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Gait Pattern Classification with Integrated Shoes

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Abstract— **In this paper, we aim to study and classify gait patterns among flat walking, descending stairs, and ascending stairs using inertial measurement unit (IMU) including triaxial accelerometers and gyroscopes. Six subjects were invited to gather gait data of flat walking, descending stairs, and ascending stairs wearing the shoe-integrated system with free speeds. The design of the classifier for identifying gait patterns based on continuous kinematic signals is composed of three steps. In the first step, we separate gait signals of the six sensors in the same period into gait segments which are further used as the units for pattern feature analysis. Secondly, based on discrete wavelet transform (DWT), the average sum of squares of wavelet coefficients of each segment for anteroposterior acceleration, vertical acceleration, and sagittal plane angular rate are demonstrated and selected as the common features for gait pattern classification. At the last step, the fuzzy logic based classifier is proposed according to the distribution of the common features of different gait patterns. Experimental results demonstrate the proposed methodology is efficient for classifying gait patterns during humans' daily activity.**

I. INTRODUCTION

As one of the most common daily activities, walking attracts most of the researchers' attentions. Studying and monitoring ambulatory patterns is of significance, especially for children and elders. Some adolescents are with the problem of inappropriate walking habits, resulting in skelecton deformities. Most elders face the risk of falling which has become the potential killer for them in recent years. Assessment of different gait patterns of daily living could provides useful information in studying one individual's stability and mobility during locomotion. As the foundation of better assessment for different gait patterns, the ability to automatically identity different patterns and walking surroundings provides valuable information for further understanding the relations between gait pattern and energy consumption. Classification of gait patterns in daily activity is also helpful for evaluating the amount of daily exercise especially for elders. Besides, the ankle-foot orthotic device, which is designed for the patients of foot problems, can work better with the ability to understand the gait pattern with which the individual is walking.

In our daily activities, most of the gait patterns are related to flat walking, descending stairs, and ascending stairs. Therefore, classification of gait patterns including flat walking, descending stairs, and ascending stairs is the primal ability for the gait pattern classification system we proposed. Several studies have been proposed for gait pattern classification. Wervey et al. studied the plantar pressure characteristics of level walking, stair climbing, and stair descent using force sensing resistors [1]. Considering kinematic signals provide useful information for estimating energy expenditure, the kinematic sensors were selected by most researches to monitor different gait patterns. Mäntyjärvi et al. used acceleration sensors to investigate the use of principal component analysis (PCA) and independent component analysis (ICA) with wavelet transform for feature generation in the problem of human activity recognition [2]. Sekine et al. studied the walking patterns by using the wavelet-based fractal analysis method based on a triaxial accelerometer unit attached on the subject's back [3]. M.N. Nyan et al. classified gait patterns in the time-frequency domain by installing the vertical and anteroposterior accelerometers on the shoulder position of a garment [4].

In this paper, we propose an intelligent shoe-integrated system for classifying different gait patterns involving flat walking, descending stairs, and ascending stairs. Different from the previous works, the kinematic sensors are fixed on the surface of a shoe which provides the method for studying the kinematic characteristics of foot with different gait patterns. Besides, the shoe-integrated system realizes the non-intrusive monitoring without attaching any hardware onto the body. Discrete wavelet transform (DWT) is applied for generating and extracting the useful features for our application. Based on the generated features, fuzzy logic based classifier is designed with the membership functions and rules associated with the distribution of selected features.

This paper is organized as follows. In section II and III, the architecture of the shoe-integrated system and the experimental design for gait pattern classification are introduced. We describe the proposed method of how to extract gait segments, apply DWT for feature generation and reduction, as well as design fuzzy logic based classifier in section IV. Experimental results are discussed in section V. We draw the conclusion and proposed future improvements in the final section.

II. MEASUREMENT SYSTEM

Fig. 1 shows the system architecture, including the three major components: inertial measurement unit (IMU) board, microprocessor-based data gathering module, and wireless communication subsystem. The whole system is compact and

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lightweight so that it is easily integrated with the individual's own shoe.

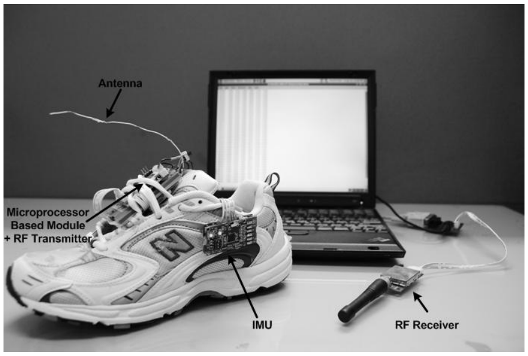

Fig. 1. Experimental set-up

Kinematic data are important parameters for gait analysis, therefore, we design the IMU board (dimensions: 51×25×7 mm) as one of the most essential parts of the system for gait pattern classification. Thanks to the development of MEMS technology, safe, mini-sized, and low-cost sensors are available. The 3-axis acceleration sensor MMA7260Q (Freescale Semiconductor) is selected due to its low power, high sensitivity with low noise, and small package. The dimension, weight, and selectable sensitivity range of MMA7260Q are 6×6×1.45 mm, 2 grams, and ±1.5g/2g/4g/6g. Each uniaxial signal is calibrated by measuring the outputs of +1g and -1g (g = 9.81m/s^2) under the control of positioning its sensitive axis orthogonal to the earth's surface and 180° rotation. Two types of angular rate sensors are utilized for our application. They are Analog Devices ADXRS150 gyroscope (size: 7×7×3 mm, weight: $<$ 0.5 gram, range: ±150°/s) and the Murata ENC-03M gyroscope (size: 12.2×7.0×2.6 mm, weight: 0.4 gram, range: ±300°/s). The ADXRS150 is a yaw gyroscope which measures the rotation about the axis perpendicular to the plane of the sensor. In contrast, the rotating axis of ENC-03M is parallel to the long side of the sensor. In order to measure three-axis rotation on one plane of circuit board, two ENC-03M (ENC-03MA and ENC-03MB) gyroscopes are placed perpendicularly to each other, with the ADXRS150 placed in the same plane.

The IMU is connected to the microprocessor-based data gathering module which includes a low-power and high-performance 8-bit AVR microprocessor-ATmega16L, peripheral components (resisters, capacitors, etc.), and one battery. In the IMU board, the analog-to-digital converter (ADS7844, Texas Instruments) is used for transforming analog voltage generated from IMU into digital data. Furthermore, these digital data are packaged via microprocessor-based data gathering module which effectively decreases the transmission error and increases the sampling frequency.

In our system, the small amount of digital data makes it possible to use wireless communication at a high sampling rate of 100 Hz. Thus, a low-power radio frequency (RF) communication module, GW100B (56×28×7 mm in size), is selected for realizing wirelessly transmission in realtime. The RF transmitter and receiver are connected with the microprocessor and a laptop respectively. The forward error correction (FEC) processing of GW100B achieving a low error rate makes the whole system reliable.

III. EXPERIMENTAL DESIGN

The experiments were performed on 6 subjects (4 females and 2 males) with age between 24 and 31 years. Their heights and weights are ranged between 1.62 and 1.74 m, and 50 and 65 kg. The IMU is securely attached to the side of the (right) shoe with glue in order to ensure the fastness and consistency of the sensors' sensitive axes during the experiments. The IMU location and reference axes & planes for the acceleration sensor & gyroscopes are shown as Fig. 2. According to the sensor placement, the x-axis of the accelerometer records acceleration signals regarding the anteroposterior movement; the y-axis records the vertical movement; and the z-axis records the lateral movement. The ADXRS150 is applied to measure the angular rate of the foot in the sagittal plane. The sensitive axes of ENC-03MA and ENC-03MB gyroscopes are perpendicularly to the transverse and coronal planes respectively.

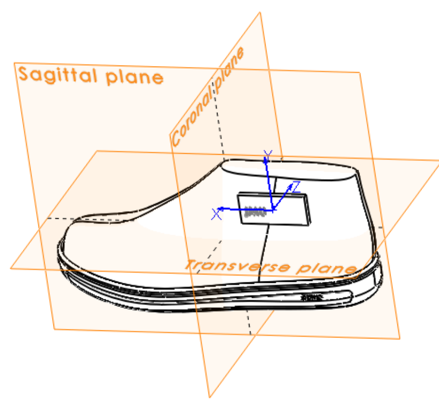

Fig. 2. IMU location and reference axes & planes for accelerometers & gyroscopes

Gait pattern data were recorded for each subject wearing the integrated shoe in three steps. In the first step, they were asked to walk continuously under outside environment on the flat ground at their own selected walking speeds. In the second step, the subjects walked down the staircases at a slope of 34° continuously. In the last step, they walked up the same staircases as the second step.

IV. METHOD

A. Gait Segments Separation

In order to detect which gait pattern the coming signal belonged to, firstly, we separate gait signals into gait segments which are further used as the units for gait pattern classification. Based on the knowledge of gait, in order to provide basic functions and minimize required energy, all locomotion of horizontal walking, stair ascending, and stair descending involves the gait event called foot flat. During the foot-flat period, the foot is with its entire length in contact with the ground, which results in the moment of all the kinematic sensors keeping the faint change. Therefore, we define the gait signal between the consecutive two foot-flat periods as the gait segment. The problem of separating gait segments is transformed into how to well define "foot-flat period".

As mentioned in section III, each subject used free speed to finish the gait patterns of flat walking, stair ascending, and stair descending. Besides, even for the same gait pattern, they were not required keeping the regular speed. On this condition, it is unreasonable to define the uniform length of the foot-flat period based on the experience. To solve this problem, firstly, the data of x-axis acceleration are low-pass filtered, with 10-order Butterworth coefficients and 10Hz cutoff frequency. We extract the symbol points (e.g. the peaks) of each gait cycle (shown as Fig. 3). The distance between each two consecutive symbol points is defined as the factor of length (FOL) changing along with different subjects, different patterns, or different speeds.

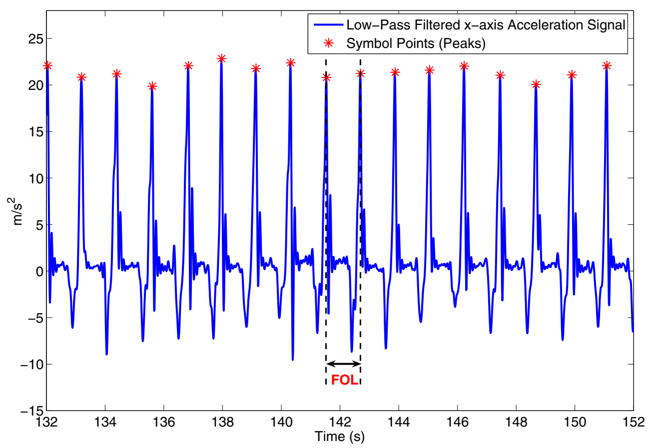

Fig. 3. Symbol points extraction

During the period of each two consecutive symbol points, the successive gait sampling points of which the amplitudes vary in a small range and the data length is more than 1/5 of FOL are selected. The center of the above selected segment is regarded as the center of the foot-flat segment. The start point of the foot-flat segment is 1/6 length of FOL ahead of the center, and the end point is 1/6 length of FOL after the center point. The start and end points of each foot-flat segment are applied as the reference points of gait segment separation for each of the six sensor signals. Fig. 4 shows the results of separating gait segments for one subject's flat walking pattern. All of the six sensor signals are low-pass filtered with 30 Hz cutoff frequency.

B. Discrete Wavelet Transform Based Feature Extraction

1) Discrete Wavelet Transform Theory: Wavelet decomposition in the application of signal feature reduction and extraction has been proved as an useful tool in the field of gait

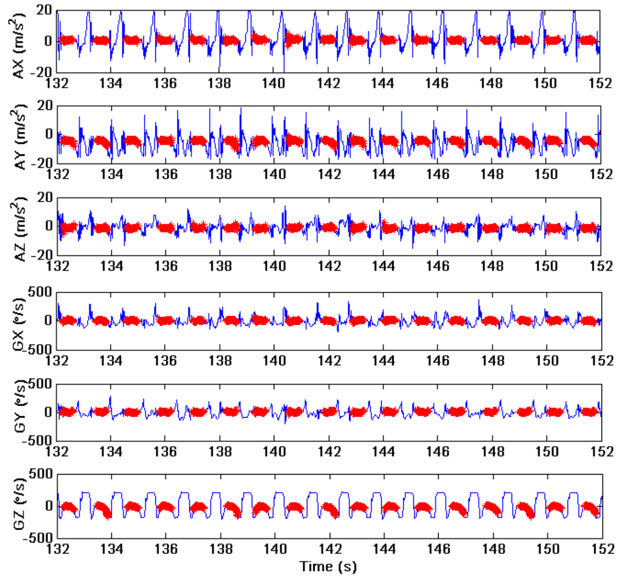

Fig. 4. Results of separating gait segments for one subject's flat walking. Red points denote the foot-flat periods. The blue curves between each two consecutive foot-flat periods are gait segments

analysis [5] [6]. Compared with frequency-based approaches, such as Fourier transform, wavelet transform shows main advantage of illuminating both frequency and time domain information simultaneously. Using wavelet decomposition, it is possible to describe and extract localized signal features as well as the global characteristics.

Discrete wavelet transform (DWT) decomposes the original signal $s(t)$ into the approximations $a_j(k)$ and the details $d_j(k)$ which relies on scaling function $\varphi_{j,k}(t)$ and wavelet function $\psi_{j,k}(t)$, respectively:

$$\varphi_{j,k}(t) = 2^{-j/2}\varphi(2^{-j}t - k) \tag{1}$$

$$\psi_{j,k}(t) = 2^{-j/2}\psi(2^{-j}t - k) \tag{2}$$

Here, j represents the scaling factor which controls the compression or dilation for both scaling function φ and wavelet function ψ. The shifting parameter k denotes the position shifting along the time axis.

The approximations and details of DWT are then defined as follows:

$$a_j(k) = \int s(t)\varphi_{j,k}(t)dt \tag{3}$$

$$d_j(k) = \int s(t)\psi^*_{j,k}(t)dt \tag{4}$$

where the operator $(*)$ indicates the complex conjugate.

Therefore, the original signal $s(t)$ can be reconstructed by the sum of the approximation at the depth of decomposition level J and the details from level 1 to level J:

$$s(t) = \sum_{k\in Z} a_J(k)\varphi_{J,k}(t) + \sum_{k\in Z}\sum_{j=1}^{J} d_j(k)\psi_{j,k}(t) \tag{5}$$

Since the wavelet function ψ and scaling function φ are determined by the high-pass and low-pass filters respectively,

TABLE I
KINEMATIC PARAMETER DEFINITION

i	Kinematic Parameter
1	Anteroposterior Acceleration
2	Vertical Acceleration
3	Lateral Acceleration
4	Sagittal Plane Angular Rate
5	Transverse Plane Angular Rate
6	Coronal Plane Angular Rate

the DWT can be efficiently implemented by iteratively convolving the signals with a pair of high-pass and low-pass finite impulse response filters denoted as $g(n)$ and $h(n)$. The outputs of the filters are then downsampled by 2.

$$a_j(n) = \sum_{k \in Z} a_{j-1}(k) h(k-2n) \tag{6}$$

$$d_j(n) = \sum_{k \in Z} a_{j-1}(k) g(k-2n) \tag{7}$$

2) Feature Extraction: For each gait pattern, every extracted gait segment for each kinematic parameter at the same period is decomposed into six scales by haar mother wavelet. The average sum of squares of approximation coefficients at level 6 ($E^i_{a_6}$) and the detail coefficients from level 1 to level 6 ($E^i_{d_j}$ $j = 1, 2, 3, ..., 6$) are composed as the candidate feature vector T^i for the parameter i (listed as Table I):

$$T^i = [\ E^i_{a_6},\ \ E^i_{d_6},\ \ E^i_{d_5},\ \ E^i_{d_4},\ \ E^i_{d_3},\ \ E^i_{d_2},\ \ E^i_{d_1}\ ] \tag{8}$$

$$E^i_{a_6} = \frac{\sum_{k=1}^{n_0} \left[a^i_6(k)\right]^2}{n_0} \tag{9}$$

$$E^i_{d_j} = \frac{\sum_{k=1}^{n_j} \left[d^i_j(k)\right]^2}{n_j}, j = 1, 2, 3, ..., 6 \tag{10}$$

where n_0 represents the number of the approximation coefficients at level 6, n_j denotes the number of the detail coefficients at level j.

By observation, from all the candidate features, the obvious features are selected as the common ones for representing the characteristics of the gait patterns that we study. They are $E^1_{a_6}$ (the average sum of squares of approximation coefficients at level 6 for the Anteroposterior Acceleration), $E^1_{d_6}$ (the average sum of squares of detail coefficients at level 6 for the Anteroposterior Acceleration), $E^2_{d_6}$ (the average sum of squares of detail coefficients at level 6 for the Vertical Acceleration), $E^4_{a_6}$ (the average sum of squares of approximation coefficients at level 6 for the Sagittal Plane Angular Rate), $E^4_{d_5}$ (the average sum of squares of detail coefficients at level 5 for the Sagittal Plane Angular Rate), and $E^4_{d_2}$ (the average sum of squares of detail coefficients at level 2 for the Sagittal Plane Angular Rate). Fig. 5 to Fig. 10 display the normalized distribution of each selected feature for the gait patterns of flat walking, descending stairs, and ascending stairs.

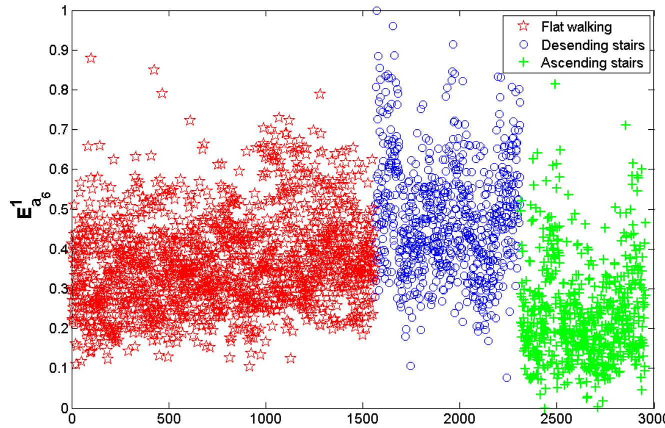

Fig. 5. Normalized $E^1_{a_6}$ for flat walking, descending stairs, and ascending stairs from the 6 subjects and their relationship in classification

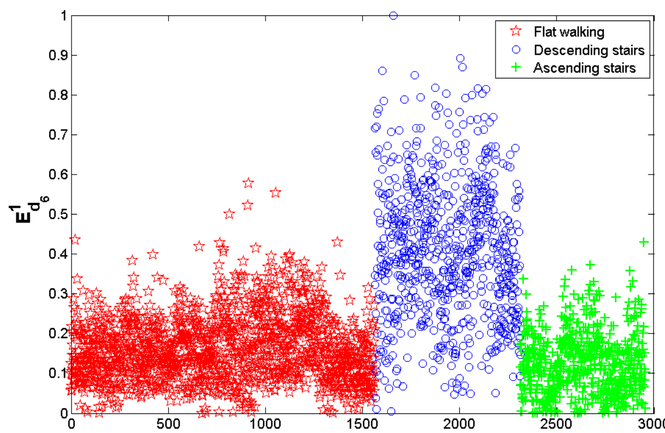

Fig. 6. Normalized $E^1_{d_6}$ for flat walking, descending stairs, and ascending stairs from the 6 subjects and their relationship in classification

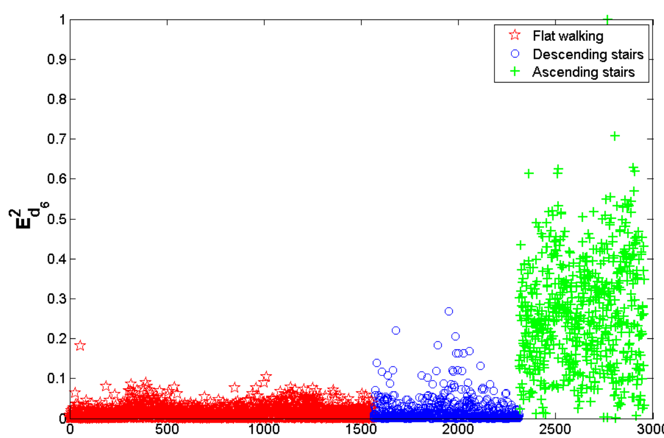

Fig. 7. Normalized $E^2_{d_6}$ for flat walking, descending stairs, and ascending stairs from the 6 subjects and their relationship in classification

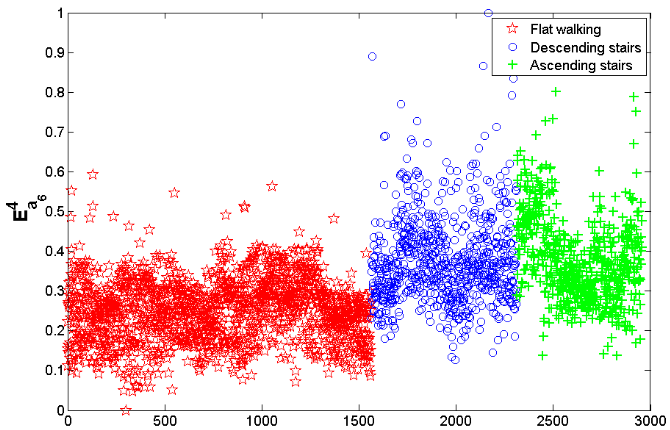

Fig. 8. Normalized $E^4_{a_6}$ for flat walking, descending stairs, and ascending stairs from the 6 subjects and their relationship in classification

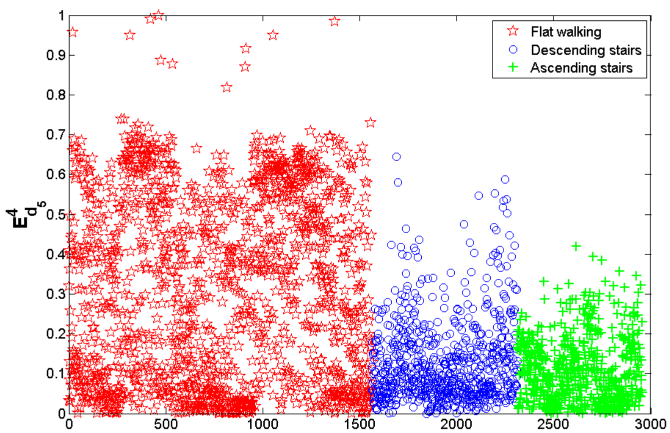

Fig. 9. Normalized $E^4_{d_5}$ for flat walking, descending stairs, and ascending stairs from the 6 subjects and their relationship in classification

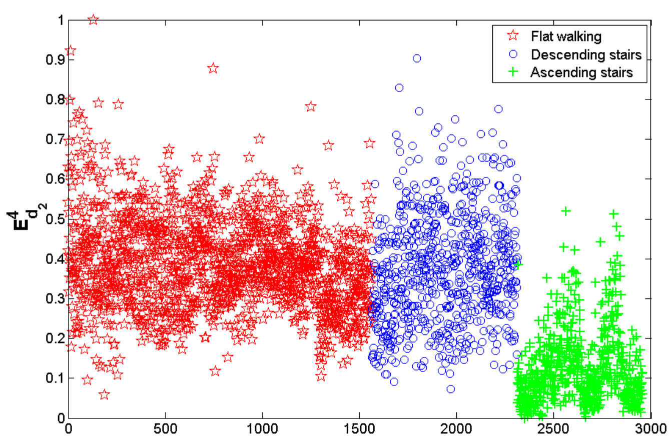

Fig. 10. Normalized $E^4_{d_2}$ for flat walking, descending stairs, and ascending stairs from the 6 subjects and their relationship in classification

C. Fuzzy Logic Classifier

Based on the selected features, a simple approach for gait pattern classification is the threshold-based method. However, considering the number of selected features and the overlap of distribution region happening for some features, fuzzy logic provides a suitable method for feature fusion and generates the classifier for our propose.

For designing the fuzzy logic classifier, two major problems are considered: 1) how to determine the degree of which input features belong to each of the predefined linguistic variables ("low" and "high") and 2) how the classification rules are defined and interpreted in programmable logic.

1) Membership Function: Solving the first question is equivalent to design the membership functions (MFs) for each input. For our problem, each input has two MFs displayed as Fig. 11. Table II lists the types of membership functions applying for each input. Based on the understanding of the feature distributions in Fig. 5 to Fig. 10, two kinds of membership functions are applied i.e. Z-shaped membership function ($z-shaped$) and two-sided Gaussian curve membership function ($Gaussian2$). Z-shaped membership function describes the asymmetrical polynomial curve expressed as (11):

$$f^{zmf}(x) = \begin{cases} 1, x \leq a \\ 1 - 2(\frac{x-a}{a-b})^2, a < x \leq \frac{a+b}{2} \\ 2(\frac{b-x}{a-b})^2, \frac{a+b}{2} < x \leq b \\ 0, x \geq b \end{cases} \tag{11}$$

where the parameter a is the threshold value smaller than which the degree of membership is equal to 1 and larger than which the degree begins to decline. The parameter b locates the position from where the degree reaches the minimum zero.

Two-sided Gaussian membership function depends on two Gaussian functions which are denoted as (12) and (13):

$$f_1^{gmf}(x) = e^{\frac{-(x-c_1)^2}{2\sigma_1^2}} \tag{12}$$

$$f_2^{gmf}(x) = e^{\frac{-(x-c_2)^2}{2\sigma_2^2}} \tag{13}$$

The first function specified by the parameters c_1 and σ_1 decides the left-most shape of the two-sided Gaussian membership function. The second one specified by c_2 and σ_2 determines the right-most shape. If c_1 is smaller than c_2, the degree of the membership function is at unity (1.0) in case the interval is between c_1 and c_2. Otherwise, the membership value is the product of the two Gaussian functions.

2) Rule: If-then rules are established to formulate the conditional statements of fuzzy logic classifier. The "if" part of rules describes the inputs' situations. The corresponding "then" part describes the fuzzy system's output in these situations. A set of rules for classifying gait patterns are listed in Table III. For example, If $E^1_{a_6}$ is in the range of 'high', $E^1_{d_6}$ is 'low', $E^2_{d_6}$ is 'low', $E^4_{a_6}$ is 'low', $E^4_{d_5}$ is 'high', and $E^4_{d_2}$ is 'high'; then the human is with the locomotion of 'flat walking'.

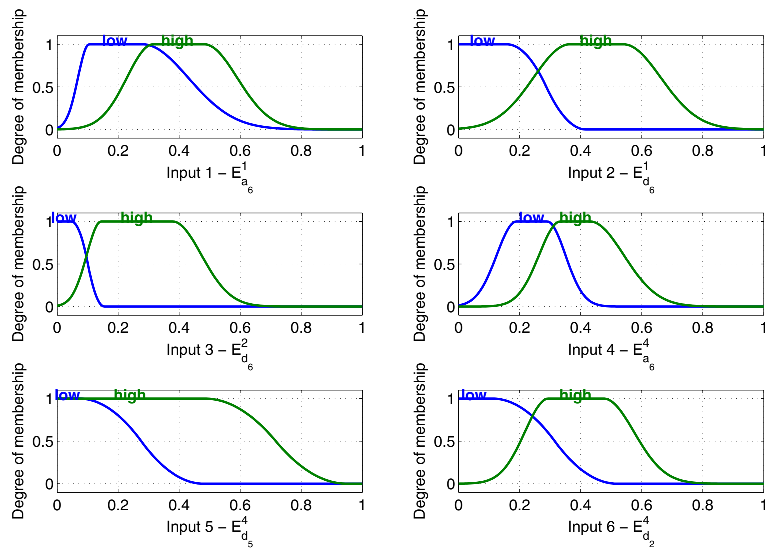

Fig. 11. Input membership functions

TABLE II

MEMBERSHIP FUNCTIONS FOR INPUTS

Input No.	MF 1 (low)	MF 2 (high)
1	$Gaussian2$	$Gaussian2$
2	$z-shaped$	$Gaussian2$
3	$z-shaped$	$Gaussian2$
4	$Gaussian2$	$Gaussian2$
5	$z-shaped$	$z-shaped$
6	$z-shaped$	$Gaussian2$

TABLE III

IF-THEN RULES

IF						THEN
$E^1_{a_6}$	$E^1_{d_6}$	$E^2_{d_6}$	$E^4_{a_6}$	$E^4_{d_5}$	$E^4_{d_2}$	Gait Pattern
high	low	low	low	high	high	Flat Walking
high	high	low	high	low	high	Descending
low	low	high	high	low	low	Ascending

V. EXPERIMENTAL RESULTS

We classify gait patterns into flat walking, descending stairs, and ascending stairs based on the fuzzy logic classifier we propose. The detailed classification results for all the six subjects are listed in Table IV. The classifier's performance is evaluated using the common measures: sensitivity (Se) and specificity (Sp):

$$Se = \frac{TP}{TP+FN} \tag{14}$$

$$Sp = \frac{TN}{TN+FP} \tag{15}$$

In the above equations, TP, FN, TN, and FP denotes the number of true positives, false negatives, true negatives, and false positives, respectively. Take the sensitivity and specificity of "Flat Walking" for example, TP is equivalence to the number of segments for flat walking that are correctly classified as flat walking. Whereas, FN is the number of segments for flat walking which are wrongly assigned as the other two classes (descending or ascending stairs). TN is equal to the number of segments for the other two classes that are correctly identify as the corresponding class. Whereas, FP represents the number of segments for the other two classes which are incorrectly assigned as flat walking.

As listed in Table IV, for the six subjects, the overall gait segments of flat walking, descending stairs, and ascending stairs are 1563, 749, 644, respectively. It is found that the average sensitivity is 93.91% for flat walking segments, 91.52% for descending segments, and 93.36% for ascending segments. While the values of specificity are 95.38% for flat walking segments, 94.30% for descending segments, and 99.45% for ascending segments. Except for the six subjects whose gait data were analyzed for designing the fuzzy logic classifier, another four subjects were invited to evaluate the performance of the system. Table V lists the classification

TABLE IV
CLASSIFICATION RESULTS

	Flat Walking			Descending Stairs			Ascending Stairs		
Subject No.	Segment	Se (%)	Sp (%)	Segment	Se (%)	Sp (%)	Segment	Se (%)	Sp (%)
1	271	90.04	98.03	123	96.75	93.27	135	96.30	98.91
2	275	98.18	97.64	143	96.50	97.98	71	97.18	100
3	207	92.75	97.48	126	94.44	92.42	123	91.87	99.68
4	195	88.21	94.53	111	85.59	92.07	95	100	98.16
5	345	96.52	94.06	119	91.60	94.09	115	84.35	100
6	270	97.78	90.58	127	84.25	95.99	105	90.48	100
Total	1563	-	-	749	-	-	644	-	-
Avg.	260	93.91	95.38	124	91.52	94.30	107	93.36	99.45

TABLE V
CLASSIFICATION RESULTS FOR THE TEST SUBJECTS

	Flat Walking			Descending Stairs			Ascending Stairs		
Subject No.	Segment	Se (%)	Sp (%)	Segment	Se (%)	Sp (%)	Segment	Se (%)	Sp (%)
1	183	91.80	96.88	115	93.91	94.22	112	97.32	99.64
2	245	90.61	92.83	140	86.43	91.12	93	92.47	99.13
3	257	94.16	97.07	144	93.75	95.88	134	97.01	98.95
4	229	91.70	98.16	123	96.75	92.40	101	93.07	99.70
Total	914	-	-	522	-	-	440	-	-
Avg.	228	92.06	96.23	130	92.71	93.40	110	94.96	99.35

results of the four test subjects.

VI. CONCLUSIONS AND FUTURE WORKS

In this paper, we present a shoe-integrated system for classifying different gait patterns among flat walking, descending stairs, and ascending stairs. First, the prototype of the intelligent system is designed which mainly includes a suite of sensors for acquiring kinematic parameters of foot. Secondly, since the goal of this study is to investigate the approach for detecting gait patterns, we apply discrete wavelet transform (DWT) for feature generation and fuzzy logic based approach for designing the multi-class classifier. Anteroposterior acceleration, vertical acceleration, and sagittal plane angular rate are demonstrated to provide useful information for classifying the gait patterns on which we focus, and the other kinematic parameters are almost useless. Experimental results of the six training and four testing subjects demonstrate that the selected features of the average sum of squares of wavelet coefficients efficiently represent the characteristics of the gait patterns we study. Also fuzzy logic based classifier well describes the distribution of the features. The compact, wireless, and wearable system has the promising application for assisting to evaluate walking energy expenditure.

In the future work, we will do more experiments for investigate the device's long-term effect. More individuals especially elders will be invited for the trial to show if the features used in this paper are still consistent and obvious. Based on the same selected features, other intelligent learning algorithms, such as neural networks, support vector machines (SVM) will also be introduced for comparing the classification results with the fuzzy logic classifier we propose in this paper. The scalable and programmable platform can be further used for other exciting research directions, such as gait pattern based human control interface.

REFERENCES

[1] Roy A. Wervey, Gerald F. Harris, and Jacqueline J. Wertsch, "Plantar Pressure Characteristics During Stair Climbing and Descent", *Proceedings 19th International Conference IEEE/EMBS*, 1997, pp. 1746-1748.

[2] Jani Mäntyjärvi, Johan Himberg, and Tapio Seppänen, "Recognizing Human Motion with Multiple Acceleration Sensors", *IEEE International Conference on Systems, Man, and Cybernetics*, vol. 2, 2001, pp. 747-752.

[3] Masaki Sekine, Toshiyo Tamura, Metin Akay, Toshiro Fujimoto, Tatsuo Togawa, and Yasuhiro Fukui, "Discrimination of Walking Patterns Using Wavelet-Based Fractal Analysis", *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 10, no. 3, 2002, pp. 188-196.

[4] M.N. Nyan, F.E.H. Tay, K.H.W. Seah, and Y.Y. Sitoh "Classification of Gait Patterns in the Time-Frequency Domain", *Journal of Biomechanics*, vol. 39, no. 14, 2006, pp. 2647-2656.

[5] F. Verdini, T. Leo, S. Fioretti, M.G. Benedetti, F. Catani, and S. Giannini,"Analysis of Ground Reaction Forces by means of Wavelet Transform", *Clinical Biomechanics*, vol. 15, no. 8, 2000, pp. 607-610.

[6] A. De Stefano, R. Allen, J.H. Burridge, and V.T. Yule, "Application of Complex Wavelets for EMG Analysis during Gait of Asymptomatic and Pathological Subjects", *International Journal of Wavelets, Multiresolution and Information Processing*, vol. 1, no. 4, 2003, pp. 425-448.