ISSN: 2513-2504

MAPPING ON-ROAD DRIVER EXPERIENCES OF MAIN ROADS: APPLICATION OF ARTIFICIAL INTELLIGENCE, GIS, AND GOOGLE MAPS

Hashanka Galagedara[1], Niroshan Bandara[2]
University of Moratuwa
[1]*galagedarakh@gmail.com*,
[2]*niroshansnj@gmail.com*

ABSTRACT - The user experience reveals valuable information about the surrounding environment and how individuals feel about the moment emotionally. Researchers have shown the impact of emotions on decision-making, including driving-related decisions in a positive mood tended to maintain a safer driving performance. With the development of intelligent human-machine systems, emotion recognition has become emerging topics for transport-related research works. The methodlogy recognizes the facial expressions of vehicle drivers to map drivers' experiences with Google Maps data. Findings show how intersections and traffic conditions affect the driver's emotional changes during the driving situation. This new information layer can be use to identify driver feedback during different traffic and as a valuable dataset to technological enhancements to play a major role in better driving performance and fewer accidents.

Keywords: Emotions; Facial Expression Recognition (FER); Google Maps; Artificial Intelligence; GIS.

1. INTRODUCTION AND RELATED WORK

Emotions have a spatial and relational character: they are a means to understanding practices and interpretations of the surrounding environment. Emotions influence driving performance and are closely associated with surrounding incidents. On-road driver expression recognition research is lacking in industries which manufacture essential autonomous vehicles, despite its importance for human-machine systems in transportation. Expressions on the face are movements, both voluntary and involuntary, caused by the activation of one or more of the facial muscles. Human facial expressions convey to the observer the emotional state and behavioural intentions, or action requests of the poser FER has been recognized as more accurate due to the inefficient methods and inaccurate outcomes of conventional methods such as questionnaire surveys, interviews, and wearable devices [1]. FER models have been a growing trend of utilizing deep learning techniques to simultaneously learn feature extraction and recognition for real-time measurement of emotional responses. The driver's facial expression mirrors the driver's emotional state [2]. Anger is caused when driving a motor vehicle in difficult conditions [3]. Also, in opposite if a driver is driving while sad or nervous it reduces the driving concentration [4]. The number of road traffic fatalities continues to rise, and the inability to regulate one's emotions has been identified in previous research studies. It is noteworthy as previous recognition of driver facial expressions did not address the challenge of authentic driver facial expressions.

2. MATERIALS AND METHODS

2.1. Study Area and Site Selection

The experiment was carried out on A1 Kandy Road covering the Kiribathgoda town area which experiences high traffic congestion. Road segments have been pre-defined with typical traffic data to identify potential locations for the study. A 1.5km length road segment was selected for the study which consists of 4 intersections which connect A, B class roads and minor roads with signalized and unsignalized junctions.

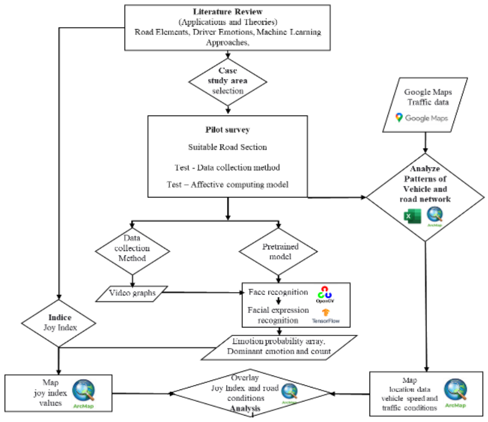

Figure 1. Methodology framework

ISSN: 2513-2504

2.2. Data Collection

Participants - Randomly selected ten licensed, both male and female drivers aged 25-50 years from the local community have been used for this research. The driving experience ranged from 5+ years of age.

Data Collection Equipment and Protocol - Recording cameras have been placed in front of vehicles to collect data covering the road view and the driver's face. Google Maps has been taken as the data source for the traffic level of the place. Participants were verbally instructed regarding the protocol of collecting visual data before and after the data collection process. Also, instructed to navigate freely along the selected road segment. A data collection assistant was present in the vehicle throughout the study to avoid interfering with the driver and to record GPS and google maps data. data was collected under the conditions of dry road surfaces and during evening peak hours (5-6 pm).

Figure 2. Experimental setup: driver facial expression recording, road scenario recording, navigation of the test

Ethics statement, Data Processing and Emotion extraction

Initially, the selected participants were aware of the video graphs, and that they have the right to withdraw from the study at any point. After the data collection participants were informed that facial movements will be used specifically in the experiment but will not be published without their permission. Participants' video recordings were only included in the dataset after they verbally consented to their use for research purposes. Rondinelli Morais, an expert in artificial intelligence and big data, designed the model used for emotion extraction. This model serves as a framework for facial recognition and attribute analysis in this research. The collected video data has been divided into 100m road segments which have different traffic flow levels. Then add the given as the input data for the model. The FER model generates results based on an accurate facial attribute analysis of five facial expressions, including angry, neutral, sad, joyful, and surprised, with an accuracy of 86.6% in Kappa analysis. Figure 4 shows both video and expression data output results of the FER model.

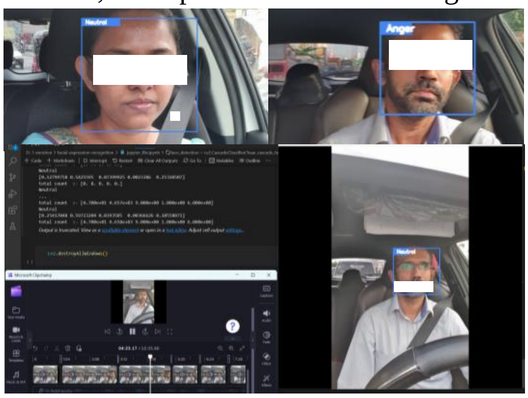

Figure 3. FER Model output results

Mapping on-road driver experience.

ArcMap 10.8 GIS software has been used for the mapping process. The results of the FER are mapped according to its location data by scaling it with neutral and other positive and negative emotions which reduce the concentration of the driver. This study proposes a place-based human emotion measurement indices to evaluate the level of the emotional state in various locations: based on the 'Neutral' score as the neutral expression is the most occurred during a driving concentrated scenario. The index is computed using extracted images from the video graphs and the normalized difference between the number of neutral faces and the number of non-neutral faces.

Figure 4. Spatial distribution map of driver experience

ISSN: 2513-2504

3. RESULTS AND DISCUSSION

Correlation between Traffic data, crossing intersections and emotional state of the driver.

The research attempts to explore the change of emotions with the driving scenario. As previously mentioned, different factors may interrupt the driving scenario and may lead to accidents. Intersections are the most dangerous locations in urban traffic [5]. Also, there is a hypothesis that exposure to traffic congestion may lead to frustration and aggression [6]. Considering those factors traffic conditions and road intersections have been recorded in this study. The correlation analysis revealed a strong positive correlation of 0.71 between the emotion change and the visibility of intersections. This indicates that as emotional change increases, there is a corresponding increase in the visibility of intersections, demonstrating a clear and consistent relationship between the two variables. The correlation analysis revealed a weak positive correlation of 0.16 between the emotion change and exposure to traffic congestion, which was also proven in previous research [6].

4. LIMITATIONS, FUTURE WORKS AND CONCLUSION

The research has been conducted by using pre-trained AI models which haven't been trained by using on-road driver facial datasets and used mostly performed on lab-captured datasets. Also, research haven studies the correlation between factors such as sunlight, vehicle noises, vehicle data, temporal activities and other data which can affect the emotional change of the driver. The results would have been more reliable if the research was conducted with more participant data and more road type data such as expressways and other road elements. The research can be extended by using various data such as vehicle data (angle of the steering wheel, pressure on the accelerator etc.) road elements (crossings, name boards, visibility of physical elements) and the change of emotional state to the interpretation of visual stimuli, assessing potential dangers, decision making, and strategic planning for both the driver and the automobile.

The paper shows a methodology to collect and assess on-road driver facial expression data to identify the driving experience and the conditions of the road networks. These data and results can use as a new layer of data for further applications on autopilot vehicles, human-machine systems and planning for safety to improve human-machine transport and it can reduce driving risk.

REFERENCES

1. P. Zeile, S. Höffken and G. Papastefanou, "Mapping people: The measurement of physiological data in city areas and the potential benefit for urban planning," in *REAL CORP 2009: CITIES 3.0 – Smart, Sustainable, Integrative*, Sitges, 2009.
2. W. Li, G. Zeng, J. Zhang, Y. Xu, Y. Xing, R. Zhou, G. Guo, Y. Shen, D. Cao and F. Y. Wang, "CogEmoNet: A Cognitive-Feature-Augmented Driver Emotion Recognition Model for Smart Cockpit," *IEEE Transactions on Computational Social Systems*, vol. 9, no. 3, pp. 667 - 678, 2021.
3. M. Jeon, "Towards affect-integrated driving behaviour research," *Theoretical Issues in Ergonomics Science*, no. 16(6), p. 553–585, 2015.
4. D. Tao, R. Zhang and X. Qu, "The role of personality traits and driving experience in self-reported risky driving behaviors and accident risk among Chinese drivers," *Accident Analysis & Prevention*, vol. 99, pp. 228-235, 2017.
5. G. Li , Y. Wang, F. Zhu, X. Sui, N. Wang, X. Qu and P. Green, "Drivers' visual scanning behavior at signalized and unsignalized intersections: A naturalistic driving study in China," *Journal of Safety Research*, vol. 71, pp. 219-229, 2019.
6. Lajunen, D. Parker and H. Summala, "Does tra• c congestion increase driver aggression?," *Transportation Research Part F 2*, pp. 225-236, 1999. `