International Journal of Physical Education & Sports Sciences
Vol. 13, Issue No. 2, April-2018, ISSN 2231-3745

Multi-Feature Fusion Method for Gait Analysis of Post-Crash Emiparetic Patient

Yamini Sharma*

Assistant Professor, Department of Physiotherapy, Galgotias University, Greater Noida, Uttar Pradesh, India

Abstract – For daily jobs, walking is a key need. Neurological conditions like strokes can significantly affect one's gait and therefore restrict one's daily activities. Previous experiments have shown that time parameters are helpful in characterising post-stroke hemiparetic gaiting. However, no prior study has analysed the symmetry, regularity and consistency of post-stroke hemiparetic gasit. The study enthusiasm and empirical mode based on deterioration dynamic time warping (DTW) results in three types of gasketing functions. Studies on 15 stable individuals and 15 post-stroke cases were carried out. Experimental findings indicate that the properties of a Mann-Whitney trial vary greatly from stable controls for hemiparetic patients (with a p-value of less than 0.05). The potential capacity of the hemiparetic patient to discriminate against healthier subjects was also assessed across four representative classifications. The total area under the curve was 0.94 in the nearest area (kNN). The encouraging findings show that the proposed characteristics could contribute to the future development of clinical practise automated gas analysis systems.

Keywords – Walking, Hemiparetic Gait, Electrostatic Field Sensing, Gait Feature Extraction

---------------------------------x---------------------------------

1. INTRODUCTION

7,2 million people in America were trapped with an average previous and current stroke of 795,000 in a survey by the American Heart Association. In China, the world's largest developing country, the number of stroke victims is 22.3 million. In addition, literature suggests that between 2016 and 2040, stroke will be the world's second biggest cause of death loss (YLLs). After the stroke, approximately 10 percent of persons may die, and survivors will have partial disabilities, such as hemiplegia, that can significantly impair their mobility and damage their independence from daily life.

Any of the people with strokes are disabled on their walking. It is characterised in contrast with safe people by a marked clinical involvement of gait asymmetry. One research earlier found that stroke could reduce the weight-bearing performance of the lower limb by up to 43%. Moreover, the direction and duration of the swing on the parallel foot are shortened in stroke patients. The speed and length of the measures are both reduced. The regeneration of the motor activities of hemiplegia patients' needs motor therapy. In order to formulate successful treatment strategies of stroke patients, it is important to properly collect, diagnose and evaluate their gastronomic abnormalities. Some surveys currently still focus on the most common diagnosis and evaluation method for patients with hemiplegia, especially in the developing country. While standard questionnaires have been applied for many years and the test results are widely accepted in various fields, the use of questionnaires may lead to subjective results that depend heavily on experience of specialists. Therefore, an unbiased assessment of patient gas abnormalities is essential to current nursing practises and helps specialists to develop a more personalised rehabilitation approach and objective assessment of treatment outcomes.

Different measurement technologies also simplified the collection of different types of gear data when walking, making it very possible to generate an automatic gait study. A sensing system for visual activity (such as VICON) may provide markers in the body immediately to determine a gasket Researchers also developed a Foot Planter pressurizer that contains sensors mounted under a mat that can be used to process a gait parameter. These equipment will measure gait parameters correctly. However, they have a drawback over a lengthy cycle of workload, thanks to their technical expertise, their cost and their restrictions in laboratory settings. Ses defects significantly restrict the usage of these gas analysis systems.

Consequently, scientists developed cost-effective and portable gastric analysing wearable sensors. Mounting equipment such as accelerometers, gyroscopes, stress measurements and corporal électromyography for gait calculation. The IMU (Inertial Units of Measurement), which comprises accelerometer and gyroscopy combinations, may be included in the assessment of the gasket. Wearable sensors for gear prediction were used due to miniaturization, low power, durable, low-cost and high mobility. For this purpose, wearable sensors were used. However, these wearable sensors share a common inconvenience: They also require an obstructive device that is capable of being mounted on the subject. In comparison, wireless networks typically store data on storage cards or transfer data to personal computers utilising Bluetooth devices that have a large energy requirement and are unable to analyse signal over long-term.

Researchers also merged gasket data of various sensor styles with extraction methods and classification models to include automatic and precise diagnostic aid systems as machine learning technology increases rapidly. For eg, several recent research has focused on detecting gait abnormality. In these tests, predictive and time-frequency domain methods were used to derive features from gasket signals and to instantly detect an erratic gait in some classifications. The classification characteristics which achieve a respectable classification result but are not capable of accurate pathology. The characteristics of the classifier should be applicable to the properties of the disorder, to achieve a better generalisation result.

In our recent research, we developed an EDA technology (EFS) which provides cheap, wear-free and long-term monitoring and can track Gait Parameters continuously while working on a day-to-day basis. Our previous paper develops and expands into a different field: the automated patient patient gait analysis for post-stroke hemiplegia. A multi-time gait parameter can be efficiently achieved using the EFS technique. Gait is intuitively explained by parameters such as gear biking, speed position step, time swing phase, gear cadence, etc. But these temporal parameters cannot be justified by fluctuations in a gait signal that cause those gait parameters to be overlooked. Several other components have therefore been included, seldom introduced before, including gear symmetry, difficulties characteristics and stability index. After the review, the final output was achieved by four representative classification classifications.

The aim of this paper is to provide an integrated solution for post-crash disease diagnosis and diagnosis by means of EFS method gait data. The rest of this manuscript has been organised in the following sections. Section 2 provides a quick overview of the philosophy and framework of the EFS method, feature extraction, the classification model and the data collection mechanism.

Section 3 indicates the findings and classification accuracy of the attribute analysis. In Section 4 we discuss the relationship between characteristics and after-hitting. The final points and findings of Article 5 are concluded.

2. MATERIALS AND METHODS

2.1 Subjects

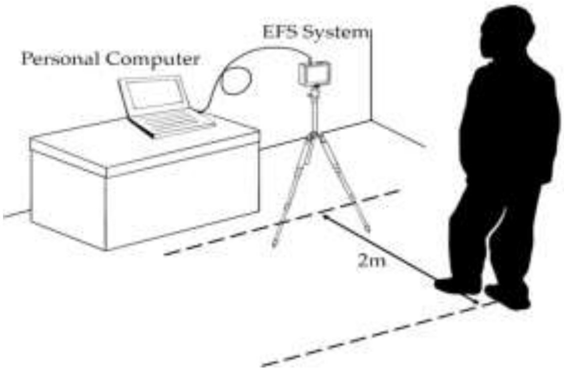
Study has been carried out in 15 post-stroke hemiparetic patients (HPs) of Zhongshan People's Hospital, Guangdong, China (nine male and six female). It weighed 72.4 kilos, averaged 1.55 m and averages 46 years, from 1.54 to 1.74 m, 26.5 m (range: 23.6 to 28.8). During that time, 15 paired healthy volunteers (HC) became the normal population of reference (neine men, six females). The total size for this was approximately 65 kg (45 to 79 kg), 29 years (24-33), an average of 22.1 kg (185.5 to 24.3) and an average size of 1.72 m (range: 1,56 to 1,81 m).

The skills used by the pathologist group included (1) moving or walking without supporting equipment and (3) recognising and cooperating with experimental therapies, as shown with the usage of computer tomography and magnet resonance imaging, for other diseases which have an influential effect on the gait. (2) Capacity for at least 1 minute. The exclusion criteria included neurological or lower limbs, air or health, mental or foolish problems as well as maternity with the regular sample contrast. The report of the respondent's Ethics Committee from the People's Hospital Zhongshan has adopted and signed an informed declaration of approval.

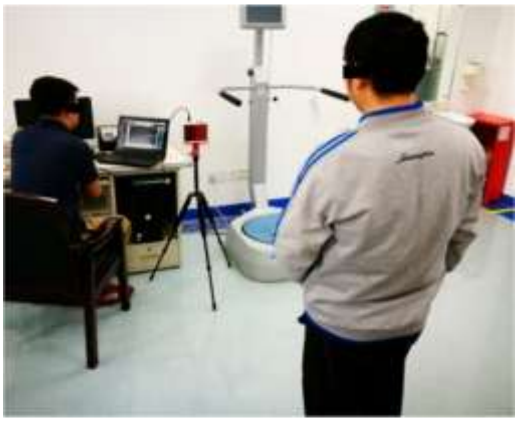
2.2 Electrostatic Field Sensing System

The human body is charged because of friction of the skin and clothing. Previous study has shown that improvement in the human body's electrical field is mostly due to foot movement. Changing the electric field also causes foot movement in the human body. Our previous research defined the comprehensive theory of electrostatic field sensing mechanism and system implementation (EFS). We used the same EFS measurement method and a brief description for this analysis: The electrode induction was used to detect electrical field alterations induced by the movement of human foot. The foot-moving transmitted power was converted into a measurable voltage signal by the IV converter and service amplifier. A low-frequency electrical field with a normal frequency of 1 to 2 Hz is a field perturbing induced by human foot. We also developed a 20 Hz low pass filter to prevent interference in the grid power frequency and high frequency electrical fields (50 Hz). The analogue signal was then converted into a digital signal by an analogue to digital (AD) acquisition. The sample rate was 1 kHz in this report. The optical signal obtained by AD was sent to a personal computer for the transmission of data using USB cable systems.

By adjusting the sensitivity of the metering device, the effective measurement distance of the system was changed to 3 m. In order to minimise the measurement failure caused by the corner between the human body and the electrode, the subject decided to keep his coronary plane parallel to the electrode in the test Figure 1a shows the scheme for the electrostatic measuring instrument. The circuit was mounted in a screened, waterproof box to reduce the humidity of the circuit surface. A hospital research trial as seen in Figure 1b,c.



(**a**)



(**b**)

(**c**)

Figure 1: Illustration and electrical installation prototype diagram. (a) Electrostatic measuring plant illustration diagram; (b) a hospital-based clinical examination; (c) a hospital-based clinical test.

2.3 Experimental Conditions

During the study the subjects had to go constantly for at least 30 s to obtain adequate gasket knowledge at their most comfortable speed. In order to ensure the measurement effect, the subjects had a rigorous rest during the measuring interval. Participants usually have a period of change until they continue, although 2 s of data have been omitted to keep them valid at the beginning and the end of the measurement. In a hospital laboratory the whole procedure has been performed at 25 1°C and 65% relative humidity (RH) to reduce the temperature and humidity impact on EFS methods.

2.4 Feature Extraction

- **Gait Symmetry**

Gait symmetry is a major characteristic of human gait, and conditions in the brain such as stroke will significantly change the symmetry of a gait. The symmetry of the gait can provide data for the lower limb movement control, which are distinct from conventional features, including time parameters, which may help to assess the comparisons between the lower extremities using clinic-therapy methods. In contrast to customary symmetry gaiting equations the gap for dynamic time Warping (D TW) was also used. Study of time series DTW is a renowned method used to measure the similarity of two sequence of times. The DTW algorithm defines the best match between two time series and by adjusting the time, measures their similarity.

From the definition, if the left foot gait signal sequence is symmetric to the right foot, the effect calculated from this formula is minimal, and if they are asymmetric, the value is large. The above formula results are weak. Thus with the measure DTW, which can then be used as a symetry of gait, the symmetry from right and left foot is inversed.

- **Stability Index**

A non-stationary non-linear sequence of time is a chain of gaskets. Therefore, the standard time domain parameters obtained did not fully reflect its characteristics. The EMD methodology is a new analytical method, which has shown to be suitable for non-linear and non-stationary signal processing. An adjustable, multi-scale and long-term, data-driven signal processing platform is the EMD processing framework. It is also ideal for non-linear, non-static study of time series. The EMD scheme was used in this analysis to analyse the features of the gait signal frequency domain and a formula for calculating stability of the gait index was suggested.

Four Methods have been used to address classification issues in non-linear function collections: the learning machines (SVM), the decision tree (DT), multi layer perceptive neural networks (MLP) and the closest neighbour (kNN).

SVM builds limits which optimise the distance between the closest points and the hyperplanes of the division in both classes. The complete SVM classification is random. In order to construct a linear hyperplane defining non-linear issues, the SVM has used kernel methods to map data to a greater dimension. In theory, SVM regards the two classes of data sets as a perfect hyperplane, based on the quadratic scheduling process. In this study the well-known RBF kernel was used and evaluated.

Decision trees are classifiers that can help predict and map a specific input to a given destination. For building the tree with input- and machine learning-focused algorithms, ID3, C4.5 and C5.0. The benefits of this are the basic composition, modelling and tempo.

MLP is the feed-forward architecture of an artificial neural network widely used. The complex, non-linear, input-to-output variables are an efficient non-linear classificator. Three fully connected Neuron layers are used in the MLP network: (1) input, (2) hidden and (3) output node. The MLP calculates the contribution of many functional sources and moves across the secret layers to the output layers. In this research MLP was used to train with the back propagation algorithm, which amended MLP parameters by reducing the square error between the performance and the goal.

KNN is a testing method under which labelling of the closest neighbouring spaces is classified. kNN determines the label of the sample by determining the class most prevalent of the nearest k sets of instruction. KNN is a lazy learning form which does not provide any pre-use estimation of parameters and planning.

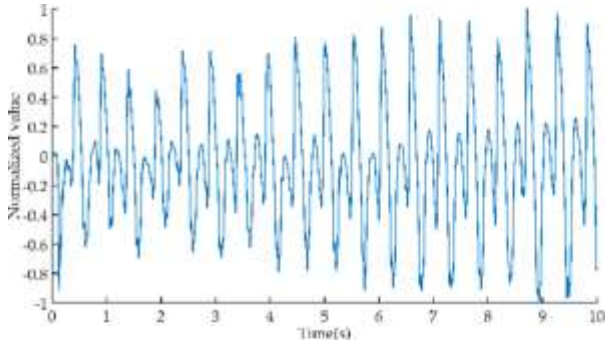
In order to assess the general classifiers ability to avoid overlapping and enable complete application of experimental data, a tenfold cross validation technique Has been seen too. The field under the courve (AUC) was used to evaluate classifier accuracy. There was a higher AUC rating with a higher classification production.

2.5 Analysis

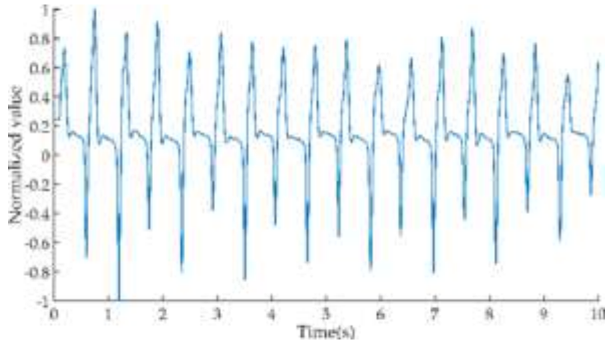
The electrostatic signal sequence with a length of 30 s, repeated five times daily, could achieve 150 electrostatic signal sessions for 30 subjects each, according to a total of 150 gait sessions. Next, for each gait sequence, the power of amplitude was normalised for subsequent analyses. In each gear series three categories of features have been derived and used for classification purposes. In analysing and classifying results, Matlab has been used. There is a mean and standard disparity between the patient's HP and HC characteristics. In a Mann-Whitney test the functioning of the HP-HC community using SPSS version 20.0 has undergone a major difference. The disparities between the two groups when the $p<0.05$ is statistically significant.

3. RESULTS

Figure 2 shows the time domain waveform (HP) and safe controls (HC) obtained via the EFS process in one test.



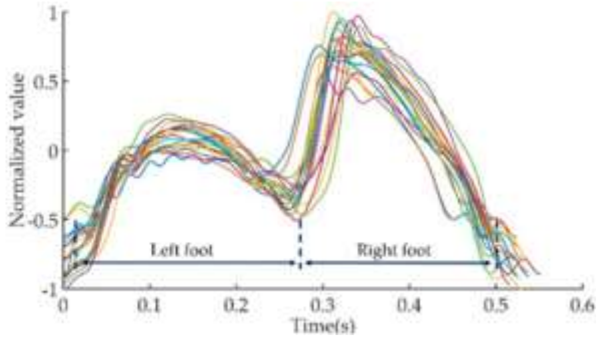
(a)



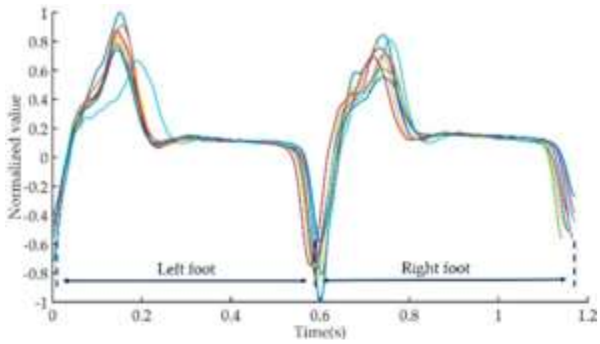
(b)

Figure 2: Hemiparetic (HP) time domain waveform and healthy regulation (HC). (a) HP electrostatic gastric signal; (b) HC electrostatic gastric signal.

In order to enable detection of signal characteristics, we have isolated the 10 s signal from the full 30s signal for example. We then divided the 10's time-domain structure into several waveforms of the gait cycle by using the procedure in the literature. The maximum point of the local waveform was opposed to moments where the foot was further from the target, when the local minimum point of the waveform coincidenced with the intervals when the foot affected the ground. The whole gait loop waveforms of HP and HC are shown in the same diagram in figure 3.



(a)

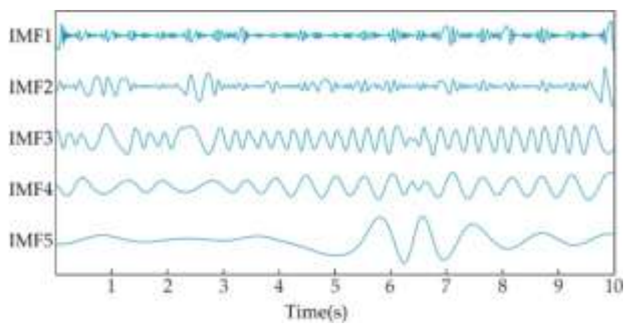


(b)

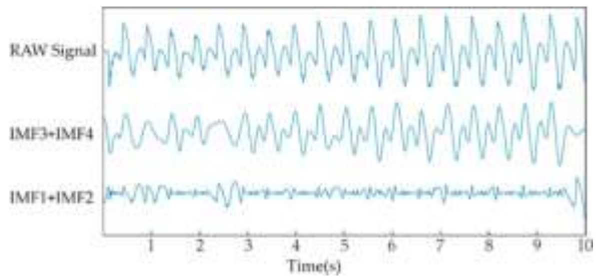
Figure 3: The illustration of gait cycle sequences. (a) Gait cycle sequences of HP; (b) gait cycle sequences of HC.

In order to calculate the gait symmetry with the DTW, the gait time series can also be separated into the gait sequences and the right foot gait sequences.

Figure 2a shows the first five IMFs in the same HP gait sequence. Illustration 4a. From relatively high to low frequency items the 5 IMFs were viewed continually. Figure 4b displays a crude electrostatic sequence with the same HP theme, dominant frequency patterns of gait and variations in high frequency sequence achieved with EMD.



(a)



(b)

Figure 4: The intrinsic mode is based on the EMD approach from an HP topic. (a) HP-subject IMF1–IMF5; and (b) high-frequency variations in gait series embodied IMF3 or IMF4 prevailing gait frequency trends and IMF3 and IMF4.

In the three Gait Electrostatic series values Table 1. displays techniques and default levels for HP and HC. Table 2 Table 2. Table 2. Table 1 reveals that the means and standard deviations for HC artefacts are less than HP objects with the gait symmetry function, implying that the Gait symmetry of HC subjects is enhanced and a longer gear system is retained. The SampEn values of HP subjects are visible even in table 1 above those of HC subjects, which shows that the sequence of patients electrostatically is more complicated. Table 1 shows that HP subjects produce higher frequency energies than HC subjects in the gait sequence. In relation to the measure of equilibrium. The result was in line with our assumption of a more consistent trend for higher SI values. Tests of statistical variations between participants of HP and HC from Mann–Whitney, Table 1. Test results. For the three functions, the p values were all below 0.05.

Table 1: Means, default anomalies, and p values of the three gait functions HC and HP Mann–Whitney measure.

HP		HC	*p*-ValueGait
Symmetry	7.89 ± 4.17	3.45 ± 1.88	0.000
SampEn	2.56 ± 0.25	2.06 ± 0.09	0.012
Stability Index	0.59 ± 0.49	1.75 ± 0.56	0.000

Table 2 shows the values of AUC for the classifications of HP and HC.

Table 2: Value of AUC for the classifications of HP and HC.

	HP versus HC
SVM	0.91
DT	0.87
KNN	0.94
MLP	0.86

4. DISCUSSION

Gait is a symmetric, synchronized and rhythmic regular movement, which can be stroked in. We used gait symmetry to characterised hemiplegic patients thus in our study. We recommend new approaches to gait symmetry when analysing the DTW period between the electrostatic gait sequence of diverse lower limbs. The results of Table 1 reveal that the DTW difference is far larger in hemiplegia patients than in healthy subjects. This was because people who were after the vaccination could not stabilise one end of the lower limbs of the patient and could not maintain normal height and speed. Moreover, the usual variation between the DTW time was significantly larger in post-stroke patients than in healthy samples. The symmetry of the patient's handling over a long term has greatly altered, and biped operation cannot maintain stability in relation to healthy controls.

We assume that the symmetry of the gait should be retainable, because it can have detrimental associations, with both practitioners and scholars. Increased energy intake, increased risk of dropping and lower limb lesions and lower capacity for movement will contribute to problems with balancing gait. It is therefore necessary to find a method of gait symmetry acquisition and analysis. One alternate mechanism for quantifying the post-stroke patients gasket symmetries can be used in the suggested electrostatic series DTW distance.

We used the SampEn algorithm to measure the gait electrostatic series to quantify the discrepancy between the regularity of the gait signal. Sample entropy was commonly utilised in pathological signal processing, where greater entropy values signify reduced regularity in a time series. Table 1 indicates that HP SampEns were substantially higher than the control group of healthy subjects which meant that the gait signal frequency of HP subjects during a journey was worse than the control group of healthy subjects. In other terms, in comparison with post-stroke patients the gait series of safe participants was greater in uniformity and Monotonicity. Moreover, the normal SampEn variance indicates that the gait signal in patients who receive a post-stroke shows a more heterosensitive distribution relative to stable controls. The findings showed that the inhomogeneous components of the post-stroke patient sequences were considerably greater than the subjects of stable control. This may be attributed to the assumption that the post-stroke disease alters the neuromuscular structure which results in a reduction in gait variability.

Previous experiments have shown a comparatively limited fluctuation in safe management topics and that differences in gastric parameters are held to a lower degree. In post-stroke patients, though, the mechanics of the gait are considerably changed, and thus it is extremely important to acquire and analyse the regularity transition between post-stroke gait and stable control gait.

With regard to gait stability, an empirical stability index has been established based on decomposition (SI). Our findings showed that a possible valuable standard for walking stability was this updated index. Existing methods that represent smooth gait series are usually focused on spectral analyses such as the STFT or the autocorrelation function. Gait sequence is therefore a not linear and not stationary time series, and the concepts of validity that underlie such procedures cannot be discussed. The EMD and the proposal for SI, on the other hand, are focused on a self-adaptive system in which, with no previous hypotheses, the data itself determines the boundary and the signal is immediately broken down from high to low frequencies. Besides the SI, researchers will also be able to examine each intrinsic mode function (IMF) in some intrinsic scales of gait patterns and their association with various pathological variables.

Table 1 findings illustrate that the links between the sequence of the gait and the mode functions support the SI description. In post-stroke patients the SI was slightly smaller than for stable controls. The theory of this phenomena is that a "balanced" gear pattern should have more energy (IMF3 and IMF4) inside the core element and less energy in high-frequency components (IMF1 and IMF2).

As shown in Table 2, the significance AUC for post-stroke distinction between patients and safe controls hit 0.94 the KNN classifier suggests that the feature proposed was strongly discriminatory. Our features and classifier have achieved a higher accuracy of classification compared with the literature in which inertial sensors are used to collect and interpret gait signals. Consequently, the three styles of features suggested will efficiently represent the gait features of post-stroke patients and have great diagnostic potential.

This article even has a few weaknesses. (1) Only 30 sts of gait sequence were the data used. The effect of sequence time on the functions should be taken into consideration in potential studies. (2) The three proposed types of features is right in the differentiation between patients and healthy controls, but more research needs to be undertaken if the degree changes in illness may also be distinguished from these features. (3) A further study in a wider sample will be necessary to determine the capability of these features, while the results collected during the trial have demonstrated the utility of these features. The suggested Gait signal analysis solution focused on the EFS sensor is also a good way to measure patient gas conditions above and beyond certain limits. Since hospital discharges need to be completed at home, our method can help specialists monitor and change the situation of rehabilitation of patients at home.

5. CONCLUSIONS

In short, we proposed a new approach for analysing the Gait chain, focused on three different forms of derived characteristics, using the EFS sensory signal. In order to achieve the symmetry, complexity characteristics and gradual consistency of gait signals, Used the DTW algorithm, entropy samples and decomposition in analytical mode. The study revealed that these characteristics could theoretically make hemiparetic gait diagnosis easier. Moreover, the experimental findings of the classifier reveal that these novel characteristics are highly predictive. Our analysis therefore indicates that a hemiparetic gait review can offer serious consideration to gait symmetry, difficulty features, and stepping stability.

REFERENCES

1. Benjamin, E.J.; Virani, S.S.; Callaway, C.W.; Chamberlain, A.M.; Chang, A.R.; Cheng, S.; Chiuve, S.E.; Cushman, M.; Delling, F.N.; Deo, R.; et. al. (2018). Heart disease and stroke statistics—2018 update: A report from the American Heart Association. Circulation, 137, pp. E67–E492.

2. Wang, W.; Jiang, B.; Sun, H.; Ru, X.; Sun, D.; Wang, L.; Wang, L.; Jiang, Y.; Li, Y.; Wang, Y.; et. al. (2017). Prevalence, Incidence, and Mortality of Stroke in China: Results from a Nationwide Population-Based Survey of 480 687 Adults. Circulation, 135, pp. 759–771.

3. Foreman, K.J.; Marquez, N.; Dolgert, A.; Fukutaki, K.; Fullman, N.; McGaughey, M.; Pletcher, M.A.; Smith, A.E.; Tang, K.; Yuan, C.-W.; et. al. (2018). Forecasting life expectancy, years of life lost, and all-cause and cause-specific mortality for 250 causes of death: Reference and alternative scenarios for 2016-40 for 195 countries and territories. Lancet 392, pp. 2052–2090.

4. Solanki, D.; Lahiri, U. (2018). Design of instrumented shoes for gait characterization: A usability study with healthy and post-stroke hemiplegic individuals. Front. Neurosci. 12, pp. 1–16.

5. Ma, C.C.; Rao, N.; Muthukrishnan, S.; Aruin, A.S. (2017). A textured insole improves gait symmetry in individuals with stroke. Disabil. Rehabil., 0, pp. 1–5.

6. Chen, G.; Patten, C.; Kothari, D.H.; Zajac, F.E. (2005). Gait differences between individuals with post-stroke hemiparesis and non-disabled controls at matched speeds. Gait Posture, 22, pp. 51–56.

7. Pfister, A.; West, A.M.; Bronner, S.; Noah, J.A. (2014). Comparative abilities of Microsoft Kinect and Vicon 3D motion capture for gait analysis. J. Med. Eng. Technol., 38, pp. 274–280.

8. Abdul Razak, A.H.; Zayegh, A.; Begg, R.K.; Wahab, Y. (2012). Foot plantar pressure measurement system: A review. Sensors, 12, pp. 9884–9912.

9. Jasiewicz, J.M.; Allum, J.H.J.; Middleton, J.W.; Barriskill, A.; Condie, P.; Purcell, B.; Li, R.C.T. (2006). Gait event detection using linear accelerometers or angular velocity transducers in able-bodied and spinal-cord injured individuals. Gait Posture, 24, pp. 502–509.

10. Greene, B.R.; McGrath, D.; O'Neill, R.; O'Donovan, K.J.; Burns, A.; Caulfield, B. (2010). An adaptive gyroscope-based algorithm for temporal gait analysis. Med. Biol. Eng. Comput., 48, pp. 1251–1260.

11. Catalfamo, P.; Moser, D.; Ghoussayni, S.; Ewins, D. (2008). Detection of gait events using an F-Scan in-shoe pressure measurement system. Gait Posture, 28, pp. 420–426.

12. Wentink, E.C.; Schut, V.G.H.; Prinsen, E.C.; Rietman, J.S.; Veltink, P.H. (2014). Detection of the onset of gait initiation using kinematic sensors and EMG in transfemoral amputees. Gait Posture, 39, pp. 391–396.

13. Storm, F.A.; Buckley, C.J.; Mazzà, C. (2016). Gait event detection in laboratory and real life settings: Accuracy of ankle and waist sensor based methods. Gait Posture, 50, pp. 42–46.

14. Dehzangi, O.; Taherisadr, M.; ChangalVala, R. (2017). IMU-based gait recognition using convolutional neural networks and multi-sensor fusion. Sensors, 17, pp. 2735.]

15. Bastas, G.; Fleck, J.J.; Peters, R.A.; Zelik, K.E. (2018). IMU-based gait analysis in lower limb prosthesis users: Comparison of step demarcation algorithms. Gait Posture, 64, pp. 30–37.

16. Wahid, F.; Begg, R.K.; Hass, C.J.; Halgamuge, S.; Ackland, D.C. (2015). Classification of Parkinson's disease gait using spatial-temporal gait features. IEEE J. Biomed. Health Inform., 19, pp. 1794–1802.

17. Dolatabadi, E.; Taati, B.; Mihailidis, A. (2017). An automated classification of pathological gait using unobtrusive sensing

technology. IEEE Trans. Neural Syst. Rehabil. Eng., 25, pp. 2336–2346.

18. Kamruzzaman, J.; Begg, R.; Campus, C.; Box, P.O.; Mc, M.C. (2006). Support Vector Machines and other Pattern Recognition Approaches to the Diagnosis of Cerebral Palsy Gait Corresponding author: Centre for Ageing, Rehabilitation, Exercise & Sport Science. IEEE Trans. Biomed. Eng., 53, pp. 1–32.

19. Daliri, M.R. (2013). Chi-square distance kernel of the gaits for the diagnosis of Parkinson’s disease. Biomed. Signal Process. Control, 8, pp. 66–70.

20. Li, M.; Li, P.; Tian, S.; Tang, K.; Chen, X. (2018). Estimation of temporal gait parameters using a human body electrostatic sensing-based method. Sensors 2018, 18, pp. 1737.

Corresponding Author

Yamini Sharma*

Assistant Professor, Department of Physiotherapy, Galgotias University, Greater Noida, Uttar Pradesh, India