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Intelligent Shoes for Abnormal Gait Detection

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***Abstract*— In this paper we introduce a shoe-integrated system for human abnormal gait detection. This intelligent system focuses on detecting the following patterns: normal gait, toe in, toe out, oversupination, and heel walking gait abnormalities. An inertial measurement unit (IMU) consisting of three-dimensional gyroscopes and accelerometers is employed to measure angular velocities and accelerations of the foot. Four force sensing resistors (FSRs) and one bend sensor are installed on the insole of each foot for force and flexion information acquisition. The proposed detection method is mainly based on Principal Component Analysis (PCA) for feature generation and Support Vector Machine (SVM) for multi-pattern classification. In the present study, four subjects tested the shoe-integrated device in outdoor environments. Experimental results demonstrate that the proposed approach is robust and efficient in detecting abnormal gait patterns. Our goal is to provide a cost-effective system for detecting gait abnormalities in order to assist persons with abnormal gaits in the developing of a normal walking pattern in their daily life.**

I. INTRODUCTION

A. Motivation

Human gait can be generally divided into normal and abnormal ones. An abnormal gait pattern will ultimately lead to pain in the feet, ankles, legs and even skeletal disease if prolonged. By monitoring the gait pattern of a human, proper motion adjustments can be advised so as to improve their walking style and long-term well being. Considering the variety of gait abnormalities, we select the typical ones including macroscopic abnormalities ("toe in" and "toe out") and inconspicuous ones ("heel walking" and "oversupination"-walking on the lateral portion of the foot). All of them are known as the most common gait abnormalities generated either by inborn reason or ill habit. We propose an intelligent shoe-integrated system from which the information derived can give efficient assistance in determining and alarming the persons associated with abnormal gait patterns focusing on the above gait abnormalities. This device is of particular significance to provide feedback in the application of gait abnormality rectification.

B. Related Work

In the past decade, as more and more studies on human gait have been conducted, numerous systems for human gait data acquisition and analysis were proposed, including camera-based, floor-mounted, and in-shoe configuration systems. However, among all the available system, the in-shoe device is most utilized due to the outstanding merit of extending the usable location for human gait study. An in-shoe multisensory data acquisition system was developed by Morley et al. in 2001 [1]. In the system, including pressure sensors, temperature and humidity sensors were located in a shoe to monitor the corresponding information. However, the system mainly focused on the hardware design and little discussion on data interpretation and analysis was introduced. Pappas proposed a gait phase detection system based on a gyroscope and three force resistors [2]. Their system can distinguish the phases of the stance as heel-off, swing or heel-strike in order to the application of drop-foot walking dysfunction. Also, Morris has developed a wireless sensor system for realtime data acquisition which has the potential use in clinical gait analysis [3]. The prototype design was presented and the pattern recognition method was not mentioned in detail. In addition, the Pedar insole system (Novel, Munich) is a commercially available system which is widely used in clinic sites and laboratories due to its repeatability and accuracy [4]. J. Ray used to utilize the Novel Pedar in-shoe system for gait analysis on subjects with overpronated (fallen arches) and oversupination [5]. However, the limitations of Pedar insole system still exist, including a heavy wireless and memory storage module, a thick insole, and an expensive price.

In our group at CUHK, we have already developed the platform for a shoe-integrated system. Based on this platform, we developed an input device called Shoe-Mouse, which can be used by people who have difficulties in using their hands to operate computers or devices [6]. In [7], the intelligent shoe-integrated system has been developed to measure both the pressure distribution under eight special plantar regions and the mean plantar pressure during a subject's normal walking. Ideal experimental results show that it is possible to use only eight force sensing resistors (FSRs) to calculate the mean pressure which used to be acquired by a device equipped with numerous sensors, such as the Pedar insole.

C. Overview of This Paper

In this paper, we aim to develop a cost-effective shoe-integrated system for detecting human abnormal gaits. The proposed pattern recognition approach is based on Principal Component Analysis (PCA) for feature generation and Support Vector Machine (SVM) for multi-classification. This intelligent system has the potential application for gait abnormality rectification. Fig. 1 displays the outside view of the prototype.

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Fig. 1. Outside view of the intelligent shoe

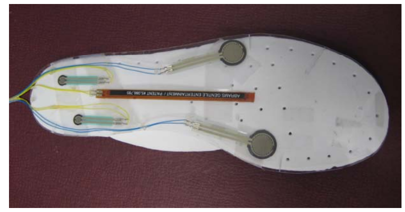

Fig. 3. Photograph of the insole

This paper is organized as follows. In section II, the architecture of the shoe-integrated system is introduced. We describe the proposed approach of how to apply PCA for feature generation and SVM for multi-classification in section III. Experimental results are discussed in section IV. We draw the conclusion and proposed future improvements in the final section.

II. SYSTEM DESIGN

Fig. 2 shows the system architecture, including the four major components: insole, inertial measurement unit (IMU) board, microprocessor-based data gathering module, and wireless communication subsystem. The whole system is compact and light so that it is easily integrated with a user's shoes.

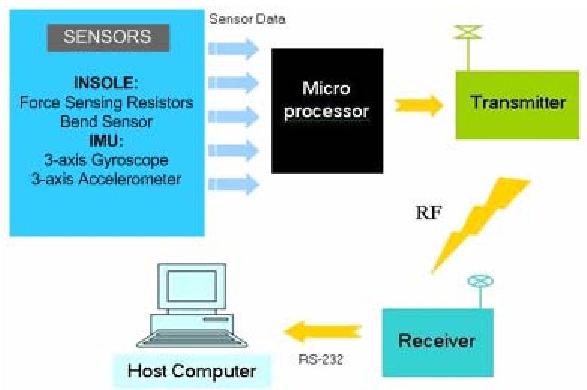

Fig. 2. Outline of the system design

A. Insole Subsystem

The insole subsystem shown in Fig. 3 is a flexible instrumented part for sensing the force and flexion parameters inside the shoe. Four FSRs (Interlink Electronics, Santa Barbara, CA) and one bend sensor (Bend Sensor Images SI, Inc.) are installed on one side of a thin insole made of plastic. Considering the different sizes of subcutaneous bony prominences, we select two kinds of FSRs. Two FSR-402s (12.7 mm diameter active surface) are used under the first metatarsal head and the position between the forth and fifth metatarsal heads. Two FSR-400s (5 mm diameter) are placed under the heel (which is divided into a posterior and inside portion). The bend sensor is located at the center of the insole in order to provide the flexion information of human foot.

Both the FSR and bend sensors exhibit changes in resistance when force or bend are applied to the active area. In our circuit design, a voltage divider is used to measure the resistance change in order to obtain the relationship between the applied force or bend degree and the voltage.

B. IMU Board

In biomechanics, body segment orientations (3D angles) and kinematic data (such as 3D accelerations) are important parameters for gait analysis, therefore, we designed the inertial measurement unit (IMU) as one of the essential parts for the whole system. Thanks to the development of MEMS technology, environmentally safe and low-cost sensors are available. The IMU board ($51 \times 25 \times 7$ mm in size) mainly consists of two parts: the MEMS sensors and an analog-to-digital converter. We select three single-axis gyroscopes and one three-axis accelerometer to detect the angular rates and accelerations of foot motion for the X, Y, and Z axes. The analog-to-digital converter (ADS7844, Texas Instruments) is used for transforming the analog voltage into a digital signal which is then transmitted to the microprocessor for data packaging.

C. Microprocessor-Based Data Gathering Subsystem

The subsystem used to gather information from the insole and IMU is mainly composed of a microprocessor-based circuit board (in Fig. 4). It includes a low-power and high-performance 8-bit AVR microprocessor-ATmega16L, peripheral components (resisters, capacitors, etc.), and one battery. The microprocessor runs at a clock frequency of 8 MHz. All circuitry operates with 5 V power which is generated by a LM78L05 regulator and powered by one 7.4 V/Li-ion battery. We use five ADC channels with 10-bit resolution to transform the analog voltage information generated from the FSRs and bend sensor into scaled digital data.

Fig. 4. Circuit board together with battery

D. Wireless Communication Subsystem

The aim of this subsystem is to wirelessly transfer the digital data processed by the ATmega16L to the host computer in realtime. There were two major transfer methods of previous in-shoe data acquisition systems. One was to restore the original information in FLASH RAM and then download the data to PC after the gait test through a parallel port for further analysis [8]. The other method was to transmit the data immediately via the RS232 serial port [1]. Both approaches introduce few transmission errors which make the analysis result relatively stable. Despite this, there are some limitations. For the former, it is impossible to monitor human motion and provide the feedback in realtime. For the latter, the wire between the data acquisition system and the host computer makes it difficult to perform detection in a relatively large space.

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

III. HUMAN GAIT DETECTION USING MACHINE LEARNING

We aim to separate the human gaits including both normal and abnormal ones into five classes: normal, toe in, toe out, oversupination, and heel walking, according to a group of features. The process of generating SVM multi-classifier mainly consists of the following parts:
(1) Set up gait database of "normal", "toe in", "toe out", "oversupination", and "heel walking", based on the data obtained from each subject wearing the shoe-integrated system;
(2) Use Fast Fourier Transform (FFT) to convert data from the time domain to the frequency domain;
(3) Apply Principal Component Analysis (PCA) for feature generation;
(4) Train with Support Vector Machines and generate SVM multi-classifier.

Fig. 5 and Fig. 6 respectively illustrate the frameworks for training and detection.

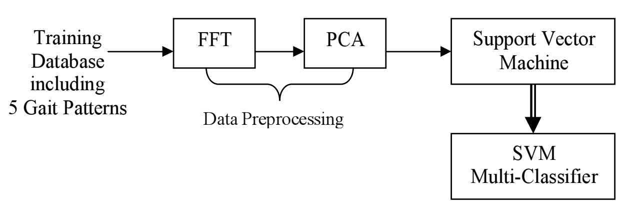

Fig. 5. Training framework

A. PCA for Feature Generation

It is necessary and important to apply feature generation and reduction in data preprocessing for modeling human gait patterns, since failures in feature selection can significantly diminish the efficiency of system performance. In addition, even though the present features contain enough information about the classification problem, they cannot be used for

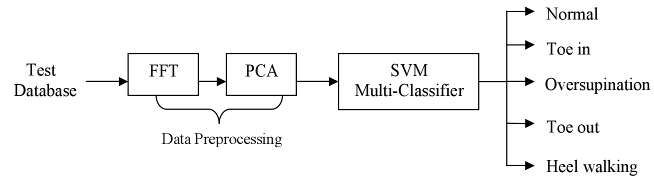

Fig. 6. Detecting framework

predicting the output result correctly since the dimension of the feature space is so large that it requires large numbers of instances to determine the result.

Among several feature extraction methods, Principal Component Analysis (PCA) is widely utilized in the field of pattern recognition and in many signal processing applications. PCA generates a new set of variables, called principal components (PCs), by projecting the original variables to mutually orthogonal axes. In the routine, singular value decomposition (SVD) is applied to efficiently computer PCs [9].

B. Support Vector Machines

We address our classification problem as a multi-pattern recognition using support vector machines (SVMs). The feasibility of support vector machine in the application of classification problem has been proved, being used in the fields of musical genre classification, image classification, gender classification and so on.

(1) *Support Vector Classification (Binary Case)*

The basic training principle of SVMs is to map a set of training data $\{(x_1, y_1), \cdots, (x_l, y_l)\}$, ($x_i \in X \subseteq R^n$, $y_i \in \{-1, 1\}$, l is the total number of training samples) from the input space X into a high-dimensional feature space via a nonlinear function ϕ so that the optimal separating hyperplane (OSH) can be found with the maximum margin between the two classes. A separating hyperplane in canonical form (Vapnik, 1995) determines a function that can classify unseen examples accurately with the following constraints:

$$y_i[\langle \omega, x_i \rangle + b] \geq 1, \qquad i = 1, \cdots, l. \tag{1}$$

where $\langle \cdot, \cdot \rangle$ denotes the dot product in X.

Among several separating hyperplanes, the optimal one is given by maximizing the margin which is the distance between the hyperplane and the closet point of each class. Since the distance is $\frac{2}{\|\omega\|}$ with the constraints of (1), finding the OSH is equivalent to minimizing the following equation:

$$\Phi(\omega) = \frac{1}{2} \|\omega\|^2 \tag{2}$$

Considering in most cases, the data is linearly nonseparable, we introduce positive slack variables ξ_i ($i = 1, \cdots, l$) to deal with these cases. Equation (2) can be transformed into the following equation:

$$min \qquad \Phi(\omega, \xi) = \tfrac{1}{2} \|\omega\|^2 + C \sum_{i=1}^{l} \xi_i \tag{3}$$

$$s.t. \quad y_i[\langle \omega, x_i \rangle + b] \geq 1 - \xi_i, \qquad i = 1, \cdots, l. \tag{4}$$

In (3), minimizing the term $\frac{1}{2}\|\omega\|^2$ which is called as the regularized term will make the function as flat as possible. The second term, $\sum\limits_{i=1}^{l}\xi_i$, representing the empirical risk, is calculated by ε-insensitive loss, which is the most widely used cost function [10]. The parameter C, which is selected empirically by users, calculates the penalties to errors by determining the trade-off between the empirical risk and the regularized term. The larger the value of C, the more penalties are assigned to errors.

We then construct a Lagrange function under the constraints of (4) in order to solve the optimization problem of (3):

$$\begin{aligned} L = &\frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{l}\xi_i - \sum_{i=1}^{l}\beta_i\xi_i \\ &- \sum_{i=1}^{l}\alpha_i(y_i[\langle\omega, x_i\rangle + b] - 1 + \xi_i) \end{aligned} \tag{5}$$

where α, β are the Lagrange multipliers. Because classical Lagrangian duality can solve the primal problem, (5) can be transformed to its dual problem which is given by,

$$\begin{array}{ll} max & W(\alpha) = \sum\limits_{i=1}^{l}\alpha_i - \frac{1}{2}\sum\limits_{i=1}^{l}\sum\limits_{j=1}^{l}\alpha_i\alpha_j y_i y_j x_i.x_j \\ s.t. & \begin{array}{l} 0 \le \alpha_i \le C \quad i = 1, \cdots, l, \\ \sum\limits_{i=1}^{l}\alpha_i y_i = 0. \end{array} \end{array} \tag{6}$$

By replacing x with its mapping in the feature space $\Phi(x)$, (6) can be rewritten as:

$$\begin{aligned} W(\alpha) &= \sum_{i=1}^{l}\alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}\alpha_i\alpha_j y_i y_j \Phi(x_i).\Phi(x_j) \\ &= \sum_{i=1}^{l}\alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}\alpha_i\alpha_j y_i y_j K(x_i, x_j) \end{aligned} \tag{7}$$

As shown in (7), the dot product can be replaced with a function $K(x_i, x_j)$ defined as the kernel function. The advantage of using the kernel function is that the dot product can be performed in a high-dimensional feature space without having to know the nonlinear transformation $\phi(x)$ explicitly. Any function that satisfies Mercer's condition can be used as the kernel function. Radial Basis Function (RBF) kernel $K(x_i, x_j) = \exp(-\gamma\|x_i - x_j\|^2), \gamma > 0$ and polynomial kernel $K(x_i, x_j) = (x_i \cdot x_j + 1)^d$ are the commonly used kernel functions for the classification problem in nonlinear SVMs.

Only a number of nonzero Lagrange multipliers α_i , α_j which fulfill the requirement can be used for the construction of the optimal hyperplane. Any vector x_i corresponding to a nonzero α is defined as the support vector (SV) of the optimal hyperplane. As a remark, the sparsity of the SVM classifier is regarded because support vectors are usually a small subset of the training data points.

The decision function for identifying the class of the input data x is obtained by

$$y(x) = sgn(\sum_{i=1}^{l} y_i\alpha_i K(x_i, x) + b) \tag{8}$$

(2) *Multi-Classification with SVMs*

Two of the conventional approaches that apply SVMs to multi-classification problem are one-against-one and one-against-rest. The kernel concept of each approach is to convert the multiple problem into several binary ones. In order to reduce the training time, we select the one-against-one method in which $\frac{N(N-1)}{2}$ classifiers are created for N total classes.

The binary classification problem for training data x_k from class i and class j can be shown in the following equation:

$$\begin{array}{ll} min & \Phi(\omega^{ij}, \xi^{ij}) = \frac{1}{2}\left\|\omega^{ij}\right\|^2 + C\sum\limits_{k}\xi_k^{ij} \\ & (\langle\omega^{ij}, x_k\rangle + b^{ij}) \ge 1 - \xi_k^{ij},\ x_k \in class\ i \\ s.t. & (\langle\omega^{ij}, x_k\rangle + b^{ij}) \le -1 + \xi_k^{ij},\ x_k \in class\ j \\ & \xi_k^{ij} \ge 0. \end{array} \tag{9}$$

We regard each binary classification as a voting. Then for the test observation sequence x_t will be designated into the class with maximum number of votes. If more than one class has identical votes, x_t is unclassifiable. We comply with the strategy of selecting the class with the smallest index.

IV. EXPERIMENTS AND ANALYSIS

A. Data Acquisition and Database Formation

After A/D transformation, the digital data of all sensors are packaged, which effectively decrease the transmission error and increase the sampling frequency to 50 Hz which is adequate for the activity of walking [11]. Then in the host computer, we obtain the corresponding information applied for each sensor based on data reconstruction and calibration. Fig. 7 and Fig. 8 respectively display the force waveforms under each FSR and 3D inertial parameters during Subject A' s normal walking as a function of time.

Four healthy adults with normal weight and height were invited for this investigation. Since we do data analysis by examining both the left and right feet, the training data segment in a 3010×22 matrix for each of the five gait patterns is produced. After applying Fast Fourier Transform (FFT) processing, we transfer each data segment into a 3000×66 matrix with three primary coefficients selected. Since the number of inputs for a SVM model cannot be too large, we apply Principal Component Analysis (PCA) for feature generation which reduces the data segments from 66-D to 10-D. Experimental results demonstrate that the training process of SVM model becomes more efficient after reducing the dimension of the input data.

B. SVM Model Selection

For what has been discussed in Section III-B, SVM model and parameter selection are very important for obtaining the best generalization in SVM training. In comparison with

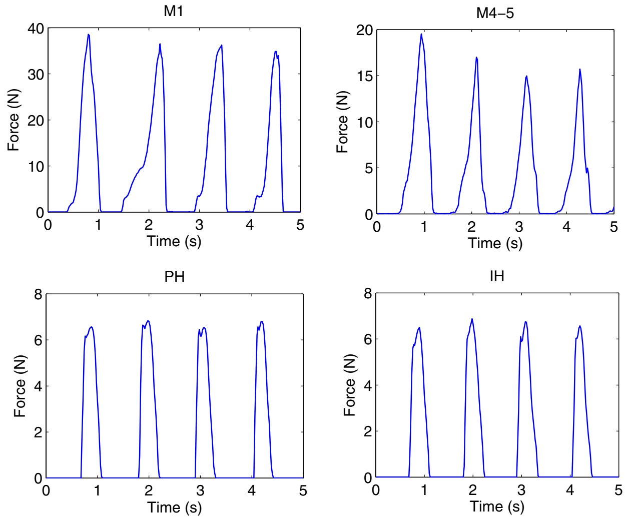

Fig. 7. Force waveforms under 4 right foot regions during normal walking (M1 = 1st metatarsal head, M4-5 = the position between 4th and 5th metatarsal heads, PH = posterior heel, and IH = inside heel)

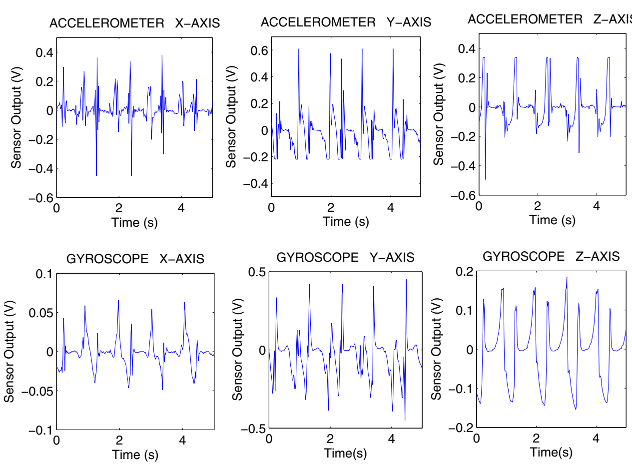

Fig. 8. Accelerations and angular rates in 3D

other generally used kernel functions, RBF kernel is selected for our experiments because of the following reasons. Firstly, unlike the linear kernel function, RBF kernel can nonlinearly map training data into the high-dimensional feature space in order to solve the problem when the relationship between attributes and different classes is not linear. The second reason is that the RBF kernel function has less hyperparamters that influences the complexity of model selection than polynomial and sigmoid kernels.

γ and the cost of constraints violation C which controls the balance between model complexity and the training error are the two parameters while using RBF kernel function and *C-SVM* proposed by Vapnik. We set γ as $\frac{1}{k}$, where k means the number of attributes in the input data. Since the dimension of input data is 10, the value of γ equals 0.1. We compare the number of iterations and the number of support vectors (SVs) for the SVM model with the parameter C set to 1, 5, 10, 20, 50, and 100. The value range of C is usually from 1 to 1000, however, large C will result in overfitting problem. The comparison results for Subject A are shown in Fig. 9 and Fig. 10.

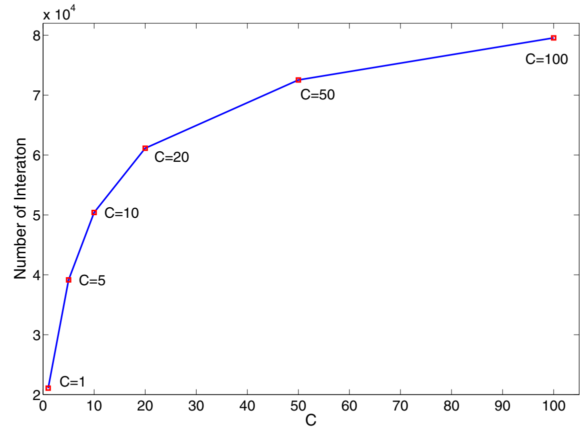

Fig. 9. Number of iterations versus C (Subject A)

After several experiments, we find that the variation of success rate is settled in a small region less than 1% with C set to 1, 5, 10, 20, 50, and 100. The same investigation result happens for all the four subjects. However, as shown in Fig. 9, larger C corresponds to more iteration steps. When C equals 1, the number of iteration is 21089, while C increases to 100, the number of iteration increases to 79556. Fig. 10 displays the comparison results for the number of support vectors when different values of C are selected. As contrasted with the regularity of iteration versus C, less C corresponds to more number of support vectors. Considering the above experiment results and avoiding overfitting problem, we select C equal to 1.

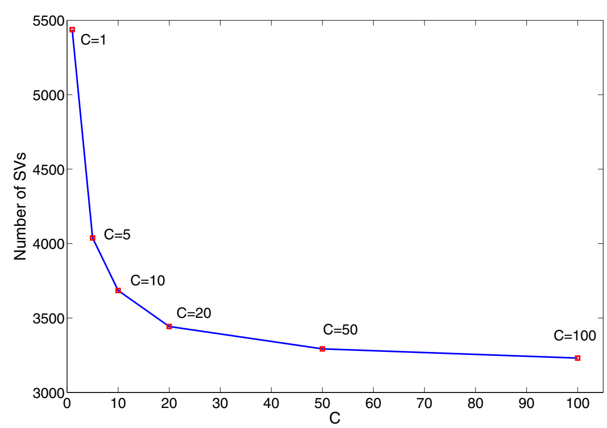

Fig. 10. Number of SVs versus C (Subject A)

C. Sensor Configuration Evaluation

The multi-classification results for the four subjects based on the trained SVM classifiers with C=1 are shown in Fig. 11. For each subject's each gait pattern, 1000 sampling points are selected as the testing data. The average success rates listed in Table I demonstrate the SVM classifiers we built are robust and efficient for the problem of human abnormal gait detection.

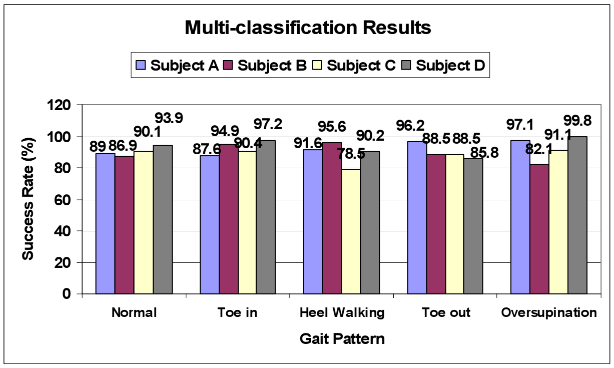

Fig. 11. Multi-classification results for the 4 subjects

TABLE I
AVERAGE SUCCESS RATES FOR THE FOUR SUBJECTS

Subject ID	A	B	C	D
Average Success Rate	92.3%	89.6%	87.72%	93.38%

Moreover, we make comparisons of the classification results utilizing insole sensors and IMU inputs respectively, in order to find the possibility of reducing the hardware design of the intelligent shoe focusing on our problem. Table II lists the detailed experiment results for Subject A only using insole or IMU sensors. We found that the average success rate of using insole sensors is higher than only using IMU and around 3.5% lower than the value of utilizing both IMU and insole sensors. Based on the same experimental method for the other three subjects, we obtain the conclusion that insole sensors play a more important role in solving our classification problem and it is still necessary to utilize both IMU and insole parameters for the analysis in order to obtain the better detection result.

TABLE II
COMPARISON OF CLASSIFICATION RESULTS USING DIFFERENT SENSOR PARAMETERS

Gait Pattern	Success Rate	
	Insole	IMU
Toe in (1000 samples)	82.3%	84.7%
Toe out (1000 samples)	94.5%	90.9%
Oversupination (1000 samples)	96.9%	74.2%
Heel Walking (1000 samples)	85.4%	79.5%
Normal Pattern (1000 samples)	85.1%	79.4%
Total (5000 samples)	88.84%	81.74%

V. CONCLUSIONS AND FUTURE WORKS

In this paper, we present a shoe-integrated system for detecting human abnormal gaits. First, the prototype of the intelligent system is designed which includes a suite of sensors for acquiring force, flexion, three dimensional angular rate and acceleration parameters of foot. Secondly, since the goal of this study is to investigate the approach for detecting gait abnormalities, focusing on toe in, toe out, oversupination, and heel walking, we apply Principal Component Analysis (PCA) for feature generation and Support Vector Machine (SVM) for multi-class classification. Experimental results of the four subjects demonstrate the proposed method is robust and efficient in solving the problem of abnormal gait detection. The compact, wireless, and wearable system has the potential application for detecting gait abnormalities in order to assist persons with abnormal gaits in developing normal walking pattern in their daily life.

In the future work, we will do more experiments for abnormal gait pattern recognition not only focusing on the gait abnormalities mentioned above but also others. Other intelligent learning algorithms, such as Cascade Neural Networks with Node-Decoupled Extended Kalman Filtering (CNN-NDEKF) will be introduced to built multi-pattern model for our problem. The scalable and programmable platform can be further used for other exciting research directions, such as gait-based human-computer interface.

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