Research Article

Human Moving Pattern Recognition toward Channel Number Reduction Based on Multipressure Sensor Network

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A pair of sensing shoes for measuring foot pressure was developed. This system aims at recognizing human movement in unlimited environments. The multipressure sensor network of seven sensors on one insole was set up. Analysis for discriminating the user's movements from foot pressure distribution was carried out, considering the movements of standing, walking, going upstairs, and going downstairs. These actions were discriminated using characteristics extracted from the data of sensors. The classifier based on SVM showed highly accurate movement recognition. Specifically, to improve the classification performance, PCA based dimensionality reduction and channel reduction based data fusion were introduced. Experimental outcomes verified the testing speed of the classification function which was improved without affecting the accuracy rate. The results confirmed that this discriminant analysis can be employed for automatically recognizing human moving pattern based on foot pressure signal.

1. Introduction

Wearable robots, which can acquire physiological state and movement information, provide people with opportunities to wear sensors and intelligent devices in the daily life. This system is in the form of a mechanical structure that is combined with the exterior of a human body to enhance the power of the wearer in various environments [1]. In the field of healthcare, one major goal is to monitor activities of free-living subjects. Daily activities can provide information for doctors to accurately diagnose chronic diseases and design care plan of patients [2–5]. On the other hand, for military use, wearable robots can successfully maneuver heavy loads over unstructured terrain like forests, jungles, and deserts [6]. The first energetically autonomous lower extremity exoskeleton for soldiers, disaster relief workers, and wildfire fighters, as well as other emergency personnel to carry major loads, like food, rescue equipment, first-aid supplies, communications gear, and weaponry has been demonstrated at U.C. Berkeley [7]. Considerable kinds of sensors are employed to obtain human motion. Currently, a number of wearable robots are different in the selection of sensors, the position where sensors distribute, and the analysis of sensor data. Present researches tend to focus on daily worn wristwatch, glasses and shoes where sensors can be embedded into. With embedded sensors, noninvasive detection is available for providing action assistant. However, researchers never give up the intention to recognize users’ condition to give appropriate action support. The acquisition of users’ motion signal for controlling strategy of wearable robots still remains to be the key point.

Owing to the importance of data collection, various measuring techniques have already been developed to cater to the development of human-robot interaction. In many robotic systems, sensors are installed at toe or heel to recognize movements by thresholds [8, 9]. However, this method lacks of accuracy especially in identifying different moving stages [10]. Taking the advantage of multisensor technology has been a focus of interest within the last few years. Adopting the methodology of information cognition from multisensor...
was regarded not only efficient but also reliable [11–14]. Multisensor networks have already been deployed in a considerable number of detecting and monitoring tasks, such as aircraft structural performance detection [15], mobile health biomonitoring [16], alcohol continuous measuring within interstitial fluid [17], and forest fire alarming [18]. Studies emerged has paved a way for further researches on the distinctiveness of sensor networks in wearable robots. For example, the EMG based multisensor system is generally employed to measure muscular activity signals [19], whereas, this sensor has to be directly attached to the skin, which requires high sampling frequencies for signal collection and is difficult to quantify the signals [20].

According to the aforementioned issues, aiming at releasing physical and mental burdens on users, this paper preliminarily concentrates on developing a pair of foot pressure sensing shoes for users’ movement identification. Foot pressure signal is both viable and effective for identifying behavior, for human movement and posture are well reflected in foot pressure distribution. To the best of our knowledge, plenty of researches are about foot pressure detecting system, but few studies have deeply discussed the effects of sensor distribution [21–23]. And the minority researches about the sensor positioning depend merely on foundational theoretical derivation. Therefore, in the present study, a sensor network based automatic motion signal acquisition system was analyzed to demonstrate the essential impact of sensor positioning. The relationship between recognition effect and sensor distribution was discussed to guide the design of the controlling strategy of wearable robots.

This reminder of this paper is arranged in the following order. Section 2 presented the setup of the foot pressure sensing shoes. Section 3 illustrates the development of the proposed sensor network scheme and feature representation for different motions. In Section 4, the feature selection method is depicted. Section 5 describes data fusion based movement identification algorithm. Section 6 reports the experimental results. We draw the conclusion in Section 7.

2. System Description

The primary feature of foot pressure sensing shoes is its convenience of wearability. The wearable nature of shoes allows it to collect user’s motion signal freely. The schematic of the pressure sensing system is presented in Figure 1.

Each insole of the shoe was equipped with seven pressure sensing elements respectively. The pressure sensors we employed in this system are FSR402, which are force-sensitive resistor sensor. FSR402 sensor is kind of flexible printed circuit with a thickness of 0.5 mm. It is obvious that the more sensors placed, the higher precision of plantar pressure distribution can be measured. However, we are aiming at optimizing the number of measurement points, because the number of sensors affects the amount of data processing, and power consumption. The seven sensors were installed on the insole as shown in Figure 2 and the appearance of
the foot pressure pattern could be classified according to the recognition results. Consequently, the sensor sets were applied to the feature extraction algorithm, which project the data onto a lower dimensional space, where most of the information is retained. It uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of uncorrelated variables called principal components (PCs). The number of PCs should be less than or equal to that of original variables. This transformation is defined in such a way that the first PC has as high variance as possible, which accounts for as much of the variability in the data as possible. Each succeeding component has the highest variance possible under the constraint that it be orthogonal to preceding components.

Assuming that we have a set of centered input vectors of foot pressure \( x_t \) (\( t = 1, \ldots, l \) and \( \sum_{t=1}^{l} x_t = 0 \)) measured by sensor system, each of which is of \( m \) dimension \( x_t = (x_t(1), x_t(2), \ldots, x_t(m))^T \), PCA linearly transforms each vector \( x_t \) into a new one \( s_t \):

\[
s_t = U^T x_t, \quad (1)
\]

where \( U \) is the \( m \cdot m \) orthogonal matrix whose \( i \)th column \( u_i \) is the \( i \)th eigenvector of the sample covariance matrix \( C = (1/l) \sum_{t=1}^{l} x_t x_t^T \). Hence, eigenvalues of \( C \) were obtained and \( u_i \) is the corresponding eigenvector:

\[
\lambda_i u_i = C u_i, \quad i = 1, \ldots, m. \quad (2)
\]

Based on the estimated \( u_i \), the components of \( s_t \) were therefore calculated as the orthogonal transformations of \( x_t \):

\[
s_t(i) = u_i^T x_t, \quad i = 1, \ldots, m. \quad (3)
\]

Thus, in PCA, the directions of the calculated PCs are uncorrelated with each other and computed by maximal variance. The new components we got are within a new dimensional space. By employing only a finite set of eigenvectors in the descending order of eigenvalues, the number of principal components in \( s_t \) will be reduced. Therefore, the cumulative contribution rate of the first several components would be expressed as \( (1/l) \sum_{i=1}^{m} s_t(i) \). Usually the contribution rate value is over 95% to characterize the original data.

### 3. Feature Extraction Based on PCA

The block diagram of foot pressure signal processing and analysis is exhibited in Figure 4, which consists of a feature abstracting module, a sensor network based data fusion part, and a classification module. These units are integrated in one system for moving pattern identification. Initially, raw pressure signals collected from the acquisition system had to be prepared for analysis. The purpose of data decomposition was to segment signal into subvectors. The normalized sample sets were applied to the feature extraction algorithm, which extract a series of feature elements from the inputs. Further, through the statistical feature transformation step, the data would be simplified into optimal form. For the purpose of optimizing the processing procedure, we applied multisensor based data fusion to reduce the number of detecting channels. With the construction of classifier, processed data were to be sent into the model for training and testing. These process, the recognition results were listed respectively. Consequently, the foot pressure pattern could be classified according to the utilizing demand. We preliminarily aim at holding that simple classifiers can achieve high accuracy as long as the feature is robust and representative, which is important in practical application.

Feature extraction is a major process of obtaining signal characteristics from time series data. Aiming at discriminating the reference class from other classes, feature selection can be considered as a data-compression process which removes irrelevant information and preserves relevant information from the raw data [24]. Typically, feature extraction approach applied to raw signals precedes the classification procedure.

Principal component analysis (PCA) is the most commonly technique applied to data reduction in pattern recognition and classification [25]. The basic idea of PCA is to project the data onto a lower dimensional space, where most of the information is retained. It uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of uncorrelated variables called principal components (PCs). The number of PCs should be less than or equal to that of original variables. This transformation is defined in such a way that the first PC has as high variance as possible, which accounts for as much of the variability in the data as possible. Each succeeding component has the highest variance possible under the constraint that it be orthogonal to preceding components.

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### 4. Pattern Recognition with SVM

During the recognition phase, the features from the foot pressure signals have been extracted by combined methods.
And they were fed into a classifier. Within this research, we took support vector machine to find the matching output by using these features. Support vector machine (SVM), which represents a major development in machine learning algorithms, is based on the foundation of statistical learning theory [26]. This algorithm is characterized by the ability to resolve problems of high-dimensional data and to represent the decision-making boundary in the form of training subsets, which is the general meaning of support vector [27, 28]. SVM has been widely applied to plenty of fields, such as pattern identification, regression analysis, and function approximating, and so forth [29, 30]. The results give the evidence that this technique cannot only satisfy from the theoretical perspective, but also can lead to high accuracy in practical applications. In this test, foot pressure detection is formulated as a classification problem, wherein the classifier is used to decide the moving pattern. Accordingly, the goal is to separate the moving pattern classes by a function which is induced from available examples.

The basic SVM is to classify a series of points into two different classes of data (Figure 5). The SVM attempts to place a linear boundary represented by a solid line between the two different classes and tries to orient the boundary in such a fashion that the distance between the boundary and the nearest data point in each class is maximal. Given the training vectors \( x_i \in \mathbb{R}^n \), \( i = 1, \ldots, N \), in two classes, and an indicator \( y_i \in \{-1, +1\} \), SVM constructs a linear function:

\[
f(x) = w^T x + b.
\]
The parameters $w$ and $b$ are defined according to a primal optimization problem:

$$
\min J(w, \xi) = \min \left( \frac{1}{2} w^T w + C \sum_{i=1}^{N} \xi_i \right),
$$

$$(y_i (w^T \Phi(x_i) + b) \geq 1 - \xi_i, \xi_i \geq 0, \ i = 1, \ldots, N),
$$

where $C$ is for controlling the trade-off between the model complexity and empirical risk [31]. We set another parameter for the classifier $G$ representing the kernel function for modeling. In this case, we utilize the kernel function into map input vector $x_i$ to a higher-dimensional space through a nonlinear mapping $\Phi(x_i)$; the kernel concept can be written as:

$$K(x_i, x_j) = \Phi^T(x_i) \Phi(x_j).$$

Due to the possible high dimensionality of the vector variable $w$, we introduced Lagrange multipliers $\alpha_i \geq 0, \ i = 1, 2, \ldots, N$, one for each of the constraints in (1), and we get the following Lagrangian:

$$L(w, b, \alpha) = \frac{1}{2} \|w\|^2 - \sum_{i=1}^{N} y_i \alpha_i (w x_i - b) + \sum_{i=1}^{N} \alpha_i.$$

Then the task is to minimize (7) with respect to $w$ and $b$ and to maximize it with $\alpha_i$. At the very optimal point, we have

$$w = \sum_{i=1}^{N} y_i \alpha_i x_i, \quad \sum_{i=1}^{N} \alpha_i y_i = 0.$$

It is shown that $w$ is contained in the subspace spanned by $x_i$ in (8). By substituting (8) into (7), the decision function of SVM model can be derived as

$$f(x) = \text{sign} \left( \sum_{i=1}^{N} \alpha_i y_i (x_i, x) + b \right).$$

The formula above results in an optimization problem with convex constrains, which is readily to be solved by the interior point method. For the moving pattern recognition issue, we preliminarily took the foot pressure signals of the seven points in Figure 2 as input vectors. Thus the SVM classifier was enabled to identify different kinds of movements.

5. Channel Reduction

During testing, the sensors transmit information about a common movement and the objective is to obtain an accurate identification of the moving pattern in the sensor field. Generally speaking, with more signal acquisition channels we can get more information. However, increasing the number of channel will definitely increase the complexity of computation and analysis that may lead to slow discrimination response. To overcome this limitation, we tend to find a way of using a reduced number of sensitive elements without compromising classification accuracy. On the other hand, the priority should be given to explore the relationship between the number of foot pressure sensors and the classification errors, respectively. Sensors on each insole can be regarded as a sensor network, which has independent power supply, regulator as well as signal conditioning module. For pilot phase, the information from data sets would be fused and for recognition. Data fusion of sensor network refers to the acquisition, processing, and synergistic combination of information gathered by various sensors to provide a better understanding of the phenomenon under consideration [32]. Therefore, the cooperative nature of the sensors can be exploited to improve the efficiency of resource utilization and the sensing performance [33]. Particularly, we focus on the number and distribution of pressure sensors in the sensor network. By analyzing the data fusion outcomes of sensors on different positions, the feasibility of channel reduction would be carried out.

Due to the laboratory deployment, channel number of each foot would be reduced from 7 to 4 with a decrement step of 1. All possible combinations for a reduced number of channels were to be evaluated by classification accuracy for different movement classes. Consequently, the sensor distribution that produced the lowest classification error for each number of channels would be considered as the optimal channel configurations.

6. Experimental Results and Analysis

The experiment was conducted to develop an automatic measuring system for revealing the relations between human motions and cumulative foot pressure characteristics. The experimental devices attached to the tester are shown in Figure 6. Our tests were carried out using a 24-year-old...
female wearer, 1.66 m tall. With the power supplied, foot pressure signals were gathered by FSR402 sensors every 40 ms and transmitted virtually through the data processing board to the computer wirelessly. The waveforms of each sensor on both feet were exhibited on the desktop simultaneously for monitoring. The signal processing procedure was implemented by Matlab 2010a, running on a PC with 2 G, 2 GHZ CPU.

To evaluate the effectiveness of proposed methods in recognition, we choose four kinds of basic movements, which are standing still, walking, going upstairs, and going downstairs. Raw data on foot pressure distributions for each moving pattern were acquired with the developed foot pressure sensing shoes. Variation of foot pressure for each kind of movement was displayed in Figure 7. Pressure level represents the output value of digital information into which voltage is converted.

According to the figure, when not moving, the values of foot pressure basically stay constant. For walking, it is clear that the patterns change in shape and the ratio of the time, which depend on pressurization to depressurization in each step, in agreement with the way we use our feet. In case of going upstairs and downstairs, a higher peak value within each step can be observed; however the wave patterns are different for each. Therein, we are aiming at identifying these movements based on the corresponding foot pressure.

6.1. Feature and Feature Selection. In this study, five internal time-domain parameters were picked up as eigenvalue, which are average value, standard deviation, maximum value, and minimum value as well as difference deviation. Features that represented the pressure signal were memorized in matrix and sent to the classifier. We picked up 630 sets of data samples of each moving pattern: the former 420 are for classifier training and the latter for testing. The training data and training label are used to form the whole training set. For the training part, we got an optimal $C$ of 724 and $G$ of 8 by cross-validation. The optimization of these two parameters is for obtaining a high recognition rate based on current training samples. The radial basis function (RBF) kernel is employed. Due to the use of SVM classifier in this study, foot pressure and corresponding moving states were classified into the four categories, respectively. The cross validation result (contour map and 3D view) of parameter selection is shown in Figure 8.

The classification model was applied to predict the output category for testing samples identification. According to Figure 9, we summarize the classification performance results achieved by this SVM classifier. The average accuracy with all seven sensors is at 92.9% for all four kinds of movements and the diagnosis accuracy for each moving pattern is in Table 2.

The running time calculated by Matlab is 0.46 seconds. Compared with the preset inputs, we sent the input matrix
to PCA processing algorithm for dimensionality reduction beforehand. Due to the aforementioned cumulative component rate in paragraph 3, we took the first three columns of PCs which occupied over 95% information of original data. A few numbers of new input eigenvectors provided sufficient information for foot pressure coding and movement recognition. The accuracy rate can be obtained when $C = 1024$ and $G = 32$, it reaches as high as 88.7% (Figure 10). The outcome of inputting the new eigenvectors in classifier is shown in Table 3. It could be noted that if a SVM classifier is used, declining recognition rate of moving patterns would be caused by PCA. Whereas, the classification time with proposed PCA algorithm did have a higher recognition speed, which was only 0.21 seconds. It decreased 0.25 seconds compared to the former classification.

### Table 2: Accuracy of different movements with seven sensors.

| Moving pattern       | Training accuracy (%) | Testing accuracy (%) |
|----------------------|-----------------------|----------------------|
| Standing still       | 100                   | 100                  |
| Walking              | 91.2                  | 91.0                 |
| Going upstairs       | 93.1                  | 93.7                 |
| Going downstairs     | 90.0                  | 86.7                 |

### Table 3: Accuracy of different movements with PCA.

| Moving pattern       | Training accuracy (%) | Testing accuracy (%) |
|----------------------|-----------------------|----------------------|
| Standing still       | 99.8                  | 100                  |
| Walking              | 89.3                  | 80.5                 |
| Going upstairs       | 90.8                  | 88.6                 |
| Going downstairs     | 89.8                  | 86.2                 |

#### 6.2 Channel Reduction Outcome

Dimensionality reduction algorithm based on PCA recorded the variation of recognition accuracy and speed but does not show the influence of sensor distribution on the insole. In this study, the impact of acquisition channels on the recognition rate and recognition
time will be tested. In previous researches, sensors were generally placed at toe, little ball, great ball, and toe heel on human physiological characteristics, which are position 1, 2, 7, and 4 in Figure 2, respectively [34, 35]. We took the data of FSR1, FSR2, FSR4, and FSR7 for data fusion. And then the testing result for combing the four sensors was obtained. Using sensors of different positions could produce similar intraposition classification performance, but distinct classification accuracy. The average recognition accuracy rate is 84.4% (Table 4), which was significantly different from that of 92.9% (seven sensors). However, the classification only took 0.13 s.

With the same procedure, the number of multisensor decreasing from 6 to 4 was analyzed. The four basic sensors were FSR1, FSR2, FSR4, and FSR7 as mentioned before. Totally, the average classification accuracy across all positions is shown in Table 5.

With the increase of sensor number, the multisensor network seems to be more sensitive to different moving patterns. The SVM classifier was trained and tested using data multiple positions. For the sake of comparison, the average accuracy rate was changed with distinguished sensor data fused. When the foot pressure data from positions 1, 2, 3, 4, 6, and 7 were involved in the training set, the average classification accuracy reached a maximum value of 91.1% (Table 6). It is also noteworthy that this data set led to a shortest running time, which is only 60 ms. Therefore, using six optimally selected channels produced 91.1% average classification accuracy and 60 ms response time over four motions, compared with 92.9% and 460 ms of seven sensors. The optimal arrangement of foot pressure sensor distribution is shown in Figure II.

The recognition error could be explained due to the finite measured data in that it was impossible to have an identical collection environment. Yet we cannot have a 100% accurate rate. Hence, this method can be encapsulated and embedded into one single program for simplifying operation, with different sorts of foot pressure signals. So we dare to say, with the ability of the SVM classifier, the detecting system applied has got more reliable results, whose service performance and effectiveness can cater to the need of monitoring in commercial use.

7. Conclusion

In this paper we suggested a laboratory setup for human moving pattern recognition based on foot pressure sensing. Pressure sensors, signal-conditioning module, microcontroller, as well as wireless transmitting devices, and so forth were integrated for signal acquisition and PCA, and data fusion of channel reduction and SVM were used to conduct the classification of several kinds of moving patterns. This laboratory setup has finished the following issues.

(1) With the design of insole equipped with pressure sensors, foot pressure was obtained exactly and freely.

(2) Specifically, to study the potential connections between moving patterns and foot pressure, we established an SVM based classifier. PCA algorithm was for feature dimension descending and multi-sensor data fusion for channel reduction.

(3) We compared the outcome between PCA dimensionality reduction and channel in order to address a better identification way.

(4) Data fusion technique can find an optimal number of sensors. This recognition can be better than that of PCA method for feature extraction. And the optimized SVM can improve the classification accuracy because of the best parameters.
The recognition accuracy of our optimal classification is as high as 90.13%, which does have a fast time response at the same time. However, we have to point out that there still exists some deficiency. With the application of an advanced processor, that is, DSP, higher acquisition rate and conversion accuracy will be available, thus leading to a better classification performance. It should be noted that the testing of this study was only carried on one tester. In actual monitoring, other wearers’ movement should also be trained and classified. Owing to the existing problems, further steps will be taken to focus on gait transaction, which is more applicable for the controlling strategy of wearable robots. In spite of these limitations, this study did put forward its significance. And these issues will be discussed in further studies.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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