# A Wireless IoT System Towards Gait Detection in Stroke Patients

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***Abstract*- Gait monitoring through the Internet of Things (IoT) is able to provide an overall assessment of daily living. All existing systems for predicting abnormality in gait mainly consider the gait related parameters. Their accuracy is limited because consequences due to injuries are significantly affected by different events in the gait. The objective of this study is to present a multisensory system that investigates walking patterns to predict a cautious gait in stroke patient. For this study, a smartphone built-in sensor and an IoT-shoe with a Wi-Fi communication module is used to discreetly monitor insole pressure and accelerations of the patient's motion. To the best of our knowledge, we are the first to use the gait spatiotemporal parameters implemented in smartphones to predict a cautious gait in a stroke patient. The proposed system can warn the user about their abnormal gait and possibly save them from forthcoming injuries from fear of falling.**

***Keywords- IoT, Stroke, Gait, Smartphone, Sensor.***

## I. INTRODUCTION

Injuries due to a heart attack are a major health problem all over the world [1]. More than 85% of heart attack patients regain the capacity to walk but their gait differs from that of healthy subjects [2]. Hemiplegic gait of a heart patient is characterized by alterations in spatio-temporal and kinematic parameters [3]. In older adults, the fear of falling after a stroke, named ‘‘cautious gait,’’ leads to a specific gait pattern with reduced stride length and gait velocity [4]. Therefore, it could be hypothesized that the adaptive phase observed by clinicians at the beginning of a gait analysis session in stroke patients could be related to cautious gait. Analysis of the human gait for predicting falls due to cautious gait is the subject of many current research projects. Accurate reliable knowledge of one's gait characteristics at a given time and, even more importantly, monitoring and evaluating them over time, will enable early diagnosis of abnormality in gait to predict falls. This diagnosis will also help to predict and prevent users from an injury. Stroke is one of the leading causes of morbidity and mortality in adults, accounting for 17.3 million deaths per year. By 2030, it is estimated that more than 23.6 million stroke patients in United States will die from an indirect result of the stroke [5]. So, the automatic detection of cautious gait in stroke patients would help reduce the arrival time of a medical caregiver and, accordingly decrease the mortality rate [6].

This high risk of stroke among the growing elderly population influenced scientific research on gait monitoring [3]. After completing standard rehabilitation, approximately 50%-60% of stroke patients still experience some degree of motor impairment, and approximately 50% are partly dependent in Activities-of-Daily-Living (ADL) [7]. Strokes significantly contribute to reduced gait performance. The majority of stroke patients do not reach a walking level that enables them to perform all their daily activities [8]. Gait recovery is a major objective in the rehabilitation program for stroke patients. Therefore, for many decades, hemiplegic gait has been the object of study for the development of methods for gait analysis and rehabilitation [9].

Many previous studies have emphasized that fear of falling is frequent after a stroke and could influence gait parameters [10-11]. In a study by Verghese, et al., three phases have been introduced to characterize gait performance in elderly persons [6]: the first phase is best represented by cadence, swing time, and stance time. The second phase is best represented by gait speed and stride length. The third phase is best represented by stride length variability. Variation within gait phases over time in stroke patient can lead to a fall. Several clinical studies have demonstrated that most falls are affected by gait parameters.

One criticism of the available risk indicators has been the lack of consideration of fall-related factors and loading conditions, which may considerably affect the predicted fall risk [12-13]. Thus, much attention has been directed towards gait prediction using smartphone and Internet of things (IoT) devices. To the best of our knowledge, we are the first to use subject-specific IoT-based gait evaluation implemented on smartphones to accurately detect abnormality in gait events in predicting injuries in a stroke patient.

IoT has created an explosion of sensor data due to the increased number of devices with embedded sensors. With recent developments, smartphones have increased their processing capabilities and have been equipped with a number of built-in multimodal sensors. As self-contained devices, smartphones present a mature hardware and software environment for developing various health monitoring systems. Smartphone-based gait monitoring systems can function almost everywhere, because mobile phones are highly portable. Ideally, integrated sensors along with the pressure sensor shoes (*IoT-shoe*) can automatically

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detect gait patterns. Researchers have already developed some smartphone-based gait detection systems, especially for stroke patients [14]. However, in all of these previous studies, the system detects a gait related injury only after it has already occurred. By preventing injuries from happening, the number of falls or other injuries and their consequences are reduced. We believe the best way to reduce the number of injuries is to alert users about their abnormal gait and the possibility of falling due to cautious gait.

Therefore, our focus is on gait detection (followed by patient awareness) which will help to predict injuries due to cautious gait in stroke patients. To address the issue of gait detection, the aim of this study is to determine if the gait of stroke patients changes significantly over successive gait trials using smartphones. Data from a pressure-sensor embedded shoe and smartphone sensor were used to validate the proposed approach and to identify fear of falling with cautious gait.

### A. Major Contributions

In this paper, we propose to use IoT systems for developing gait assistance systems for predicting cautious gait because they naturally combine the detection and communication components. Our major contributions are as follows: we

- *developed subject-specific IoT systems for gait assistant.*
- *proposed a smartphone-based gait assistance system with a wearable IoT-shoe for elderly people as a novel application for predicting cautious gait.*
- *used built-in accelerometer and GPS of the smartphone and pressure distribution of IoT-shoe to identify abnormal gait pattern in users.*
- *designed a system that monitors a stroke patient's status in real time and sends the results to a caregiver or loved one.*

The rest of the paper is organized as follows: First, we discuss the relevant related work, and describe the difference between our system and the existing ones. Second, we discuss the details of the proposed IoT system. Third we evaluate our smartphone-based prototype system. Finally, we conclude with some future research directions.

## II. RELATED WORK

Health-risk identification using gait patterns with embedded IoT sensors has been the subject of many studies over the past decade. Most of the previous approaches regarding gait recognition utilize accelerometers attached to the subject for gathering data. Therefore, they have very limited accuracy in predicting abnormal gait, like cautious gait for a specific individual.

Past studies have shown that stroke patients exhibit great fatigability during gait [15]. These studies have established that, after a stroke, walking performance declines over relatively short periods of functionally-relevant ambulation [16]. In addition, there are several research projects within mobile ECG recording using Internet solutions, Bluetooth technology, cellular phones, and wireless local area networks, Wireless and WLAN Sensor Networks [17]. In [18], the author developed a wireless diagnosis system integrating digital telemetry, a homecare station and a remote clinical station. A gait monitoring system has been proposed based on mobile platform which transmits abnormal walking identified in a patient-worn unit [19].

In [20], the author developed a smartphone based gait detection system that can alert the users about their abnormal walking patterns. The authors validated their system using a decision tree with cross validation and found 99.8% accuracy in gait abnormality detection using smartphone sensors data. They also have developed the system [21] which equips an IoT-shoe with smartphone sensors to analyze the data using the same method to show the fall prediction accuracy. They did not consider predicting cautious gait that can lead to a fall. In [22], the author described how spatiotemporal and kinematic parameters changes in patients with stroke. They used a data base of a clinical gait analysis to validate their claim.

To address the drawbacks of the above-mentioned research, in this paper, we propose a gait assistant system using IoT. Our system is designed to address directly some of the drawbacks of the existing systems and potentially yield good prediction results. To the best of our knowledge, our system is the first IoT-based gait assistance for predicting cautious gait, especially in stroke patients. We illustrate the difference between our system and the other related works in Table I.

TABLE I. COMPARISON OF EXISTING WORK BASED ON DIFFERENT FEATURES

| **Approach** | **Use IoT Device** | **Mobility** | **Support High Sampling Rate** | **Cyber Physical System** | **Cost Effective** |
|---|---|---|---|---|---|
| Alwan [14] | No | Yes | No | No | No |
| Duncan [23] | No | Yes | No | No | No |
| Iosa [15] | No | Yes | Yes | No | No |
| Hyngstrom [24] | No | Yes | No | No | Yes |
| Jonkers [25] | No | Yes | No | Yes | Yes |
| Mellone [26] | No | No | No | Yes | No |
| Mirelman [27] | No | Yes | No | Yes | No |
| B-Shoe [28] | Yes | No | No | Yes | No |
| Lee [29] | No | No | No | Yes | No |
| Zhang [30] | No | No | No | Yes | No |
| Duschau [31] | Yes | No | No | Yes | Yes |
| Popescu [32] | No | No | N0 | Yes | No |
| Bourke [33] | Yes | No | No | Yes | No |
| Forrester [34] | No | No | Yes | Yes | No |
| **Our Approach** | **Yes** | **Yes** | **Yes** | **Yes** | **Yes** |

## III. SYSTEM ARCHITECTURE AND DATA COLLECTION

The strength of our proposed IoT system is dependent on existing wireless communication technologies to provide a low cost solution with maximum freedom of movement. In addition, we have used a smartphone and a sensor embedded IoT-shoe that are user friendly. The architecture of the system is shown in Figure 1. The system then generates gait assistive information based on gait spatiotemporal parameters while walking.

To analyze the spatiotemporal parameters and kinematic motion of the gait, four piezo-resistive pressure sensors were placed at the bottom of the shoe to assess the pressure distribution. It is observed that more than 70% body pressure is measured from the front foot and back foot regions while walking. Considering this, we have placed two of our sensors in the forefoot region, and two in the rear foot region as described in Table II. In this system, the piezo-resistive force sensor is used to measure the foot pressure while walking. The accelerometer and GPS of the smartphone is used to measure the acceleration of the body and the user's location information. Along with the four pressure sensors, the IoT-shoe includes a communication module. The module is comprised of an Arduino™ and a Wi-fly module with a battery power supply. The Arduino is an open-source physical computing platform based on a simple I/O. The Wi-Fly Shield equips the Arduino with the ability to connect to 802.11b/g wireless networks.

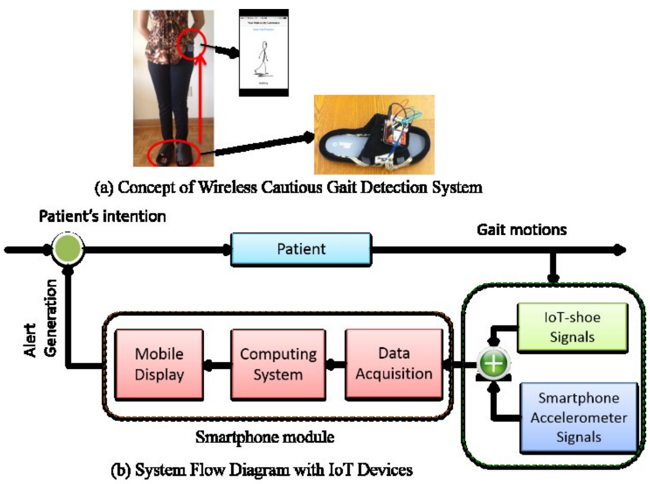



Fig. 1: Overview of proposed IoT sensing system

In order to process the pressure data, the communication module has two different software tasks. One is for the Arduino and another is for the smartphone. In the Arduino, we read an analog signal from the shoe sensors and buffer the signal that is sent to the smartphone through a Wi-Fi network. Sensor data was collected over a period of time and, each time, a subject was tested with a simulated cautious gait.

TABLE II. INSOLE SENSING POSITION

| Sensor | Position | |
|---|---|---|
| FS 1 and FS 2 | Rear foot | FS 1: Posterior Metatarsal |
| | | FS 2: Hind foot |
| FS 3 and FS 4 | Forefoot | FS 3: Great Ball |
| | | FS 4: Little Ball |

### A. Experimental Setup

To test the effectiveness of our proposed system, we collected data from the IoT-shoe sensor and the smartphone sensor using a smartphone. We used multiple subjects and collected data for different events of a gait cycle. Data for each subject was collected for 12 60-second trials from a smartphone placed in the subject's wrist.

### B. Data Collection Process

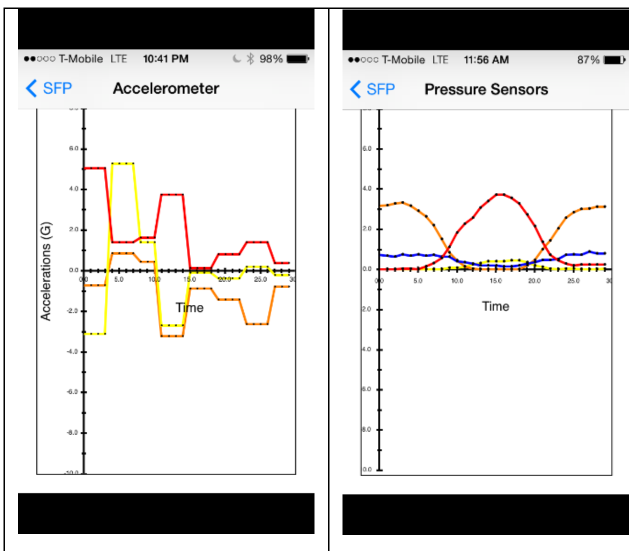
For the data collection, we have developed a prototype application of the system for smartphone. The screenshots of the prototype application with visualization of pressure variation in different sensors and variation of body acceleration are shown in Figure 2. In Figure 2(a), the interface is shown, which is used to visualize the 3-axis accelerations variations while walking for a period of time. We also have developed the interface for graphically picturing all four insole sensors, as shown in Figure 2(b). We have used our prototype application for data collection and for evaluating our system.

Volunteers were recruited for the validation of the IoT system. The testing involved placing the IoT-shoe instrumentation on the subjects' own walking shoes and attached the phone to his/her wrist. Each subject was asked to perform a series of walking tasks, while systems simultaneously collected data from the shoe and the smartphone sensors.

TABLE III. SUMMARY OF SUBJECT CHARACTERISTICS.

| Gender | Ages [yrs.] | Height [cm] |
|---|---|---|
| Female: 3 | 20-30: 6 | 150-159: 2 |
| Male: 7 | 31-40: 4 | 160-169: 1 |
| | | 170-179: 4 |
| | | 180-189: 3 |

Since, we cannot test potential injuries due to fear of falling with a real stroke patient, we recruited 10 participants from both genders. Characteristics for each group are summarized in table III. Each subject first walked at his or her own self-selected natural pace for 2 to 4 trials, termed "free gait." Then we asked them to walk with cautious gait (shortening the step in a sort of drag motion and displaying a lateral deviation of the entire trunk).




(a) Real-time 3-axis accelerations while walking

(b) Real-time pressure variation while walking

Fig. 2: Screenshots of IoT-based wireless gait collector prototype

We first used these datasets for the training of our system. Later we used the trained system with real people to verify the gait detection accuracy of the system. We established a baseline walk period for each of the walking traces. This was achieved by manually finding the walk-start ($t_{start}$) and walk-end ($t_{end}$) events.

We optimized the gait parameters using the manually-determined ground truth walk periods.

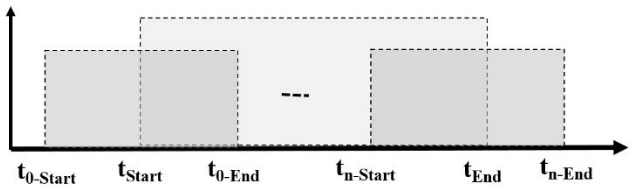



Fig. 3. Illustration of Walking Intervals

For $t_{0-Start} \leq t_{Start} \leq t_{0-End}$ and $t_{n-Start} \leq t_{End} \leq t_{n-End}$ as shown in Figure 3, we define the false positive error, false negative error and total error as follows,

$$\epsilon_P = (t_{Start} - t_{0-Start}) + (t_{n-End} - t_{End})$$

$$\epsilon_N = \sum_{i=1}^{n} \left(t_{i:start} - t_{(i-1):End}\right)$$

$$\epsilon_{total} = \epsilon_p + \epsilon_N \qquad (1)$$

To minimize the error in the sample data, we eliminated 100 initial and end data samples in each interval of data collection.

Currently, the collected data can fully or partially process on the IoT embedded device. The onboard data processing depends on the IoT application. Mainly, it includes novel Feature Extraction signal classification. However, due to the constraints on the capabilities of low-power IoT devices including computation and memory limitations, the on-board processing must be optimized. Hardware and software optimizations are needed to make the on-board processing efficient and affordable. To overcome the limitations, we used the smartphone as a platform, which has the capability of analyzing the data in real-time to detect the cautious gait in stroke patient. The smartphone in the system is used for data acquisition, computation, and communication. An onboard sensors' data process using embedded IoT components is shown in Figure 4.

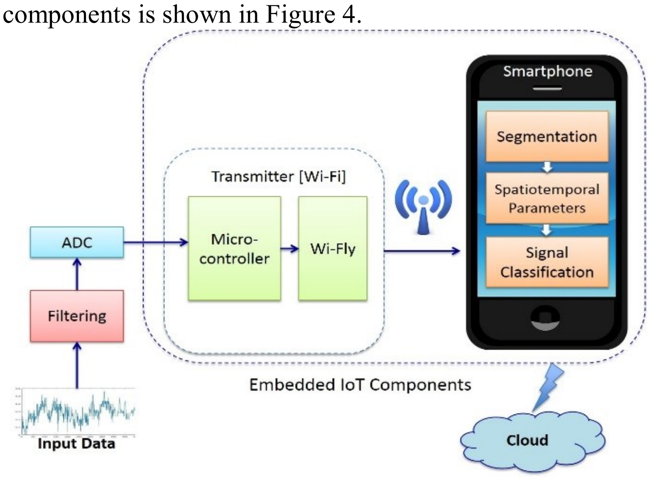



Fig. 4. Sensor Data Processing using Embedded IoT Components

## IV. OVERVIEW OF SIGNAL CLASSIFICATION APPROACH

We used the following approaches of signal classification to analyze the IoT-shoe and smartphone sensors data to identify cautious gait in stroke patient.

*Phase Space Reconstruction*

The Phase Space Representation (RPS) is a transformation mapping a time series into a multidimensional space, where each dimension represents an independent variable describing the system under study. There are several variants of this transformation; however, the most famous is extracted from Takens' embedding theorem [35]. The works of Takens and Sauer, et al., [36] are used as a theoretical basis for our signal classification process. This work states that a time series of observations sampled from a single state variable of a system can be used to reconstruct a space topologically equivalent to the original system.

Given a time series $x = x_n, \quad n = 1 \ldots\ldots N,$ a sequence of state variable observations, a trajectory matrix X of dimension $d$ and time lag $\zeta$ is defined as,

$$X = \begin{bmatrix} X_{1+(d-1)\zeta} \\ X_{2+(d-1)\zeta} \\ \vdots \\ X_N \end{bmatrix} = \begin{bmatrix} x_{1+(d-1)\zeta} & \cdots & x_{1+\zeta} & \cdots & x_1 \\ x_{2+(d-1)\zeta} & \cdots & x_{2+\zeta} & \cdots & x_2 \\ . & & . & & \\ . & & . & & \\ . & & . & & \\ x_N & \cdots & x_{N-(d-2)\zeta} & \cdots & x_{N-(d-1)\zeta} \end{bmatrix} \qquad (2)$$

where each row vector in the matrix represents a single point in the space:

$$\mathbf{X}_n = x_{n-(d-1)\zeta} \quad \cdots \quad x_{n-\zeta} \quad x_n \qquad (3)$$

where, $n = (1 + (d-1)\zeta) \ldots\ldots\ldots N.$ a row vector $x_n$ is a point in the RPS.

The dimension, $d$, is greater than twice the box counting dimension of the original system which is a sufficient condition for topological equivalence [33]. In Takens' original work, $\zeta$=1. However, in practice it has been found that the appropriate selection of the time lag can reduce the required RPS dimension.

The proposed classification approach is capable of distinguishing between signals generated by topologically different systems because of the representational capability of RPSs. This theoretical capability is demonstrated empirically across different complex real-world application domains.

## V. EVALUATION OF THE SYSTEM

To evaluate our proposed system, we have developed a prototype application and investigated its performance. We evaluated the prototype with extensive experiments. In this section, we present how the data are analyzed and performance is measured.

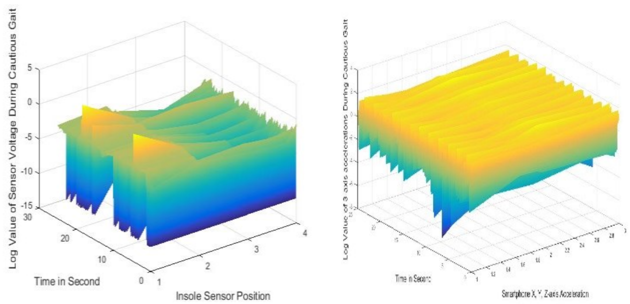
### *A. Result Analysis*

In this section, we discuss the performance of the IoT system.

### Pressure Maps and Accelerations of Human Motion

An example of pressure maps that can be extracted from the developed pressure-sensitive insoles is described in Figure 5a: the stated maps represent typical in-sole pressure patterns for a test subject during the walking. An interesting finding of this study is the gait insole variation. The variation of insole pressure with time varies from person to person. Several users have the distribution of pressure from forefoot to rearfoot and some users have the variation from rearfoot to forefoot.

Observed acceleration from the smartphone sensor is described in Figure 5b. It is interesting to note that the observed acceleration for free gait is somewhat similar to that of simulated cautious gait. Explicitly, it is basically a short period of acceleration value followed by a small impact. The average measured peak acceleration for free gait is greater than the average peak for acceleration with cautious gait.




(a) (b)

Fig. 5. (a) Pressure maps under the IoT-shoe while walking with cautious gait. The weight is distributed on the heel region. (b) 3-axis acceleration of the user while walking with cautious gait.

### Spatiotemporal Parameters Analysis

To test the validity and long term feasibility of our proposed system, we calculated cadence, stride length, stride time and speed of the participant's trial for free gait and simulated cautious gait. The parameters measured from the insole pressure variation from an IoT-shoe and from the accelerometer of the smartphone was calculated to investigate common information between the parameters. Parameters with a higher coefficient were interpreted as being significant contributors to normal or abnormal walking detection. Table IV shows a spatiotemporal parameters for a sample test subject.

TABLE IV. SPATIOTEMPORAL PARAMETERS FOR A SAMPLE TEST SUBJECT

| Parameters / Gait | Cadence (steps/min) | Stride length(cm) | Stride time (sec) | Speed (m/sec) |
|---|---|---|---|---|
| Cautious Gait | 127.463 | 101.852 | 1.352 | 0.840 |
| Free Gait | 103.35 | 108 | 1.161 | 0.93 |

We investigated the relative error of spatiotemporal gait parameters of free gait with respect to parameters from the simulated cautious gait. We observed that cadence and stride time for cautious gait is higher than free gait for each trial. However, the stride length and speed of cautious gait are smaller than free gait. For predictive analytics of the system, we used information of parameter variations for the above mentioned two different gaits.

### Signal classification for gait pattern recognition

As discussed above, our approach to signal classification is to build a predictive model of signal trajectory densities in an RPS and differentiate between signals. First, we will analyze data from IoT-shoe sensors, which includes embedding the signals and estimating the time lag and dimension of the RPS. Then, learn the models for each signal class for signal classification, which is done with a Maximum Likelihood Estimator (MLE) technique.

First, we applied our technique to the two data sets generated from free gait and simulated cautious gait events. It was observed that the pressure variation with one or two sensors during cautious gait was much higher than free gait with respect to subject's gender age, height and weight. We used the average pressure variation of these pressure values while determining spatiotemporal parameters for each subject. We can also see the variations of different walking patterns for different subjects.

Next, we modeled the dynamics using Gaussian Mixture Models (GMM). The particular models used here are statistical distributions that can be learned over RPSs and then used to classify signals. Our experimental results do not show the desired accuracy with the predictive model for walking, as our analysis is for simulated data. However, for the model prediction, there is still room for classification accuracy improvement to greater satisfaction. We expect our accuracy to improve when data is collected from a real subjects with chronic heart problems.

## VI. CONCLUSIONS

In this paper, we presented a wireless system to analyze gait using IoT-shoe and smartphone sensors through a real-time detection of abnormality in users' gait patterns. The proposed IoT system can detect and predict cautious gait that can lead to a fall. We presented preliminary results from a patient using the embedded IoT system and showed that the data can be used to analyze the cautious gait. The system may also find multiple applications in gait behavior detection for people with various disabilities who are at a high risk of falls related injuries with location information.

To test the chronological permanence and long-term feasibility of our approach in the future, we plan start testing our system with data from elderly people who suffer from chronic heart problems. Also, we plan to compare healthy and stroke patients' data where the pairs are closely comparable based on weight, height, age, and gender. Additionally, the system can be used in the smart home monitoring system to connect gait to digital worlds for future wireless technology.

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