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Driver Fatigue detection using Infrared sensor and Adaptive Neuro-Fuzzy Inference System

Hemasai K
Department of Electronics and Communication Engineering, Amrita School of Engineering, Coimbatore, Amrita Vishwa Vidyapeetham, India.
kumar.hemasai@gmail.com

Dr. Ramachandran KI
Center for Computational Engineering and Networking (CEN), Amrita School of Engineering, Coimbatore, Amrita Vishwa Vidyapeetham, India.
ki_ram.k@cb.amrita.edu

Adarsh S
Department of Electronics and Communication Engineering, Amrita School of Engineering, Coimbatore, Amrita Vishwa Vidyapeetham, India.
s_adarsh@cb.amrita.edu

Abstract — **This paper discusses a non-invasive and non-intrusive approach for driver fatigue detection.The fatigue condition of the driver is identified with the help of a trained neuro- fuzzy system mitigating the risk of a road accident. In this work, we have analyzed the facial temperature variations of the driver for estimating the level offatigue.Infrared sensor is used for acquisition of facial temperature of subjects and adjacent environment temperature changes. The temperature information of the subjects is segregated into facial temperature and environment temperature and is used for training the adaptive neuro fuzzy system. Therefore, the fuzzy system will provide a numerical output which helps in determiningthe fatigue condition of the subject under consideration. Hence the fuzzy system is well trained with all facial temperatures of the subject, fatigue is determined accurately.**

Keywords: fatigue, facial temperature, neuro-fuzzy system

I. INTRODUCTION

Currently, fatigue detection systems available in the market use vision cameras, electrodes and pressure sensors. In addition,the sensors which are used for monitoring EEG signals, electro-dermal activity and physical characteristics of the subject under driving conditions are proven to be either intrusive to the driver activity or increase self-consciousness of the drivers [1] [2]. Insufficiency of mental and physicalrest will increase fatigue,which leads to at least 60% of accidents of trucksand nearly 20% of all accidents, according to a report of The Royal Society for the Prevention of Accidents information (ROSPA)[3]. The National Highway Traffic Safety Administration (NHTSA) has estimated that 100,000 reported crashes are the direct result of driver fatigue annually [4]. The inability of the drivers to realize fatigue state, will increase the risk of accident involving both driver and passengers. This paper explains theuse of ANFIS, which analyzes the datasets of facial temperature of various subjectsfor test cases acquired at different time and period of the subject from IR sensor [5]. The combinations of the facial temperature datasets acquired will increase with respect to number of subjects under trial, duration and timing of the experiments. Certain assumptions like the positioning of the subject and fixed seating position (distance between sensor and face of the subject in a vehicle). Hence ANFIS is helpful in determination of driver fatigue state.

II. LITERATURE REVIEW

Hirokazu Genno *et al* (1997) analyzed facial temperature differences using thermistors [6]. At definite intervals of time, five stage stress loading experiments were conducted. Rest period is predefined at regular intervals. It is noted that the temperature of nose decreases with increase in duration of task (induce stress).The author validates fatigue with temperature changes due to variation in autonomic nerve activity in Fig.1.

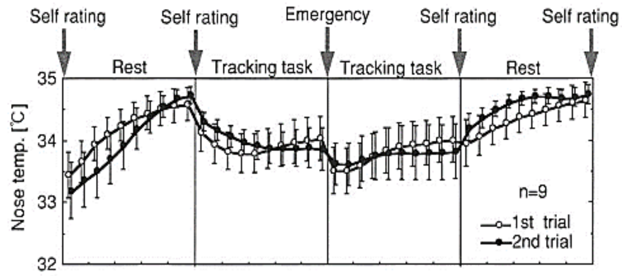


Fig. 1. Variation in skin and nose temperatures
(HirokazuGenno, Ryuuzi Suzuki & Masato Osumi. (1997))

Driver's mental workload is evaluated, for which driving like simulations are created [7]. Primary factorsanalyzed for detection of fatigueare the changes in facial temperature and electro dermal activity. The author attributes psychological stress (increase in vehicle speed in simulation) to onset of driver fatigue partially with the help of facial temperature variations. Psychological stress in terms of change in facial temperature, due to increase in speed of vehicle from average of 60 km/hand 180 km/h is represented in Fig. 2. with the changes in temperature (Δd) and time duration (t)

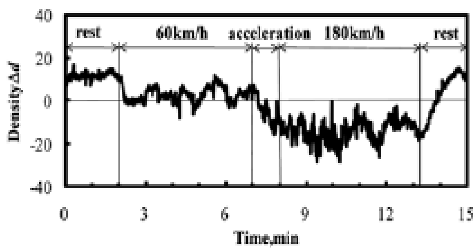


Fig. 2. Experimental result by driving simulator
(Kajiwara S (2013))

Joseph T Kider et.al (2011) have analyzed several fatigue factors like physical exertion and exhaustion of body.

Vasoconstriction, contraction of muscles, reduces blood flow to the muscles during intense motions, thereby decreasing the outer skin temperature of the body. Fig 3. shows the rate of change of body temperature both internally and externally

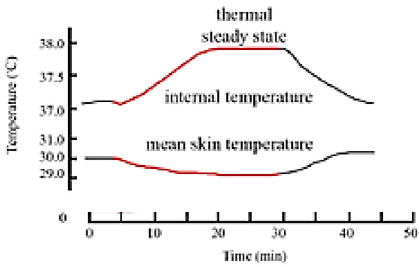
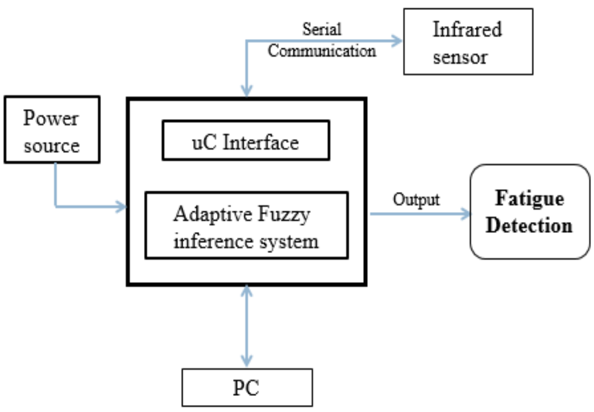


Fig 3 Temperature changes of the internal body and peripheral skin (Joseph T Kider(2011))

III. EXPERIMENT SETUP

Various types of subjects,15 numbers,were selected for observation, including male and female subjects of average age group of 25 years. The information of the subjects is noted

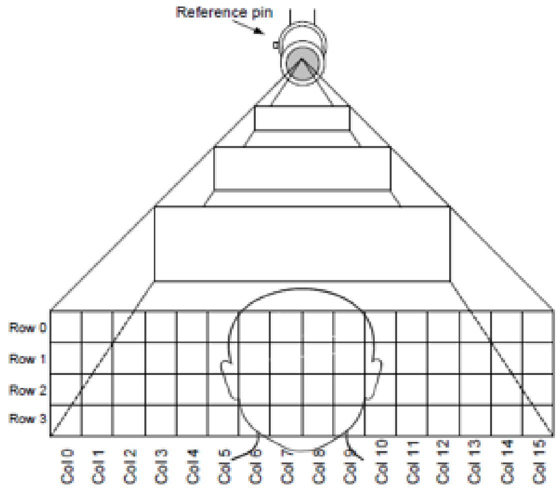


before the recording of the temperature data (current conditions i.e., Fatigue or non-fatigue).A schematic of the setup is shown in Fig 4.

Fig 4 Schematic layout of the experiment

A. Sensor setup:

In the experiment, Infrared sensor MLX90621is used to obtain temperature information. The sensor is a digital active thermopile array of 16x4, and each pixel of the array measures the average temperature of all objects in its own Field Of View (called nFOV). Fig. 5. shows a 3-dimensional representation of the field of view. A small reference pin of the sensor provides information for placement of the sensor [9]. The average distance between the driver and the sun visor is approximately 300 mm. So the placement of sensor is ideal if it is placed near the visor in order to obtain the facial temperature of the subjects. Hence for an experimental setup the sensor is placed at



a nominal height (y-axis) and distance (x-axis). In addition to the placement of sensor, a face resting support is used which is adjustable according the subject height. Thereby the sensor is fixed and the face support is variable in y-axis only.

Fig 5. Field of view of the sensor

MLX90621 comprises four pins namely ground (GND), power (VDD), serial clock (SCL) and serial data (SDA). The VDD and GND forms the power rails of the sensor, SCL and SDL forms the communication with the controller. The functional block diagram of the digital thermopile array is shown in Fig. 6. The sensor has an inbuilt memory and communication provision.

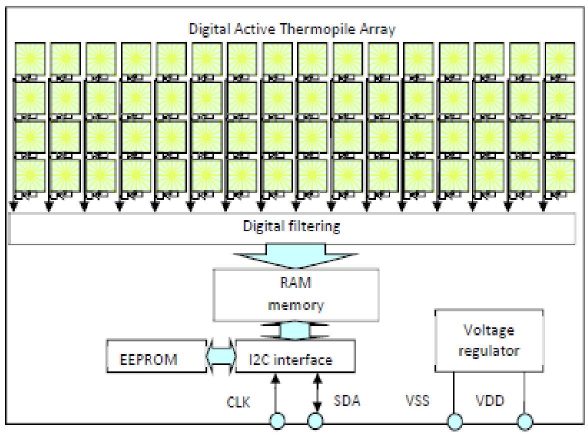


Fig 6.Functional block diagram of MLX90621

B. Hardware circuit:

MLX90621 requires supply voltage of 2.6V to 3.2V, the device is calibrated and performs best at VDD=2.6V and 5mA.Arduino Uno controller is used as interface between the sensor andsystem. LM317 voltage regulator is used to control the supply voltage to the board.LM317 provides an output range of 1.5V to 3.7Vwith the help of an adjust pin by controlling the supply of voltage. The voltage is regulated using two resistors whose specifications are calculated using voltage divider rule of the regulator.The power supply for the sensor through Arduino board should be made constant without any fluctuation. Since the A4 and A5 pins Arduino are the analog pinscorresponding to the I2C communication, the SCL and SDL pins are connected with A4 and A5 respectively.Pull up resistors are used to make the output of MLX to active high from active low [10].The circuit is placed at a distance as the heat generated from the circuit affects the calibration and working of the sensor.

C. Conversion of sensor output:

The internal RAM of the sensor stores the output values of 64 IR pixels, aided by an analogue to digital converter. The values stored in internal RAM is accessed by I2C bus, SCL and SDL pins of Arduino is used for it. The output available (64 pixels) is obtained as 16x4 columns and row sequentially. Through I2C communication the Arduino is programmed to provide the output of the sensor in a serial monitor of the Arduino software as shown in Fig.7.

```
14  15  19  20  20  24  24  25  26  25  22  24  24  23  21  23   0
14  19  21  23  22  24  28  29  28  28  28  27  26  26  27  22   1
14  20  20  21  22  24  26  26  29  29  24  23  22  24  21  20   2
13  16  19  21  21  23  24  28  26  25  25  24  21  25  23  21   3
```

Fig.7. Output of the sensor in a serial monitor

The data of a single cycle is converted into datasets, usable for training of Fuzzy logic controller. Firstly, the data is separated into three columns of A, B and C. Secondly the temperature readings of the individual columns are averaged independently. This average is stored as values in individual cells. The ambient temperature of the sensor acquired is also stored in line with the temperature readings of the subject. In most cases column B is of our primary interest as this contains the average of the facial temperature information of the subjects. Column B corresponds to the center area of field of view of the sensor, where the subject head rests for entire duration of the experiment. Fig.8. shows the processing of the sensor output.

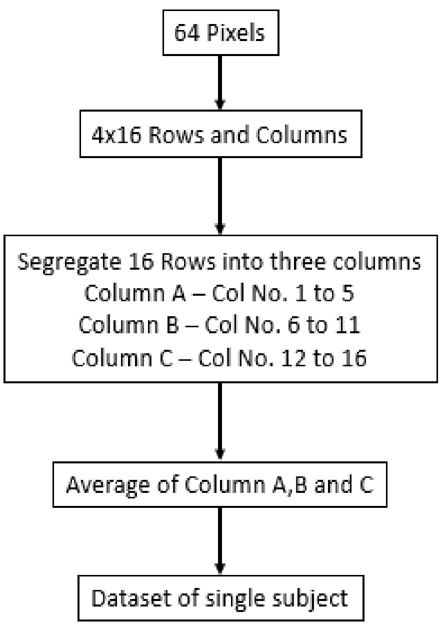


Fig. 8. Processing of sensor output

Each individual pixel is combined in anyone of the columns. So each single row of the dataset contains three average temperature value and one ambient temperature value of the sensor.

D. Labelling of Datasets:

A vital step of the experiment is to label the dataset appropriately based on the input from the subject. This step is completely dependent on the subject's response. The readings are taken at different duration of the day and different period of time across various subjects. A 0 is assigned to the dataset if the subject is having fatigue and 1 is assigned if the subject having no fatigue. Table 1 is a representative of a single line of dataset, all temperature details are mentioned in degree Celsius.

TABLE I. Part sample of dataset

A	**B**	**C**	**Ambient**	**Fuzzy O/P**
24.06	30.28	23.91	29.23	0 or 1

Two type of trials are conducted for datasets, these datasets are compiled for training of the same in ANFIS, which are

a) Trial A - Multiple subjects under fatigue and non-fatigue condition (15 subjects - shorter durations).
b) Trial B - Single subject for longer durations.

The readings of the subjects are compiled based on the type of trial into any one of the above mentioned categories.

IV. ANFIS DESIGN:

A well designed Adaptive Neuro-Fuzzy inference system provides the desired numerical value output based on the correlation between inputs and training of fuzzy system with available datasets [11]. Fig. 9. explains the neuro fuzzy designer data flow.

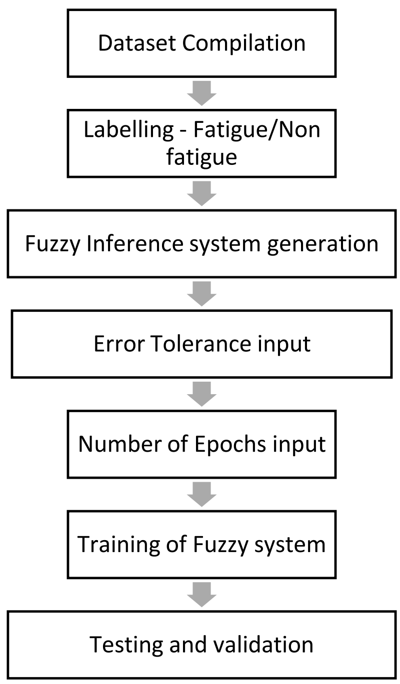


Fig. 9. ANFIS design data flow process

Using MATLAB ANFIS suite, selectingsugeno method and selecting training data, input of all compiled data is loaded to the fuzzy inference system, either as a file (any format supportable by ANFIS) or from MATLAB workspace.A triangular membership method is used with four number of inputs and one output an FIS is created. Totally three membership functions are generated for each input. The Fuzzy rule generator will generate predefined rules taking the training data into consideration for the FIS. In total 81(3^4numbers) rules are generated within the FIS structure, since 4 inputs with 3 membership functions for each input. The Fuzzy rule generator will assign a range of values for each input. Hence for each input, the range of input varies with each rule, where the combination of rules are as follows starting the combination from {1 1 1 11}, {1 1 1 2 2}, {1 1 1 3 3}, {1 1 2 1 4} ….{3 3 3 3 81}.Fig. 10. shows the Fuzzy system

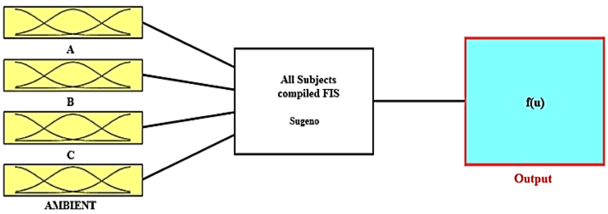


Fig 10. Sugeno type Fuzzy system

The training for FIS is completed after setting the number of epochs and error tolerance of the FIS generated. The total number of iterations for the training depends on the number of epochs provided prior to the beginning of training of FIS. Fig. 11 is an image of the plot of the number of epochs against the training error of the FIS structure generated for the Trial A data of first set of cross validation in neuro fuzzy designer suite of MATLAB environment.

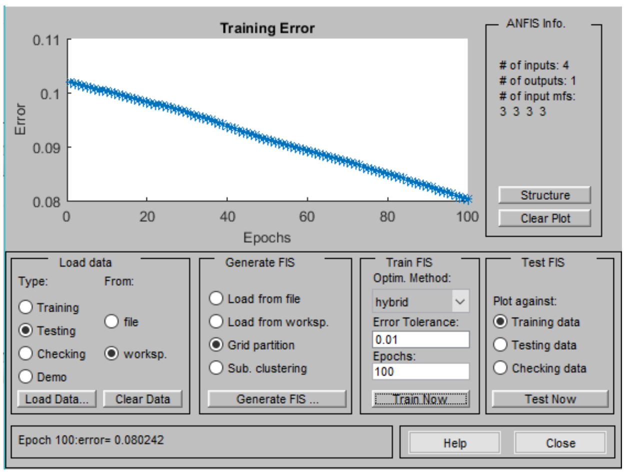
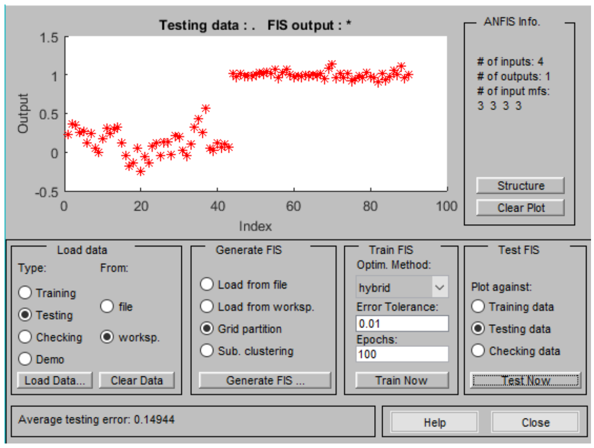


Fig. 11. Number of epochs vs error for training data

The Fig.12. shows the plot of number of epochs against error of the testing data of the first fold of crossfold validation of Trial



A, which also shows average testing error of the FIS as 0.149.

Fig. 12. Number of epochs vs error for testing data

V. TESTING AND VALIDATION OF ANFIS:

The fuzzy inference system created is evaluated inMATLAB environment. The serial monitor output isobtained andconverted in MATLAB workspace for validating the FIS structure. A tenfold validation is done by cross validation method.The cross validation are done by partitioning first 10 percent of data for test and remaining for training and are validated. Next 10 percent data will be partitioned as test data and remaining as training data. Numerical outputs of the FIS, with range from 0 to 1, is then processed further for accuracy calculation. The output values are rounded off to either 0 or 1, with 0.5 value being non deterministic value. A confusion matrix (error matrix) is created for testing accuracy of the output obtained through the FIS [12]. The confusion matrix has four classes like

a) True Positive – Subject is fatigue and system output calculated to 1
b) False Positive – Subject is not fatigue but system output calculated to 1
c) True negative – Subject is not fatigue and system output calculated to 0
d) False Negative – Subject is fatigue but system doutput calculated to 0

The validated sample sets from the output is shown in Table 2. with segregation of output values with comparison between actual and predicted value

TABLE 2. Sample set classification after threshold

A	B	C	Ambient	Actual	FIS O/P Prediction	After threshold	Classification
27.19	31.30	27.82	34.22	0	0.132	0	TN
25.56	30.02	27.42	32.17	1	1.083	1	TP

VI. RESULTS:

Totally 1000 readings for Trial A and 7500 readings (longer time period) for Trial B are used with 10 percent cross fold validation. Confusion matrices are generated for ten-fold cross validation is done for both trials, multiple subject trial and single subject trial. The Table3.shows the training and testing error rate of the FIS generation in MATLAB.

TABLE 3. Testing and Training error of the FISs generated

FIS	FIS of Trial A		FIS of Trial B	
	Training error	Testing error	Training error	Testing error
FIS 1	0.080	0.149	0.176	0.518
FIS 2	0.059	0.249	0.135	0.485
FIS 3	0.068	0.212	0.167	0.491
FIS 4	0.079	0.100	0.192	0.228
FIS 5	0.077	0.623	0.174	0.328
FIS 6	0.080	0.069	0.184	0.279
FIS 7	0.077	0.400	0.192	0.198
FIS 8	0.078	0.104	0.185	0.270
FIS 9	0.080	0.090	0.194	0.195
FIS 10	0.067	0.276	0.178	0.280

After applying threshold for the output of the ANFIS, the averages of accuracy of all confusion matrix is calculated for both trials as follows

Accuracy of fatigue detection in Trial A – 97%.

Accuracy of fatigue detection in Trial B – 94%.

VII. CONCLUSION AND FUTURE DIRECTIONS:

In this study, a system of infrared sensor coupled with ANFIS is used to identify the driver fatigue. The ANFIS system developedcorrelates the subject's facial temperature, environment temperature and the ambient temperature, and provide appropriate result with good accuracy. In future ANFIS can be trained to identify fatigue, with help of many other input parameters like the image of face, the rate of eye movement and the blinking of eye for further analysis in order to provide a robust and fail-safe fatigue detection system.

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