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Classification of Single-Axis Spinal Motion Using a Wearable System of Stretch Sensors for At-home Physical Therapy

[1]Jiuxu Chen, [2]Jorge Caviedes, Member, IEEE, and [3]Baoxin Li, Member, IEEE

***Abstract*— Physical therapy (PT) has demonstrated therapeutic effectiveness for treating low back pain, a prevalent health condition. However, it is challenging to achieve such effectiveness through at-home PT without supervision of a therapist. Towards enabling realtime biofeedback for ensuring correct execution of PT exercises at home, we are building a wearable system that employs light-weight stretch sensors for estimating the spinal posture of a patient performing PT exercises. A basic task is to detect single-axis spinal motions from the sensor measurements. This work presents the design and evaluation of our approach for this task. Three subjects of different body shapes were recruited to wear the system and perform sequences of arbitrary single-axis spinal exercises. The collected data were used to train and test an SVM-based classification algorithm. Experimental results demonstrate that it is feasible to rely on only a small number of stretch sensors to estimate the spinal motion. The results also suggest the existence of strong inter-person variability and thus a practical system should include calibration for ensuring high accuracy.**

***Index Terms*— biofeedback, stretch sensors, therapeutic exercise, wearable sensors, signal processing, classification**

I. INTRODUCTION

Low back pain (LBP) is defined as pain or discomfort between the 12th rib and the gluteal fold, which can be called chronic when the complaints last longer than 12 weeks [1]. LBP can affect people of all ages. It is estimated that about 80% of all the population are affected at some point in life [2, 3]. Some early reports estimated that more than 85 billion dollars were spent annually on direct medical expenditures in the United States due to back pain [3, 4], suggesting that LBP has become a major public health problem.

Physical therapy (PT) is an evidence-based treatment for non-specific chronic LBP, whose effectiveness was documented in a 2018 report [5]. The therapeutic effectiveness of a PT program depends on both the accurate performance of the exercises and adherence to the prescribed routine. Although PT has been widely used for LBP, extending therapeutic exercises for patients with LBP into an “at-home” setting has had limited success. Research has illustrated that, without supervision from a therapist, patients at home often have difficulty correctly performing and/or adhering to the prescribed exercises. Considering the social-distancing restrictions due to the current pandemic, it is of particular urgency to develop new technologies/systems that support and enable greater precision during unsupervised PT exercise at home. This work presents our effort on the task of estimating spinal posture, which is a necessary step for developing such new systems.

[1]Jiuxu Chen is a PhD student with School of Computing, Informatics, and Decision Systems Engineering, Arizona State University, Tempe, AZ, USA Jiuxu.Chen@asu.edu

[2]Jorge Caviedes is a Research Professor with School of Computing, Informatics, and Decision Systems Engineering, Arizona State University, Tempe, AZ, USA Jorge.Caviedes@asu.edu

[3]Baoxin Li is a Professor with School of Computing, Informatics, and Decision Systems Engineering, Arizona State University, Tempe, AZ, USA Baoxin.Li@asu.edu

Fig. 1. Left figure shows a triangular configuration with 3 stretch sensors reported in [7]. Right figure shows the new cross configuration with 4 sensors.

Following the footsteps and predictions of the first decade of efforts on wearable systems to enable ”at-home” clinical monitoring [6] and considering the potential of stretch sensors (e-textiles) approaches to close the digital-physical gap between sensor data and 3D spine posture during lower back therapy, we propose a wearable system with four light-weight stretch sensors configured in an X pattern, different from our prior work on scoliosis [7], as illustrated in Fig.1 (where the design of [7] is also shown for comparison). We use the same stretch sensors, Bluetooth transmitter, calibration, and software described in [7] to conduct our experiments. While our ultimate goal is to employ the sensors in building a system for evaluating PT exercises and providing real-time feedback to a patient, the current paper deals with only the specific task of classifying single-axis spinal motion using data streams from the sensors. This classification forms a critical building block for the task of detecting and tracking general spinal posture and motion, which can be decomposed into single-axis motions.

II. MATERIAL AND METHODOLOGY

A. *Defining Single-Axis Spinal Exercises*

Human spine is both strong and flexible, supporting versatile movements that may be difficult to model computationally. In [8, 9], three basic types of spinal motions are considered: flexion/extension, axial rotation and lateral bending. These basic types of motions can be used to form more complex spinal movements, such as those from exercises in physical therapy [10]. Although sometimes these basic spinal motions may be inconsistently coupled [8, 11], using them for modeling spinal motion leads to desired simplicity. Hence, similar to [12], in this work we define and consider six single-axis spinal motions performed around any one of the three axes in the physical world, where (with a subject standing upright) the x-axis is the line connecting both hip bones (left and right), the y-axis is the vertical line passing through the spine, and the z-axis is the line pointing forward from the subject. These motions/exercises are summarized in Table I. We also define a Neutral Posture (NP) motion, which refers to the upright standing pose.

In this work, subjects wearing stretch sensors are asked to perform these single-axis spinal motions, and the goal is to estimate the subject's motion from the sensor readings. To facilitate automated analysis of the data, we further introduce the following protocols:

- A sequence of exercises can be any combination of the above seven motions. However, each exercise in the sequence is supposed to start from NP and end at NP. (e.g a valid sequence can be [NP, Flex, NP, Bend Left, NP,...,NP, Rotate Right, NP])
- Once an exercise sequence starts and before it ends, a NP staying no less than 5 seconds must be performed.
- every single-axis spinal exercise should be performed within a duration no less than 10 seconds, and NP motions performed between any 2 single-axis exercises must stay no less than 3 seconds.
- Hip is not supposed to move with body during execution of any single-axis spine exercise.
- Head should face the same direction as body and neck should be perpendicular to the should line during execution of any single-axis spine exercise.

B. Stretch Sensor Configuration

Our prior work [7] has successfully used stretch sensors to monitor some types of spinal motions, and thus we choose to employ these light-weight sensors in this study, although we propose a new configuration of four sensors in an X configuration to capture the wider range of spinal posture in this work. As shown in Fig. 1, Sensor #1 is fixed on the left shoulder position, Sensor #2 on the right shoulder, Sensor #3 on the left hip, and Sensor #4 on the right hip. The other end of each sensor is connected to a metal ring fixed at the center position of the patient's back. As done in [7, 13], the sensors are connected to Bluetooth transmitter, which sends the sensor readings to an Android App that can visualize and save the data for further analysis.

We would like to elaborate the key reason for adopting the new configuration (as opposed to using the triangular configuration in [7]). It was found that the triangular configuration could not reliably distinguish rotation motions from bending motions. On the other hand, in the new design of the X configuration, this ambiguity is solved neatly: motions of Flex or Extend stretch or shrink all 4 sensors; motions of Bend stretch mostly only 2 sensors on either left-hand side or right-hand side but shrink 2 sensors on the other side; motions of Rotate stretch mostly 2 sensors on either diagonal of the X configuration and shrink 2 sensors on the other diagonal.

C. Data Acquisition & Pre-processing

In total, 19 sequences of single-axis spine exercises were acquired from three subjects who are of different body shapes, as described in Table II. With our wearable system, a sequence of spine exercises is captured by the stretch sensors in unit of pico Farad. The sensor readings are generated as raw data signals and transmitted to the Android APP through the Bluetooth transmitter. The APP receives the signals and stores them as a sequence floating-valued samples in a CSV file on the mobile device. The data sampling rate is 20Hz. For each subject, one sequence is chosen for testing, and the rest for training. Hence the training set has 16 sequences and the testing test has 3 sequences.

As shown in the left-hand side of Fig. 2, each sample in the raw data sequence can be viewed as a 4-Dimensional data array. However, the raw sensor readings are not amenable to analysis for the following reasons. First, the signals are noisy (e.g., due to sensor noise, transmitter noise, or respiration movement of the subjects), as shown in the top-right plot of Fig.2. Second, stretch sensors generate raw data in unit of picoFarad (pF), which is the unit describing capacitance and not intuitively related to body motion. Third, raw signals from the sensors do not have a common 0 position because of the body shape difference of the subjects (the garment hosting the sensors is fixed and the same for all subjects). Therefore, we introduce the following preprocessing steps.

First, a low-pass filter is applied to the samples for reducing signal noise, similar to [7]. Next, based on the specifications given by the sensor manufacturer, the capacitance values are mapped to length values, using a linear approximation. In practice, this needs to be calibrated further for each sensor due to sensor-specific variability of the

TABLE I

SINGLE-AXIS SPINAL EXERCISES

Exercise	Label	Description
Bend Left	1	bend in plane xy to left
Bend Right	2	bend in plane xy to right
Rotate Left	3	rotate in plane xz counterclockwisely
Rotate Right	4	rotate in plane xz clockwisely
Flex	5	flex in plane yz to front
Extend	6	extend in plane yz to backward
Neutral Posture	0	hold initial posture

TABLE II

SUBJECTS DESCRIPTION

Subject	Age	Height	Weight	Body Shape	Deformity
#1	24	174cm	58kg	Slim	No
#2	29	185cm	87.5kg	Medium	No
#3	24	179cm	75kg	Slim	No

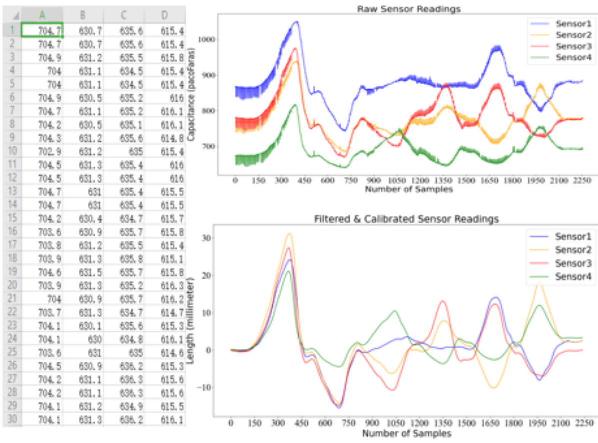

Fig. 2. Left figure shows raw data samples generated from 4 fabric stretch sensors. Top right figure visualize the raw sensor readings. Bottom right figure shows signals after calibration.

mapping function. Hence, for each sensor, we capture its minimum stretch reading as baseline value, maximum stretch reading and 1/3 stretch reading by stretch it step by step from initial status to maximum and from maximum to initial status. The lengths are measured and the linear mapping estimated accordingly. Last, for calibrating with respect to the subjects, we average a small number of NP readings for each of the sensors and use that as the baseline. Then we subtract the sensor readings by its respectively baseline (of the NP value). With this, we are able to calibrate the four sensor readings to have a common horizontal ”0” axis, as shown in bottom right of Fig. 2, which is more intuitive and supportive for interpretation.

D. An SVM Approach to Motion Classification

To facilitate the design and evaluation of a classification algorithm, all sequences were labelled, which was assisted by video recordings of the subjects when performing exercises (the orders of motions were also predefined to simplify the labelling task, although that does not completely define the labels since out-of-order exceptions may happen and temporal segmentation is still needed). The task of motion classification is to classify each 4-d sample (corresponding to four calibrated sensor readings) into one of the seven motions defined earlier.

We employ multi-class SVM [14] for classification instead of other techniques such as K Nearest Neighbour [15], neural networks, or Dynamic Time Warping [16] etc., since in this application the training set is relatively small and there is no “standard” motion patterns to compare against. However, we introduce the following technique to allow temporal correlation of the samples to be considered in classification: instead of using each 4-d sample as a data point, we use multiple samples in a slide window as an ensemble for SVM training and testing. For example, with a window size 5 and current timestamp t, an ensemble is formed by five sample, [S_{t-2},S_{t-1},S_t,S_{t+1},S_{t+2}], i.e., a 20-d data array. The label of the sample at t is given to this ensemble.

size=1	Test on All	Test on #1	Test on #2	Test on #3
Train for all	0.854	0.926	0.795	0.821
Train for #1	0.862	0.924	0.911	0.718
Train for #2	0.817	0.779675	0.93	0.69
Train for #3	0.758	0.7746	0.6695	0.8715

size=181	Test on All	Test on #1	Test on #2	Test on #3
Train for all	0.884	0.919	0.8415	0.8887
Train for #1	0.8485	0.9375	0.876	0.705
Train for #2	0.8088	0.791	0.912686	0.671
Train for #3	0.733	0.6524	0.687	0.8955

size=261	Test on All	Test on #1	Test on #2	Test on #3
Train for all	0.8989	0.935	0.8486	0.91
Train for #1	0.8457	0.9426	0.8636	0.7065
Train for #2	0.8165	0.8022	0.9276	0.662
Train for #3	0.78	0.7213	0.7317	0.921766

size=591	Test on All	Test on #1	Test on #2	Test on #3
Train for all	0.9108	0.94	0.8447	0.9453
Train for #1	0.83657	0.943	0.862	0.67
Train for #2	0.767	0.7887	0.928868	0.4827
Train for #3	0.844	0.8598	0.774	0.9399

size=641	Test on All	Test on #1	Test on #2	Test on #3
Train for all	0.906	0.9436	0.8305	0.9456
Train for #1	0.8267	0.948	0.834	0.671875
Train for #2	0.798	0.82435	0.885	0.627
Train for #3	0.843	0.86869	0.759	0.9483

size=741	Test on All	Test on #1	Test on #2	Test on #3
Train for all	0.8947	0.9459	0.8	0.943
Train for #1	0.8028	0.95374	0.76478	0.687
Train for #2	0.8077	0.83757	0.854859	0.6949
Train for #3	0.822	0.885	0.6899	0.96494

Fig. 3. This figure shows classification accuracy computed in various conditions where we train for any particular subject and test on sequence from any one of subjects, or we train for all subjects and test on all subjects.

III. Results

The entire data set of 19 sequences of single-axis spinal exercises includes 71143 data samples. As mentioned previously, 16 sequences including 59754 samples are used for training a multi-class SVM classifier with different window sizes, varying from 1 to 741, for searching for optimal parametrization. The remaining 3 sequences of 11389 samples (one sequence per subject) are used for testing. Particularly when we train with all subjects (first row in each sub-table in Fig. 3), we use ”Leave-One-Out” protocol and do 5 runs, each with one sequence of each subject being left out for testing. Then we average the accuracy for all 5 runs to be the result for this cell. The accuracy from each run was found to be very consistent since the variance is very small. When window size = 1, it basically means we treat each sample in the sequences as an individual data point to train and test the model and the accuracy of classification is shown in the first table in Fig. 3. Though 85.4% as an overall accuracy is achieved, other results show that different body shapes from different subjects do affect the ability of the system to recognize the spinal postures, if the training and testing subjects are different.

From the tables in Fig. 3, we can also see that the best overall testing accuracy when training with all three subjects can reach 91.08% with window size 591. Fig. 4 provides an intuitive view on significant improvement of classification accuracy when the window size goes from 1 to 261). However, as also shown in the tables, when the window

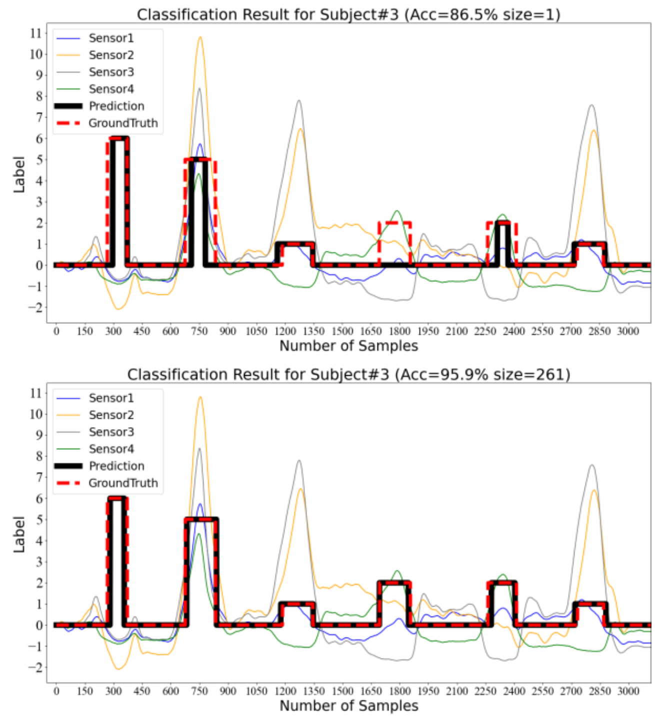

Fig. 4. This figure shows classification accuracy when size=1, size=261 trained for all 3 subjects, tested on Subject#3 in another set of randomly chosen data compared with its groundtruth.

size increases to 641 or 741, the performance actually drops, which is also intuitive: given the fixed and finite sampling rate, if the window size gets too large, it may start to include samples of different motions into the same ensemble, hence baffling the classifier.

IV. Discussion

The key motivation behind using an ensemble of samples within a window for training and testing is to allow the temporal correlation of the samples to be captured. Besides the sampling rate issue mentioned above, the speed at which the motions were performed may also impact the choice of the optimal window size. While these may point to the difficulty of being able to narrow down to an optimal window size, the results from the previous section clearly suggest that the window size should not be too small (like too close to 1) or too large (like reaching the typical duration of the individual single-axis motions). In practical system design, this may be one of the configurable system parameters that a user can adjust, and therefore we do not foresee this uncertainty may become a real issue.

Another evident limitation of this study is the small number of subjects, which suggests that it is unknown whether the current results may generalize to other body shapes. Nevertheless, as the three subjects in this study have very diverse body shapes, and the cross-subject training and testing performance is always significantly better than random guess, we expect that the overall approach should work for new subjects, although the current results also point to the necessity of calibration: when a new subject starts to use the system, he/she may be asked to perform a short sequence of the predefined single-axis motions, and the recorded data will be used to update the classifier for achieving user adaptivity.

V. Conclusion

Being able to determine spinal posture using only light-weight sensors is an essential capability for a wearable system that can provide realtime biofeedback for patients doing PT exercises at home. This paper reports an effort on this regard, considering spinal exercises involving only single-axis motions. Light-weight stretch sensors were employed, and a special X pattern was designed. After calibration and preprocessing, the sensor readings were used for classification. The classifier is based on SVM, which operates on a sliding window of the samples. Initial results based on three subjects of different body shapes demonstrate the approach is promising. In future work, we will further evaluate the approach on larger set of subjects before extending the work to more general spinal motions.

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