Real-Time Non-Intrusive Driver Fatigue Detection System using Belief Rule-Based Expert System

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Abstract

This paper presents a non-intrusive system for detecting driver fatigue in real-time. To determine the level of fatigue the system uses various visual features, namely head nodding, eye closure duration and yawning. A state-of-the-art facial landmark detector 'IntraFace' has been adopted to determine the eye state, mouth state and head pose estimation. However, different forms of uncertainties such as vagueness, imprecision, ambiguity and incompleteness are involved in calculating these visual parameters. Therefore, a Belief Rule-Based Expert System (BRBES) is employed, which has the ability to handle the uncertainties. The information of the visual parameters is sent to BRBES as input to determine the level of fatigue. An optimal learning model has been developed to improve the performance and accuracy of the BRBES. A comparison between the system and the fuzzy rule-based expert system has been carried out. The system generates more effective and reliable results than the fuzzy rule-based expert system.

Keywords: Belief Rule Base, Driver Fatigue, Fatigue Detection, Expert System, Uncertainty

1 Introduction

Statistics show that traffic accident is one of the leading causes of death, and driver fatigue plays a vital role in most of the traffic accident [27, 7]. The US National Highway Traffic Safety Administration (NHTSA) has reported that from 2011 to 2015 total of 153,297 crashes and 166,990 fatalities occurred, where drowsy driving was responsible for 3,662 crashes and 4,121 fatalities [26]. In Europe, driver fatigue was involved in 10 to 20 percent of all road crashes [7]. Drowsy drivers often don't have any idea about the level of drowsiness of their own. It is a significant matter because it is not only dangerous for those who are driving but also for other road users. Therefore, a system is necessary, which can keep track of a driver's level of vigilance in real-time and can help to prevent road accidents.

Different approaches have been used to assess driver fatigue automatically. The existing systems can be divided into four categories based on physiological measures, vehicle characteristics, and directly

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noticeable visual characteristics and hybrid techniques [12]. The first category uses physiological signals such as electrocardiograph, electroencephalogram signals, pulse rate, etc. from the driver's body. Special sensors and instruments are set on the body of the driver to calculate the signals, which may be an inconvenience and obstructive to the driver. Therefore, the approaches in this category are intrusive. In the second category, different vehicle characteristics are involved, such as time to line crossings, movement of the steering wheel and lateral lane position to determine the driver's fatigue level. These approaches are non-invasive. But there are limitations because of the inexperienced driver, road conditions and types of vehicles, etc. During microsleep, on a straight road section, these systems do not work. The third category uses different visual characteristics observable from a driver such as slow eyelid movement, nodding, yawning, longer blink duration, the degree of eye-opening, etc. These approaches sometimes face challenges due to lighting, changing the background, vehicle vibration, etc. Hybrid approaches combine the techniques of the second and third categories for improving the sensitivity and reliability in fatigue detection. These approaches use the visual characteristics of the driver to measure his/her state. Then the gathered data of the driver's state is combined with the vehicle characteristics to determine the condition of the driver. However, among those approaches, the visual characteristics-based approach is a natural, non-intrusive and convenient to monitor driver's vigilance [11]. So, this approach has been considered in our system. But, in this approach, many factors appear with uncertainties like randomness, vagueness, ambiguity, incompleteness, imprecision, ignorance, as shown in Table 1. These uncertainties may arise due to vehicle vibration, various light conditions, frame drops, etc. These uncertainties may create problems to generate a reliable result. In the existing visual characteristic-based approaches, different methods have been used like knowledge-based systems, the Bayesian network, different types of machine learning techniques, and image processing techniques like skin color segmentation, etc. But these methods cannot handle the uncertainties.

As far as we know, no previous study has investigated the uncertainties involved in driver fatigue detection. However, the fuzzy expert system can handle uncertainties due to ambiguity, imprecision, and vagueness but not the others[3, 17, 14]. Thus, handling all types of uncertainties in driver fatigue assessment is still a challenging research domain. Belief rule-based expert system (BRBES) is a hybrid rule-based system based on fuzzy logic, Dempster-Shafer theory of evidence and decision theory. In BRBES, the IF-THEN structure is used for modeling rule bases, and the ER approach is used for inference. Traditional IF-THEN rules are not able to capture intricate causal relationships as well as uncertainties between different factors, but BRBES can do [4, 16, 28, 21, 13]. To capture uncertainties in data, several knowledge representation parameters such as rule weight, antecedent attribute weight and belief degrees are used. The robustness of BRB over other expert systems is that it is designed with belief degrees associated with all possible terms of a rule to capture the causes of uncertainty [30, 2, 18, 20, 25]. Therefore, the proposed system is designed and implemented using BRBES as it is capable of handling all types of uncertainties mentioned above [35].

The paper is arranged as follows: Section 2 presents a review of the existing approaches, Section 3 gives the overview of belief rule-based expert system, Section 4 describes the steps of the system including architecture and implementation of the system, Section 5 shows experimental results, Section 6 summarizes the work and discusses the future work.

2 Literature Review

The drowsiness of the driver shows different visual characteristics noticeable from the changes in the driver's facial features like the face, eyes, and head. In a visual characteristics-based approach, a different combination of parameters and different algorithms are used by researchers to find a solution to the drowsiness detection problem. The percent of closure (PERCLOS) of eyes of the driver has been mainly

Table 1: Uncertainty in driver fatigue assessment factors

Factors	Uncertainty Types	Reasons
Facial features detection	Vagueness, Ambiguity, Imprecision	Vehicle vibration, Various light conditions, Frame Drop
Yawning	Incompleteness,Vagueness	Hand on mouth
Eye Detection	Vagueness	Use of sunglasses or glasses

focused on researches among visual characteristics to assess the drowsiness of the driver [24, 23, 37]. It had been considered as the most dependable drowsiness detection technique among other techniques according to [29, 22, 8] and the Federal Highway Administration [10]. Some of the significant visual characteristics based approaches are summarized:

Zhang et al. [37] proposed a real-time fatigue detection scheme based on eye-tracking. They have used a nonlinear unscented Kalman filter for detecting driver's fatigue, where Haar algorithm is used to localize the driver's face. To extract the eyes from the image, different image processing techniques are used. The number of pixels around the eyes region is counted to detect eye closure.

Bergasa et al. [7] proposed a fatigue detection system for real-time monitoring of driver's attention based on six parameters: face position, eye closure duration, percent of Eye closure (PERCLOS), nodding frequency, fixed gaze and blinks frequency. A fuzzy classifier was used to combine these parameters to infer the level of drowsiness of the driver. And the system failed for drivers wearing glasses. Although a large number of parameters increases the accuracy of the system, the computational time is also increased, which is not bearable in real-time systems.

Flores et al. [12] used Viola-Jones object detector, cascade classifier and AdaBoost technique for localizing face and for face tracking, and a tracker has been executed using a neural network jointly with Condensation Algorithm (CA), which was used for tracking active contours. In the eye detection step, using the face anthropometric properties, the left eye rectangle (RL) and right eye rectangle (RR) are obtained. Finally, they have used an SVM classifier for determining the eye state.

Azim et al. [5] adopted multiple visual parameters such as yawning and eye closure to determine the level of drowsiness. First, the Viola-Jones face detection technique was used to locate the face. Then, using spatial fuzzy c-means (s-FCM) clustering a mouth window is extracted from the. In the next stage, Fuzzy Expert System (FES) is used to classify the actual state of the driver by analyzing the eye and mouth state information. The performance of the system is robust at night, but it decreases during the daytime, especially on bright days. And for users wearing glasses, the system did not work.

Vural et al. [31] used machine learning techniques to investigate facial gestures in fatigue periods. These facial gestures include eye-gaze, yawning, blinking gestures, arising eyebrow and other movements that are represented using the Facial Action Coding system (FACS) [6]. For units of each action, the SVM classifiers are trained by using a training dataset. Finally, AdaBoost and multinomial ridge regression are involved, and a comparison is carried out between them for the classification of the action unit outputs and to predict driver fatigue.

Abtahi et al. [1] proposed a new technique of using yawning for detecting driver drowsiness. They used several algorithms in their proposed approach, which are insensitive to geometrical facial features, skin types and various lighting situations. Although they have used eyes as verification criteria to avoid false detection, still the system is based on a single visual cue which is yawning. So, there is a chance

for system failure, if the system fails to detect mouth.

3 Belief Rule-Based Expert System

An Expert system has two main parts: the knowledge base and the inference engine. In BRBES, the knowledge base is constructed using a belief rule base. In contrast, the evidential reasoning approach is used as an inference procedure in which several steps are involved, namely input transformation, calculation of rule activation weight, updating belief degree and rule aggregation [35].

3.1 Knowledge Representation using BRB

The belief rule base is the extension of the traditional IF-THEN rule base. Traditional IF-THEN rules are not capable of capturing intricate causal relationships between different factors, but BRB is. The key elements of a BRB are the belief rules, including belief degree [15]. A belief rule consists of an antecedent part and a consequent part. The antecedent part contains single or multiple antecedent attributes including related referential values, while the consequent part contains a single consequent attribute. Various knowledge representation parameters namely rule weight, antecedent attribute weight, and degree of belief are employed for capturing the uncertainties involved in data. The following equation defines a belief rule:

$$R_k = \begin{cases} IF\ (P_1\ is\ A_{1k}^k) \cap (P_2\ is\ A_{2k}^k) \cap (P_3\ is\ A_{3k}^k) \cap \ldots. \cap (P_N\ is\ A_{Nk}^k) \\ Then\ \ \{(C_1,\beta_{1k}),(C_2,\beta_{2k}),(C_3,\beta_{3k}),\ldots.(C_N,\beta_{Nk})\} \end{cases} \tag{1}$$

With a belief degree β_{ik} ($\beta_{ik} \geq 0, \sum_{j=1}^{N}(\beta_{ik}) \leq 1$), a rule weight θ_k,and attribute weights (δ_{k1}, δ_{k2} , δ_{k3} ,.... δ_{kNk} $k \in 1,\ldots L$). Here, P_1, P_2, P_3, ... are the antecedent attributes of the k_{th} rule. A_i denotes one of the referential values of the i_{th} antecedent attribute P_i while C_i is one of the consequent reference values of the rule. $\beta_{ik}(i = 1,\ldots N, k = 1,\ldots.,L)$ is the degree of belief to which the consequent reference value is believed to be true. The k_{th} rule is said to be complete if $\sum_{j=1}^{N}(\beta_{ik}) = 1$. The rule may be incomplete due to ignorance or incomplete information, in that time the summation will be less than 1. The following equation is used to calculate the total number of rules:

$$L = \prod_{i=1}^{T}(j_i) \tag{2}$$

3.2 BRBES Inference Procedures

3.2.1 Input transformation

In this step, the input values of an antecedent attribute are transformed into a distribution of belief degrees of different referential values of that antecedent [35]. For example, there are three antecedent attributes in (1), with three referential values for each. The input values of the antecedent attributes are collected from input data, and the referential values of the antecedent attributes are considered as high (hi3), medium (hi2), and low (hi1). The degrees of belief of the input values to the associated referential values are determined by (3),(4). The calculated degree of belief or matching degree of the associated referential values corresponding to the all antecedent attribute is assigned to the rules. Then the rule is considered to be active, and it is known as packet antecedent of a rule.

$If\ \ h_{i3} \geq \sum i \geq h_{i2}$ Then,

$$\alpha_{i2} = \frac{h_{i3} - \sum i}{h_{i3} - h_{i2}};\ \alpha_{i3} = 1 - \alpha_{i2}\ and\ \alpha_{i1} = 1 - (\alpha_{i2} + \alpha_{i3}) \tag{3}$$

$If \;\; h_{i2} \geq \sum i \geq h_{i1}$ Then,

$$\alpha_{i1} = \frac{h_{i2} - \sum i}{h_{i2} - h_{i1}};\ \alpha_{i2} = 1 - \alpha_{i1}\ and\ \alpha_{i3} = 1 - (\alpha_{i1} + \alpha_{i2}) \tag{4}$$

3.2.2 Activation weight calculation

In this step, calculation of combined matching degree and rule weights are involved. Though a rule has single or multiple antecedent attributes, as shown in (1). Therefore first the combined matching degree must be determined in order to compute the rule activation weight. This can be obtained by employing a multiplicative function, [shown in (5)] that allows the incorporation between the antecedents of a rule [35].

$$\alpha_k = \prod_{i=1}^{T_k} (\alpha_i^k)^{\delta_{ki}},\ \delta_{ki} = \frac{\delta_{ki}}{max_{i=1,\ldots,T_k}(\delta_{ki})} \tag{5}$$

so that $0 \leq \delta_{ki} \leq 1$ where $\delta_{ki}(i = 1, ..., T_k)$ is the relative weight of ith antecedent attribute in the kth rule that can be obtained by dividing the weight of ith antecedent with the highest weight of all the antecedents. Here, $\delta_{ik} = 0$ is implying that the attribute which has no effect on the aggregation procedure, while $\delta_{ik} = 1$ denotes the significant effect. The activation weight (ω_k) of a rule indicates the corresponding significance of the rule in the BRB, which is calculated for each rule of the belief rule base using the predetermined matching degree by (6) as follows [35]:

$$\omega_k = \frac{\theta_k \alpha_k}{\sum_{i=1}^{k} \theta_i \alpha_i} \tag{6}$$

When $\omega_k = 0$ it implies that the rule has no effect in the belief rule base, while $\omega_k = 1$ denotes the significant effect.

3.2.3 Belief degree update

Uncertainties may occur during fatigue detection as discussed in Table 1 and input values of all the antecedent attributes may not be calculated. As a result, the summation of the degree of belief will be less than zero for a rule, which makes the rule incomplete. In this type of case, belief degree needs to be updated by using (7) [35]

$$\beta_{ik} = \bar{\beta_{ik}} \frac{\sum_{i=1}^{T_k} (\tau(t,k) \sum_{j=0}^{j_t} \alpha_{tj})}{\sum_{i=1}^{T_k} (\tau(t,k))} \tag{7}$$

3.2.4 Rule aggregation

In the calculation of the final belief degree β_j, the analytical ER algorithm is effective than recursive evidential reasoning to reduce the computational complexity. Hence, an analytical approach is used for rule aggregation as shown in (8) [35]

$$\beta_j = \frac{\mu \times [\prod_{k=1}^{L} (\omega_k \beta_{kj} + 1 - \omega_k \sum_{j=1}^{N} \beta_{kj}) - \prod_{k=1}^{L} (1 - \omega_k \sum_{j=1}^{N} \beta_{kj})]}{1 - \mu \times [\prod_{k=1}^{L} (1 - \omega_k)]} \tag{8}$$

with,

$$\mu = [\sum_{j=1}^{N} \prod_{k=1}^{L} (\omega_k \beta_{kj} + 1 - \omega_k \sum_{j=1}^{N} \beta_{kj}) - (N-1) \times \prod_{k=1}^{L} (1 - \omega_k \sum_{j=1}^{N} \beta_{kj})]^{-1}$$

The final output generated by ER is represented by $(C_1,\beta_1),(C_2,\beta_2),...,(C_n,\beta_n)$ where β_j is the final belief degree attached to the jth referential value C_j of the consequent attribute C, which is obtained after all activated rules in the BRB are combined by using ER. By assigning utility score to each referential value of the consequent attribute, this value can be transformed into a crisp value using the following (9) [35]:

$$y_m = \sum_{j=1}^{N} (u(C_j)B_j) \tag{9}$$

3.2.5 BRBES Learning Methodology

The parameters used for learning methodology are: consequent belief degrees, rule weights and attribute weights $(\beta_{i,k},\theta_i,\delta_i)$. These parameters can be gathered from domain experts, or it is possible to generate them for a BRB randomly. The parameters acquired from the trained BRB may not be 100% accurate using historical data for training [36]. The BRB learning module is developed with the aim of acquiring an optimal set of parameters $(\beta_{i,k},\theta_i,\delta_i)$, which will diminish the difference $\xi(P)$ between the Simulated output (y_m) and Observed output $\hat{y}_m$. The optimal learning model [35] for the fatigue assessment has been shown in Figure 1.

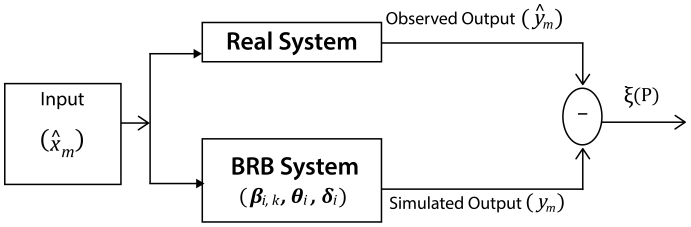

Figure 1: Optimal learning model

Following equation is used to reduce the difference $\xi(P)$

$$\xi(P) = \frac{1}{M}\sum_{m=1}^{M}(\hat{y}_m - y_m) \tag{10}$$

4 The Proposed System

The proposed system is based on the driver's visual characteristics and it integrates three facial expression changes: yawning, nodding and eye closing.

4.1 Detection and features extraction

To determine drowsiness through visual characteristics, we have considered the steps shown in Fig 2.

4.1.1 Image acquisition

In this stage video frames captured by the camera are broken into a stream of images. In such a manner, the video frames are taken so that driver's face is appropriately captured and observable visual features could be collected for fatigue analysis.

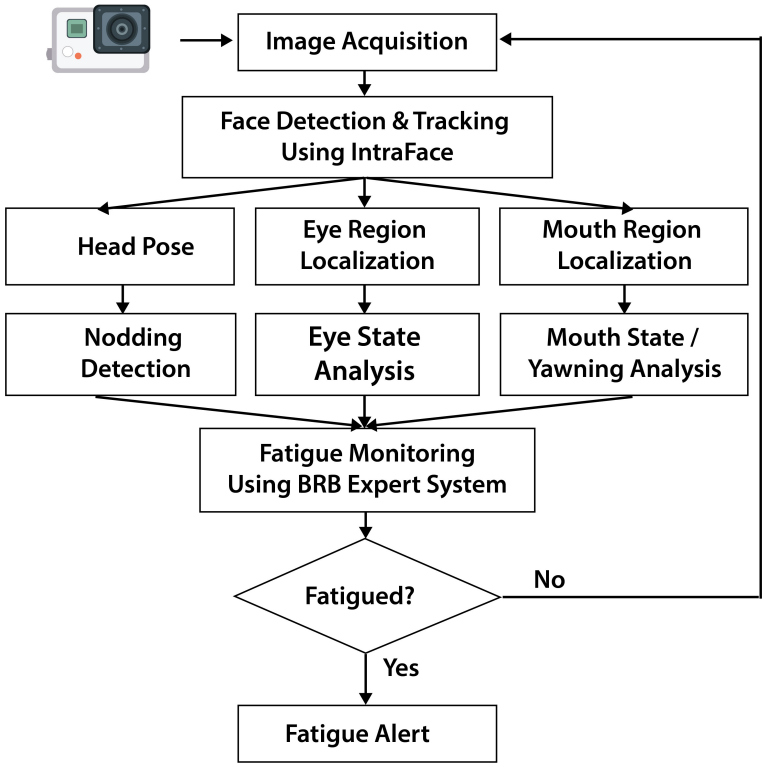

Figure 2: Flowchart of the system

4.1.2 Face detection and tracking

We have adopted IntraFace (IF), an open-source software package for automated facial feature tracking and analysis, and head-pose evaluation [9]. The process starts with extracting facial landmarks using an SDM tracker, and in the next stage, w.r.t. to scale and rotation, the image is normalized. After that, at each landmark HoG features are extracted and concatenated in a vector x. In the final stage, for each one of the attributes, a linear SVM classifier is learned. The attribute classifiers were trained using the PubFig dataset [33]. In IntraFace, the implemented landmark detector produces 49 (x, y)-coordinates that map to specific facial structures which are indexable, shown in Fig 3. So for extracting eyes and mouth region set of landmark indices are used.

4.1.3 Eye Region Localization

For each consecutive frame of a video sequence, the eye landmarks are detected by using *IntraFace* for further processing of the eye region. In order to access eye regions, we can use the set of landmarks (20-31), as we can see in the image in Figure 3. The right eye region can be accessed using the landmarks (20-25) and the left eye region can be accessed using (26-31).

4.1.4 Mouth Region Localization

The region of mouth is accessed through the points (32-49), as we can see in the image in Figure 3. By estimating the positions of these 16 landmark points, the mouth region is localized.

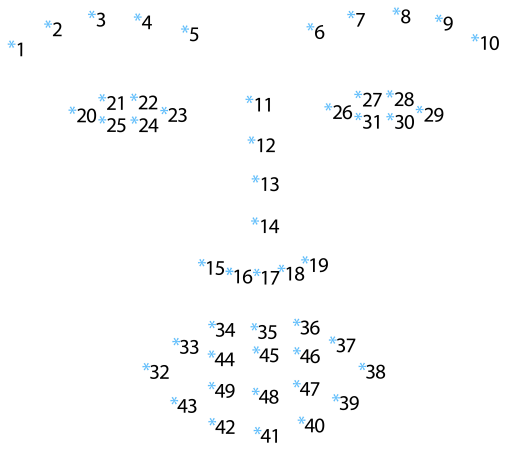

Figure 3: Facial landmark coordinates generated by IntraFace [32]

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4.1.5 Head Pose Estimation

Approaches of head pose estimation based on landmark seem to be considered straightforward. IntraFace [9] includes a head pose estimator which shows excellent robustness in estimating head pose in various head orientations, although no information on the underlying method is available.

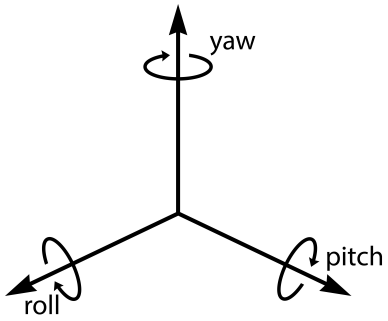


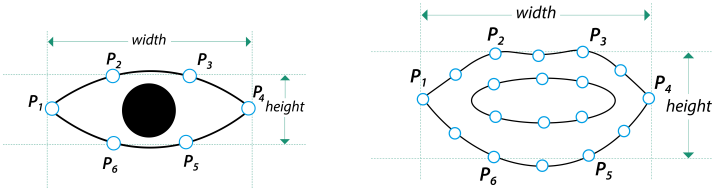
Figure 4: Head orientation in terms of pitch, roll and yaw movements.

4.1.6 Eye and mouth state analysis

We have used aspect ratio for analyzing the eye and mouth state for every frame through the landmarks. As shown in Figure 5, the formula of aspect ratio between height and width of the eye or mouth is computed by (11) where the distances between points p2-p6, p3-p5 and p1-p4 are calculated by using Euclidean distance. The distances of p2-p6 and p3-p5 are averaged and it gives the height of the eye and mouth, and the distance of point p1 and p4 gives the width of the eye and mouth.

$$AR = \frac{||p_2 - p_6|| + ||p_3 - p_5||}{2||p_1 - p_4||} \tag{11}$$

In the case of eyes, after calculating the aspect ratio of both the left and right eye, the average aspect ratio of the eyes is measured. From the measured aspect ratio of the eyes and the mouth, the state of the eyes and the mouth are categorized into three levels: open state, half-open state, and closed state based on previous studies.



(a) Eye (b) Mouth

Figure 5: Visualising aspect ratio of eye and mouth.

4.1.7 Nodding detection

Nodding is detected from the pitch rotation angel. When the nodding is forwarded, the pitch rotation angle is positively increased, and for backward nodding, the pitch rotation angle is negatively increased. Based on previous studies, the nodding state can be categorized into three-level, Normal, Medium, Extreme.

4.2 Driver state analysis using BRBES

The gathered information of eye state, mouth state and head rotation angel are passed to BRBES for further processing. The driver fatigue detection procedure using BRBES is described briefly in the following section.

4.2.1 Architecture and implementation

A system architecture can be defined how its components are organized. It is also essential to know the pattern of system organization, which is known as the architectural style. BRBES presented in this article follows three-layer architecture, consisting of the input layer, application layer and database management layer as shown in Fig 6.

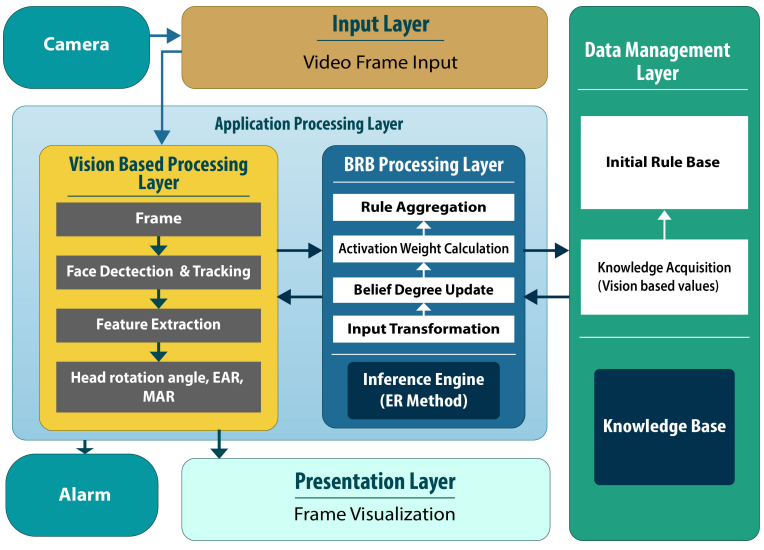


Figure 6: Layers of system architecture at implementation level

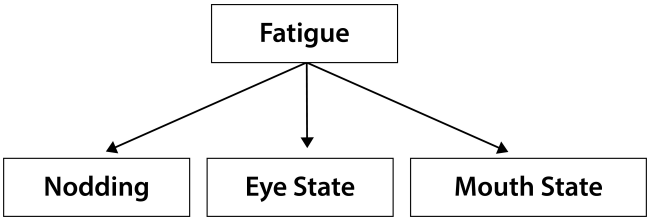


Figure 7: BRB hierarchical structure of fatigue assessment.

Table 2: A sample of initial belief rule base

Rule Id	Rule Weight	If driver condition			Then driver fatigue		
		Nodding	Eye State	Mouth State	High	Medium	Low
R1	1	Extreme	Open	Open	1	0	0
R2	1	Extreme	Open	Half-open	1	0	0
R3	1	Extreme	Open	Close	1	0	0
...	...	...	...	...	...	...	...
R25	1	Normal	Close	Open	0.8	0.2	0
R26	1	Normal	Close	Half-open	0.9	0.1	0
R27	1	Normal	Close	Close	1	0	0

4.2.2 Knowledge base construction in BRB

The knowledge-base development comprises building up a BRB tree by distinguishing the important antecedent and consequent attributes. Figure 7 demonstrates the single level BRB structure to measure driver fatigue. The leaf nodes and root node represent the antecedent and consequent attributes, respectively. In the proposed system, there are 27 rules in BRB, as it contains three antecedents with three referential values for each, that is calculated by (2). An example of such a rule is:

$$R_k = \begin{cases} IF\,(Nodding\ is\ medium)\ and\ (Eye\ aspect\ ratio\ is\ medium)\ and\ (Mouth\ aspect\ ratio\ is\ low) \\ Then\ Fatigue\ is\ \{(High,(0.8)),(Medium,(0.2)),(Low,(0))\} \end{cases}$$

There are several ways to develop BRB, such as by gathering expert knowledge, collecting data, using predefined rules and developing rules randomly having to previous knowledge [34]. In this study, the initial BRB has been developed by acquiring knowledge of previous researches. In BRB the rule weight for each rule and each antecedent attribute's weight is considered as "1". Table 2 illustrates the initial belief rule base of the BRBES.

4.2.3 Determining Driver's Fatigue Level using BRBES

After the information of eye state, mouth state and head rotation angle are gathered from the facial features; the values are passed to BRBES for further processing. As the maximum value of Eye Aspect Ratio (EAR) can vary from person to person, So adaptive thresholding is needed for computing the maximum value of EAR of the driver. An initial phase is considered where the EAR values of the first three hundred frames containing face are recorded. From the values of these 300 frames, the average of 150 maximum values is considered as a higher threshold for EAR. The minimum threshold value of Mouth Aspect Ratio (MAR) is also computed from the initial phase. The values of the EAR, MAR and head rotation angle are on different scales. Hence, the values are normalized to the scale of 0-to-1 before passing to BRBES as inputs.

As illustrated in Section 3.2 the inference procedure of the Belief Rule-based expert system consists of input transformation, activation weight calculation, belief degree update and rule aggregation using evidential reasoning. At the end of the inference procedure, BRBES generates a result based on the input values. For determining fatigue level, a large window of 30 consecutive frames is chosen. Because it was observed a window of 30 consecutive frames gives a more reliable result. So, when the output value lies within the range of high fatigue level for 30 consecutive frames, then a warning will be generated indicating the driver is in danger.

5 Experiments and Results

Driver drowsiness video dataset collected by NTHU Computer Vision Lab [32] was used to evaluate the proposed system, that contains video sequences of different ethnicities. The video sequences are recorded under various simulated driving scenarios with or without wearing sunglasses or glasses, under day and night illumination conditions. The video resolution is 640x480 in AVI format. The videos of sunglasses, glasses, no-glasses scenario were 30 frames per second and Night glasses, and Night no-glasses scenario was captured at 15 frames per second. From the training dataset, videos of 18 subjects were used to train the model. The performance of the proposed system was evaluated using the evaluation dataset containing 20 videos.

In the proposed work, IntraFace was used for detecting facial landmark coordinates. However, IntraFace fails to detect the driver's face in case of extreme nodding and when the driver is completely looking aside. In such scenarios, these frames are considered dropped. Table 3 shows the percentage of the dropped frame.

We have tested the system using the processed dataset. The fatigue level was categorized into three

Table 3: Overview of videos and frames

Category	No of Videos	No of Frames Extracted by IntraFace	Percentage of frames not detected by IntraFace
With glasses	36	103,131	13%
Without glasses	36	106,224	11%
Night with glasses	32	48,251	28%
Night without glasses	34	50,984	21%
With sunglasses	36	107,090	20%

levels: high, medium and low. The range of the fatigue level output was chosen between [0-1]. When the values are in the range of [0-0.4] then the fatigue level is low, the fatigue level is medium when the value is between [0.4-0.75] and the fatigue level is high when the value exceeds the 0.75 markups. Table 4 shows the sample values of different parameters for different fatigue levels.

Figure 8 shows the fatigue levels of a driver in different frames. Figure 9 shows the fatigue level of the driver observed by BRBES of 70 sample frames of a video sequence for different input levels.

In frames 1-12 the eye state is open, the mouth state is close, and the nodding is normal, as a result, the fatigue level is low. In 13-19 frames, the fatigue level is medium because during these frames the eye state is half-open, the mouth state is close, and nodding is normal, which shows that in these frames the eye state plays an important role. During 20-70 frames, the fatigue level is high when the eye state is half-open and close; mouth state is open, half-open and close, nodding is normal. In these frames, the eye state and mouth state influence the fatigue level most. To compare the accuracy and reliability of the proposed BRBES, we developed a fuzzy expert system (FES) for fatigue assessment in MATLAB

Table 4: Sample values of different parameters for different fatigue levels

Nodding	EAR	MAR	BRB Output	Fatigue Level
0.11	0.84	0.59	0.32	Low
0.15	0.87	0.98	0.54	Medium
0.11	0.86	0.15	0.25	Low
0.16	0.81	0.12	0.34	Low
0.85	0.11	0.18	0.94	High
0.18	0.16	0.89	0.89	High

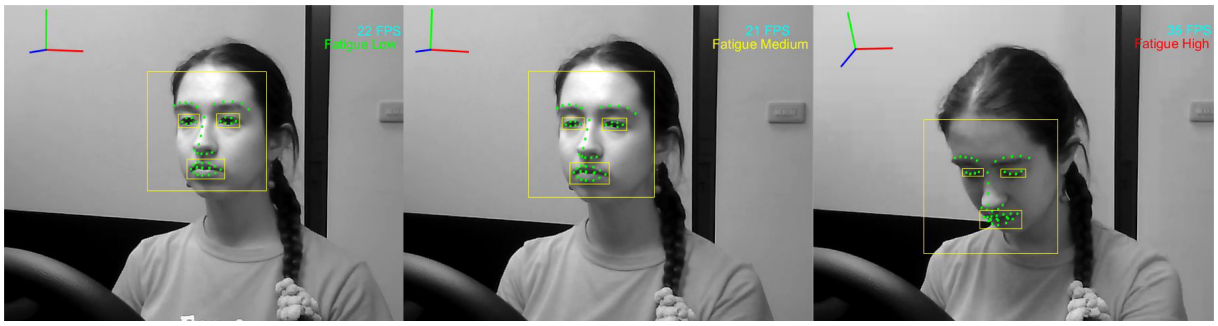


Figure 8: Visualizing the fatigue levels of a driver in different frames.

and tested it with the same data. Figure 10 shows the graphical representation of the output generated by BRBES and FES for 10 sample frames.

The results of the BRBES and Fuzzy expert system for different categories are compared with the result of the NTHU dataset by using the evaluation function provided by NTHU Computer Vision Lab. The accuracy of BRBES, fuzzy expert system(FES) and [19] are presented in Table 5.

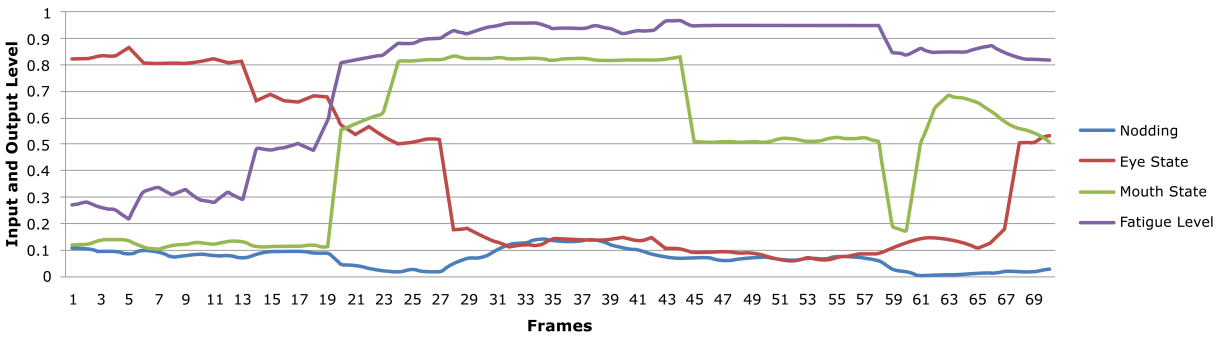


Figure 9: Fatigue level based on eye state, mouth state and nodding

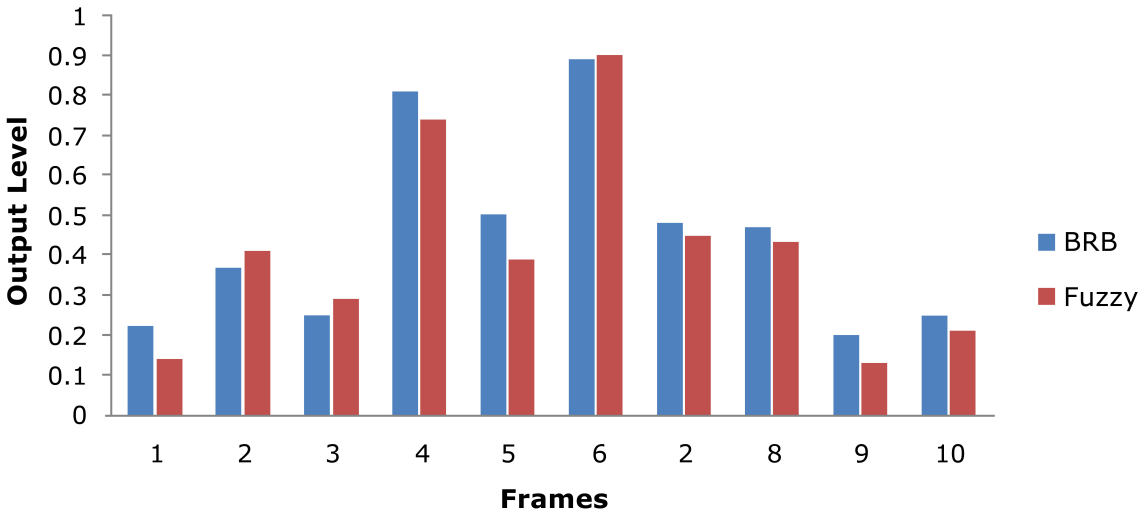


Figure 10: Fatigue output by BRBES and Fuzzy Logic.

Table 5: Accuracy per driving scenarios.

Category	BRBES	FES	[19]
With glasses	89.72	85.83	84.85
Without glasses	93.46	90.40	87.12
Night with glasses	82.35	78.23	76.15
Night without glasses	87.46	83.16	81.40
With sunglasses	75.54	74.65	75.12
Average	85.71	82.45	80.93

In [19], they obtained an accuracy of 80 by using Deep Neural Networks on the same dataset that we have used in our experiment. The proposed system was implemented on core i3, 2.4 GHz, 8GB RAM, Intel HD 4000 using the Matlab environment. The execution time of the BRB algorithm was 39.3 milliseconds.

6 Conclusion

This paper presents the design and implementation of a real time, non-intrusive driver fatigue detection system. During driver fatigue detection many factors appear with uncertainties like vagueness, ambiguity, incompleteness, imprecision that may arise due to vehicle vibration, various light conditions, frame drops,etc. Therefore, a Belief Rule-Based Expert System (BRBES) is employed, which has the ability to handle the uncertainties. The system uses three visual parameters of the driver: nodding, eye closure duration and yawning for assessing the level of driver fatigue. For detecting and tracking these parameters IntraFace (IF) is adopted in the system. After detecting and tracking, the system measures the condition of eye and mouth state (open, half-open, closed) by calculating the aspect ratio from the facial landmark values, and the condition of head-pose (normal, medium, extreme) from the pitch values. The measured information of input parameters is passed to the BRBES as input. BRBES categorizes fatigue into three levels: high, medium and low based on the inputs. At the end of the inference procedure, BRBES generates a result based on the input values. After performance evaluation and comparing the result of the proposed system with other techniques, it is proved that optimized BRBES is much more reliable and robust than other systems.

As far as we know, no previous study has investigated the uncertainties involved in driver fatigue detection. The significant aspect of the proposed system is that it can handle the uncertainties that may arise during driver fatigue detection.

In the future, there are specific improvements that can be made to the current system. It can be conceptually expanded to include more input factors of information such as measuring heart rate from the facial video, which will make the system more reliable. Driver distraction detection module can also be integrated with the system by analyzing head rotation while the driver is looking aside for a certain period. The proposed system was tested in the computer: on the collection of dataset videos which were recorded under the lab environment and in a controlled way. For future work, it would be better for the system to be tested with a real driving scenario in various light illumination conditions to reduce the false detection error in the real-time condition.

References

[1] S. Abtahi, B. Hariri, and S. Shirmohammadi. Driver drowsiness monitoring based on yawning detection. In *Proc. of the 2011 IEEE International Instrumentation and Measurement Technology Conference (IMTC'11), Hangzhou, China*, pages 1–4. IEEE, May 2011.

[2] F. Ahmed, M. S. Hossain, R. U. Islam, and K. Andersson. An evolutionary belief rule-based clinical decision support system to predict covid-19 severity under uncertainty. *Applied Sciences*, 11(13):5810, January 2021.

[3] S. T. Alharbi, M. S. Hossain, and A. A. Monrat. A belief rule based expert system to assess autism under uncertainty. In *Proc. of the 2015 World Congress on Engineering and Computer Science (WCECS'15), San Francisco, California, USA*, volume 1. Newswood Limited, October 2015.

[4] K. Andersson and M. S. Hossain. Smart risk assessment systems using belief-rule-based dss and wsn technologies. In *Proc. of the 4th International Conference on Wireless Communications, Vehicular Technology, Information Theory and Aerospace & Electronic Systems (VITAE'14), Aalborg, Denmark*, pages 1–5. IEEE, May 2014.

[5] T. Azim, M. A. Jaffar, and A. M. Mirza. Fully automated real time fatigue detection of drivers through fuzzy expert systems. *Applied Soft Computing*, 18:25–38, May 2014.

[6] M. S. Bartlett, G. Littlewort, M. G. Frank, C. Lainscsek, I. R. Fasel, J. R. Movellan, et al. Automatic recognition of facial actions in spontaneous expressions. *J. Multim.*, 1(6):22–35, September 2006.

[7] L. M. Bergasa, J. Nuevo, M. A. Sotelo, R. Barea, and M. E. Lopez. Real-time system for monitoring driver vigilance. *IEEE Transactions on Intelligent Transportation Systems*, 7(1):63–77, March 2006.

[8] M. S. Bhuiyan. Driver assistance systems to rate drowsiness: A preliminary study. In *New advances in intelligent decision technologies*, volume 199 of *Studies in Computational Intelligence*, pages 415–425. Springer, Berlin, Heidelberg, 2009.

[9] F. De la Torre, W.-S. Chu, X. Xiong, F. Vicente, X. Ding, and J. Cohn. Intraface. In *Proc. of the 11th IEEE international conference and Workshops on Automatic Face and Gesture Recognition (FG'15), Ljubljana, Slovenia*, volume 1, pages 1–8. IEEE, May 2015.

[10] D. Dinges and R. Grace. Perclos: A valid psychophysiological measure of alertness as assessed by psychomotor vigilance. us dept. transportation, federal highway admin., washington. Technical report, DC, Tech. Rep. Publication No. FHWA-MCRT-98-006 1998, 1998.

[11] Y. Du, P. Ma, X. Su, and Y. Zhang. Driver fatigue detection based on eye state analysis. In *Proc. of the 11th Joint Conference on Information Sciences (JCIS'08), Kaohsiung, Taiwan*. Atlantis Press, December 2008.

[12] M. J. Flores, J. M. Armingol, and A. de la Escalera. Real-time drowsiness detection system for an intelligent vehicle. In *Proc. of the 2008 IEEE Intelligent Vehicles Symposium (IV'08), Eindhoven, Netherlands*, pages 637–642. IEEE, June 2008.

[13] M. S. Hossain, A. Al Hasan, S. Guha, and K. Andersson. A belief rule based expert system to predict earthquake under uncertainty. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications*, 9(2):26–41, June 2018.

[14] M. S. Hossain, M. A. Hasan, M. Uddin, M. M. Islam, and R. Mustafa. A belief rule based expert system to assess lung cancer under uncertainty. In *Proc. of the 18th international conference on computer and information technology (ICCIT'15), Dhaka, Bangladesh*, pages 413–418. IEEE, December 2015.

[15] M. S. Hossain, E. Hossain, M. S. Khalid, and M. A. Haque. A belief rule-based (brb) decision support system for assessing clinical asthma suspicion. In *Proc. of the 2014 Scandinavian Conference on Health Informatics, University of Agder, Grimstad, Norway*, pages 83–89. Linköping University Electronic Press, August 2014.

[16] M. S. Hossain, A. A. Monrat, M. Hasan, R. Karim, T. A. Bhuiyan, and M. S. Khalid. A belief rule-based expert system to assess mental disorder under uncertainty. In *Proc. of the 5th International Conference on Informatics, Electronics and Vision (ICIEV'16), Dhaka, Bangladesh*, pages 1089–1094. IEEE, May 2016.

[17] M. S. Hossain, H. Sinha, and R. Mustafa. A belief rule based expert system to control traffic signals under uncertainty. In *Proc. of the 2015 International Conference on Computer and Information Engineering (ICCIE'15), Rajshahi, Bangladesh*, pages 83–86. IEEE, November 2015.

[18] R. U. Islam, M. S. Hossain, and K. Andersson. A deep learning inspired belief rule-based expert system. *IEEE Access*, 8:190637–190651, October 2020.

[19] R. Jabbar, K. Al-Khalifa, M. Kharbeche, W. Alhajyaseen, M. Jafari, and S. Jiang. Real-time driver drowsiness detection for android application using deep neural networks techniques. *Procedia computer science*, 130:400–407, January 2018.

[20] M. N. Jamil, M. S. Hossain, R. ul Islam, and K. Andersson. A belief rule based expert system for evaluating technological innovation capability of high-tech firms under uncertainty. In *Proc. of the Joint 8th International Conference on Informatics, Electronics & Vision (ICIEV'19) and 3rd International Conference on Imaging, Vision & Pattern Recognition (icIVPR'19), Spokane, Washington, USA*, pages 330–335. IEEE, May 2019.

[21] R. Karim, M. S. Hossain, M. S. Khalid, R. Mustafa, and T. A. Bhuiyan. A belief rule-based expert system to assess bronchiolitis suspicion from signs and symptoms under uncertainty. In *Proc. of the 2016 SAI Intelligent Systems Conference (IntelliSys'16), London, UK*, pages 331–343. Springer International Publishing, September 2016.

[22] R. R. Knipling. The technologies, economics, and psychology of commercial motor vehicle driver fatigue management. In *Proc. of the 8th Annual Meeting and Exposition: Transportation Technology for Tomorrow: Detroit Michigan, USA*, 1998.

[23] D. Liu, P. Sun, Y. Xiao, and Y. Yin. Drowsiness detection based on eyelid movement. In *Proc. of the 2nd International Workshop on Education Technology and Computer Science (ETCS'10), Wuhan, China*, volume 2, pages 49–52. IEEE, March 2010.

[24] R. A. McKinley, L. K. McIntire, R. Schmidt, D. W. Repperger, and J. A. Caldwell. Evaluation of eye metrics as a detector of fatigue. *Human factors*, 53(4):403–414, August 2011.

[25] A. A. Monrat, R. U. Islam, M. S. Hossain, and K. Andersson. A belief rule based flood risk assessment expert system using real time sensor data streaming. In *Proc. of the 43rd IEEE Conference on Local Computer Networks Workshops (LCN Workshops'18), Chicago, Illinois, USA*, pages 38–45. IEEE, October 2018.

[26] NATIONAL HIGHWAY TRAFFIC SAFETY ADMINISTRATION. Traffic safety facts. `https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812446`" [Online; accessed on November 10, 2021], 2015.

[27] W. H. Organization et al. Global status report on road safety 2015: World health organization, 2015.

[28] S. Rahaman, M. M. Islam, and M. S. Hossain. A belief rule based clinical decision support system framework. In *Proc. of the 17th international conference on computer and information technology (ICCIT'14), Dhaka, Bangladesh*, pages 165–169. IEEE, December 2014.

[29] J. H. Skipper and W. W. Wierwille. Drowsy driver detection using discriminant analysis. *Human Factors*, 28(5):527–540, October 1986.

[30] Z. Sultana, L. Nahar, N. Basnin, and M. S. Hossain. Inference and learning methodology of belief rule based expert system to assess chikungunya. In *Proc. of the 1st International Conference on Applied Intelligence and Informatics (AII'21), Nottingham, UK*, volume 1435 of *Communications in Computer and Information Science*, pages 3–16. Springer, Cham, July 2021.

[31] E. Vural, M. Cetin, A. Ercil, G. Littlewort, M. Bartlett, and J. Movellan. Drowsy driver detection through

facial movement analysis. In *Proc. of the 2007 IEEE International Workshop Human-Computer Interaction (HCI'07), Rio de Janeiro, Brazil*, volume 4796 of *Lecture Notes in Computer Science*, pages 6–18. Springer, Berlin, Heidelberg, October 2007.

[32] C.-H. Weng, Y.-H. Lai, and S.-H. Lai. Driver drowsiness detection via a hierarchical temporal deep belief network. In *Proc. of the 2016 Asian Conference on Computer Vision (ACCV'16), Taipei, Taiwan*, volume 118 of *Lecture Notes in Computer Science*, pages 117–133. Springer, Cham, November 2016.

[33] X. Xiong and F. De la Torre. Supervised descent method and its applications to face alignment. In *Proc. of the 2013 IEEE conference on computer vision and pattern recognition (CVPR'13), Portland, Oregon, USA*, pages 532–539. IEEE, 2013.

[34] D.-L. Xu, J. Liu, J.-B. Yang, G.-P. Liu, J. Wang, I. Jenkinson, and J. Ren. Inference and learning methodology of belief-rule-based expert system for pipeline leak detection. *Expert Systems with Applications*, 32(1):103–113, January 2007.

[35] J.-B. Yang, J. Liu, J. Wang, H.-S. Sii, and H.-W. Wang. Belief rule-base inference methodology using the evidential reasoning approach-rimer. *IEEE Transactions on systems, Man, and Cybernetics-part A: Systems and Humans*, 36(2):266–285, March 2006.

[36] J.-B. Yang, J. Liu, D.-L. Xu, J. Wang, and H. Wang. Optimization models for training belief-rule-based systems. *IEEE Transactions on systems, Man, and Cybernetics-part A: Systems and Humans*, 37(4):569–585, 2007.

[37] Z. Zhang and J. Zhang. A new real-time eye tracking based on nonlinear unscented kalman filter for monitoring driver fatigue. *Journal of Control Theory and Applications*, 8(2):181–188, May 2010.

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