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USING OF INERTIAL MEASUREMENT UNIT (IMU) IN MOVEMENT ANALYSIS IN PERSONS WITH PARKINSON'S DISEASE

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SUMMARY

Parkinson's disease (PD) is a second commonest neurodegenerative disorder, followed by the presence of motor symptoms that affect the functioning of a person in the community. Technology development and implementation of various diagnostic and assessment procedures can improve the rehabilitation process of this population. IMU sensors have the potential to identify and provide valuable information about motor performances and behavior, as well as the quality of movements. The aim of this paper is to present the possibilities of using Inertial Measurement Units sensors in movement analysis in persons with Parkinson's disease. Analyzed papers were selected by researching electronic databases: PubMed/MEDLINE, Science Direct, Scindeks, and Google Scholar and published between 2014 and 2020. The analyzed researches have shown that the IMU can be used in the evaluation of motion range and amplitude, repetitive finger taping parameters, characteristics of movements and activities important for everyday living, gait characteristics and parameters, as well as PD related symptoms, such as bradykinesia, tremor, festination, freezing of gait. Sensors, consisted in IMU, also can be fused together to provide a 3D picture of human motion.

Key words: accelerometer, gait, gyroscope, magnetometer, motor behavior, motor performances

INTRODUCTION

Parkinson's disease (PD) is a complex, chronic and long-term neurodegenerative disorder, which progressively deteriorates the motor functions of the individual, and characterized by the appearance of motor symptoms such as bradykinesia, dyskinesia, tremor, and rigidity, usually between 50 and 70 years of age (Aghanavesi et al., 2020; Nguyen et al., 2018). It is predicted that by the 2020, about 3% of the world population above 65 years of age is likely to be affected (Palakurthi & Burugupally, 2019). The disease is named after the London physician James Parkinson, in 1817, identified the basic characteristics of the disease, in his monography An Essay on Shaking Palsy (Kostić, 2009). James Parkinson's famous essay was published towards the end of his career, and presumably it must have taken him a long time to collect the six cases he presented; at this time neurology was a descriptive subject, and this is why Parkinson characterised the cases, even from a distance, but did not examine patients in detail (Hindle, 2008, p. 5). Besides the motor symptomatology, PD is characterized by some non-motor symptoms such as hyposmia, rapid eye movements, sleep behavior disorder, cognitive disorders, personality changes, pain, paresthesias, and depression (Baker &

Gershanik, 2006). The disease progresses over time, as well as the severity and quality of the symptoms, increasing the chance of severe complications (Caramia et al., 2018).

Many experts and persons demand to know more information on their current position and movements to work better and more efficient (Ahmad et al., 2013). Individual characteristics in motor function profile, different stages of the disease, presence of the accompanying problems and difficulties which impair the everyday functioning of an individual with PD, as well as a technology improvement, are just some of reasons for the implementation of different tools and systems for assessment of motor functions and biomechanical characteristic of the individual. For an understanding of pato-physiological phenomena, by quantitative assessment, it is necessary to collect accurate and unbiased results (Pasluosta, Gassner, Winkler, Klucken & Eskofier, 2015). Ideal technological platforms must be simple to use, applicable for everyday clinical practice, and preferably low-cost (Caramia et al., 2018). Inertial Measurement Unit (IMU) sensors, are used widely in many different movable applications (Ahmad et al., 2013), and cost-effective. These sensors often include accelerometers, gyroscopes and magnetometers, allowing the derivation of movement of various body segments (Witchel et al., 2018). Nguyen et al., (2018), points that the wearable sensors, such as inertial measurement units, have been widely used to measure the quantity of physical activities during daily living in healthy and individuals with movement disorders. Monitoring of PD patients, with inertia sensors, is a relevant method for a better assessment of symptoms and their quantification based on motion data (Piro et al., 2016). In population with movement disorders, such is PD, IMU sensors have potential to identify and provide valuable information about quality of movement (Nguyen et al., 2018), leg agility, pronation-supination movement of hands, walking (Aghanavesi et al., 2020), finger movement, taping durations, rhythm, fingers open and close speed, tapping angle, as well as patient's motor performance (Đurić-Jovičić et al., 2018).

Based on theoretical assumptions, by collecting and analyzing the literature research articles, the aim of this paper is to present the possibilities of using Inertial Measurement Units sensors in movement analysis in persons with Parkinson's disease.

Parkinson's disease

PD is a common adult-onset neurodegenerative disorder, whose disabling signs are engendered by the loss of specific subsets of neurons, including dopaminergic neurons in the substantia nigra (Przedborski, 2015), and second neurodegenerative commonest disorder (Meara & Hobson, 2008), diagnosed based on motor impairment (Knežević et al., 2019). PD is a universal disorder, with a crude incidence rate of 4.5–19 per 100 000 population per year, and it has been recognized that a small proportion of persons develop the disease at an early age (Baker & Gershanik, 2008). The aforementioned authors also emphasize that a patients with the disease before 40 years of age are generally designated as having "early-onset" PD. Among them, those beginning between 21 and 40 years are called "young-onset" PD, while those beginning before the age of 20 years are called "juvenile Parkinsonism". Approximate 5% of patients are diagnosed before the age of 40 years (Knežević et al., 2019).

Substantia nigra is an elongated nucleus in the midbrain, made of two parts: pars reticulata and pars compacta, which consist of pigmented neurons that use dopamine as a transmitter (Kostić, 2009). One of the most important roles of the substantia nigra pars compacta is reflected in motor control and signal transmission to the cerebral cortex responsible for initiating motor activity. According to the previously mentioned facts, it can be concluded that the neuron deficiency in this part of substantia nigra has a great impact on motion, therefore the motor activity of every person. Primary damage in PD is progressive degeneration and extinction of dopaminergic neurons in pars compacta substantia nigra (Kostić, 2009). Although, the pathogenesis of PD is not completely explained, by identification and sharing information about PD, contributes to solving the mystery associated with the causative agents (Table 1) (Goldman and Tanner, 2015).

A considerable number of problems associated with motoric functioning, that lead to difficulties in performing activities of daily living, are the main characteristic of PD. The symptoms of PD are predominantly motor-based such as tremor, rigidity, bradykinesia, postural instability, hypomimia, micrographia, festination, shuffling gait, dysarthria, and dystonia (Palakurthi & Burugupally, 2019). Kostić (2009) emphasizes that the primary cause of functional disability is caused by bradykinesia, which includes a lack of spontaneous motoric, difficulties in movement initiation, slow movement performance, with decreasing amplitude, and losses of rhythm in performance of motor activities. In addition to bradykinesia, PD is characterized by the appearance of rigidity (increased muscle tone). Because of the existence of this problem, persons with PD take a specific body position with semiflexion in the trunk, legs (in knees), and hands (in elbows). As a consequence of an absence of resistance during movement performance, it is characteristic of the emergence of "cogwheel phenomenon". In later stages of the disease, dyskinesia, and fluctuation in motor response occurs as a result of a decrease in levodopa concentration. In addition to bradykinesia, PD is characterized by the appearance of static tremor, which is initially intermittent, asymmetrical, and most commonly occurs on one arm. Tremor can affect several parts of the body, most commonly the extremities, with characteristic alternating opposition of the thumb and other fingers, which is reminiscent of movements of "pills-rolling" (Kostić, 2009; Zach, Dirkx, Bloem, & Helmich, 2015). The stance is also disturbed in persons with PD. Decreased stability during both static and dynamic motor tasks and the risk of falling represents a serious and disabling issue that affects daily life and personal autonomy (Santamato et al., 2015). Gait is difficult, unstable, and decreased speed, with the characteristic appearance of "festinating" and "magnetic" gait.

Table 1. *Factors associated with increased and decreased risk for PD (Source Goldman & Tanner, 2015, p. 107-108)*

Factors for increased risk		Factors for decreased risk
Demographic factors Increasing age Male gender White race Family history of PD Lifestyle Head trauma Diet (dietary products, animal fats) Biometric and comorbid conditions Lower blood cholesterol Lower serum uric acid	Oophorectomy Environmental exposures Pesticides Industrial agents Solvents Metals Rural residence Drinking well water Farming Pulp mills Occupations (health care, teaching, woodworking, religious work)	Cigarette smoking and tobacco use Coffee and tea drinking History of gout Diet "Mediterrenean" diet Polyunsaturated fats Uricogenic diet High physical activity Medications Calcium channel blockers Nonsteroidal anti-inflammatory drugs Statins

Mirleman et al., (2019) described three stages of PD, with characteristic motor symptoms:

1) *Early stage*, which is characterized by, reduced arm swing and step length, decreased left arm swing, arm swing asymmetry, reduced axial rotation, slower gait speed, and postural changes.
2) *Mild to moderate PD stage*, which is characterized by, bilateral arm swing reduction, reduced step length, bradykinesia, reduced postural control and stability, shuffling steps, stopped posture and increased cadence.
3) *Advanced PD stage,* which is characterized by, reduced step length, bradykinesia, reduced postural control and stability, defragmentation of turns, reduced walking capacity, freezing of gait during turns and dual tasks or gait initiation, and severe postural changes and postural control.

Inertial measurement units (IMU) sensors application in movement assessment

Movement, motor behavior, and biomechanical characteristics of the individual for different reasons, were an area of interest between different scientists. Specifically, motor activity is important for the functioning of the individual in the community, the realization of everyday activities, but also the planning of a rehabilitation plan and program due to the presence of various conditions and diseases. In the course of biomechanical analysis, for the purpose of the accuracy of data, it is necessary to follow a certain procedure, namely: to determine the movement that is the subject of analysis, to enter all details related to the analysis of the technique in the software for kinematic analysis and to make an adequate record of all participants and the execution of the technique within the realization of assessment (Bubanj, Bubanj, Stanković, & Đorđević, 2010).

IMU sensors are used widely in motion measurement (Zhao & Wang, 2012), as well as in many different movable applications (Ahmad et al., 2013). Caramia et al., (2018), by analyzing the literature explain that IMU sensors were originally introduced in the field aerospace engineering, as means to attitude of flying objects, and to help guidance in navigation system. IMUs can be roughly divided into two groups: IMU made from two sensors type (accelerometer and gyroscope) and IMU newer generation, made from three sensors type (accelerometer, gyroscope and magnetometer) (Figure 1). Both sensors typically have three degree of freedom to measure from three axis (Ahmad et al., 2013) (x, y and z axis). The role of sensors is reflected in the tracking of movement and bio-feedback. Aceelometers are used to measure inertial acceleration, while gyroscopes are used for measuring angular velocity and rotation angle. Magnetometers are used to measure the bearing magnetic direction, as well as angle rotation, thus it can improve the reading of gyroscope (Ahmad et al., 2013). An IMU provides four to nine degrees of freedom, which refers to the type of used sensors and movement, that person performs in a 3D plane. According to mentioned, IMU with two types of sensors has in total between four and six degrees of freedom, while IMU with three types of sensors has nine degrees of freedom in total. The degree of freedom determines the number of independent parameters in the system (Ahmad et al., 2013). All signals can be sent to the host computer form each sensor, usually via Bluetooth connection, or saved on SD card.

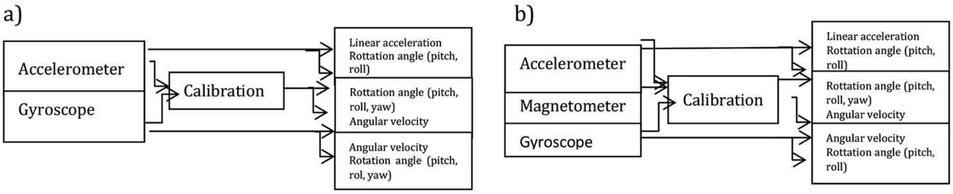

Figure 1. IMU sensors types
(a) two types of sensors b) three types of sensors) (Ahmad et al., 2013)

With the availability of new-generation miniaturized wearable IMU sensors, there is a growing opportunity for functional assessment of motor skills in various disciplines and fields, such as medicine, sports, and ergonomics (Fusca et al., 2018). In clinical practice, IMU sensors have begun to be applied for the purpose of motion analysis (Caramia et al., 2018) and objective assessment of movement patterns during the implementation of functional activities (Al-Amri et al., 2018), namely speed of execution, acceleration, orientation and angular velocities in joints (Ahmad et al., 2013) and other characteristics. The application of these sensors provides objective and sensitive indicators of movement disability, which may indicate the occurrence of different risks in various conditions (Witchel et al., 2018). In order for motion and motor activity assessment, all sensors must be placed on a body segment, whose characteristics will be assessed.

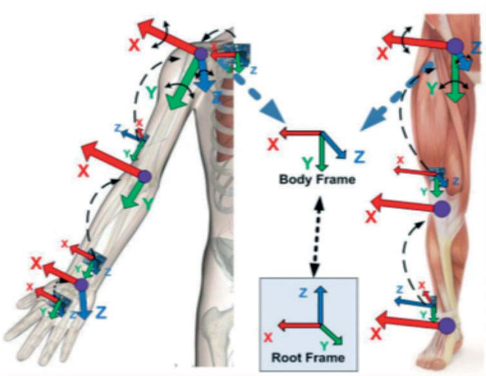

Figure 2. IMU position on arm and leg
(Chen, 2013, p. 22)

IMU system could be useful for experts, patients, and for clinicians to support their decisions, as long as it is: a user friendly system, suitable to be used outdoors in real life, and not only in the laboratory, capable for monitoring subject in natural conditions, without altering the natural and normal execution of movements and activities, and without collaboration process (Fusca et al., 2018). The aforementioned group of authors emphasizes that a system could objectively, qualitatively and quantitatively measure the movements and gait of patients with neurologic and orthopedic impairments that affect motor control.

METHOD

All collected and analysed scientific data had to be in accordance with the theoretical framework and aim of this article. Analyzed papers were selected by researching electronic databases: PubMed/MEDLINE, Science Direct, SCIndex and Google Scholar. For this purpose the method of selection was used. In order to cover bibliography more precisely, the criteria set for the purposes of the search were: research papers published in their entirety based on use of IMU system in kinematic assessment of persons with Parkinson's disease. All research papers must be published between year 2014 and 2020. The following key words were used to search for the papers: inertial measurement units (IMU), Parkinson's disease (PD), accelerometer, gyroscope, magnetometer, 3D motion tracking, motion, motor performance, movement, mobility, biomechanical, kinematic. The applied methods for the selection and analysing the articles included: the selection method, the description method, the systematization method, the analysis method, the synthesis method, and the comparison method.

RESULTS WITH DISCUSSION

Figure 3. Data collection process

Figure 3 presents the process of collecting data from research articles. Following the aim and the set criteria of this article, ten articles were selected, and all indicated to the use of IMU sensors in the assessment of motion and motor characteristics in persons with PD (Table 2).

Table 2. *An overview of the collected and analyzed research studies*

First author (year)	Aim	Sample characteristics			Method and assessed elements	Conclusion
		N	Age	Gend.		
Aghanavesi (2020)	Compare Treatment Response Index from Multiple Sensors (TRIMS) to sensor indexes derived from individual motor tasks in persons with PD.	19	71.4 (6.3)	14 M 5 F	Two type IMU (three axial accelerometer and three axial gyroscope). The evaluation of multiple and connected measurements of motor tests (leg agility, pronation-supination movements of hands and walking) in PD based on data collected by multiple motion sensors.	Using the fusion of upper- and lower-limbs sensor data to construct TRIMS provided accurate PD motor states estimation and responsive to treatment. In addition, quantification of upper-limb sensor data during walking test provided strong results. TRIMS was highly correlated to dyskinesia (R = 0.85), bradykinesia (R=0.84) and gait (R=0.79).
Azevedo Coste (2014)	Adapt and extend freezing of gait (FOG) detectors in order to include other associated gait pattern changes, like festination, with assessment based on a inertial sensors use placed on lower limbs.	4	73 +/-3	4 M	Three type IMU. Evaluation of walk along 10 meters corridor with several proposed dual tasks.	Existing frequency-based freezing detectors are not sufficient to detect all FOG and festination episodes and the observation of some gait parameters such as stride length and cadence are valuable inputs to anticipate the occurrence of upcoming FOG.
Caramia (2018)	Identify which of the gait features are able to better distinguish the presence of PD from age matched healthy subjects.	50 (25 PD/ 25 HS)	43-88 41-79	13 M 12 F 13 M 12 F	Three type IMUs, placed on the lower and upper limbs. Participants included into a set of 6 different machine learning (ML) techniques, processing 18 different configurations of gait parameters (range of motion, spatiotemporal parameters) taken from 8 IMU sensors.	The ability of IMU-based gait analysis to discriminate patients with PD at different severity stages from age-matched healthy individuals has been shown in this study to relevantly depend on the number and location of sensors used to extract the parameters. Best results were obtained with the knee range of motion, calculated with 4 IMUs, placed bilaterally.
Dai (2015)	Introduce a wearable bradykinesia assessment system, whose core component is composed of an inertial measurement unit.	15 (8 PD/ 7 HS)	72.8 ± 10.0/ 57. 1 ± 21. 1	-	Two type IMU The grasping ranges are the three-dimensional peak-to-peak values, which are calculated separately, during grasping cycles of a bradykinesia task.	System has greater correlation with the evaluations by neurologists than other parkinsonian bradykinesia assessment systems. The modified mean range was verified as the major bradykinesia parameter (key indicator).

First author (year)	Aim	Sample characteristics N	Age	Gend.	Method and assessed elements	Conclusion
Đurić-Jovičić (2016)	Investigate repetitive finger tapping patterns in patients with Parkinson's disease (PD), progressive supranuclear palsy–Richardson syndrome (PSP-R), or multiple system atrophy of parkinsonian type (MSA-P).	56 (13 PD 15 PSP-R 14 MSA-P 14 HS)	60.9 ± 9.9 65.8 ± 8.7 58.0 ± 4.5 56.8 ± 9.0		The system included two inertial measurement sensor units, miniature sensors positioned on the thumb and index finger, providing spatiotemporal and kinematic parameters.	The main finding was the lack or only minimal progressive reduction in amplitude during the finger tapping in PSP-R patients, similar to HC, but significantly different from the sequence effect (progressive decrement) in both PD and MSA-P patients. The mean negative amplitude slope of -0.12°/cycle revealed less progression of amplitude decrement even in comparison to HC (-0.21°/cycle, $p = 0.032$), and particularly from PD (-0.56°/cycle, $p = 0.001$), and MSA-P patients (-1.48°/cycle, $p = 0.003$). No significant differences were found in the average finger separation amplitudes between PD, PSP-R and MSA-P patients.
Lonin (2018)	Investigate how to efficiently collect wearable sensor data for the detection of bradykinesia and tremor in the upper extremities, based on the location of wearable sensors used, types of tasks performed by participants and the number of data collection sessions performed.	20	63.35 ± 9.63	13 M 7 F	Two type IMU sensors were placed on the dorsal part of each hand, in each tight proximal of the femur epicondyle, and on each forearm on top of the flexor carpi radialis. During each session, participants performed 13 different motor tasks. Clinician rated the severity of tremor, bradykinesia and dyskinesia in upper extremities for the left and right side, during the execution of each task.	A single wearable sensor on the back of the hand is sufficient for detecting bradykinesia and tremor, in the upper extremities, whereas using sensors on both sides does not improve performance. The prevalence of tremor was substantially lower and more variable than that of bradykinesia; 8 individuals showed dyskinesia during more than one task performance so the models for the detection of dyskinesia are not developed. PD symptoms can be detected during a variety of activities and are best modeled by a dataset incorporating many individuals.
Lukšys (2018)	Examine selected tremor parameters (frequency, root mean square and approximated entropy) in order to quantify the characteristics of persons with PD, compared with healthy persons, and compare the parameters by dividing persons with PD according to Unified Parkinson's Disease Rating Scale (UPDRS) assessment.	31 (PD 13 HS 12)	61.53 ± 10.81 57.83 ± 7.58	8 M 11 F 6 M 6 F	Three type IMU was used. For the quantitative estimation of kinetic and postural tremors, several parameters were selected and calculated from the measured angular velocity and linear acceleration signals. The finger-to-nose test for examining kinetic tremor features and holding an outstretched arm for examination of postural tremor features, were used for assessment.	Statistically significant differences between PD patients and control groups were observed in approximated entropy acceleration signal of kinetic tremor, approximated entropy angular velocity signal of kinetic tremor, approximated entropy angular velocity of postural tremor, frequency acceleration signal of postural tremor, and RMS angular speed kinetic tremor.

First author (year)	Aim	Sample characteristics			Method and assessed elements	Conclusion
		N	Age	Gend.		
Nguyen (2018)	Develop detection and segmentation algorithms based on IMUs to isolate activities of daily living (ADL) in persons with PD in a simulated free-living environment.	9	66.1 ± 2.7 M 66.5 ± 12.0 F	7 M 2 F	17 Three Type IMUs positioned on each limb, trunk, and head segment to capture full-body 3D movement. ADL such as *sit down* (on a chair), *stand up* (from a chair), *reach*(*ground*, *mid*, *high*), *walk,* and *turn* were identified for detection and segmentation	IMU demonstrated great accuracy in the detection of *sit down* and *stand up*, which could be used to measure performance in PD population. Reaching activities were detected with almost 90% sensitivity, but the accuracy decreases when reaching tasks are separated by levels. The beginnings and endings of *turn* were segmented with a median difference of 0.68s within the manual segmentation. *Turn* can occur abruptly during sharp angle (turn 180° or 90°) or more gradually during walking. Even with the largest variation (SD = 1.09s), *turn* was detected with almost 83% accuracy. Lastly, there were over 350 bouts of walking classified manually by the examiner and about 92% of it was detected using the sensors. Within the detected walking bouts, the differences between the manual and sensor segmentation was approximately 0.63s. The high detection rate and low segmentation time differences illustrate the potential of using IMUs in clinical setting to quickly measure and analyze the quality of movement in PD population.
Sijobert (2014)	Early detection of freezing of gait (FOG) and festination episodes in order to trigger functional electrical stimulation (FES) assistance. Detect results of FOG and festination detection, including frequency analysis and gait parameters (stride length and cadence) changes.	7	70 ± 5	6 M 1 F	One, two type IMU was used to detect freezing of gait and festination episodes, while a person walks along 20 meters long corridor (several dual tasks were proposed in order to maximize the number of FOG). IMU sensor data was processed in order to compute freezing index (FI), the ratio between the signal (limb acceleration) power in the "freeze" band and the signal power in the "locomotor" band) and freezing of gait criterion indexes (FOGC).	The FI method detected 32 of FOG episodes, and the FOGC method detected 41 of these episodes. Concerning the 31 main FOG events, FI "missed" 11 FOG events and FOGC missed only 5 of them. None of festination episodes was detected by the FI method whereas FOGC detected all of them. Stride length and cadence could for instance be interesting to observe in order to detect gait changes including FOG and festination.

First author (year)	Aim	Sample characteristics			Method and assessed elements	Conclusion
		N	Age	Gend.		
Zago (2018)	Investigate whether a commercially available inertial sensor can reliably provide basic spatiotemporal parameters in persons with PD, during a walking. Compare IMU applicability to a gold standard optoelectronic motion capture system.	22	69.4 ± 6.1	10 M 12 F	Three type IMU and the optical system was used to determinate eight spatiotemporal parameters describing the step cycle (cadence, velocity, stride length, stride duration, step length, stance, swing and double support duration). Results were compared between the two systems. The IMU and the optical system reported comparable gait parameters, with the exception of walking velocity.	All the gait variables measured with the two systems resulted to be not statistically different, with the exception of the gait velocity ($p<0.05$). Positive, high correlations were obtained for cadence, velocity, stride duration and stride length; positive, moderate correlation for the other parameters. All correlations were statistically significant. The IMU system is sufficiently accurate in the assessment of fundamental gait spatiotemporal parameters. The fast and simplified data recording process allowed by wearables makes this technology appealing and represents a possible solution for the quantification of gait in the clinical context, especially when using a traditional 3D optoelectronic gait analysis is not possible.

Legend: Gend.- Gender; M- male, F- female; HS- healthy subject, IMU- inertial measurement unit

Following the results of the analyzed studies, shown in Table 2, it is observed that the use of IMU plays a significant role in the assessment of various motor activities in individuals with PD. During assessment wearable sensors have to be fixed properly and firmly to the human body so as to avoid vibration artefact on the IMU measuring (Fusca et al., 2018). The aforementioned authors also emphasize that the bad alignment of the measuring could introduce drift in the measurement so this setup parameter has to be controlled and compensated. The use of different types of IMU is applied in the assessment of both the functioning of the upper and lower extremities and the overall motor functioning of the individual, as well as the detection of possible, accompanying difficulties in the implementation of the motor task.

To measure 3D linear accelerations and angular velocities in three axes (X, Y, and Z) from upper and lower limbs, four inertial measurement units (IMUs) were used, and each IMU provided inertial sensing via tri-axial accelerometer and tri-axial gyroscope. To capture as much as data from lower limbs during walking and foot tapping data, the IMUs were placed just above the ankle joints facing outwards, while to record the upper limb data during hand rotation and also walking, participants put on the IMUs next to the ulna bone on the outside of the wrist (Aghanavsi et al., 2020). All of sensors continuously recorded movement, when they were turned on, and readings included the acceleration and angular velocity measurements and the total stream of the signals was visualized. Identification of the walking signals was done by recognizing the signals for previous and later tests. The number of collected observations per motor tests was 224 for leg agility (LA), 230 for pronation-supination movements of hands (PSM) and 223 for walking. Results of study indicates that from upper-limb tests (PSM and ULM-W) the majority of the selected features were based on accelerometers (10 out of 18 for PSM, 8 out of 8 for ULM-W), whereas from lower limb tests (LA and LLM-W) the majority of the selected features were originated from gyroscope sensors (4 out of 7 for LLM-W, 4 out of 6 for LA). All of obtained results (from examining correlation of Treatment response index and reference scores) showed high correlation to dyskinesia, bradykinesia and gait, and low correlations to leg agility and pronation-supination movements of hands.

In the study of Nguyen et al., (2018) IMU was used for detection of characteristics in activities of daily living, such as sit down (on a chair), stand up (from a chair), reach (ground, mid, high), walk, and turn. For nine participants with PD, a simulated free-living apartment (7m x 8m) was set up to induce a daily living task of cleaning and all of objects were strategically placed throughout the apartment at different locations and heights. During assessment IMUs were positioned on each limb, trunk and head segment to capture full-body 3D movement. Each module contains a 3-axis accelerometer (linear acceleration), a 3-axis gyroscope (angular velocity), and magnetometer (magnetic north heading). While the method was developed using a continuous Timed Up and Go task, the fundamental processes of detecting and segmenting these activities remained the same. In the cleaning task, kinematics peaks were used to identify an activity and the maximum/minimum to the left/right of these peaks was used to estimate the duration (segmentation) of an activity (Nguyen et al., 2018). Sit down and stand up was detected using several kinematic data extracted from different IMUs and segmented using the acceleration of the trunk, the sacrum acceleration was added to ensure synchronicity of movement of the trunk and the hip during these activities, while the symmetry of the left and right hip flexion was used to discriminate from other activities such as reach ground, where PD participants often performed with one knee touching the ground. Walk was classified using the magnitude of the linear acceleration of the left and right IMU on the shin in the x and z direction. Reaching activities were detected using the normalized angle of the trunk, hip, knee, and shoulder. Authors in results of study indicate that across all activities, classification using the sensors signals was about 90% accurate (sensitivity = 89.8%, specificity = 97.9%). During sit down (N = 84), the median of the time difference between the manual and sensor segmentation was 0.34 s, during stand up 0.18 s, the three reaching activities, median difference was 0.2). Within the detected walking bouts, the differences between the manual and sensor segmentation was approximately 0.63 s. The high detection rate and low segmentation time differences illustrate the potential of using IMUs in clinical setting to quickly measure and analyze the quality of movement in PD population.

With aim to introduce a wearable bradykinesia assessment system, whose core component is composed of an inertial measurement unit, Dai et al., (2015), tracked the finger's activity by an inertial measurement unit (IMU) on the top side of the patient's middle finger, which includes a three-axis gyroscope and a three-axis accelerometer; the gyroscope is used as the primary source of orientation information, while the accelerometer is used for roll–pitch drift correction because it has no drift over time. Only the gravity vector of the accelerometer is used for the drift detection. A 10 second whole task was chosen as the assessment action in persons with PD. An IMU, attached to the middle finger, was used to measure the angular displacement of the middle finger during the bradykinesia assessment task. The hand grasping angles obtained from patients with mild bradykinesia have a consistent amplitude and frequency, and appear sinusoidal. However, hand grasping angles of persons with severe bradykinesia have much lower and more inconsistent amplitudes and frequencies. Speeds, amplitudes, halts, hesitations, and any decline in amplitude are evaluated. Results of evaluation indicate that the akinesia affects the cycles of the hand grasps, thus the dominant frequency was reduced. Calculated bradykinesia parameter (modified mean range, instead of mean and standard deviation of the grasp ranges) correlated well with the evaluations of a neurologist (Pearson's correlation coefficient $r = -0.83$, $p < 0.001$). Result also indicates that the age of subjects may influence performance of hand grasping, as well as that the modified mean range can be defined as the major parkinsonian bradykinesia parameter. Đurić-Jovičić et al., (2016) investigated the repetitive finger tapping patterns in persons with PD, and two other conditions (supranuclear palsy–Richardson syndrome- PSPR and multiple system atrophy of parkinsonian type-MSAP). Kinematic parameters followed by sensors were angle amplitude in degrees, cycle duration, speed. Tapping amplitude was defined as the angle between the long axes of the thumb and index finger, while closing and opening velocities were the peak velocities of aperture closure and opening within a cycle. The slope of change in amplitude was used to assess progressive hypokinesia or "decrement" and the slope of change in speed that encompassed both amplitude and duration was used to assess progressive slowing of movement. Obtained results showed that persons with PD had significantly shorter duration per cycle than healthy subjects and persons with PSPR. The amplitude slope in PSPR was significantly less negative compared to PD group. The amplitude and speed slopes were more negative in the PD and MSAP groups. In the PD group, 27.3% (3/11) of patients with hypokinesia were without decrement, while the remaining 72.7% (8/11) had hypokinesia with decrement ($p = 0.0002$).

Research based on recording movement data from 6 body-conforming flexible wearable sensors attached to the hands, arms, and thighs, and trained a machine learning classifier, with aim to detect the presence of tremor or bradykinesia in upper extremities, as individuals with PD performed a series of common daily activities and standard tasks used in clinical assessments, was conducted by Lonin et al., (2018). Obtained results indicate that the mean proportion of task performances showing symptoms across participants were 48.5% for bradykinesia, 22% for tremor, and 8% for dyskinesias. The prevalence of tremor was substantially lower and more variable than that of bradykinesia, with one participant showing no manifestation of tremor at all. Eight persons with PD showed dyskinesia during more than one task performance, while using data from sensors on both hands to detect symptoms did not significantly improve performance. Bradykinesia detection during fine motor tasks and walking yielded the highest mean across participants.

A nine degree freedom wireless inertial measurement unit, consisted from six wireless sensors, was used by Lukšys et al., (2018) to examine tremor parameters in order to quantify the characteristics of persons with PD in comparison with healthy persons. Used IMU was consisted from accelerometer, gyroscope and magnetometer. In order to reach the goal, each participant performed motor tasks specific do certain tremor: finger-to-nose test for examining kinetic tremor features and holding an outstretched arm for examination of postural tremor features. Several parameters were selected and calculated from the measured angular velocity and linear acceleration signals for quantification of kinetic and postural tremors (dominant frequency, root mean square-used to evaluate the intensity of tremors and approximated entropya). Significant differences between PD patients and control groups were observed in approximated entropy acceleration signal of kinetic tremor, approximated entropy angular velocity signal of kinetic tremor, approximated entropy angular velocity of postural tremor, frequency acceleration signal of postural tremor, and root mean square angular speed kinetic tremor.

Gait and characteristics of walking are the areas of interest between many experts, who conduct researches with various aims. "Can gait features predict the presence of PD?" is one of the questions who asked Caramia et al., (2018) in their research. The measuring instrumentation in research of previously mentioned group of authors included the Motion capture system Tech-MCS, consisted of eight IMUs (each consisted from accelerometer, gyroscope and magnetometer), located in the lower and upper parts of the body (each foot dorsum, each shank, each thigh, chest and bon back side of lumbar zone). Range of motion and spatio-temporal parameters (step length, step time, stride time and stride speed) were extracted as parameters from raw data. The ability of IMU-based gait analysis to discriminate patients with PD at different severity stages from age-matched healthy individuals relevantly depend on the number and location of sensors used to extract the parameters. Best results were obtained with

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a Approximate entropy is a technique that quantifies the degree of irregularity and the unpredictability of fluctuations in time series data (Lukšys et al., 2018).

the knee range of motion, calculated with 4 IMUs, placed bilaterally. Spatio-temporal parameters also were examined in study of Zago et al., (2018). In mentioned study three type IMU and the optical system was used to determinate eight spatiotemporal parameters describing the step cycle (cadence, velocity, stride length, stride duration, step length, stance, swing and double support duration). For assessment of parameters authors implemented “Walk” protocol, which requires that the sensor must be placed at the L5 level by means of a provided elastic belt. Five trials were acquired with both the optoelectronic and IMU-based systems, asking participants to walk barefoot along a 10-m walkway at their self-selected walking speed. The values of the three central trials were used for systems comparison. Parameters, obtained with two systems, were not significantly different, with the exception of the gait velocity ($p < 0.05$), which was significantly higher in the measurements by the wearable system. Positive, high correlations were obtained for cadence, velocity, stride duration and stride length, while positive, moderate correlation was obtained for the other parameters. All correlations were statistically significant. By introducing a new approach for the observation of gait changes and the detection of FOG events, the so-called FOG criterion (FOGC) based on the continuous evaluation of two gait parameters: cadence and stride length, Azevedo Coste et al., (2014), used inertia sensor-based walking speed estimation methods. Namely, authors explain that this method is based on the segmentation of gait data into strides using gyroscopic data. Within each stride the acceleration data is integrated in order to obtain the forward leg displacement. The initial velocity of the leg at the stride onset is obtained using gyroscopic signal. At the end of the stride, a correction is performed. IMU signals and video were recorded during 1.730 s. Video from the sessions were analyzed by the neurologist who identified and labeled 44 freezing of gait episodes. IMU sensor data was processed in order to compute freeze index (FI; the ratio between the signal (limb acceleration) power in the “freeze” band and the signal power in the “locomotor” band) and FOGC indexes. The FI method detected 26 of these episodes and the FOGC method detected 35 of these episodes. Concerning the 26 main FOG events (labeled red and orange), FI “missed” nine FOG events and FOGC missed only four of them. On the end, authors conclude that the existing frequency-based freezing detectors are not sufficient to detect all FOG and festination episodes and the observation of some gait parameters such as stride length and cadence are valuable inputs to anticipate the occurrence of upcoming FOG. Similar method of detecting freezing of gait and festination episodes during walk in persons with PD was used by Sijobert et al., (2014). In this study IMU sensor data was processed in order to compute freezing index (FI), the ratio between the signal (limb acceleration) power in the “freeze” band and the signal power in the “locomotor” band) and freezing of gait criterion indexes (FOGC). After collected data, authors concluded that the FI method detected 32 of FOG episodes, and the FOGC method detected 41 of these episodes. Concerning the 31 main FOG events, FI “missed” 11 FOG events and FOGC missed only 5 of them. None of festination episodes was detected by the FI method whereas FOGC detected all of them. Stride length and cadence could for instance be interesting to observe in order to detect gait changes including FOG and festination.

According to the previously described results and procedures, IMU can be used in assessment of different characteristics of motor behavior, performances and motor symptoms in persons with PD. instruments has many advantages with "gold standard" considered system in terms of feasibility, portability and cost (Fusca et al., 2018). Besides a small sample size, the limitations of conducted and analyzed researches are insufficient and inadequate described testing procedures, applicability of non-standardized motor assessment tools in some research. Applicability IMU in work with persons with PD and other conditions, which can result in severe disability, can have a predictable role in the therapeutic process. As motion capture is available with IMU, application of them in different scientific areas can be useful as a toll for diagnostic of various conditions and diseases. IMU system represents a promising and viable alternative to the standard gait analysis systems (Zago et al., 2018), as well as other segments of motor behavior important for performing activities of daily living important for the improvement of quality of life in every person. Use of IMU will provide two major advantages: (a) overcome the intraindividual variability at different times of the day in a single person due to the disease fluctuations, thanks to prolonged recording times; (b) provide the staff with technology suitable to make accurate diagnoses, and to develop a more effective targeted therapy, thanks to objective, long-term measurements of treatment outcomes (Zago et al., 2018).

CONCLUSION

Parkinson's disease is second commonest neurodegenerative, motor disorder, which leads to the functional disability in elderly. Technology development, implementation of various diagnostic and therapeutic procedures, can decrease the percent of persons in advanced stage of PD. IMU based assessment of motor behavior and kinematic characteristics can be support in aforementioned process.

The analyzed researches has shown that the IMU can be used in evaluation of motion range and amplitude, characteristics of movements and activities important for everyday living, gait characteristics, as well as PD related symptoms, such as bradykinesia, tremor, festination, freezing of gait. Sensors, consisted in IMU, also can be fused together to provide a 3D picture of human motion.

The importance of this systematic review article is oriented toward contributing to the creation of a general viewpoint on the implementation of IMU in the assessment of motor task performance in persons with PD. Around the world and in our country, a small percent of studies are based on the assessment of persons with PD with the use of IMU. The previously mentioned fact represents a proper foundation for a comprehensive consideration of the problem in further studies.

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