Wearable Sensor Array Design for Spine Posture Monitoring During Exercise Incorporating Biofeedback

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Abstract—Spine conditions and disorders manifested as back pain affect nearly everyone at some point in life. Physical therapy is an evidence-based treatment for non-specific chronic back pain, and monitoring spine posture during unsupervised therapeutic exercise is essential to achieve optimum results. Our research builds upon the progress in wearable sensor technology, spinal posture monitoring, and biomechanical biofeedback methods to address the need for monitoring compliance and correctness and support data collection to enable improved assessment of the effectiveness of physical therapy for spinal conditions. We designed and tested a minimalistic stretch sensor array, including best method to mount the sensors, and conducted proof-of-concept tests to demonstrate the feasibility of an end-to-end system including sensor setup, data capture, and real-time pattern recognition algorithm. Results for exercise correctness detection show encouraging sensitivity and specificity values obtained from multiple tests using a simulator and two sensor mounting options. Values ranged between 70-100% sensitivity and 100% specificity. A companion mobile app performed flawlessly, matching the results of the off-line setup while demonstrating real-time feedback (auditory and visual) after each exercise completion. The work is a major step towards a large study and future clinical trials which would lead to a new support system for treatment of low back pain (LBP) and other spinal conditions. The most significant transformative effect on physical therapy for the at-home component is that our method has the potential to solve the challenge of monitoring compliance and correctness with benefits across the board from individual patients to the general field of physical therapy.

Index Terms—biofeedback, soft sensors, spine posture monitoring, stretch sensors, therapeutic exercise, wearable sensors

I. INTRODUCTION

Spinal exercise physiology deals with improving strength, flexibility, and stability through therapeutic and fitness exercises [1]. Monitoring compliance and progress for therapeutic and fitness exercise remains a challenge given that accurate data can only be obtained in strictly supervised or highly instrumented environments. After training a subject on a given exercise routine, a physical therapist or coach can visually verify whether the exercise has been performed correctly. Moreover, when the subject is on his/her own, an automated method to monitor execution, track progress and provide real-time feedback is not readily available. One study reported that even though each exercise was described to the patients by visually performing it, and a descriptive brochure was given to each participant, the exercises were still performed inaccurately [2].

Wearable flexible sensors are presently used to monitor human activity and human health. It is possible to monitor physiological parameters as well as biomechanical activity using pressure and strain sensors. Wireless sensor networks allow data capture and transmission according to standard protocols. For a review of wearable sensors technology, see [3]. Monitoring spine posture and motion has been tackled using three types of sensors: elongation, bend and inertial sensors. Papi et al. conducted a systematic review of the state of the art of current use of wearables for the assessment of spine kinematics and kinetics [4]. The results show that there is a broad variety of sensor types, number of sensors and placement options. The review also indicates that the small number of publications found on portable assessment of spine motion revealed limited adoption of this technique, which is at an early stage of development and translation. The authors concluded that data logging and processing, systems design and fixation are areas to be improved to fully exploit the wide applicability of wearable technologies.

Wearable sensors may offer a way to monitor exercise correctness and provide biofeedback. Such approach has been reported in an early paper by Dworkin et al. [5]. The system consists of two elastic loops, one to measure spine length (loop A) and the other (loop B) to measure and correct for the effect of breathing noise as shown in Fig. 1.

Fig. 1. Two-loop wearable system for posture monitoring [5].
When the length of the spine was reduced below a threshold as a result of bad posture, an audible signal was produced. More recently, an equivalent method has been implemented in a T-Shirt to monitor posture using inductive copper wire sensors built into the fabric [6].

Accurate real time 3D motion capture of the human spine is of interest for medical diagnosis and rehabilitation of postural disabilities. A motion sensing system comprised of 3 inertial measurement units (IMUs) attached to the head, torso and hips is used in [7], and motion modeling is coupled to a spinal model which can be animated and monitored in real time. Monitoring was conducted for regular daily activities such as sit, stand and pick up objects. Correct motion analysis or exercise routines were not included in the study.

A wearable system for seating spinal posture has been reported in [8]. It consists of a garment-integrated plastic optical fiber sensor (effectively 3 bend sensors) and demonstrated comparable accuracy to expert visual analysis of detection and transition between good and bad posture. The authors suggest it has potential for biofeedback but indicate issues with inaccuracy of the expert visual analysis used as reference criteria. A more recent paper also reports a 3 IMU based system to diagnose progressive disease of the spine by detecting spine curvature and incorrect posture leading to neck pain [9]. The system allows posture monitoring and prescribes therapeutic exercise but does not support monitoring of their correct execution.

While wearable IMUs can monitor motion, to monitor physiological muscle activity wearable electromyography (EMG) sensors have been developed. EMG biomechanical biofeedback is most widely used in rehabilitation and therapy for applications including cardiovascular accident rehabilitation and low back pain (LBP) treatment [10]. EMG biofeedback is primarily used in sport performance improvement as part of sport psychology programs [11]. Products such as biosuits by Athos™ incorporate EMG sensors to monitor major muscle group activity (see Fig. 2) and performance has been benchmarked against research grade EMG systems [12].

Corrective and therapeutic exercise methods for scoliosis treatment are very important options to avoid worsening that may lead to hard bracing and surgery [13]. The two main approaches to assess progress during treatment are (i) non-invasive measurements related to static posture and (ii) real time monitoring during exercise. Progress has been reported on non-radiological methods for static posture monitoring and evaluation [14]. Research on modeling the spine curve from the surface of the back offers an alternative to invasive imaging (see [15]). Optical or surface measurements, namely moiré fringe topography and surface mapping have been used to evaluate static posture and to measure spinal curve [16].

A product to model the spine from a static back-surface scan, Idiag M360 ©, has been commercialized (see Fig. 3). The device previously known as “spinal mouse” records the inter-vertebral distances and positions in 3D along the patient spinal curvature, then an anatomical spine model is assigned the parameters measured from the spinal curve in different postures and visualized as a 3D static model.

While wearable IMUs can monitor motion, to monitor physiological muscle activity wearable electromyography (EMG) sensors have been developed. EMG biomechanical biofeedback is most widely used in rehabilitation and therapy for applications including cardiovascular accident rehabilitation and low back pain (LBP) treatment [10]. EMG biofeedback is primarily used in sport performance improvement as part of sport psychology programs [11]. Products such as biosuits by Athos™ incorporate EMG sensors to monitor major muscle group activity (see Fig. 2) and performance has been benchmarked against research grade EMG systems [12].

The research we have reviewed indicates that spinal curvature modeling and motion tracking related to posture changes during everyday activity have been successfully addressed with a combination of IMU and torsion sensors. On the other hand, the role of wearable EMG sensors in rehabilitation exercise appears to be complementary to kinematic sensors such as IMUs.

A key enabling technology for spine posture monitoring is the algorithmic component used to process the sensor signals and recognize the unique signature of a given exercise for a specific subject. Research in human activity recognition (HAR) using on-body inertial sensors addresses the challenge of general methods suitable for machine learning (ML) algorithms, namely that they can only be trained if large amounts of data are available [20], [21]. HAR methods are

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2 https://www.liveathos.com/
3 www.idigag.ch
useful to recognize human gestures, actions, and behaviors using data intensive feature extraction and multidimensional classifiers [22, 23]. Individualized biomechanical sensor data of low dimensionality are better suited for the use of simpler single or multi-class classifiers such as K-Nearest Neighbors (KNN) which may offer a simpler solution to the problems provided that data preprocessing such as denoising, signal normalization and alignment are performed prior to classification to improve robustness. Instances of biomechanical events and exercise routines can be treated as bio signal patterns analog to simple ones like those characteristic of cardiac and neurologic activity (see for example ECG preprocessing methods used to improve classifier performance reported in [24]).

From the introductory review in this section we can summarize the following gaps and opportunities:

1. Human activity recognition has been shown feasible using IMU sensors. Although minimization of the number of sensors for motion tracking and spine curvature modeling using IMUs is down to 3 sensors, each sensor still has 3 or more signals which have an impact on model complexity.

2. Despite progress in wearable biomechanical signal monitoring, and development of dynamic posture tracking devices, analytical signal processing aimed specifically at emulating expert supervision and progress tracking for spinal exercise remains largely unexplored.

3. Biomechanical biofeedback to improve rate of correct spinal therapy exercise executions under unsupervised conditions has not been addressed beyond simple positive reinforcement systems aimed at maintaining good posture.

4. Technology based, autonomous augmented biofeedback, i.e. “when technology offers the possibility to obtain information that is out of the reach of human senses or the information that is beyond human senses capabilities [25],” such as dynamic spine model visualization may be enabled by the progress in individualized spine model synthesis coupled to the progress in wearable sensor-based monitoring and supervision.

In this paper we will address recognition of correct therapeutic exercise execution using a sensor array simpler than other published methods and its potential to enable biofeedback and augmented biofeedback. The method includes minimalistic sensor array design, pattern recognition algorithm, and mobile app-based biofeedback.

The remaining sections are organized as follows: Section II describes the sensor array design, Section III presents the pattern recognition algorithm, Section IV provides details of the experimental method, Section V includes a summary of the results, Section VI discusses biofeedback requirements and options, and Section VII presents a discussion of the work, and Section VIII provides our conclusions.

II. STRETCH SENSOR ARRAY

Accurate measurement of spinal curvature, necessary to determine appropriate treatment, is obtained by methods including radiological exam and biomechanical tests. Moiré topography rasterstereography is a method used for mass screening for scoliosis (see Fig. 4). A 3D surface of the shape of the trunk is acquired and by checking the number of contours, heights of left and right shoulder, angle of left and right shoulders, distance between right and left based on pelvic reference line, interval between pelvic and misalignment between thoracic and lumbar spines against a set of reference values, a specialist determines presence and extent of the deformity [16]. Although, the sensitivity of this technique as a screening tool is good (74%), Asamoah et al. have reported that its false-negative values between 17–25% can be improved by other non-invasive methods such as ultrasound [26].

Fig. 4. Moiré fringe topography of a normal subject and image analysis (from [16]).

In general, rasterstereography allows an analysis not only of the posterior torso surface, e.g. to assess cosmetic changes due to the deformity, but also of the underlying spine. Dynamic rasterstereography has been used to analyze dynamic spinal curvature during gait [27]. As shown in Fig. 5, a set of markers placed in triangular fashion is used during scoliotic gait analysis. The method allowed measuring the sides of the four triangles with high accuracy while the subjects walked on a treadmill. Motion analysis in turn allows quantification of spinal mobility and flexibility.

Fig. 5. Marker placement for dynamic rasterstereography (from [27]).

Another study by the same researchers indicates that in dynamic conditions the use of only three markers, one over the spinous process of the 7th cervical vertebra and two over the lumbar dimples (shown in dashed lines connecting points 0-10-
11 in Fig. 5), are sufficient for an accurate reconstruction of the back surface across time [28]. Their methodology used a simulated wooden surface to prove the concept.

Based on the finding that a minimal set of 3 landmarks on the surface of the posterior torso can be used for dynamic spinal analysis during gait, we hypothesize that a single triangle can also be used for the study of spinal exercises where, in contrast to gait studies, the landmarks are on the shoulders instead of the lumbar dimples. Thus, resulting in an upside-down triangle. Moreover, to track the lengths of the sides of the triangle, the logical approach is to use stretch sensors. We also hypothesize that the time dependent sensor signals will be sufficient to automatically detect correct execution of lumbar exercise routines used in therapy.

Fig. 6 shows the sensor array built into a sports garment and an individual sensor with wireless app. The low power Bluetooth transmitter can go in a pocket between the sensors or on a waist belt. The transmitter supports up to 10 sensors.

The capacitance vs. extension curve shown in Fig. 7 illustrates the sensor behavior function used to calibrate the signal in mm.

The data capture method includes:

- Low power Bluetooth connection to laptop and National Instruments LabView software to capture data in comma separated values (.csv) file format.
- Raw data in .csv format is calibrated (remove baseline and convert pF values to mm) before analysis.
- Matlab software implementation of pattern recognition algorithm to process .csv data off-line.
- Low power Bluetooth connected Android or iOS application, which captures data files and executes

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Min</th>
<th>Typ.</th>
<th>Max</th>
<th>Units</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline Capacitance</td>
<td>410</td>
<td>445</td>
<td>480</td>
<td>pF</td>
<td></td>
</tr>
<tr>
<td>Sensitivity</td>
<td>3.10</td>
<td>5.39</td>
<td>6.39</td>
<td>pF/mm</td>
<td></td>
</tr>
<tr>
<td>Noise With Standard</td>
<td>0.13</td>
<td>0.16</td>
<td>0.50</td>
<td>pF</td>
<td></td>
</tr>
<tr>
<td>10 Channel Circuit (3)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Operating Temperature</td>
<td>10.0</td>
<td>30.0</td>
<td>°C</td>
<td></td>
<td>Recommended range only</td>
</tr>
<tr>
<td>Connection Pitch</td>
<td>2.54</td>
<td>mm</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All values shown at 3 LC</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The capacitance includes a cable capacitance of 117 ± 3 pF.

The transmitter specs are:

**CHARACTERISTIC**: **VALUE**

- **Name (ID)**: 16G3V1.97
- **Data Communication**: SPI (Slave)
- **Sampling Rate per Channel Configuration**: 15-100KHz (10-500KHz)
- **Sensing Channels**: 5 - 10
- **Power supply**: External 3.3V supply required
- **Range (max)**: 0 - 66000pF
- ***LSB Resolution (max)**: 0.001pF
- **Resolution / channel**: 16 bit

*These max specifications are not simultaneously available see configuration - resolution for details

The sensors used in the experiments are made by StretchSense ©. The stretch sensing element is bonded onto lycra to allow sewing into garments. The specs are shown below:

<table>
<thead>
<tr>
<th>Zone</th>
<th>Length (mm)</th>
<th>Tolerance (mm)</th>
<th>Width (mm)</th>
<th>Tolerance (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Active Sensing Zone</td>
<td>290</td>
<td>±1.00</td>
<td>10.0</td>
<td>±1.00</td>
</tr>
<tr>
<td>Overall Silicone Zone</td>
<td>85.6</td>
<td>±2.00</td>
<td>22.0</td>
<td>±2.00</td>
</tr>
<tr>
<td>Fabric Backing</td>
<td>127</td>
<td>±2.00</td>
<td>35.0</td>
<td>±4.00</td>
</tr>
<tr>
<td>Caudal Cable Length</td>
<td>1900</td>
<td>±1.00</td>
<td>0.46</td>
<td>-</td>
</tr>
</tbody>
</table>

**Stretch sensors are mainly used as actuators in human computer interfaces, static measurements, and to monitor conditions subject to a threshold.**

**www.stretchsense.com**
pattern recognition algorithm in real time.

Sensor noise, exercise time variance, and noise caused by breathing are considered. The actual sampling rate over Bluetooth with PC software is 10ms (50ms for Android capture). Sensor noise amplitude was measured to be 0.08\% (averaged over 3 sensors). Exercise execution time variability depends on the subject (typical 1.5\%). We normalized the duration of the region of exercise activity by re-sampling it to a fixed duration (e.g. 700 or 1200 samples). Breathing noise amplitude was found to be 1.12\% of the zero-stretch reading averaged over 3 sensors.

As a generic noise reduction method, we apply low pass filtering using temporal averaging on a 300ms time window. Table I shows the values of sensor noise and breathing noise for 3 sensors. Prior to any test, the sensors initial stretch is adjusted so that there will not be sagging during the exercise.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Length mm</th>
<th>pF Baseline</th>
<th>Noise Variance</th>
<th>Noise Std</th>
<th>Breathing Variance</th>
<th>Breathing Std</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>120</td>
<td>355.04742</td>
<td>0.02134150</td>
<td>0.14612907</td>
<td>3.66510585</td>
<td>2.58105379</td>
</tr>
<tr>
<td>S2</td>
<td>120</td>
<td>454.31568</td>
<td>0.03519573</td>
<td>0.18758995</td>
<td>4.50382266</td>
<td>2.12209753</td>
</tr>
<tr>
<td>avg</td>
<td>120</td>
<td>369.172285</td>
<td>0.0210620</td>
<td>0.1373216</td>
<td>4.50116148</td>
<td>2.12708998</td>
</tr>
</tbody>
</table>

### III. PATTERN RECOGNITION ALGORITHM

As indicated in the introduction, although conceptually exercise correctness recognition is a HAR task, it is also a low dimensionality biomedical pattern recognition problem. Typical methods based on deep learning and clustering algorithms are also not suitable given because of the need for large numbers of training samples per individual which is not feasible with spine therapy subjects. Thus, we chose a single class KNN algorithm working in sensor stretch space calibrated in mm. To choose the minimum number of training cases we use the statistical formula to estimate \( n \), the minimum sample size for a given margin of error:

\[
  n = \left(\frac{z \sigma}{E}\right)^2
\]

Selecting a margin of error of 3mm, and standard deviation of 5mm, for a 99\% confidence interval (\( z = 2.576 \)) we obtain a minimum sample size of 19.

Training data sequences are normalized in length, and noise filtered as explained before. The pattern recognition method consists of computing the Sum of the Point-wise Mahalanobis Distances (SPMD) between an individual test sequence and the average of the training sequences as the distance metric. Since we do not have enough data for a statistical model of the distribution, we use a heuristic to set the decision boundary. A hard pass/fail threshold was chosen heuristically such that about 80\% of the training set is in the pass region unless the training set variance is too small. In such case, we use a threshold larger than the max error within the set. This rule showed good results without overfitting.

One execution is called \( E_i \); \( i \) is the execution number with a maximum of \( n \) cases, \( j \) is the normalized data index, ranging from 1 to 1200. Thus, the normalized training set is \( \{ E_{ij} \}_{i < [1,n]} \), \( j \in [1,1200] \), the SPMD between test execution point \( E_{mj} \) and the average of the training set \( \{ E_{ij} \} \) is

\[
  \text{SPMD}_j(E_{mj}, \{ E_{ij} \}_{i < [1,n]}) = \sqrt{(E_{mj} - \bar{E}_j)^T \Sigma^{-1} (E_{mj} - \bar{E}_j)}
\]

\( \bar{E}_j \) is the mean of the training sequences at index \( j \) and \( \Sigma^{-1} \) is the covariance of the test set values at index \( j \). Clearly, the execution data itself, \( E_i \), is 3 dimensional. For simplicity, we have not included the indices for the 3 dimensions in the notation.

### IV. EXPERIMENTAL METHOD

#### A. First experiment: simulated data

Prior to testing the sensor array when incorporated in a garment for testing on actual subjects, and due to the time-consuming process of building custom garment, insuring proper setup, data transmission and processing, we decided to design a simulator device on which we could mount the sensor array to run the entire process as a validation test. The signals from the stretching induced by lumbar spine exercises on the triangular sensor array would not be exactly simulated but the data patterns are realistic enough to validate the end-to-end process and run feasibility tests with as many executions as needed (the simulator, transmitter and PC data capture are shown in Fig. 8).

![Data capture simulator](Fig 8. Data capture simulator)

We placed the vertices of the triangular sensor array on the periphery of an oval-shaped wood surface that is rotated using a manual crank. To create signal patterns resembling lumbar exercise, the bottom vertex has less positional variation than the two vertices above. The triangular array vertices are mounted on 3 spring loaded sliding rollers pressed on towards the surface centroid to keep them on the outer surface during rotation. When the surface is manually rotated about its centroid, the data resulting from the stretching of the 3 sensors in one revolution represent a unique pattern as shown in Fig. 9.

![Plots of the simulator data](Fig 9. Plots of the simulator data (pF vs sample number))
We captured 86 training cases for the oval pattern shown in Fig. 8. The crank was rotated manually at approximately the same speed, with a mean cycle time of about 13 seconds. For testing, we captured 47 cases including 17 correct sequences as follows:

- 13 correct sequences no variations,
- 3 correct sequences with noticeably slow rotation
- One correct sequence with jerky rotation

And, 30 incorrect sequences including:

- 6 sequences executed in reverse rotation
- 5 sequences with irregular speed including large variations
- 3 sequences including one or multiple pauses
- 9 sequences with added or deleted rotation
- One sequence with sections of reverse rotation
- 3 sequences initially correct but swapping data across 2 channels
- 3 sequences with rushed execution

The pattern recognition algorithm and data capture ran on a laptop PC. With a pass/fail threshold set to include 83% of the training we obtained the following results:

- 13/16 true positives or 81.25% sensitivity
- 27/27 true negatives or 100% specificity
- 1 of 3 fast executions passed

We also recorded data sequences generated using a different pattern (lobe-shaped) and tested them. The simulator with the oval and lobe-shaped patterns is shown in Fig. 9.

We recorded 15 sequences using the lobe-shaped test pattern. All failed the test, again performing at 100% specificity.

B. Second experiment: scoliosis correction exercise wearing sensor equipped garment

To demonstrate the feasibility and performance of the pattern recognition algorithm on actual therapeutic exercise, prior to future clinical trials, we conducted one test on a scoliosis patient. The shift, rotation, and elongation-based exercise is a typical component of scoliosis-specific physical therapy for postural correction. For a comprehensive review of seven major schools of scoliosis specific physical therapy see [29]. Scoliosis therapy exercises are performed in a variety of positions (e.g., standing, sitting) and gym setups (standalone and assisted by special devices).

The patient is a 22-year-old female presenting a double curve, upper to the left and lower to the right. She performed the therapeutic exercise while wearing a garment equipped with the sensor array. The corrective exercise prescribed by her scoliosis therapy specialist6 consists of:

1. Right lateral bend in the lumbar spine which also raises the left shoulder.
2. Lower rib cage rotation to the right (clockwise looking from the top).
3. Rotate the upper rib cage to the left against the lower rib cage.
4. Left lateral bend in thoracic spine to level her shoulders.

Fig. 10 shows the x-ray of the spine, the garment with the sensor array, and a diagram of the corrective exercise. The stretch sensors are labeled 1 for the left side, 2 for the top side, and 3 for the right side of the inverted triangle.

![Fig. 10. Scoliosis patient, x-ray and corrective exercise.](image)

Fig. 11 shows typical sensor readings during a scoliosis correction exercise routine. Data have been calibrated in mm and noise filtered. The four phases of the exercise have been labeled.

![Fig. 11. Sensor signals for scoliosis correction exercise.](image)

For the training set, we recorded 35 correct executions. In Section III, according to formula (1) the minimum number of

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6 Dr. Andy Pivonka, [http://www.pivonkahealth.com/](http://www.pivonkahealth.com/)
samples required for a margin of error of 3mm was found to be 19. We chose 35 samples as sufficiently larger than 19. The inter-execution signal variance was very low for all three channels, so we chose a threshold of about 1.8 times the max SPMD of the training set. For the testing set, we recorded a set of 9 expert validated correct executions and 7 recordings of other spine exercises.

Running the pattern recognition algorithm and data capture on a laptop PC, the results were the following:

- 9/9 true positives or 100% sensitivity
- 7/7 true negatives or 100% specificity

The results show performance improvement with respect to prior experiments done with a different method to mount the sensors (using elastic strap bands). In that pilot study using the strapped sensor method, we captured a small set of 20 training cases, and a set of 15 test cases including 7 correct executions with some variance, and 4 incorrect executions. In that test, we had achieved 70% sensitivity and 100% specificity. For the strap sensor setup, there was more variability in the test set than for the garment case, the threshold in that case was set using the 80% rule explained before.

V. SUMMARY OF RESULTS

Table II below shows the summary of the results of the experiments. The ground truth for the test set is indicated as true positives (TP) and true negatives (TN).

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Training Set Size</th>
<th>Test Set Size</th>
<th>Sensitivity</th>
<th>Specificity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulator Oval Pattern</td>
<td>86</td>
<td>47: 17TP, 30TN</td>
<td>81.21%</td>
<td>100%</td>
</tr>
<tr>
<td>Simulator Lobe Pattern</td>
<td>86</td>
<td>15TN</td>
<td>-</td>
<td>100%</td>
</tr>
<tr>
<td>Scoliosis Therapy Exercise (garment)</td>
<td>35</td>
<td>16: 9TP, 7TN</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Scoliosis Therapy Exercise (strap)</td>
<td>20</td>
<td>15: 7TP, 4TN</td>
<td>70%</td>
<td>100%</td>
</tr>
</tbody>
</table>

VI. BIOFEEDBACK

After computing the normalized training set, we use it as input to an android app which receives data from the sensors in real time and computes the SPMD giving a pass/fail indication immediately after the exercise.

Fig. 12 shows the interface of the Android app. The right-hand side shows color bands with real time readings in pF for 10 sensors, we only use the top 3. Real-time plots of the color coded sensor signals are shown on the main area of the screen. There is a start/stop touch control at the bottom left of the screen. After touching start, the label changes to stop. When the exercise is completed, the user touches stop, and the exercise is analyzed. A pass/fail message is shown along with an audible indication. The two check buttons at the bottom allow selecting whether the test is for the simulator (SIM) or the garment (GAR). As indicated before, the pass/fail decision is based on the normalized test set and the distance threshold computed during training. The app computes the SPMD between the test data and the average of the normalized training sequences.

An algorithmic adjustment was necessary for the Android app. The sampling rate of the app is about 4 times lower than the sampling rate of the laptop PC capture, thus the filters and the normalized duration had to be scaled appropriately.

![Android app for real-time biofeedback.](image)

In order to validate the pattern recognition algorithm running on Android as compared to the PC implementation, the android app has been tested with the garment as well as the simulator setup and the same data were recorded and validated with the PC based software. We conducted two app test sessions using the garment sensors, the first with 21 executions and the second with 26 executions. The sensitivity was 80% for the first test, and 70.37% for the second test. The second test included several adjustments to see the effect of baseline stretch of the sensors and corrections of small displacements garment.

We also tested the app with the simulator input, achieving perfect specificity and sensitivity scores for 15 tests.

We demonstrated visual and auditory feedback signals (message and sound) for the pass/fail message. We are exploring more advanced forms of biofeedback, including possibly a VR visualization of an animation of the patient 3D spine model.

VII. DISCUSSION

The importance of supervision and monitoring for the success of therapeutic exercise should not be underestimated. The drive toward evidence-based medicine and cost-effectiveness analysis for LBP treatment continues although in
general it has been difficult to determine if any one physical therapy protocol is more effective than others, and there is still controversy about the overall usefulness of physical therapy treatments. Limited data suggest that the use of physical therapy is increasing, but at a slower rate than other available treatments. One study suggested that adherence to an early physical therapy program in people with acute LBP was associated with lower subsequent health care costs [30]. The effectiveness of home-based exercise programs has been tightly linked to adherence and correct execution. A recent paper concluded that clinicians must estimate expected adherence level when recommending home-based exercises and should make changes in order to increase adherence. Research on health service delivery for patients with LBP in outpatient rehabilitation is in its infancy, with only a few studies describing service delivery factors related to patient outcomes.

Regarding scoliosis specific physical therapy, a recent study by Kuru et al., suggests that Schroth exercises performed in a clinic under supervision are superior to home exercise programs only, with results indicating significant improvement in Cobb angle, quality of life and trunk rotation [31]. The paper also underlines compliance issues in the young as well as exercise learning abilities, issues addressed well by biofeedback.

Although as explained in the introduction, there are alternatives to our minimalistic stretch sensor array approach, namely EMG and IMU, such systems have not been demonstrated to work for detection of correct execution of therapeutic exercise routines in real time. The drawback of EMG is that modeling spine posture from EMG signals alone has not been successful, and EMG combined with IMU would result in a large number of variables for which the model has not been developed yet. Systems using IMU combined with torsion sensors have been able to model spinal curvature and model motion, but also have a large number of variables and have not been demonstrated for correct exercise detection.

A simple biofeedback mechanism using an android app has been demonstrated and it is a solid starting point to pursue more advanced methods. Visual biofeedback has been reported as the preferred modality for biomechanical biofeedback [25], and with the rapid evolution of immersive visualization technology we expect it to be of relevance as suggested by the emergence of a physio-games industry [32]. Effectiveness of biomechanical biofeedback depends on simplicity and relevance. For example, personalization options such as visualizing a 3D model of the individual spine model with subtle real time hints (visual or auditory) during exercise may be considered instead of adding multiple biofeedback modalities that may result in redundancy, unnecessary distraction, or cognitive overload when not designed for mutual reinforcement.

Beyond compliance and correctness monitoring, our system opens the door to incorporating biomechanical biofeedback, i.e. creating a loop including sensing motion linked to spinal posture, processing the sensor signals, and sending a message back to the subject aimed at changing activity in a desired fashion. We refer to extrinsic or augmented feedback, i.e. augmented information provided by an external source, for example by an instructor or some sort of a technical feedback device or system. It may be simple end-of-cycle correctness of the performed action (positive or negative), on-the-fly feedback, or cumulative feedback depending on the duty cycle of the system.

Future developments will need to consider the following areas:

1. Garment design is an area of great potential, which includes the use of new sensors and miniaturization of transmitters, even the use of passive sensors that do not require a battery.

2. Scalability of the triangular array method and algorithm is an important topic. Multiple parts of the anatomy could be monitored by using more than one triangular array, or a triangular mesh. This is a very attractive option to monitor large body areas which may be the target of exercise.

3. The exercises considered so far can be monitored efficiently with stretch sensors. However, we should be open to the possibility of incorporating other types of sensors without sacrificing the minimalistic approach used so far. Critical sensing needs may arise for some new cases. For example, we may need to monitor balance which would require position sensors.

VIII. CONCLUSIONS

We have presented a complete methodology to monitor compliance and correctness of therapeutic spine exercise using wearable stretch sensors which can be attached by several methods including a garment. The cost of designing a custom garment had the benefit of reduced variability in the test data. The proof of concept reported here is a key component of the pre-clinical trial. We envision a system that will reach levels of compliance and correctness comparable to those of expert supervised therapy for the home-based component of the program. Moreover, it will be possible to increase the scope of data collection and processing to meet the needs of therapists and trainers individually or as part of a health service organization by storing and analyzing compliance and correctness data for individuals, groups, and populations. This would provide a significant new approach towards the evaluation of evidence-based therapy for LBP and other spinal conditions.

The signal processing exemplified is based on a simple classifier and associated distance metric and has shown suitable performance in terms of sensitivity and specificity. Given the low-dimensionality of the problem and the need for a simple real-time error-based method to detect correct execution, the method has been deemed appropriate for the initial scope of the work. Exercise correctness detection and incorporation of biofeedback has been demonstrated. The full implications of biofeedback on spinal physical therapy and the best approach (e.g. single or multimodal, immersive or non-immersive) remain as subject of future clinical trials.

Whether the proposed solution will require changes depends on evolution of requirements such as need for more sensors, and explainable feedback. Another aspect of the signal processing
model is the dynamic aspects related to patient progress. System parameter updates may go beyond periodic updates of the training set.

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