A Review of Wearable Sensor for Stroke Patients

Hiranya Sritart[1] and **Somchat Taertulakarn**[2],

ABSTRACT

Worldwide, stroke is a serious and life-threatening problems. Without warning, stroke can bring dramatic and unexpected changes in human's lives. Paralysis, communication problems, difficulty controlling of the body and balance are the most common effects after a stroke. The rapidly developing loss of brain functions after the brain stops receiving blood flow are frequently left with a long term disability and needs medical attention for recovery. To make rehabilitation more efficient for stroke patients, the entire progress and detections of how well they have improved are required to monitor. As a powerful and practical instrument in health monitoring research and modern technology, wearable sensors have been widely accepted in the last decade especially in clinical rehabilitation. It is constantly increasing with the major effort in various fields of therapy, for example, Parkinson's disease, Alzheimer's disease and furthermore in stroke recovery. Numerous wearable devices have been used for analyzing, monitoring, and assessment in therapeutic treatment nowadays.

This review aimed to examine the available literature of wearable sensor-based device establishment in sensor types, locations and range of functions of the clinical application in people after stroke. We address and report about studies that have already investigated in clinical testing of stroke population. We, moreover, discuss their boundaries and present a range of recommendation for the future research.

Keywords: Wearable sensors, inertial sensors, stroke population, assessment of stroke rehabilitation, human activity classification and recognition.

1. INTRODUCTION

Stroke is a worldwide serious medical condition, resulting in an interruption of blood flow to an area of the brain from either a blood clot or the rupture of a blood vessel. The vast majority of stroke, 87% [1], are ischemic stroke, which causes by blockage of an artery and impairing blood flow to part of the brain. Whereas the less commonly strokes cause by bleeding in or around the brain haemorrhagic stroke- and by a mini stroke, a transient ischaemic attack, which happens when the brains blood stream is interrupted for a very brief period of time. Globally, stroke impacts approximately 17 million people annually making it one of the leading causes of disability [1]. Its sudden occurrence can cause a considerable effect in daily living problems of impairments and limitations of cognitive, language and motor functions [2]. Recovery of motor function requires intensive physical rehabilitation and interdisciplinary cares which must be personalized to each patient for enhanced effectiveness [3]. To determine the efficiency of rehabilitation as well as to provide behaviour-enhancing feedback, medical professionals need to understand the impact of clinical interventions in the real life of individuals. It is also an essential component of physical medicine and treatment to assess physical activities of stroke population; however, it is recognized that these evaluations may have some limitation in clinical practice [4-6]. For example, some clinical functional tests are performed only in a hospital setting; these, however, may not reflect the actual motor performance of patients in everyday life. Therefore, an activity monitoring in everyday life is expected to provide a more comprehensive assessment of physical functioning and assessment of post-stroke patients [4-8].

During the last decade, wearable monitoring systems have drawn enormously of attention from the research community and clinicians [9]. Due to the fact that their current capabilities provide not only physiological such as heart rate, blood pressure, body and skin temperature or biochemical sensing for example blood, sweat, breath, etc., but also motion sensing [10,11]. In human kinematic studies, accelerometer (ACC) has been adopted based on measurement of acceleration and position with respect to gravity. Measuring physical activity using ACC is preferred because acceleration is proportional to external forces and hence can reflect the intensity and frequency of human movement. Recently, a microelectromechanical system (MEMS) technology has reduced the cost of ACC in smaller form factors [12]. In fact, that sensor performance has been improved whereas the power consumption and size are greatly reduced. The technology has made it possible to fabricate inexpensive single chip ACC and gyro sensor which have been adopted into several applications where traditionally inertial sensors have been too costly [13]. Base on the small scale of the sensors, methods for long-term monitoring of physical activity and the assessment of motor functioning under real life condition are available. Numerous researchers

Manuscript received on April 20, 2016 ; revised on September 9, 2016.

[1]Department of Biomedical Engineering
HiranyaSritart@gmail.com
[2]Department of Medical Technology Faculty of Allied Health Sciences, Thammasat University Paholyothin Road, Pathumthani 12120, Thailand
Somchat@tu.ac.th

have recently shown noble test and retest reliability for assessing individuals using wearable sensors [14]. Various types of miniature sensors have been compressed for the health monitoring of wearable systems. The combination between ACC and gyroscope which is included in the inertial measurement units (IMUs) have been successfully applied for assessing gait characteristic [15-19], monitoring of elderly [20-24] and other chronic diseases [25-29]. Despite the expanding evidence to support the usage of wearable sensors for clinical application, it is still to recognize that this area remains to develop. In the rehabilitation of the consequences of stroke, it is imperative to be able to remotely classify human activities and quantitatively measure the quality of their component movements to the goal of a motion analysis outside of laboratories.

This review, therefore, describes efforts to bring wearable sensors to bear on clinical-based assessments and treatments to improve mobility-related activities after stroke. As such, it was the purpose to examine the available literature that utilized wearable sensors to apply in the clinical testing in people with stroke and provides a summary of the sensor type, location and outcome base on the literature.

2. LITERATURE SEARCH STRATEGY

We performed an electronic database search of title and abstracts using PubMed, EMBASE and Google Scholar to identify and collect the literature and considered reports published between 2005 and April 2016. The Institute of Electrical and Electronics Engineers (IEEE) Xplore digital library was searched for an additional relevant article of the bibliographies. To retrieve all relevant publications, key term searches were used to match words in the title, abstract, or key words field. The key words were: "wearable sensors", "wearable device", "wearable technology", "wearable sensors AND stroke" and "wearable sensors AND stroke rehabilitation".

3. GENERAL SEARCH RESULTS

In total 146 papers and abstract that examined development in the use of wearable sensor technology for the stroke population were examined. The papers in this review were not included if the device presented had not reached the stage of clinical testing or the experimental group of stroke subjects is lower than ten patients, or aspire for stroke rehabilitation of robot-assisted training. Table 1 summarizes the development described in the literature, utilized wearable sensor-based devices in the clinical application of rehabilitation after stroke. For the narrative review, we categorized the results into the following: sensor type detection and placement, utilizing wearable sensors in order to classification and recognition of physical activity and assessment of stroke rehabilitation.

3.1 Sensor type detection and placement

Multiple wearable sensor types were used within the included papers for both categorized purposes of physical activity classification and assessment in stroke patients. Most of studies applied an inertial sensor system (IMU) [3, 30, 35, 36, 39, 40, 41, 42]. Varied ACC: bi-axial ACC [40, 42] tri-axial ACC [3, 30, 31, 35,] and uni-axial ACC [41, 42] were consisted the wearable sensor-based devices, as well as gyroscope [30, 33, 39]. Two studies reported on systems included force sensors [32, 38]. One study utilized surface electromyographic (sEMG) into the measurement system. Two projects of research applied wearable sensor systems in the form of instrumented shoes [31, 38], whereas one study employed the wearable system of smartphone [33].

Wearable activity sensors can be placed on different parts of the body whose movement are being studied. In many cases, it is necessary to measure the whole-body movement. Thus the sensors are frequently placed on the waist or trunk [3, 30, 33, 39, 40, 41]. For the gait, walking balance or fall risk assessment test the sensors were placed on foot [31, 38], thigh [32] and shank [30, 39]. While the sensors were most attached for the monitoring functional activity and motor ability assessment in the upper part body of upper arm [32, 36, 41, 42], forearm [32, 41, 42], hand and fingers [36, 41, 42]

3.2 Classification and recognition of human activity

Recently, numerous existing recognition systems have been developed for normal activities. However, detecting abnormal activity is a particularly significant operation in security monitoring and healthcare application [43]. Monitoring a person's mobility activities outside a hospital setting becomes also valuable for clinical decision making. For clinicians, reliable data about the patient's activity is very important. Mainly, information about the type, duration, and frequency of daily behaviors can help therapists design successful rehabilitation programs [33]. To classify and recognize the physical activity of stroke population, a number of computational techniques have been used in the studies.

Machine learning techniques such as an Artificial Neural Network (ANN) [32], Support Vector Machines (SVM) [30], Hidden Markov Model (HMM) [30], Fuzzy Inference System (FIS) [3] and a decision tree model [33, 31] are applied to identify the relationship between feature set and identification task.

Zhang et al. [31] and Capela et al. [33, 34] classify the participant's activities of a consecutive series of mobility tasks by the decision tree model. In the study of Zhang et al. three features of sitting, standing and walking have been separated to detect using a wearable shoe-based sensor system which is included pressure sensors and ACC. Meanwhile Capela et al. [33] divided the activities from both stroke population and healthy subjects into standing, sitting, lying, walking, claiming upstairs and small movement using a smartphone-based system on their waist to collect the data.

Besides the basic daily-life activity recognition of sitting, standing, walking and lying, Masse et al. [3] found that integrating barometric pressure sensor into the IMU has been improved the outcome of classification. Especially in body elevation recognition of taking an elevator or climbing stairs, which is a relevant outcome for post-stroke recovery [29] can be detected clearly. Using the statistic result of the Correct Classification Rate (CCR), the barometric pressure-based classification approach was compared against two methodological techniques to classify the activities: epoch-based and event-based classification. 90.4% of CCR performance for posture/activity detections was reported; meanwhile, the CCR for body elevation is found at 98.2%. Furthermore, the classification of different pathological gait between post-stroke population and the other two groups of Huntington's disease and healthy subjects has been proposed by Mannini et al. [30] using data from IMU placed at shank and waist. The use of complementary features (HMM likelihoods and time-frequency domain features) along with an SVM classification post-processing allowed for the improvement of the classification outcomes of overall accuracy 90.5%.

3.3 Assessment of stroke rehabilitation

Many assessment tools, across various functional domains, are available to clinicians and researchers working with stroke survivors [44]. Clinical assessment of motor function using functional tests such as the Berg Balance Scale (BBS) for balance assessment or Timed Up and Go (TUG) for gait and balance evaluation or Fugl-Myer Assessment (FMA) for sensory-motor function and balance evaluation, serve a critical role in guiding rehabilitation after stroke. However, effectively implementing novel therapies and improving outcomes for recovery from stroke is the process that must be continued long after a hospital stay in the home setting. Furthermore, these scales are unfortunately not widely utilized in clinical practice because their administration is excessively time-consuming [41]. Nevertheless, to address this issue many researchers have contemplative concentrated on investigating of wearable sensor technology. Focusing on the upper extremity movement, Patel et al. [42] found in 2010 that using six ACCs attached to the arm of the effect side of stroke patients during the performance of items of the Wolf Motor Function Test (WMFT), can be used to estimate scores derived using the Functional Ability Scale (FAS) which is a clinical scale focused on quality of movement. Later, Del Din et al. [41] proposed that these data sets can be analyzed and used to estimate clinical scores derived using the FMA scale which is a clinical scale designed to assess motor impairments. They found the correlation coefficients by using different sections of FAS and FMA of total score ranged between 0.66 and 0.85. Recently, Leuenberger et al. [35] found a better correlation (r = 0.95) of the duration of gross paretic arm movements between a clinical assessment of impairment (Box and Block Test) using wearable IMU than conventional activity counts when walking phases were included (r = 0.69). Furthermore, Yu et al. [36, 37] proposed a remote quantitative FMA framework to extend the use of wearable sensor system for stroke rehabilitation in the home setting. Using two ACCs and seven flex sensors to capture the movements of the upper limb, wrist, and fingers of stroke patients can precisely predict the clinical FMA scores through ensemble machine learning method. They found that the coefficient of determination of this model can reach as high as 0.918.

On the other hands, to assess the balance, postural and gait challenges many research projects have used wearable inertial sensors. A quantitative analysis of the fall-risk assessment test is performed by Tmaura et al. [39] using inertia sensor consisted of ACC and angular velocity sensor. Focusing on the TUG Test and Four Square Step Test (FSST) the data can be assessed for the fall risk of stroke populations while wearing the sensors on patient's waist and thighs. In addition, inertia sensors were also applied in the study of Grimpampi et al. [40] to estimate the lower trunk angles lateral and frontal bending and axial rotations during the patient's walking with an abnormal gait. Whereas van Meulen et al. [38] integrated all inertia sensors into patient's shoes to assess the additional information about walking balance after stroke. They found a high correlation between walking speed and BBS scores, although no part of the BBS includes assessment of walking.

4. DISCUSSION

The reviewed research demonstrates the ability of wearable sensor-based devices to accurately detect and evaluate specific movement in stroke patients. In general, measuring and monitoring the patient's activity was effectively using multiple inertial sensors such as ACC and gyroscopes; because these sensors are portable, small,

SD: Standard deviation, IMU: Inertial Measurement Unit, sEMG: surface electromyographic, ACC: accelerometer, SP: Stroke patients, HD: Huntington's disease, HS: Healthy Subjects, LFR: low-fall-risk, HFR: high-fall-risk, TUG: time up and go, FSST: the four square step test, WMFT: The Wolf Motor Function Test, FAS: The Functional Ability Scale, FMA: The Fugl-Meyer Assessment.

and inexpensive. ACC allowed distinguishing between immobility and movement, whereas gyroscope is used for detailed evaluation of the movement pattern. A lot of studies may require very specific on-body placement. For example, the sensors have to be on the waist and other multiple locations such as hand, arms, wrist, shank or thigh. However, placing multiple sensors on the patient's body may lead to discomfort and might reduce their willingness and ability to perform of measurement.

The most challenging problem is finding the best

Table 1:: Wearable sensor-based device for stroke patients.

Purpose	Author	Wearable sensor -based devices	Experimental Groups (Mean Age ± SD years)	Time since stroke	Performing Test
Classification and recognition of physical activity	Mannini et al. (2016) [30]	IMU	15 SP (61.3 ± 13) 17 HD (54.3 ± 12.2) 10 HS (69.7 ± 5.8)	not reported	Walk back and forth for about one minute along a 12 m walkway.
	Zhang et al.	SmartShoe (2013) [31]	12 SP (not reported)	> 3 months	8 postures and activity groups.
	Roy et al. (2009) [32]	sEMG and ACC sensor system	10 SP (51.7 ± 11.4)	7.5 ± 6 years	11 activities of daily living and 10 activities used to evaluate misclassification errors.
	Capela et al. (2016) [33]	Smartphone	15 SP (55 ± 10.8) 15 HS (26 ± 8.9)	9.6 months	A consecutive series of mobility tasks.
	Massé et al. (2015) [3]	integrating BP and inertial sensor	12 SP (59.6 ± 13.6)	not reported	A set of basic activities of daily living.
Assessment in stroke therapy	Leuenberger et al. (2016) [35]	IMU	10 SP (52.7 ± 13.6)	21.6 ± 10.6 weeks	All day and night activities.
	Yu et al. (2016) [36]	ACC and flex sensors	24 SP (69.4 ± 12.8)	8.9 ± 4.2 months	7 training exercises to replace the upper limb related 33 items in FMA scale.
	van Meulen et al. (2016)	instrumented shoes	13 SP (64.1 ± 8.7)	2.4 ± 1.8 years	Twice a timed 10 meter walk at a self-selected comfortable pace along a 10 meter path.
	Tmaura et al. (2013) [39]	an inertial sensor	10 SP (65.4 ± 2.8) 13 LFR (63 ± 8.9) 27 HFR (71.1 ± 5.8) 6 HS (65.4 ± 5.2)	not reported	2 tests: TUG test and FSST.
	Grimpampi et al.(2013) [40]	IMU	24 Elderly (75 ± 7): 13 SP (not reported) 11 PD (not reported)	not reported	Walk at a self-selected speed along a 12 m rectilinear pathway.
	Del Din et al. (2011) [41]	ACC system	24 SP (57.5 ± 11.8)	4.2 ± 3.7 years	WMFT, FAS and FMA
	Patel et al. (2010) [42]	IMU	24 SP (57.5 ± 11.8)	4.2 ± 3.7 years	Functional motor tasks

balance between and the placement concerns and the wearable device function. Although the advantages of using multiple positions of attached the inertial sensors have been reported in many studies of discovery with high correlation to predict the outcome of stroke assessment. Some studies, however, focused on using a single position placed sensor. Mass et al. [3] applied a single sensor module fixed on the trunk of patients, which can superior detect the posture and activity of stroke patients with impaired mobility. Whereas, Leuenberger et al. [35] also suggested a method to quantify functionally relevant arm use relying on one single wrist-worn IMU. Further improvement in advanced sensor design and miniaturization have been also noticed in several studies invented to place the sensors in one single position: SmartShoe by Zhang et al. [31] integrated pressure sensor and ACC, instrumented shoes by van Meulen et al. [38] consisted of IMU and one 3D force/moment sensor and a smartphone comprised ACC and gyroscope by Capela et al. [33]. Using a single sensor configuration can be more transparent to the user and be part of a comfortable and non-impact environment for the patients; however, these are required to improve the shortcomings of reliability and efficiency.

In order to develop a system that proficient in employing wearable sensors in clinical application, the requirement of support automatic operation, advanced algorithms and processing power must be solved. Information extraction, pattern recognition and database evaluation for clinical validation and standardization must be developed with effort. There is still required to utilize and advance algorithms that can be simple to interpret to be embedded into one single wearable device. Besides, the need for cooperation and standardization still remain in infrastructure, communication interfaces and cooperation between patients and medical experts. Interestingly, Yu et al. [36] addressed this issue and reported the lack of awareness of the importance of rehabilitation and insufficiency of a computer in home monitoring of the stroke participants. Finally, the potential study could extend into a larger number subject of stroke survivors to pursuing the standardization of clinical assessment.

5. CONCLUSION

In recent times, the inertial sensor-based method enables automatic, continuous and long-term activity measurement not only for the purpose of a free living environment but also intensive in clinical application. Sensor-based measurement of improving mobility-related activities can provide quantitative patient information in clinical assessment and rehabilitation. Particularly in stroke population, these wearable sensor-based tools have been approached to be able to evaluate and recognize the abnormal activities in this area.

This study, consequently, examined and reported the existing literature and research to summarize appropriate wearable sensors and outcome measures of assessment in the clinical intervention of stroke patients. A class categorization of utilizing each sensor has also been presented. In addition, method and technique for classification and recognition the physical activity of stroke population has been surveyed and discussed. Although great progress has been made in the recent year, there are still some factors for improvement in term of the feasibility of wearable sensors being used in widely clinical conditions and clinical validation. With a smartphone or a single wearable embedded measurement unit and the effortless evaluation tools, we envision that these will help to widely increase the practicability for both clinical staff and patients as well as for remote monitoring of health in clinical and home setting.

CONFLICTS OF INTEREST

The authors have no conflicts of interest to report.

6. ACKNOWLEDGEMENT

The authors would like to thank the anonymous reviewers for their comments that help improve the manuscript.

References

[1] Heart Disease and Stroke Statistics–2015 Update: A Report from the American Heart Association, American Heart Association, Dallas, TX, 2014..

[2] National Institute of Neurological Disorders and Stroke (NINDS), *Stroke: Hope Through Research*, NINDS, Washington, DC, 2004.

[3] F. Massé, R. R. Gonzenbach, A. Arami, A. Paraschiv-Ionescu,A. R. Luft & K. Aminian, Improving activity recognition using a wearable barometric pressure sensor in mobility-impaired stroke patients, *Journal of Neuro Engineering and Rehabilitation*, 12, 2015, 72.

[4] P. Bonato, Advances in wearable technology and applications in physical medicine and rehabilitation, *J Neuroeng. Rehabil.*, 2(1), 2005, 2.

[5] P. Bonato, "Advances in wearable technology for rehabilitation," *Stud Health Technol. Inform.*, 145, 2009, 145-59.

[6] K. Salter, N. Campbell, M. Richardson, S. Mehta, J. Jutai, L. Zettler, M. Moses, A. McClure, R.Mays , N. Foley, R. Teasell, Outcome Measures in Stroke Rehabilitation, *Evidence-Based Review of Stroke Rehabilitation*, 2003, 1-144.

[7] K Salter, JW Jutai, R Teasell, NC Foley, J Bitensky, M Bayley. Issues for selection of outcome measures in stroke rehabilitation: ICF participation. *Disabil Rehabil.* 27, 2005, 507528.

[8] D. Rand, JJ. Eng, PF. Tang, JS. Jeng, C. Hung, How Active Are People with Stroke? *Stroke*, 40(1), 2009, 163-8.

[9] A. Pantelopoulos, N. G. Bourbakis, A Survey on Wearable Sensor-Based Systems for Health Monitoring and Prognosis, *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 40(1), 2010, 1 12.

[10] S. Patel, H. Park, P. Bonato, L. Chan, M. Rodgers, A review of wearable sensors and systems with application in rehabilitation, *J Neuroeng Rehabil.*, 9(21), 2012.

[11] P. Bonato , Wearable sensors and systems. From enabling technology to clinical applications, *IEEE Eng Med Biol Mag.*, 29(3), 2010, 25-36.

[12] CC. Yang, YL. Hsu, A Review of Accelerometry-Based Wearable Motion Detectors for Physical Activity Monitoring, *Sensors (Basel)*, 10(8), 2010, 7772-88.

[13] I. Skog, P. Handel, Calibration of a MEMS inertial measurement unit, *XVII IMEKO World Congress*, 2006, Brazil.

[14] RP. Hubble, GA. Naughton, PA. Silburn, MH. Cole. Wearable sensor use for assessing standing balance and walking stability in people with Parkinson's disease: a systematic review. *PLoS One.*, 10(4), 2015, e0123705.

[15] A. Mannini, D. Trojaniello, A. Cereatti, and A. M. Sabatini, A Machine Learning Framework for Gait Classification Using Inertial Sensors: Application to Elderly, Post-Stroke and Huntingtons Disease Patients, *Sensors (Basel).* 16(1), 2016, 134.

[16] J. Rueterbories, EG. Spaich, B. Larsen, OK. Andersen, Methods for gait event detection and analysis in ambulatory systems. *Med. Eng. Phys.* 32, 2010, 545552.

[17] RP. Troiano, D. Berrigan, KW. Dodd, LC. Msse, T. Tilert, M. McDowell, Physical activity in the United States measured by accelerometer., *Med. Sci. Sports Exerc.*, 40, 2008, 181188.

[18] M. Schwenk, J. Mohler, C. Wendel, KD Huyvetter, M. Fain, R. Taylor-Piliae, B. Najafi, Wearable Sensor-Based In-Home Assessment of Gait, Balance, and Physical Activity for Discrimination of Frailty Status: Baseline Results of the Arizona Frailty Cohort Study, *Gerontology*, 61(3), 2015, 258267.

[19] D. Trojaniello, A. Cereatti, E. Pelosin, L.

Avanzino, A. Mirelman, JM. Hausdorff, CU. Della, Estimation of step-by-step spatio-temporal parameters of normal and impaired gait using shank-mounted magneto-inertial sensors: Application to elderly, hemiparetic, parkinsonian and choreic gait. *J. Neuroeng. Rehabil.*, 11, 2014, 152160.

[20] D. Webster1, O. Celik, Systematic review of Kinect applications in elderly care and stroke rehabilitation, *J Neuroeng Rehabil.*, 11, 2014, 108.

[21] TE. Lockhart, R. Soangra, J. Zhang, X. Wu, Wavelet based automated postural event detection and activity classification with single IMU (TEMPO), *Biomed Sci Instrum.*, 49, 2013, 224233.

[22] D. Rodrguez-Martn, C. Prez-Lpez, A. Sam, J. Cabestany, A. Catal, A Wearable Inertial Measurement Unit for Long-Term Monitoring in the Dependency Care Area, *Sensors (Basel)*, 13(10), 2013, 1407914104.

[23] TE. Lockhart, HT. Yeoh, R. Soangra, M. Jongprasithporn, J. Zhang, X. Wu, A. Ghosh, Non-invasive fall risk assessment in community dwelling elderly with wireless inertial measurement units, *Biomed Sci Instrum*. 48, 2012, 260267.

[24] VH. Cheung, L. Gray, M. Karunanithi, Review of accelerometry for determining daily activity among elderly patients, *Arch Phys Med Rehabil*, 92, 2011, 9981014.

[25] C. Thanawattano, R. Pongthornseri, C. Anan, S. Dumnin, R. Bhidayasiri, Temporal fluctuations of tremor signals from inertial sensor: a preliminary study in differentiating Parkinson's disease from essential tremor, *Biomed Eng Online*. 14, 2015, 101.

[26] H.Dai, P. Zhang, TC. Lueth, Quantitative Assessment of Parkinsonian Tremor Based on an Inertial Measurement Unit, *Sensors (Basel)*. 15(10), 2015, 2505525071.

[27] H. Li, JJ. Huang, CW. Pan, HI. Chi, MC Pan, Inertial Sensing Based Assessment Methods to Quantify the Effectiveness of Post-Stroke Rehabilitation, *Sensors (Basel)*. 15(7), 2015, 1619616209.

[28] D. Rodrguez-Martn, C. Prez-Lpez, A. Sam, J. Cabestany, A. Catal, A Wearable Inertial Measurement Unit for Long-Term Monitoring in the Dependency Care Area, *Sensors (Basel)*. 13(10), 2013, 1407914104.

[29] AC. Novak, B. Brouwer, Strength and aerobic requirements during stair ambulation in persons with chronic stroke and healthy adults. *Arch Phys Med Rehabil*. 93, 2012, 6839.

[30] A. Mannini, D. Trojaniello, A. Cereatti, AM. Sabatini, A Machine Learning Framework for Gait Classification Using Inertial Sensors: Application to Elderly, Post-Stroke and Huntington's Disease Patients. *Sensors (Basel)*, 16(1), 2016, 21.

[31] T. Zhang, GD. Fulk, W. Tang, ES. Sazonov, Using decision trees to measure activities in people with stroke, *Conf Proc IEEE Eng Med Biol Soc*. 2013, 6337-40.

[32] S. Roy, M. Cheng,S. Chang, J. Moore,G. De Luca, S. Nawab, C De Luca, A Combined sEMG and Accelerometer System for Monitoring Functional Activity in Stroke. *IEEE Trans Neural Syst Rehabil Eng.*, 2014.

[33] NA. Capela, ED. Lemaire, N. Baddour, Feature selection for wearable smartphone-based human activity recognition with able bodied, elderly, and stroke patients., *PLoS One*. 10(4), 2015, e0124414.

[34] NA. Capela, ED. Lemaire, N. Baddour, Feature selection for wearable smartphone-based human activity recognition with able bodied, elderly, and stroke patients, *PLoS One*. 10(4), 2015, e0124414.

[35] K. Leuenberger, R. Gonzenbach, S. Wachter, A. Luft, R. Gassert, A method to qualitatively assess arm use in stroke survivors in the home environment, *Med Biol Eng Comput*. 2016.

[36] L. Yu, D. Xiong, L. Guo, JA Wang, A remote quantitative Fugl-Meyer assessment framework for stroke patients based on wearable sensor networks, *Comput Methods Programs Biomed*. 128, 2016, 100-10.

[37] L. Yu, D. Xiong, L Guo, JA Wang, Compressed Sensing-Based Wearable Sensor Network for Quantitative Assessment of Stroke Patients, *Sensors (Basel)*, 16(2), 2016, 202.

[38] FB. van Meulen, D. Weenk, JH. Buurke, BJ. van Beijnum, PH. Veltink, Ambulatory assessment of walking balance after stroke using instrumented shoes. *J Neuroeng Rehabil*. 13(1), 2016, 48.

[39] T. Tmaura, NA. Zakaria, Y. Kuwae, M. Sekine, K. Minato, M. Yoshida, Quantitative analysis of the fall-risk assessment test with wearable inertia sensors, *Conf Proc IEEE Eng Med Biol Soc*. 2013, 7217-20.

[40] E. Grimpampi, V. Bonnet, A. Taviani, C. Mazzé, Estimate of lower trunk angles in pathological gaits using gyroscope data, *Gait Posture*. 38(3), 2013, 523-7.

[41] S. Del Din, S. Patel, C. Cobelli, P. Bonato, Estimating Fugl-Meyer clinical scores in stroke survivors using wearable sensors, *Conf Proc IEEE Eng Med Biol Soc*. 2011, 5839-42.

[42] S. Patel, R. Hughes, T. Hester, J. Stein, M. Akay, J. Dy, P. Bonato, Tracking motor recovery in stroke survivors undergoing rehabilitation using wearable technology, *Conf Proc IEEE Eng Med Biol Soc.*, 2010, 6858-61.

[43] L. Chen, CD. Nugent, J. Biswas, J. Hoey, *Activity Recognition in Pervasive Intelligent Environments*, Atlantis Press, France, 2011.

[44] JK.Harrison, KS. McArthur, TJ. Quinn, Assessment scales in stroke: clinimetric and clinical considerations, *Clin Interv Aging*, 8, 2013, 201-11.