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Motion Sickness Detection in Autonomous Vehicle With Biosensors: A Review

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ABSTRACT

The advent of autonomous driving reduces human control and situational awareness on the road, significantly increasing the likelihood of motion sickness (MS) among passengers. This review explores key physiological measurement methods for detecting MS in autonomous vehicle environments, emphasizing the effectiveness of various biosensors—such as those monitoring body motion, brain activity, eye response, and heart rate. It highlights the potential of multi-sensor fusion methods to enhance sensor usability and provide comprehensive, real-time MS detection, ultimately improving passenger comfort.

Keywords: Motion sickness, Autonomous vehicle, Biosensors

INTRODUCTION

Traditional motion sickness (MS) assessment methods primarily rely on subjective questionnaires, such as the Motion Sickness Assessment Questionnaire and the Fast Motion Sickness Scale (Reinhard et al., 2017). While useful for statistical analysis, these tools are limited by their inability to capture real-time physiological changes and dependence on self-reporting. This subjectivity hampers accurate, continuous MS detection in autonomous vehicle settings. In contrast, biosensor technology presents a promising alternative, enabling objective measurement of physiological responses for continuous, real-time monitoring, which could enhance MS detection and passenger comfort (Wang, Liang, Monteiro, Xu, & Xiao, 2023).

The advancements in biosensor technology allow for real-time detection of MS by measuring objective physiological responses across various biological systems, including the digestive, central nervous, and autonomic systems (Koohestani et al., 2019). Biosensors convert biological responses—such as pulse rate, blood pressure, and gastrointestinal signals—into quantifiable data, offering a viable alternative to subjective MS assessments (Iskander et al., 2019). This review synthesizes experimental findings from the past decade to evaluate the effectiveness of physiological biosensors for MS detection in autonomous vehicles. It underscores the potential of multi-sensor fusion methods to provide a comprehensive, accurate framework for real-time MS monitoring, addressing individual and environmental variability to enhance passenger comfort.

METHODOLOGY

This study reviews research conducted over the past decade on MS detection using biosensors in vehicle environment. Electronic databases were searched, including SAGE Journals, IEEE Explore, Elsevier Science Direct and ACM Digital Library. Keywords used include motion sickness, detection, biosensors and autonomous vehicle. Duplicate articles were removed, articles from same author were compared and 26 most relevant articles were finally selected from 6202 for detailed review. The major inclusion criteria are:

- The study must investigate the use of biosensors in detecting motion sickness within the context of autonomous vehicles, focusing on physiological measurement methods.
- It should identify and analyse key physiological signals that contribute to real-time and objective motion sickness detection.
- The study should present findings that enhance the understanding of biosensor usability or address challenges such as individual variability and environmental factors in motion sickness monitoring.

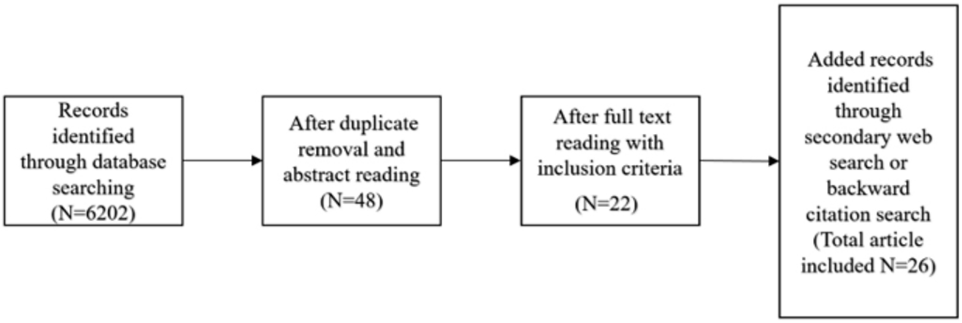

Figure 1: Flow chart for article selection process.

RESULT

The sensors involved in detecting MS are categorized according to the type of biological signal measured, including: Body Motion Detection, Brain Activity Detection, Stomach/Gastric Response Detection, Eye Response Detection, Heart/Cardiac Response Detection, Skin Response Detection, Body Temperature Detection.

Body motion sensors track postural instability linked to motion sickness (Diels & Bos, 2016). Techniques such as motion capture suits combine neural network analysis demonstrate the significant role of body movement in the onset and severity of motion sickness symptoms. Electroencephalography

(EEG) and Functional Near-Infrared Spectroscopy (fNIRS) detect brain signals during motion sickness, highlighting affected regions like the left frontal cortex (Zhang, Li, Li, Li, & Nie, 2020). Machine learning applied to EEG data shows promise in accurately predicting symptoms. Gastric activity measured by electrogastrogram (EGG) links nausea and dysrhythmia to motion sickness (Jakus, Sodnik, & Miljkovic, 2022). Although non-invasive, EGG data may vary with posture, limiting its real-time application in autonomous vehicles. Eye-tracking and pupillometry monitor indicators like blink rate and pupil size, which are associated with motion sickness (Adachi et al., 2014). While effective, these methods can be costly and face challenges with calibration and adaptability in vehicle environments. Heart rate (HR) and variability (HRV) are commonly measured using electrocardiography (ECG) or photoplethysmography (PPG) to capture autonomic responses to motion sickness. While wearable PPG devices offer convenience, inconsistent HR data suggests that further research is needed to establish reliable markers (Rauterberg, Delbressine, Terken, Md Yusof, & Karjanto, 2022). Electrodermal activity (EDA) monitors sweat response during motion sickness. Increases in EDA generally correlate with symptoms, but individual variations indicate the need for a more refined understanding of these responses (Smyth, Birrell, Woodman, & Jennings, 2021). Changes in facial and body temperature, detected via wristband or thermal imaging, have proven inconsistent as motion sickness indicators. External factors, such as climate control, can affect results, necessitating further study for reliability. Additional signals, such as respiratory rate (Keshavarz, Peck, Rezaei, & Taati, 2022) and myogenic potential changes, are also linked to motion sickness.

These findings show the complexity of physiological responses and supports the integration of multiple bio-signals for comprehensive detection. The results also outline various physiological and sensor-based indicators associated with MS, detailing the increase or decrease of each indicator under MS conditions, along with relevant studies, see Table 1.

Table 1: Biosensor detection results from selected articles.

Measurement	Indicator	Result	Reference
Body Motion	Motion Sickness Dose Values (MSDV)	Increase	(Karjanto et al., 2018)
	Head rotation variation	Increase	(Brietzke, Xuan, Dettmann, & Bullinger, 2021)
		No Change	(Irmak, Pool, & Happee, 2021)
	The number of inadvertent micro head movements	Increase	(Nooij, Bockisch, Bulthoff, & Straumann, 2021)
	Head and torso movement in mediolateral axes	Increase	(Chang, Chen, Kung, & Stoffregen, 2017)
	Head and torso movement in anteroposterior axes	No effect	(Chang et al., 2017)

Continued

Table 1: Continued

Measurement	Indicator	Result	Reference
	Mean accumulated jerks for head longitudinal movement	Increase	(Shizuka Bando, Yuri Shiogai, & Hirao, 2021)
	Variation of mean displacement of body	Increase	(Keshavarz et al., 2022)
	Pressure at seat back	Increase	(M. Beggiato, Hartwich, & Krems, 2018)
	Motion sickness incidences (MSI)	Increase	(Wada, Fujisawa, & Doi, 2018)
		Increase	(Buchheit, Schneider, Alayan, Dauth, & Strauss, 2022)
EEG	Theta power	Increase	(Henry, Bougard, Bourdin, & Bringoux, 2021)
	Alpha power	Increase	(Henry et al., 2021; Huang et al., 2021)
	Beta power	Most effect	(Recenti et al., 2021)
fNIR	Oxyhemoglobin (O2Hb): Left prefrontal cortex (TX1,TX2) Left prefrontal cortex (TX3,TX4) Right prefrontal cortex (TX1,TX2,TC3,TX4)	Increase Decrease Decrease	(Tan et al., 2022)
	Deoxyhemoglobin (HHb): Left prefrontal cortex (TX1) Left prefrontal cortex (TX2,TX3,TX4) Right prefrontal cortex (TX1,TX2,TC3,TX4)	Increase Decrease Decrease	(Tan et al., 2022)
	Total hemoglobin (tHb): Left prefrontal cortex (TX1) Left prefrontal cortex (TX2,TX3,TX4) Right prefrontal cortex (TX1,TX2,TC3,TX4)	Increase Decrease Decrease	(Tan et al., 2022)
	Oxyhemoglobin difference (HbDiff): Left prefrontal cortex (TX1,TX2) Left prefrontal cortex (TX3,TX4) Right prefrontal cortex (TX1,TX2,TC3,TX4)	Increase Decrease Decrease	(Tan et al., 2022)

Continued

Table 1: Continued

Measurement	Indicator	Result	Reference
	Cerebral oxygen exchange activity – (COS): The visual cortex of the occipital lobe (BA17 and BA18) and the frontal cortex (BA6) The visual cortex of the occipital lobe (BA17 and BA18) and the prefrontal cortex (BA10)	Highest (Striaght driving) Highest (Curved driving)	(Zhang et al., 2020)
Eye Response	The resting potential of the retina	Increase	(Adachi et al., 2014)
	Pupil diameter	Increase	(Beggiato et al., 2018; Matthias Beggiato, Hartwich, & Krems, 2019; Niermann et al., 2021)
	Interblink time	Increase	(Beggiato et al., 2018; Matthias Beggiato et al., 2019)
	Eye blink	Decrease	(Beggiato et al., 2018; Matthias Beggiato et al., 2019)
	Eye fixation	No change	(Brietzke et al., 2021)
EGG	Dominant frequency (DF)	No change Increase, significant	(Popovic et al., 2019) (Gruden et al., 2021)
	Median frequency (MF)	No change Increase, not significant	(Popovic et al., 2019) (Gruden et al., 2021)
	Crest factor (CF)	No change Decrease, significant	(Popovic et al., 2019) (Gruden et al., 2021)
	Root mean square (RMS)	Increase Increase but not significant	(Popovic et al., 2019) (Gruden et al., 2021)
	Percentage of spectral power in the normogastric range (2–4 cpm)	No change	(Popovic et al., 2019)
	Percentage of the high power spectrum density (FSD)	Increase, significant	(Gruden et al., 2021)
	Maximum magnitude of power spectrum density (MFM)	Increase but not significant	(Gruden et al., 2021)
	Percentage of tachygastria activity	Increase	(Schartmüller & Riener, 2020)
	Percentage of arrhythmia activity	Increase	(Schartmüller & Riener, 2020)

Continued

Table 1: Continued

Measurement	Indicator	Result	Reference
	Dominant frequency in contractions per minute (DF cpm)	Increase	(Schartmüller & Riener, 2020)
	Maximum power spectrum density in decibels (MPSD dB)	No effect	(Schartmüller & Riener, 2020)
	Gastric contractions (EGG)	No effect	(Keshavarz et al., 2022)
Heartbeat/Pause	HR	Decrease	(Beggiato et al., 2018; Matthias Beggiato et al., 2019; Karjanto et al., 2018; Schartmüller & Riener, 2020; Schneider et al., 2022)
		Increase	(Gruden et al., 2021; Keshavarz et al., 2022; Kojima, Ohsuga, Kamakura, Hori, & Watanabe, 2022; Tan et al., 2022)
	IBI	Decrease	(Keshavarz et al., 2022)
	RMSSD	Decrease	(Schartmüller & Riener, 2020)
	LF/HF	Decrease	(Irmak et al., 2021)
	LF	Increase	(Bando et al., 2021)
Skin Conductivity	EDA	No effect	(Beggiato et al., 2018; Matthias Beggiato et al., 2019)
		Increase	(Gruden et al., 2021; Irmak et al., 2021; Keshavarz et al., 2022; Schneider et al., 2022; Shizuka Bando et al., 2021; Tan et al., 2022)
Skin Temperature	Facial temperature	Decrease	(Keshavarz et al., 2022)
		No significant changes	(Bando et al., 2021)
	Body temperature	Increase	(Keshavarz et al., 2022)
		Increase	(Schartmüller & Riener, 2020)
		No significant changes	(Tan et al., 2022)

The table summarizes physiological indicators of motion sickness and their trends across multiple measurement domains. Body motion metrics, such as motion sickness dose values and head movements, predominantly showed increases. Brain activity revealed increases in theta, alpha, and beta power, with hemoglobin changes in fNIR demonstrating regional specificity. Eye metrics, including pupil diameter and inter-blink time, increased, while blink frequency decreased. Gastric responses showed significant increases in spectral power density and tachygastria activity. Heart rate metrics varied, with a general trend of reduced autonomic regulation. Skin conductivity and body temperature generally increased, while facial temperature changes were inconsistent. These findings provide valuable physiological insights for motion sickness detection.

DISCUSSION

The application of biosensors for detecting MS in transportation settings, particularly in autonomous vehicles, shows significant promise. The results indicate that physiological responses to MS are complex and multifaceted, with different biological signals providing complementary insights. While single-sensor approaches can capture specific aspects of MS, a multimodal fusion strategy integrating multiple biosignals—such as motion data, EEG, HRV, EDA, and gastric responses—could significantly improve detection accuracy.

Despite promising results, several challenges remain. Environmental factors (e.g., climate control affecting skin temperature), individual physiological variations, and real-time signal variability pose limitations to current sensor-based MS detection (Podoprigora, Marusin, Pegin, Karelina, & Akulov, 2022). Additionally, future research should prioritize the development of reliable and resilient multi-sensor fusion techniques that can effectively integrate physiological, vehicular motion, and environmental data for real-time MS monitoring (King et al., 2017). Advances in machine learning and deep learning algorithms can further refine signal interpretation, improving classification accuracy. Moreover, enhancing wearable sensor technology for greater usability (Liu, Zhang, Chen, Liu, & Zhang, 2021), comfort, and reliability will be crucial for practical deployment in autonomous vehicle applications.

CONCLUSION

This review underscores the potential of biosensors for achieving real-time, objective detection of motion sickness in autonomous vehicles. Despite progress, individual variability and environmental factors pose ongoing challenges to sensor reliability. Future research should prioritize sophisticated multi-sensor fusion techniques, integrating diverse physiological and environmental data, to enhance accuracy and usability in MS monitoring, ultimately promoting passenger comfort in autonomous driving contexts.

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