Gait Phase Recognition using Textile-based Sensor

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2022 7th International Conference on Computer Science and Engineering (UBMK) | 978-1-6654-7010-0/22/$31.00 ©2022 IEEE | DOI: 10.1109/UBMK55850.2022.9919491

***Abstract*—Human gait phase detection has become an emerging field of study due to its impact in various clinical studies. In this study, a system is developed to detect the toe-off, mid-swing, heel-strike, and heel-off phases of a gait cycle in real-time by using a textile-based capacitive strain sensor mounted on the kneepad. Five healthy subjects performed walks including those four phases of the gait at a constant speed and gait distance in a laboratory environment while wearing the kneepad. The phases are labeled according to the gyroscope data of the Inertial Measurement Unit (IMU) located on the kneepad. An Long Short-Term Memory (LSTM) based network is utilized to detect the phases using the capacitance data obtained from the strain sensor. Recognition of four phases with 87% accuracy is accomplished.**

Keywords —Gait Analysis, Real-time Gait Phase Recognition, Textile-based Strain Sensor, Inertial Measurement Unit, Long Short-Term Memory

I. INTRODUCTION

Gait analysis is an essential method in conducting clinical and therapeutic decisions, diagnosing neurological states and monitoring the progress of various diseases, etc [1]. Analyzing the pattern of gait in a real-time manner can lead to the development of various assistive devices and rehabilitation techniques.

By identifying the start and end point of the gait cycle which can be defined as the interval between two consecutive actions during the gait, the phases can be determined [3]. The gait cycle of a healthy individual can be divided from two up to eight different phases based on the utilized sensors and their respective locations [3]. Each cycle of gait in the lower limb motion is usually divided into two different periods which are stance and swing as in Figure 1 [4]. Here, stance covers the entire duration where the foot is in contact with the floor, whereas swing corresponds to the period where the foot is in the air [4]. The beginning of the stance phase can be defined as the initial contact of the foot with the ground, namely Heel-

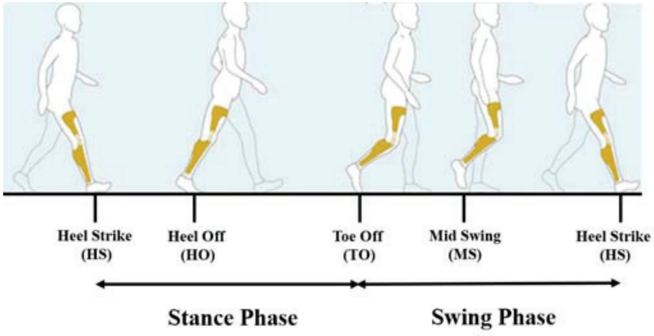

Fig. 1. The Phases of a Gait Cycle [2]

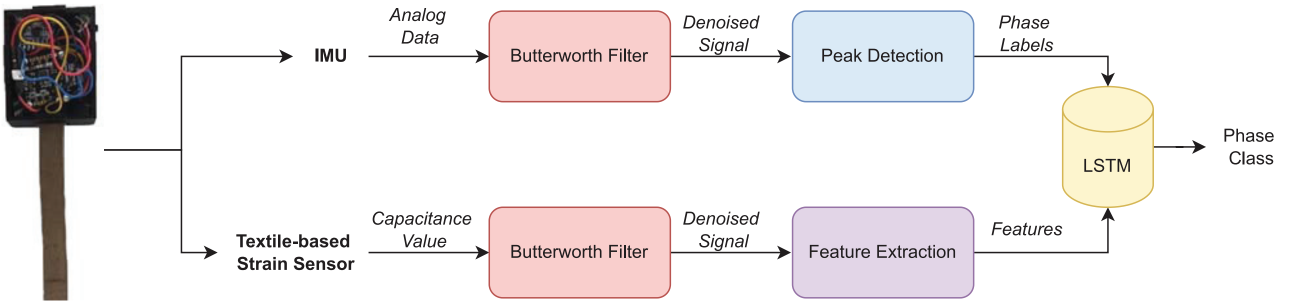

Fig. 2. Developed System for Training

Strike (HS), whereas the termination of this contact is the end of the swing phase, namely Toe-Off (TO) [5]. Mid-Swing (MS) phase of the gait corresponds to the moment when the flexion of the knee is the highest and Heel-Off (HO) occurs when the body is ready to the forward propulsion as the heel begins to lift from the ground [6].

In this study, the classification of the gait cycle phases which can be listed as toe-off, mid-swing, heel-strike, and heel-off is carried out by using a textile-based sensor attached to a kneepad worn by the participants.

The main contribution of this paper is in the methodological setup, which consists of 1) the usage of the combination of the IMU sensor for labeling and textile-based capacitive strain sensor for phase detection, 2) acquisition and analysis of the raw data obtained from both sensors, and 3) application of Deep Learning (DL) algorithm for phase detection.

The rest of the paper is organized as follows: Section II briefly explains the existing work in the field of gait segmentation. Section III describes the developed system in detail. The experiments and results are reported and analyzed in Section IV. In the last section, conclusions are drawn and suggestions for future work are provided.

II. RELATED WORK

Different aspects of the gait cycle can be determined by measuring the motion or tracking the location of the foot by utilizing various sensors including cameras, non-wearable devices such as sensor floors [1], wearable devices and their combinations [7]. In the camera-based approach, the joint angles or limb positions are extracted from each frame of the captured video, or features of the frame are learned by utilizing various machine learning methods [8], [9]. Even though vision-based and non-wearable devices provide accurate results in the gait phase detection, most of them are only available in specialised laboratory setups [10].

Wearable devices can be divided into two different groups which are force measurement sensors or angular velocity and accelerometer measurement sensors. Force measurement sensors [11] are generally in the shape of an insole, and require the shoe to be worn constantly which is not always applicable to individuals with walking abnormalities [10]. Another commonly used sensor in gait phase detection is the IMU [12], [13], which performs poorly when the individual paces at a lower speed. Thus, the IMUs are usually combined with other sensors to increase the reliability of the system [14]. Flexible strain sensors are also utilized in gait and posture classification [10], and the main idea is the change in the electrical resistance or capacitance value in accordance with the elongation of the sensor [15].

For gait segmentation, numerous Machine Learning (ML) and deep learning approaches have been implemented in order to assist the decision-making in clinical studies and develop a control system [16]–[18]. Some examples of the widely utilized models in the gait segmentation can be given as Support Vector Machine [19], Random Forest [20], k-Nearest Neighbour [20], Neural Networks [21]. Overcoming the issue of high dimensionality and high variability nature of the data and increasing the reliability of signal segmentation can be defined as advantages of DL over traditional ML techniques [18].

III. DEVELOPED SYSTEM

The flow diagram of the developed system to determine gait phases from the data obtained from the capacitive sensor is given in Figure 2. After applying the Butterworth filter to the captured data to eliminate noise due to gravity and constant motion, features of the denoised signal are extracted and fed to the LSTM network as the input. In the training session, the class label of each phase is determined according to the detected peaks of the denoised z component of the gyroscope signals obtained from the IMU. In the test session, the system estimates the phases solely based on the features.

A. Wearable Sensors

The designed sensing system is composed of textile-based strain sensor and the signal processing circuit. The control system which is capable of transmitting data obtained from the strain sensor and IMU to the computer in a wireless manner consists of MPR121 capacitive touch sensor, 3.7 Volt LiPo battery, Bluno Beetle, and 6 DOF IMU sensor.

1) Measurements based on Capacitive Strain Sensor: The highly stretchable soft sensor consists of 2 conformable electrodes with a dielectric layer in between [22]. Since an approximately linear strain–capacitance relationship exists in the developed sensor, angular position information regarding the movement of a joint can be obtained from the sensor attached to the respective joint. The developed sensor can easily be mounted on a kneepad worn by the participant via velcro straps which eases the adjustment process for each individual.

2) Measurements based on IMU Signals: The gyroscope of the IMU sensor measures angular velocity in 3 directions which can be listed as the x (pitch), y (roll), and z (yaw) axis. To obtain representative gait phase information from the gyroscope data, the IMU was placed on the knee such that the gyroscope's x-axis (gyro-x) is in the direction of gravity, y-axis (gyro-y) is parallel to the ground and the z-axis (gyro-z) is perpendicular to the surface of the leg. As a result, gyro-z measurements have a negative slope while conducting flexion and a positive slope while conducting extension motion.

B. Data Labeling

The obtained z component of the gyroscope data is filtered using a 3$^{\text{rd}}$ order Butterworth filter in order to eliminate noise due to gravity, shaking in the leg region, and other external factors. The local extrema detection method which corresponds to a point in an open interval at which the maximum or minimum value of the function is obtained has been utilized for phase detection using gyro-z data [23]–[26]. The local minima and maxima occurrences were calculated to detect phase-shifting points. For instance, in Figure 3 which plots the gyro-z data for two consecutive steps, the local minima points correspond to toe-off and heel-strike phases. In these phases, the leg performs flexion movement, which in turn produces negative angular velocity in the z-axis regions. In the mid-swing and heel-off phases, the leg moves forward and produces extension movement, which leads to positive angular velocity in the z-axis. The gathered information from these measurements is then used as ground truth values for the training of the model on capacitive sensor values.

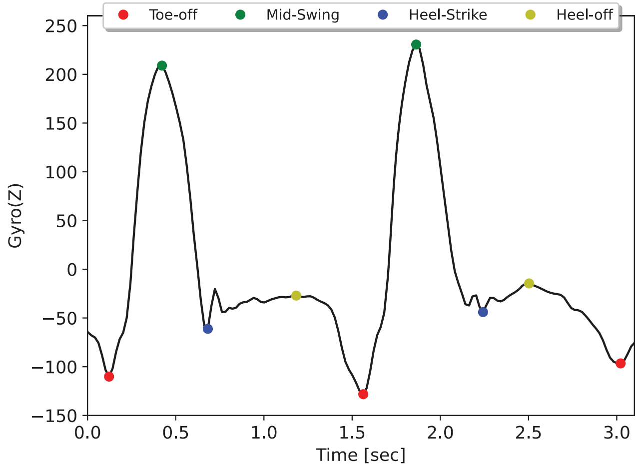

Fig. 3. Gyro-z data

C. Gait Phase Recognition

1) Data Pre-processing and Feature Extraction: For data preprocessing, the values obtained from the capacitive sensor were filtered using a 3$^{\text{rd}}$ order Butterworth filter to eliminate noise and smooth the time series data before extracting features (Figure 4). The capacitive sensor values also produce periodic signals, similar to gyro-z signals as the human conducts the gait cycle. The values peak during the mid-swing phase as the leg performs the extension movement. Features to be sent to the model are extracted from the filtered data. These features are 1$^{\text{st}}$, 2$^{\text{nd}}$, and 3$^{\text{rd}}$ derivative of the capacitance. These features are selected after observing a strong correlation between phase change regions and local extrema and inflection points of the capacitance which are points where for the former the 1$^{\text{st}}$ derivative changes signs and for the latter the 2$^{\text{nd}}$ derivative changes signs.

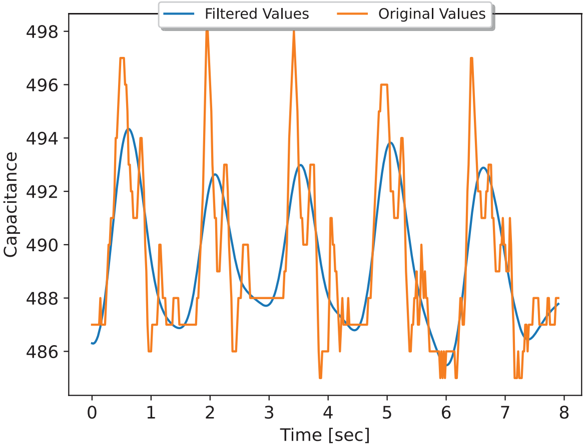

Fig. 4. Capacitance Values

2) Model Development: For the gait phase recognition model, an LSTM-based network (Figure 5) is used to take advantage of the temporal dependencies of the time-series data [27]. LSTM blocks contain gates that act as a valve in the memory block. How much of the new information should be memorized is decided by the input gate while how much of the old information should be forgotten is decided by the forget gate. The output gate controls how much of the output can be sent out by the block. This remembering and forgetting of the information mechanism make the LSTM blocks effective for the analysis of long and short-term time-series data. A fully connected layer that contains 128 neurons follows the LSTM layers. These layers are where all the inputs from one layer are connected to every activation unit of the next layer. As in most popular models, in this classifier fully connected layers are used to compile data extracted from previous layers to finalize the output.

Adam optimizer with a learning rate of 0.001 is used during the training period. As for the loss function, Cross-Entropy function is utilized as given in Equation (1). In the equation, $P^*(i)$ represents true class distribution whereas

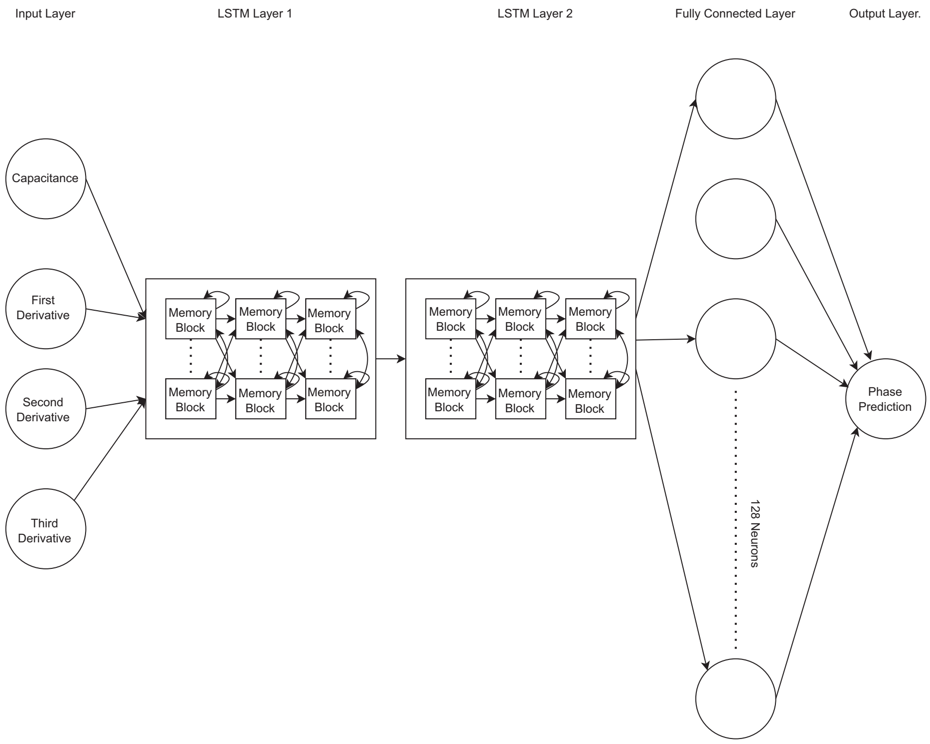

Fig. 5. LSTM Network Design

$P(i)$ represents predicted class distribution.

$$H(P^*|P) = -\sum_i P^*(i)\log P(i) \tag{1}$$

IV. EXPERIMENTS

A. Experimental Setup

For the data collection phase, 5 different healthy participants are asked to complete 15 consecutive steps for 5 times while wearing the kneepad equipped with the capacitive sensor and the control system. The demographics of the subjects can be seen in Table I. In order to have consistent results, the length as well as the speed of the gait cycle is kept constant by making use of markers placed on the ground. Collected data from the sensors are sent to the receiver Bluno Beetle connected to the computer using the Bluetooth connection.

TABLE I
DEMOGRAPHIC INFORMATION

Age	Gender	Height	Weight
21	M	170 cm	65 kg
35	F	160 cm	62 kg
32	M	165 cm	72 kg
22	F	172 cm	63 kg
21	M	183 cm	75 kg

B. Hardware and Software

The model is trained for 100 epochs using a laptop equipped with AMD Ryzen 9 5900 HX CPU and 32 GB of RAM with Python 3.10 programming language used for both parsing and preprocessing the sensor data, and conducting the training and testing phase of the classifier model.

V. RESULTS

For all subjects, the collected gait cycle data is divided into two parts: training and test set. The training set, which accounts for 60% of the data, is used to train the LSTM Network by calculating the loss function and adjusting the weights and bias of the neural network using back propagation while the test, and validation set which both take up 20% of the data, are used to test the performance of trained LSTM in every epoch and calculate the accuracy metrics.

One of these metrics is the $F1_{score}$, which is obtained by the formula in Equation (2). Macro average computes the average value of independently calculated metrics for each class. Thus, this technique treats each class equally. In micro averaging, the contribution of all classes to compute the average metric is taken into account. In Figure 6, the change in the micro and macro F1 score during the training can be seen.

$$F1_{score} = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{2}$$

One of the important metrics to consider during the training period is how the loss function changes over the training period. The value of the loss function indicates how bad the model's prediction was during that epoch. The goal of the training process is to minimize the loss function by adjusting the weights in the network to make better predictions. As it

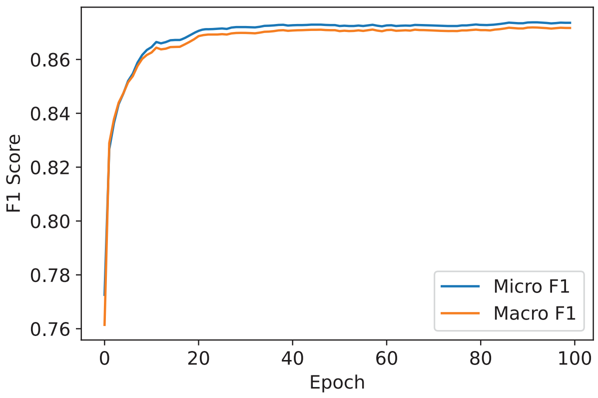

Fig. 6. Macro and Micro F1 scores

can be seen in Figure 7, the loss function's value decreases as the validation continues through the epochs.

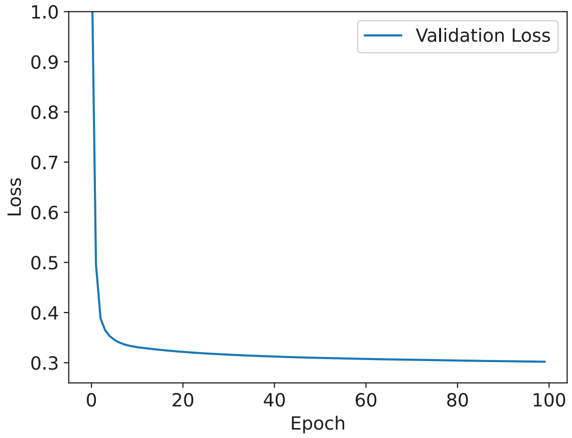

Fig. 7. Loss Plot

In Figure 8, the confusion matrix of the classifier model can be seen. The model performs similar for each class while sometimes making incorrect predictions with adjacent phases. As can be seen, the highest score is achieved in heel-off phase while obtaining over 85% accuracy in general.

In Figure 9, the model's performance against one of the test gait data can be observed. As it can be seen from the plot, the model is capable of making correct predictions and producing the correct output with minimal delay.

VI. CONCLUSION AND FUTURE WORK

In this paper, the phases of the gait cycle are determined using a textile-based strain sensor positioned on a kneepad worn by healthy participants. By using the z component of the gyroscope data of the Inertial Measurement Unit (IMU), the phases are labeled. Using the capacitance data obtained from the strain sensor, an LSTM-based network is trained to recognize the phases. Recognition of four phases of gait (toe-off, mid-swing, heel-strike, heel-off) with 87% accuracy and minimal delay in real-time was accomplished.

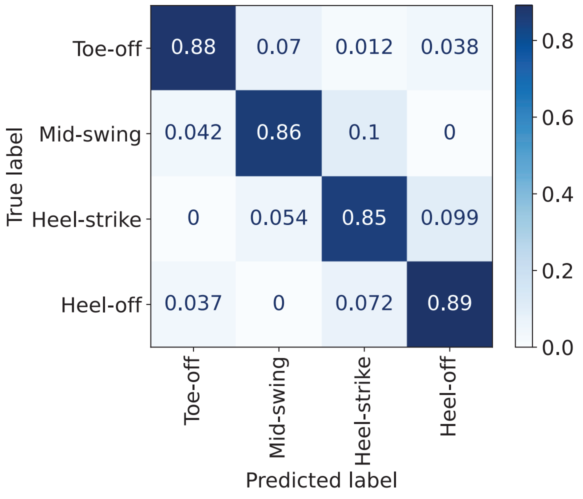

Fig. 8. Confusion Matrix

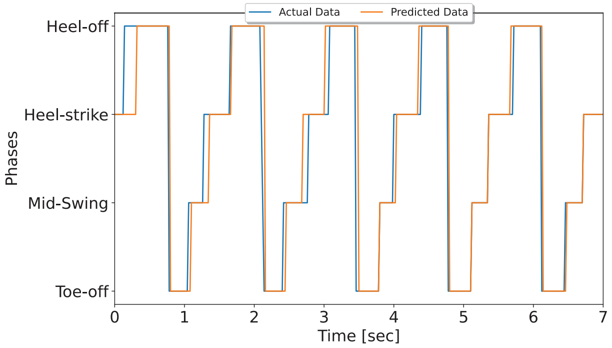

Fig. 9. Actual vs. Predicted Phase Labels

Regarding the future work, the following enhancements will be implemented so that the utilized gait phase classification will not only achieve higher accuracy scores but also will ease the usage and be more responsive to different gait styles:

- Creation of a mobile application for data collection: Currently, the Bluno that collects the sensor data is connected to a computer which leads to connection problems as the subject moves away from the computer. This problem can be solved by pairing the Bluno to a mobile phone and collecting the data on the mobile phone.
- Expanding the dataset: Improving both the volume of the data by collecting from diverse set of subjects such as people suffering from foot drop, arthritis, Parkinson's

disease, and other gait disorders will improve the data quality and prevent the model from over-fitting to the existing data which will, in turn, lead to better real-life performance and can be helpful to recognize phases of gait in other unusual types of gait.

- Labeling based on other sensors: Currently, gyroscope measurements on the z-axis are used to label the phases of gait for the deep learning model. However, most existing studies focus on techniques such as Force Resistive Sensors (FSR) on the sole of the foot, motion capture technology, and multiple IMU sensors on different regions of the body for measuring angular velocity and acceleration at different positions. These improvements will allow for more accurate labeling of the data as well as dividing the gait cycle into more than 4 phases.
- Sensor fusion: The sole data obtained from the capacitive sensor might not be enough to produce a sufficiently performing classifier. However, using other e-textile sensors such as foot pressure sensors or multiple capacitive sensors located around different parts of the leg can improve the quality of the information obtained during the gait cycle and increase the classifier's accuracy.

VII. ACKNOWLEDGEMENTS

The authors disclose the receipt of the following financial support for research and authorship. This work was funded by Scientific and Technological Research Council of Turkey (TUBITAK) Research Grant No:120C118.

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