleep patterns. Insomnia is believed to be present in about 5%–6% of the population and is mostly caused by high levels of anxiety associated with worries, traumatic event, or prolonged stress from work, depression, or other sources [3].

In summary, the major causes for human fatigue include sleep quality, circadian rhythm, and physical fitness (e.g., sleep disorders). Furthermore, circumstantial factors such as weather, temperature, type of work, and workload will also directly contribute to human fatigue. All of these factors should be considered while modeling fatigue.

B. Fatigue Measurement

Before performing human fatigue detection and prediction, a metric should be established to measure fatigue. Numerous studies have been conducted on it. Many studies have shown that measuring fatigue in any situation is a complex process and no easy method is available. Up to now, several types of fatigue measures have been typically used in laboratories and have varying level of utility in the workplace [3]. The typical ones are

physiological, behavioral, visual, and subjective performance measures.

1) Physiological Measures [3], [15]–[17]: This method has been thought to be accurate, valid, and objective to determine fatigue and sleep, and significant efforts have been made in laboratory to measure it. The popular physiological measures include the electroencephalograph (EEG) [15] and the multiple sleep latency test (MSLT) [17]. EEG is found to be useful in determining the presence of ongoing brain activity, and its measures have been used as the reference point for calibrating other measures of sleep and fatigue. MSLT measures the amount of time a test subject falls asleep in a comfortable, sleep-inducing environment. Unfortunately, most of these physiological parameters are obtained intrusively, making them unacceptable in real-world applications.

2) Behavioral Measures [3], [18]: This method has been also thought to be accurate and objective, and has gained popularity in recent years. This category of devices, most commonly known as actigraph [18], is used to measure sleep based on the frequency of body movement. The information collector is a wristwatch-like recording device that detects wrist movement and is worn by the test subject. The number of body movement recorded during a specified time period, or epoch, has been found to significantly correlate with the presence of sleep and has a significant correlation with EEG. The disadvantages of this method is that they are troublesome to administer and expensive.

3) Visual Measures: People in fatigue exhibit certain visual behaviors that are easily observable from changes in facial features like the eyes, head, and face. Visual behaviors that typically reflect a person's level of fatigue include eyelid movement, head movement, gaze, and facial expression. Various studies [19], [20] have shown that eyelid activities are the biobehavior that encodes critical information about a person's level of vigilance, intention, and needs. In fact, based on a recent study by the Federal Highway Administration [20], [21]. Percentage of eyelid closure (PERCLOS) has been found to be the most reliable and valid measure of a person's alertness level among many drowsiness detection measures. PERCLOS measures the percentage of eyelid closure over the pupil over time and reflects slow eyelid closures (droops). Another potentially good fatigue indicator is the average eye closure and opening speed (AECS). Since eye opening/closing is controlled by the muscle near the eyes, a person in fatigue may open/close eyes slowly due to either tired muscles or slower cognitive processing.

Other potentially good fatigue parameters include various parameters that characterize pupil movement, which relates to one's gaze and his/her awareness of the happenings in surroundings. The movement of a person's pupil (gaze) may have the potential to indicate one's intention and mental condition. For example, for a driver, the nominal gaze is frontal. Looking at other directions for an extended period of time may indicate fatigue or inattention. Furthermore, when people are drowsy, their visual awareness cannot cover a wide enough area, concentrating on one direction. Hence, gaze (deliberate fixation) and saccade eye movement may contain information about one's level of alertness. Besides eye activities, head movement like nodding or inclination is a good indicator of a person's fatigue or the onset of a fatigue [22]. It could also indicate one's attention. Head movement parameters such as head orientation, movement speed, frequency, etc. could potentially indicate one's level of vigilance. Finally, facial expression may also provide information about one's vigilance. For example, a typical facial expression that indicates the onset of fatigue is yawning. Our recent effort [6], [11], [12] produces a computer vision system that can extract various parameters in real time to characterize eyelid movement, gaze, head movement, and facial expression. The major benefits of the visual measures are that they can be acquired nonintrusively.

C. Fatigue Detection, Prediction, and Monitoring

Knowing what causes fatigue and how to measure fatigue, the next step (also is the most important part for human fatigue research) is to detect, predict, and monitor real-time human fatigue. Up to now, many efforts have been made in this field and the results were reviewed in [6], [10], etc. Generally, all of the efforts on the fatigue detection can be classified into the following four groups [10], [20].

1) Readiness-to-perform and fitness-for-duty technologies: This type of effort is to assess the vigilance or alertness capacity of an operator before the work is performed. The main aim of this technology is to establish whether the operator is fit for the duration of the duty period, or at the start of an extra period of work. They include Truck Operator Proficiency System [23], FACTOR 1000 [24], ART90 [25], FITR 2000 Workplace Safety Screener [10], OSPAT [10], and Psychomotor Vigilance Test (PVT) [10], [26].
2) Mathematical models of alertness dynamics joined with ambulatory technologies: They are related to the application of mathematical models that predict operator alertness/performance at different times based on interactions of sleep, circadian, and related temporal antecedents of fatigue. The key issue for these models is their predictive validity. Three of the most common systems are the Fatigue Audit Interdyne system [10], [27] the U.S. Army's Sleep Management System [28], and the Three-Process Model of Alertness [10], [29].
3) Vehicle-based performance technologies: These technologies are directed at measuring the behavior of the driver by monitoring the transportation hardware systems under the control of the operator, such as truck lane deviation, or steering or speed variability. All of these systems assume that the driver behavior or the vehicle behavior deviates from their nominal behaviors when a driver is in fatigue. The measurements include driver steering wheel movements, systems measuring driver's acceleration system on braking, gear changing, lane deviation, and distances between vehicles. These systems include the following: the steering attention monitor (SAM) [30], which monitors microcorrective movements in the steering wheel using a magnetic sensor that emits a loud warning sound when it detects "driver fatigue"

by the absence of microcorrections to steering; the DAS 2000 Road Alert System [31], which detects and warns drivers that they have inadvertently crossed the center line or right shoulder lines; the ZzzzAlert Driver Fatigue Warning System [32], which is a small computerized electronic device that monitors corrective movements of the steering wheel with a magnetic sensor; the TravAlert Early Warning System [10], [33], which loudly notifies a motor vehicle operator that the driver has lost attention to proper steering; and the System for effective Assessment of the driver state and Vehicle control in Emergency situations (SAVE) system [10], [26], which detects in real time impaired driver states and undertakes emergency handling.

4) In-vehicle on-line operator status monitoring technologies: This category of technologies seeks to record on-line biobehavioral dimension(s) of an operator, such as parameters characterizing eye movements, head movements, facial expressions, heart activities, brain electrical activity, reaction time, etc. They include electroencephalograph measures (such as EEG) for monitoring brain activity and ocular measures to characterize eyelid movement (such as PERCLOS) and characterize pupil movement (such as saccade movement versus fixation time). Other visual measures include parameters characterizing facial muscles, body postures, and head nodding.

In recent years, an increasing research interest has focused on developing systems that detect the visual facial feature changes associated with fatigue with a video camera. These facial features include eyes, head position, face, or mouth. This approach is nonintrusive and becomes more and more practical with the rapid development of camera and computer vision technology. Several studies have demonstrated their feasibility, and some of them claimed that their systems perform as effectively as the systems detecting physiological signals [34]–[38] do. However, efforts in this direction are often directed to detecting a single visual cue such as eyelid movement. Since a single visual cue is often ambiguous, uncertain with the change in time, environment, or different persons, its validity is questioned [39].

To overcome this limitation, Orden *et al.* [40] propose to combine five eye activity measures to detect fatigue changes for visual task. Nonlinear regression and neural networks are used to combine different measures. Their study shows that information from multiple eye measures may be combined to produce more accurate fatigue-related performance estimate than individual measures. While similar to our approach in spirit, their work is limited to laboratory studies because of the use of intrusive eye tracking devices (head mount eye tracking and requiring chin rest to limit head movement).

Therefore, developing new systems that can detect the change of multiple visual cues and systematically combine them over time is essential. We propose to simultaneously and nonobtrusively use multiple fatigue parameters. All these parameters, however imperfect they are individually, if combined systematically, can provide an accurate and robust characterization of a person's level of vigilance. In the sections to follow, we introduce such a system.

In summary, although many devices and technologies currently being developed show considerable promise in detecting, predicting, and monitoring fatigue, it is widely believed that satisfactory fatigue monitoring technologies for real-world applications are not yet available, and may not be available for some time [10].

III. Fatigue Modeling With Static Bayesian Networks (SBNs)

As we discussed above, human fatigue generation is a very complicated process. Several challenges present with fatigue modeling and monitoring. First, fatigue is not directly observable and it can only be inferred from the available observations. Second, the sensory observations are often ambiguous, incomplete, uncertain, and dynamically evolving over time. Furthermore, human's visual characteristics vary significantly with age, height, health, and shape of face. Third, many factors can cause fatigue. These factors include sleep quality and quantity, circadian, working environments, health, etc. Their effects on fatigue are often interacting and complex. To effectively monitor fatigue, a fatigue model is necessary. The fatigue model should systematically account for various factors causing fatigue and various observations that reflect fatigue. In addition, the model should be able to handle the uncertainties and dynamics associated with fatigue.

Various methods have been presented for fusing information from disparate sources. These methods include probabilistic methods (e.g., Bayes), evidential reasoning (e.g., Dempster–Shafer theory), Kalman filter, fuzzy theories, and neural networks, with a majority of methods based on fuzzy theories. These traditional methods, however, do not provide sufficient expressive power to capture the uncertainties, dependencies, and the dynamics exhibited by fatigue. Other benefits of Bayesian networks (BNs) include its capability of incorporating prior information (the context), its capability of explicitly modeling uncertainties and modeling temporal aspect of fatigue, and, finally, its capability of modeling data at different levels of abstractions. A probabilistic fatigue model based on the BN model is, therefore, the best option to overcome some of these limitations.

A BN is a state-of-the-art knowledge representation scheme dealing with probabilistic knowledge. Also referred to as graphical model, a BN is a graphical representation of the joint probability of a set of random variables, with the conditional independence assumption explicitly embedded in the network. Its nodes and arcs connect forming a directed acyclic graph (DAG). Each node can be viewed as a random variable that can take a set of discrete values or continuous value. An arc represents a probabilistic dependency between the parent node and the child node. Therefore, a BN is said to be a graphical model that resulted from a marriage between probability theory and graph theory, and provides a natural tool for dealing with uncertainty, knowledge representation, and inference [41]. Many of the classic multivariate probabilistic systems in fields such as statistics, systems engineering, information theory,

pattern recognition, and statistical mechanics are found to be the special cases of the general BNs. These examples include mixture models, factor analysis, hidden Markov models, Kalman filters, and Ising models. Besides advantages in knowledge and uncertainty representation, another benefit of BNs is their capability to propagate beliefs in a principled way upon the arrival of evidences in order to assess the impact of the evidences on a hypothesis of interest. This is something that human is incapable of, but human's capability in specifying local probabilities (parameters of the BN) is needed in order for BNs' belief propagation to start.

Since the introduction of the BNs in the late 1970s, numerous studies have been conducted, and many systems have been constructed based on this paradigm in a variety of application areas, including industrial applications, military, medical diagnosis, and many other commercial applications [42]. BNs can be classified into SBNs and DBNs. While SBNs are limited to modeling static events, DBNs can be used to model both static and dynamic events. In this paper, we first introduce a fatigue model based on SBNs to capture the static aspect of fatigue modeling. The static fatigue model is subsequently extended based on DBNs to account for the temporal aspect of fatigue modeling.

A. Static Bayesian Network for Fatigue Modeling

The main purpose of a BN model is to infer the unobserved events from the observed or contextual data. Therefore, the first step of BN modeling is to identify those hypothesis events and group them into a set of mutually exclusive events to form the target hypothesis variables. The second step is to identify the observable data that may reveal something about the hypothesis variables and then group them into information variables. There are also other hidden states that are needed to link the hypothesis node with the information nodes and to model the fatigue generation process. In addition, they are also needed to model the correlations among observable variables.

For fatigue modeling, fatigue is obviously the target hypothesis variable that we intend to infer while other contextual factors, which could cause fatigue, and visual cues, which are symptoms of fatigue, are information variables. Since so many factors affect human fatigue as we discussed before, it is impossible to include all of them into a BN model. Hence, only the most significant ones are incorporated in the model. As discussed in Section II-A, the most significant causes for fatigue are identified as sleep quality, circadian, work condition, work environment, and physical condition. These fatigue-causing parameters are, in turn, affected by other observable/measurable parameters. For example, the most profound factors that affect work environment include temperature, weather, and noise. The most significant factors affecting one's physical condition are sleep disorders. The factors affecting work conditions include workload and type of work. Factors seriously affecting sleep quality include sleep environment, napping, sleep time, and sleep state. Sleep state refers to the mental state during sleep such as worry or anxiety. Factors affecting sleep environment includes random noise, background light, heat, and humidity around the bed.

On the other hand, when a person is fatigued, he/she tends to exhibit various visual behaviors that deviate from the nominal behaviors. The behaviors that typically capture the cognitive state of a person include eye movement, head movement, and facial expression. Our current efforts [6], [12] in computer vision research has led to various noninvasive techniques that can compute in real time various parameters to characterize these behaviors. Specifically, for eye movement, the parameters characterize eyelid movement and gaze. For eyelid movement, the parameters are PERCLOS and AECS. For gaze movement, the parameters include gaze fixation distribution, which measures spatial distribution of gaze over time, and fixation to saccade ratio, which measures the ratio between amount of time on purposive eye movement (fixation) to amount of time of random (saccade) eye movement. For head movement, the parameter we compute is head tilt frequency, which measures frequency of head tilt to characterize head nod. Finally, for facial expression, we monitor mouth movement to detect yawning. We use YawnFreq to measure the occurrence frequency of yawning. Putting all of these factors together, the SBN for modeling fatigue is constructed as shown in Fig. 1. The target node in this model is fatigue, and the nodes above the target node represent various factors that could lead to fatigue. They are collectively referred to as the contextual information. The nodes below the target node represent visual observations from the output of computer vision system. These nodes are collectively referred to as observation nodes. The directed links represent the casual relationships between the connected nodes.

B. Construction of Conditional Probability Tables (CCPTs)

Before using the BN model for fatigue inference, the network needs to be parameterized. This requires specifying the prior probability for the root nodes and the conditional probabilities for the links. The conditional probabilities for each node are the conditional probabilities of a node given its parents. Given a node with K parents, the number of probabilities needed are 2^K, if we assume that all nodes are binary. Subjective estimation of these probabilities is difficult and inaccurate. Usually, probability is obtained from statistical analysis of a large amount of training data. Large amount of data is, however, difficult to acquire for this study. Fortunately, several series of large-scale subjective surveys [2], [3], [8], [9] provide the clues of such data. Despite the subjectivity of these data, we use them to help the parameterization of our fatigue model. Since these surveys were not designed for the parameterization of our BN model, not all needed probabilities are available and some conditional probabilities are, therefore, inferred using the so-called "noisy-or" principle [43].

The noisy-or principle states that assuming $A_1, \ldots, A_n$ are binary variables ["yes" (y) or "no" (n)] representing all the causes of the binary variable B and each event $A_i = y$ causes $B = y$ unless an inhibitor (also called preventing factor, which prevents a state of the variable to happen and has the complement probability of other state for a binary state variable) state prevents it, and the probability for that is q_i (see Fig. 2), e.g., $P(B = n|A_i = y) = q_i$, and all inhibitor states are

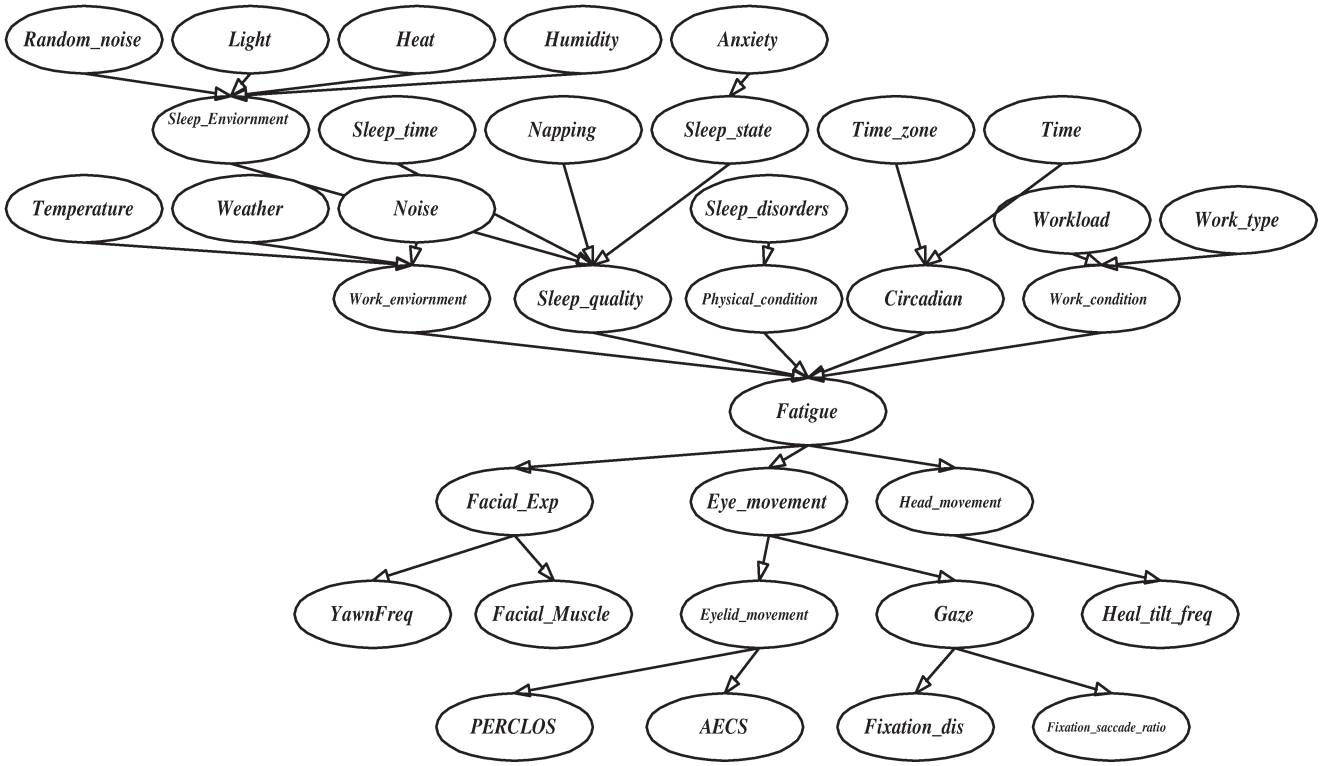

Fig. 1. SBN for modeling human fatigue.

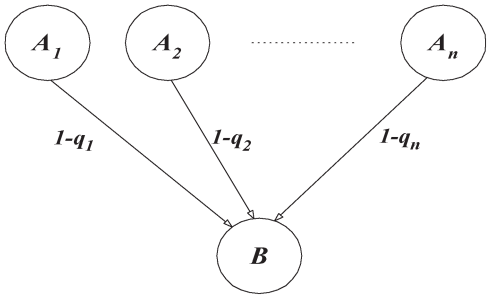

Fig. 2. Graphical explanation of the noisy-or principle.

independent, i.e.,

$$P(B = n|A_1, A_2, \ldots, A_n) = \prod_{1 \le j \le n} q_j.$$

Intuitively speaking, the noisy-or model assumes that the presence of each cause A_i is sufficient to produce the presence of the effect B and that its ability to produce that effect is independent of the presence of other causes, i.e., causal-1 independence. With the noise-or principle, it is possible for the number of the estimating conditional probabilities to grow linearly with the number of parents, therefore, to significantly reduce the number of conditional probabilities in the child nodes. The validity of the noise-or principle, however, remains to be validated for our application.

Still some prior or conditional probabilities are lacking in our model, and they are obtained by subjective estimation method [43]. With these, all the prior and conditional probabilities in our SBN model are obtained and are listed in Tables I–IX. If training data are available, the manually specified probabilities can be refined using one of the many existing learning algorithms [41], [44]–[46], such as the expected maximizaiton (EM) method [43].

TABLE I
PRIOR PROBABILITY TABLE

Nodes	State	Probability	Notes
Random_noise	yes	0.15	average of [1] [2]
	no	0.85	
Light	on	0.13	average of [1] [2]
	off	0.87	
Heat	high	0.24	average of [1] [2]
	normal	0.76	
Humidity	high	0.19	average of [1] [2]
	normal	0.81	
Sleep_time	sufficient($> 6h$)	0.90	[2]
	loss($< 6h$)	0.1	
Napping	$> 30min$:	0.22	[2]
	No	0.78	
Anxiety	yes	0.28	average of [1] [2]
	no	0.72	
Sleep_disorder	yes	0.08	average of [1] [2]
	no	0.92	
Workload	heavy	0.15	[2]
	normal	0.85	
Time	drowsy_time	0.26	[1]
	Active_time	0.74	
Time_zone	changed	0.17	[1]
	no	0.83	
Temperature	high	0.15	average of [1] [2]
	normal	0.85	
Weather	abnormal	0.10	average of [1] [2]
	normal	0.90	
Noise	high	0.15	average of [1] [2]
	normal	0.85	
Work_type	tedious	0.2	average of [1] [2]
	normal	0.8	

TABLE II
CONDITIONAL PROBABILITIES FOR SLEEP_ENVIRONMENT NODE

Parent Nodes				Sleep_environment[1]	
Light	Random_noise	Heat	Humidity	poor	normal
on	yes	high	high	0.87	0.13
			normal	0.78	0.22
		normal	high	0.79	0.21
			normal	0.65	0.35
	no	high	high	0.76	0.24
			normal	0.61	0.39
		normal	high	0.61	0.39
			normal	0.36	0.64
off	yes	high	high	0.80	0.20
			normal	0.68	0.32
		normal	high	0.68	0.32
			normal	0.47	0.53
	no	high	high	0.65	0.35
			normal	0.42	0.58
		normal	high	0.43	0.57
			normal	0.05	0.95

[1]Extracted from [8]. Given "high" humidity, the probability of poor sleep_environment is 39.5%; given background light "on", the probability of poor Sleep_environment 38.5%; given "high" Random_noise, the probability of poor Sleep_environment is 44.5%. Given these marginal probabilities, all the joint conditional probabilities of Sleep_environment given its parents variables are estimated using the noisy or principle [43].

TABLE III
CONDITIONAL PROBABILITIES FOR SLEEP_QUALITY NODE

Parent Nodes				Sleep_quality[2]	
Sleep_time	Sleep_env	Sleep_condition	Napping	poor	fair
sufficient	poor	good	$> 30min.$	0.34	0.66
			No	0.37	0.66
		bad	$> 30min.$	0.73	0.27
			No	0.75	0.25
	normal	good	$> 30min.$	0.05	0.95
			No	0.10	0.90
		bad	$> 30min.$	0.62	0.38
			No	0.64	0.36
loss	poor	good	$> 30min.$	0.73	0.27
			No	0.75	0.25
		bad	$> 30min.$	0.89	0.11
			No	0.95	0.05
	normal	good	$> 30min.$	0.62	0.38
			No	0.64	0.36
		bad	$> 30min.$	0.85	0.15
			No	0.86	0.14

[2]Extracted from [8]. Given "bad" Sleep_condition, the probability of "poor" sleep_quality is 59%. Estimated by experience, given "poor" Sleep_environment is 59%; given "loss" (< 6h) Sleep_time, the probability of "poor" Sleep_quality is 40%; given "No" Napping, the probability of "poor" Sleep_quality is 5%. Given these marginal probabilities, all the joint conditional, probabilities of Sleep_quality given its parent variables are estimated using noisy or principle [43].

TABLE IV
CONDITIONAL PROBABILITIES FOR PHYSICAL_CONDITION NODE AND SLEEP CONDITION NODE

Parent Nodes	Physical_condition[3]	
Sleep_disorder	poor	healthy
yes	0.95	0.05
no	0.1	0.90
Parent Nodes	Sleep_condition	
Anxiety	good	bad
Yes	0.30	0.70
No	0.90	0.10

[3]All of the conditional probabilities are estimated by experience.

TABLE V
CONDITIONAL PROBABILITIES FOR WORK_ENVIRONMENT NODE

Parent Nodes			Work_environment[4]	
Temperature	Noise	Weather	poor	fair
high	high	normal	0.94	0.06
		abnormal	0.99	0.01
	normal	normal	0.80	0.20
		abnormal	0.96	0.04
normal	high	normal	0.73	0.27
		abnormal	0.95	0.05
	normal	normal	0.10	0.90
		abnormal	0.82	0.18

[4]Extracted from [8]. Given "high" temperature, the probability of "poor" Work_environment is 77.5%; given "abnormal" weather, the probability of "poor" Work_environment is 80%. Given these marginal probabilities, all the joint conditional Work_environment given its parent variables are estimated using noisy or principle [43].

TABLE VI
CONDITIONAL PROBABILITIES FOR CIRCADIAN NODE

Parent Nodes		Circadian[3]	
Time_zone	Time	drowsy	awake
changed	drowsy_time	0.90	0.10
	active_time	0.30	0.70
no	drowsy_time	0.60	0.40
	active_time	0.05	0.95

TABLE VII
CONDITIONAL PROBABILITIES FOR WORK_CONDITION NODE

Parent Nodes		Work_condition[5]	
Workload	Work_type	poor	normal
heavy	tedious_monotonous	0.89	0.11
	normal	0.62	0.38
normal	tedious_monotonous	0.72	0.28
	normal	0.05	0.95

[5]Extracted from [2], given "heavy" workload, "poor" Work_condition is 60%; given "tedious_monotonous" Work_type, "poor" Work_condition is 70%. Given these marginal probabilities, all the joint conditional probabilities of Work_condition given its parent variables are extimated using noisy or principle [43].

IV. FATIGUE MODELING WITH DBNS

As pointed out by recent studies [7], fatigue has an accumulative property and fatigue is developed over time. For example, a driver's fatigue level in the beginning of driving may be low, but it will become higher and higher as time progresses. This fact indicates that, in addition to sleep, circadian, and some other environment factors, fatigue status at the previous time instant is also a factor for the fatigue status at the present time. Furthermore, for fatigue detection, it is the persistent presence of certain visual behaviors over time instead of the presence of the behavior at a particular instance that leads to the detection of fatigue. It is, therefore, important to account for the temporal aspect of fatigue and integrate fatigue evidences over time. Obviously, the static model fails to capture these dynamic aspects since it does not provide a direct mechanism for implementing such properties. Therefore, in order to more effectively monitor human fatigue, the creation of a dynamic fatigue model is necessary. A dynamic fatigue model allows to monitor and detect fatigue by integrating fatigue evidences both spatially and temporally. In the sections to follow, we propose such a dynamic fatigue model based on DBNs.

TABLE VIII
CONDITIONAL PROBABILITIES FOR FATIGUE NODE

Parent Nodes					Fatigue[6]	
Work_ env	Sleep quality	Physical condition	Circadian	Work condition	yes	no
poor	poor	poor	drowsy	poor	0.98	0.02
				normal	0.95	0.05
			awake	poor	0.96	0.04
				normal	0.89	0.11
		healthy	drowsy	poor	0.97	0.03
				normal	0.91	0.09
			awake	poor	0.94	0.06
				normal	0.83	0.17
	fair	poor	drowsy	poor	0.96	0.04
				normal	0.87	0.13
			awake	poor	0.91	0.09
				normal	0.74	0.26
		healthy	drowsy	poor	0.93	0.07
				normal	0.79	0.21
			awake	poor	0.85	0.15
				normal	0.57	0.43
fair	poor	poor	drowsy	poor	0.96	0.04
				normal	0.88	0.12
			awake	poor	0.92	0.08
				normal	0.77	0.33
		healthy	drowsy	poor	0.93	0.07
				normal	0.81	0.19
			awake	poor	0.87	0.13
				normal	0.62	0.38
	fair	poor	drowsy	poor	0.90	0.10
				normal	0.71	0.29
			awake	poor	0.80	0.20
				normal	0.43	0.57
		healthy	drowsy	poor	0.83	0.27
				normal	0.53	0.47
			awake	poor	0.67	0.33
				normal	0.05	0.95

[6]Extracted from [8]. Given "poor" Sleep_quality, Fatigue is 60%; given "drowsy" Circadian, Fatigue 70%; given "poor" Work_condition, Fatigue is 65%; Estimated by experience the given "poor" Work_environment, Fatigue is 55%; given "poor" Physical_condition, Fatigue is 40%. Given these marginal probabilities, all the joint conditional probabilities of Fatigue given its parent variables are estimated using the noisy or principle [43].

TABLE IX
CONDITIONAL PROBABILITIES FOR THE CHILDREN NODES OF FATIGUE NODE

Nodes Name	Parent Node	Parent State Variable	Child State Variable	Condition[7] Probability
Facial_Exp	Fatigue	yes	drowsy_exp	0.30
		yes	normal	0.70
		no	drowsy_exp	0.05
		no	normal	0.95
YawnFreq	Facial_Exp	drowsy_exp	high	0.95
		drowsy_exp	normal	0.05
		normal	yawn	0.05
		normal	normal	0.95
Facial_Muscle	Facial_Exp	drowsy_exp	lagging	0.80
		drowsy_exp	normal	0.20
		normal	lagging	0.02
		normal	normal	0.98
Eye_mov	Fatigue	yes	abnormal	0.50
		yes	normal	0.50
		no	abnormal	0.02
		no	normal	0.98
Eyelid movement	Eye movement	abnormal	abnormal	0.99
		abnormal	normal	0.01
		normal	abnormal	0.05
		normal	normal	0.95
Gaze	Eye movement	abnormal	normal	0.05
		abnormal	abnormal	0.95
		normal	normal	0.90
		normal	abnormal	0.10
Head movement	Fatigue	yes	abnormal	0.40
		yes	normal	0.60
		no	abnormal	0.05
		no	normal	0.95
PERCLOS	Eyelid movement	abnormal	abnormal	0.98
		abnormal	normal	0.02
		normal	abnormal	0.05
		normal	normal	0.95
AECS	Eyelid movement	abnormal	slow	0.97
		abnormal	normal	0.03
		normal	slow	0.05
		normal	normal	0.95
Fixation_dis	Gaze	normal	narrow	0.90
		normal	diffusive	0.10
		abnormal	narrow	0.90
		abnormal	diffusive	0.10
Fixation _saccade _ratio	Gaze	normal	high	0.10
		normal	low	0.90
		abnormal	high	0.85
		abnormal	low	0.15
Head _tilt _freq	Head movement	abnormal	high	0.60
		abnormal	normal	0.40
		normal	high	0.05
		normal	normal	0.95

[7]Some of these conditional probabilities are obtained from the experiment results in [47].

A. Dynamic Bayesian Networks

In artificial intelligence (AI) field, a DBN model describes a system that dynamically changes or evolves over time and that enables the user to monitor and update the system as time proceeds, and even predicts the behavior of the system over time. Its utility lies in explicitly modeling events that are not detected on a particular point of time, but they can be described through multiple states of observation that produce a judgment of one complete final event. Usually, there are three broad categories of approaches to achieve this [48], namely: 1) models that use static BNs and formal grammars to represent temporal dimension [known as probabilistic temporal networks (PTNs)]; 2) models that use a mixture of probabilistic and nonprobabilistic frameworks; and 3) models that introduce temporal nodes into static BNs structure to represent time dependence. The third category is the most widely used, and we will base on it to construct our dynamic fatigue model. In this category, a time slice is used to represent the snapshot of an evolving temporal process at a time instant, and the DBNs can be considered to consist of a sequence of time slices, each representing the system at a particular point or interval of time. These time slices are interconnected by temporal relations, which are represented by the arcs joining particular variables from two consecutive slices. Such a DBN is usually regarded as a generalization of the singly connected BNs, specifically aiming at modeling time series [48]. States of any system described as a DBN satisfy the Markovian condition: The state of a system at time t depends only on its immediate past, i.e., its state at time $t-1$. Hence, DBNs are often regarded as a generalization of the hidden Markov models [49]. Therefore, a fatigue model based on the DBNs is naturally the best option to model and predict fatigue over time.

A simple illustrative DBN is shown in Fig. 3, and its joint probability distribution function (pdf) on the sequence of T time slices consists of a hypothesis node H_t, hidden states

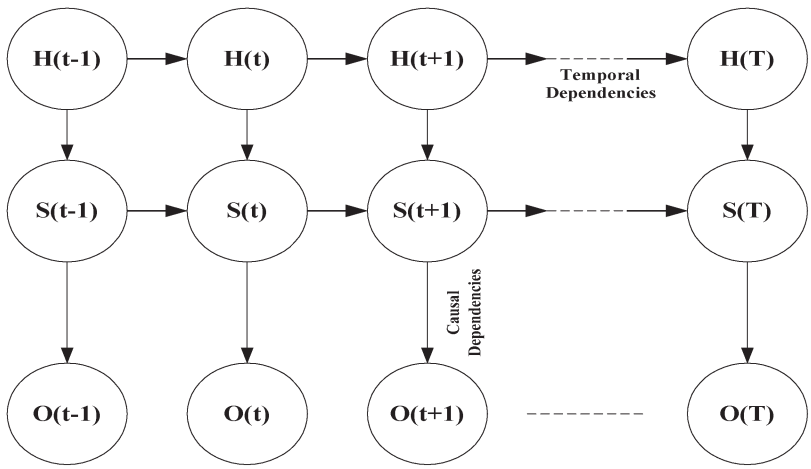

Fig. 3. Generic DBN structure, where $H(t)$ represents the hypothesis to infer at time t, $S(t)$ represents hidden states at time t, $O(t)$ represents sensory observations at time t, and T is the time boundary.

S_t, and observations O_t. Given the DBN topology as shown in Fig. 3, we assume that the hidden state variables $S = \{s_0, \ldots, s_{T-1}\}$, observable variables $O = \{o_0, \ldots, o_{T-1}\}$, and hypothesis variables $H = \{h_0, \ldots, h_{T-1}\}$, where T is the time boundary. The joint probability distribution of DBNs can be theoretically expressed as

$$P(H,S,O) = P(H_0) \prod_{t=1}^{T-1} P(H_t|H_{t-1}) \times \prod_{t=0}^{T-1} P(S_t|H_t) \prod_{t=1}^{T-1} P(S_t|S_{t-1}) \prod_{t=0}^{T-1} P(O_t|S_t). \quad (1)$$

Therefore, in order to completely specify a DBN, we need to define four sets of parameters as follows:

1) state transition pdfs $\Pr(S_t|S_{t-1})$ and $\Pr(H_t|H_{t-1})$, which specify time dependencies between the states;
2) hypothesis generation pdf $\Pr(S_t|H_t)$, which specifies how the hidden states relate to the hypothesis;
3) observation pdf $\Pr(O_t|S_t)$, which specifies dependencies of observation nodes regarding to other nodes at time slice t;
4) initial state distribution $\Pr(H_0)$, which brings initial probability distribution in the beginning of the process.

Except for the transitional probabilities, the specification of other parameters remains the same for all time slices as the static BNs since they characterize the static aspect of the DBNs. The transitional probabilities specify the state transition between two neighboring time slices. Theoretically, they may be stationary or may dynamically vary over time.

Based on general DBNs principles [43], [48], [50] and the above considerations, a DBN model for modeling human fatigue is constructed as shown in Fig. 4. The basic idea of this model is that some hidden nodes (also referred to as temporal nodes) at the previous time slice are connected to the corresponding nodes at current time. The previous nodes, therefore, provide a diagnostic support for the corresponding variables at present time. Thus, fatigue at current time is inferred from fatigue at the previous time, along with current observations. These changes allow to perform fatigue estimation over time by integrating information over time. It also affords to predict fatigue over time by the temporal causality of DBNs. Other nodes such as the leave nodes and the contextual variable nodes are considered as static nodes, therefore, having no temporal links between corresponding nodes in two time slices.

The DBNs are implemented by keeping in memory two slices at any one time, representing previous time interval and current time interval, respectively. The slice at the previous time interval provides diagnostic support for current slice. The two slices are rotated such that old slices are dropped and new slices are used as time progresses. Specifically, at the start time slice, fatigue is inferred from the static fatigue BN model in Fig. 1. Starting from the second time slice, the static fatigue model is expanded dynamically with additional temporal links that connect the intermediate nodes at previous time slice to the corresponding nodes at current time slice. Fatigue inference is then performed on the expanded static fatigue model. This repeats with different probabilities for the previous nodes that are connected to current model. All the CPTs in the model are time invariant. Part of the CPTs and prior probabilities in the model are adapted from the previous SBN model and the transitional probabilities are specified subjectively.

V. Interfacing With the Vision System

To perform real-time human fatigue monitoring, the visual module from computer vision technology was developed [12], and the fatigue model must be combined via an interface program such that the output of the vision system can be used by the fatigue model to update its belief of fatigue in real time. Details on the computer vision module may be found in [12]. Such interfaces have been built. Fig. 5 shows the appearance of the interface program. Basically, the interface program periodically (every 1 s or shorter time interim) examines the output (evidences) of the vision module and detects any evidence change. If a change is detected, the interface program instantiates the corresponding observation nodes in the fatigue

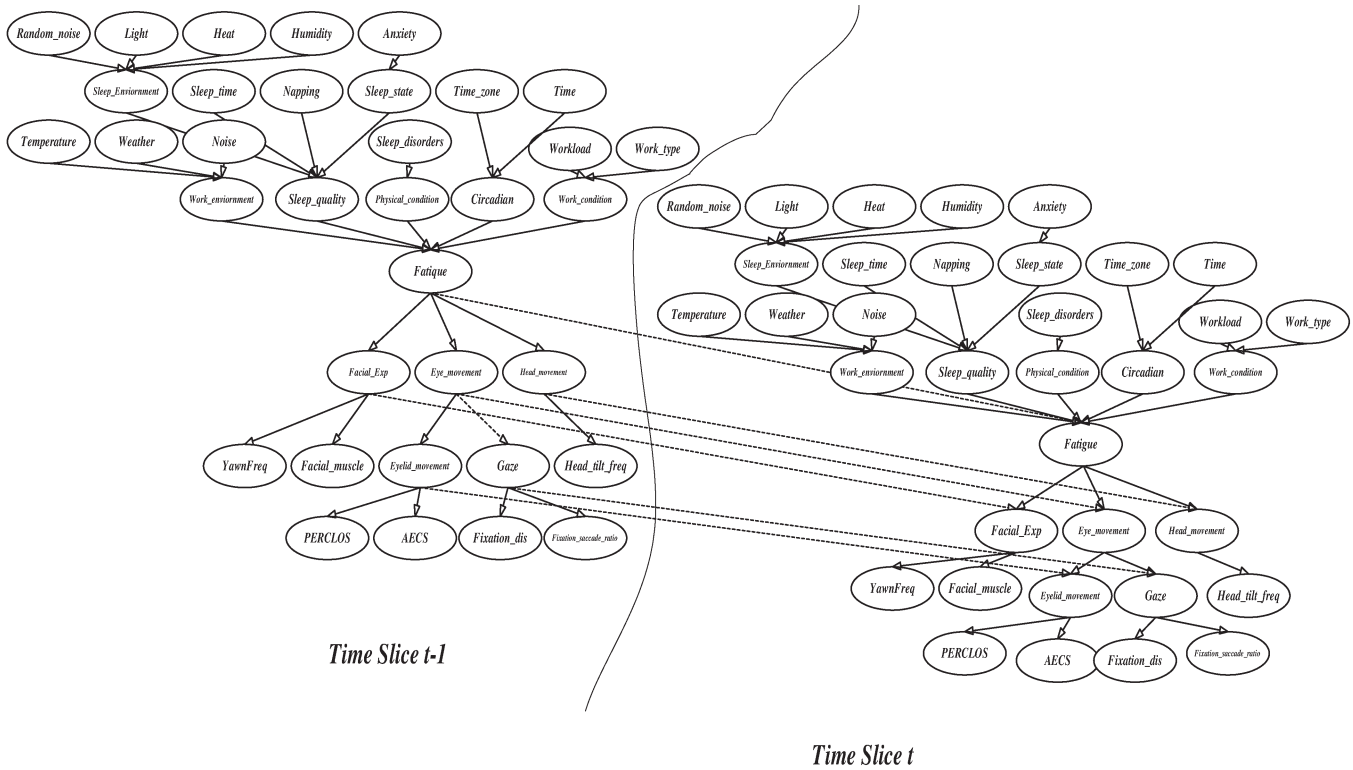

Fig. 4. DBN model for monitoring human fatigue. While static nodes repeat in slices, corresponding temporal nodes in neighboring slices are connected via dotted links representing temporal causality.

model, which then activates its inference engine, and obtain the new fatigue level. In the interface, the inference result (fatigue level) is displayed as a real-time curve in a window as shown in Fig. 5. In addition, the interface appearance also varies with user fatigue level. When the fatigue level is within the normal range (e.g., below 0.85), it displays a comfortable green background color screen. If the fatigue level is between 0.85 and 0.95, which is close to the dangerous level, it displays a yellow-background-color screen with an alerting prompt accompanied by a notifying sound. If the fatigue level is at the critical level or higher, the color of the screen becomes red and the warning color flashes continuously, accompanied by a warning sound to alert the driver. Also displayed in the interface are the buttons for both visual evidences and contextual factors. These buttons allow the visual evidences and the contextual factors be input manually. Finally, the interface program allows to record the fatigue index and the visual parameters for subsequent analysis and display.

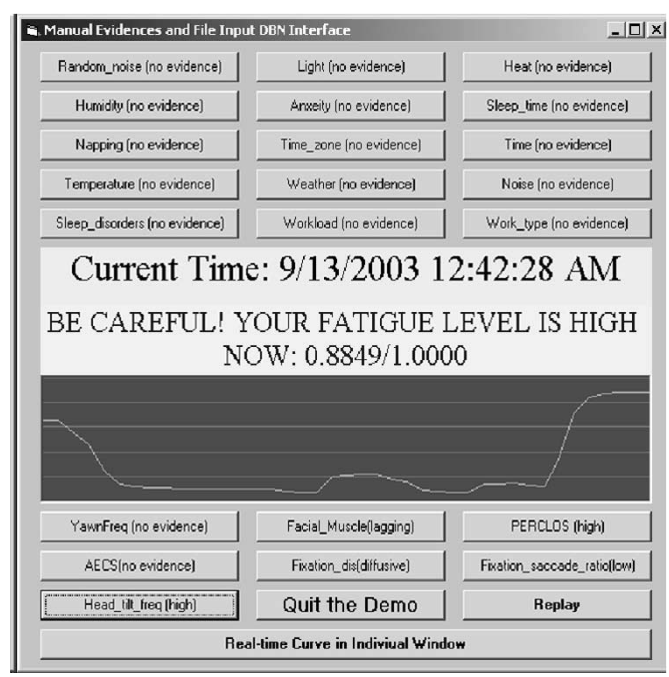

Fig. 5. Interface of the real-time fatigue monitor.

VI. Experiments

In this section, we present experimental results involving synthetic data and real data to characterize the performance of the proposed fatigue model.

A. Experiment Results With Synthetic Data

Given the parameterized model, the fatigue inference can commence upon the arrival of visual evidences via belief propagation. Given the network shown in Fig. 4, with 22 instantiable nodes (leave nodes and root nodes) and two states for each node, theoretically, there are 2^{22} possible inference results. Hence, it is very difficult to enumerate all possible combinations of evidences. Here, only those typical combinations of evidences, which are related to fatigue node and that are most likely to occur in the real world, are instantiated in the model, and their results are summarized in Table X. From Table X,

TABLE X
INFERENCE RESULTS OF THE FATIGUE

No.	Evidences	Fatigue (yes)
1	No evidence	0.57
2	YawnFreq (high)	0.82
3	Facial_Muscle (lagging)	0.81
4	PERCLOS (high)	0.86
5	AECS (abnormal)	0.86
6	Fixation_dis (narrow)	0.81
7	Fixation_saccade_ratio (low)	0.80
8	Head_tilt_freq (high)	0.85
9	Temperature (high)	0.72
10	Weather (abnormal)	0.72
11	Noise (high)	0.70
12	Time_zone (changed)	0.63
13	Sleep_disorders (yes)	0.72
14	Napping (No)	0.58
15	Workload (heavy)	0.72
16	Work_type (tedious_monotonous)	0.74
17	Anxiety (yes)	0.64
18	Random_Noise (yes)	0.60
19	YawnFreq (high), Facial_muscle (drowsy)	0.90
20	PERCLOS (high), Fixation_dis (abnormal)	0.95
21	PERCLOS (abnormal), YawnFreq (high)	0.96
22	Fixation_dist (abnormal), Facial_muscle (lagging)	0.95
23	AECS (slow), Head_tilt_freq (high)	0.96
24	PERCLOS (high), Head_tilt_freq (high), AECS (slow)	0.99
25	Head_tilt_freq (high), YawnFreq (high), Temperature (high), Anxiety (yes)	0.98
26	Time (drowsy_time), humidity (high) Sleep_disorders (yes), Sleep_time (loss(>6h)), Work_type (tedious_monotonous), Weather (abnormal), Anxiety (yes), Workload (heavy)	0.90

it can be seen that the prior probability of fatigue (e.g., when there is no evidence) is 0.57 (ref. no. 1), representing the average fatigue level for the commercial pilots or truck drivers in their normal working time. The observation of a single visual evidence (ref. nos. 2–8 in Table X) does not provide conclusive finding since the estimated fatigue probability is less than the critical value 0.95 (arbitrarily chosen, varying with applications). Even when the evidence of eyelid movement (e.g., PERCLOS) is instantiated, the fatigue still fails to reach the critical level, despite the fact that the eyelid movement has been regarded as the most accurate measurement of fatigue [6], [11]. The same is true if only a single contextual factor (ref. nos. 9–18) is given. The combination of PERCLOS and any other visual evidences (ref. nos. 20 and 21) leads to critical fatigue level. Any combination of three visual cues guarantees the estimated fatigue probability to exceed the critical value (ref. no. 24). With some contextual evidences, any two visual cue evidence combinations achieve the same purpose (ref. no. 25). This demonstrates the importance of contextual information. In fact, the simultaneous presence of all contextual evidences only almost guarantees the occurrence of fatigue (ref. no. 26). These inference results, though preliminary and subjective, demonstrate the utility of the proposed framework for predicting and modeling fatigue through systematic fusion of information from different sources.

To further validate the performance of our fatigue model, especially its performance over time, we performed an additional experiment. For this experiment, we implemented a fatigue generator based on the proposed fatigue model. The fatigue generator allows to dynamically vary the fatigue level and produce the sensory observations at each time instant.

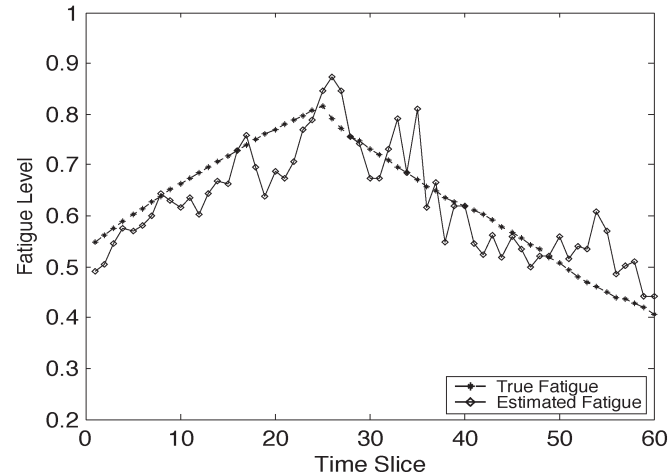

Fig. 6. Plots of the ground-truth fatigue (dotted line marked with stars) and the estimated fatigue (solid line marked with circles) over time. The two curves apparently match each other well, therefore, indicating their strong correlations.

The produced observations are subsequently perturbed and the perturbed evidences are then used by our fatigue model to infer the fatigue level. The performance of our fatigue model is studied by comparing the estimated fatigue level with the ground-truth fatigue level and computing their correlations. The experimental results are presented in Fig. 6.

It can be seen in Fig. 6 that two curves representing the true fatigue and the estimated curve track each other well. This, once again, demonstrates the validity of the proposed fatigue model.

B. Validation Experiments With Human Subjects

In this section, we present results from validation studies of the proposed fatigue monitor using human subjects. For this experiment, we performed a human subject study. The study included a total of eight subjects. Two test bouts were performed for each subject. The first test was done when they first arrived in the lab at 9 P.M. and when they were fully alert. The second test was performed about 12 h later early in morning at about 7 A.M. the following day, after the subjects have been deprived of sleep for a total of 25 h.

During the study, the subjects are asked to perform a test of variables of attention (TOVA) test. The TOVA test consists of a 20-min psychomotor test, which requires the subject to sustain attention and respond to a randomly appearing light on a computer screen by pressing a button. The TOVA test was selected as the validation task because operating a machine is primarily a vigilance task requiring psychomotor reactions and psychomotor vigilance. Among several performance measures maintained by TOVA, which include the response time, omission errors, commission errors, the response time is selected as a metric to quantify the subject's performance [20]. During each session, we also acquire various visual parameters characterizing eyelid movement, gaze movement, facial expression, and head movement.

For each subject, a twofold cross-validation is performed on the collected data by dividing the data equally into training set and test set. The training data are used to refine the parameters of the fatigue model while the testing data are used to

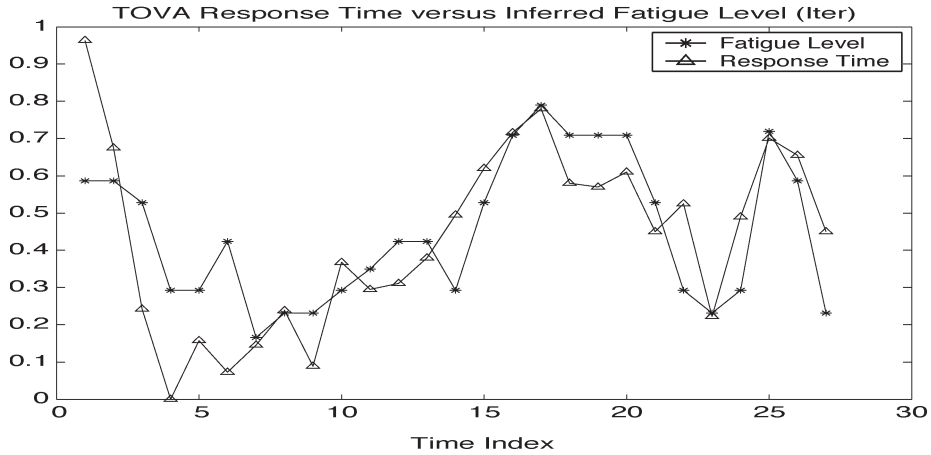

Fig. 7. Estimated composite fatigue score (marked with stars) versus the normalized TOVA response time (marked with triangles). The two curves track each other well. The horizontal axis represents times when the subject responds to the stimulus while the vertical axis represents the probability (for fatigue) and the normalized response time (normalized between 0 and 1).

validate the model. The final performance for each individual is then averaged over the two trials. Fig. 7 plots the average response times versus the estimated fatigue score over time for one subject. The figure clearly shows that the composite fatigue score based on combining different fatigue parameters (as represented by the leave nodes in Fig. 1) highly correlates with the subject's response time. Similar curves are obtained for other subjects.

It is clear that the two curves' fluctuations match well, qualitatively proving their correlation and covariation. Furthermore, the correlation of the two curves are quantitatively characterized by their correlation coefficient, which is estimated as 0.953, therefore, quantitatively proving the validity of the composite fatigue score in quantifying vigilance and performance.

VII. Conclusion

Fatigue is one of the most important safety concerns in modern commercial transportation industry. Monitoring and preventing fatigue are crucial to ensuring safety. Fatigue is affected by many complicated factors. Sleep and circadian are two of the fundamental physiological factors. For the commercial transportation drivers and pilots, many other factors, such as environment factors, physical conditions, and type of work, will also significantly affect their fatigue. In addition, fatigue exhibits different observations, varying over time and with uncertainties. Through the research presented in this paper, a probabilistic framework based on the BN to model fatigue, the associated factors, and the sensory observations in a principled way is proposed. Specifically, a static fatigue model based on the static BN model was developed to model the static aspects of fatigue and to allow integration of the relevant contextual information and the available sensory data spatially. The static fatigue model is then extended based on DBNs to better model the dynamic and evolutionary aspects of fatigue development. Experimental results involving both synthetic and real data demonstrate the validity of the proposed fatigue model in modeling and real-time inferring fatigue based on simultaneous combination of various parameters over time and under uncertainty.

In summary, through this research, it is believed that we have proposed a state-of-the art fatigue model that allows to systematically represent various factors related to fatigue and account for the inherent uncertainties associated with these factors. The framework allows to perform fatigue inference over time and under uncertainty. While the focus of this research is not on developing a high-fidelity fatigue model, but rather on providing a theoretical framework that can model fatigue in a principled way, further research work is needed to improve the fatigue model structure and to improve model parameterization.

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