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Review of Driver Behavior Detection Methodologies in VANET

S. Cloudin[1], Dr. P Mohan Kumar[2],
KCG College of Technology[1],
Jeppiaar Engineering College[2],
Chennai, India.

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Abstract

Intelligent Transport System (ITS) strives towards improving the road safety by adopting predictive and corrective measures to ensure the same. Many researchers and statistical reports of road transport authorities claim that the mistakes of drivers are the prominent reason for road accidents and the loss of life of the human beings. As a result many authors proposed different methodologies to predict the behavior of the driver while driving. The level of drowsiness of the driver has strong influence over the level of alertness and most of the prediction methodologies focus towards the detection of drowsiness level of the driver. Not only the drowsiness, there are few other factors like distraction of the driver such as talking over cell phones, tuning radios etc. are also the cause of mishaps on the road. The future transportation system aims towards automated driverless vehicles to be operated on the roads. The vehicle must build with an intelligent decision making system to adopt with the behavior of the nearby vehicles. Vehicular Adhoc Network (VANET) provides a backbone for the implementation of ITS and it aims to maintain a seamless network connectivity among the vehicles on the road and the network behavior also influenced by the driving behavior of the driver. Detailed research in the area is required for the accurate prediction of driver behavior and appropriate decisions to be taken quickly to avoid accidents. This paper discusses and gives an insight into on the prediction methodologies of human behavior and this paper explores the research avenues for the new researchers in the area of prediction of driver behavior to improve the road safety.

***Key Words*: VANET, ITS, Driver Behavior**

1 INTRODUCTION

Intelligent transportation system (ITS) aims to provide innovative services to ensure the road safety. The system supports the road users by providing an information and control mechanism on traffic management, which ensures the safety and coordination among the vehicles on the road. It relies on information and communication technologies applied in road traffic management. Vehicular Ad Hoc Network (VANET) form communication among fast moving vehicles on the road to offer safety services. This network comes under the category of the distributed and self-organizing Dedicated Short Range Communication (DSRC) system developed upon the family of IEEE 802.11 standards. In general, the coverage range of VANET is approximately 100 to 300 meters. This kind of network on the road supports ITS to accomplish its goals of reducing road accidents, distribution of traffic load to reduce congestion in road, driver assistance and infotainment. It broadly supports accurate decision making by the prediction of the factors influence the road safety. ITS requires the VANET to establish different possible ways of communication architectures. (1) Vehicle-to-Vehicle (V2V), does no require any physical communication infrastruecture to establish multi hop wireless communication between the moving vehicles on the road,(2)Vehicle-to-Infrastructure(V2I), makes use of road side infrastures as access point, to create connectivity between the vehicles and to establish communication between vehicle and other networks such as cellular networks, WiMax ,WiFi. (3) Hybrid architecture, combines both V2V and V2I to create a communication to cover long distance, normally used in the highways, where the density of vehicles is low comparing with city scenario. Establishment of direct wireless communication between fast moving vehicles on the road ensures the exchange of data between them even in the absence of any previously deployed communication infrastructure like road side access points and base stations[1].Fast moving vehicles on the road changes its position rapidly and keeps the network topology more dynamic. The movement pattern of vehicles constitutes the mobility model [2] which mimics the traffic scenario on the road and it plays a vital role in the evaluation of the performance of the network. Number of lanes, traffic signals, speed regulations, diversion, obstacles, direction of movement, traffic jam in road junctions and behavior of the driver are few of the parameters effect the mobility scenario of the network.

It is the fact that erratic behavior of the driver is the major cause for road accidents. Mistakes of drivers like diversion due to distraction and lack of concentration due to sleepiness causes serious problem of number of road accidents. Many times, continuous and sleepless driving will make drivers fatigue and drowsy and it diminishes the alertness level of drivers. The motivation for our research is to support the Intelligent Transport System (ITS), which strives for accident prevention system, to predict the erratic behavior of the driver accurately and to disseminate warning messages to the nearby vehicles and to take appropriate actions to avoid accidents.

2 DRIVER BEHAVIOUR DETECTION

In general, the driver behavior detection methodologies are classified as follows: (1) Ocular measure, the detection mechanism based on eye blinking rate, pupil response time, eye closure and eye movement frequencies (2) Bio behavioral notations, a measure based on the expressions on facial muscles, variations in body postures, mouth and yawning analysis and head movements (3) Driver physiological analysis which measures the health parameters of the driver such as heart rate and pulse rate using Electroencephalogram (EEG) and measure of brain waves using head band device (4) Vehicle Parameter measurement analysis in which the movement of streeing wheel, keeping the lane, movement of acceleration pedal and braking are considered.

Saif Al-Sultan [3] presented a work which focuses on developing a novel and non-intrusive driver behaviour detection system for Intelligent Transportation System (ITS). This system uses a context-aware system in VANET to detect abnormal behaviours exhibited by drivers, and to warn other vehicles on the road so as to prevent accidents from happening. A probabilistic model based on Dynamic Bayesian Networks (DBN) for real time inferring four types of driving behaviour (normal, drunk, reckless and fatigue) by combining contextual information about the driver, vehicle and the environment is presented.

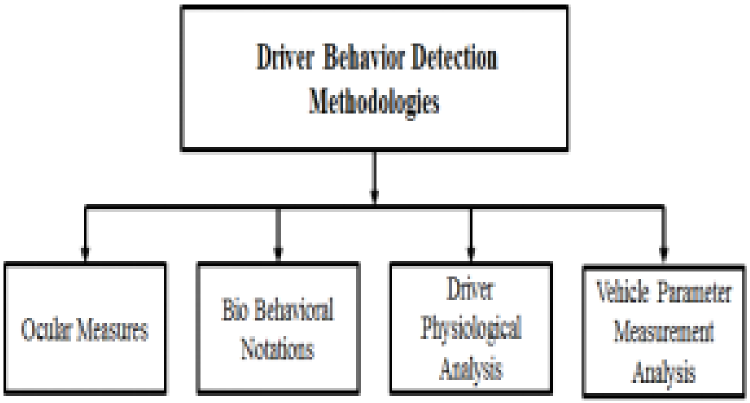

Figure 1 Driver Behavior Detection Methodologies

3 OCULAR MEASURES

The ocular measure is mainly focusing towards the eye state analysis in which standard templates for 'eye open' and 'eye closed' are maintained in the database. The driver will be given an alert if the online measure varies from the stored template. The level of fatiguness and drowsiness is measured by eye blinking analysis, by means of measuring the frequency of eye blinking. It is the fact theat level of eye blinking frequency will be high, if a driver feels drowsy or sleepy due to tiredness.

Taner Danisman et. al. [4] proposed an eye blink pattern using image processing technique. the region of interest on eye pupil image has been divided into two partitions as lower and upper parts subject to a threshold value. The symmetry property is used to discriminate between the closed eyes and normal eyes. Since the pupil of the eye is circular in shape, the open eye pattern normally exhibits a property of horizontal symmetry. But this property will not be explosed when the eyes are found closed.

Jaeik Jo et. al. [5] proposed a system for detecting the drowsiness of the driver using feature level fusion and classification of user specific patterns. First step on this approach was face and eye detection and tracking, in which the detection methods like Adaboost and Blob were used for face and eye detection, and adaptive template matching methology was used for face and eye tracking. Then the eye valtidation was done using Support Vector Machine (SVM) classifier based Principle Component Analysis (PCA) and Linear Discriminant Analysis (LDA). In the second step, the eye state classification was performed using SVM classifer and Maximum a Posteriori (MAP) classfier which is a user spefiic classification methodlogy. Finally the decision on the drowsiness was taken based on the measuring parameters like PERcent eye CLOSure (PERCLOS) and Eye Closure Duration (ECD) combined with the user specific pattern of normal blinking based on 2D Gaussian PDF.

Mehrdad Sabet et.al [6] proposed a system for the detection of drowsiness and distraction of the driver in which the Adaboost methodology was used for the eye state detection. SVM classifier was used in this methodology to analyse the state of the eye. After the detection of the status of the eye, the eye characteristcs were extracted using Local Binary Pattern (LBP).

Boguslaw Cyganek et.al [7] proposed a hybrid system to recognize the state of eyes of driver and to monitor the level of fatiguness of the driver. In this methodology, the eye detection was performed using Near Infrared Images (NIR) using nonlinear filtering, pupil detection, iris detection and eye region hypothesis verification. The eye methodology was designed to fit into the NIR image processing specifications. Then the eye detection was performed in the visible spectrum to detect the status of the eyes in colour images. The eye candidate regions were detected first and then refined using higher-order singular value decomposition (HOSVD) classifier by which the prototype patterns related to the daioy normal light conditions are trained. Finally the the cascading of the eye classification chain with geometrically deformed prototypes of eyes was performed and for each pattern of prototype, a tensor is obtained.

Schmidt et. al [8] proposed a driver assistant system by monitoring the state of the driver during conditionally automated driving (CAD). In conditionally automated driving (CAD) the driver no need to observe the environment and react accordingly. The framework was based on the analysis of the drivers eye closure and head movements provided by a driver observation camera. Driver observation camera was used to detect the eye closure and head movements of the driver and the input data was further analysed. In the scenario of CAD, unlike manual driving, closed eyes are not the direct indicator of drowsiness, since closure of eyes might be due to relaxation. To ensure the alertness of the driver during CAD, together with a short acoustical indication a visual alert was displayed in the central console. The PERCLOS signal was combined with a micro-sleep detection (more than 80% closed eyes during one second), to evaluate the status of the drivers eyes for short and long durations. The driver was expected to give respone within a predefined time period. The proposed algorithm checked the peaks in the derivated velocity signal and the threshold values were used to determine the alertness level of the driver. Algorithms running on the framework alert the driver if the eye closure and head movement goes beyond the threshold value. This work revealed a correlation between drowsiness and eye closure, which could be successfully integrated into a novel algorithm for driver monitoring during conditionally automated driving.

L. Bergasa et. al. [9] used head mounted eye tracker to monitor eyelid movement and eye gaze. percent eye closure (PERCLOS), eye closure duration, blink frequency, nodding frequency, face position, and fixed gaze are the parameters combined using a fuzzy classifier to infer the level of inattentiveness of the driver. Knowledge base configuration tool was used for the fuzzy implementation. The mentioned parameters related to the ocular and face pose measures are fused onto the fuzzy systm to evaluate the driver's inattentiveness level (DIL).

Qiang Ji et al. [10] described a real time robust nonintrusive eye tracking mechanism to monitor and predict the driver's fatigue using Bayesian Networks. In this approach, two remotely located charge coupled device cameras equipped with active infrared (IR) illuminators are fixed on the dash board to capture the images under variable lighting conditions and facial orientations. The eye detection mechanism used Support Vector Machine (SVM) classifier based eye detection algorithm to correctly identify the real eye region. Two stage eye traking algorithm was proposed by combining the bright puplil based Kalman filter eye tracker with the mean shift eye tracker. The eye lid movement was computed based on the ocular measures like Percentage of eye closure over time (PERCLOS) and average eye closure speed (AECS). Face orientation estimation was done using automatic 3D facial model and pose initialization.

Fabio Tango et. al. [11] proposed a real time detection system of visual distraction of driver, using vehicle dynamics data without using the eye tracker data as inputs to classifiers. Different driver distraction classifiers based on Machine Learning techniques were presented and the performance of Feedforward Neural Networks (FFNN), Layer recurrent Neural Networks (LRNN), Adaptive Neuro Fuzzy Inference Systems (ANFIS) and Support Vector Machine (SVM), it has been proven that SVM outperformed all the other classifiers.

4 BIO BEHAVIORAL NOTATIONS

Normally the fatigue or drowsy condition of any driver may be conclude by certain bio behavioural notations like yawning, head movement and facial expressions. It is important to do the facial analysis to compute and conclude the level of abnormality of the driver. The sleepy level of the driver is analysed using yawning measurement also. Yawning is triggered by the fatigue and drowsy condition of the driver which induces an involuntary intake of more oxygen from the atmosphere by opening the mouth widely. In this analysis, cascade classifiers are used to detect the face of the driver and tracked in the frame shots taken in series by the camera. Face detection algorithms are used to detect the location of the mouth. Mouth opening in large vertical level and changes in the mouth outline boundary is modelled. The boundary becomes wider than normal mouth while yawning and it gives the indication of fatigue or drowsy condition of the driver.

Xiaoning Meng et. al. [13] proposed a intelligent vehicle security system by accessing the human driving behavior. The face recognition system was developed based on Hidden Markov Models.(HMM), the procedure for recognizing different drivers was demonstated by deriving individual driving behavior model. By using HMM, the driving pattern of different drivers were learned from training data and the deviation will be recognized as unauthorized driver.

Nawal Aliousa et. al. [14] presented a fatigue detection system based on yawning extraction in which the face detection was done using the SVM classifier for the face extraction, localization of mouth region and the detection of wide mouth open. Circular Hough Transform (CHT) was applied on the wide open mouth edge detector to improve the level of accuracy of fatigue detection. High yawning frequency is the measure of fatiguness and the corresponding counter set for the wide open mouth was incremented if the mouth kept wide open more than 2 seconds, considers as yawning and warning signal is generated.

Shabnam Abtahi et.al [15] proposed a monitoring mechnasim of driver drowsiness based on the detection of yawning. Front facing camera was used to record the face continuously and the series of frame shots taken by the camera was used to detect and track the face. The location of the mouth was detected and geometrical features of mouth was used to detect the yawn.

Nanxiang Li et. al [16] presented a multimodel approach to track distraction level of drivers in real driving scenarios, by using noninvasive sensors. Real driving conditions are recorded with a multimodel database using UTDrive platform which is a car platform belongs the research centre at The University of Texas at Dallas. In this approach, front facing video camera was used to capture the face of the driver and microphone was used to capture the audio. Gaussian Mixture model was used to analyze the driver behavior due to secondary tasks like tuning a radio, operating and monitoring the navigation system, operating and talking over cellular phone and talking with co passengers. The average accuracy of the prediction system was 77.2%.

Ashish Tawari et. al. [17] proposed a model to predict the focus of attention level of the driver using head movement estimation. This work presented a distributed camera framework to track facial features and analyses the head pose using a 3D model. The study was made with different camera configurations and a head pose data set from naturalistic on-road driving under streets and freeways of urban area was collected for further experimental evaluations, A continuous head movement estimator (CoHMEt), a component for monitoring the driver in an uninterrupted manner. The accuracy of head pose trakcing and the computation time was improved by the incorporation of automatic facial feature detecton by constrained local model (CLM) and the pictorial structure matching (PSM).

5 DRIVER PHYSIOLOGICAL ANALYSIS

The behavior of the driver shall be analysed also by using non-visual features of the driver. The brain activity and heart reate of the driver are the widely used non-visual parameters to analyse the behavior of the driver. The physiological index of any person will be directly affected by the fatigue and drowsiness. A deviatation can be observed between the physiological index of a normal person and a person feels drowsy and fatigue. As a result, the drowsiness of a driver shall be assessed by measuring the physiological indexes like electroencephalogram (EEG), electoococulogram (EOG) and electromyogram (EMG) of the driver. EEG signals are normally collected by wearing a electode helment by drivers in which the data from the brain is obtained by various electrode sensors embedded in the helmet. It has been concluded by the researchers that EEG is the indicating measure of shifting between different stages of sleep. Researches were conducted either by simulation or in real vehicles and it has been proved that EEG measurement is the important index to measure the fatigue level of the driver.

Chi Zhang et. al [18] presented an automated detection of driver fatigue based on entrophy and complexity measures. Recorded values of electroencephalogram (EEG), electoococulogram (EOG) and electromyogram (EMG) signals were assessed to compute the different levels of driver fatiguness, normal state, mild fatigue, mood swing and excessive fatigue. This approach used non linear, time varying, space varying and non stationary recorded signals for the assessment. Entropy based features like wavelet entropy, peak to peak value of sample entropy were extracted from the collected signals to estimate the driving fatigue stages. Accuracy of 95% is obtained while using EEG, EMG and EOG signals for classification.

P. Artaud et. al [19] claims that the drowsiness of the driver is the main cause of road accidents. In the system proposed by the authors, data from physiological recording such as EEG (Electroencephalogram) and behavioral recording was used to fix a reference to measure the alertness level of the driver. A Multisensor approach was presented, in which the driver behavior analysis was done based on the respiratory signal and processing the recording of the driver's face.

6 VEHICLE PARAMETER MEASUREMENT ANALYSIS

The state of the fatigue and drowsiness of the driver is also identified using analysis on the vehicle movement parameterslike movement of steering wheel, keeping the lane, movement of acceleration pedal and braking. Normally a steering angle sensor mounted on the steering column used to measure the Steering Wheel Movement (SWM). Cross winds, speed breakers, bad condition of the roads necessesiates the mirco correction in the streering operation. Mechanisms like sideslip angle estmation which is an adaptive steering control system based on the Human Mechanical Impedance Properties (HIMPs) and be adopted in vehicles to alert drivers to avoid accidents. Standard Deviation of Lane Position (SDLP) is the measure of changing level of assigned lane, entering into the opposite lane or moving away from the road, used to interpret the driver inattention levels. T Dan Yu et. al [20] contributed towards an aggressive model and concluded that the aggressive nature based on the vehicle movement in grids. They have simulated a mixed traffic flow in a single lane, comprising two different kinds of vehicles for which the maximum speed differs. A vehicle which moves 5 grids for one time will be considered as aggressive behavior and a vehicle which moves 3 grids for one time will be considered as normally driving. The work was contributed towards the relationship among discrete of traffic flow, traffic density and chaos. Rear-end accident risk assessment was done based on the distance headway condition and velocity condition.

Jin Hyuk Hong et. al [21] presented a model to detect the aggressive behavior using three different approaches. Driving violation was concluded based on the (1) history of driving nature of a particular driver, (2) driving behavior questionnaire approach in which response of fifty scenarios where analyzed and driver behavior has been categorized as (i) errors; (ii) slips and lapses; and (iii) violations, and (3) driving style modeling in which the speed, acceleration and change of lane.

TABLE 1 Driver Behaviour Detection Methodologies

Author	Techniques	Devices used	Driver Body Dedection Part	Vehicle Measurements	Environment Factor
P. Artaud	On-board system for detecting lapses	Multi Sensor	Face	-	Real Time
Schmidt	Conditional Automated Driving	Camera	Head Movement,Eye	-	Real Time
Chi Zhang	Entropy and Complexity Method	EEG	Brain, Heart	-	Real Time
Qiany Ji	Real Time Robust Non-intrusive eye tracking mechanism	Camera	Face,Eye	-	Real Time
Luis M Bergasa	Non-intrusive prototype computer vision system	Camera, IR Illuminator	Face Position,Eye	-	Real Time
Dan Yu	Traffic flow characteristic method	Lane,Vehicle	-	Vehicle Density	Simulation
Jin yunk Hong	Vehicle sensing platform using smart phone	Smart phone	-	Vehicle Movement	Simulation
Nanxiang	Multi model approach to track the destruction level of driver	Camera	Face	-	Real Time

7 CONCLUSION

In future, the drivers of vehicles will be assisted by the high tech intelligent electronic controllers governed by high speed computing algorithms. Communication will be established between each and every vehicle on the road and with the road side units. Vision enhancement devices will be used in the next generation vehicles to assist the driver to navigate through different environmental factors like weather, condition of the road and obstacles. The alert system will either alert the driver to take decision based on the driving behavior of the neighbor vehicles or take intelligent decisions automatically to safeguard the vehicle from accidents.

In this paper, we have presented a study about the strategies used for the prediction of driver behavior and the different approaches by different authors are tabulated in table 1. It has been observed most of the work towards the driver behavior analysis carried out on real time basis rather than simulation. Few papers have considered the effect of traffic density and movement of vehicles. The measurement on the body parts are not uniformly taken into account, different measures are considered by different authors. It is being concluded that a wider opportunity is open for researchers in developing an intelligent decision making system adaptable to human behavior.

References

[1] Balasubramani, L. Karthikeyan, V. Deepalakshmi. Comparative Study on Non-Delay Tolerant Routing Protocols in Vehicular Networks. Procedia Computer Science, 2015.

[2] S. Cloudin1, P. Mohan Kumar. Challenges on Mobility Models Suitable to Vanet. Journal of Software, 2016.

[3] S. Al-Sultan, A. H. Al-Bayatti and H. Zedan. Context-Aware Driver Behavior Detection System in Intelligent Transportation Systems. IEEE Transactions on Vehicular Technology, 2013.

[4] T. Danisman, I. M. Bilasco, C. Djeraba, and N. Ihaddadene. Drowsy driver detection system using eye blink patterns. Universit Lille 1 & Telecom Lille 1, Marconi, France, 2010.

[5] J. Jo, S. J. Lee, K. R. Park, I.-J. Kim, and J. Kim. Detecting driver drowsiness using feature-level fusion and user-specific classification. Expert Syst. Appl., Mar. 2014.

[6] M. Sabet, R. A. Zoroofi, K. Sadeghniiat-Haghighit, and M. Sabbaghian. A new system for driver drowsiness and distraction detection. 20th ICEE, Tehran, Iran, 2012.

[7] B. Cyganek and S. Gruszczy nski.Hybrid computer vision system for drivers' eye recognition and fatigue monitoring. Neurocomputing, 2014.

[8] Schmidt, Jurgen, Christian Braunagel, Wolfgang Stolzmann, and Katja Karrer-Gaub. Driver drowsiness and behavior detection in prolonged conditionally automated drives. Intelligent Vehicles Symposium (IV), IEEE, 2016.

[9] L. Bergasa, J. Nuevo, M. Sotelo, R. Barea, and M. Lopez. Real-time system for monitoring driver vigilance. IEEE Trans. Intell. Transport. Syst., 2006.

[10] Qiang Ji, Zhiwei Zhu, and Peilin Lan. Real-Time Nonintrusive Monitoring and Prediction of Driver Fatigue. IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, 2004.

[11] Fabio Tango and Marco Botta. Real-Time Detection System of Driver Distraction Using Machine Learning. IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS, 2013.

[12] Xiang, Weidong, Paul Richardson, and Jinhua Guo. Introduction and preliminary experimental results of wireless access for vehicular environments (WAVE) systems. Mobile and Ubiquitous Systems-Workshops, 3rd Annual International Conference IEEE, 2006.

[13] Nawal Alioua, Aouatif Amine, Mohammed Rziza1. Driver's Fatigue Detection Based on Yawning Extraction. International Journal of Vehicular Technology, 2014.

[14] S. Abtahi, S. Shirmohammadi, B. Hariri, D. Laroche, and L. Martel, yawning measurement method using embedded smart cameras, Distrib. Collab. Virtual Environ. Res. Lab., Univ. Ottawa, Ottawa, ON, Canada, 2012.

[15] Nanxiang Li, Jinesh J. Jain, and Carlos Busso. Modeling of Driver Behavior in RealWorld Scenarios Using Multiple Noninvasive Sensors. IEEE TRANSACTIONS ON MULTIMEDIA, 2013.

[16] Tawari, Ashish, Sujitha Martin, and Mohan Manubhai Trivedi. Continuous head movement estimator for driver assistance: Issues, algorithms, and on-road evaluations. IEEE Transactions on Intelligent Transportation Systems, 2014.

[17] Chi Zhang, Hong Wang, and Rongrong Fu. Automated Detection of Driver Fatigue Based on Entropy and Complexity Measures. IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS, 2014.

[18] P. Artaud, S. Planque, C. Lavergne, H. Cara, P. de Lepine, C. Tarriere, and B. Gueguen. An on-board system for detecting lapses of alertness in car driving. presented at the 14th Int. Conf. Enhanced Safety of Vehicles, 1994.

[19] D. Yu, Y. Wu and N. Yang. Influence of Aggressive Driving Behavior on Traffic Flow Character in Following Flow. Eighth International Conference on Measuring Technology and Mechatronics Automation (ICMTMA), Macau, 2016.

[20] Jin-Hyuk Hong, Ben Margines, and Anind K. Dey. A smartphone-based sensing platform to model aggressive driving behaviors. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 2014.

[21] Ramesh D., Jose D., Keerthana R., Krishnaveni V. Detection of pulmonary nodules using thresholding and fractal analysis. Lecture Notes in Computational Vision and Biomechanics, Springer, Coimbatore India, 2018.

[22] Jose D., Chitra M., Nirmal Kumar P. Reliability improvement of partitioned VLSI systems for fault tolerance. International Journal of Applied Engineering Research, 2015.

[23] Jose D., Tamilselvan R. Fault tolerant and energy efficient signal processing on FPGA using evolutionary techniques. Advances in Intelligent Systems and Computing, 2016.