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Application Scenarios for Gait Analysis with Wearable Sensors and Machine Learning

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Abstract – **The digital revolution that characterizes the beginning of the 4.0 Era has already prompted out a variety of smart living technologies, which rely on the pervasive connectivity granted by the Internet of Things. These technologies are having a relevant impact on health systems, working and domestic environments, sports and rehabilitation, by enabling new promising practices for human body kinematic studies. This paper provides a specific discussion on how kinematic studies in clinical diagnosis, rehabilitation and sport, take benefit from the use of the recent smart living technologies. More specifically, in exploring the latest trends in the application of gait analysis using wearable sensors and Machine Learning techniques.**

I. INTRODUCTION

As well known, smart sensors are about designing systems people can and will use, regardless of the contexts they are living or working in. Their innovation is pervasive and impacts a variety of fields, such as Home, Workplace, Governance, Manufacturing, Commerce, Health, Infrastructure, Agriculture, Mobility, Energy and many others.

Internet of things (IoT) technologies are the recognized tools to operate on these playgrounds and transform the traditional solutions into innovative schemes, capable of enabling the smart services that are expected to watermark the 4.0 Era.

A number of novel sensors with built-in IoT solutions for (wireless) data transfer to the cloud are receiving more and more attention. Among the others, the compact inertial measurement units (IMU), which embed tri-axial accelerometers, gyroscopes, and magnetic field sensors, are widely integrated into smartphones, smartwatches, or sold as nice wearable accessories, that are aimed at monitoring biological and bio-mechanical parameters, and are perhaps the most promising; the compact inertial measurement units (IMU), are in general widely used to measure kinematic parameters[1, 2].

The gait analysis deals with the scientific evaluation of the human locomotion, which requires the measurement of the kinetic and kinematic parameters characterizing the stride as the basic constituent of the walk. The traditional practice used video camera systems [3] to perform qualitative monitoring approaches. But, the analysis of video recordings obtained from multi-camera systems required laboratories, expensive equipment and extended times for system calibration and subject preparation. Nonetheless, the tests carried out in the laboratory did not perfectly reflect the natural movements because of the patient's behavior in a laboratory, could be different from that in everyday life [4].

At present, the gait analysis is taking benefits from the use of wearable sensors, which are quite inexpensive, suitable for tests outside the laboratory environment, and capable of recording physiological conditions and movement activities in unspoiled conditions.

Hereinafter, the attention is mainly paid to the gait analysis, which is receiving more and more credit as a viable tool for ergonomics, training program evaluation for athletes, and clinical assessment in orthopedics, neurology, and several other fields focused on musculoskeletal disorders [5, 6] . For example, gait analysis provides useful indicators for the early diagnosis of Parkinson's disease. Specifically, the affected patients exhibit poor movement of the facial, upper and lower limb muscles, and flexed-forward trunk, that implies difficulty with stop and turn movements. Consequently, the space and time parameters of the gait cycle, such as gait velocity, cadence, stride time, and length are different with respect to those measured for healthy subjects [7].

Gait analyses are useful for objectively evaluating the functionality after arthroplasty and identifying joint overloads with possible gait deficits. For example, the presence of persistent walking abnormalities after knee arthroplasty surgery is sometimes detected in clinically asymptomatic patients, and significant alterations of kinematic parameters, such as reduction in walking speed, increase in the stance phase duration, decrease in a joint excursion, can be detected even a long time after surgery [8]. The walking speed is commonly lower than in normal subjects, even in the presence of good clinical conditions and absence of pain [9]. To give an example, gait analysis plays a role in rehabilitation treatment planning, choice/adaptation of an orthosis, functional surgery proposal, pre- and post-operative comparison in the rehabilitation of stroke victims. It is at the bases of rehabilitation programs for patients with lower limb prostheses, or patients that have suf-

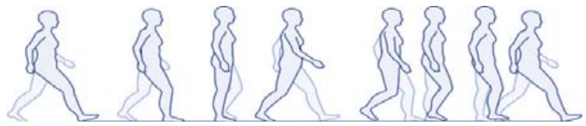

Fig. 1. Gait phases of a normal gait cycle: stance phase and swing phase

fered bone lesions or fractures. The outcomes of the analysis allow suitable refinements of the rehabilitation program and reduce any abnormal stresses on the prosthetic or injured limb. The remote control offers many advantages, such as allowing continuous monitoring of the patient, which is not available in classic monitoring. During rehabilitation, the caregiver can remotely guide the patient in carrying out exercises and eventually modifying the rehabilitation program. The clinical history of the patient is easily available, and large savings related to the monitoring costs of hospital structures are possible [10, 11].

The purpose of the paper is providing a discussion on the main applications where gait kinematic analysis takes benefits by means of IMU sensors and machine learning. To this end, the possibilities of gait analysis, as a means to perform clinical assessment in orthopedics and neurology, diagnosis of musculoskeletal disorders, as well as to plan training programs for athletes, fall prevention and detection, is first extensively discussed. In particular, more technical details related to gait analysis and examples of signals are given in Section II. In Section III , interesting and very recent applications based on machine learning paradigms for gait analysis are reviewed. Finally, concluding remarks and plans for future studies are summarized in Section IV.

II. FUNDAMENTALS OF GAIT ANALYSIS

A. *Gait phases and parameters*

The gait analysis pays attention to the gait or stride cycle, which consists in a series of basic movements that are continuously repeated by an individual. A single stride is performed in the time interval delimited by two successive initial ground contacts for the same foot, and it is shown in Figure 1. The time interval of the stride is the reference for all the other time parameters related to muscle activities. The stride is divided into stance and swing, and the time intervals corresponding to them are in turn divided each one into three sub-intervals. Specifically, the stance includes the initial double support, single support, and double terminal support; these movements are performed in the related time intervals that are defined in the following.

- Initial double support: the time interval in which both feet have contact with the ground.
- Single support: the time interval during which the opposite foot comes off and swings.
- Double terminal support: the time interval delimited by the initial contact of the contra-lateral foot, and the support limb detachment precluding a swing.

The swing includes the initial swing, the intermediate swing or mid swing, and the terminal swing; these constituent movements are performed in the related time intervals that are defined in the following.

- Initial swing: the time interval that starts with lifting the foot from the ground, and ends when the swinging limb is parallel to the supporting foot.
- Intermediate swing: the time interval that begins when the swinging limb is opposite to the supporting limb, and ends when the first shows the tibia in vertical position during its advancing.
- Terminal swing: the time interval that starts with the tibia in vertical position, and ends when the foot makes contact with the ground.

B. *Measurements*

Measurements are related to space and time parameters obtained by processing raw data from acceleration and gyroscope signals. The most common parameters useful in human kinematic studies, and in particular in gait analysis, are given hereinafter.

- evaluated steps: number of steps considered in the analysis;
- gait cycle time (GTC) (seconds): duration of a complete cycle in seconds;
- cadence (steps/min): number of steps per minute;
- swing duration (% GCT): average value of the duration of the right and left swing movements as a percentage of GTC, further divided into right swing duration, expressed as percentage of the gait cycle the right foot is off the ground (% GCT), and left swing duration, expressed as percentage of the gait cycle the left foot is off the ground (% GCT);
- stance duration (% GCT): average value of the duration of the right and left support phases as a percentage of the gait cycle duration, further divided into right stance duration, expressed as percentage of the gait cycle the right foot is on the ground (% GCT), and left stance duration, expressed as percentage of the gait cycle the left foot is on the ground (% GCT);
- double support duration (% GCT): percentage of the gait cycle both feet are on the ground;
- single support duration (% GCT): average value of the single right and left support duration as a percentage of GCT;

- stride length: average value of the distances between each initial contact and the next of the same foot for left and right side;
- normalized stride length (% height): stride length is normalized to the height of the individual body;
- stride velocity: average value of the right and left limb velocity.
- normalized stride velocity (% height): Stride velocity normalized to the height of the body.

Several additional parameters are also defined by combining the aforementioned ones, like the symmetry index, which provides the percentage of symmetry between the acceleration curves of the right and left foot during the gait cycle. The symmetry index provides information on the general balance during the walk; it is dimensionless and its values are up to 100, where the value 100 indicates total balance between both feet. As an example, two typical signals acquired with different protocols and sensors are reported. The first example in Figure 2 shows the acceleration signals of the right and left feet. The signals are acquired with an IMU sensor positioned between the vertebrae S1-S2. By observing each graph in Figure 2, it is possible to distinguish the double support phase and the single support phase. A descending trend characterizes the acceleration signal during the double support phase and an ascending trend during the single support phase, which starts with the detachment of the contra-lateral foot, and ends with the ground contact of the contra-lateral foot. The single support phase is delimited in the upper graphic by the vertical cursors, represented with dashed lines. The tilted line that connects the beginning and endpoints of the single support phase highlights the propulsion, and its inclination quantifies the propulsion index. High values for the propulsion index highlight strong capacities at advancing. The second example in Figure 3 shows a signal produced by a gyroscope monitoring the angular velocity of the shank. The signals are acquired with an IMU sensor positioned on the shanks of the subject. The higher angular velocity values correspond to the swing, the lower to the stance. Estimates of the time parameters can be obtained from the angular velocity signal; the repetitiveness of the movements allows both estimates of individual occurrences and average values.

III. APPLICATION SCENARIOS

The practice of gait analysis is at present one among the most promising diagnostic tools in a variety of application scenarios, discussed in the following.

Long-term high-intensity training affects athletes and can even lead to injuries, which in turn prevent them from keeping on training and/or taking part to the scheduled

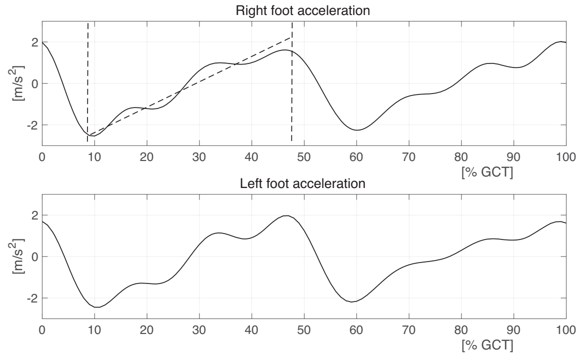

Fig. 2. Acceleration signals of the right and left foot in anterior-posterior component acquired by a typical accelerometer positioned by the Venus dimples aside the S1-S2 vertebrae.

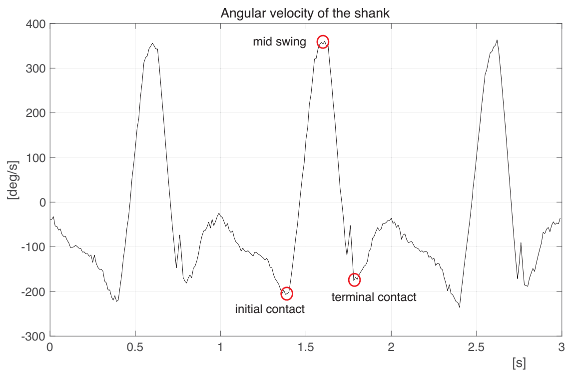

Fig. 3. Portion of the signal related to the angular velocity of the shank, angle in the sagittal plane, acquired by means of a typical wearable gyroscope.

competitions. A prognostic system to predict risks of injuries is discussed in [12], where a machine-learning approach to evaluate the anterior cruciate ligament injury risk is proposed. The anterior cruciate is one of the four main ligaments of the knee and its injury represents the main issue affecting players, especially in contact sports. The study analyzes the stress of the ligament through experiments performed on 39 basketball players, when performing monopodalic jumps or single-leg power squat, the latter executed maintaining the arms with the hands on the hip and extending the resting leg in front of the body. The duration of the basic movements required by each exercise are considered as features of interest. Their values are normalized to the stabilization time, defined as the time between the contact with the ground and the instant in which the active leg is stable, which corresponds to the local minimum of the angular velocity of the shank after ground contact. The study considers data collected by IMU sensors, placed on the shank by means of an elastic belt designed to avoid movement artifacts. Data are processed using supervised machine learning approaches for injury prediction, either based on support vector machine, or k-nearest neighbor, or decision tree concepts. The results of the study highlight the capability of the linear support vector machine, as the best performant approach, of accomplishing 95% accuracy in the classification. Methods like gait analysis are also exploited to improve the performance of athletes or prevent injuries. The skill in sport is in fact improved also by investing in training tools and systems. Traditional training methods such as coach supervising or video recording have some disadvantages, such as time-consumption and/or limits imposed by the environment. Differently, wearable sensors for gait analysis offer the possibility to non intrusively measuring the performance, and by coding the experience of the trainer, also to automatically providing feedbacks. The study [13] developed a system for recognizing the Baduanjin movements and evaluating their accuracy using wearable devices. The system can be used to help students in learning from their mistakes during use by comparing their movements with teachers' ones. Fifty-four volunteers, among students and teachers, participated in the experiment and several sequence-based techniques were used, such as dynamic time distortion (DTW) combined with different types of classifiers, the hidden Markov model (HMM), and recurrent neural networks (RNN). Three methods, nameley DTW + k-NN, DTW + SVM, and HMM, had the best accuracy, scoring over 99 % in evaluating and recognizing Baduanjin movements.

Instead, the studio [14] developed a system for player evaluation and classification of five prototype tennis strokes in real-time. An imu sensor mounted on the participants' wrists and connected to an Android smartphone via Bluetooth wireless technology, was used. The experiment was attended by 36 participants with average age equal to 25 years. The processing of the IMU data includes the preprocessing, segmentation, feature extraction, dimensionality reduction, and classification phases. The pre-processing phase involves noise reduction and the compilation of missing data cases. Different types of SVM classifiers were used, such as MinMaxScaler, MaxAbsScaler, StandardScaler, MinMaxScaler, MinMaxScaler. The study showed that SVM (StandardScaler), SVM (MinMaxScaler) and SVM (MaxAbsScaler) classifiers achieve, respectively, 90 %, 88 % and 89 % accuracy, while the SVM (RobustScaler) and SVM (Normalizer) provide 85 % and 77 % accuracy, respectively.

Falls are widespread among older people, and responsible of severe physical and/or psychological consequences, that can affect the quality of life. Fall detection systems should be capable of distinguishing falls from routine activities, in order to provide immediate medical assistance in the former case. The study presented in [15] reports a fall detection system enabled by wearable inertial sensors placed on the chest, waist, head, right wrist, right ankle, and right thigh. The system can transmit the data via wireless link to a remote PC. The study considers 14 volunteers that perform 16 daily life activities and 20 fall actions. It uses the PCA method to reduce the features dimensionality, and set up a fall detection system based on a convolutional neural network with 8 layers, that offer 98.27% classification accuracy. An alternative fall detection system, also enabled by the use of inertial sensors, is illustrated in [16]. The proposed system uses the event-triggered approach to acquire the pre-impact, impact and post-impact phases, evidenced by the acceleration signal. The pre-impact is recognized by an acceleration peak greater than an experimental threshold, and it is characterized by subsequent peaks precluding to a highest peak, corresponding to the moment when the subject hits the ground. Further samples are collected for recording the post-impact phase, characterized by an absence of peaks. The study reports about 46 healthy subjects acting 14 falls, and several activities of daily living, for 23 minutes each one. The extracted features are 27 and relates to the pre-impact, impact and post-impact phases. The proposed classifiers, based on k-NN and SVM approaches, reach accuracy equal to 95.6% and 97.2%, respectively.

It has been underlined in the previous Sections that gait analysis has become an interesting research topic due to the widespread availability of inertial sensors in wearable devices, and that activity recognition provides reliable information about the functional abilities and lifestyle of an individual. The study presented in [17] uses data collected by means of inertial sensors in smartphones, and an artificial neural networks to perform human activity recognition and classification. The optimal architecture is implemented with 100 neurons in the input layer, 60 in hidden layer 1, 20 in hidden layer 2, and 12 in the output layer for recognizing 12 classes of activities: standing, sitting, lying down, walking, walking upstairs, walking downstairs, stand-to-sit, sit-to-stand, sit-to-lying, lying-to-sit, stand-to-lying, lying-to-stand. The extracted spatio-temporal features are followed by dimension reduction based on PCA. A total of 7767 and 3162 events are used for training and testing phases, respectively, where each event is made of 561 features. The proposed ANN can achieve 89% accuracy, following by the alternative SVM method that scores 82% in activities classification.

The study [18] classifies six different human-walking styles using kinematic parameters obtained from sensors placed on six joints for twenty-five volunteers. From the IMU signals, space-time parameters were extracted for training neural networks. The neural network with the highest accuracy approximately 90 %, is made of three hidden layers with 100 neurons, 6 inputs neurons, and 6 output neurons corresponding to 6 walking activities. Instead, the study [19] proposes different combinations of deep learning architectures based on convolution neural network for human walking activities recognition reaching 97 % accuracy.

Gait and balance analysis represent recognized practices in many clinical areas to distinguish between healthy patients from patients affected by diseases such as cerebral palsy, spinal cord injury, hemiplegia, hip dysplasia, geriatric disorder, osteoarthritis, orthopedic and others [20].

Patients with neurodegenerative disorders can undergone freezing of gait (FOG), that consists in a loss of movement, despite their resolute intention to walk; FOG commonly arises in patients with the Parkinson disease. The study presented in [21] describes a reliable FOG prediction system, realized with machine learning algorithms that process data gained by means of inertial sensors. The proposed system is capable of recognizing the degradation of the walking preceding FOG in patients with Parkinson. To this end, it uses the timed-up-and-go (TUG) and exploits inertial sensors placed on the shins to gather measurement information. The clinical TUG test, aims at measuring how long the subject takes to standing up from a chair, walking 7 meters, turning 180 degrees, walking back to the chair and sitting down. The feature extraction is performed analyzing the angular velocity signals in the time and frequency domains. Subsequently, wrapper techniques are deployed to select the features that can optimize the machine learning classifiers for detecting pre-FOG episodes. Classifiers based on SVM and k-NN approaches show an accuracy of 92.1% and 89.8%, respectively.

Osteoarthritis (OA) is a common musculoskeletal disorder affecting the older population, and resulting in chronic pain and disability. Gait retraining is an effective intervention for patients with osteoarthritis of the medial compartment knee, that aims at reducing knee adduction moment (KAM). The study presented in [22], shows how estimating KAM during walking by using machine learning techniques applied to data collected from low-cost IMU sensors placed on the malleoli. Participants, both with knee OA and healthy, are invited to walk along a 20 meter path. It is shown that a neural network with 10 fully connected layers, composed by 256 neurons in layers 1-6, 128 neurons in layers 7-8, and 64 neurons in layers 9-10 allows accurate KAM evaluations.

Brain stroke is a widespread cause of disability, and rehabilitation exercises represent essential steps for post stroke recovery, as discussed in Section 2.1. The physical exercises performed in the laboratory under the supervision of a specialist represent, however, a poor recovery program, that needs to be complemented with home exercise programs. Making conclusions about the correctness of rehabilitation exercises in both clinical settings requires reliable methods. The study presented in [23] proposes an approach based on machine learning techniques for the remote rehabilitation of lower limbs in post stroke patients. In detail, the study analyzes the data related to 2 volunteers with stroke, during the rehabilitation sessions performed along 4 days; the data are collected by means of inertial sensors placed on triceps and ankles. Using PCA method, 36 features are distinguished and analyzed by means of machine learning techniques based on SVM, RF, and ANN, which show typical accuracy equal to 72.5%, 76.5%, and 79%, respectively, in assessing the success of the exercise.

IV. CONCLUSIONS AND FUTURE RESEARCH

Smart sensors are playing an essential role in enabling novel services and applications aimed at improving the quality of life. Wearable sensors have been revolutionary for some systems and practices, for instance, in gait analysis, where they offer quantitative and repeatable results for long periods at a low cost. The integration of multiple wearable sensors with low size and data transfer capabilities allows the automation of processes that relied on empirical bases in the past. The most significant applications concern: (i) clinical practice, where gait analysis permits the diagnosis of neurodegenerative diseases and the implementation of rehabilitation programs for injured subjects; (ii) sport, where the smart systems can be applied to prevent injuries and improve the performance of athletes; (iii) fall prevention and detection. Special attention has been paid to the gait analysis and the measurement of the human gait parameters, which include walking speed, stride and step length, swing and stance times. The key role of the novel technologies, and in particular of the wearable sensors, that allow measuring the parameters of interest over long periods of time during daily activities, has been evidenced. Examples of typical signals acquired with different acquisition protocols have also been given. Secondly, an overview on interesting and very recent applications based on machine learning paradigms and IMU sensors for gait analysis, have been shown.

Future research is going to pay attention to the following issues, namely: sensor improvement, power consumption, data processing, and management. Concerning sensor improvement, it is necessary to develop new wearable sensors that provide new space-time parameters. More specifically, new sensors need to provide more accurate measurements such as segment position, orientation, velocity, and joint angles; it is also interesting recognizing optimal sensor positions. Power consumption is a crucial issue of the current wearable systems for gait analysis since it affects the capacity of the system to measure and monitor over long periods. Future research should develop new systems characterized by reduced energy consumption, and batteries with extended battery life duration. Finally, new signal processing algorithms to both improve the reliability of the results and produce additional insight are also expected.

REFERENCES

[1] Weizman, Yehuda, et al. "Recent State of Wearable IMU Sensors Use in People Living with Spasticity: A Systematic Review", Vol.22, No.5, Sensors, 2022, 1791.

[2] H. Geng, Z. Huan, J. Liang, Z. Hou, S. Lv and Y. Wang, "Segmentation and Recognition Model for Complex Action Sequences," in IEEE Sensors Journal, vol. 22, no. 5, pp. 4347-4358, 1 March1, 2022, doi: 10.1109/JSEN.2022.3144157

[3] Y. Wang et al., "SAIL: A Deep-Learning-Based System for Automatic Gait Assessment From TUG Videos," in IEEE Transactions on Human-Machine Systems, vol. 52, no. 1, Feb. 2022, pp. 110-122, doi: 10.1109/THMS.2021.3123232.

[4] X. Chen, X. Luo, J. Weng, W. Luo, H. Li and Q. Tian, "Multi-View Gait Image Generation for Cross-View Gait Recognition," in IEEE Transactions on Image Processing, vol. 30, 2021, pp. 3041-3055, doi:10.1109/TIP.2021.3055936.

[5] Celik, Yunus, et al. "Gait analysis in neurological populations: Progression in the use of wearables." Medical Engineering & Physics, vol.87,2021, 9-29.

[6] Desai, Radhika, et al. "Postural control and gait measures derived from wearable inertial measurement unit devices in Huntington's disease: Recommendations for clinical outcomes." Clinical Biomechanics, 2022, 105658.

[7] Lin, Chin-Hsien, et al. "Early Detection of Parkinson s Disease by Neural Network Models", IEEE Access, vol.10, 2022, 19033-19044.

[8] Kim, Jeong-Kyun, et al. "Explainable Artificial Intelligence and Wearable Sensor-Based Gait Analysis to Identify Patients with Osteopenia and Sarcopenia in Daily Life." Biosensors 12.3, 2022, 167.

[9] Prill, Robert, et al. "A Systematic Review of Diagnostic Accuracy and Clinical Applications of Wearable Movement Sensors for Knee Joint Rehabilitation." Sensors, vol.21, No.24, 2021, 8221.

[10] Bolam, Scott M., et al. "Remote Patient Monitoring with Wearable Sensors Following Knee Arthroplasty." Sensors, Vol.21, No.15, 2021, 5143.

[11] Zhao, Wenbing, Shunkun Yang, and Xiong Luo. "Towards rehabilitation at home after total knee replacement." Tsinghua Science and Technology, vol.26,No.6 , 2021, 791-799.

[12] Taborri, Juri; Molinaro, Luca; Santospagnuolo, Adriano; Vetrano, Mario; Vulpiani, Maria Chiara; Rossi, Stefano. "A Machine-Learning Approach to Measure the Anterior Cruciate Ligament Injury Risk in Female Basketball Players",Sensors, vol.21, No.9,2021.

[13] Li, H.; Khoo, S.; Yap, H.J. "Implementation of Sequence-Based Classification Methods for Motion Assessment and Recognition in a Traditional Chinese Sport (Baduanjin)", Int. J. Environ. Res. Public Health, vol.19, 2022, 1744. https://doi.org/10.3390/ijerph19031744

[14] Wu, Mingyue, et al. "A Real-Time Tennis Level Evaluation and Strokes Classification System Based on the Internet of Things." Internet of Things 2022, 100494.

[15] Alarifi, A.; Alwadain, A. Killer heuristic optimized convolution neural network-based fall detection with wearable IoT sensor devices. Measurement , vol.167, 2021, 108258.

[16] I. Putra; J. Brusey; E. Gaura; R. Vesilo, An event-triggered machine learning approach for accelerometer-based fall detection. Sensors , vol.18, No.1, 2017,20.

[17] Hassan, M. M.; Uddin, M. Z.; Mohamed, A.; Almogren, A. "Robust human activity recognition system using smartphone sensors and deep learning", Future Generation Computer Systems , vol.81, 2018, 307-313.

[18] Semwal, Vijay Bhaskar, et al. "Pattern identification of different human joints for different human walking styles using inertial measurement unit (IMU) sensor", Artificial Intelligence Review, Vol.55, No2 ,2022, 1149-1169.

[19] Semwal, Vijay Bhaskar, Anjali Gupta, and Praveen Lalwani. "An optimized hybrid deep learning model using ensemble learning approach for human walking activities recognition", The Journal of Supercomputing Vol.77, No.11 ,2021, 12256-12279.

[20] Krutaraniyom, S., Sengchuai, K., Booranawong, A., and Jaruenpunyasak, J. " Pilot Study on Gait Classification Using Machine Learning", In 2022 International Electrical Engineering Congress (iEECON), IEEE, 2022 March, pp. 1-4.

[21] Borzi, L.; Mazzetta, I.; Zampogna, A.; Suppa, A.; Olmo, G.; Irrera, F. "Prediction of freezing of gait in Parkinson's disease using wearables and machine learning" Sensors, 2021 , Vol.21, No.2, 614.

[22] Wang, Chao ; Chan, Peter PK ; Lam, Ben MF; Wang, Sizhong ; Zhang, Janet H ; Chan, Zoe YS ; Chan, Rosa HM ; Ho, Kevin KW ; Cheung, Roy TH "Real time estimation of knee adduction moment for gait retraining in patients with knee osteoarthritis", IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol.28, No.4, 2020, 888-894.

[23] Espinoza Bernal VC; Hiremath SV; Wolf B, Riley B; Mendonca RJ; Johnson MJ. "Classifying and tracking rehabilitation interventions through machine-learning algorithms in individuals with stroke", Journal of Rehabilitation and Assistive Technologies Engineering, 2021.