

# **EE 626P POST GRADUATION PROJECT REPORT**

**PRE-FALL DETECTION BASED ON HUMAN  
GAIT**

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# 1 Introduction

Human balance is the capacity to keep the body in a stable position within predetermined limitations, and it applies to all activities of everyday living. Elderly people frequently lose their balance, and the age-related reduction in stability recovery ability raises the danger of falling[3]. As humans, we have developed the capacity to keep our bodies balanced and have become adept at doing so. Our body posture and gait are synchronized with our state of health and well-being. If we assume that some component of our body isn't functioning properly, our entire bodily structure is in danger. Now that our older generation lacks this ability to create equilibrium, it is actually the most prevalent issue relating to fall related accident. Indeed, with an estimated 420,000[7] fatalities each year, falls rank as the second most common cause of accidental death resulting from avoidable injury. Those over 60 make up the majority of this rate. 50 percent of them cause significant problems to the elderly[8], such as long-term hospitalization, loss of independence, disability, and premature death.

For these reasons, over the last ten years, health care institutions have been employing considerable resources to develop technologies and strategies to reduce or prevent falls and injuries. This leads to open many reason to think it is possible to predict if a person is about to fall based on the Human Gait cycle[3]. There are most earlier researcher are based on the computer visions technique but they have the problem of scalability so there some researches are thinking of making use of the IMU (Inertial Measurement Units) sensors or sEMG sensors to make a prediction based on the movement of the body and the at the same time the electrical pulses generated by these motion. In the next section, we shall first understand the Human Gait cycle.

## 1.1 Human Gait cycle

Human gait may be defined as the analysis of our body's joint or moment trajectory with regard to time in numerous cycles. There are mainly two sub-cycle of gait called stance and swing. During motion our either of our legs is in stance and swing cycle. The gait cycle begins for a typical person when they take their first step from a standing posture, also known as the First double limb support. After this we either take left or right leg forward, depending upon the choice of leg the one which is in air goes into the swing phase and the leg which is into the ground is in the stance phase.

Now for the First double limb support both of our leg is in stance phase[9]. In second limb support one of the leg is in swing phase other is in stance. For the second double limb support again both of the leg will be in stance phase and second limb support is same as first limb support but with opposite leg. This phases of gait cycle produces the pattern which can be extract for processing. Gait cycle is the time interval between two successive occurrences

of one relative repetitive movement of the events.

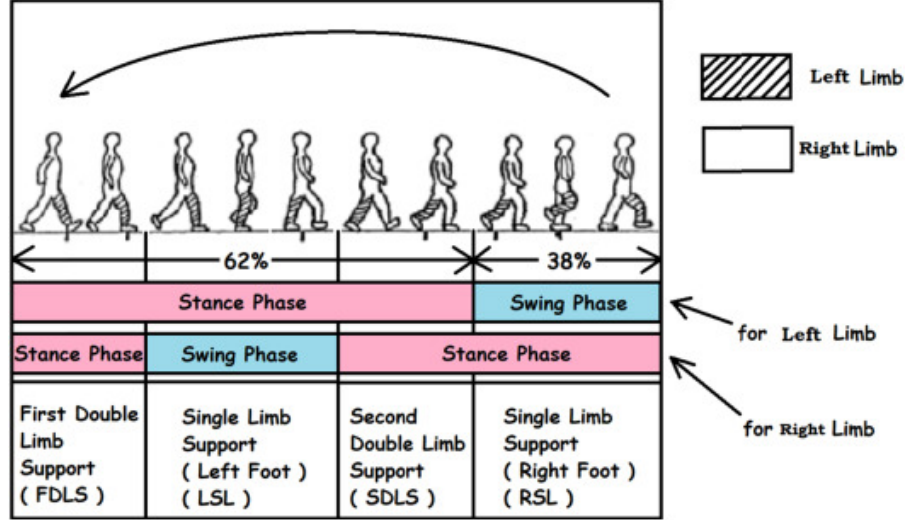


Figure 1: A complete gait cycle showing the swing and stance phase for each left and right leg. Image credits- Modern Methods for Affordable Clinical Gait Analysis[9]

The gait cycle there is the overlapping between the stance phase of the limb and the swing phase of the other limb. With the help of this stance and swing phase we can study the different pattern of the body.

## 1.2 Gait Measurement sensors

In papers on gait prediction, two different types of sensors have been primarily employed to evaluate the human gait pattern. These sensors can be positioned all around our body. The device's data collection in its raw form needs to be further evaluated. IMU and EMG sensors are introduced in the following paragraph.

### IMU Sensors

We need a sensor that can convert motion into an understandable signal in order to examine the motion-related anticipation of any phenomena. We have IMU, or inertial measurement unit, sensors, for this.

IMU[10] sensors are nine-axis-senses, which means they combine the magnetometer, gyroscope, and accelerometer sensors. An accelerometer measures acceleration in the x, y, and z directions, a gyroscope measures orientation change, and a magnetometer is a device that measures magnetic field or magnetic dipole moment that isn't related to field of research.

An accelerometer sensor will be helpful in deriving details from the gait cycle in order to understand the movements.

### **sEMG Sensors**

Electromyography is a technique for measuring the electrical pulses produced by nerve stimulation. EMG monitors the electrical activity of the pulse during muscle contraction and has been utilised to understand the anomalies of the muscle reacting to brain pulses.

Muscles do not normally produce electrical impulses, but when stressed, they do produce electrical signals that surface electromyography sensors detect. Many articles[11] have been published in order to study a person's electrical reaction when walking. We will use sensors to identify the trait of the person while they are at that stage because they can fall at any time.

## **2 Literature Review**

VTT Technical Research Center of Finland[12] first time has conducted the research to establish that human gait can be used to identify the recognized the person. Their approach was basic they used concept of signal processing a template matching technique using cross-correlation. They have use an accelerometer fasten on the waist of the 36 test subject they have achieved the (EER) Equal Error rate of 6.4 percent.

[Nguyen et al,13] were the first who found out that the convolutional neural network based on architecture can recognize the gait pattern generated from the accelerometer and gyroscope sensors. They have shown that their EER is 10.43 percent.

[Delgado et al,14] Have found very much significant distinction between weather accerelometer or gyroscope based is good feature for the gait based prediction. Their finding is that when the model is trained on the Accelerometer work better then gyroscope.Furthermore, the system using both sensors performed better in all cases.

[Gadalat and Rossi,15] was the first to use deep-learning (CNN) to extract the feature. They used the five consecutive gait cycle. Once the feature are extracted from the CNN the extracted feature are feed to the one class SVM(Support Vector MACHine) classifier.

[Rescio et al,6] were the first to use data from sEMG sensors to train a machine learning model. They employed a set of four sEMG sensors on different parts of the test participant. They took a guided approach. They took data from the subject for walking, sitting, bending, and standing. In

controlled condition they have predicted the fall of a person before the impact of about 775ms.

### 3 TinyML and Edge Computing

Tiny machine learning is a rapidly expanding field of machine learning technologies and applications that include hardware[1], algorithms, and software capable of performing on-device sensor data analytic at extremely low power, typically in the mW range and below, enabling a wide range of always-on use-cases and targeting battery-powered devices[2].

The biggest challenge of the Embed devices is that they have few hundred kilobytes of RAM , or sometime much less that that.

Embedded devices still come with some tough resource constraints, though , they have clock cycle of around 10MHz or less. This configuration make extremely difficult to run ML/DL model on device.Has been overcome by the Tiny-ML approach in fact the Google has launched a TensorFlow-lite-Micro framework for the Tiny-ML application development.

With the help of TinyML we can make the faster inferences where the data is been generated.

### 4 Our Approach

From the literature survey it is evident that research is been moving the direction of making a model which can detect the pre-fall of a person and around this many model has been developed and they are making to make it a model which can make inferences in the embeded setting.

Though three are several papers who talks about the deployment of the model but our approach is to make the model aware of the deployment. In tinyML we have to make the model aware of the deployment scenario. Our vision is to make the edge device which can make the prediction by capturing the gait pattern through the sensors like IMU or sEMG and start giving the alert even before it happens.

We are implementing on the Edge device which will helps us to make the faster inference. The work of [Rescio et al,6] have shown that they make prediction of fall of a person 775ms before. We with this project we are aiming to make prediction even before it.

### 5 About the Dataset

ZJU-GaitAcc[5] is the first publicly available data-set of gait acceleration series. It contains the gait acceleration series of 175 subjects. where every record contains 5 gait acceleration series simultaneously measured at the the

right wrist, left upper arm, right side of pelvis, left thigh, and right ankle, respectively. The Data-set have about 2/3 are male, 1/3 are female Age is between 16 and 40 , Height is between 1.5 and 1.9 m

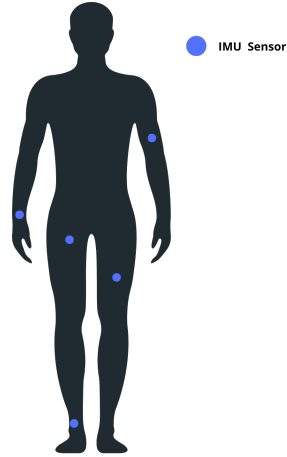


Figure 2: Location of the IMU sensors. Body location are the right wrist,the left upper arm, the right side of pelvis,the left thigh,the right ankle

# Bibliography

- [1] V. Rajapakse, I. Karunanayake, and N. Ahmed, “Intelligence at the Extreme Edge: A Survey on Reformable TinyML.” arXiv, Apr. 02, 2022. Accessed: Jul. 15, 2022. [Online]. Available: <http://arxiv.org/abs/2204.00827>
- [2] C. Banbury et al., “MicroNets: Neural Network Architectures for Deploying TinyML Applications on Commodity Microcontrollers.” arXiv, Apr. 12, 2021. Accessed: Jul. 15, 2022. [Online]. Available: <http://arxiv.org/abs/2010.11267>
- [3] J. Nogas, S. S. Khan, and A. Mihailidis, “DeepFall – Non-invasive Fall Detection with Deep Spatio-Temporal Convolutional Autoencoders.” arXiv, Apr. 27, 2020. Accessed: Jul. 15, 2022. [Online]. Available: <http://arxiv.org/abs/1809.00977>
- [4] Q. Zou, Y. Wang, Q. Wang, Y. Zhao, and Q. Li, “Deep Learning-Based Gait Recognition Using Smartphones in the Wild.” arXiv, Apr. 29, 2020. Accessed: Jul. 15, 2022. [Online]. Available: <http://arxiv.org/abs/1811.00338>
- [5] Yuting Zhang, Gang Pan, Kui Jia, Minlong Lu, Yueming Wang, Zhaohui Wu, “Accelerometer-based Gait Recognition by Sparse Representation of Signature Points with Clusters”, IEEE Transactions on Cybernetics, vol. 45, no. 9, pp. 1864-1875, September 2015.
- [6] Rescio, Gabriele, Alessandro Leone, and Pietro Siciliano. ”Supervised machine learning scheme for electromyography-based pre-fall detection system.” Expert Systems with Applications 100 (2018): 95-105.
- [7] Lockhart, Thurmon E., James L. Smith, and Jeffrey C. Woldstad. ”Effects of aging on the biomechanics of slips and falls.” Human factors 47, no. 4 (2005): 708-729.



- [8] Sadigh, S., Reimers, A., Andersson, R. and Laffamme, L., 2004. Falls and fall-related injuries among the elderly: a survey of residential-care facilities in a Swedish municipality. *Journal of community health*, 29(2), pp.129-140.
- [9] Nandy, A., Chakraborty, S., Chakraborty, J. and Venture, G., 2021. *Modern methods for affordable clinical gait analysis: theories and applications in healthcare systems*. Academic Press.
- [10] Pons, J.L., Ceres, R. and Calderon, L., 2008. Introduction to wearable robotics. *Wearable Robots: Biomechatronic Exoskeletons*, pp.1-16.
- [11] Weiss, J.M., Weiss, L.D. and Silver, J.K., 2021. *Easy EMG-E-Book: A Guide to Performing Nerve Conduction Studies and Electromyography*. Elsevier Health Sciences.
- [12] H. J. Ailisto, M. Lindholm, J. Mantyjarvi, E. Vildjiounaite, S.-M. Makela, Identifying people from gait pattern with accelerometers, in: *Proc. SPIE*, Vol. 5779, 2005, pp. 5779 – 5779.
- [13] H. Lu, J. Huang, T. Saha, L. Nachman, Unobtrusive gait verification for mobile phones, in: *Proceedings of the 2014 ACM International Symposium on Wearable Computers, ISWC '14*, ACM, New York, NY, USA, 2014, pp. 91 – 98.
- [14] R. Delgado-Escao, F. M. Castro, J. R. Czar, M. J. Marn-Jimnez, N. Guil, An end-to-end multi-task and fusion cnn for inertial-based gait recognition, *IEEE Access* 7 (2019) 1897–1908
- [15] M. Gadaleta, M. Rossi, Idnet: Smartphone-based gait recognition with convolutional neural networks, *Pattern Recognition* 74 (2018) 25 – 37.