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

Peilin Lan, Qiang Ji, Carl G. Looney

***Abstract*— In this paper, we introduce a probabilistic framework based on the Bayesian Networks (BNs) for modelling and real-time inferring human fatigue by integrating information from various visual cues and certain relevant contextual information. We first present a static Bayesian network that captures the static relationships between fatigue, significant factors that cause fatigue, and various visual cues that typically result from fatigue. The static fatigue model is subsequently parameterized based on the statistics extracted from recent studies on fatigue and on subjective knowledge. Such a model provides mathematically coherent and sound basis for systematically aggregating visual 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 BNs model is extended based on the Dynamic Bayesian Networks (DBNs). The dynamic fatigue model allows to integrate fatigue evidences not only spatially but also temporally, therefore leading to a more robust fatigue modelling and inference.**

This paper also includes a review of modern physiological and behavioral studies on human fatigue and a detailed critical review of the existing techniques for fatigue monitoring and detection. The paper ends with a discussion of the interface program we developed, that combines our computer vision system for visual cues extraction with the fatigue inference engine for real-time non-intrusive human fatigue monitoring and detection.

***Index Terms*— Bayesian Networks, human fatigue monitoring, information fusion, Dynamic Bayesian Networks**

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I. Introduction

Fatigue has been widely accepted as a significant factor in a variety of transportation accidents [5]. 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 with fatigue [5]. A survey from 1,488 corporate crew members in US 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 [38]. In highway, the National Highway Traffic Safety Administration (NHTSA) estimates that 100,000 crashes are caused by drowsy drivers, which results in more than 1,500 fatalities and 71,000 injuries each year in US. This amounts to about 1.6%

of all crashes and about 3.6% of fatal crashes [5]. In marine, a 1996 US Coast Guard (USCG) analysis of 279 incidents showed that fatigue contributed to 16% of critical vessel casualties and 33% of personal injuries [5]. In railroad, an analysis from the Safety Board of Federal Railroad Administration (FRA) reported that there were also 18 cases which were coded ”operator fell asleep” as a causal or contributing factor from January 1990 to February 1999 [5]. Therefore, it is hard to overstate that human fatigue prevention is very essential to improving transportation safety.

Since several decades ago, 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 [43] [37] [11]. The second thrust focuses on developing human fatigue monitors for commercial transportation based on the achievements from the first effort [28] [43]. So far, these fatigue monitoring systems can be classified into two categories [51]: (a) measuring the extent and time-course of loss of driver alertness and (b) 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 [38] [9] [43] [39]. Up to now, the fatigue mechanism is still not well understood and few of these existing monitoring systems are effectively used in 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 [21], many more efforts are still needed to develop systems for fatigue prevention in commercial transportation.

In our previous study [28] [27], we developed a non-invasive computer vision system for extracting various visual parameters that typically characterize human fatigue. The systematic integration of these visual parameters, however, requires a fatigue model that models the fatigue generation process and 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 [38] [9] [51] [43] [39] and our previous successful studies [28] [27], we present a probabilistic and dynamic framework based on the Bayesian Networks for human fatigue modeling and monitoring. The framework combines different information sources spatially and temporally to monitor and infer human fatigue.

II. Literature Review

A. Significant causes for fatigue

From the physiological view, it is widely accepted that fatigue, alertness and performance are physiologically determined [38] [9] [39] [37]. 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.

The modern scientific research has proved that sleep is a vital physiological human being need like food, water and air. 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 [37]. Although the world record of staying awake is up to 264 hours, the average sleep time of a person requires about 8 hours every day regardless of the change of seasons [38] [9] [39] [37].

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 thing is that these factors often interact with each other [38] [9] [37]. A survey [38] from the corporate flight crew members in U.S. corporate/executive aviation operations by Ames Research Center at NASA revealed that the most often identified factors that interfere with their home sleep are: 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 Ames Research Center at NASA [39] [43] reported more detailed but similar information on the factors that affect the sleep in home and bunk. Napping is identified by the drivers in truck transportation [51] [13] as one of the significant factors that prevent fatigue. Some investigations showed that naps of 20-30 minutes have very important benefits by increasing alertness and reducing fatigue. 44% of the drivers took at least one nap during a duty cycle. These naps increased their principal sleep periods an average of 27 minutes, for an 11% increase in average daily sleep time [51] [13].

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 [38] [9]. For example, the investigation [51] [13] in real-life commercial truck transportation revealed that the average quantity of sleep obtained by the drivers during their principal sleep periods was an average of two hours less sleep than their daily ”ideal” requirements. Although the quality of their sleep period was high, probably due to their lack of sufficient time in bed, laboratory tests show that a sleep loss of as little as two hours can affect alertness and performance. In fact, these drivers were later detected drowsy while driving about 5% of the time. 14% of the drivers accounted for 54% of all observed drowsiness episodes in video tapes.

The circadian rhythm has been found to virtually control all physiological functions of the body, including sleep/wake, digestion, and immune function. The circadian rhythm is regulated by the circadian clock that has been found at a certain place in the brain [38] [9] [37] [11]. 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 [38] [11]. 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 9-11 a.m. and 9-11 p.m.. During this period, human may be difficult to fall sleep even if his sleep was deprived in the previous night [38] [9] [37] [11]. 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 3-6 a.m. [11] [20]. This is further verified by a large scale study of fatigue factors in the North American commercial truck transportation [51] [13], 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.

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 [38] [9] [11].

Besides sleep and circadian, there are many environmental or contextual factors that may contribute/cause human fatigue. Recent years, a series of large-scale survey of fatigue factors in aviation and land transportation [38] [9] [43] [39] [51] identified some important fatigue-causing factors. In aviation, the survey from 1,488 corporate flight crew members in U.S. corporate/executive aviation operations by Ames Research Center at NASA [38] showed that besides sleep loss and time of day of operation, the most often cited factors that affect their fatigue in flight are: greater than 7 flying segments in the same duty, severe turbulence, illness, heavy workload, late arrival, 4-6 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 pre-trip strategies to prevent fatigue were: healthy diet (41%), exercise (28%), flight planning activities(26%), and caffeine (16%). Another survey of fatigue factors from 1,424 crew members in U.S. regional airline operation by Ames Research Center at NASA [9] obtained similar results.

In land transportation, the US Federal Highway Administration's Office of Motor Carriers, in cooperation with the Trucking Research Institute, and Safety and Security Transport Canada, conducted the largest and most comprehensive over-the-road study on driver fatigue and alertness in North America from 1993 to 1996 to evaluate driver fatigue, alertness, and physiological and subjective states of drivers as they performed in real-life trips [51]. The study showed that although some details were different, the main factors, which affected the pilot's fatigue in aviation, also contributed to the fatigue of drivers in commercial truck transportation.

In railroad, the on-line research report [43] by University of Denver, *Fatigue Countermeasures in the Railroad Industry-Past and Current Developments*, reported the study results of the past and current fatigue countermeasures projects in almost all of the railroad companies in North America. It presented much similar statistical information about fatigue in the railroad industry to those in aviation and highway transportation.

In addition to the above factors, some clinical studies [43] found that about one third of the population suffers from several different types of clinical disturbances of sleep, which meet various diagnostic criteria and significantly affect fatigue and alertness. These disturbances are insomnia, which refers to too little sleep, hypersomnia, which refers to too much sleep, and parasomnia, which refers to a deviation from normal sleep patterns. Insomnia is believed to be present in about 5-6% population and mostly caused by high levels of anxiety associated with worries, traumatic event or prolonged stress from work, depression or other sources [43]. Hypersomnia usually demonstrates itself as a difficulty to stay awake in typical daily activity such as travelling as a passenger in a car, watching TV, listening to a lecture, or reading a newspaper. Snoring and sleep apnea are thought as the common signs of hypersomnia [43]. Parasominas are disturbances during sleep and are mostly caused by nightmares, sleep walking, restless legs and bruxism or gnashing of teeth [43]. Sleep inertia is also found to have effect on fatigue and there have been many studies on it [43]. Usually it is thought to have negative effect on fatigue but since it does not last long time, it does not significantly interfere with people's work, such as driving.

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, and type of work, will also directly contribute to human fatigue. All of these factors should be considered while modelling 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 [43]. The typical ones are physiological, behavioral, visual, and subjective performance measures.

Physiological Measures [43] [17] [35] [7]: 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) [17] and the multiple sleep latency test (MSLT) [7]. 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 inapplicable in real world applications.

Behavioral Measure [43] [40]: This method has been also thought to be accurate and objective, and gained popularity in recent years. This category of devices, most commonly known as actigraph [40], 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.

Visual Measures: People in fatigue exhibit certain visual behaviors, which 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 [48] [15] have shown that eyelid activities are the bio-behavior 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 [49] [15], 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. Since eye open/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 invalidated but 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 (conscious 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 [3]. 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 [28] [27] 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 non-intrusively.

Performance Measures [43] [50]: This method uses a number of performance tasks to determine the effects of sleep and sleep deprivation. In the test, various tasks ranging from simple to complex have been examined including reaction time to visual and auditory stimuli and vigilance tests. This method has been extensively used by various studies including Walter Reed Performance Assessment Battery (PAB) and the Denver Fatigue Inventory (a computer assisted cognitive test battery) [46]. The advantage of this method is indirect and the drawbacks are non-self-administered, need expert data analysis, and is limited to laboratory studies.

Subjective performance [43] [23]: Also called Self-Report Measures. A variety of subjective performance measures have been developed to determine fatigue sleepiness and alertness. The most famous ones include the Stanford Sleepiness Scale (SSS) [23], Visual Analog Scale (VAS) [34], mood descriptors [45], and diary method [36]. SSS [23] method consists of seven grades of fatigue, ranging from "wide awake" to "cannot stay awake" and has been validated against performance measures as a function of sleep deprivation. SSS is thought as the most widely used subjective measure of sleepiness. VAS [34] consists of a single horizontal line presented on a piece of paper. At either end of the lines, an anchoring descriptor is displayed such as "wide awake" or "about to fall asleep". In the test, the participants are instructed to place an X on the horizontal line between the anchors to indicate the extent to which they best describe their current state. VAS was initially developed for use in educational research and has also been used in symptom measurement. The mood descriptor lists a series of adjectives that indicate a variety of different mood states. Subjects must then choose the adjective that best describes their current state. The typical mood descriptor is Thayer Activation-Deactivation Adjective Checklist [45]. The diary method [36] requires the participants to keep detailed logs of their activities including work and sleep. These dairies are then used to develop descriptions of the sleep-wake cycle of the participants and develop a baseline for further studies. The advantages of these methods are inexpensive, practical and readily accepted. The drawbacks are less accurate and cannot be used for monitoring real-time fatigue.

Multiple Measures: Since a single measurement always has some limitations or drawbacks, multiple measurements are often taken to obtain comprehensive parameters in a single study. For example, in the over-the-road study on driver fatigue in US and Canada [51], many measures were taken at the same time. These measures included driving task performance (lane tracking and steering wheel movement), driving speed and distance monitoring, performance on three surrogate tests of tasks related to safe driving performance (code substitution, critical tracking test, simple response vigilance test). Moreover, the drivers were under continuous video monitoring. During the same test, various physiological measures were taken. The measures include Polysomnography (PSG) during sleep, Electroencephalogram (EEG), Electrooculogram (EOG), Electromyogram (EMG), Respiratory effort (sensors on chest), Oxygen saturation of arterial blood, finger probe, PSG during driving (EEG and EOG only), body temperature during waking hours, and Electrocardiography (ECG) during driving and sleep. Other data collected include driver-supplied information (pre-participation questionnaire on sleep habits, daily log (stops, meals, noteworthy driving events, etc.), and Stanford Sleepiness Scale (SSS) rating. Environmental factors such as cab temperature, relative humidity, 8-hour concentrations of carbon monoxide and nitrogen dioxide were also recorded. Doing so, a comprehensive research results were obtained in the study.

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 by [28] [21] etc.. Generally, all of the efforts on the fatigue detection can be classified into the following four groups [15] [21].

(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 [44], FACTOR 1000 [2], ART90 [8], FITR 2000 Workplace Safety Screener [21], OSPAT [21], and Psychomotor Vigilance Test (PVT) [21] [32].

(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 [12] [21], the US Army's Sleep Management System [4], and the Three-Process Model of Alertness [1] [21].

(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 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 Steering Attention Monitor (S.A.M.) [52], which monitors micro-corrective movements in the steering wheel using a magnetic sensor that emits a loud warning sound when it detects "driver fatigue" by the absence of micro-corrections to steering; the DAS 2000

Road Alert System [10], which detects and warns drivers that they have inadvertently crossed the center line or right shoulder lines; ZzzzAlert Driver Fatigue Warning System [16], which is a small computerized electronic device that monitors corrective movements of the steering wheel with a magnetic sensor; TravAlert Early Warning System [21] [24], which loudly notifies a motor vehicle operator that the driver has lost attention to proper steering; and the SAVE system [21] [32] (*S*ystem for effective *A*ssessment of the driver state and *V*ehicle control in *E*mergency situations) 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 bio-behavioral dimension(s) of an operator, such as parameters characterizing eye movements, head movements, facial expressions, heart activities, brain electrical activity, reaction time etc., on-line (i.e., continuously, during driving). They include Electroencephalograph Measures (such as Electroencephalograph (EEG)) for monitoring brain activity, ocular measures to characterize eyelid movement (such as PERCLOS) and characterize pupil movement (such as saccade movement v.s. 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 non-intrusive and becomes more and more practical with the speedy 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 [6] [25] [41] [47] [19] 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 [22]. Therefore, developing new systems that can detect the change of multiple visual cues and systematically combine them over time is essential in future. In the sections to follow, we introduce such a system.

In summary, although many devices and technologies currently being developed show considerable promise in detection, prediction 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 [21].

III. Fatigue Modelling with Static Bayesian Networks (SBNs)

As we discussed above, human fatigue generation is a very complicated process. Several challenges present with fatigue modelling and monitoring. First, fatigue is not 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 be 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. A probabilistic fatigue model based on the Bayesian Networks (BNs) model is the best option to deal with such an issue.

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 together forming a directed acyclic graph (DAG). Each node can be viewed as a domain 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. So, a BN is said to be a graphical model resulted from a marriage between probability theory and graph theory, and provides a natural tool for dealing with uncertainty, knowledge representation, and inference [29]. 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.

Since the introduction of the BNs in late 70's, 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 [31]. BNs can be classified into static BNs (SBNs) and dynamic Bayesian Networks (DBNs). While SBNs is limited to modelling 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 modelling. The static fatigue model is subsequently extended based on DBNs to account for the temporal aspect of fatigue modelling.

A. Static Bayesian Network for Fatigue Modelling

The main purpose of a BNs model is to infer the unobserved events from the observed or contextual data. So, the first step of BNs modelling 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.

For fatigue modelling, 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 (Sleep_quality), circadian, work condition (Work_condition), work environment (Work_environment) and physical condition(Physical_condition). 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 (Sleep_disorders). The factors affecting work conditions include workload and type of work (Work_type). Factors seriously affecting sleep quality include sleep environment (Sleep_Enviornment), napping, sleep time (Sleep_time) and sleep state (Sleep_state). Sleep state refers to the mental state during sleep such as worry or anxiety. Factors affecting sleep environment includes random noise (Random_noise), background light (Light), heat (Heat) and humidity around the bed (Humidity).

On the other hand, when a person is fatigue, he 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(Eye_movement), head movement(Head_movement), and facial expression (Facial_Exp). Our current efforts [28] in computer vision research has led to various non-invasive techniques that can compute in real time various parameters to characterize these behaviors. Specifically, for eye movement, the parameters characterize eyelid movement (Eyelid_movement) and gaze (Gaze). For eyelid movement, the parameters are PERCLOS and the average eye closure/open speed (AECS). For gaze, the parameters include gaze fixation distribution (Fixation_dis), which measures spatial distribution of gaze over time, and Fixation Saccade ratio(Fixation_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 (Head_tilt_freq), which measures frequency of head tilt to characterize head nod. And 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 Static Bayesian Network for modelling 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.

B. Construction of conditional probability tables (CPTs)

Before using the BNs model for fatigue inference, the network need be parameterized. This requires to specify 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 all nodes are binary. Subjective estimation of these probabilities are 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 [38] [9] [43] [39] provide the clues of such data. Despite the subjectivity of these data, we use them to help the parametrization of our fatigue model. Since these surveys were not designed for the parametrization of our BNs model, not all needed probabilities are available and some conditional probabilities are therefore inferred using the so-called *noisy-or* principle [26].

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

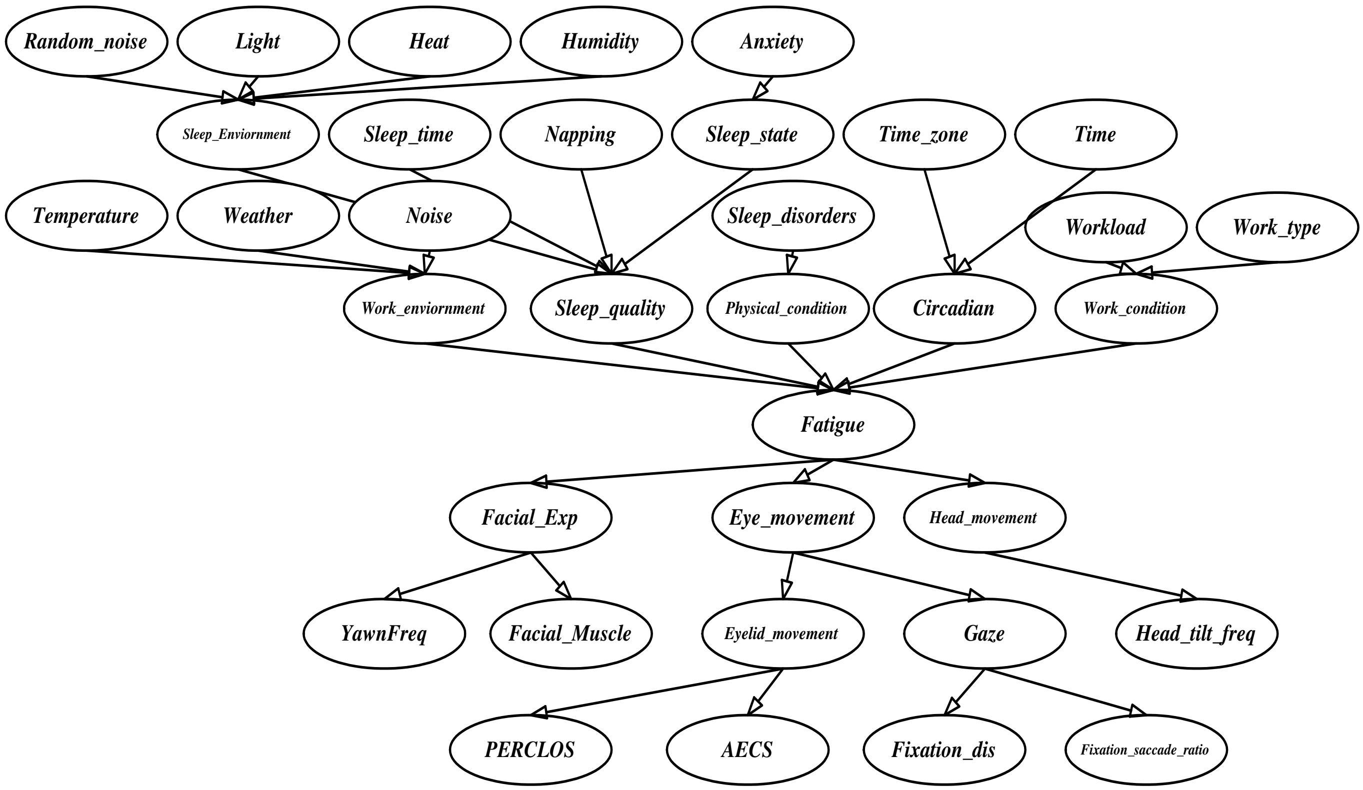

Fig. 1. A Static Bayesian Network for Modelling Human Fatigue.

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 independent, i.e.,

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

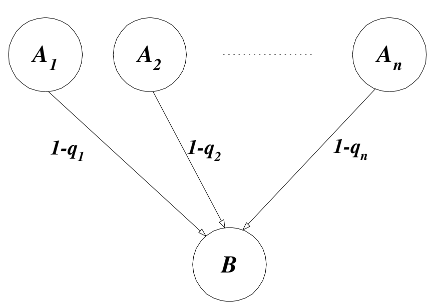

Fig. 2. The graphical explanation of the *noisy-or* principle

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 [26]. With these, all the prior and conditional probabilities in our SBNs model are obtained and are listed in Tables I, II, III, IV, V, VI, VII, VIII, and IX.

[1]Inferred from [9]. Given 'high' humidity, the probability of poor sleep_environment is 39.5%; given background light 'on', the probability of poor Sleep_environment is 38.5%; given 'high' Random_noise, the probability of poor Sleep_environment is 44.5%. Assuming that the relationship between children nodes and parent node is a *noisy or*, all the conditional probabilities of Sleep_environment given its parents variables are estimated with *noisy or* principle [26].

TABLE I

PRIOR PROBABILITY TABLE

Nodes	State	Probability	Notes
Random_noise	yes	0.15	average of [38] [9]
	no	0.85	
Light	on	0.13	average of [38] [9]
	off	0.87	
Heat	high	0.24	average of [38] [9]
	normal	0.76	
Humidity	high	0.19	average of [38] [9]
	normal	0.81	
Sleep_time	sufficient($> 6h$)	0.90	[9]
	loss($< 6h$)	0.1	
Napping	$> 30min.$	0.22	[9]
	No	0.78	
Anxiety	yes	0.28	average of [38] [9]
	no	0.72	
Sleep_disorder	yes	0.08	average of [38] [9]
	no	0.92	
Workload	heavy	0.15	[9]
	normal	0.85	
Time	drowsy_time	0.26	[38]
	Active_time	0.74	
Time_zone	changed	0.17	[38]
	no	0.83	
Temperature	high	0.15	average of [38] [9]
	normal	0.85	
Weather	abnormal	0.10	average of [38] [9]
	normal	0.90	
Noise	high	0.15	average of [38] [9]
	normal	0.85	
Work_type	tedious	0.2	average of [38] [9]
	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

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

TABLE IV

CONDITIONAL PROBABILITIES FOR PHYSICAL_CONDITION NODE & 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[3]	
Anxiety	good	bad
Yes	0.30	0.70
No	0.90	0.10

[2]Inferred from [9]. Given 'bad' Sleep_condition, the probability of 'poor' sleep_quality is 59%. Estimated by experience, given 'poor' Sleep_environment, the probability of 'poor' Sleep_quality 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%. Assuming that the relationship between children nodes and parent node is a *noisy or*, all the conditional probabilities of Sleep_quality given its parent variables are estimated with *noisy or* principle [26].

[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

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

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

[4]Inferred from [9]. Given 'high' temperature, the probability of 'poor' Work_environment is 77.5%; given 'abnormal' weather, the probability of 'poor' Work_environment is 80%. Assuming that the relationship between children nodes and parent node is a *noisy or*, all of the conditional probabilities of Work_environment given its parent variables are estimated with *noisy or* principle [26].

[5]Inferred from [38], given 'heavy' workload, 'poor' Work_condition is 60%; given 'tedious_monotonous' Work_type, 'poor' Work_conditionis 70%. Assuming that the relationship between child nodes and parent nodes is a *noisy or*, all of the conditional probabilities of Work_condition given its parent variables are estimated by the *noisy-or* principle [26].

[6]Inferred from [9]. Given 'poor' Sleep_quality, Fatigue is 60%; given 'drowsy' Circadian, Fatigue 70%; given 'poor' Work_condition, Fatigue is 65%; Estimated by experience that given 'poor' Work_environment, Fatigue is 55%; given 'poor' Physical_condition, Fatigue is 40%; Assuming that the relationship between children nodes and parent node is a *noisy or*, all of the conditional probabilities of Fatigue given its parent variables are estimated with *noisy or* principle [26].

[7]Some of these conditional probabilities are obtained from the experiment results in [14].

TABLE IX

CONDITIONAL PROBABILITIES FOR THE CHILDREN NODES OF FATIGUE NODE

Nodes Name	Parent Node	Parent State Variable	Child State Variable	Condition[3] 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 [7]	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

IV. FATIGUE MONITORING MODELLING WITH DYNAMIC BAYESIAN NETWORKS

As pointed by recent studies [51], 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 became higher and higher as the time passes. 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 based on the DBNs is necessary. A dynamic fatigue model allows to monitor and detect fatigue by integrating fatigue evidences both spatially and temporally.

A. *Dynamic Bayesian Networks*

In Artificial Intelligence (AI) field, a DBNs 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 explicit modelling 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 [33]:

(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 non-probabilistic frameworks; and (3) models that introduce temporal nodes into static BNs structure to represent time dependence. The third category is most widely used and we will base 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 DBNs is usually regarded as a generalization of the singly connected BNs, specifically aiming at modelling time series [33]. 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 [18]. As an extension of the traditional static Bayesian Networks, DBNs describes a system that is dynamically evolving over time and enables the user to monitor and update the system as time proceeds. It even predicts the behavior of the system over time. Therefore, a fatigue model based on the DBNs is naturally the best option to model and predict fatigue over time.

A simple illustrative DBNs is showed in Figure 3 and it's joint probability distribution function on the sequence of T time slices consists of a hypothesis node H_t, hidden states S_t, and observations O_t. Given the DBN topology as shown in Fig. 3, we assume that, the hidden state variables $S = \{s_0, ..., s_{T-1}\}$, observable variables $O = \{o_0, ..., o_{T-1}\}$, and hypothesis variables $H = \{h_0, ..., h_{T-1}\}$, where T is the time boundary. The probability distribution of DBNs can be theoretically expressed as

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

So, in order to completely specify a DBNs, we need to define four sets of parameters:

- State transition probability distribution functions (pdfs) $Pr(S_t|S_{t-1})$ and $Pr(H_t|H_{t-1})$, that specifies time dependencies between the states
- Hypothesis generation pdfs $Pr(S_t|H_t)$, that specifies how the hidden states relate to the hypothesis.
- Observation pdfs $Pr(O_t|S_t)$, that specifies dependencies of observation nodes regarding to other nodes at time slice t.
- Initial state distribution $Pr(H_0)$, that 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 dynamically vary over time.

Based on general DBNs principles [26] [33] [42] and the above considerations, a DBNs model for modeling human fatigue is constructed as shown in Figure 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

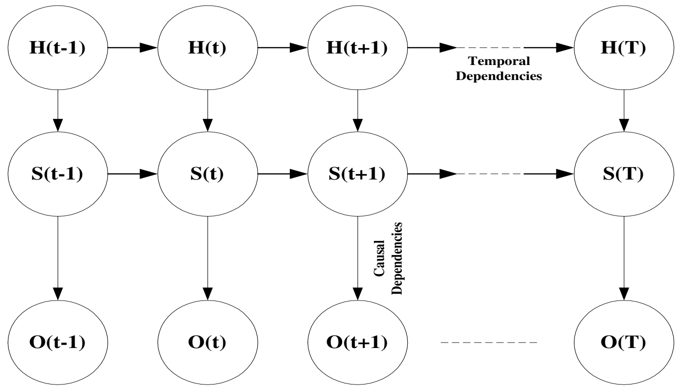

Fig. 3. A generic DBN structure, where $H(t)$ represents the hypothesis to infer at time t; $S(t)$ represent hidden states at time t; $O(t)$ represents sensory observations at time t; and T is the time boundary.

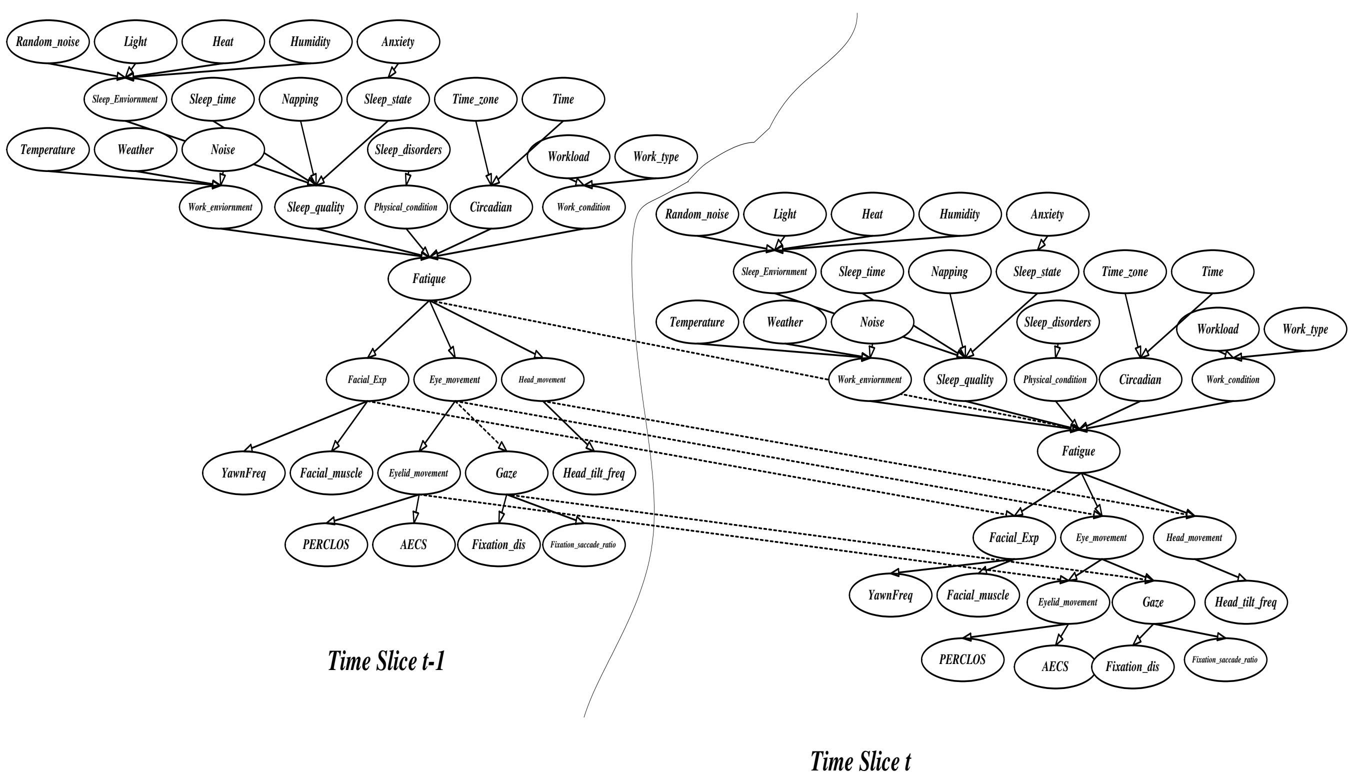

Fig. 4. A Dynamic Bayesian Networks Model for Monitoring Human Fatigue. While static nodes repeat in slices, corresponding temporal nodes in neighboring slices are connected via temporal causality.

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.

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 such programmed that they rotate as 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 BNs model in Figure 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 is time-invariant. Part of the CPTs and prior probabilities in the model are adopted from the previous SBNs model and the transitional probabilities are specified subjectively.

V. Experiments

In this section, we present our experimental results to evaluate the proposed fatigue model.

A. The Experiment Results of SBNs Model

Given the parameterized model, the fatigue inference can commence upon the arrival of visual evidences via belief propagation. MSBNx software [30] is used to perform the inference in this static model and both top-down and bottom-up belief propagations are performed.

Given the network shown in Figure 1, with 22 evidence nodes and two states for each node, theoretically, there are 2^{22} possible inference results. So, 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, it can been seen that the prior probability of fatigue (e.g. when there is not any evidence) is 0.57 (*ref. No.1*), representing the the average fatigue level for the commercial pilots or truck drivers in their normal working time. The observation of a single visual evidence (*ref. No. 2-8* in table X) does not provide conclusive finding since the estimated fatigue probability is less than the critical value 0.95. 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 [28] [27]. The same is true if only a single contextual factor (*ref. No. 9-18*) is given. The combination of PERCLOS and any other visual evidences (*ref. No. 20, 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 modelling fatigue, through systematic fusion of information from different sources.

B. Evaluation of Dynamic Bayesian Network Model for Monitoring Fatigue

The typical evaluating results from the dynamic BNs models and their comparisons with the static BNs model are shown in Figures 5 6 and 7.

From Figure 5, it can been seen that if there is not any evidence observed, the fatigue level basically monotonically increases as time passes by. But for SBN model, the fatigue index remains unchanged over time. From the view of driving in the real world, the situation

TABLE X

THE INFERENCE RESULTS OF STATIC FATIGUE BAYESIAN NETWORK MODEL

No.	Evidences	Fatigue (yes)
1	No any 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), Heat_tilt_freq(high),humidity(high) Sleep_disorders(yes), Sleep_time (loss(¿6h)), Work_type (tedious_monotonous), Weather(abnormal),Anxiety(yes),Workload(heavy)	0.90

in DBNs model is more reasonable. The driver may feel alert at the start of driving but as the time passes by, fatigue begins to get built up gradually.

Figure 6 plots the fatigue index for both models over time, with the observation of high PERCLOS value at different time slices. It is clear that the two models respond to evidences differently. In general, the fatigue curve for dynamic fatigue model changes gradually upon the arrival of an evidence or disappearance of an evidence. On the other hand, the fatigue curve for the static model changes drastically with evidence arrival or disappearance, as represented by sharp turns. The curves also show that the presence of high PERCLOS at one time slice (slice 2) does not cause a significant fatigue change for the dynamic model while it can lead to a sudden change for the static model. However, if high PERCLOS value is observed continuously (e.g. from time 11 to 20), this will cause a gradual increase of fatigue for the dynamic model. The fatigue index of static model stays unchanged over this period. As soon as disappearance of the PERCLOS evidence, the fatigue index of static model drops immediately while the fatigue index of dynamic model gradually decreases. Therefore, the dynamic fatigue model is more compatible with fatigue development. And, the dynamic model is more tolerant to external signal disturbance. The fatigue index from the dynamic fatigue model begins to change only after persistent and continuous observations of certain visual behavior.

We can reach the similar conclusion from Figure 7, where multiple fatigue parameters may be instantiated simultaneously. In addition, it is observed that after the disappearance of evidences from frame 26 and on, the fatigue index of DBN model fatigue number begins to increase to reflect time factor while the fatigue index of SBN fatigue number remains unchanged. In summary, the DBN model demonstrates more powerful capability to model and monitor human fatigue. It can more accurately characterize and monitor human fatigue. In addition, the dynamic fatigue model is less sensitive to external signal disturbance and to erroneous sensory observations.

C. Interfacing with the Vision System

To perform real-time driver's fatigue monitoring, the visual module from computer vision technology and the fatigue model must be combined via an interface program such that the output of the vision system can be

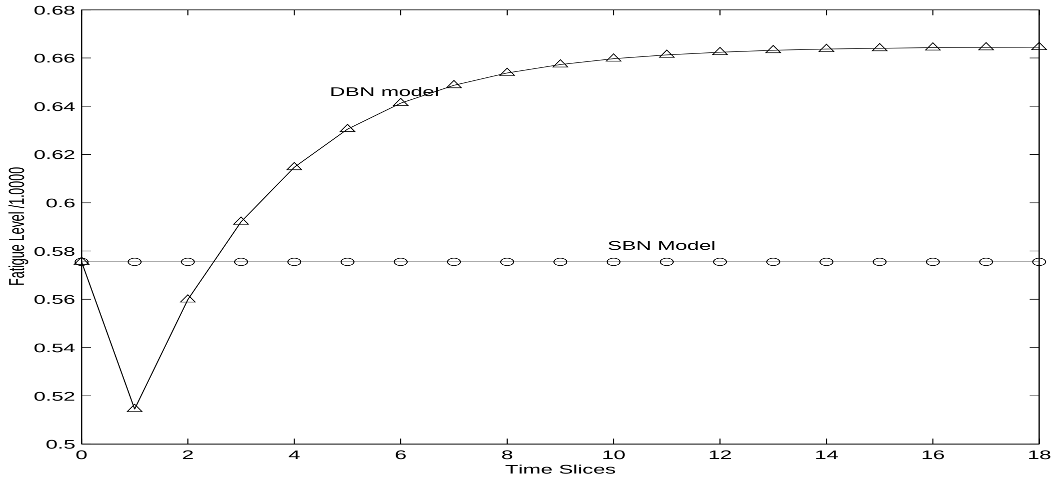

Fig. 5. Fatigue level plot over time for SBN and DBN models without any evidence observed.

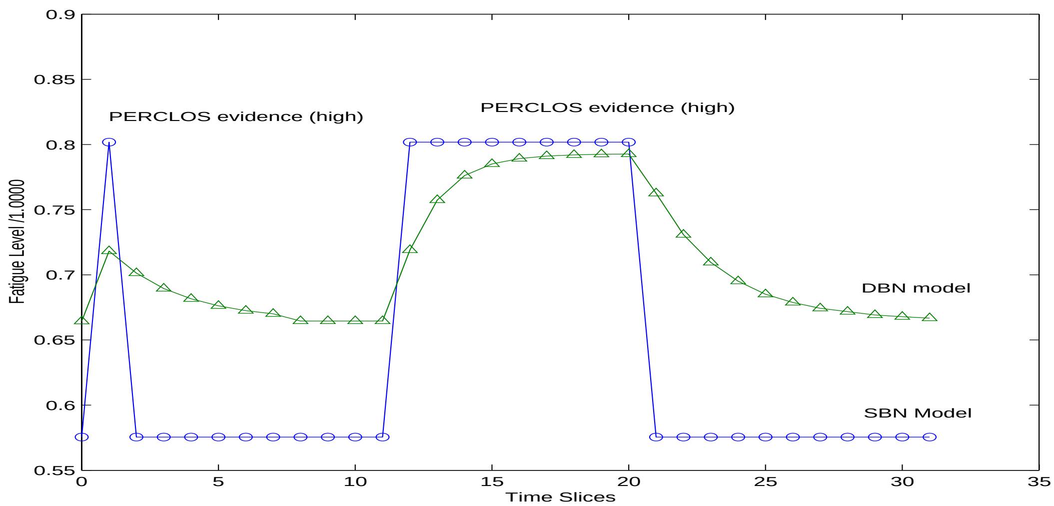

Fig. 6. Fatigue level changes over time for both the static and dynamic fatigue models with observation of high PERCLOS value at time slice 1 and between time slice 12 and 20.

used by the fatigue model to update its belief of fatigue in real time. Such interfaces have been built. Figure 8 shows the appearance of the interface program. Basically, the interface program periodically (every 1 second 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 observations nodes in the fatigue 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 figure 8. 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

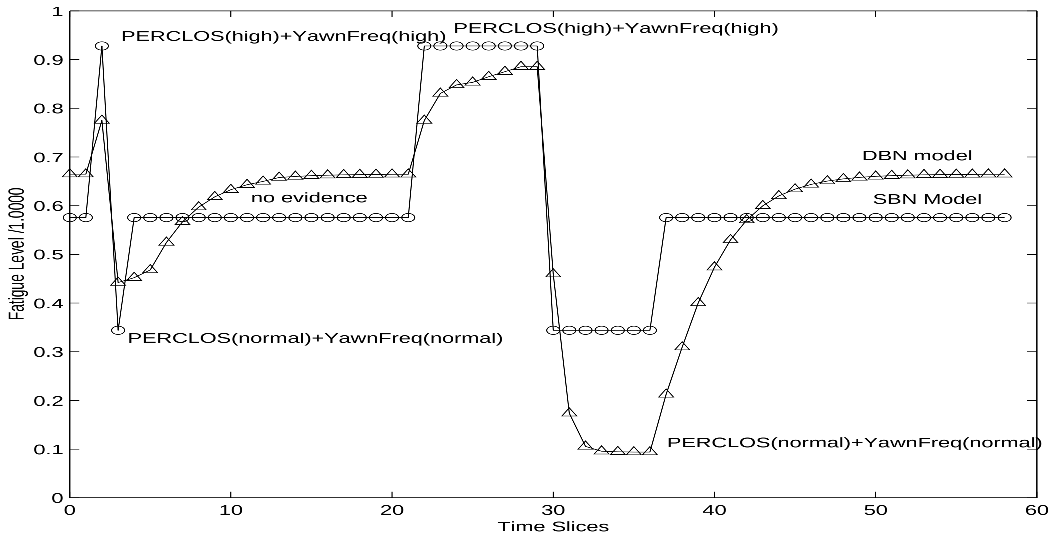

Fig. 7. Fatigue level changes over time for both the static and dynamic fatigue models with observation of multiple evidences at different time slices. The evidence from PERCLOS (high) and YawnFreq (high) are observed at time slice 2 and between 22 and 29, and the evidences from PERCLOS(normal) and YawnFreq (normal) are observed at time slice 3 and between time slice 30 and 36

become 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.

VI. Conclusion and Future Work

Fatigue is one of the most important safety concern in modern commercial transportation industry. Monitoring and preventing fatigue are crucial to improving the 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, type of works, 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, we propose a probabilistic framework based on the Bayesian network to model fatigue and the associated factors and observations in a principled way. Specifically, a static fatigue model based on the static Bayesian Networks model was developed to model the static aspects of fatigue and to allow to integrate the relevant contextual information and the available visual cues spatially. The static fatigue model is then extended based on DBNs to better model the dynamic and evolutionary aspects of fatigue development.

Experimental results demonstrate the importance of simultaneous combination of various parameters as well as the advantage of dynamic fatigue model over the static fatigue model to more accurately and robustly model and detect human fatigue and produce more accurate fatigue prediction. The inference results, though preliminary and still subjective, demonstrate the utility of the proposed framework for consistently, robustly, and accurately predicting and modelling fatigue under uncertainty.

Though the parameters used to parameterize the net-

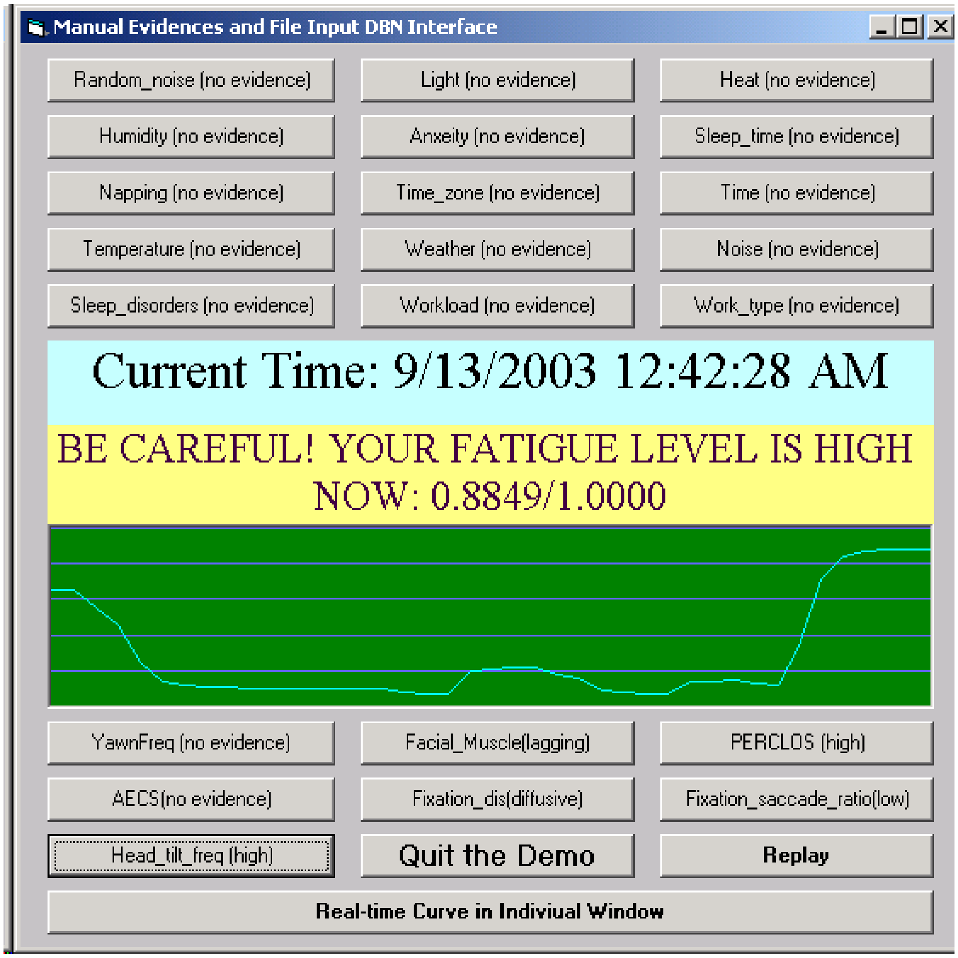

Fig. 8. Interface for DBN model

works are sometimes subjective and the data used may not accurately reflect the actual situation, the current focus of our 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. Work is currently under way to refine the parameters of the model with more and better data and knowledge. This requires close collaboration with human factors experts, requiring studies involving human subjects. Another work to be carried out soon is to perform a systematic and scientific validation (involving human subjects) of our fatigue model against the established fatigue criteria such as EEG, EOG, and psychomotor vigilance task (PVT). This also allows to acquire training data to help parameterize our model.

Acknowledgment

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