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Postural Kyphosis Detection Using Intelligent Shoes

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Abstract— **Postural kyphosis as one of the most common kinds of kyphosis is usually diagnosed in adolescents and young adults. Long-term kyphosis will not only affect the persons' appearance, but also result in thoracic deformity accompanied by pain. In this paper, we introduce a cost-effective shoe-integrated system which mainly consists of 8 force sensing resistors (FSRs) for gathering the pressure information under the 8 bony prominences. Based on the gathered plantar pressure information, the methodology of Cascade Neural Networks with Node-Decoupled Extended Kalman Filtering (CNN-NDEKF) is applied for training the model of detecting the gait pattern associated with postural kyphosis. Experimental results demonstrate that the proposed approach is efficient. This device is of particular significance to provide feedback in the application of postural kyphosis rectification.**

I. INTRODUCTION

Kyphosis generally refers to an increased curvature of the thoracic spine in the sagittal plane. Long-term kyphosis will result in thoracic deformity accompanied by pain. Since spine is of a consecutive multi-segmented structure, kyphosis can affect not only the thoracic spine, but also the cervical (upper) and lumbar (lower) spine. The exaggerated curves of cervical and lumbar spine happen in the inward direction to compensate for the increased outward curve in the thoracic spine.

To be one of the most common types of kyphosis, postural kyphosis is mainly attributed to slouching posture. Different from Scheuermann's kyphosis, postural kyphosis presents a smooth curvature while the patient bends forward. Postural kyphosis is usually diagnosed in adolescents and young adults. The traditional treatment for postural kyphosis is with education of proper posture and suitable exercises to strengthen the back and abdomen muscles so as to support proper posture. After long-term postural training, postural kyphosis will be effectively corrected and lead to no problem in the patients' future life.

Keeping proper posture in daily life is the key to amend postural kyphosis. However, few adolescents can self-consciously correct their slouching posture. In this condition, the brace is introduced for curve correction which is custom-made for each patient. Besides, E. Lou et al. introduced a garment including two 3-axis accelerometers to monitor the kyphosis angle and provide vibration feedback to children [1]. The limitation for both brace and garment approaches is to affect the upper body appearance so as to make patients feel uncomfortable during the wearing process. Based on the study of plantar pressure for human walking, the plantar pressure distribution will shift along with the increase of curvature for the thoracic spine. That is to say, gait analysis especially based on plantar pressure provides an indirect approach for detecting postural kyphosis. We propose an intelligent shoe-integrated system from which the pressure information derived can give efficient assistance in determining and alarming the persons associated with postural kyphosis. Fig. 1 displays the postures of slouching and proper walking.

(a) (b)

Fig. 1. (a) Slouching walking (b) Proper walking

The Pedar insole system (Novel, Munich) with 99 capacitance transducers for planter pressure measurement is a commercially available system which is widely used in clinic sites and laboratories due to its repeatability and accuracy [2]. However, the limitations of this device include a heavy wireless and memory storage module, a thick insole, and an expensive price. The heavy weight of wireless and memory storage module limits the period of gait trial. Since Pedar insole system utilizes the capacitance transducer which is thicker (approximately 2 mm) in comparison with other types of sensors for in-shoe force measurement, it makes subjects feel a little uncomfortable when they wear their shoes together with this insole. The price is relatively expensive (approximately USD 31,000), which is impossible to be afforded by most patients, even for some clinics. In our research group at CUHK, we have already developed the platform for a shoe-integrated system. In [3], this 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 gait. 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

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device equipped with numerous sensors, such as the Pedar insole.

In this paper, a cost-effective shoe-integrated system for detecting postural kyphosis is introduced. Only 8 FSRs are used for gathering the pressure information under the 8 bony prominences of each foot. The proposed pattern recognition approach is based on Cascade Neural Networks with Node-Decoupled Extended Kalman Filtering (CNN-NDEKF).

This paper is organized as follows. In section II, the architecture of the shoe-integrated system is introduced. We describe the methodology for detecting postural kyphosis 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 three major components: insole, microprocessor-based data gathering module, and wireless communication subsystem. The whole system is compact and light (82g) so that it is easily integrated with users' own shoes.

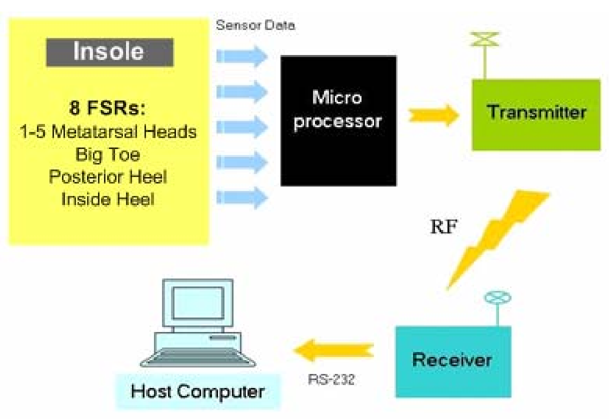

Fig. 2. Outline of the system design

A. Insole Subsystem

Insole subsystem shown in Fig. 3 is a flexible instrumented part for sensing the force parameters inside the shoe. Eight FSRs (Interlink Electronics, Santa Barbara, CA) are installed on one side of a thin insole under subcutaneous bony prominences: 1-5 metatarsal heads, hallux (big toe), and the heel (which is divided into a posterior and inside portion). Considering the different sizes of bony prominences, we select two kinds of FSRs. Two FSR-402s (12.7 mm diameter active surface, 0.5 mm thick) are used in the first metatarsal head and hallux. Six FSR-400s (5 mm diameter, 0.4 mm thick) are placed under the other positions.

FSR is a type of polymer thick film (PTF) device exhibiting a decrease in resistance when an increase in the force is applied to the active area. In our circuit design, a voltage divider is used to measure the resistance change of the FSR in order to obtain the relationship between the applied force and the voltage.

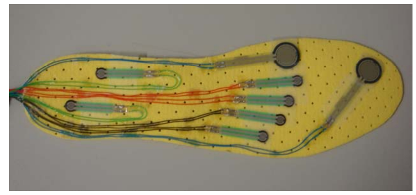

Fig. 3. Photograph of the insole

B. Microprocessor-Based Data Gathering Subsystem

The subsystem used to gather information from the insole 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 8 ADC channels with 10-bit resolution to transform the analog voltage information generated from the FSRs into scaled digital data.

Fig. 4. Circuit board together with battery

C. 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 [4]. The other method was to transmit the data immediately via the RS232 serial port [5]. 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 ($56\times28\times7$ 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. METHOD

A. FSR Sensor Calibration

In order to compensate for the nonlinearity of FSR, each sensor needs to be calibrated after it has been located on the surface of the insole. The popular digital force gauge DPS-20 (IMADA CO., LTD) is used to detect a discrete force in the range from 0 to 10 kg for the FSR-400 and 0 to 20 kg for the FSR-402. The digital outputs of the force gauge are stored in the PC via RS232. Then we can get the calibration result for each sensor according to the relationship between the applied force and the corresponding digital output of the FSR. Experimental results demonstrate that the exponential function is fit well to the calibration data. One calibration curve of the FSR-402 under the big toe of the right foot is displayed in Fig. 5.

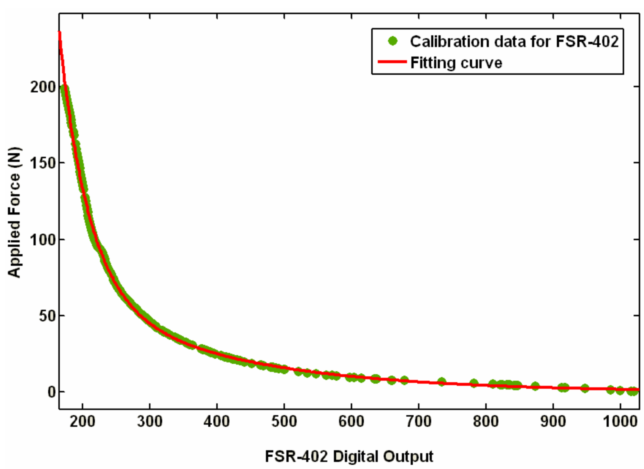

Fig. 5. One FSR-402 calibration curve

Equation (1) describes the relationship f between the FSR-402 digital output x and the applied force in newton:

$$f = a \cdot e^{b \cdot x} + c \cdot e^{d \cdot x} \tag{1}$$

Coefficient	Value
a	7324
b	-0.02291
c	136.4
d	-0.004305

B. Cascade Neural Networks with Node-Decoupled Extended Kalman Filtering for Gait Modeling

Gait analysis based on plantar pressure distribution provides an indirect way for detecting postural kyphosis. Human gait of either proper or kyphosis walking is regarded as the measurable stochastic process. The methodology that we are considering is to model human gait for realizing postural kyphosis detection. The CNN-NDEKF is applied to generate the classifier for this binary pattern recognition problem.

Nechyba and Xu proposed a new learning architecture of neural network, which combines (1) cascade neural networks (CNN), dynamically improving the architecture of the neural network to be part of the training process, and (2) node-decoupled extended Kalman filtering (NDEKF), a efficient convergent alternative to gradient-descent training algorithms. They analyzed the computational complexity of the proposed approach and demonstrated the significant improvement in learning times and/or error convergence of CNN-NDEKF compared with other machine learning approaches [6]. In our research group, CNN-NDEKF has found successful applications in learning human control strategy [7], modeling human strategy in controlling a dynamically stabilized robot [8], modeling human sensation in virtual environments [9], and learning human navigational skill for smart wheelchair [10]. In the following, we briefly summarize the CNN-NDEKF algorithm and the reason for us to adopt this algorithm for modeling human gait associated with proper and postural kyphosis walking.

First, there is no prior assumption for the network architecture. Hidden units will be dynamically added into an initially minimal network once at a time. Fig. 6 illustrates the growth process for the initial two-input, one-output network with two hidden units installed one by one. Note that each new hidden unit will not only receive one input-connection from each input unit, but also from each pre-existing hidden unit. Therefore, a cascade neural network with m_i input units (including the bias unit), m_h hidden units, and m_o output units, has m_w connections where,

$$m_w = m_i m_o + m_h(m_i + m_o) + (m_h - 1)\frac{m_h}{2} \tag{2}$$

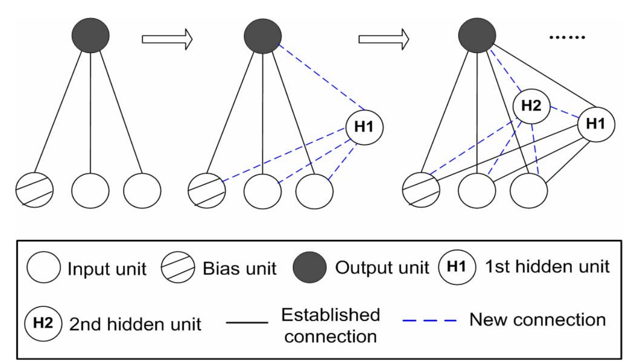

Fig. 6. The cascade learning architecture: adding hidden units once at a time to the initial two-input, one-output network

Secondly, the activation function of each hidden unit is not constrained to be the particular type. For each new hidden unit, the activation function, which mostly reduces RMS error (e_{RMS}) for the training data will be selected. Sinusoidal, Bessel, and Gaussian functions are the typical alternatives to the standard sigmoidal activation function.

Thirdly, node-decoupled extended Kalman filtering (NDEKF) [11] fits seamlessly within the cascade learning framework, which shows better convergence properties with less computation than gradient-descent techniques (e.g. backpropagation and quickprop algorithm).

Suppose P is a $w \times w$ conditional error covariance matrix storing the interdependence of every pair of w weights in the given neural network. The weight recursion of NDEKF is given by

$$\omega_{n+1}^{i} = \omega_{n}^{i} + \{(\psi_{n}^{i})^{T}(A_{n}\xi_{n})\}\phi_{n}^{i} \tag{3}$$

where ω_{n}^{i} is denoted as the input weight vector at iteration n, for unit $i \in \{0, 1, \ldots, m_o\}$. ξ_n is the m_o-dimensional error vector for the current training mode, ψ_{n}^{i} is the m_o-dimensional vector for the partial derivatives of the output unit signals related to the ith unit's net input, and

$$\phi_{n}^{i} = P_{n}^{i}\zeta_{n}^{i} \tag{4}$$

$$A_n = \left[I + \sum_{i=0}^{m_o} \{(\zeta_{n}^{i})^{T}\phi_{n}^{i}\}[\psi_{n}^{i}(\psi_{n}^{i})^{T}] \right]^{-1} \tag{5}$$

$$P_{n+1}^{i} = P_{n}^{i} - \{(\psi_{n}^{i})^{T}(A_{n}\psi_{n}^{i})\}[\phi_{n}^{i}(\phi_{n}^{i})^{T}] + \eta_{q}I \tag{6}$$

where ζ_{n}^{i} is the w_i-dimensional input vector for the ith node, P_{n}^{i} is the $w_i \times w_i$ conditional error covariance matrix for the ith node, and η_q is used to alleviate singularity problem of P_{n}^{i}. In (3) to (6), $[]$'s, $\{\}$'s, and $()$'s respectively represent matrices, scalars, and vectors.

The flexible architecture of cascade neural network is ideal for modeling human gait of proper and kyphosis walking. The model parameters are updated during the learning procedure which ensures the model to get the best classification performance. The process for CNN-NDEKF-based learning algorithm is summarized as follows. Initially, the network architecture begins with some inputs and one or more output units based on the requirement of special applications. There are no hidden units in the network architecture. Every input unit is directly connected to each output unit through a connection with pre-trained weight. With no significant e_{RMS} reduction, the first hidden unit is picked up from the pool of candidate units. As soon as the hidden unit is installed, all input weights to the hidden unit are frozen, while the weights to the output units are trained using NDEKF. The process will repeat until the e_{RMS} reduces sufficiently or the number of hidden units achieves the predefined maximum number.

IV. EXPERIMENTS AND ANALYSIS

A. Data Acquisition and Database Formation

After A/D transformation, the digital data of all FSRs are packaged, which effectively decrease the transmission error and increase the sampling frequency to 50 Hz which is adequate for the activity of walking [12]. 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 individually display the force

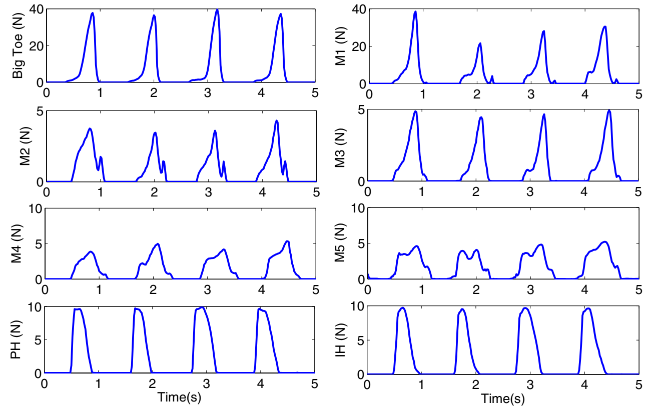

Fig. 7. Force waveforms under 8 right foot regions during proper walking posture (M1 = 1st metatarsal head, M2 = 2nd metatarsal head, M3 = 3rd metatarsal head, M4 = 4th metatarsal head, M5 = 5th metatarsal heads, PH = posterior heel, and IH = inside heel)

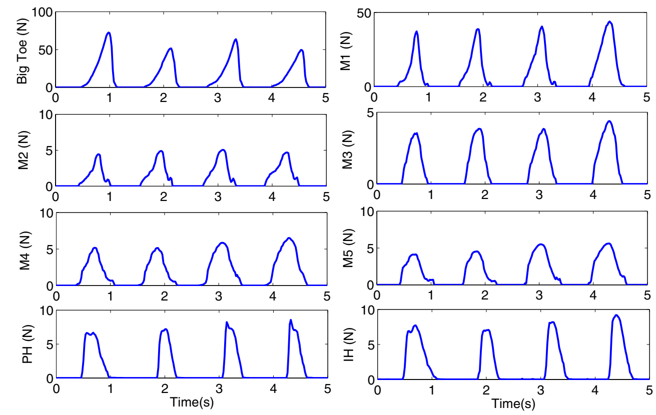

Fig. 8. Force waveforms under 8 right foot regions during kyphosis walking (M1 = 1st metatarsal head, M2 = 2nd metatarsal head, M3 = 3rd metatarsal head, M4 = 4th metatarsal head, M5 = 5th metatarsal heads, PH = posterior heel, and IH = inside heel)

waveforms under each FSR for proper and kyphosis walking as a function of time.

One young volunteer with no kyphosis was invited for this investigation. The training data with 10000 sampling points (5000 sampling points for either positive or negative sample) is gathered in outdoor environments which is then used for training the CNN-NDEKF model. Since we do data analysis by examining both the left and right feet, the dimension of the original data is 16.

B. Data Preprocessing

It is necessary and important to apply feature extraction in data preprocessing for modeling proper walking gait and the kyphosis one, since failures in feature generation can significantly diminish the efficiency of the system performance. Among the several feature extraction methods, Fast Fourier Transform (FFT), Principal Component Analysis (PCA), and Independent Component Analysis (ICA) are widely used in the application of pattern recognition.

In order to obtain the best performance of detecting postural kyphosis, different preprocessing approaches are utilized, including only using the original data, FFT, PCA, ICA, FFT+PCA, and FFT+ICA. After that, the retrieved data is applied to be the input for training CNN-NDEKF model. Table I lists the generated data dimension after preprocessing, errors of detecting proper walking, errors of detecting postural kyphosis, and the average success rate of classification corresponding to each preprocessing method with the same training and testing samples (1500 sampling points for either positive or negative sample). We can find that the preprocessing approach of FFT is most effective for realizing the best classification performance compared with the other approaches mentioned above.

TABLE I

TESTING RESULTS USING DIFFERENT PREPROCESSING APPROACHES

Preprocessing Method	Data Dimension	Errors of Proper Walking	Errors of Postural Kyphosis	Ave. Success Rate
Original Date	16	98	38	95.4%
FFT	48	18	0	99.4%
PCA	10	259	126	87.1%
ICA	10	276	95	87.6%
FFT + PCA	16	256	158	86.2%
FFT + PCA	10	320	123	85.2%
FFT+ ICA	16	86	14	96.6%
FFT+ ICA	10	410	156	81.1%

C. Testing Results

The classification results for the volunteer based on the trained CNN-NDEKF model with 3 order FFT preprocessing are listed in Table II. For either proper walking or kyphosis walking, 1500, 2500, and 3500 sampling points are respectively selected as the testing data. The total success rate can reach 98% which demonstrates the shoe-integrated system we built is efficient for the problem of detecting postural kyphosis.

TABLE II

TESTING RESULTS

Gait Pattern	Total	Correct	Failed	Success Rate
Proper Walking	1500	1482	18	98.8%
	2500	2416	84	96.6%
	3500	3342	158	95.4%
Postural Kyphosis	1500	1500	0	100%
	2500	2495	5	99.8%
	3500	3479	21	99.4%
TOTAL	15000	14714	286	98%

V. CONCLUSIONS AND FUTURE WORKS

In this paper, we present a methodology for detecting postural kyphosis under the framework of the shoe-integrated system. First, the prototype of the intelligent system is introduced which includes 8 FSRs for acquiring the pressure parameters under the 8 bony prominences of each foot. Secondly, we apply Cascade Neural Networks with Node-Decoupled Extended Kalman Filtering (CNN-NDEKF) to train the model for this binary classification problem. Experimental results demonstrate that Fast Fourier Transform (FFT) is the suitable data preprocessing approach for our problem. The total success rate for 15000 test samples reaches 98%. The compact, wireless, and wearable system has the potential application for detecting postural kyphosis in order to assist persons in developing proper walking posture in their daily life.

In the future work, we will do more experiments for investigate the device's long-term effect and more individuals will be invited for the clinical trial. Other intelligent learning algorithms, such as support vector machines (SVM) and hidden Markov model (HMM) will also be introduced for this classification problem.

VI. ACKNOWLEDGMENTS

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