ONLINE IDENTIFICATION OF DROWSY DRIVER USING EXPERT SYSTEM

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Abstract: This paper discusses the use of Expert System for identification of drowsy driver. To investigate the effectiveness of the usage of Expert System in identifying drowsy driver, a system consisting of data acquisition system and a Forward Chaining reasoning engine was developed in this study. The Knowledge Base (*KB*) for this system was developed based on previous study of drowsy driver. A KB development tool, the *Simple Expert System Development Tool (SESDT)*, was used to generate the rules. Altogether, the system that was developed in this study consists of 98 rules. The rules combines' effects from five parameters to identify drowsiness (time of driving, period of driving, head movement along Y-axis, steering wheel reversal rate and Percentage of Eye Closure (PERCLOS)). Preliminary results were promising and it was observed that The Expert System was able to sufficiently identify drowsy driver using the above reasoning engine and KB.

Keywords: Expert System, Drowsiness detection, Data acquisition

INTRODUCTION

Drowsiness detection is not a simple task because it involves a lot of parameter. Much research has been done to provide accurate detection. The concept of drowsiness detection involves sensing various driver-related and driving variables [10]. Most previous research [6, 9] on drowsiness is involved around finding suitable parameter or variable for drowsiness sensing. The main aim of this paper is to present the use of expert system as an online identification to drowsy driver. The driving variable or parameter is selected based on previous research. This paper highlights the technique to gather all information related to drowsiness and producing suitable result.

Expert system

Expert system is a computer program capable of performing at the level of a human expert in a narrow domain. Five basic component of expert system is the knowledge base, the database, the inference engine, the explanation facilities and the user interface. A rule base expert system has five components [12]:

- Knowledge base: contains the domain knowledge useful for problem solving. It also known as production memory and represented as a set of rule. The rules contained within knowledge based are called production rules and seen as a way of transforming a string of symbols into another string of symbols that understandable by the system.
- Database: include a set of facts used to match against IF (condition) parts of rules stored in the knowledge base.
- Inference engine: carries out the reasoning whereby the expert system reaches a solution. It links the rule given in the knowledge base with the facts provided in the database.
- The explanation facilities: explains the expert system reasoning to the user.
- User interface: communication between user and expert system.

Expert systems rely on logical inference and decision tree and focus on modeling human reasoning. Expert System treats human brain as a black-box. Knowledge in a rule base expert system is represented by IF-THEN production rules collected by observing or interviewing human expert. Human expert in this research is physiologists that study human fatigue and their behaviors to driving. Typical expert system is limited on knowledge acquisition task. The task is quite difficult and expensive. In addition, once rules are stored in the knowledge base, they cannot be modified by the expert system itself. In this paper, Simple Expert System Development Tool (SESDT) provides an expert system tool which is reliable and easy to be use. Knowledge in expert system can be divided into individual rules and the user can see and understand the piece of knowledge applied by the system. Although expert system cannot learn, it can explain on how it arrives at a particular solution.

MATERIALS AND METHODS

The basic idea behind vehicle based detection is to monitor the driver unobtrusively by means of an on-board system that can detect when the driver is materially impaired by drowsiness [10]. On-board detection would gather signal from sensors in the vehicle, process the signals into measures and then compute the algorithms to determine whether drowsiness threshold has been exceeded. Most previous research is emphasize on finding parameter or driving variable related to drowsiness. This is where the expert system plays its role, which is to provide algorithm that define drowsiness by examining all driver related parameter into one system.

SESDT is a tool to develop expert system KB. SESDT is simple graphical system to generate expert system. The development is base on decision tree structure. Figure 1 shows the development of knowledge base using SESDT.

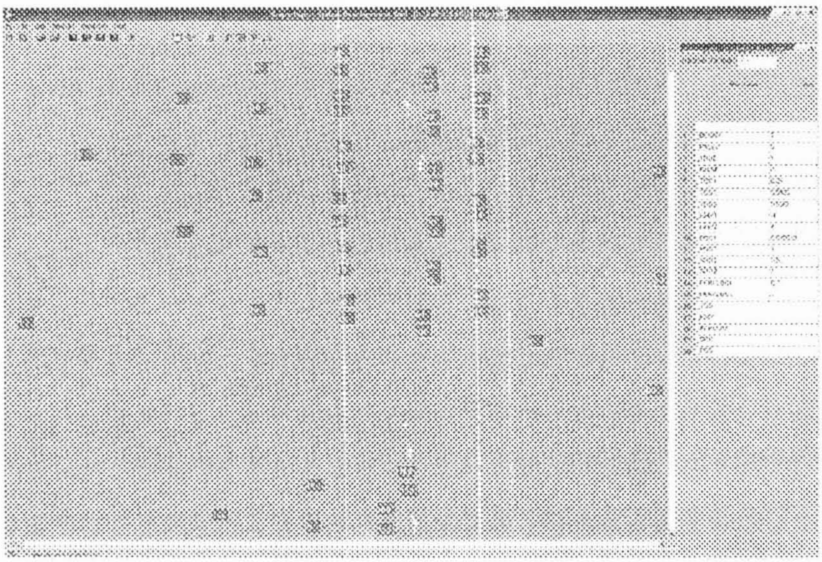


Figure 1: Knowledge Base Development using Expert System

Inference Engine

The expert system developed use Forward Chaining as a reasoning process. An element is linked to another element to generate a rule in form of IF <*antecedent*> THEN <*consequent*> until no path connects to the element. A rule can be made of a single element or a combination of more than one element. The elements are linked together with a tree like structure that propagates from a single initial condition to multiple conditions. Branching is based on how a condition at each element is fulfilled. The final element which contains the description for the final consequence can be identified as follow [7,8]:

$$F(N) = \begin{cases} true, \; if & \sum_{i=1}^{n_{\max}} G_N(i) \geq n_o \\ false, \; if & \sum_{i=1}^{n_{\max}} G_N(i) \leq n_o \end{cases}$$

Where, N = Connection to the next element
i = number of next element node
n_0 = initial value
n_{max} = maximum number of node

Rules generated due to the propagation through the elements can be defined as follow:

$$R_n = \begin{cases} R_{n-1} \cup C_n & if\ F_c(i) = -1 \\ R_{n-1} \cup r_{n,i} & if\ F_c(i) \neq -1 \end{cases}$$

$F_c(i)$ = Connection function to next element n
R_n = Cumulative rule arriving at n-th element.
$r_{n,i}$ = Rule at the i-th node of the n-th element.
C_n = Consequence at the n-th element.

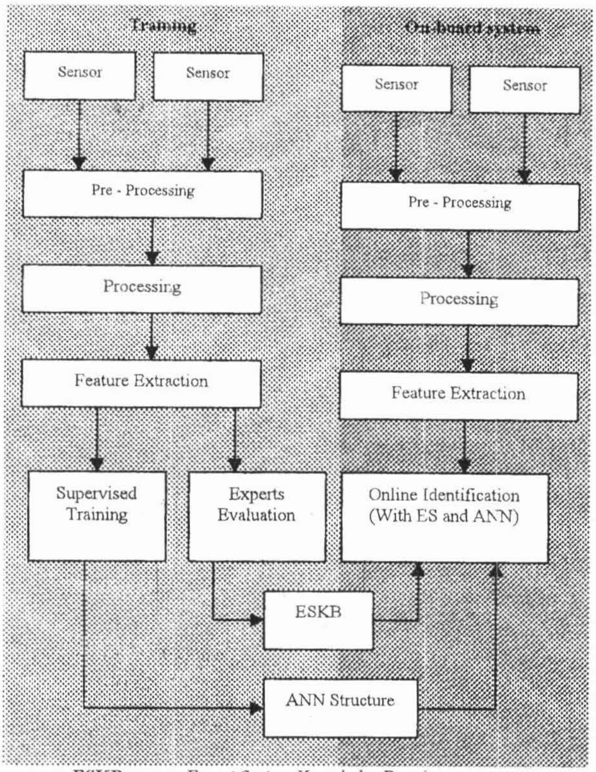
The reasoning process can be easily extended to increase the effectiveness of this framework. Rules are automatically generated from the decision tree created on SESDT. Current knowledge base contain total of 98 rules. Example is shown below. Each parameter value, for example (_HMY) can be changed in variable file (*.var). This value is base on previous studies done.

Rule : 1
IF _TOD < _TOD1 AND _HMY < _HMY1 AND _POD < _POD1 AND _SRR < _SRR1 AND
_PERCLOS < _PERCLOS1 THEN DL = 0.4
Rule : 2
IF _TOD < _TOD1 AND _HMY < _HMY1 AND _POD < _POD1 AND _SRR < _SRR1 AND
_PERCLOS < _PERCLOS2 THEN DL = 0.55
Rule : 3
IF _TOD < _TOD1 AND _HMY < _HMY1 AND _POD < _POD1 AND _SRR < _SRR2 AND
_PERCLOS < _PERCLOS1 THEN DL = 0.75

Figure 2: Rule generated using SESDT

Drowsiness Detection and Expert System

Expert system is embedded into Driver Fitness Monitoring and Training System (DFMTS) software. The system workflow is shown in figure 3 below. DFMTS is software use for training data and receives inputs (steering displacement, head movement, etc) and evaluates the driver's fitness accordingly using expert system. For onboard system, Driver Fitness Monitoring System (DFMS) was developed as an embedded application running on WinCE operating system.



ESKB Expert System Knowledge Based
ANN Artificial Neural Network

Figure 3: System workflow

Parameter Used for Drowsiness Detection

Five selected parameters were used to identify driver's drowsiness. The parameters are:

1. Steering Reversal Rate (SRR)
   Steering wheel reversal rate decreases as a function of time on the road or driver fatigue. Steering wheel reversal generally increased over time thus suggesting fatigue induced reduction in vigilance and decreased driver performance. The trend was frequently observed. High individual variability, however, was thought by the researchers to be the factor that limited the utility of this measure [2, 3, 5].

   During a long-duration simulator-based driving task, the number of steering reversals greater than two degrees increased while the numbers of small steering reversals (one-half to two degrees) were found to decrease [13]. Average steering reversal amplitude and standard deviation also increased over time. Fatigued drivers, therefore, are more likely to make fewer, more coarse corrections. Steering reversal rate is chosen as the main parameter extracted from the steering wheel for classification of drowsy driver.

2. Image Based Data
   Image based data was used extensively by researchers the world over in determining suitable parameters for drowsiness detection. Two image based data used in this study is head movement and eye blinking.

   - Head Movement
     A survey done by NTHSA in 2002 shows that 37% of the driving population have nodded off for at least a moment or fallen asleep while driving at some time in life [11]. 92% of driver admit have nodded of while driving that they startled awake. The percentage show that head movement data or head nodding is a valid indicator of drowsiness.

- Eye Blinking
  Eye parameters are reliable drowsiness indicator. It is represented in many ways. One of them is PERCLOS (PERcentage of eye CLOSure) .In previous studies. PERCLOS has been identified as valid monitor for drowsy driver. PERCLOS is percentage of eyelid closure over the pupil over time and reflect slow eyelid closure ("droops") rather than blinks. PERCLOS has three drowsiness metrics [4]:

Table 2: PERCLOS drowsiness metric

PERCLOS Metric	Definition
P70	The proportion of time the eyes were closed at least 70 percent
P80	The proportion of the time the eyes were closed at least 80 percent
EYEMAS (EM)	The mean square percentage of the eyelid closure rating

3. Time Of Day (TOD) and Period Of Driving (POD)
   Two exogenous parameters used in this study are time of driving and time of task. Driving performance is affected by TOD. This factor is due to the circadian cycle of human body. POD is considered as time taken on how long the driver has been driving without break On average, drivers will be able to drive for almost three hours before they nodded off [11]. Both parameters found to be linearly correlated to drowsiness.

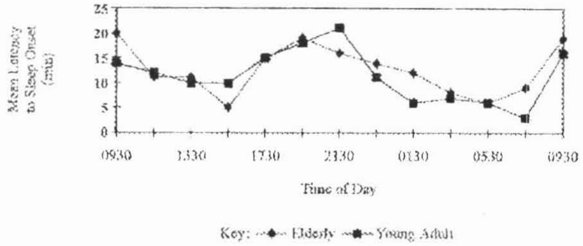


Figure 4: Time of Day factor (circadian cycle) [10]

All in all, the parameters below were used:

Table 3: Parameters use for detection

#	Parameter Name	Definition	Max. Value
1	PERCLOS	Percent Of Eye Closure	Total eye area
2	HMY	Head movement along y-axis	25% of face height
3	SRR	Steering Reversal Rate	360°
4	TOD	Time of driving.	a normalized function of drowsiness throughout the day
5	POD	Period of driving	1440 minutes (24 hours)

RESULTS AND CONCLUSION

Initial testing show that the expert system capable to work for training drowsiness detection. Expert system ability is dependant on the knowledge base created. Currently, we worked with psychology department to develop complete expert system that can precisely detect drowsiness driver. The system tested on simple simulator provided at Dynamic and Automotive Lab at the Department of Material and Mechanical Engineering, UKM. Figure 5 show current interface for training session and the simulator to test the system.

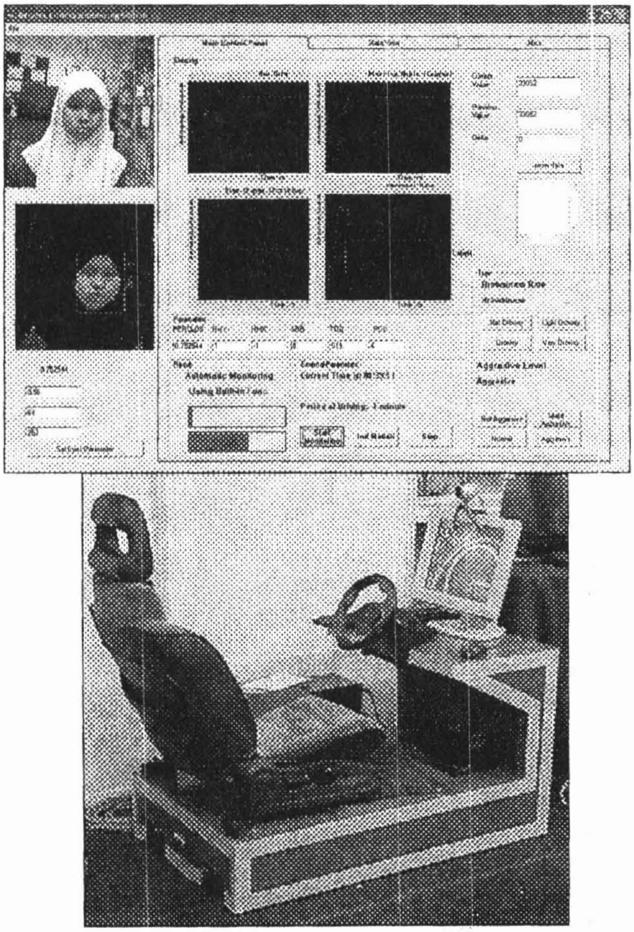


Figure 5: Interface of Training Session and it's simulator to test the system

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