Available online at www.sciencedirect.com

SciVerse ScienceDirect

Procedia Computer Science 00 (2016) 000–000

Procedia Computer Science

www.elsevier.com/locate/procedia

The 8th International Conference on Emerging Ubiquitous Systems and Pervasive Networks (EUSPN 2017)

A Mutlimodal Approach to Measure the Levels Distraction of Pedestrians using Mobile Sensing

Sara Pizzamiglio[a], Usman Naeem[a], Shafiq ur Réhman[a,c], Mhd Saeed Sharif[a], Hassan Abdalla[a], Duncan L. Turner[b]

[a]*The School of Architecture, Computing and Engineering, University of East London, E16 2RD, United Kingdom.*
[b]*Neurorehabilitation Unit, School of Health, Sport and Bioscience, University of East London, E15 4LZ, United Kingdom.*
[c]*Department of Applied Physics and Electronics, Umeå University, SE-90187, Sweden.*

Abstract

The emergence of smart phones has had a positive impact on society as the range of features and automation has allowed people to become more productive while they are on the move. On the contrary, the use of these devices has also become a distraction and hindrance, especially for pedestrians who use their phones whilst walking on the streets. This is reinforced by the fact that pedestrian injuries due to the use of mobile phones has now exceeded mobile phone related driver injuries. This paper describes an approach that measures the different levels of distraction encountered by pedestrians whilst they are walking. To distinguish between the distractions within the brain the proposed work analyses data collected from mobile sensors (accelerometers for movement, mobile EEG for electroencephalogram signals from the brain). The long-term motivation of the proposed work is to provide pedestrians with notifications as they approach potential hazards while they walk on the street conducting multiple tasks such as using a smart phone.

Peer-review under responsibility of the Conference Program Chairs.

Keywords: Electroencephalogram (EEG) Signals; Pedestrian Safety; Safety Awareness; Mobile Sensing; Walking Behavior; Working Memory

1. Introduction

Over the last decade, the usage of smart mobile phones has increased exponentially, which has led to these devices becoming an integral part of people's daily lives, such as shopping, banking, social media interaction, playing games, listening to music or even watching movies. The ubiquitous nature of the

* Sara Pizzamiglio. Tel.: +44-8223-3000 ; fax: +44-8223-2963
E-mail address: S.Pizzamiglio@uel.ac.uk

1877-0509
Peer-review under responsibility of the Conference Program Chairs.

services provided by a smart phone allows the end user to engage with them on the go. Recent statistics show that over 68 percent of the world's population own a mobile phone, this is expected to increase to 72 percent by 2019 [1]. Even though these devices offer convenience, they also pose a threat to the safety and well-being of the end users. Studies have shown that pedestrians have slower reaction times and decreased situation awareness whilst using a mobile phone are more prone to be involved in motor vehicle collisions [2,3]. This is a concern, as the increase in the availability of mobile phones naturally leads to an increase in the time spent using them, hence if this trend continues then the number of injuries related to mobile phones is also likely to increase [4]. Being able to understand and recognise the impact of distractions can be complex, as many researchers have attempted this by collecting and interpreting data from multiple sensors. The work in this paper looks to build on existing work, with the emphasis on the correlation of the data captured from body movements (accelerometers) and the signals (mobile EEG) from the brain. This paper proposes a multi-modal based approach that measures the different levels (with and without a mobile phone) of distraction encountered by pedestrians whilst they are walking. The motivation of this work is to distinguish between the types of distractions caused while working. A series of experiments have been conducted to measure the levels of distraction while walking on the street. The novelty aspect of this work is the adoption of a *multimodal approach* where data has been analysed from mobile sensors such accelerometers, sensors to measure muscle movement and brain signals from the brain captured from a mobile EEG unit. The remainder of the paper is organised as follows. Section 2 provides an overview of the related literature, while Section 3 describes the key characteristics of the proposed approach. Section 4 describes the user study and experimental set up followed by the results in Section 5 that validate the findings of the proposed work.

2. Related Work

A study by Nasar and Troyer [4] compared the number of injuries between drivers and pedestrians who were using a mobile phone while walking and driving. This study revealed that the number of injuries among pedestrians in the USA was around 1506. The nature of these injuries ranged from contusions to fractures around different parts of the body (e.g. head, limbs, back, chest). The number of mobile phone related injuries to pedestrians is likely to increase due to the surge in mobile phones, as in 2017 the population of people with mobile phones reached 4.77 billion worldwide and 53.7 million in the United Kingdom [1].

Gallahan et al. [5] developed a system to reduce distractions encountered by drivers by inferring potential distractions based on the head and neck movement of the driver. This system was based on the deployment of a series of sensors that detected movement in the head and upper Skelton. An example of the detected movement would be reaching an object, talking on the phone or looking away from the road. If any of these movements was constant for more than 2 seconds then the system would alert the drivers by using sounds at different frequencies. A limitation of this system is the potential false positives that could be generated given the neck movement, as the inclusion of motion capture and eye tracking would improve distraction recognition results.

EEG signals have been used in another study [6] to measure attention during controlled movements. This study recorded these signals in three different conditions: sitting, cycling and walking. Beside EEG; EOG and EMG signals have been also acquired to measure the event related potentials which were used as a measure of cognitive activity reflecting the attention. It was claimed that the available approaches of measuring attention during movement were not adequate, as kinematic research study have mainly concentrated on the employment of the motion sensing systems. These systems are accurate and can provide a quantitative approach, however they do not provide an effective brain activity acquisition to measure the attention. Hence the work by Killane et al [6] measured the cortical activity through the amplitude and latency of event related potentials. Where the low amplitude or rise in latency could refer to cognitive descend or cognitive ascend. However, this work did not show the relation between gait and attention and how this relation can benefit the movement of mobile activities.

Pedestrians can be distracted on the road by approaching vehicles, especially during crossing. Hamaoka et al. [7] analysed the head movement of pedestrians crossing the road while a vehicle is approaching them. The frequency of the head turning increased at the beginning of the crosswalk and at the unfamiliar point. This frequency also changed based on the time (day-night) and the people (young-elderly). Therefore, pedestrians safety can be ensured based on some key locations that can be used to determine the vehicle approaching. In another study [8], mobile phone were used to detect the attention gait phase and gait velocity approaches. However, a drawback was that it takes a long time to detect a change and it needs an accurate step detection to be implemented at the same time, which makes the immediate detection not possible.

Another example of driver distraction related work was conducted by Mizoguchi et al. [9] , where the approach was based on utilising eye-movement data. However, this approach was one dimensional, as the need of multiple sources would have provided meaningful analysis. For example, the inclusion of EEG signals could have enhanced the recognition of the distraction. Zaki et al. investigated the possibility of detecting pedestrians level of distractions by utilising their gait parameters [10]. It was stated that walking patterns can be changed based on the complexity of what activity is being conducted. The distracted behaviour was recognised based on the analysis of video dataset, however again this data was one dimensional and the use of a richer dataset from multiple sources would have enhanced the recognition process. In [11] the pedestrian distraction data was manually collected through monitoring the crossing without using EEG sensing. The analysis of this data showed that using mobile Internet is more likely to lead to traffic accidents among the young pedestrians. It was found that the use of the phone can lead to significant alterations in the walking patterns and body posture [12].

Schwebel et al. investigated the impact on the safety of pedestrians while they use their mobile phones [13]. However, this study did not consider the cognitive demands of pedestrian and the effect of the distraction. Also, mobile internet on the go can have an impact on the daily life of people and can lead to distraction while walking in different environments. This type of distraction leads to delay in crossing, missing some safe chances to cross, taking longer to initiate a cross, looking away for longer time, with an increasing possibility to be hit by the coming vehicle [14,15]. The young people were not affected by changing the environmental setting (high distraction level) while texting and walking, which leads to growing concerns about the safety of these pedestrians [16,17].

EEG signals have been captured in [18] to evaluate the driver distraction in a simulated driving sessions, where the results showed that the cognitive assignment affected and distract the driver performance. This study was conducted in a simulated environment without any pedestrians, therefore a higher distraction level is expected in the real driving environment. EEG signals have also been captured to assess the brain activity against musical distraction within different conditions [19]. Another study showed that measuring the EEG signals in a real environment represents a challenge within the increment of the brain load cognitive activity [20].

Uemura et al. [21] deployed a method based on an acceleration sensing to infer distracted pedestrians, who are walking while consuming working memory. It was assumed that the pedestrians go through the distracted state when working memory is highly used which leads to divert the walking pattern from normal. The result was based on the case of thinking about something which is not enough, as the consumption of working memory varies widely based on the other brain activities (e.g. talking) and the personality of the participants. Besides that, this work did not capture EEG signals to recognise distracted pedestrians, also it did not distinguish different levels of distraction. Moreover, people with disabilities would be discriminated by only using the acceleration sensor.

The objective of the work described in this paper is much the same as that of the approaches mentioned above, however the proposed work extends existing work by adopting a *multimodal approach*, where data has been captured and analysed from multiple sensors such as accelerometers and a mobile EEG unit.

3. Distraction Recognition

The *multimodal approach* that has been proposed in this paper for distraction recognition is based on three sub components; modeling walking behavior, the brain activity modeling and analysis, which is based on a correlation phase and working memory.

3.1. Modeling Walking Behavior: Extraction of Gait Measurements

First of all various gait parameters are recorded in order to model the walking behavior. The parameters selected were based on data extracted from Force Sensing Resistor Sensors (FSRs), accelerometers and gyroscope. These gait measurements are used to differentiate various gait patterns. It is assumed that if the pedestrian is distracted then the most reliable indicator could be the change in the walking behavior. The walking behavior is also influenced by the leg muscle activities. An evidence could be a decrease or increase in these activities. These activities could be modeled from the right and left Tibialis Anterior (TA) and Soleus using EMG measurements. All these measurements could lead to dependable gait properties for modeling and extricate walking patterns.

3.2. The Brain Activity Modeling: EEG Signal Extraction

The brain wave patterns are commonly considered helpful in order to obtained the type and location of the activity in the brain during a task. One of the accepted method is electroencephalography (EEG) that is an electrophysiological monitoring method to record electrical activity of the brain. The EEG mean Power Spectral Density (PSD) in the Frequency bands of Interest (FOI) of θ (4-7 Hz), α (8-12 Hz) and β (15-30 Hz) could provide decisive results. The quantitative Electroencephalography (qEEG) brain map are considered in this study.

3.3. Analysis: Correlation Phase and Working Memory

The EEG and EMG data recording is synchronized to heel strikes, pre-processed and eventually segmented into epochs (capturing a full stride). The Root Mean Square (RMS) of each muscle activity is calculated epoch-by epoch and then averaged across epochs. The EEG mean Power Spectral Density (PSD) in the Frequency bands of Interest (FOI) of θ (4-7 Hz), α (8-12 Hz) and β (15-30 Hz), is calculated for each epoch, and then averaged across epochs for correlation.

The PSD in one Region of Interest (ROI) including pre-frontal and frontal electrodes(PFC) is considered for each FOI during walking behavior. The statical analysis (such as T-test, etc) provides critical insight. For our study we have considered the paired-samples t-Tests to assess statistical differences between the two walking behaviors (i.e., distracted and non-distracted) for each one of the aforementioned gait, muscular and neural variables.

4. User Study and Data Collection

In this user study, the participants were asked to complete two scenarios; i.e., *Single Task (ST): Natural Walking* scenarios- where they completed a round of walk without engaging with smart phone, and a *Dual Task (DT) : Walking & Texting* scenarios- where they completed a round of walk while reply an email.

4.1. Experimental protocol

Fourteen right-handed healthy young adults [age mean ($\pm$ standard deviation; SD) = 25 ($\pm$ 3), 5 male/9 female] with no previous history of neurological or gait disorders, volunteered for the study by giving written informed consent. The study was approved by the University of East London Ethics Committee (UREC-1415-29) and all experiments were conducted in accordance with the Declaration of Helsinki.

Fig. 1: A typical participant wearing high-density 64 channel Waveguard Cap and other measurement sensors. (a) Front view , b) Back view and (c) Walking & texting during experiment.

Experiments were conducted at the University of East London, Stratford Campus. Subjects were first prepared in the laboratory room and then guided outside into the garden of the campus. Subjects walked along a predefined path naturally or texting with their smartphone. To standardise the dual-task condition, subjects read and replied to a standard email. In each condition, subjects walked the predefined path twice covering a total distance of 200 metres.

4.2. Experimental Setup

The fully mobile setup allowed the recording of brain activity via a high-density 64 channel Waveguard cap (ANT Neuro, Enschede, Netherlands), as well as of muscle activity from the right/left Tibialis Anterior and Soleus by superficial electrodes. EMG and EEG activities were simultaneously recorded by an EEGoPro amplifier (ANT Neuro, Enschede, Netherlands) at a sampling frequency of 1 kHz. During the recording, EEG data were referenced to the FCz channel and electrodes impedances were kept below 5 kOhm. A Samsung Galaxy S4 mini smart phone was fixed at the subject's lower back with an elastic belt and data from its internal accelerometers and gyroscope were recorded at a frequency of 200 Hz. Data from two digital Force Sensing Resistor Sensors (FSRs), placed underneath the subject's heels to detect times of heel strikes, were recorded at 1 kHz by a 14 bit analog-to-digital converter fixed at the subject's hip by the elastic belt. A digital button was also connected to the converter and pressed by the subject at the beginning and at the end of each condition to define time points of start and finish. Elastic bands were also placed around the subject thighs to fix the cables of contact switches and surface EMG electrodes to prevent the subject from falling (see Figure 1). Data synchronization between the different devices was obtained by sending a common TTL pulse at the beginning and in the end of the recording, further used to realign the time axes.

5. Results and Discussion

After the experiment, the raw data was collected and Paired-samples t-test were performed to calculate the 't 'and 'p ' -values. Table 1 shows total seventeen measures of gait of interests for both scenarios (Single

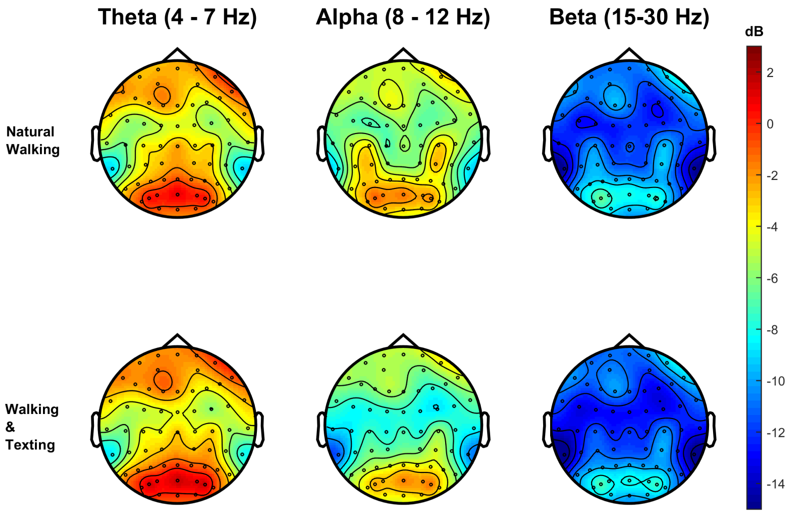

Fig. 2: The Quantitative Electroencephalography (qEEG) brain mapping of a typical participant during Single- and Dual-task conditions; i.e., Natural Walking and Walking & Texting.

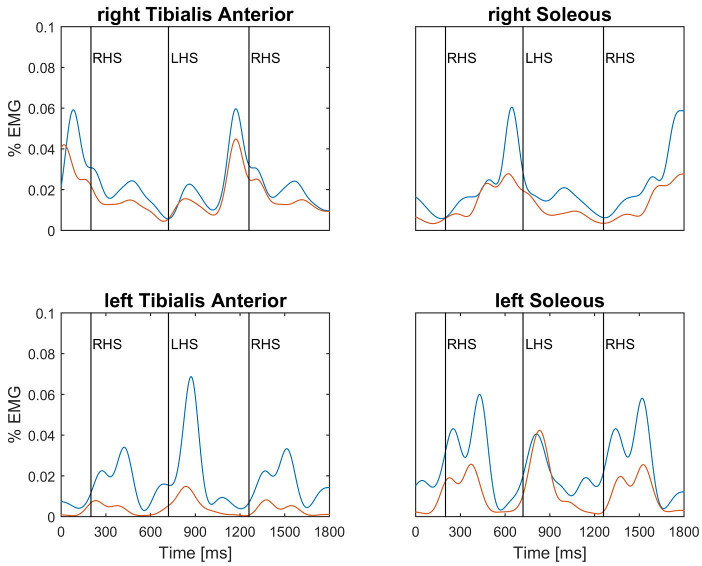

Fig. 3: A typical participant's muscle activity record from the right/left Tibialis Anterior and Soleus by superficial electrodes.

Task (ST): Natural Walking and Dual Task (DT) : Walking & Texting). It can be seen that twelve p value are below 0.05, depicting that these are statistical significant.

Table 2 shows the root mean square (RMS) results of the right and left Tibialis Anterior (TA) and Soleus from EMG measurements for both scenarios. It can be seen from these muscle activities p values that the gait pattern were significantly impacted. The Figure 3 shows the Single- and Dual-task conditions EMG measurements for a typical subject. It can be seen that texting while walking has considerable impact on the

Table 1: **Single- and Dual-task conditions Gait measures**. Condition-by-condition (n = 3) mean (± std) of the measures of gait of interest. Paired-samples t-test 't 'and 'p ' -values are reported in the last two columns on the right and significant comparisons are highlighted with '* '.

Measures of gait of interest	**Single Task (ST): Natural Walking**	**Dual Task (DT) : Walking & Texting**	**t - value**	**p - value**
Stride Duration (ms)	1054 (±87)	1106 (±107) *	-3.793	0.002
Cadence (step/min)	107 (±10)	99 (±16) *	2.772	0.016
Mean Step Length (m)	0.53 (±0.06)	0.51 (±0.07)	1.370	N.S.
Velocity (m/s)	0.90 (±0.10)	0.78 (±0.12) *	6.847	0.001
Vertical(Ver)-RMS	2.65 (±0.56)	2.26 (±0.63) *	4.880	0.001
Medio-Lateral(ML) RMS	1.48 (±0.32)	1.37 (±0.40) *	3.100	0.008
Antero-Posterior-RMS	2.19 (±0.28)	0.96 (±0.33) *	4.848	0.001
Vertical(ver)-RMSR	0.70 (±0.05)	0.67 (±0.06) *	2.325	0.037
Medio-Lateral-RMSR	0.40 (±0.07)	0.41 (±0.08)	-1.674	N.S.
Antero-Posterior(AP) RMSR	0.59 (±0.06)	0.60 (±0.06)	-.1910	N.S.
Ver-Step Regularity	0.75 (±0.09)	0.69 (±0.13) *	2.700	0.018
Ver-Stride Regularity	0.75 (±0.07)	0.65 (±0.16) *	2.802	0.015
Ver-Symmetry	0.03 (±0.02)	0.06 (±0.04)	-2.085	N.S.
AP-Step Regularity	0.76 (±0.09)	0.71 (±0.09) *	3.542	0.004
AP-Stride Regularity	0.72 (±0.08)	0.65 (±0.12) *	3.061	0.009
AP-Symmetry	0.03 (±0.02)	0.07 (±0.05) *	-2.418	0.031
ML-Stride Regularity	0.46 (±0.20)	0.35 (±0.16)	2.078	N.S.

Table 2: **Single- and Dual-task conditions EMG measures**. Condition-by-condition (n = 3) mean (± std) of the measures of Root Mean Square (RMS) for each lower limb muscle. Paired-samples t-test 't 'and 'p ' -values are reported in the last two columns on the right and significant comparisons are highlighted with '* '.

Muscle RMS [a.u.]	**Single Task: Natural Walking**	**Dual Task: Walking & Texting**	**t-value**	**p - value**
Right Tibialis Anterior	0.03 (±0.01)	0.02 (±0.01) *	3.653	0.003
Right Soleus	0.023 (±0.01)	0.02 (±0.01) *	2.855	0.014
Left Tibialis Anterior	0.02 (±0.01)	0.02 (±0.01)	2.158	N.S.
Left Soleus	0.02 (±0.01)	0.01 (±0.01) *	3.256	0.006

Table 3: **Single- and Dual-task conditions Power Spectral Density (PSD) measures**. Average PSD (mean (±std)) across subjects (N = 14) is here reported for the region of interest PFC = (Pre-) Frontal Cortex for each frequency band of interest (θ (4-7 Hz), α (8-12 Hz) and β (15-30 Hz)) in each experimental condition. Reported values are in dB. Paired-samples t-test t and p values are reported in the last two columns on the right.

ROIs	**FOIs**	**Single Task: Natural Walking**	**Dual Task: Walking & Texting**	**t - value**	**p - value**
PFC	θ	-3.0 (±2.4)	-3.2 (±2.4)	0.950	N.S.
	α	-5.3 (±3.1)	-5.9 (±2.9)	10.708	N.S.
	β	-11.1 (±3.1)	-11.3 (±2.8)	1.716	N.S.

gait. Table 3 show the average power spectral density(PSD) across the participants for the region of interest PFC = (Pre-) Frontal Cortex for each frequency band of interest; i.e., θ (4-7 Hz), α (8-12 Hz) and β (15-30 Hz). A slight decrease of activity is observed when walking and texting in comparison to naturally walking, even if no statistical significance is reached. The Figure 2 shows the quantitative Electroencephalography (qEEG) brain map of a typical subject. The high brain activity was recorded when the participants where walking and texting as compared to walking alone.

6. Conclusion

This paper described a *multimodal approach* to measure the distraction of pedestrians with and without a mobile phone. The experiment results indicate that the proposed approach has considerable potential for recognising distractions while pedestrians are walking. This initial work is a good foundation for achieving the long term motivation of our work, which is to provide pedestrians with safety notifications as they approach potential hazards while they conduct multiple tasks such as using a smart phone while walking.

References

1. The Statistics Portal. *https://www.statista.com/statistics/274774/forecast-of-mobile-phone-users-worldwide/*, 2017.
2. Caird, J. K., Willness, C. R., Steel, P., and Scialfa, C. (2008). A meta-analysis of the effects of cell phones on driver performance. Accident Analysis and Prevention, 40(4), 1282-1293.
3. Strayer, D. L., and Johnston, W. A. (2001). Driven to distraction: Dual-task studies of simulated driving and conversing on a cellular telephone. Psychological science, 12(6), 462-466.
4. Nasar, J. L., and Troyer, D. (2013). Pedestrian injuries due to mobile phone use in public places. Accident Analysis and Prevention, 57, 91-95.
5. Gallahan, S. L., Golzar, G. F., Jain, A. P., Samay, A. E., Trerotola, T. J., Weisskopf, J. G., and Lau, N. (2013, April). Detecting and mitigating driver distraction with motion capture technology: Distracted driving warning system. In Systems and Information Engineering Design Symposium (SIEDS), 2013 IEEE (pp. 76-81). IEEE.
6. Killane, I., Browett, G., and Reilly, R. B. (2013, July). Measurement of attention during movement: Acquisition of ambulatory EEG and cognitive performance from healthy young adults. In Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE (pp. 6397-6400). IEEE.
7. Hamaoka, H., Hagiwara, T., Masahiro, T. A. D. A., and Munehiro, K. (2013). A study on the behavior of pedestrians when confirming approach of right/left-turning vehicle while crossing a crosswalk. Journal of the Eastern Asia Society for Transportation Studies, 10, 2109-2122.
8. Music, J., Stancic, I., and Zanchi, V. (2013, July). Is it possible to detect mobile phone user's attention based on accelerometer measurment of gait pattern?. In Computers and Communications (ISCC), 2013 IEEE Symposium on (pp. 000522-000527). IEEE.
9. Mizoguchi, F., Nishiyama, H., and Iwasaki, H. (2014, August). A new approach to detecting distracted car drivers using eye-movement data. In Cognitive Informatics and Cognitive Computing (ICCI* CC), 2014 IEEE 13th International Conference on (pp. 266-272). IEEE.
10. Zaki, M. H., and Sayed, T. (2016). Exploring walking gait features for the automated recognition of distracted pedestrians. IET Intelligent Transport Systems, 10(2), 106-113.
11. Li, H., and Ming, X. (2016). Study on the Effect of Distraction for Pedestrian Crossing.
12. Agostini, V., Fermo, F. L., Massazza, G., and Knaflitz, M. (2015). Does texting while walking really affect gait in young adults?. Journal of neuroengineering and rehabilitation, 12(1), 86.
13. Schwebel, D. C., Stavrinos, D., Byington, K. W., Davis, T., O'Neal, E. E., and De Jong, D. (2012). Distraction and pedestrian safety: how talking on the phone, texting, and listening to music impact crossing the street. Accident Analysis and Prevention, 45, 266-271.
14. Byington, K. W., and Schwebel, D. C. (2013). Effects of mobile Internet use on college student pedestrian injury risk. Accident Analysis and Prevention, 51, 78-83.
15. Nasar, J., Hecht, P., and Wener, R. (2008). Mobile telephones, distracted attention, and pedestrian safety. Accident analysis and prevention, 40(1), 69-75.
16. Plummer, P., Apple, S., Dowd, C., and Keith, E. (2015). Texting and walking: Effect of environmental setting and task prioritization on dual-task interference in healthy young adults. Gait and posture, 41(1), 46-51.
17. Schabrun, S. M., van den Hoorn, W., Moorcroft, A., Greenland, C., and Hodges, P. W. (2014). Texting and walking: strategies for postural control and implications for safety. PLoS One, 9(1), e84312.
18. Almahasneh, H., Chooi, W. T., Kamel, N., and Malik, A. S. (2014). Deep in thought while driving: An EEG study on drivers' cognitive distraction. Transportation research part F: traffic psychology and behaviour, 26, 218-226.
19. Bigliassi, M., Karageorghis, C. I., Nowicky, A. V., Wright, M. J., and Orgs, G. (2017). Effects of auditory distraction on voluntary movements: exploring the underlying mechanisms associated with parallel processing. Psychological Research, 1-14.
20. Zink, R., Hunyadi, B., Van Huffel, S., and De Vos, M. (2016). Mobile EEG on the bike: disentangling attentional and physical contributions to auditory attention tasks. Journal of Neural Engineering, 13(4), 046017.
21. Uemura, Y., Kajiwara, Y., and Shimakawa, H. (2016, December). Estimating Distracted Pedestrian from Deviated Walking Considering Consumption of Working Memory. In Computational Science and Computational Intelligence (CSCI), 2016 International Conference on (pp. 1164-1167). IEEE.