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Smooth and Continuous Human Gait Phase Detection Based on Foot Pressure Patterns

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***Abstract*— Measurement of ground contact forces (GCF) provides necessary information to detect human gait phases. In this paper, a new analysis method of the GCF signals is discussed for detection of the gait phases. Human gaits are complicated, and the gait phases can not be exactly distinguished by comparing sensor outputs to a threshold. This paper mainly discusses how to detect the gait phases continuously and smoothly. The proposed analysis method is intended for applications to power assistive devices for patients, as well as diagnostics of pathological gait. Smooth and continuous detection of the gait phases enables a full use of information obtained from GCF sensors. For experimental verification, smart shoes have been developed. Each smart shoe has four GCF sensors embedded between the cushion pad and the sole. The performances are experimentally verified for both normal and abnormal gaits, and a means for quantification of abnormalities in the gait is also introduced in this paper.**

I. Introduction

WALKING is a basic capability that allows humans to pursue their daily lives and to function as productive members of society. Walking involves a repetitious sequence of limb motion to move the body forward while simultaneously maintaining stance stability [1]. Walking is characterized by the gait [1]. 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 effective 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. Modern sensing and mechatronics technologies may be utilized in many ways to assist elderly people and patients with walking problems. Motion capture technology utilizing passive and active markers and infrared video cameras such as VICON [2] has helped the analysis and diagnostics of the pathological gait. Also, there have been various rehabilitation devices with monitoring and actuation capabilities installed in hospitals, e.g. LOCOMAT developed by HOCOMA in Switzerland [3,4]. In recent years, active orthoses and exoskeletons to assist patients in their daily lives have been developed: e.g. Hybrid Assistive Limb (HAL) [5] and Active Ankle Foot Orthosis (AAFO) [6].

Sensing and mechatronic technologies, however, have not been fully exploited to assist patients in their gaits. In the viewpoint of control systems, a human has a fully closed control loop without any exogenous inputs because the desired motion is intrinsically generated by an intention or a reflex. Since it is impossible to directly measure the human intention, controllers in power-augmenting devices usually set the desired assistive forces based on estimated values obtained from biological sensors [5,7,8]. For examples, HAL applies electromyography (EMG) sensors to measure muscular efforts [5], and EXPOS applies a novel sensor called a muscle fiber expansion (MFE) sensor [7,8]. Such methods, however, may not be necessarily the best for assistive purposes because they are due to biological responses in a human body and may not reliable in certain patients. For rehabilitation purposes, an impedance control method [4,9] has been applied recently. In the impedance control, the desired motion of a human body is usually predefined [4], and it may be suitable for the limited environment such as a treadmill.

For more reliable assistance, measurement of ground contact forces (GCF) based on foot pressure sensors may provide necessary information [10,11]. 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 for better estimation of the feedback signals. Motion phases during walking are characterized by the gait phases, and each gait phase has a unique GCF pattern. In gaits of certain patients, the GCF patterns are vague sometimes. A threshold method may not detect such low signals, which may be important in medical diagnostics. Therefore a smooth and continuous detection method is required for a full use of information obtained from the GCF sensors. The smooth and continuous detection also contributes to a smooth transition of the algorithms in assistive devices even in a rapid change of the motion phases. In this paper, fuzzy logic is utilized for the smooth and continuous detection of gait phases.

This paper is organized as follows. Definitions of the gait phases and the basic idea to detect the gait phases are introduced in section II. Section III discusses the fuzzy logic algorithm for smooth and continuous detection of the gait phases. In section IV, an implementation method is introduced and the performances are verified by experiments

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on normal and abnormal gaits. A means for quantification of abnormalities in gaits is also discussed in section IV. Summary and conclusion are in section V.

II. Human Gait Phases and Foot Pressure Patterns

Body weight is transferred to feet through bones and the bones in the feet exert forces to the ground. The GCF sensors should be located based on anatomical information. Although the force is distributed by the flesh, the maximum force still occurs at the location of the bone. Therefore, it is reasonable to locate sensors at joints of bones in the foot. Fig. 1 shows bones in a foot. The first sensor is located at the heel ((d) in Fig. 1). In addition, two sensors are located at the joints of forefoot ((b) and (c) in Fig. 1) and one at the end of foot ((a) in Fig. 1).

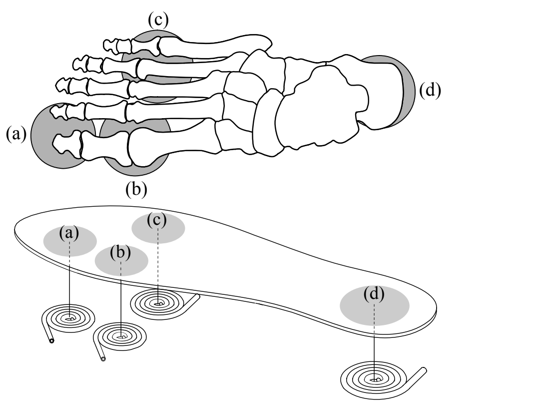


Fig. 1 Location of sensing area:
(a), (b), (c) and (d) represent the location of the Hallux, the first Metatarsal, the fourth Metatarsal and Heel respectively.

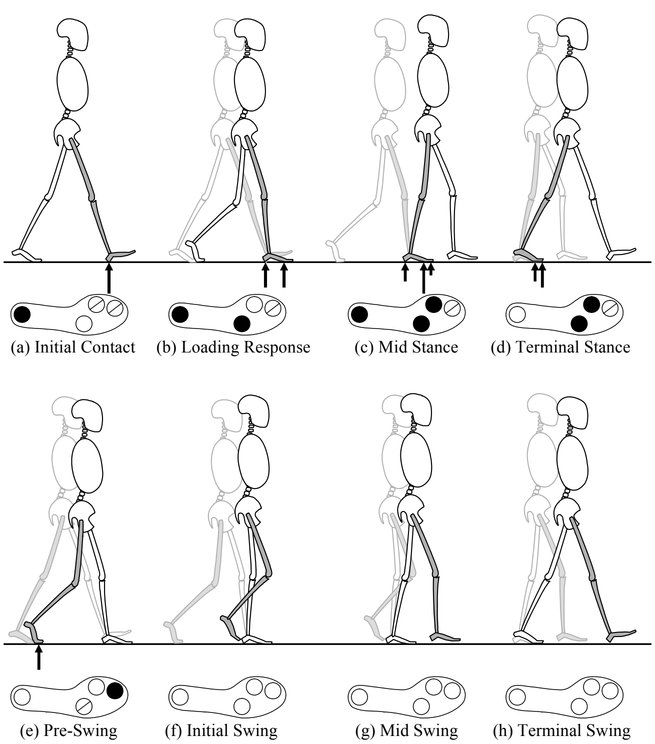


Fig. 2 Fundamental gait phases and expected sensor signal patterns

To provide the basic functions required for walking and to minimize its required energy, walking motion involves unique patterns called gait phases. The basic divisions of the gait cycle are stance and swing. These two motion phases can be easily recognized with only one pressure switch on each foot. The human gait, however, is more complicated and the dynamics varies even in the same stance motion. Therefore, it is usually divided into eight functional patterns (Fig. 2) developed by the Rancho Los Amigos gait analysis committee [1].

In Fig. 2, four circles in each foot shape represent the expected GCF patterns in each gait phase. ● and ○ mean that the GCF signal is higher and lower than a threshold respectively. ⊘ represents that the signal is not used in the condition. For example, when only the signal from the heel is higher than the threshold ((a) in Fig. 2), the algorithm detects the *Initial Contact* phase. When every signal is lower than the threshold ((f)-(h) in Fig. 2), the *Swing* phases are detected. The details of gait phases are as follows:

A. Phase 1: Initial Contact

The shaded leg in Fig. 2 starts to contact the ground and the GCF measurement unit on the heel measures the force as shown in Fig. 2(a).

B. Phase 2: Loading Response

The forefoot and the heel start to contact the ground as shown in Fig. 2(b). In the case of the normal gait, the contact point usually moves from the outside to the inside of the forefoot.

C. Phase 3: Mid Stance

When the inside of the forefoot touches the ground in the end of the *Loading Response* phase, the *Mid Stance* phase starts. Depending on individual gait patterns, the thumb toe may or may not touch the ground.

D. Phase 4: Terminal Stance

As the center of body mass moves forward in the *Terminal Stance* phase, the heel starts to take off as shown in Fig. 2(d).

E. Phase 5: Pre-Swing

The *Pre-Swing* phase is the last phase of stance motion. In this phase, only the thumb toe part touches the ground. This phase is very important because the hip joint starts to move forward and the knee joint bends quickly as shown in Fig. 2(e). The *Pre-Swing* phase and the *Terminal Stance* phase require the largest muscular power to propel the body forward.

F. Phase 6~8: Swing Phases

The foot does not touch the ground so that the GCF signals are expected to remain zero. It may be possible to detect the phases by utilizing the signals from the other foot. However, since the gait patterns are slightly different from person to person and from time to time, this method may not be reliable. Therefore, other sensors such as a goniometer and an inclinometer should be introduced to recognize the specific phases in the swing motion.

III. Smooth and Continuous Detection: Fuzzy Logic Approaches

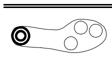
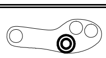
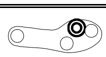
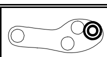
A simple way to detect the gait phases in Fig. 2 is a threshold method. The threshold method, or a discrete events analysis method, is effective when changes of the signal are very distinct, e.g. a digital signal is an extreme case. Normally the ground contact forces (GCF) in feet change very smoothly and continuously to protect a human body from impact forces. The signals may be more smoothened due to cushioning materials in shoes. Therefore, a human gait is not a set of discrete events, and a new method to smoothly detect the gait phases is required.

Fuzzy logic method may be suitable for this purpose. In the case of fuzzy logic, a human gait is analyzed as a set of whole gait phases defined in Fig. 2, and each gait phase is reliable as much as each fuzzy membership value (FMV). For example, if FMV of the *Initial Contact* phase is one while those of the other phases are zero, the human may act the motion of Fig. 2(a). If FMV's of both the *Initial Contact* and the *Loading Response* phases are 0.5, the human motion may be in a transition of the phases (Fig. 2 (a) and (b)).

The fuzzy logic method has been applied for various applications of the human-machine interaction such as the decision making [12], the machine learning [13] and the sensor fusion [14].Generally speaking, the fuzzy logic method is a useful method when a set of rules may be established based on a sound understanding of the problem. Making rules in the fuzzy logic for the gait analysis is as defined in Fig. 2. For example, a condition for the *Initial Contact* phase in Fig. 2 is interpreted as "If GCF of the heel is large while those of the other parts are small, then the human motion is in the *Initial Contact* phase." In the language of fuzzy logic, the statement is expressed as "…, then the foot is in the *Initial Contact* phase (i.e. FMV of the *Initial Contact* phase is close to one.)"

Table I shows a set of the rules for detection of the phases during walking. μ_{Swing} implies FMV for all three phases during swinging, i.e. the *Initial Swing*, the *Mid Swing* and the *Terminal Swing* in Fig. 2, which are not distinguished from the GCF signals. Several trivial conditions are ignored. The rules in Table I are equivalent to the conditions of Fig. 2.

TABLE I
FUZZY RULE BASES FOR GAIT ANALYSIS

				Fuzzy Membership Value
Large	Small			$\mu_{Initial\ Contact} \to 1$
Large	Large	Small		$\mu_{Loading\ Response} \to 1$
Large	Large	Large		$\mu_{Mid\ Stance} \to 1$
Small	Large	Large		$\mu_{Terminal\ Stance} \to 1$
Small		Small	Large	$\mu_{Pre-Swing} \to 1$
Small	Small	Small	Small	$\mu_{Swing} \to 1$

Two major questions are remained: 1) how large is large or how small is small and 2) how the rules are interpreted in programmable logics. The first question is equivalent to a design problem of membership functions in the fuzzy logic method. In this paper, a membership function which applies the hyperbolic tangent function is used: i.e.

$$f^{Large}(x) = \frac{1}{2}\left[\tanh(s(x - x_0)) + 1\right] \in [0,1] \tag{1}$$

where x, x_0 and s represent the measured GCF, the threshold value and the sensitivity coefficient respectively. This membership function is useful because,

1) it is continuous and smooth over the entire range: This contributes to continuity and smoothness of the resultant outputs from the fuzzy logic.
2) it is a symmetric function, such that the contra membership function is simply expressed as,

$$f^{Small}(x) = 1 - f^{Large}(x) \in [0,1] \tag{2}$$

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 because 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 above. Derivative of Eq.(1) at the threshold is,

$$\left.\frac{df^{Large}(x)}{dx}\right|_{x=x_0} = \frac{1}{2}s \tag{3}$$

where,

$$\frac{df^{Large}(x)}{dx} = \frac{1}{2}s[1 - \tanh^2(s(x - x_0))] \tag{4}$$

As s increases, the membership function becomes more distinct but more sensitive to the change of the threshold value. Note that the membership function is asymptotic to the one for the crisp logic as $s\to\infty$. Fig. 3 shows the shape of the membership function of Eq. (1).

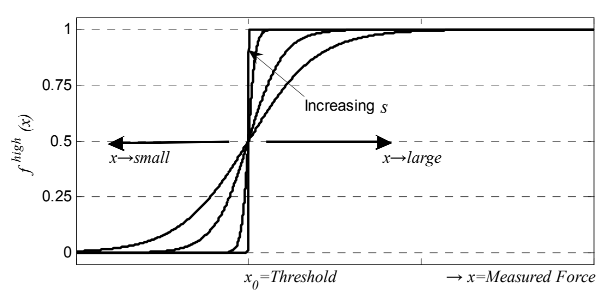


Fig. 3 Fuzzy membership function

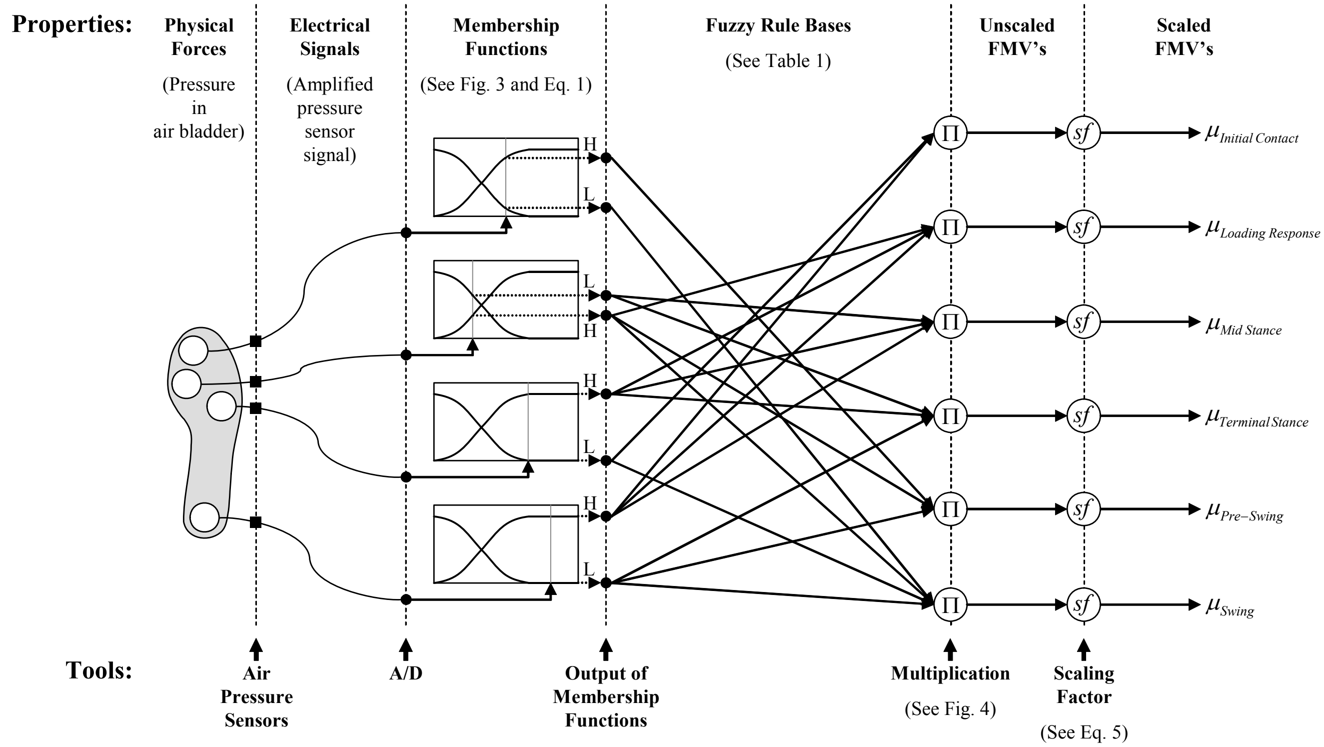


Fig. 4 Overall fuzzy logic for detection of gait phases

If x_{heel} is Large and x_{meta4} is Small, then $\mu_{Initial\ Contact} \rightarrow 1$

$$\boxed{f^{Large}(x_{heel}) \rightarrow 1} \times \boxed{f^{Small}(x_{meta4}) \rightarrow 1} = \boxed{\mu_{Initial\ Contact} \rightarrow 1}$$

$$\mu_{Initial\ Contact} = f^{Large}(x_{heel}) \times f^{Small}(x_{meta4})$$

Fig. 5 Mathematical interpretation of the rule for the Initial Contact phase

For implementation of the fuzzy rule bases in Table I, the Larsen product implication method [15] is used as the inference operator. Fig. 5 shows how the rules in Table I are converted to mathematical expressions in the case of the *Initial Contact* phase. The other phases follow the same logic. The statement of "x is Large" is equivalent to "$f^{Large}(x) \rightarrow 1$." It should be noted that each FMV is close to one only if its all conditions are satisfied.

Since the summation of all FMV's should be one for all the time, a scaling factor is introduced as,

$$sf(k) = \frac{1}{\sum \mu_{Phase,i}(k)} \tag{5}$$

where k represents a time index and $\mu_{Phase,j}(k)$ means the FMV of each gait phase, e.g. $\mu_{Phase,1}(k) = \mu_{Initial\ Contact}(k)$, $\mu_{Phase,2}(k) = \mu_{Loading\ Response}(k)$, etc.

The scaling factor also provides information on the amount of abnormalities in the gait. 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. 2 and Table I. When the scaling factor is less than one, it means that more than one gait phase are detected. If it is larger than one, there may be no proper phase to explain the motion of the subject. In addition, since it is a time function as defined in Eq. (5), it can be observed in which phase the subject has a problem.

Fig. 4 shows the entire fuzzy logic. Information in each step is manipulated and passes into the next step by applying the tools shown in Fig. 4. Arrows represent the signal flow and all steps are realized in one sampling time.

Fig. 6 Shoes with GCF measurement system: Air bladders and air pressure sensors are installed for measurement of ground contact forces.

IV. EXPERIMENTAL RESULTS ON NORMAL AND ABNORMAL GAITS

A. Implementation

The GCF measurement system using air bladders and air pressure sensors is embedded in the sole of between the cushion pad and a shoe shown in Fig. 6. When a foot presses the air bladder, it is deformed and its pressure change is measured by the air pressure sensor. Four air bladders are placed at each location shown in Fig. 1. The weight of each measurement unit including an air bladder and an air pressure sensor is less than 20 grams so that the sensors do not disturb user's motion. The air pressure sensor has a built-in amplification circuit, and no signal processing is required. For more detailed information such as characteristics of the sensing unit and the design of the Smart Shoes, see [16].

B. Normal gait

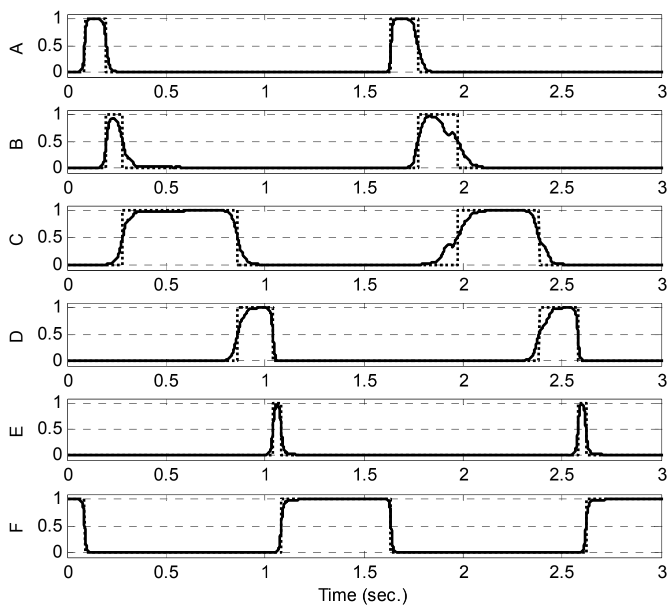


Fig. 7 Experimental results for the normal gait case:
A = $\mu_{Initial\ Contact}$ B = $\mu_{Loading\ Response}$ C = $\mu_{Mid\ Stance}$
D = $\mu_{TerminalStance}$ E = $\mu_{Pre\text{-}Swing}$ F = μ_{Swing}
Continuous lines = Fuzzy logic analysis
Dotted lines = Discrete events analysis

Fig. 7 shows results of the fuzzy logic analysis for a normal gait. Each graph shows the estimated fuzzy membership value (FMV) for each gait phase over the time. The initial time of graphs is the start time of measurement and set to 0 second. It should be noted that FMV's (Continuous lines in Fig. 7) pass through about 0.5 when the result from the discrete events analysis method (Dotted lines in Fig. 7) changes. This also means that the proposed algorithm does not introduce any time delay. The estimated FMV's are continuous and smooth over the entire range.

C. Abnormal gait

Generally, the normal gait represents a walking pattern that all eight phases shown in Fig. 2 appear sequentially. In other words, some of the phases are missing in an abnormal gait. Since people who need a help of power assistive devices have sometimes the abnormal gait due to musculoskeletal disorders or nervous system diseases, the proposed detection method of the gait phases should work even for the abnormal gait. For the experiments, parameters in the algorithm (e.g. x_0 and s in Eq. (1), and locations of sensors) can be adjusted according to the individual physical characteristics such as body weight and foot size. It is also reasonable to set the parameters based on the accuracy and the resolution of the GCF measurement system which are not related to individual information.

Fig. 8 shows the experimental results for an abnormal gait. All settings are the same to the normal gait case in Fig. 7. The subject has weak ankle extensor muscles so that the GCF signal from the thumb toe ((a) in Fig. 1) is weak. Note that the discrete events analysis method (Dotted lines in Fig. 8) does not detect the *Pre-Swing* phase because the weak signal is ignored by the threshold method. Nevertheless, the fuzzy logic catches the *Pre-Swing* phase (See 1 and 2.6 seconds in graph E of Fig. 8), even though FMV is not that high. Unlike the case of the normal gait, FMV's do not pass through 0.5 at the transition points.

As stated above, the scaling factor in Eq. (5) can be one of the performance indexes. Fig. 9 shows the scaling factors calculated in real-time for the normal gait in Fig. 7 and the abnormal gait in Fig. 8. Note that the scaling factor for the normal gait is close to one for all the time, while that of the abnormal gait is relatively larger than one in some cases. Note that the scaling factor has a large value when the *Pre-Swing* phase is detected. This is reasonable because the subject has a problem with the *Pre-Swing* phase and no phase exactly matches the motion of the subject. Since the other gait phases are normal, the scaling factor is close to one for those phases.

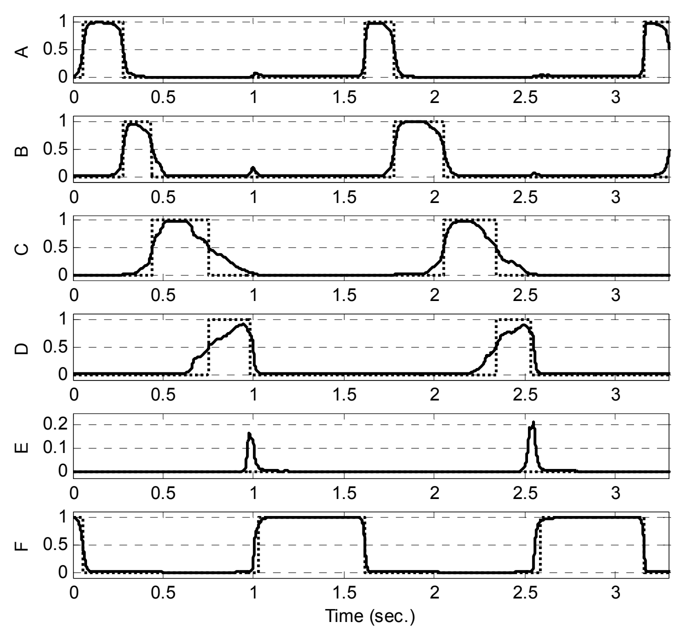


Fig. 8 Experimental results for the abnormal gait case:
A = $\mu_{Initial\ Contact}$ B = $\mu_{Loading\ Response}$ C = $\mu_{Mid\ Stance}$
D = $\mu_{TerminalStance}$ E = $\mu_{Pre\text{-}Swing}$ F = μ_{Swing}
Continuous lines = Fuzzy logic analysis
Dotted lines = Discrete events analysis

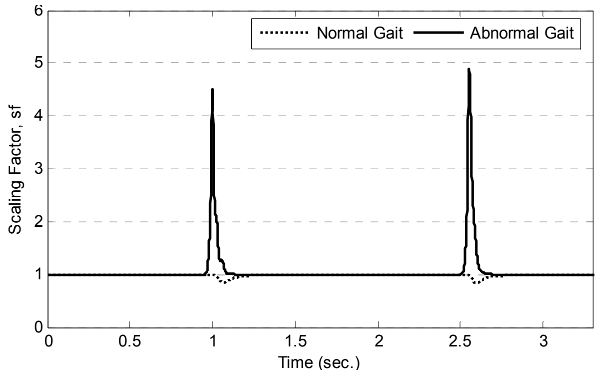


Fig. 9 Scaling factors for the normal and abnormal gaits

V. Conclusion and Future Works

A method for detecting gait phases was proposed in this paper. The outputs of the proposed method were smooth and continuous. Also, its scaling factor was related to the amount of abnormalities in the gait. The proposed method was verified by experiments on an abnormal gait as well as a normal gait. The performance was compared with a threshold method, and it detected an abnormal phase with very low signals which is not detectable with the threshold method.

Since the proposed method provides information on phases in a human gait, it is possible to design an advanced algorithm that detects abnormalities in the gait. Also, the proposed method will be verified by various subjects including patients with severe walking problems. Based on these results, an intelligent gait monitoring system will be designed for patients with problems walking. Recently, we have introduced an algorithm that applies a vector analysis method for this purpose [17]. In addition to the gait monitoring systems, these methods will be integrated into an assistive device for the improved assistance and for better estimation of feedback signals in the control of the device.

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