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# An Advanced Gait Monitoring System Based on Air Pressure Sensor Embedded in a Shoe

Abinaya.B[a] , Latha.V[b] , Suchetha.M[c]

[a] *Student, Velammal Engineering College, Chennai-600066, India*
*Tel.:7299322152,E-mail address: abisankari84@gmail.com*
[b] *Assistant Professor, Velammal Engineering College, Chennai-600066, India*
*E-mail address: lathavenkatesanpnag@gmail.com*
[c] *Assistant Professor, Velammal Engineering College, Chennai-600066, India*
*E-mail address: suchethashivani@gmail.com*

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## Abstract

Human gaits are complicated, and the gait phases cannot be exactly distinguished by comparing sensor outputs to a threshold. Measurement of GCF provides information to detect human gait phases. In gaits of certain patients, the GCF patterns are sometimes vague. A higher level algorithm that monitors the degree of abnormalities in the gait phases detected by the fuzzy logic is proposed. When it is measured by force sensors in shoes, it may be more smoothened due to the flesh as well as the cushioning materials in the sole of the shoe. For this purpose, fuzzy logic is suitable. In this project, air bladders are used for measuring GCF. The proposed methods are implemented by using signals from sensor-embedded shoes called smart shoes. Each smart shoe has four GCF sensors installed between the cushion pad and the sole. The GCF sensor applies an air pressure sensor connected to an air bladder.

*Keywords- Abnormality detection; gait monitoring device; human gait phase detection; smart shoes.*

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## 1. Introduction

Walking is a basic capability that allows humans to pursue their daily lives and function as productive members of society. Walking involves a repetitious sequence of limb motion to move the body forward while simultaneously maintaining stance stability. Walking is characterized by the gait. A typical gait involves one foot placed forward with the second placed the same distance beyond the first. The gait of a normal person, often called the normal gait, is a very efficient gait pattern in terms of power and gait velocity so that a human can walk easily for a long time. Furthermore, the normal gait allows the human to remain agile so that he/she may easily ascend and descent stairs, change walking directions, and swiftly avoid obstacles. Because of these advantages of the normal gait, patients with nervous or muscular disorders strive to rehabilitate and resume the normal gait even though they may have been impaired severely. In this paper, a sensor-embedded shoe is developed for the use in interactive rehabilitation devices as well as in clinical gait monitoring systems. For such applications, measurement of ground contact forces (GCFs) provides necessary information. Although the GCF signals do not directly provide feedback signals for the control of assistive devices, they do provide a foundation for detecting human motion phases and enable assistive devices to adaptively change the algorithms for each motion phase.

Since the GCF signals do not directly provide information on the dynamic state of a human body, an algorithm that extracts such information from the sensor signals should be introduced. Motion phases during walking are characterized by the gait phases, and each gait phase has a unique GCF pattern. The smooth and continuous detection also contributes to a smooth transition of the algorithms in higher level mechatronic devices even in a rapid change of the motion phases. In this paper, a method based on fuzzy logic for smoothly and continuously detecting the gait phases is proposed. In gaits of certain patients, the GCF patterns are sometimes vague. The gait monitoring algorithm should be able to evaluate the amount of abnormalities in the gait patterns, such that physical therapists can monitor the rehabilitation process quantitatively, and robotic rehabilitation devices can adaptively select a proper control algorithm for each patient. In this paper, a higher level algorithm that monitors the degree of abnormalities in the gait phases detected by the fuzzy logic is proposed. The abnormalities to be monitored by the proposed method include: 1) an improper distribution of the GCF pattern and 2) an incorrect sequence of the gait phases. This paper discusses the following topics:

1) the design and the verification of a force sensing unit for measuring the GCF in a shoe;

2) the design of an algorithm that smoothly and continuously detects phases in a human gait from the measured GCF;

3) the design of a higher level algorithm that evaluates the amount of abnormalities in the detected gait phases.

## 2. Related Works

Recently, sensor-embedded shoes have attracted great attention as a sensing device for human motions. For example, Carrozza *et al.* developed an advanced high-level control interface (ACHILLE) based on the sensor-embedded shoes to obtain an appropriate command sequence to control remote devices [6]. Ye *et al.* introduced Shoe-Mouse for hand trauma sufferers to operate computers without hands [7]. Similarly, No Hands-Mouse (Hunter Digital, Inc., USA) is a commercialized foot interface for operating computers with a foot [8]. For the purpose of clinical gait analyses, Gait Shoe (MIT) [9] and Intelligent-Shoe (Chinese University of Hong Kong) [10], [11] are noteworthy.

The Gait Shoe is a wireless sensing device that integrates various sensors, e.g., a triaxial accelerometer, a triaxial gyroscope, four force sensors, etc. The Intelligent-Shoe also utilizes various sensors, such as tilt angle sensors and bending sensors. For the measurement of GCF, various force sensors have been studied; Kothari *et al.* proposed a capacitive sensor for measuring the pressure between a foot and a shoe [13], and Razian and Pepper developed a triaxial pressure sensor utilizing a piezoelectric copolymer film [14]. The most common sensor for this application is force-sensitive resistors (FSRs) [7], [9]-[12]. However, the FSRs are not necessarily the best solution due to the low durability and the nonlinearity. Many approaches have been proposed to detect such gait phases: Pappas *et al.* proposed a pattern recognition algorithm to detect the transitions during the gait cycle based on three FSRs located on an insole and a gyroscope [12] and Huang *et al.* introduced a gait event detection method based on support vector machinery [10]. However, the currently developed methods detect the gait phases as discrete events, while the actual human motion phases cannot be discretely distinguished. Therefore, a smooth and continuous detection method is required for the full use of information obtained from the GCF sensors.

## 3. Methodology

### 3.1 Design of Force Sensing Unit

The body weight is transferred to feet through bones, and the bones in the feet exert forces to the ground. Due to cushioning materials such as flesh in the sole of the foot and a soft pad in a shoe, the force is distributed over the large area. Therefore, sensors that measure the force in a small area such as FSRs and load cells are not suitable for measuring the GCFs. Moreover, the practicality of FSRs has not been established from the viewpoints of durability and calibration; for example, Huang *et al.* used a ninth-order polynomial function to compensate for the nonlinearity of FSRs used in the Intelligent-Shoe [10]. In this paper, an air pressure sensor is applied to measure the GCF. A sensing unit is constituted by an air bladder made by winding soft silicone tubes and an air pressure sensor.

Requirements of an air bladder are as follows.

1) It causes minimal discomfort.
2) It has reasonable durability under normal loads (i.e., body weight).
3) The range of pressure changes under the normal loads is within the measurable range of an air pressure sensor.
4) It is easy to fabricate.
5) The magnitude of pressure changes is linearly proportional to that of applied forces.

The end of the tube is tied firmly and bonded by an epoxy adhesive such that it is sealed. Fig. 1 shows the schematic sketch of the proposed sensing unit. When a foot presses the air bladder, it is deformed, and its pressure change is measured by the air pressure sensor. The pressure change in the air bladder is proportional to the exerted force, i.e., $P = F/A$.

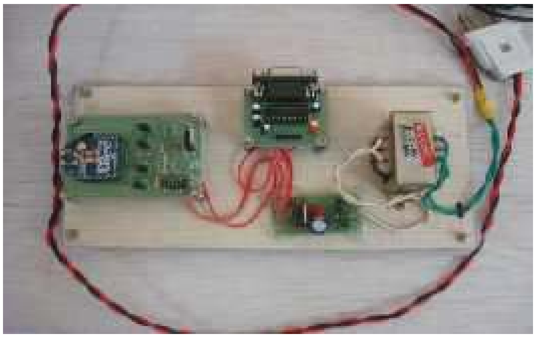
Fig. 1. Model of shoe with three air bladders

### 3.2 Implementation of Sensors in Shoe

The proposed sensing unit is implemented in a shoe, as shown in Fig. 2.The weight of each sensing unit including an air bladder and an air pressure sensor is less than 20 g such that

(a)

(b)



(c)

Fig.2. Implementation of GCF sensing unit (a) Sensor box(Transmitter), (b) Sole of the Smart Shoe, (c) Receiver Section

it may cause minimal changes on human motions. In a shoe, sensor box includes three air pressure sensors as shown in fig 2(a) and three air bladders are installed under the sole of a shoe, as shown in fig 2(b).The pressure value is displayed with the help of RS232 cable from Receiver Section as shown in fig 2(c)

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## 4. Smooth and Continuous Detection of Gait Phases

### 4.1 Motion Phases in Human Gait

The human gait is usually divided into eight functional patterns. In Fig. 3, GCF patterns for different gait phases are shown. The swing phase consists of three phases: initial swing, mid-swing, and terminal swing phases.

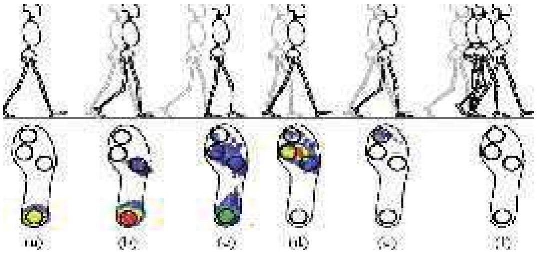
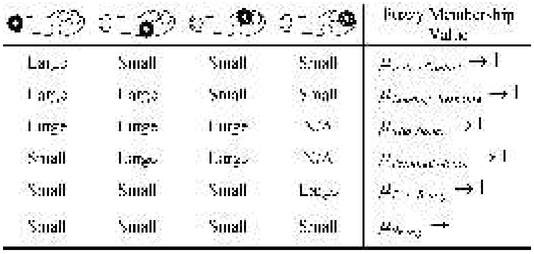


Fig. 3. Fundamental gait phases of a leg (shaded) [1] and their associated GCF patterns in the right foot. (a) Initial contact (b) Loading response. (c) Mid stance. (d) Terminal stance. (e) Preswing. (f) Swing.

Since the leg does not touch the ground, the three phases may not be distinguished by the GCF patterns. Therefore, they are combined into one phase in Fig. 3(f), and a gait is analyzed with the six phases in this paper.

### 4.2 Detection of Gait Phases by GCF Measurements

A simple and naive way to detect the gait phases shown in Fig. 3 would be to apply a threshold to the GCF measurements. The threshold method is effective when changes of the signal are very distinct, e.g., a digital signal. Normally, GCF in feet, however, changes smoothly and continuously to protect joints from impact forces. When it is measured by force sensors in shoes, it may be more smoothened due to the flesh as well as the cushioning materials in the sole of the shoe. For this purpose, fuzzy logic is suitable. In the case of fuzzy logic, a human gait is analyzed as a set of whole gait phases, where the likelihood of each gait phase is determined by each fuzzy membership value (FMV, *μ*). For example, when an FMV of a gait phase is close to one, the leg of which GCF pattern is measured is quite likely in the phase. If FMVs of two phases are about 0.5 at the same time, the leg may be in a transition between the two phases.



| | | | | Fuzzy Membership Value |
|---|---|---|---|---|
| Large | Small | Small | Small | $\mu_{Initial\ Contact} \rightarrow 1$ |
| Large | Large | Small | Small | $\mu_{Loading\ Response} \rightarrow 1$ |
| Large | Large | Large | N/A | $\mu_{Mid\ Stance} \rightarrow 1$ |
| Small | Large | Large | N/A | $\mu_{Terminal\ Stance} \rightarrow 1$ |
| Small | Small | Small | Large | $\mu_{Pre\ Swing} \rightarrow 1$ |
| Small | Small | Small | Small | $\mu_{Swing} \rightarrow$ |

Table I Fuzzy Rules Bases for Gait Analysis

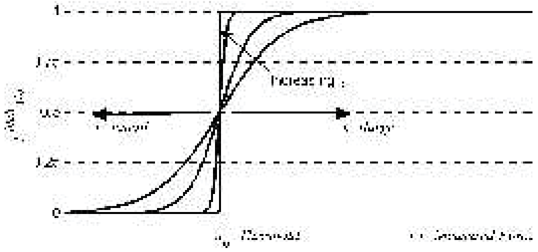


Fig .4. Fuzzy logic function

Fig. 4 shows the shape of the membership function.

For example, only heel is expected to show a large GCF in the initial contact phase [see Fig. 3(a)], and therefore its likelihood (i.e., $\mu_{\text{initial contact}}$) is close to one only if the heel shows a large GCF while the others are small. Table I shows a set of the rules for detecting the six gait phases shown in Fig. 3. In the table, some ambiguous conditions are ignored and marked by N/A. In this paper, a membership function that applies the hyperbolic tangent function is used,

$$f_{\text{Large}}(x) = 1/2\,[\tanh(s(x - x_0)) + 1] \in [0, 1] \qquad (1)$$

where $x$, $x_0$, and $s$ represent the measured GCF, the threshold value, and the sensitivity coefficient, respectively. The membership function in (1) has the following benefits.

1) It is continuous and smooth over the entire range: This contributes to continuity and smoothness of the resultant outputs of the fuzzy logic.

2) It is a symmetric function, such that the contra membership function is simply obtained by

$$f_{\text{Small}}(x) = 1 - f_{\text{Large}}(x) \in [0, 1]. \qquad (2)$$

This reduces the calculation time in real-time applications.

3) It returns 0.5 when the measured GCF is equal to the threshold: Intuitively this is reasonable since the threshold value means neither large nor small.

4) It is easy to adjust the sensitivity: By adjusting one parameter $s$, the slope of the membership function changes without loss of other characteristics stated before.

## 5. Detection of Abnormalities in Gait Phases

The GCF patterns in an abnormal gait may be different from those in a normal gait. The abnormality can be defined by two major conditions: 1) when the current GCF pattern cannot be explained by the desired patterns in a normal gait and 2) when the sequence of the gait phases obtained by analyzing the GCF patterns is incorrect. Using the smart shoes proposed in this paper, both abnormalities are monitored by an algorithm built on top of the fuzzy logic.

### 5.1 Detection of Abnormalities in GCF Patterns

The scaling factor provides information on the amount of abnormalities in a gait at a given time. Intuitively, the scaling factor should be one if all parameters in the fuzzy logic are adequate, and a subject has the normal gait as defined in Fig. 9.

When the scaling factor is less than one, it means that more than one gait phase is detected (note that $\mu \in [0, 1]$). If it is greater than one, no expected GCF pattern in Fig. 3 exactly matches the current pattern. This method measures the abnormality by monitoring the sum of FMVs at a given time; it does not necessarily detect all of the abnormalities.

### 5.2 Detection of Abnormalities in Gait Phase Sequences

In a normal gait pattern, the phases shown in Fig. 3 appear sequentially. Otherwise, the walking motion is unnatural and is characterized by an abnormal gait. For example, a patient dragging his/her foot may miss the swing phases, i.e., the leg shows the initial contact phase after the preswing phase. Therefore, another abnormality is observed by monitoring the sequence of gait phases.

## 6. Results

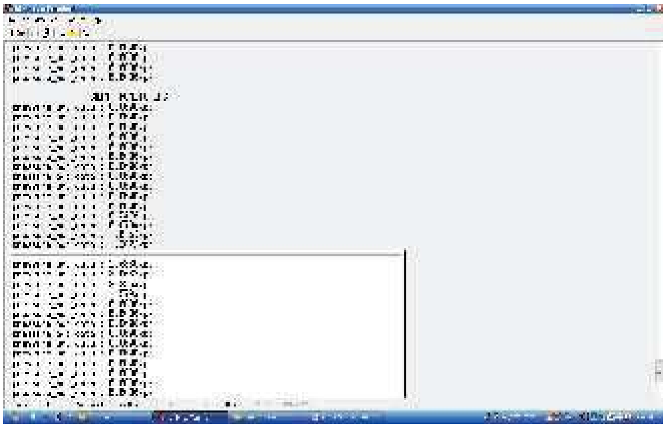


Fig.5. Output Window

The obtained output of transmitter and receiver section is to display the pressure value in the window screen as shown in fig 5.

## 7. Summary and Conclusion

In this paper, a gait monitoring system for motion phases and abnormalities in a human gait was introduced. The proposed system is constituted by three main parts: 1) a new sensor embedded shoe that measures the GCFs; 2) an algorithm that detects motion phases from the measured signals; and 3) a higher level algorithm that evaluates the degree of abnormalities in the detected motion phases. The proposed sensor-embedded shoe called a smart shoe has three sensing units in the sole of the shoe. Each sensing unit consists of an air bladder and an air pressure sensor. When the contact force is exerted by a foot, the air bladder is deformed and the inside pressure change is measured by the pressure sensor.

A method for detecting motion phases in a human gait from the measured signal was designed based on the fuzzy logic in this paper. The outputs of the proposed method were related to the likelihood of each phase.

In addition to the phase detection algorithm, a higher level algorithm that monitors abnormalities in the detected gait phases was proposed in this paper.

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