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Smartphone Inertial Sensors Applications in Medical Care Field: A Comprehensive Review

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ABSTRACT

Sensors of various types are built into the majority of current smartphones each with a distinct function that aids the device's performance. Micro-Electro-Mechanical System (MEMS) inertial sensors, such as gyroscopes (gyros) and accelerometers, are built into smartphones. These embedded inertial sensors have improved user experience and accelerated smartphone development and it can be used to detect events or collect information about human activities. Additionally, machine learning algorithms applied to smartphone sensor data could have a wide range of uses in entertainment, health care, finance and other fields. There have been massive financial gains when a smartphone is utilized to provide telemedicine and remote healthcare assistance. This paper provides a brief overview of all the recent work that have been done in the medical care field by utilizing inertial navigation sensors (gyroscopes and accelerometers) whether the inertial sensors were used together or separately. The goal of this review is to outline the most recent trends in four topics. First, we'll go over fall detection systems released research publications. Second, we'll go over the most recent scholarly papers on human activity monitoring systems that have been published. Third, we'll review the most recently released research publications on epilepsy detection. Last, we'll look over the recently released papers on Parkinson's disease. This work also includes some important applications that use external inertial sensors for comparison purposes.

Key Words: Inertial Navigation Sensors, Fall Detection, Epilepsy Detection, Human Activity Recognition, Parkinson's disease.

1. INTRODUCTION

Mobile phone is a technological item that primarily supports wireless communications over cellular network [1]. Smartphones are a more modern innovation than mobile phones, which has been commonly used for decades. In addition to standard functionality like voice and text communication, they have advanced processing and transmission abilities, including internet connectivity and geo-positioning systems. Smartphones have larger, higher-resolution display screens than previous mobile phones. Additional functions include high-quality cameras, on-board personal management software, and recording equipment. in the majority of the newer generation of smartphones [2]. The majority of modern smartphones include a variety of sensors that can measure a variety of parameters such as rotation, location, and other environmental factors. Motion sensors (gravity, accelerometer, gyroscope, linear accelerometer, and rotation vector), environment sensors (humidity, temperature, light and pressure), position sensors (proximity, geomagnetic field, and orientation), are the three basic categories of sensors (Figure 1 shows the sensors in smart phones) [3]. It is apparent that mobile communication has enormous potential to alter healthcare and therapeutic approaches in the community. Numerous prior research have looked at how smartphones can help with healthcare and public health activities, including data collecting, healthcare teaching, and community clinical practice [2]. An inertial navigation system makes use of the inertial properties of sensors to perform the navigation function. The most basic sensors for measuring linear accelerations and angular velocities are accelerometers and gyroscopes, respectively. There are many different types of accelerometers and gyroscopes available nowadays, with MEMS (Microelectromechanical systems) and NEMS (Nanoelectromechanical systems) sensors being the most popular. Low cost, compact size, light weight, and easy connection to electronic circuits are all advantages of these sensors. Currently, inertial navigation system is used in military, agriculture, industrial, commercial, and medical applications [4]. Some interesting applications that use externally inertial sensors for comparison reasons are also included in this paper. As a result of this review, it was demonstrated and confirmed that using inertial navigation system in medical care field, a high-efficiency system for determining precise and quick positioning along with attitude calculation will indeed be achieved.

Fig. 1. Mobile Phones Sensors [3]

2. Related Work

Now let us restrict our subject of interest to the available sensor technology which has the potential to facilitate many home-based activities monitoring such as fall detection, epilepsy seizure detection, gait analysis and Parkinson's disease patient monitoring etc.

2.1 Fall Detection

Humans are vulnerable to falls, which can result in serious injuries and even death in the elderly. Fall accidents are more common in older adults than in other age groups, and the risk of falling increases with age. Falls also pose a significant risk to riders, skiers, builders, and many others. Thankfully, technological improvements have resulted in a significant increase in the number of suggested fall detecting devices and gadgets, some of which are already on the market [5]. The majority of work in the field of fall detection has used video cameras. However, there was one major issue with the usage of cameras: they only work at a specific view angle and under specific lighting conditions. Furthermore, if the person moves outside of these parameters, the system will be unable to accurately record and detect a true fall. There will be a false alarm even if the person travels under normal conditions (no fall). This is due to the absence of other characteristics connected to falls, such as vital signs [6]. Inertial sensors including accelerometers, inertial measurement units (IMUs), gyroscopes, and pressure sensors are employed in fall detection devices. There's also a tendency toward including fall detection systems into smartphones because they're already extremely portable, and all of the sensing and communication elements are built-in, so no additional device is required [5].

I. N. Figueiredo et al. proposed a novel fall detection algorithm and assess its effectiveness in both gathered data and a publicly available dataset. The suggested technique is designed to identify a smartphone user's fall (a sudden, uncontrollable drop). It is a threshold-based algorithm that solely uses data from the smartphone's accelerometer (it doesn't use other built-in sensors such as magnetic sensors, gyroscopes or other sensors such as microphone, camera or proximity sensor). These traits are critical since they aid in the reduction of battery energy usage, it is critical to create fall detection algorithm that is less complicated and thus uses less processing power in order to extend battery life. The algorithm's sensitivity and specificity were both evaluated at 100 percent and 93 percent, respectively, in the collected data. Furthermore, testing on a public dataset was compared to other smartphone-based fall detection techniques. demonstrates the proposed algorithm has great potential [7].

Y. W. Hsu et al. presented a fall detection algorithm. The suggested algorithm is divided into two sections: (A) feature extraction and (B) recognition processing. The raw accelerometer data from smartphones was gathered and submitted to the feature extraction phase, where the six most essential features were determined. The principal feature, acceleration in gravity vector direction, worked as a trigger key in the recognition processing, allowing a valid set of six characteristics from the feature extraction phase to be selected. The Support Vector Machine (SVM) clustered the valid six feature set into the fall phase or non-fall phase. It was possible to acquire a sensitivity of 96.67 percent and a specificity of 95 percent [8].

Y. Lee et al. the researchers presented a novel real-time position monitoring system for seniors that makes advantage of the accelerometers in smartphones. When a fall is detected, the suggested system notifies the administrator, and it uses Google's 3D mapping technology to perform real-time location monitoring when the subject moves. The real-time falling data acquired from the devices is utilized to address any subsequent critical conditions and to intervene quickly in the event of an emergency. Because Google's 3D mapping service can provide more precise information on nearby buildings, including their shapes, than

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visual 2D or text-based services, it is possible to intervene quickly on behalf of seniors when such information is available. In terms of precision and speed, this system performed admirably [9].

G. G. Torres et al. created a portable sensor for ultra-low-power networks connected to a smart home system. The data is gathered by a 3-axis gyroscope and accelerometer on the wearable sensor, and the sensor data was saved and used to calculate the threshold values. Each movement is made up of four different forms of data (gyroscope data, accelerometer data, angles inclination on X and Z planes). EnOcean is a wireless home automation standard that heavily relies on energy harvesting technologies. The device becomes part of the smart home system designed to provide convenience and observation for the elderly thanks to its integration with the Home Assistant Platform. The system is able to detecting efficiently 4 different types of falls and four different forms of Activities of Daily Living (ADL), and after the event of a falling the device will detect and transmit an alarm telegram [10].

J. C. Dogan and M. S. Hossain gathered data from smartphone sensors and used it to provide a brand-new two-step fall detection algorithm. A fall can occur in a variety of ways. Sitting, jogging, walking or possibly sleeping can cause a person to fall. All falls have different patterns. To distinguish between falls and non-falls, it's crucial to understand the different sorts of falls. As a result, this method starts by identifying the right type of fall using multi-class classification. This method generates a binary decision based on multiclass prediction in the second phase. To test the suggested fall detection approach, data were gathered from ten users. Each participant did five regular activities, including jogging, standing, sitting, walking and lying, and then fell after each one. The researchers ran experiments with five typical smartphone sensors which are: gyroscope, magnetometer, accelerometer, linear acceleration and gravity. They also examined 5 machine learning classifier which are: Decision Tree, Support Vector Machine, K-Nearest Neighbors, Random Forest, and Naive Bayes. The maximum accuracy of this two-step fall detection system was 95.65% [11].

F. Hussain et al. a wearable sensor based continuously fall monitoring system able of detecting a fall and identifying falling patterns as well as the activities related with fall incidence was proposed. For detecting and recognizing falling activity, the suggested method for fall detection and recognition blends machine learning with traditional signal processing approach. The suggested method constantly captures sensor data in short and small chunks of 10 seconds by using a non-overlapping window in the case of real-time fall monitoring. The information gathered is then analyzed in order to make a judgement about the likelihood of a fall. When a fall is observed, the system uses supervised learning to further evaluate the data in order to identify the falling behavior. As a result, the suggested system is aware of the activities that lead to a fall and is able to detect and recognize any fall incidence. Three machine learning algorithms, support vector machine, K-Nearest Neighbors (KNNs), and random forest, were utilized in a series of tests to investigate the performance of the suggested system. The presented method has the best fall detection accuracy of 99.80% when using the KNN classifier, and the best falling activity recognition accuracy of 96.82 percent when utilizing Random Forest. When comparing the accelerometer's performance of and the gyroscope's performance in falling detecting action, it was noticed that the gyroscope outperforms the accelerometer [12].

2.2 Human Activity Monitoring and Recognition

Physical activities are extremely beneficial to people's physical and mental health. Physical inactivity might have a negative impact on their overall well-being. A suitable health and lifestyle coaching system that detects user behavior in real time and gives appropriate motivational feedback is required. If implemented effectively, such coaching methods can help governments, employers, and insurance companies lower total costs associated with people's poor health and bad lifestyles while also improving people's well-being. People's activities must first be recognized in order to provide appropriate motivational feedback [13]. The use of cameras to monitor human activity has proven to be quite effective at capturing motion characteristics, but it raises privacy concerns and limits its application to limited environments. As a result, several researchers have chosen to build inertial sensor-based human motion monitoring systems because the volunteers in the studies do not feel like they are being watched [14]. In recent years, smartphones have been intensively explored for recognizing various physical activities. Smartphone are being used in activity monitoring and recognition because people are already carrying them and because they are coupled with various sensors, like gyroscopes and accelerometers that can be used to construct well-being coaching applications [13].

C. A. Ronao and S. B. Cho proposed a deep convolutional neural network to achieve an effective and efficient human activity recognition. Human activity recognition (HAR) infers from actions time-series sensor data, an area that has gotten a considerable attention in past few years because of its high demand in many application fields. The proposed system used smartphone's accelerometer and gyroscope by exploiting the inherent properties of 1D time series signals and activities while also providing a way to extract substantial features from raw data automatically and data-adaptively. Experiments reveal that with each new layer, convnets derive more meaningful and complicated features. The achieved accuracy with raw sensor data was 94.79% and 95.75% with extra information from the HAR dataset of temporal Fast Fourier Transform. This great level of precision is particularly due

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in large part to the relatively close classification of moving activities. Particularly similar behaviors, such as stepping down the stairs and upstairs, which were previously thought to be difficult to distinguish [15].

A. Vaughn et al. created sensor data collection technique to investigate how the data could be used to distinguish patterns in user physical gestures. Sensor data was used to differentiate multiple behaviors in this study. They concentrated in their research on three types of human activity: walking, standing, and running. The sensor input while the gadget is in a stationary position is included in the data. They created an Android-based smartphone application to collect data from a mobile device. The smartphone accelerometer and gyroscope will be used in the research to detect the device motion. They utilized a naïve Bayes technique and k-means clustering to distinguish each activity in the dataset using a dataset of 500 sensor data entries, the model achieved an accuracy of 85 percent in activity classification. Finally, their findings suggest that smartphone internal sensors can aid in the detection of human activity [16].

M. M. Hassan et al. conducted a study and the major goal of the study was to create a reliable human activity recognition system by using data from smartphone sensors. by using inertial sensors of the smartphone like gyroscope and accelerometer sensors, a novel approach for activity identification has been developed. Multiple robust features were obtained from the sensor signals, followed by dimension reduction using Kernel Principal Component Analysis (KPCA). Furthermore, for activity training and recognition, the substantial features have been integrated with Deep Belief Network (DBN), a deep learning approach. When compared to a typical multiclass Support Vector Machine (SVM) strategy, the proposed method was found to be superior. The system was tested for twelve different physical activities, with an overall accuracy of 95.85 percent and mean recognition rate of 89.61 percent. Other traditional methodologies, on the other hand, could only manage an average recognition rate of 82.02 percent and a total accuracy of 94.12 percent at best. Furthermore, it has demonstrated its capability to differentiate between fundamental non- transitional and transitional tasks [17].

S. Lee et al. used the motion sensors on an Android smartphone to create the mHealth application to monitor and record rotational data in real time. The mHealth is used to track the body motions of three volunteers while walking with their smartphones on their waists. The gravity, gyroscope, magnetic sensors and accelerometer are all utilized in this app. By using gravity and magnetic sensors the rotation matrix was calculated. Data was gathered from three individuals: two healthy adults (1 male and 1 female) and another man with back discomfort. The participants held their smartphone in the middle of their waist. The roll, yaw, and pitch angles of the human body were measured as the participant was walking using a rotation vector derived by the rotation matrix in the smartphone. To determine the variance in each individual's walking motion, each xyz-rotation vector datum was computed. This study demonstrates that mHealth program, that relies on smartphone sensors and rotation vectors, can detect differences in people's walking movements between people [18].

2.3 Epilepsy Detection

Epilepsy is a frequently diagnosed illness that affects millions of people throughout the world. The majority of those who are affected can be successfully treated with medication or neurosurgical treatments. Despite this, 25% of those infected are unable to be treated with any available treatment. It has been proven that extensive monitoring using electroencephalogram (EEG) and video over a lengthy period of time helps with the management of daily care and pharmacological therapy adjustments in resistant patients who continue to experience frequent seizures. Long-term EEG and video monitoring can be distressing for patients, and evaluating huge amounts of EEG/video data is time consuming for medical workers. Furthermore, this approach is not yet suitable for real-time applications. All of the aforementioned factors have necessitated the search for patient-friendly sensors capable of efficient automatic detection of epileptic seizures [19].

Helmy and A. Helmy introduced Seizario, the very first mobile application for continuous, energy-efficient seizure and fall detection in the context of ambient assisted living for people with epilepsy and a risk of falling. Seizario is a scalable, cost-effective solution that uses (only) smartphones to provide two main features: fully automated recognition of seizure spasm and fall emergency situations, and instant communication of crucial data to emergency contact numbers. Seizario uses intricate finite-state machines and innovative accelerometer-based learning algorithms to automatically detect epileptic fits and dangerous falls. Seizario also has a number of important features that can help with providing assistance to the affected individuals. Seizario's detection algorithms are built to perform swiftly and effectively on smartphones, and they've shown a lot of promise, with a detection rate of over 95% for both seizures and falls, and a low amount of false alarms [20].

A. Y. Adwitiya et al. used the smartphone motion sensors and "fall detection" algorithm as an alert system. It can play an SOS alarm, then make a direct call from the smartphone contact numbers and also send a text alarm with GPS locations. This warning system was put to the test in the lab in four categories: GPS coordinate's function, mobile network quality, smartphone

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installation, and people's age. The finest instalment is the Smartphone on the forehead and the upper arm. By subject falling on the bed, the GPS coordinate-based has a success rate of 90%. The success rate of mobile communication is almost 100%. The final category is based on age, ranging from 7 to 32 years old, with a success rate of 60-70 percent. Finally, an epilepsy aid tool might recognize the second of falling and send an SOS alert sound, SMS, direct call, and GPS coordinates to a healthcare provider or a relative so they can seek help faster [21].

S. A. Makki and M. Fahmy proposed an epilepsy classification system. It is primarily regarded as an app that is created as a classification system that is trained with instances represented by sensor signal patterns. The proposed system is primarily constructed as any pattern recognition system depending on model enrolment and instances. The signals generated by an accelerometer sensor are used to illustrate these examples. Experiments revealed that the proposed application performs well in a variety of epileptic conditions. The outcomes of the correlation test performed after testing the system with the epileptic movement in comparison to the other movements revealed that there is a very good connection between the input test example of an epileptic case and the instances recorded in the database. Between the input epilepsy case and the enrolled one, the algorithm has obtained a nearly 99 percent correlation [22] [23].

2.4 Parkinson’s disease

Parkinson’s disease (PD) is a central nervous system condition caused by dopamine neuron degeneration in the midbrain, which manifests as motor difficulties. The most prevalent signs and symptoms of Parkinson's disease include bradykinesia, postural instability, tremor, Freezing of Gait (FoG), and stiffness. Tremor is described as an uncontrollable and periodic muscle contractions that dictates a partial or entire rhythmic condition of body parts, and it is one of the most weakening symptoms of the disease. FoG is another crucial visible trait in Parkinson's disease patients. Walking through limited places, such as arriving at a destination, a doorway, or coming across a barrier, all activate FoG**.** The quick and frequent reduction of step length is a feature of FoG. The length of each episode could range from a few seconds to more than 30 seconds. We can see in the patients that their toe or foot doesn’t leave the ground throughout these occurrences. There are many studies now that show the use of an inertial system in clinical monitoring of individuals with motor dysfunctions. Magnetometers, gyroscopes and accelerometers are commonly used to measure tremor, rigidity, bradykinesia and FoG in Parkinson's disease patients[24].

A. Tay et al. presented a real-time Parkinson Disease monitoring and biofeedback system based on low-price wearable sensors. The gait monitoring system can analyze real-time sensor data and detect Freezing of Gait, then play audio and vibration biofeedback to avoid or lessen freezing. A triaxial accelerometer, gyroscope, and magnetic compass are included in the low-price wearable wireless sensor nodes. 2 integrated sensors are mounted at each ankle point in the prototype system to track gait motions. Local storage capabilities are included in the system, that is useful for FoG detection while patients are outside of the clinic environment or home. Patients with Parkinson's disease will be more conscious of their danger of falling as a result of this system, and will also gain from frequent cueing to time their steps following a FoG event, so improving their gait function [25].

M. Delrobaei et al. conducted a study for assessing the full-body tremor, which is the most well-known Parkinson's disease symptom. A forty Parkinson's disease patients and twenty-two healthy people were enlisted. The researchers used an (IMU) inertial measurement unit-based motion capture system. They created a new scale and tested its clinical value by comparing their results to the gold standard, the Unified Parkinson's Disease Rating Scale (UPDRS) scores. For the tasks chosen, there was a significant association between the tremor severity levels and UPDRS. The findings imply that using the proposed precise tremor scale for the evaluation of PD patients is possible and clinically useful. Additionally, this portable diagnostic instrument could be utilized at home to monitor PD tremor and give clinicians real-time feedback on the intensity of different symptoms, allowing them to improve the dosing and timing of a prescribed medical intervention [26].

G. V. Prateek et al. developed a system to identify the beginning and extent of FoG (Freezing of Gait) in persons with PD (Parkinson's disease) in real time. A MEMS-based IMU (inertial measurement unit) with a three-axis gyroscope and a three-axis accelerometer was utilized to capture gait motion. The participant's IMU is attached to the heel of his or her foot. The detecting, tracking, and filtration modules are the three modules that make up the system design. They used real data from Parkinson's disease patients who conducted a set of gait tasks to evaluate the performance of the suggested system. This FoG detection findings are compared to those of an existing approach that just uses accelerometer data. The findings show that this system detects FOG occurrences with an accuracy of 81.03 percent and a three-fold lower false-alarm rate than the previous existing method [27].

O. Bazgir et al. presented a robust design of a classification system to quantify the hand tremors of Parkinson's disease patients based on UPDRS. For reliable and non-invasive data collection, a smartphone accelerometer sensor was used. A short time Fourier transform was used to 52 PD patients' time series data. The degree of PD patients' hand tremor was used to extract

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features. To find the best discriminative subset of the retrieved characteristics, the wrapper technique was used. For the highest potential accuracy in the assessment of Parkinson's disease hand tremor based on UPDRS; 4 distinct classifiers were implemented. The Nave Bayesian technique showed to be the most successful of the four classifiers examined. By picking an optimal mix of extracted features from the collected acceleration signal, the classification outcome for the evaluation of PD tremor came near to 100 percent accuracy. The suggested algorithm was also tested on a cost-effective embedded system using a microcontroller for home health care monitoring, and the developed classification algorithm achieved a 93.8 percent average accuracy [28].

P. Pierleoni et al. created a system that relied on a wearable device that includes a tri-axial magnetometer, a tri-axial gyroscope, and a tri-axial accelerometer to form a MARG sensor (Magnetic, Angular Rate, and Gravity), as well as effective data fusion algorithms were built in the device. These algorithms are able to provide the right orientation of the body in terms of pitch, yaw, and roll angles referring to the Earth reference system starting with raw data. All raw data was collected and processed before being sent to a user's device (tablet, laptop, smartphone) using Bluetooth. The wearable device also comes with external SD card for data storage, which is important in the event of a lost or broken radio connection. A series of tests were performed for the system validation on a sample of healthy volunteers and PD patients in accordance with an established experimental protocol, with a video recording system present, and under the direction of a neurologist’s team. The findings collected a system's accuracy of 97.7% for classifying tremors and 99.7% for detecting FoG events [24].

CONCLUSION

In this review paper we explored the most recent trends in four topics, fall detection, human activity monitoring, epilepsy detection and Parkinson’s disease assessment systems that relied on smartphone and wearable sensor-based approaches. The kinds of sensors used, their location, the dataset being utilized for investigation, the machine learning algorithm used, and their effectiveness findings were all included in the survey. According to our findings, algorithms used on different datasets in the review provide diverse levels of efficiency. This means that the algorithms' performance is influenced by a variety of parameters, including the type and location of the sensors and the dataset's properties. It's also worth noting that there aren't many datasets available to support study in this field. While public datasets are valuable for preliminary comparative studies, the majority of study has been conducted using datasets generated through experiments. Our research shows that smartphone sensor and wearable devices approaches have the advantage of being less invasive, especially for the older adults, and that machine learning approaches can work on sensor data with an acceptable level of accuracy.

REFERENCES

[1] R. H. H. Al-Hashemy and I. M. Saadoon,(2021) . An intelligent algorithm to reduce and eliminate coverage holes in the mobile network. *J. Intell. Syst.*, vol. 30, no. 1, pp. 920–930, 2021. https://doi.org/10.1515/jisys-2021-0046

[2] M. N. K. Boulos, S. Wheeler, C. Tavares, and R. Jones, (2011). How smartphones are changing the face of mobile and participatory healthcare: An overview, with example from eCAALYX. *Biomed. Eng. Online*, vol. 10, pp. 1–14, 2011. https://doi.org/10.1186/1475-925X-10-24.

[3] C. Pereral, A. Zaslavsky, P. Christen, A. Salehi, and D. Georgakopoulos, (2012). Capturing Sensor Data from Mobile Phones using Global Sensor Network Middleware. pp. 24–29, 2012. https://doi.org/10.1109/PIMRC.2012.6362778

[4] R. N. Effect and C. Radiotherapy, (2018). Applications of Inertial Navigation Systems in Medical Engineering. no. December 2016, pp. 435–446, 2018.

[5] Z. Wang, V. Ramamoorthy, U. Gal, and A. Guez, (2020). Possible life saver: A review on human fall detection technology. *Robotics*, vol. 8, no. 3, pp. 1–19, 2020, https://doi.org/10.3390/robotics9030055.

[6] M. M. Baig and H. Gholamhosseini, (2013). Smart health monitoring systems: An overview of design and modeling. *J. Med. Syst.*, vol. 37, no. 2, 2013, https://doi.org/10.1007/s10916-012-9898-z.

[7] I. N. Figueiredo, C. Leal, L. Pinto, J. Bolito, and A. Lemos, (2016). Exploring smartphone sensors for fall detection. *mUX J. Mob. User Exp.*, vol. 5, no. 1, pp. 1–17, 2016, http://dx.doi.org/10.1186/s13678-016-0004-1.

[8] Y. W. Hsu, K. H. Chen, J. J. Yang, and F. S. Jaw, (2016). Smartphone-based fall detection algorithm using feature

DOI : 10.31695/IJERAT.2022.8.10.3

extraction. *Proc. - 2016 9th Int. Congr. Image Signal Process. Biomed. Eng. Informatics, CISP-BMEI 2016*, pp. 1535–1540, 2017, https://doi.org/10.1109/CISP-BMEI.2016.7852959.

[9] Y. Lee, H. Yeh, K. H. Kim, and O. Choi, (2018). A real-time fall detection system based on the acceleration sensor of smartphone. *Int. J. Eng. Bus. Manag.*, vol. 10, pp. 1–8, 2018, http://dx.doi.org/10.1177/1847979017750669.

[10] G. G. Torres, R. V. Bayan Henriques, C. E. Pereira, and I. Müller, (2018). An EnOcean Wearable Device with Fall Detection Algorithm Integrated with a Smart Home System. *IFAC-PapersOnLine*, vol. 51, no. 10, pp. 9–14, 2018, https://doi.org/10.1016/j.ifacol.2018.06.228.

[11] J. C. Dogan and M. S. Hossain, (2019). A novel two-step fall detection method using smartphone sensors. *Proc. - 2019 IEEE Int. Conf. Smart Comput. SMARTCOMP 2019*, pp. 434–438, 2019, https://doi.org/10.1109/SMARTCOMP.2019.00083.

[12] F. Hussain, F. Hussain, M. Ehatisham-Ul-Haq, and M. A. Azam, (2019). Activity-Aware Fall Detection and Recognition Based on Wearable Sensors. *IEEE Sens. J.*, vol. 19, no. 12, pp. 4528–4536, 2019, https://doi.org/10.1109/JSEN.2019.2898891.

[13] M. Shoaib, H. Scholten, and P. J. M. Havinga, (2013). Towards physical activity recognition using smartphone sensors. *Proc. - IEEE 10th Int. Conf. Ubiquitous Intell. Comput. UIC 2013 IEEE 10th Int. Conf. Auton. Trust. Comput. ATC 2013*, pp. 80–87, 2013, https://doi.org/10.1109/UIC-ATC.2013.43.

[14] A. Olivares, J. Ramírez, J. M. Górriz, G. Olivares, and M. Damas, (2012). Detection of (In)activity periods in human body motion using inertial sensors: A comparative study. *Sensors (Switzerland)*, vol. 12, no. 5, pp. 5791–5814, 2012, https://doi.org/10.3390/s120505791.

[15] C. A. Ronao and S. B. Cho, (2016). Human activity recognition with smartphone sensors using deep learning neural networks. *Expert Syst. Appl.*, vol. 59, pp. 235–244, 2016, https://doi.org/10.1016/j.eswa.2016.04.032.

[16] A. Vaughn, P. Biocco, Y. Liu, and M. Anwar, (2018). Activity detection and analysis using smartphone sensors. *Proc. - 2018 IEEE 19th Int. Conf. Inf. Reuse Integr. Data Sci. IRI 2018*, pp. 102–107, 2018, https://doi.org/10.1109/IRI.2018.00022.

[17] M. M. Hassan, M. Z. Uddin, A. Mohamed, and A. Almogren, (2018). A robust human activity recognition system using smartphone sensors and deep learning. *Futur. Gener. Comput. Syst.*, vol. 81, pp. 307–313, 2018, https://doi.org/10.1016/j.future.2017.11.029.

[18] S. Lee, R. M. Walker, Y. Kim, and H. Lee, (2021) Measurement of human walking movements by using a mobile health app: Motion sensor data analysis. *JMIR mHealth uHealth*, vol. 9, no. 3, pp. 1–15, 2021, https://doi.org/10.2196/24194.

[19] G. Borujeny, M. Yazdi, A. Keshavarz-Haddad, and A. Borujeny, (2013) Detection of Epileptic Seizure Using Wireless Sensor Networks. *J. Med. Signals Sens.*, vol. 3, no. 2, pp. 63–68, 2013, http://dx.doi.org/10.4103/2228-7477.114373.

[20] A. Helmy and A. Helmy, (2015). Seizario: Novel mobile algorithms for seizure and fall detection. *IEEE Globecom Work. GC Wkshps 2015 - Proc.*, 2015, https://doi.org/10.1109/GLOCOMW.2015.7414193.

[21] A. Y. Adwitiya, D. H. Hareva, and I. A. Lazarusli, (2018). Epileptic alert system on smartphone. *Proc. - 2017 Int. Conf. Soft Comput. Intell. Syst. Inf. Technol. Build. Intell. Through IOT Big Data, ICSIIT 2017*, vol. 2018-Janua, pp. 288–291, 2017, https://doi.org/10.1109/ICSIIT.2017.59.

[22] S. A. Makki and M. Fahmy, (2021). An Epilepsy Detection System based on Smartphone Acceleration Sensors. pp. 3747–3757, 2021.

[23] S. A. Makki and M. Fahmy, (2021). A new Smartphone Accelerometers Sensors Utilization for Epilepsy Patients Warning System. pp. 6348–6358, 2021.

DOI : 10.31695/IJERAT.2022.8.10.3

[24] P. Pierleoni, A. Belli, O. Bazgir, L. Maurizi, M. Paniccia, and L. Palma, (2019). A Smart Inertial System for 24h Monitoring and Classification of Tremor and Freezing of Gait in Parkinson's Disease. *IEEE Sens. J.*, vol. 19, no. 23, pp. 11612–11623, 2019, http://dx.doi.org/10.1109/JSEN.2019.2932584.

[25] A. Tay *et al.*, (*2015*). Freezing of Gait (FoG) detection for Parkinson Disease. *10th Asian Control Conf. Emerg. Control Tech. a Sustain. World, ASCC 2015*, pp. 0–5, 2015, https://doi.org/10.1109/ASCC.2015.7244608.

[26] M. Delrobaei, S. Memar, M. Pieterman, T. W. Stratton, K. McIsaac, and M. Jog, (2018). Towards remote monitoring of Parkinson's disease tremor using wearable motion capture systems. *J. Neurol. Sci.*, vol. 384, pp. 38–45, 2018, https://doi.org/10.1016/j.jns.2017.11.004.

[27] G. V. Prateek, I. Skog, M. E. McNeely, R. P. Duncan, G. M. Earhart, and A. Nehorai, (2018). Modeling, detecting, and tracking freezing of gait in Parkinson disease using inertial sensors. *IEEE Trans. Biomed. Eng.*, vol. 65, no. 10, pp. 2152–2161, 2018, https://doi.org/10.1109/tbme.2017.2785625.

[28] O. Bazgir, S. H. Habibi, L. Palma, P. Pierleoni, and S. Nafees, (2018). A classification system for assessment and home monitoring of tremor in patients with Parkinson's disease. *J. Med. Signals Sensors*, vol. 8, no. 2, p. 65, 2018, http://dx.doi.org/10.4103/jmss.JMSS_50_17.

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