Information Fusion with Bayesian Networks for Monitoring Human Fatigue

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Abstract – *In this paper, we introduce a probabilistic model based on Bayesian Networks (BNs) for inferring human fatigue by integrating information from various visual cues and certain relevant contextual information. First, we briefly review the modern physiological and behavioral studies on human fatigue to identify the major causes for human fatigue and the significant factors affecting fatigue. These factors are then extracted from those studies and form the contextual information variables in our fatigue model. Visual parameters, typically characterizing the cognitive states of a person including parameters related to eyelid movement, gaze, head movement, and facial expression, serve as the sensory observations in the fatigue model. The fatigue model is subsequently parameterized based on the statistics extracted from recent studies on fatigue and on our 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 inference results produced by running the fatigue model using Microsoft BNs engine MSBNX demonstrate the utility of the proposed framework for predicting and modeling fatigue.*

Keywords: Bayesian Networks, human fatigue, information fusion

1 Introduction

Fatigue is not a disease and can be overcome by simply taking a rest or sleep. However when fatigue appears in a time when a person drives a commercial airplane, a bus, a railroad train or other vehicles that requires constant attention, fatigue may cause serious accidents for it is not often permitted to take these easy remedies. Unfortunately, fatigue often appears during such a time. A survey [1] 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 in their corporate operation. Even more terrible, 71% of these pilots had "nodded off" during some flights. According to an official report [3], 43,000 Americans are killed in transportation accidents every year. The investigations revealed that many of these fatal accidents were caused by drivers in fatigue. For example in [4], the study by National Transportation Safety Board (NTSB) on 182 fatal heavy truck accidents found that driver impairment due to fatigue was the most frequently cited single cause or factor (33%). The well-known aviation accident [4] is that a DC-8 freighter crashed in August 1995 while landing on the Leeward Point Airfield at the U.S. Naval Air Station, Gunatanamo Bay, Cuba. In this accident, the airplane was destroyed and three flight crew members were seriously injured. The late investigation by the NTSB showed that the most probable causes were the impaired judgment, decision-making and flying abilities of the captain and flight crew. Therefore, it is hard to overstate that driver or pilot's fatigue prevention is very essential to improve the commercial aviation and transportation safety.

Many efforts [5, 10, 11] have been made to understand the physiological mechanism of human fatigue and on how to measure fatigue level in the last twenty five years. Based on all of these studies, many active safety systems to monitor human fatigue have been developed [6, 5]. But the studies have found that human fatigue results from a very complicated mechanism and many factors affect fatigue in interacted ways [1, 2, 5, 8]. Most of the present safety systems only acquire information from very limited sources and perform fatigue monitoring with low efficiency and often intrusively . So, much more efforts are needed to develop the systems for fatigue prevention in aviation and land transportation.

In our previous study [6, 7], we developed an 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 contextual information. In this paper, based on the modern research achievements of fatigue studies [1, 2, 5, 8] and our previous successful studies, we constructed a probabilistic framework based on Bayesian Networks for fatigue modeling and for systematically combining different information sources to consistently and robustly infer fatigue.

2 Literature Review

Although the study of the role of fatigue in railway transportation started as early as the beginning of 20's century, the detailed study has only appeared during the last twenty-five years [5]. It was reported that there are over 400 scientific studies investigating sleep topics [5]. Up to now, much progress has been achieved to understand the medical and physiological mechanism of fatigue, measurement of fatigue, and monitoring fatigue.

2.1 Significant causes for fatigue

From the physiological view, it is widely accepted that fatigue, alertness and performance are physiologically determined [1, 2, 8, 10]. Two physiological factors - sleep and circadian, are thought fundamental to determine fatigue and alertness. Therefore, all the factors that affect sleep and the 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 in an uncontrolled and spontaneous way, your brain can shut you down regardless of your situation [10]. 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 [1, 2, 8, 10]. 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 things are that these factors interact with one with another [1, 2, 10]. 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 [1, 2].
The circadian rhythm has been found to virtually control all physiological functions of the body including sleep/wake, digestion, immune function. The circadian rhythm is regulated by the circadian clock that has been found in the brain [1, 2, 10, 11]. Generally, sleep is programmed at night and being awake is programmed during daytime. In addition, it is found that there are two peaks of sleepiness and alertness each day [1, 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. This theory is 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, 12]. The two alertness peaks happen about 9-11 a.m. and 9-11 p.m.. During this time, human may be difficult to get sleep even if his sleep was deprived in the last night [1, 2, 10, 11]. Circadian system is very difficult to adjust immediately to the need of work/rest schedule or time zone changes. Circadian disruption can cause sleep loss and finally results in fatigue [1, 2, 11].
Besides these two main factors, the study 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 [5]. These disturbances are insomnia, which refers to too little sleep, hypersomnia, which refers to too much sleep, and parasomnia, which refers to 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 [5]. Hypersomnia usually demonstrates itself as a difficulty to stay awake in typical daily activity such as traveling 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 cause of hypersomnia [5]. Parasominas are disturbances during sleep and are mostly caused by nightmares, sleep walking, restless legs and bruxism or gnashing of teeth [5].
Sleep inertia is also found to have the effect on fatigue and there have been many studies on it. 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.

2.2 Subjective survey of fatigue factors in commercial aviation and land transportation

Although drivers and pilots in commercial aviation and land transportation are also common people and share the sa me fatigue mechanism, they work in a special environment and may encounter special situation that effects their fatigue. Since fatigue is a vital factor for the safety of their work, it is important to investigate them. Particularly in recent years, series of large-scale surveys of fatigue factors in aviation and land transportation have be en conducted and much valuable information has been revealed [1, 2, 5, 8]. The survey [1] from 1 ,488 corporate flight crewmembers in U.S. corporate/executive aviation operations by Ames Research Center at NASA revealed many valuable statistical information about the factors that affected the crew member's sleep in home and fatigue in workplace. Some of the noticeable statistical information included that 8% of these people have sleep problem. The five most often identified factors that promoted their home sleep were: pillow (13%), sleep surface (12%), ventilation (10%), and comfortable clothing (8%); The most often identified factor that interfere with t heir home sleep are: thought (19%), heat (17%), high humidity (15%), random noise events (9%), and background light (8%); The most often mentioned pre-trip strategies to prevent fatigue were: sleeping or napping (73%), healthy diet (41%), exercise (28%), flight planning activities(26%), and caffeine (16%); The most often cited factors that affect their fatigue in flight are: greater than 7 flying segments in the same duty, severe turbulence, sleep loss time of day of operation, illness, heavy workload, late arrival, 4-6 flight legs, high temperature, early morning departure, no auto-pilot. Another survey [2] of fatigue factors from 1,424 crewmembers in U.S. regional airline operation by Ames Research Center at NASA showed the similar results with the survey in corporate/executive operation as above. The survey of sleep quantity and quality in On-Board crew rest facilities by Ames at NASA [8] reported more details on the factors that affect the sleep in home and bunk. The on-line res earch report [5] from University of Denver, *Fatigue Countermeasures in the Railroad Industry-Past an d Current Developments*, reported the results of the past and current fatigue countermeasures projects in almost a all the railroad companies in North America. It presented wealthy statistical information about fatigue issue in the railroad industry. The inherent limitation of all the survey study is subjective and the subjectivity results in inaccurate data.

2.3 Measures of Fatigue

It is widely accepted that [5] measuring fatigue in any situation is a complex process and no easy method is available. Up to now, four kinds of fatigue measuring have been typically used in the laboratory and have varying levels of utility in the workplace. They are physiological, behavioral, subjective performance measures. Multiple measures have been tried to triangulate the truth but the correlation between them is often low [5].

Physiological Measures [5]: This method has been thought to be accurate, valid and objective to determine fatigue and sleep, and countless efforts have been made in laboratory. The popular physiological measures are the electroencephalograph (EEG) and the multiple sleep latency test (MSLT). The 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. The 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.

Behavioral Measure [5]: 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, 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 have 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 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 [22, 24] have shown that besides physiological signals like EEG, EOG, etc., 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 [23, 24], of the many drowsiness-detection measures, PERCLOS was found to be the most reliable and valid measure of a person's alertness level. PERCLOS measures the percentage of eyelid closure over the pupil over time and reflects slow eyelid closures (*droops*). Other unvalidated 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 pilot, 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. Besides eye activities, head movement like nodding or inclination is a good indicator of a person's fatigue or the onset of a fatigue [25]. 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. Our recent effort [6, 7] produces a computer vision system that can extract various parameters in real time to characterize eyelid movement, gaze, head movement, and facial expression.

Performance Measures [5]: 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 in a various studies including Walter Reed Performance Assessment Battery (PAB) and the Denver Fatigue Inventory (a computer assisted cognitive test battery). The advantage of this method is indirect and the drawbacks are non-self-administered and need expert data analysis.

Other Measures [5]: A variety of other measures have been developed to determine fatigue sleepiness and alertness. The most famous ones are the Stanford Sleepiness Scale (SSS), Visual Analog Scale (VAS), mood descriptors, and diary method. The advantages of these methods are inexpensive, practical and readily accepted. The drawbacks are less accurate and unable to be used for monitoring real-time fatigue.

2.4 Fatigue monitoring

Since fatigue's occurrence is often difficult to predict and control, it is crucial to monitor people's fatigue in real-time. Theoretically, all the objective fatigue measure methods, which detect the physiological signals, can be used to monitor fatigue because they are valid and real-time. Many efforts have been made in this direction and the results were reviewed by [6]. The problems are that most of them are intrusive and therefore not suitable in driving or flying conditions. In recent years, an increasing research interest has been 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 become more and more practical with the speedy development of camera and computer image processing technology. Several studies have demonstrated their feasibility and some of them claimed that their systems perform as effectively as the systems detecting physiological signals do [13, 14, 15, 16]. However, these efforts in this direction are always directed to detect a single visual cue such as eyelid movement. If a single visual cue is uncertain with the change of time, environment or different person, the validity is questioned. Therefore, developing new systems that can detect the change of multiple visual cues and utilize as much as possible other information related to fatigue is essential in future.

3 Fatigue Modeling Using Bayesian Networks

A Bayesian Network (BN) is a state-of-the-art knowledge representation scheme dealing with probabilistic knowledge. Basically, it consists of nodes and arcs connected 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 a graphical model resulted from a marriage between probability theory and graph theory, and provides a natural tool for dealing with uncertainty and complexity [17]. 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 BN. These examples include mixture models, factor analysis, hidden Markov models, Kalman filters and Ising models. Since BN was developed to model the distribution processing in reading comprehension in the late of 1970'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 commercial applications [18, 19].

As we discussed above, human fatigue generation is a very complicated process. Several uncertainties may be present in this process. First, fatigue is not observable and it can only be inferred from the available information. In fact, fatigue can be regarded as the result of many contextual variables such as working environments, health, sleep quality and the cause of many symptoms, e.g. the visual cues, such as irregular eyelid movement, yawning, and frequent head tilts. Second, human's visual characteristics vary significantly with age, height, health, and shape of face. To effectively monitor fatigue, a system that integrates evidences from multiple sources into one representative format, is needed and naturally a BN model is the best option to deal with such an issue.

3.1 Bayesian Networks construction for fatigue monitoring

The main purpose of a BN model is to infer the unobserved events from the observed or contextual data. So, the first step BN modeling is to identify those hypothesis events and group them into a set of mutually exclusive events to form the target hypothesis variable. The second step is to identify the observable data that may reveal something about the hypothesis variable 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 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. Of many factors that can cause fatigue, the most significant ones are sleep quality, circadian, work condition, work environment and physical condition. The most profound factors that affect work condition, include temperature, weather and noise; the most significant factors that affect physical condition are age, sleep disorders and food; the factors affecting work conditions include workload and type of work. Factors affecting sleep quality include sleep environment, sleep time and worry. The sleep environment includes random noise, background light, heat and humidity around the bed. From our previous studies [5, 6], we developed a prototype computer vision system that computes various visual parameters related to facial expression (including mouth and facial muscles), eye movement (including eyelid movement through PERCLOS and AECS, and gaze though fixation time and ratio of fixation time and saccade time), head movement through head tilt frequency, and posture. Putting all factors together, the BN model for monitoring fatigue is constructed as shown in Fig. 1. The target node is fatigue and the nodes above the target node represent various major factors that could lead to one's fatigue. They are collectively referred to as contextual information. The nodes below the target node represent visual observations from the output of our computer vision system. These nodes are collectively referred to as observation nodes.

3.2 Construction of conditional probability table (CPT)

Before the use of the BN for fatigue inference, the network needs parameterized. This requires to specify the prior probability for the root nodes and the conditional probabilities for the links. Usually, probability is obtained from statistical analysis of a large amount of training data. Large amount of data is, however, difficult to acquire. Fortunately, several series of large-scale subjective surveys [1, 2, 5, 8] provide many such data. Despite the subjectivity with these data, we use them to help parameterize 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 from them using the so-called *noisy-or* principle [20]. The *noisy-or* principle states that assuming $A_1, \ldots, A_n$ be binary variables (yes (y) and no (n) state) listing all the causes of the binary variable B and each event $A_i = y$ cause $B{=}y$ unless an inhibitor prevents it, and the probabilities for that is q_i (see Fig. 2), e.g. $P(B{=}n|A_i{=}y){=}q_i$, and all inhibitors are independent, then

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

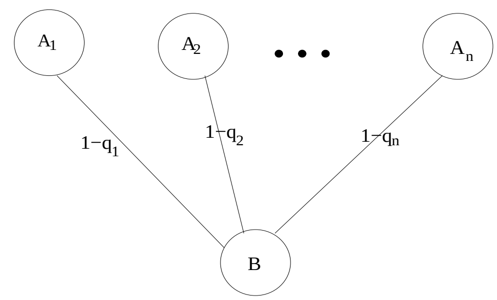

Figure 2: The general principle for noisy-or

Still some prior or conditional probabilities are lacking in our model and they are obtained by subjective estimates methods [20]. With this, all the prior and conditional probabilities in our BN model are obtained and typical ones are listed in Tables 1 and 2.

4 The Experiment Results

Given the parameterized model, fatigue inference can then commence upon the arrival of visual evidences via belief propagation. MSBNX software [21] is used to perform the inference and both top-down and bottom-up belief propagations are performed.
Theoretically, there are 2^{36} possible inference results. Even if only the information variables (the evidences can be obtained) are considered, there are also 2^{24} possible inference results for fatigue node. So, it is impossible to list all of the possible inference results here and only the typical combination of evidences are manipulated in the model and their results are summarized in Table 3. From Table 3, it can been seen that the prior probability of fatigue (e.g. when there is no any evidence) is 0.59 (ref. No. 1-20). The observation of single visual evidence does not provide conclusive finding since the estimated fatigue probability is less

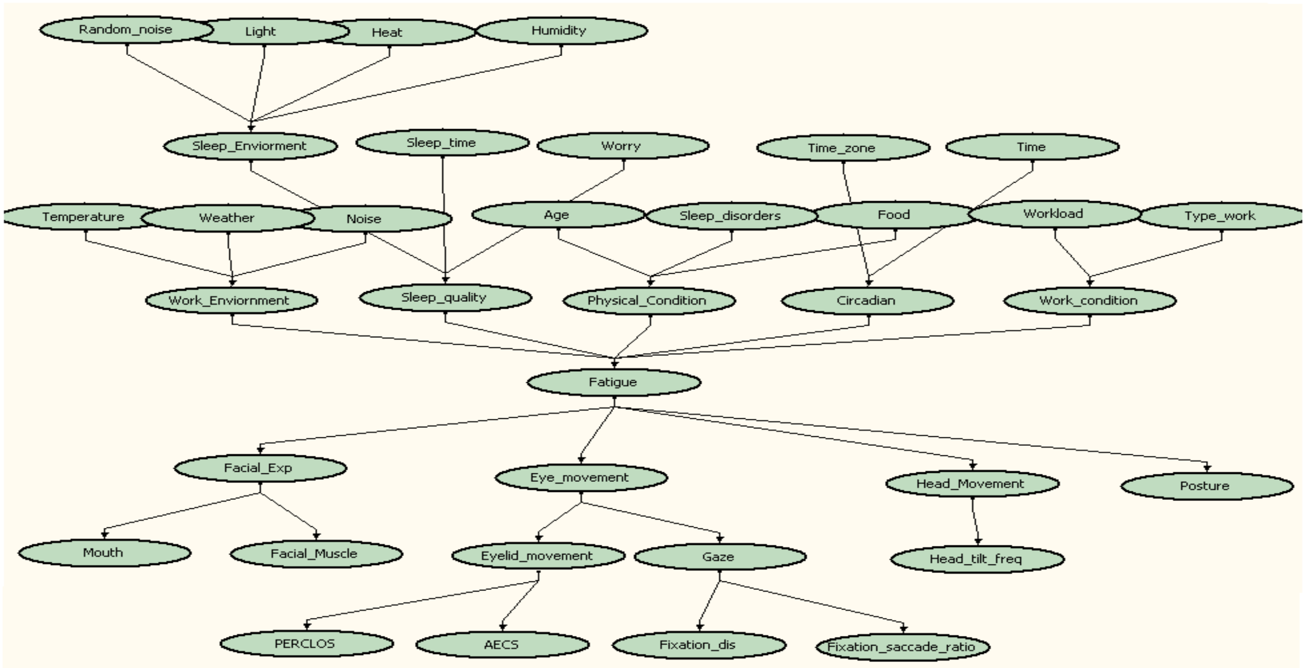

Figure 1: Bayesian Network Model for Monitoring Human Fatigue

Table 1: 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_s	high	0.19	average of [1, 2]
	normal	0.81	
Sleep_time	sufficient	0.90	[2]
	loss	0.1	
Worry	yes	0.28	average of [1, 2]
	no	0.72	
Age	< 45	0.25	average of [1, 8]
	> 45	0.75	
Sleep_disorder	yes	0.08	average of [1, 2]
	no	0.92	
Food	sufficient	0.85	[1]
	hungry	0.15	
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	0.15	average of [1, 2]
	normal	0.90	
Noise	high	0.15	average of [1, 2]
	normal	0.85	
Type_work	tedious	0.2	average of [1, 2]
	normal	0.8	

then the critical value 0.95. Only when the evidence of eyelid movement (e.g. PERCLOS) is instantiated, the fatigue almost reaches the critical level, for eyelid movement has been regarded as the most accurate measurement of fatigue [6, 7]. The combination of PERCLOS and any other visual evidences (ref. No. 22, 23), leads to fatigue probability higher than 0.95 but the combination of any two visual evidences except for PERCLOS does not often lead to fatigue probability higher than 0.95 (ref.No. 24, 25). Any combination of three visual cues guarantees the estimated fatigue probability exceeds the critical value (ref. No. 26). With some contextual evidences, any two visual cue evidence combinations achieve the same purpose (ref. No. 27). 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. 28). These inference results, thought preliminary, demonstrate the utility of the proposed framework for predicting and modeling fatigue.

5 Conclusions and future works

Fatigue is one of the most important safety concern in modern commercial aviation and land transportation industry. Monitoring and preventing fatigue is

Table 2: Conditional Probabilities for the Children Nodes of Fatigue Node

Nodes Name	Parent Node	Parent State Variable	Child State Variable	Condition Probability
Facial_Exp	Fatigue	yes	drowsy_exp	0.30
		yes	normal	0.70
		no	drowsy_exp	0.05
		no	normal	0.95
Mouth	Facial_Exp	drowsy_exp	yawn	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_movement	Fatigue	yes	abnormal	0.50
		yes	normal	0.50
		no	abnormal	0.02
		no	normal	0.98
Eyelid movement	Eyet 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
Posture	Fatigue	yes	abnormal	0.60
		yes	normal	0.40
		no	abnormal	0.15
		no	normal	0.85
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 frequency	Head movement	abnormal	high	0.60
		abnormal	normal	0.40
		normal	high	0.05
		normal	normal	0.95
Notes: all conditional probabilities are estimated by experience.				

Table 3: The Inference Results of Fatigue Bayesian Network Model

No.	Evidences	Fatigue
1	No any evidence	0.59
2	Mouth (yawn)	0.83
3	Facial Muscle (lagging)	0.82
4	PERCLOS (abnormal)	0.87
5	AECS (abnormal)	0.87
6	Fixation distance (narrow)	0.82
7	Ratio of fixation to saccade(low)	0.82
8	Head tilt frequency (high)	0.84
9	Posture (abnormal)	0.80
10	Temperature (high)	0.73
11	Weather(abnormal (fog, rain, windy)	0.73
12	Noise (high)	0.71
13	Age ($> 45y$)	0.61
14	Time zone (changed)	0.65
15	Sleep disorder (yes)	0.62
16	Food (hungry)	0.64
17	Workload (heavy)	0.73
18	Type work (tedious)	0.75
19	Worry (yes)	0.70
20	Random Noise (yes)	0.61
21	Mouth (yawn), Facial muscle (drowsy expression)	0.90
22	PERCLOS (abnormal), Fixation distance (abnormal)	0.95
23	PERCLOS (abnormal), Mouth (yawn)	0.96
24	Fixation distance (abnormal), Facial muscle (drowsy expression)	0.93
25	AECS (abnormal), Head tilt frequency (high)	0.93
26	Head tilt frequency (high), Posture (abnormal), AECS (abnormal)	0.98
27	Head tilt frequency (high), Mouth (yawn), Temperature (high), Worry (yes)	0.98
28	Age ($> 45y$), Time (drowsy_time (EM, LN, EA), Food (hungry), Heat (high), Sleep humidity(high) Sleep disorder (yes), Sleep time (loss), Type work (tedious & monotonous), Weather (abnormal (fog, rain, windy), Workload (heavy), Worry (yes)	0.98

crucial to improving the safety.

Fatigue is affected by many complicated factors (or called contextual information factors). Sleep and circadian are two fundamental physiological factors. For the vehicle drivers or plane pilots, many other factors, such as environment factors, physical conditions, type of works, will also significantly affect fatigue. Fatigue causes the human visual cues change (or visual cue information) that can be effectively detected by the image processing technology. An individual visual cue or contextual information does not provide enough information to determine human fatigue.

A Bayesian network provides an effective way to deal with uncertainty and complexity. Through the research presented in this paper, a Bayesian network model was developed to fuse as many as possible contextual and visual cue information for monitoring human fatigue. The inference results, though preliminary, display the utility of the proposed framework for predicting and modeling fatigue.

In the near future, the dynamic and active structures of this Bayesian network model will be constructed and discussed.

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