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Detection of Spine Curvature using Wireless Sensors
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Abstract: Ankylosing spondylitis (AS) is a progressive disease of the spine where the spine slowly stiffens and can eventually become completely inflexible. It can be difficult to diagnose in primary care, and thus there is often a 10-year delay in diagnosis. Within this study an intelligent wearable system is designed and developed to detect the displacement of the spine and provide the subject with a continuous posture monitoring and feedback signals when an incorrect posture is detected using accelerometer and gyroscope sensors. This wearable system can be used both to diagnose AS in early stages and to prevent subjects from lower back and neck pain caused by incorrect posture. We outline here the system which detects the curvature of the spine by using Shimmer sensors placed on the back and provides relevant exercises based on the user's pain records.
Keywords— Ankylosing spondylitis (AS); Shimmer sensors; Accelerometer; Gyroscope; Wearable devices

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All authors have checked the manuscript and have agreed to the submission.

Yours truly,

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Abstract: Ankylosing spondylitis (AS) is a progressive disease of the spine where the spine slowly stiffens and can eventually become completely inflexible. It can be difficult to diagnose in primary care, and thus there is often a 10-year delay in diagnosis. Within this study an intelligent wearable system is designed and developed to detect the displacement of the spine and provide the subject with a continuous posture monitoring and feedback signals when an incorrect posture is detected using accelerometer and gyroscope sensors. This wearable system can be used both to diagnose AS in early stages and to prevent subjects from lower back and neck pain caused by incorrect posture. We outline here the system which detects the curvature of the spine by using Shimmer sensors placed on the back and provides relevant exercises based on the user's pain records.

1. Introduction

Per the Office for National Statistics (ONS), the number of people with Lower Back Pain (LBP) and neck pain is increasing. There was almost 31 million days of work lost in 2013/2014 due to back and neck pains [3]. A common health problem amongst society is Lower back pain (LBP) which is a leading cause of activity limitation and work. This can be an economic burden on individuals, families, governments, industry and society at large. At least 50% of the European population will experience back and neck pain at some time in their lives [10]. Back pain can be caused by many different factors such as diseases, sprains, strains, injuries, or a pinched or irritated nerve which is caused by [24] bending uneasily or for long period of time, slouching in chairs, lifting, carrying, pushing or pulling heavy items, twisting uncomfortably, overstretching, driving or sitting in a hunched back position or for long times without taking a break or overusing the muscles during activities such as sport. Many people believe back pain is an ordinary symptom, but in some cases, back pain can be due to more than a strained muscle or other injuries. It can be caused by a chronic condition called Ankylosing Spondylitis (AS).

Ankylosing spondylitis (AS) is a progressive disease of the spine where the spine slowly stiffens and can eventually become completely inflexible. It is arthritis that strikes the spine, but it can move to other joints. [23]. In AS, the stiffness and chronic pain is caused by inflammation, and the degree of pain can vary from one person to another. AS is incurable, but the living condition can be made easier using medications and practicing healthy lifestyle tactics. It can be difficult to diagnose AS in primary care, and thus there is often a 10-year delay in diagnosis. It is not uncommon to see young people between the ages of 17 and 45 presenting to a rheumatologist for the first time having already developed severe and permanent stiffening of the spine due to AS [16]. Back pain is extremely common whereas AS is quite uncommon and many GPs have not been trained in detecting it. There are no symptoms that reliably point to the diagnosis although a questionnaire can help to diagnose it. This questionnaire consists of 6 questions related to 5 major symptoms: fatigue, spinal pain, joint pain/swelling, areas of localized tenderness, morning stiffness. X-rays and MRI scans can fail to detect the condition for several years after it has started. One of the most important clinical tests for early AS is a simple tape measure test: Schober's test[1] [9] [13]. This test essentially detects a loss of displacement or elongation in the lumbar spine when someone bends forward. Unfortunately, this test is usually not performed in primary care and the diagnosis is missed. Spinal movements in other directions can also be affected in AS: reduced rotation and lateral flexion of the spine, reduced chest expansion. The neck can be affected as well as the lower part of the spine. However, it is uncommon to develop problems in those areas without some reduction in Schober's test. Stiffness in AS is worse in the morning – if patients attend clinic in the afternoon the test may be normal. An ambulatory test may be more sensitive in detecting those with stiffness in the morning [4]. Previous approaches to measure spinal deformities (increased bend in the thoracic spine, straightening of the lumbar spine) are limited [11]. To date, work has not been carried out on measuring dynamic movement in the spine in AS. Ulster University has developed a system coupled with wearable gloves to measurement Rheumatoid Arthritis (RA) in finger joints [2,3,11,12]. The need to be able to measure stiffness objectively applies to AS even more than in RA, where other outcome measures exist to measure disease activity. Whilst there has been some work with wearable gloves, spinal movement research has not yet been applied to the study of AS. The ISRC team has therefore been developing expertise with conductive wearable fabrics merged with intelligent systems for stiffness measurements [11,12].

This research presents a wearable system with piezo-resistive stretchable fabric for the detection of displacement in the lumbar spine [19] using Shimmer sensors. This will facilitate an ambulatory test for people with back pain to achieve early diagnosis of AS; allowing monitoring of stiffness, daily posture and encouraging exercise. Patients with AS are normally given a list of specific spinal exercises to carry out over a 30-minute period each day. This technology will also be used to obtain objective measures of outcome in terms of spinal flexibility. The current clinical process relies heavily on questionnaires which asks the patient to rate the severity of their stiffness and pain. However, by the time the patients visit the clinic, they can forget their symptoms and the severity of their pains. The system therefore has a daily checkup section which allows the user to input their symptoms and the severity of them which is then calculated per the Bath Ankylosing Spondylitis Disease Activity Index (BASDAI) scoring method. Based on their BASDAI score the system

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[1] http://youtu.be/YULeqz1G1HU

promotes individual detailed exercises for the patient. Another important symptom of the AS disease is the kyphosis which is the medical term for "hunchback" appearance. When AS has affected the upper part of the neck, it creates major kyphosis which causes the head to collapse forward [22]. So being able to recognize hunchback appearance at the early stage can help in diagnosing AS.

2. Related Work

This section provides an overview of existing works on methods for detecting the curvature of the spine and maintaining a correct posture. In [5], an MRI scan was used to to validate a method of predicting the lumbar spine geometry from external (non-invasive electro goniometer) measurements. This allowed for the correct representation of the vertebral position and orientation relative to the sacrum using scaled anthropometric data and individual goniometric measurements. The results achieved by the research had a high degree of accuracy but the main problem is the degree of practicality as it is not practical and easy to have radiograph images taken anywhere. Another study [1] described the design and the development of a wearable smart T-shirt system which can estimate the lumbar arch length. This is estimated by processing the raw sensor data through a hybrid model developed to describe the peculiar characteristics of the e-textile sensors. This system used both e-textile and accelerometer sensors. The system has been tested in comparison with a stereo photogrammetric system showing a 2% error in length estimation. This study has no information on how the user's postures in different positions were handled. In [15], the study presented the use of novel textile strain sensor to detect a bend on the subjects back. The sensors used had a linear resistance vs. strain characteristics and a negligible hysteresis. The resulting measurement error was ±3.5% over a strain range of up to 100%. A garment prototype was developed by connecting the strain sensors with a silicone film on the back area of a tight-fitting stretchy garment. Even though this system showed a good result, they do not calculate the force of gravity against the subject. This can result in system failure if the subject is standing or sitting on an uneven surface.

A. Intertial Sensors

Inertial sensors are primarily accelerometers and gyroscope sensors and are based on inertia. An accelerometer measures specific force and acceleration, and a gyroscope measures the rate of change of angles. An inertial measurement unit combines multiple accelerometer and gyros (usually three of each) to generate a 3-dimentiaonal (3-D) measurements of accelerations and the rate of angle change, this produces data from x, y and z axis of both accelerometer and gyroscope sensors. These sensors are popular amongst health monitoring systems as they are usually very small, have long battery life and are easily attached to human body. DorsaVi ViMove sensor are inertial sensors, popular with many health clinics. DorsaVi's hardware contains two movement sensors, two EMG (muscle activity) sensors, a recording and feedback device, and a charging dock. The movement sensors consist of a 3-D accelerometer, a gyroscope, and magnetometer which collects movement data in three dimensions as well as measuring the force and the impact. The collected data are transferred wirelessly to the recording device. The data can be collected remotely for up to 24 hours or live data can be received by connecting directly to the PC [6].

B. E-Textile Sensors

E-textiles are fabrics that can be stretched and allow electronics and interconnections to be embedded into them, offering physical flexibility that cannot be accomplished as easily with other electronic manufacturing techniques. There are two different categories of smart textiles: one is aesthetic and second is performance enhancing. Aesthetic instances are fabrics that can change their color. Many of these smart textile fabrics receive energy from the environment by harnessing harnessing vibrations, sound or heat, reacting to this input. There are also performance enhancing textiles sensors, which are very useful within the sport and military industries. These smart textiles assist in controlling and adjusting the body temperature, its can control the vibration within muscles, and reduce the resistance of the wind. These can all have a huge impact on an athletic performance. There are other smart textile fabrics that can protect the wearer from dangerous environmental threats such as space travel effects and radiation. Bend can also be sensed by textile sensors by detecting the fabric being shortened or stretched which is calculated by evaluating the percentage of change in electrical resistance. Many studies have used textile sensors to detect the curvature of the back [14,15,18,21].

C. X-ray Sensors

Another approach to detect the curvature of the spine and recognize incorrect posture in the human body is via radiograph imaging which includes techniques such as computer tomography (CT) and magnetic resonance imaging (MRI). These techniques are widely used as they can create a detailed image of the human spine. However, these systems cannot monitor spine during daily activity and thus cannot provide the awareness that comes with monitoring and user feedback. This technique is more suitable for clinics and hospitals but is not suitable for personal and field use [8].

D. Fiber-Optic Bend Sensors

When detecting the curvature of spine and incorrect posture, fiber-optic sensors are a popular approach. Fiber-optic bend sensors (or optical goniometers) include a light source, a plastic optical fiber (POF) with an abraded section in between and a photosensitive detector. Light is released into the POF at one end and next it is detected at the other end.

When the optical-fiber is bent, the light (intensity) is lowered. When a section of POF has been cut, polished or raised, the loss of light is often increased. Due to the sensing principle, single fiber-optical bend sensors are unipolar devices [7].

3. Methodology

Our system collects posture data using 3 sensors placed on a subject's back. The collected data is classified as one of the incorrect sitting posture, so when a user changed their correct posture to an incorrect posture the system can recognize it and notify the user. If the subject is sitting in an incorrect posture, the system should notify the user on the specific incorrectness of the posture. The system will be able to save the users daily posture record which can help the doctors to diagnose specific diseases such as AS. The system saves each test record for patients. The user is asked to fill in a daily questionnaire to assess their level of AS. The system will calculate a grade based on user answers. Then, depending on their score, it will provide the user with specific exercises and instructions on how they should be done. The grade is calculated using the Gold standard for measuring and evaluating disease activity in Ankylosing Spondylitis, which is called BASDAI (Bath Ankylosing Spondylitis Disease Activity Index).

A. System Design

The system was developed using 3 wearable wireless sensors created by Shimmer to collect accelerometer and gyroscope data. The dimension of these sensors are 51mm*34mm*14mm and they include highly accurate and scientifically reliable raw, calibrated or un-calibrated data to allow complete control over capture and interpretation of sensed data in real-time. The Shimmer sensors were placed on the participant's back using piezo-resistive stretchable fabric. Sensor 1 was placed on Cervical spine, second sensor was placed in between all Thoracic spine and sensor 3 was placed on lower Lumbar spine. Figure 1 shows the positions that the sensors were placed on the body. MATLAB software is used to connect to the sensors and record the receiving data to .dat files. The system includes a graphical user interface to create a user friendly application.
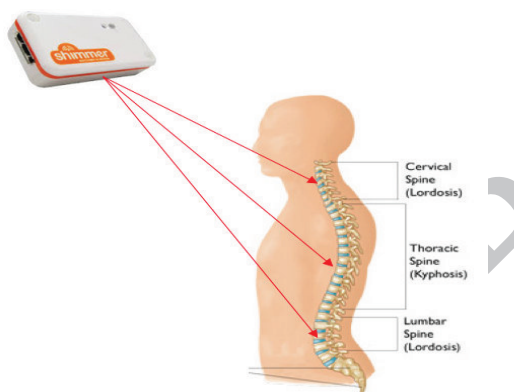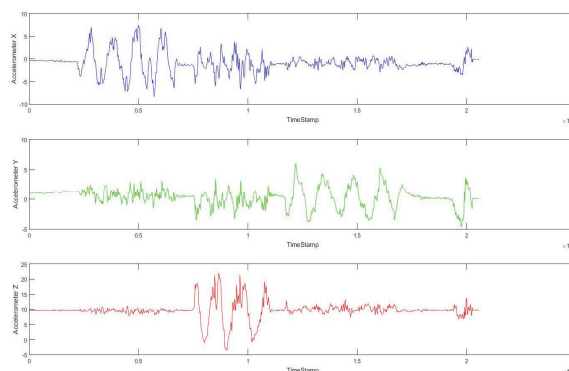

Figure 1 - Sensor Location

Figure 2 - Sensors Setting Validation

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B. Data Collection

The data was collected from 3 sensors placed on 5 subjects backs. Each subject was asked to perform two incorrect posture associated with AS (Hunchback and slouching back). They were recorded 4 times, which in total gave us 120 data files. 60 for hunched back posture and 60 for slouching back posture. This gave us 20 test runs for each sensor. The recorded data library is then used to train and test the system. Before the data collection process began, the shimmer sensors had to be tested that are working and are set correctly. This process was done by testing each shimmer sensor's accelerometer and gyroscope with a 60 second running time. For the first 10 seconds, the X axis was moved, then in the next 10 seconds there was no action performed so that we could distinguish between the two actions. The same process was repeated on the other two axes (Y and Z) with 20 seconds spent on each. Figure 2 presents the plotted accelerometer data to validate the shimmer sensors setting. Each test data was labeled uniquely to represent the body posture type the subject was performing during the recording process, which sensor (s1, s2, s3) and the test number. For example, HBs1t1.dat represents the recorded data from subject in a hunched back position with sensor number 1 placed on cervical spine and assigned test number 1.

C. Data Pre-processing

In order to remove the noise from the data, a mean signal filter was applied to all the row accelerometer and gyroscope data imported by the meanSignalGenerator Function file. The mean signal filter (Function meansignal (signal, windowlength, overlap, zeropad)) calculates windowed (over- and non-overlapping) mean of a signal using the specified

window length. signal is a 1-D vector, windowlength is an integer length of the mean signal window in samples, overlap is the number of samples to overlap adjacent windows, zeropad is a flag for zero padding the end of the data. The window size and the overlap size given to the mean signal filter were 10 and 9 respectively. Decreasing the window size allowing faster activity detection, as well as reduced resources and energy needs. Large data windows are normally considered for the recognition of more complex activities.

D. Feature Extraction

Next, after all the row accelerometer and gyroscope data was cleaned of noise and pre-processed, the signals were uploaded to create a template for each sensors accelerometer and gyroscope x, y and z axis within the two different incorrect seated posture categories related to AS. This process was done by developing function files, templatesfrom1data, templatesfrom5data and templatesfrom20data functions.
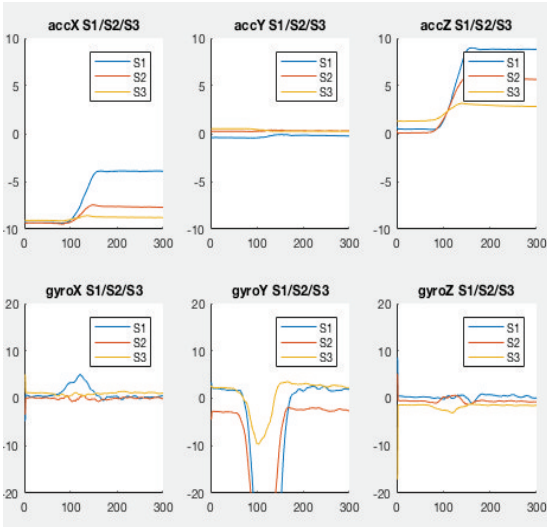

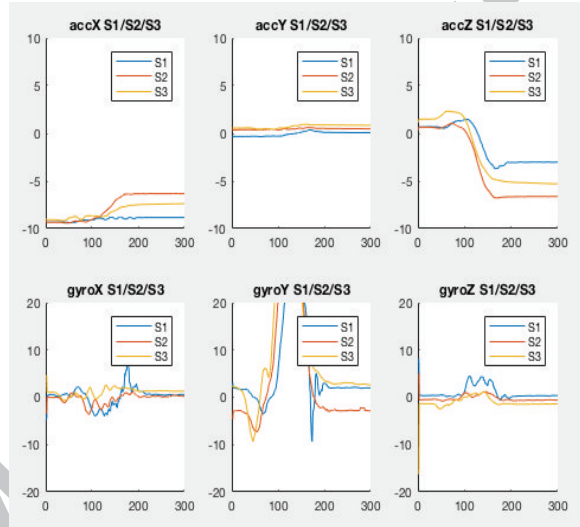Figure 3 - Hunchback Posture Template   Figure 4 - Slouch back Posture Template

The templatesfrom1data function assigned the cleaned data from tests 1 in all the postures to templates. This was done for testing purposes in order to have a larger test data set. This was repeated for templatesfrom5data and templatesfrom20data. All these function files, call the signalCleaning function. The signalCleaning function imports the recorded data for each posture, where then the mean value for the signals is calculated using the meanSignal function described earlier in the data pre-processing section. These template functions then receive the pre-processed data and use the generatesignalTemplate function file to create templates. The generatesignalTemplate function file was developed to find the average of given inputs/signals using *signalAverage =(data+data+…)/dataLenght;* method. Next within the templates function, 6 new variables are created for each sensor in each posture category (Hunch Back/ slouch back sensor 1/2/3 (accelerometer x, y, z and gyroscope x, y, z)) using the generateSignalTemplate function file, which calculates the average of the given signals. After the templates were created, they were plotted to show a visual understanding of each templates unique shape. Figure 3 and 4 are the plotted version of the 36 calculated variables of the accelerometer and gyroscope x, y and z axis (18 hunch back variables and 18 slouch back variables). Once the reflective samples are created, we can use them in the correlation process.

E. Classification

We used the SAX (Symbolic Aggregate approXimation) method for posture classification (see Figure 5). This method allows for dimensionality reduction and indexing with a lower-bounding distance measure [20]. This method decreases the dimensionality of a numerical series, which involves converting a time series into a short chain of characters. SAX involves a two-step process: (1) Piecewise Aggregate Approximation (PAA) and (2) conversion of a PAA sequence into a series of letters. PAA divides the data set of length n into w equally spaced segments or bins, and computes the average of each segment [17].
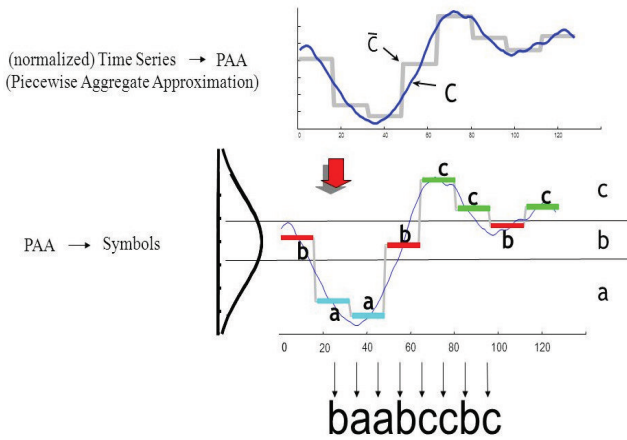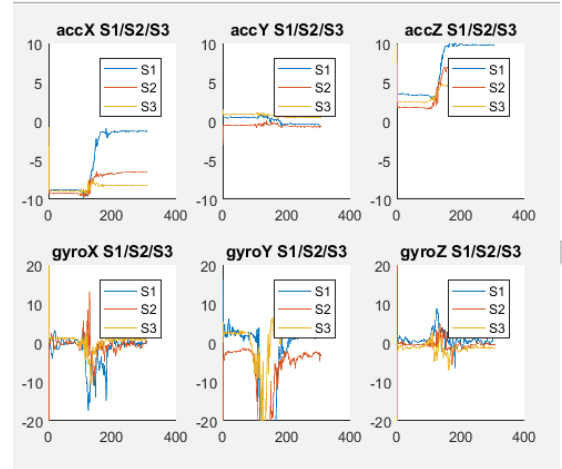
Figure 5 - Symbolic Aggregate approXimation

Figure 6 - Hunched Back posture test data

There are two main functions within the SAX source, firstly the timeseries2symbol function which takes in a time series and converts it to a string. This function receives 4 inputs, the raw time series (data), the length of the sliding window or the length of the raw data (N), the number of symbols in the low dimensional approximation of the sub sequence (n) and the number of discrete symbols (alphabet_size). This function returns two outputs, a matrix of symbolic data (symbolic_data) and the location of the first occurrences of the strings (pointers) [20]. The timeseries2symbol function is used to convert all of the templates to a symbolic string. This function then is called when the new data is collected to be tested. So the new test raw time series is converted to a symbolic string and is compared against the all of the posture template symbols. The second main function in the SAX method is the min_dist, which processes the minimum (lower-bounding) distance between the two strings. Here the test data string is compared to each of the template strings. The smallest number means the least distance which means that the test data is very close to a specific posture template, hence the system can notify the user of the incorrect posture they are adopting.

4. Results

A. Testing and Results

This system was developed based on data received from 3 Shimmer sensors. 3 was the minimum number of sensors that could be used in order to lead to accurate classification. A larger number of sensors can be used but it will not have any more significant impact in the classification results would be more expensive for such a commercial system. When designing the system, two approaches were taken. One was to use the pre-recorded data, which allows a user to choose a test, import the file and compare it with the templates symbols. We could then evaluate the correlation between the signals. This was developed mainly for development and testing purposes. The second approach of data classification is continuous throughout the recording of new accelerometer and gyroscope data.
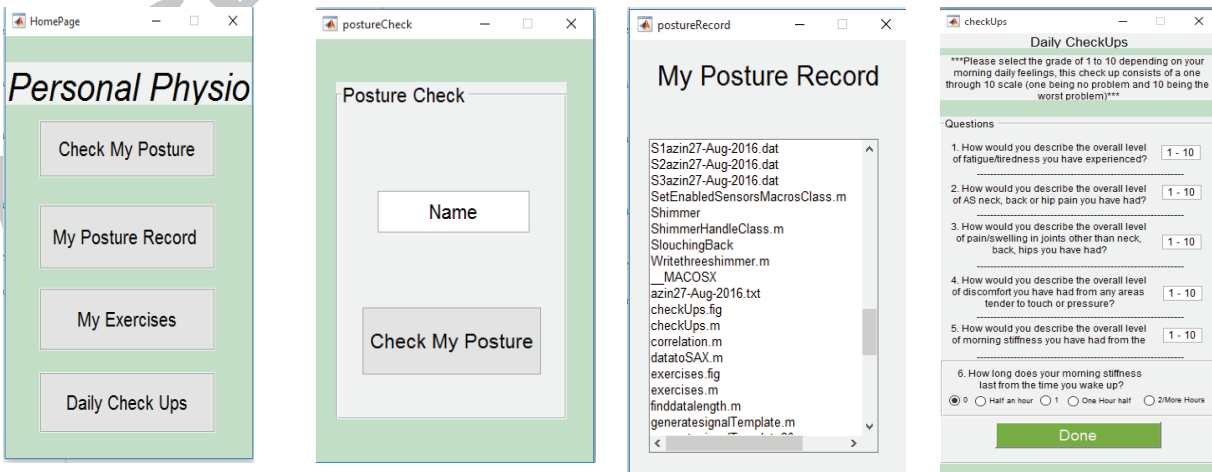

Figure 7 (a) Home Page   *(b) Posture Check*   *(c) Posture Record*   *(b) Daily Checkups*

This process was completed by comparing the performance of the posture recognition approaches on the 10 second long testing scenarios. The test was recorded using a limited number of 5 healthy subjects (2 male and 3 female aged between 25 and 60). The user can check their posture by recording new data files at anytime through visual assistance in the GUI. When recording a new posture data point, the system provides a selection of responses to the user, such as a text box to inform the user of their posture and 3 visual graphs. These graphs are the plotted graph of the users recorded posture data and the posture templates. Figure 6 represents the plotted graph of a user testing the system while in a hunched back posture. It can be seen that the new data and the template are almost identical. The systems graphical user interface was developed in Matlab. Figure 7a represents the first screen the users will interact with.Figure 7b is the posture check view where the user can input their name and check their posture. The system receives the name and using the computers date, it creates new files to record the subject's posture data. Then the system cleans, filters and classifies the data against the training dataset and informs the user about their posture details. The user or their GP can access the users posture record by simply looking up the posture record view (Figure 7c) named with the user's name and the date the recording was done. The user will have to do a daily check up (Figure 7d) in order to access their daily exercises. The daily check up calculates the score and when the user is going to the exercises section, depending on the calculated score the appropriate exercise is displayed for the user (figure 8).
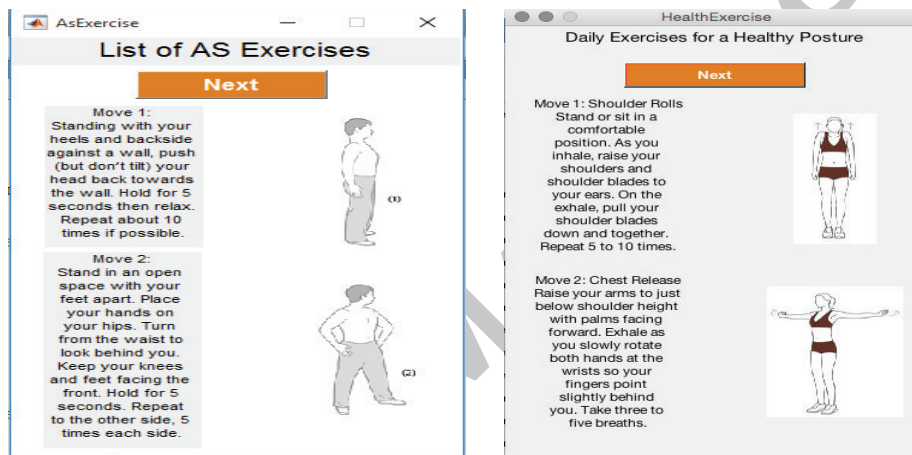

Figure 8 - Daily Exercises

A series of tests were carried out to produce results from each posture. These results can be seen in tables 1, 2 and 3. The testing was done in 3 different ways. The first stage of the process involved using the templatesfrom1data function file. The posture templates for the postures were created using one datasets (test1) for each category. This gave us a larger data set for testing (test2 to test20). Table 1 represent the classification result with 85% accuracy. Within tables 1, 2 and 3, '1' represents correct classification and the value next to 1 is the value of the minimum distance between the test data and the template. '0' represents incorrect classification. The results from the templatesfrom5data function are in table 2. The system classified the data with 95% accuracy.

	Hunched Back (HB)	Slouched Back (SB)
Test 1	1 | 4.3466	1 | 6.1788
Test 2	1 | 1.003	1 | 4.8118
Test 3	1 | 5.377	0
Test 4	1 | 2.4034	1 | 2.3899
Test 5	1 | 2.0336	1 | 2.8663
Test 6	1 | 6.8973	1 | 6.0978
Test 7	0	1 | 6.1202
Test 8	1 | 5.2967	0
Test 9	1 | 3.5106	1 | 1.91
Test 10	1 | 3.5818	1 | 4.7469
Total	9/10 90%	8/10 80%
Total %	85%	

Table 1 - Classification Result (1 Training Data)

	Hunched Back (HB)	Slouched Back (SB)
Test 1	1 | 6.444	1 | 1.0465
Test 2	1 | 5.2296	1 | 3.5186
Test 3	1 | 5.1433	0
Test 4	1 | 1.4649	1 | 2.3899
Test 5	1 | 2.5007	1 | 2.8663
Test 6	1 | 4.7836	1 | 5.0978
Test 7	1 | 2.7452	1 | 4.1202
Test 8	1 | 3.5306	1 | 1.0978
Test 9	1 | 6.5106	1 | 2.4001
Test 10	1 | 4.0681	1 | 4.1
Total	10/10 100%	9/10 90%
Total %	95%	

Table 2 - Classification Result (5 Training Data)

The last stage of testing involved using the templatesfrom20data function file. The posture templates for the postures were created using 20 datasets. Table 3 represents the classification results with 100% accuracy for all tests. This shows that the larger the training dataset is, the more accurately the system can distinguish between the postures.

	Hunched Back (HB)	Slouched Back (SB)
	Hunched Back (HB)	Slouched Back (SB)
Test 1	1 | 1.0406	1 | 2.7483
Test 2	1 | 1.9202	1 | 2.3581
Test 3	1 | 0	1 | 4.1943
Test 4	1 | 3.0092	1 | 5.9834
Test 5	1 | 1.1543	1 | 1.1154
Test 6	1 | 2.9854	1 | 2.9547
Test 7	1 | 5.5284	1 | 6.8511
Test 8	1 | 1.0944	1 | 1.2023
Test 9	1 | 5.1633	1 | 1.9403
Test 10	1 | 3.8564	1 | 3.5488
Total	10/10 100%	10/10 100%
Total %	100%	

Table 3 - Classification Result (20 Training Data)

B. System Performance Evaluation

The results show the validity in using off-the-shelf sensors for detecting the curvature of the spine. Larger training sets led to higher accuracies in the classification process. The shimmer sensor battery life is quite good allowing for days of running and testing without needing to be recharged. There was however times that sensor connections were lost leading to restarts in testing. During the testing process, it was also noticed that the Shimmer sensors needed to be placed in the same orientation as template data in order to result in correct posture detection. While the orientation of the sensors is important, the location of the sensors do not have to be on the same spot as the templates so long as they are placed within the area of the 3 spine locations i.e. (Sensor 1 on Cervical spine, sensor 2 on Thoracic spine and sensor 3 on lower Lumbar spine). They will have record accurately and can be classified correctly. Currently the system records data when so instructed. This was done, as a proof of concepts but ideally the system should be monitoring the subjects continuously to be able to have a valid posture record and diagnosing AS. For example, in AS disease the patient spine slowly stiffens and can eventually become completely inflexible which results in a hunched back appearance. The hunch back appearance can gradually get worse, but with the system continuously monitoring the users, it can detect the condition getting worse and adapt their exercises according to the degree of condition.

C. Future Work

This system aims to help diagnose and monitor the stages of AS. The system can be improved to not only detect and record seated postures, but also to detect and record incorrect standing and walking postures. This can be achieved by adding more data to train the system and then to transfer the actual system from the computer on to a mobile phone. An automatic Schober's test could be added to the system. Schober's test is a measurement used for AS, which measures the Lumbar spine mobility. In this examination the patient is standing up with their feet hip width apart and with their back to the examiner. The examiner determines the location of the lumbosacral junction by outlining the location of the dimples of Venus. The intersection on the top of the dimples of Venus are marked by drawing a horizontal line. This line acts as the landmark. The second line is marked 10 cm above the first and the third is marked 5 cm below the first line. The difference between the measurements in erect and flexion positions indicates the outcome of the lumbar flexion. An examiner physically present can do this easily but our system can be modified to perform the test without the need for the presence of an examiner. In order to develop this, accelerometer and gyroscope are not sufficient as there is no way that the system can determine the distance between each sensor. Therefore, the best option is to design the system in such a way that the phone camera can be used to do the Schober's test. Here the image would be acquired using a mobile phone with the exact locations marked and recognised through image processing so the distance between the locations can be measured. The approach would be practical and allow subjects to monitor their curvature progress from home while minimizing the use of X-rays and MRIs. In future, a larger number of subjects would be useful in order to solidify the validity of the results. We would also of course need to conduct a clinical study to validate our results. Finally, the Shimmer sensors are portable but a superior approach would be where the accelerometer and gyroscope are embedded within wearable clothing.

5. Conclusion

This paper outlines the development of a system to detect incorrect posture as an early symptom of Ankylosing spondylitis (AS) disease. The system classification performance was tested and shows that the system is reliable with a high accuracy. This was accomplished by collecting, processing, cleaning and filtering raw accelerometer and gyroscope data collected from 4 subjects. The system was trained to distinguish between two incorrect posture (Hunch Back and Slouch Back) related to AS using prerecorded data. The user can check their posture in real-time, the recorded posture in then classified and each user is notified of their postures. The subject's posture is then saved with the date they were recorded allowing a physician to monitor each patient. The user also completes a daily questionnaire in order to be offered recommended individual exercises.

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