Postural Data Analysis using AI-powered Classification Models

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***Abstract*—Nowadays, more and more people are working remotely or in professions that require them to sit for long periods of time. Unfortunately, spending too much time in a seated position can lead to a range of physical and mental health problems, such as musculoskeletal discomfort, headaches, and respiratory issues. These problems are often exacerbated by poor posture, which is common when sitting for extended periods of time.**

To address this issue, we have developed a system for classifying sitting postures using sensors and machine learning algorithms, achieving 100% of accuracy with a set of seven fiber Bragg grating sensors. We have further optimized the multisensor system by studying the optimal number of sensors and their positioning on the spine, achieving over 95% accuracy in classifying upright, kyphotic, and lordotic positions with as little as only two devices.

***Index Terms*—Postural Analysis; Machine Learning, Feature Selection; Soft Strain Sensor; Fiber Bragg Grating; Flexible Wearable**

I. Introduction

Back pain is a common problem, affecting over 550 million people worldwide today [1], [2]. This discomfort can have various causes, including age, stress, lack of sleep, sedentary lifestyles, and poor posture, among others. These factors can impede diaphragm mobility, respiratory function, and chest expansion, leading to an increased risk of cardiovascular diseases [3]–[5].

To address this issue, posture analysis is continuously exploring cutting-edge methods to produce increasingly accurate results and better therapeutic decisions. Artificial Intelligence and Machine Learning have demonstrated their ability to quickly and accurately process large amounts of biomechanical data, making them ideal for analyzing posture.

Postural analysis evaluates the alignment and positioning of the body during standing, sitting, or movement, by assessing the interactions between anatomical structures and their relative arrangements. To enhance the accuracy of current postural analysis methodologies, we propose a system based on fiber Bragg grating (FBG) sensors and machine learning techniques. This system can accurately categorize the three most common human postures: upright, kyphotic, and lordotic (see Figure 1).

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Fig. 1: The three sitting positions involved in the acquisition protocol: (a) Upright; (b) Kyphotic; (c) Lordotic.

The aim of the work is thus to present a new system to assess the human posture and alleviate the major drawbacks of the current methods, which include:

- *Visual Observation*: it is the approach used more frequently in clinical settings to evaluate posture. The fact that this procedure doesn't need any equipment is its lone and unique benefit. Quantitative data cannot be collected using this strategy. Hence, slight postural changes cannot be seen [6].
- *Posture Grid Analysis*: it is an approach for postural analysis in which the alignment of the body is evaluated using a grid. The therapist assesses the patient's alignment by comparing it to the grid's lines when they stand on it. Posture grid analysis has the advantage of being an easy, affordable method that doesn't need sophisticated equipment. One disadvantage, though, is that it only offers a 2D picture of the body's alignment and ignores mobility or dynamic posture [7].
- *Static and Dynamic Posturography*: it involves measuring the center of pressure using a force plate, which can be done while standing or walking to assess balance and stability. Static and dynamic posturography have the advantage of providing objective, quantifiable information about postural control, which is helpful for tracking progress and detecting particular areas of deficiency. The fact that it needs specific tools and knowledge, however, makes it a more expensive and time-consuming procedure [8].

- *Photogrammetry*: the patient is photographed from various perspectives, and the photos are then processed to determine the patient's alignment and posture. The fact that photogrammetry offers a non-intrusive and non-radiating method for assessing posture is one of its advantages. Furthermore, it can record 3-dimensional postural data and deliver a more thorough assessment of body alignment. The process is more expensive and time-consuming since it takes specialized software and knowledge to interpret the photos [9].
- *Gait Analysis*: In order to assess the patient's posture and body alignment, the walking pattern is examined. The therapist may assess the patient's gait using a force plate or video camera. Gait analysis offers a dynamic evaluation of postural control, which is one of its advantages. The need for specific tools and knowledge, however, makes it a more expensive and time-consuming procedure. Also, it might not be appropriate for those who are unable to walk on their own or who have severe mobility issues [10].

Contrary to visual observation and manual measurements, which are susceptible to human error, artificial intelligence can offer a standardized and quantitative study of posture, enabling more precise and dependable results in various medical fields such as decision-support systems, computer-aided diagnosis [11], and predictive modeling for treatment results [12]–[14], either exploiting clinical notes [15] or imaging [16].

To obtain more objective data and more specialised treatment regimes for each patient, we developed a system consisting of a chain of seven fiber Bragg grating based sensors (FBG) placed along the vertebral column [17], and a two-steps machine learning-based pipeline. In the first step, we determined how many and which sensors were most relevant to the analysis (i.e., feature selection) through a Decision Tree (DT). This step is crucial for reducing the number of sensors, thus improving system efficiency by reducing costs and enhancing the user's comfort and usability. Secondly, we trained and evaluated the performance of a few classifiers, i.e., DT and Support Vector Machine (SVM), to identify the aforementioned human postures (upright, kyphotic, and lordotic) over the number of the sensors employed.

Our system achieves 100% of classification accuracy and over 95% with as little as two (DT) or three sensors (SVM), and can be exploited in real-time. Moreover, these machine learning models are fast to be trained, requiring a relatively small amount of data (if compared with more recent deep learning methods), and are light enough to be employed on edge (i.e., the wearable system) in further developments. Other state-of-the-art approaches are based on the use of smart cushions employing pressure sensors. Although they provide a non-invasive and easy-to-use solution, our system based on wearable sensors applied to the spine offers accurate and real-time data detection, as they can capture the slightest changes in the alignment of the spine. Therefore this feature makes our solution usable not only in sitting postures but also in other scenarios, solving the major drawback of those other systems.

II. Materials and Methods

This Section describes the wearable system used to collect the experimental data, the experimental protocol, the signal pre-processing techniques, the feature selection algorithms, and the classification models used to classify the three postures.

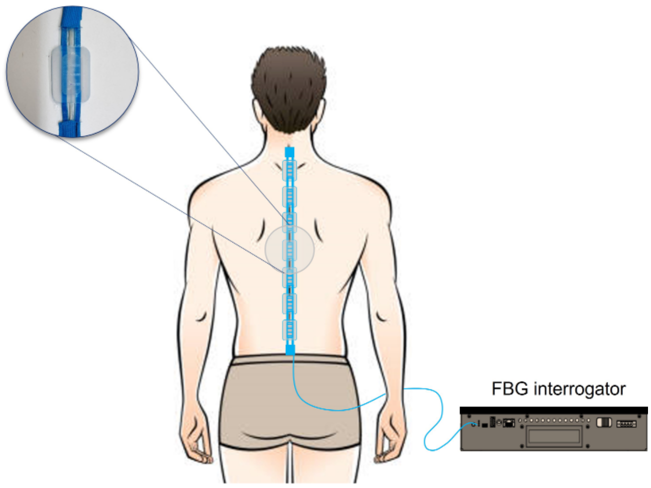


Fig. 2: Acquisition hardware, i.e., seven fiber Bragg grating sensors (FBGs) integrated in a chain of soft sensing elements (SSEs), and its disposition along the wearer's spine.

A. Acquisition Hardware

The acquisition hardware consists of a custom-made wearable measuring system described in detail in [18], [19]. This system is a device, consisting of a chain of seven Soft Sensing Elements (SSEs), that can be placed along the wearer's spine as shown in Figure 2. It embeds 7 fiber Bragg grating sensors (FBG), which are sensitive to strain and largely used in medical applications [20]–[22]. The 7 commercial FBGs (AtGrating Technologies, Shenzhen, China) were encapsulated within a polymeric matrix (i.e., a bi-component silicone rubber, Dragon SkinTM30, Smooth-On, Inc.) to allow a good adhesion with the back curvature.

FBG sensors are microstructures within an optical fiber that selectively reflect specific wavelengths of light, known as the Bragg wavelength, while allowing other wavelengths to pass through. The Bragg wavelength λ_B is determined by the period of the microstructure Λ and the effective refractive index of the core η_{eff}, as given by the equation

$$\lambda_B = 2\eta_{eff}\Lambda$$

Any deformation of the FBG can alter the Bragg wavelength, leading to a shift in the reflected light.

FBG sensors can thus be used to detect changes in deformation, such as those caused by back movements. When a deformation occurs, the FBG sensors output the results as a value called $\Delta\lambda_B$, which represents the shift in the Bragg wavelength. This shift can be measured and analyzed to perform postural analysis, assessing the changes in deformation and posture, with a sampling frequency of 100 Hz.

B. Acquisition Protocol

The system's feasibility in classifying postures has been assessed with a clinical trial involving 7 healthy females and 3 healthy males. The Ethics Committee of Università Campus Bio-Medico di Roma approved the trial. Each participant used the custom wearable system, which was applied to the back using hypoallergenic tape. The 7 sensors embedded in the wearable system were placed on specific anatomical repere points (as detailed in [18]). The 10 healthy volunteers were asked to breathe normally in three different postures, i.e., upright sitting, kyphotic sitting, and lordotic sitting, as schematically shown in Figure 1. Each posture was taken for 10 min.

C. Signal Pre-processing

After collecting the wavelength signals from our experimental setup, we pre-processed the data by averaging the signal values every second using a window function. Next, we standardized the features in the dataset to ensure that they were on a comparable scale and had similar statistical properties. Specifically, we used the following equation

$$X_i^{'} = \frac{X_i - \mu_{t,i}}{\sigma_{t,i}}$$

where X_i and $X_i^{'}$ indicate the vector of the $i-th$ feature from all the samples in the set, and its transformation, while $\mu_{t,i}$ and $\sigma_{t,i}$ are the mean and the standard deviation, respectively, of the $i-th$ feature retrieved from the training set (indicated with the t subscript). This process prevents any feature from having an undue influence on the outcomes due to its scale, which can help machine learning algorithms perform better and become more robust. The dataset thus obtained consists of a total of 18000 samples, with 600 samples per class per subject, providing a comprehensive set of data for analysis and classification of the sitting postures.

D. Feature Selection

In real-world situations, it is often difficult to identify the most significant features for accurate data analysis. Therefore, many candidate features are introduced to ensure that the domain is accurately represented. However, a significant number of these features can be redundant or irrelevant [23]. Thus, the feature selection step is crucial for reducing the number of sensors, thus reducing costs and enhancing the user's comfort and usability.

To address this issue, we adopted the decision tree (*DT*) algorithm as our feature selection method to determine which sensors are critical for accurate measurements [24]. With this approach, feature selection is incorporated during the process of building the decision tree. Each feature is evaluated based on a set of criteria for each layer of partition samples, providing us with the ability to choose only the most relevant sensors, thus reducing costs and discomforts for the subject.

To build the DT we employed the *Gini Index* for the construction of the DT to evaluate the data level of impurity across nodes. The Gini index (at a specific node of the tree) is expressed by the mathematical formula

$$GiniIndex = 1 - \sum_{i=1}^{n}(P_i)^2 \in [0,1]$$

where P_i stands for the likelihood that an element will be assigned to a specific class, and n indicates the number of classes. The importance of each feature is computed as the (normalized) total reduction (across all the nodes of the built tree) of the impurity criterion brought by that feature[1]. In other words, the larger the decrease in impurity a feature brings, the more relevant that feature is for the classification task.

E. Classification Models

By iteratively removing features (i.e. sensors) from the least important to the most important, we trained two classification models — *Support Vector Machine* and *Decision Tree* — to classify and recognize the three sitting postures and determine the precise number of sensors necessary for it, and subsequently optimize the multisensor system.

Given its robustness to noise and ability to handle large amounts of data, we used a Support Vector Machine, which is often used in literature to handle supervised learning classification problems [25]. We employed the decomposition algorithm to handle the multi-class classification, using the *one-vs-one* technique in which we train many binary classifiers looking for the best separation surface for the two classes. Specifically, we used a linear kernel to find a linear boundary (straight or hyperplane) for separation and a Radial Basis Function (RBF) kernel to handle non-linearly separable data (curve or non-linear surface) [26], [27].

On the other hand, we chosen the Decision Tree because of its excellent degree of explainability, i.e., the ability to provide a human-interpretable explanation of the decisions made by the model. Its supervised learning algorithm is based on the main idea of repeatedly dividing the dataset into smaller subsets based on feature values, using these divisions to create the tree. In this way, each subset represents a node in the decision tree, down to the leaves representing the output classes, integrating a succession of fundamental tests based on threshold values to build the model [28], [29].

F. Experimental setup

To evaluate the effectiveness of the machine learning models, an iterative technique called K-fold cross-validation was used, which divides the original dataset into k folds of equal size. During each iteration, one fold is used as the test set, while the remaining k-1 folds serve as the training set. This process is repeated k times, so that each fold is used once as a test set. Using K-fold cross-validation enables us to generate a more reliable estimate of model performance, providing a

[1]https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html

more accurate assessment of the model's ability to generalize to new data. For our experiments, we fixed k equal to 5.

III. Results

A. Feature Selection

The feature selection analysis of the data shows that some sensors are more crucial than others for training the subsequent models, even if they all were strategically positioned alongside the wearer's spine. Figure 3 shows the relative importance of each sensor in a range between 0 and 1.

When compared to the others, it becomes clear that SSE number 6 is crucial for collecting reliable data, as expected given the placement on the lumbar region. On the contrary, SSE3 and SSE4 placed along the thoracic vertebrae show almost no effects at inference time. We hypothesize that their low impact may be due in particular to the greater influence exerted by respiratory acts.

The figure also shows that SSE5, which substantially aids in measuring, is the second-most important sensor after the others. After that, SSE1 is the third-most critical sensor, and SSE2 and SSE7 yield some contribution.

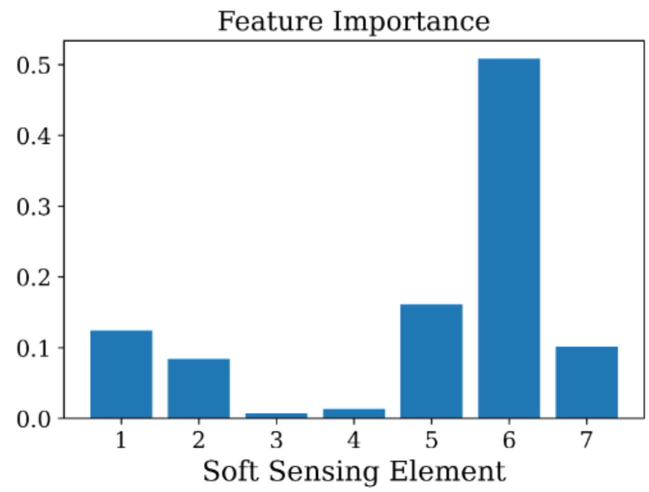
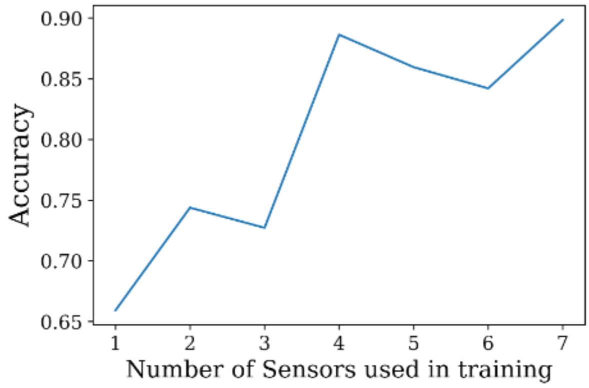
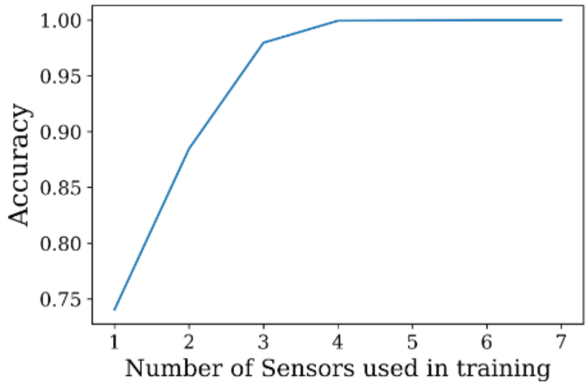


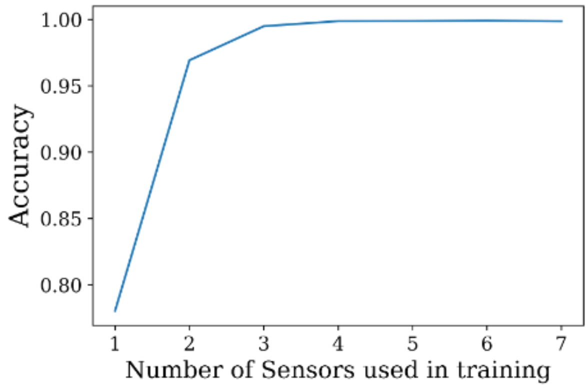
Fig. 3: Feature Importance ($\in [0,1]$) for each FBG sensor integrated with the related soft sensing element (SSE1, ..., SSE7) in the wearable measuring system employed.



(a) Linear SVM



(b) SVM-RBF



(c) Decision Tree

Fig. 4: Accuracy over the number of sensors of our proposed models.

B. Classification

Figure 4 presents a comparison of the outcomes of the two classifier models used in the analysis. The plots clearly indicate that the SVM with RBF kernel and Decision Tree achieved 100% of accuracy with the complete set of seven sensors and over 95% accuracy with only the three most relevant sensors. This showcases the effectiveness of both models in accurately identifying data with a limited number of sensors.

However, the SVM with the linear kernel (Linear SVM, Figure 4a) performs worst even with all the set of sensors, highlighting that the connections between the target variable and the sensor values are not linear.

Upon closer inspection of the SVM model with RBF kernel (SVM-RBF, Figure 4b) and the Decision Tree (Figure 4c), it becomes apparent that their outputs are similar. However, the Decision Tree model outperforms the SVM model, achieving the same accuracy of 97% using only two sensors, meaning one sensor less than the SVM. The performance difference can be attributed to using a tree-based method in both the feature selection and the classification processes.This underscores the importance of carefully selecting the appropriate algorithm during the feature selection phase and taking into account the capabilities of the algorithms used to produce the best results.

IV. Conclusions

This study utilized a wearable multi-sensor system to identify and categorize three different sitting types. Through the use of classification models and supervised learning, we were able to achieve 100% accuracy on data collected from seven sensors. By implementing a feature selection procedure we found that the accuracy remained high even with a reduced number of sensors, maintaining the classification accuracy over 95% with as little as two (DT) or three (SVM-RBF) sensors. We highlighted the number of sensors, as well as their placement, that are most significant for the task at hand, providing a foundation for future development of the multi-sensor wearable system. Reducing the number of sensors not only improves system efficiency, but it also reduces costs and enhances user comfort and usability. The use of a system based on the combination of wearable sensors and machine learning algorithms paves the path for various future developments such as the implementation of the system not only for the classification of sitting postures but also of standing postures. In addition, numerous integrations with other technologies such as augmented reality and virtual reality can be applied to create an environment where posture can be trained by giving the patient immediate feedback.

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