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Spinal sagittal alignment: investigation of postoperative pelvic kinematic improvement in patients with spinal sagittal imbalance using machine learning methods

Sadegh Madadi* Mostafa Rostami† Hadi Farahani‡ Farshad Nikouee§ Mohammad Samadian¶ Ram Haddas‖

Abstract

Background: Pelvic plays an important role in human movement, and it is the foundation that provides stability during activities such as walking. An abnormal condition of the pelvic, whether it is an abnormality of alignment or function, requires timely treatment intervention. Traditionally, pelvic examination has been performed through static two-dimensional imaging with very limited insight into real-time pelvic dynamics. More specifically, IMU sensors are already very powerful in acquiring all nuances of movement mechanics; with the addition of ML techniques, they can serve as an effective methodology for forecasting pelvic movement patterns for different activities. Material and Methods: The present study investigates the gait pattern of 50 female patients with SSI compared to 50 controls. Various machine learning models were applied using IMU data collected during gait analysis in order to identify and assess abnormalities in movement. Results: SVM has the best accuracy in the IMU data-based classification of pelvic movement disorders. The most relevant features, providing separation of patients from controls using the model, were identified pre- and post-surgery. Conclusion: Surgical patients with pelvic malalignment demonstrated asymmetric movements in the postoperative period. IMU combined with ML techniques provided a valid method for quantification and analysis of pelvic dynamics.

Keywords: Spine, Gait analysis, Machine learning

*Department of Biomedical Engineering, Amirkabir University of Technology, smadadi@aut.ac.ir

†Corresponding author. Department of Biomedical Engineering, Amirkabir University of Technology, rostami@ut.ac.ir

‡Department of Computer and Data Sciences, Faculty of Mathematical Sciences, Shahid Beheshti University, h_farahani@sbu.ac.ir

§Bone and Joint Reconstruction Research Center, Shafa Orthopedic Hospital, Iran University of Medical Sciences, farshadnikooei@gmail.com

¶Department of Neurosurgery, Shahid Beheshti University of Medical Sciences, mdsamadian@gmail.com

‖University of Rochester Medical Center, Rochester, ram_haddas@urmc.rochester.edu

1 Introduction

Spinal sagittal imbalance (SSI) is a complex condition that encompasses back pain, nerve involvement, and muscle weakness—all seriously reducing the quality of a patient's life. It occurs because of a change in the natural curvature of the spine in the sagittal plane, leading to misalignment with possible postural and functional changes [1–3]. The principal sources of pain in patients with SSI are the ones related to the nerve compression and muscle tensions [4].

Quantitative methods, such as the use of sensors, have been employed to evaluate walking. In recent years, there has been a growing application of Inertial Measurement Unit (IMU) sensors in clinical settings. These sensors can be used for gait analysis, sports movements, performance monitoring, rehabilitation, fall detection, and gait analysis for disease diagnosis. The goal is to improve quality of life and reduce the risk of injury [5-7]. IMU technology allows for the measurement of movements in both patients and healthy individuals, without any spatial limitations, using these sensor devices [8].

Machine learning (ML) methods can sub-group the gait signal and detect interesting features that help classify the gait signals [9–10]. These methods make it possible to quickly assess complex movements, such as walking easily. But with this new approach comes a new problem of how to manage the large amount of walking data generated by these technologies. ML has also been used to analyze gait patterns related to spinal disorders [11–13]. As for other ML methods, support vector machines (SVMs) were found to always provide better performance in terms of recognizing walking patterns [14–16]. When analyzing patient motion, it was found that ML techniques, especially SVM, provide significant results in terms of classification of walking tasks and approximation of nonlinear dynamics of patient walking [17–18].

The aim of this study is to investigate pelvic kinematics in a patient group by comparing their walking with a control group. This is done using inertial measurement unit (IMU) data and machine learning methods to detect any gait disturbances. The main objective is to identify and analyze the key parameters that have a significant effect on the pelvic patterns during patient walking.

Section 2 outlines the materials and methods, detailing the procedures for data collection, pre-processing, and preparation for training the machine learning models. Section 3 presents the training outcomes of the supervised ML models for each sensor, along with the statistical analysis of the most significant features. Section 4 interprets and discusses the results from Section 3, while Section 5 summarizes the key findings from the entire study.

2 Materials and methods

2.1 Study design and participants

This study specifically focused on female participants to investigate pelvic changes in walking in patients with SSI (Table 1). The reason for choosing female subjects is because of the anatomical and physiological differences between men and women, such as hip width, muscle mass, spine structure, and previous articles that confirm this distinction [19-20]. This study includes 100 participants, including 50 female patients diagnosed with SSI and 50 female controls. In the patient group, inclusion criteria required a consistent diagnosis of SSI with a vertical sagittal axis value greater than 5 cm [21-22].

Participants in the control group had no history of spinal surgery or movement disorders that could affect walking. All participants were screened for the absence of cardiovascular disease, psychiatric illness, and the use of medications that could affect motor performance. Exclusion criteria included active wounds, swelling in motor organs, and recent joint surgeries. Ethical approval was granted by the committee of Iran University of Medical Sciences (IR.IUMS.REC.1403.456), and subjects completed informed consent forms and screening questionnaires.

2.2 Data Collection

Data acquisition was done using a 9-axis inertial measurement unit (IMU) system (MyoMotion sensor (Noraxon USA Inc., Scottsdale, USA)). Before the study, the IMU sensor was calibrated according to the manufacturer's instructions to ensure the accuracy of the measurements. Participants were trained to walk a 10-meter track in a controlled laboratory environment. The IMU sensor was strategically placed on the hip region of the participant (Figure 1). The goal was to have the participants walk at a self-selected pace that closely resembled natural walking conditions.

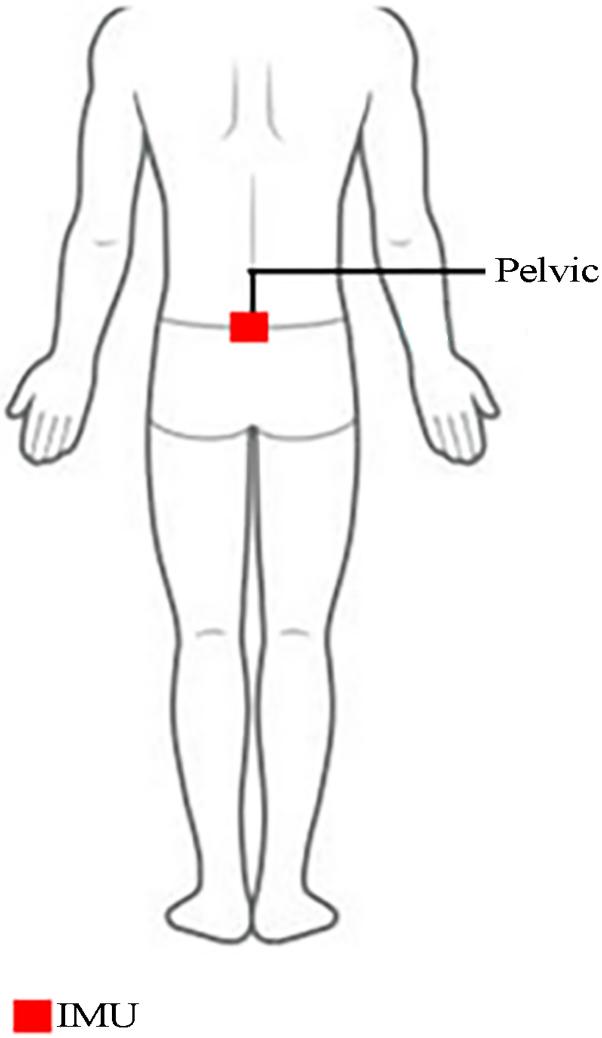

Figure 1: Sensor placement on the participants' body

Table 1: Information of subjects participating in the study, highlighting the demographics of patient and control groups.

Group	Age (years)	Height (cm)	Weight (kg)	Sex (female)
Patient (n=50)	50 ± 4.94	161 ± 4.37	86 ± 6.7	female
Control (n=50)	49 ± 1.48	162 ± 2.3	84 ± 2.9	female

2.3 Data analysis

To ensure the signals are collected accurately throughout the gait cycle, the signals received from the IMU sensor underwent noise removal and were then divided into units corresponding to each gait cycle. Subsequently, the signal from the previous step was processed using a Butterworth low-pass filter with a cutoff frequency of 6 Hz and an order of 4 [23]. This filtering operation, depicted in Figure 2, was then implemented. By segmenting the signals into distinct time intervals, we were able to focus on the pertinent gait information. This approach facilitated the isolation of individual gait cycles and allowed for the extraction of detailed features from specific segments of the gait data [24], as illustrated in Figure 2.

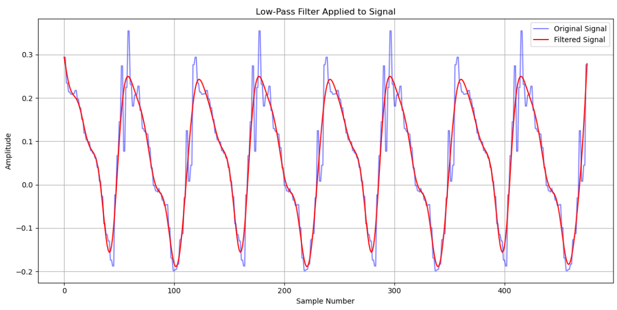

Figure 2: Segmentation of patient gait data from IMU in terms of gait cycles

2.4 Feature extraction

The main features include time and frequency features (Table 2) [25-26] calculated on all preprocessed data from IMU sensor. These features include linear acceleration, angular velocity, equivalent acceleration, equivalent angular velocity, and rotation angle (pitch, yaw, roll). The output of this section is a large number of features that will be examined in the feature selection section. In the feature extraction process, we have used both parametric and non-parametric variables (Table 2) to ensure the reliability and strength of the results and to match different features of the data. This approach will provide a comprehensive analysis and strengthen the validity of the study findings [27].

Table 2: Final features extracted from IMU data.

Time Feature	**Frequency Feature**
Average and Median	Fast Fourier Transform
Variance	Entropy FFT
Standard Deviation	Energy FFT
Min and Max Value	Average FFT
Skewness	IQR FFT
Interquartile Range (IQR)	Power Spectrum
Total Energy	Average Power Spectrum
Mean Absolute Deviation	Variance Power Spectrum
Root Mean Square (RMS)	Entropy Power Spectrum
Kurtosis	
Lyapunov	

2.5 Feature selection

Feature selection is a crucial step in machine learning (ML) as it helps identify the most relevant features from a given dataset. In this study, we propose a feature selection approach that utilizes Support Vector Machines (SVM) and model validation techniques. The objective is to determine the optimal features that significantly enhance the predictive ability of the model. For classification purposes, we have chosen the SVM model, while below, we present other models for comparison. The radial basis function (RBF) kernel is employed as it is widely used in nonlinear classification problems.

The RBF kernel is defined based on the two input vectors x and y as follows:

$$K(x, y) = \exp(-\gamma \|x - y\|_2^2) \tag{1}$$

where,

$$\|x - y\|_2^2 = \sum_{i=1}^{P} (x_i - y_i)^2 \tag{2}$$

In equation (1), K(x, y) represents the kernel function applied to the input vectors x and y. The exp. represents the exponential function. γ (gamma) is a meta parameter that controls the width of the Gaussian distribution ($\frac{1}{2\sigma^2} = \gamma$) and determines the impact of each training example on the decision boundary. A more minor value results in a broader distribution and a smoother decision boundary, while a larger value makes the distribution narrower, resulting in a more localized decision boundary. The expression ($\|x-y\|_2^2$) represents the squared Euclidean distance between the vectors x and y [28].

The most important parameters of the features are presented in Table 3. This review highlights which features in the time series data are more significant and warrant further attention and investigation about sensor.

2.6 Model training

The use of ML has facilitated previous research trends in studying lower extremity variability in this specific patient population. By harnessing the power of data-driven analysis and ML, it becomes possible to gain a comprehensive understanding of the subtle changes in the lower limbs of individuals with preoperative SSI [29]. To test the learning performance of the models, the number of features in the dataset is reduced, and it is then divided into two separate subsets: training data (80% of the dataset) and test data (20% of the dataset) [30-33]. To examine the dataset and identify the primary features, unsupervised models were utilized. Table 4 illustrates the results of this clustering and the accuracy of each model. These model results can aid in selecting the appropriate clustering model and validation algorithms for analyzing movement data in the groups under study.

Using 10-fold cross-validation, the data was divided into separate groups for testing and training. To prevent data leakage, each group was normalized individually within the range of [-1, 1]. This scaling process aims to enhance classification accuracy. The resulting features and labels from the training data were then inputted into the SVM algorithm, and labeled as the training matrix. For nonlinear classification tasks, an SVM model with an RBF kernel is frequently chosen. Additionally, network search is employed to identify the best meta-parameters for improving model performance [30].

The steps discussed in the preceding sections have been elaborated upon. Moreover, to validate and compare the outputs, various machine learning techniques, such as LDA, k-NN (k nearest neighbors), and Naive Bayes models, have been employed [34-36]. The sensor is checked for all models to examine movement disorders more closely. This is necessary because these individuals lack movement symmetry and exhibit abnormal movement.

3 Results

3.1 Model selection

Different ML models were trained on the sensor separately, and the output of the test and train data is provided in Table 5. The analysis utilized SVM, k-nearest neighbor (k-NN), LDA, and Naive Bayes models [30]. Table 5 demonstrates that the SVM model, as indicated by previous studies [17–18], is effective for examining motion data and SSI patients.

According to the selected features shown in Table 3, the models were examined, tested, and trained based on the selected priority. One of the goals was to train and evaluate the model using both the least and best possible number of features while preventing overfitting.

3.2 post-surgery analysis

A detailed comparison of the developed ML models showed that SVM consistently outperformed the others in terms of accuracy. However, the k-NN and LDA models also performed very well, especially on datasets with distinct walking patterns. These models were somewhat less effective in more variable situations, where the presence of non-linear relationships made SVM more useful. The simple Bayes model, although simple, performed well enough on small and simplified data sets but proved insufficient for the dimensional feature space of walking data. This emphasizes the importance of choosing appropriate models based on the specific characteristics of the data being analyzed.

Using the results of the SVM model trained on the data of the patients and the control group, the post-surgery data of the patients were classified, and the post-surgery results showed that, considering that in the static state, the condition of the patient group was different from the condition of the group. The control is similar, but they have different kinematics when walking, and 78% of patients after surgery still have the same behavior as before surgery, and 22% have the same behavior as the control group (Figure 3).

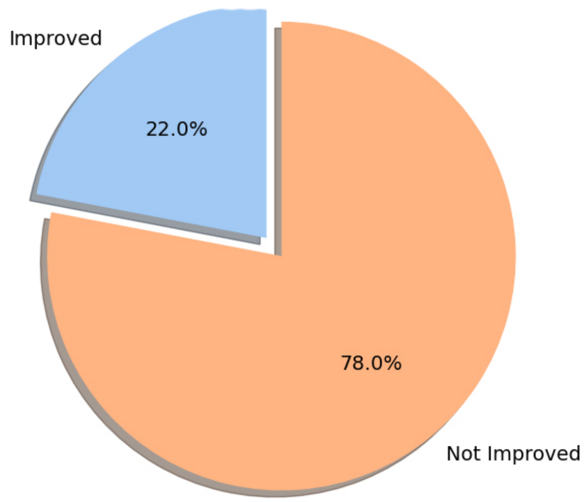

Figure 3: The output of the machine learning model to determine the condition of patients after surgery

Table 3: Performance metrics for various methods across different datasets.

Dataset	Method	Accuracy	Precision	Recall	F1-score
Pelvic	SVM	99.07%	97.70%	98.00%	98.87%
	k-NN	98.95%	97.50%	98.00%	98.73%
	LDA	99.00%	98.00%	98.30%	99.00%
	Naive Bayes	98.60%	96.70%	98.00%	98.32%

3.3 Statistical results

The output data from the feature selection section, which was used as input for training the machine learning models, was analyzed using ANOVA [37] statistical criteria. The detailed findings are presented in Table 5, demonstrating a significant difference with a P-value < 0.05. This significance is observed in all sensor outputs and indicates that the selected features have a notable impact on the model performance, highlighting the effectiveness of the feature selection process in distinguishing between different features.

4 Discussion

In this study, we investigated the kinematics of the lower limbs of SSI patients using IMU sensor. We employed ML-supervised algorithms to analyze main gait characteristics and diagnose movement disorders in these patients. The SVM model proved to have the highest classification accuracy, followed by other models with similar performance. SVM successfully identified the most important features for diagnosing gait disorders and achieved a highly accurate classification of both the control group and the patient group (Table 4). These findings demonstrate the efficacy of SVM in gait prediction and suggest the potential usefulness of other methods such as k-NN, LDA, and Naive Bayes.

Pelvic outputs revealed significant differences in the linear acceleration data between the two groups in the anterior-posterior (AP) direction. These differences were observed during both walking and forward bending conditions in the patient group. One compensatory mechanism observed in the patients was posterior pelvic tilt. This occurs when the body attempts to adjust the center of gravity on the hips and legs. As a result, the pelvic tilts forward (anterior tilt), and to compensate for this, the body rotates the pelvic backward (posterior tilt). This alteration in pelvic movement significantly distinguishes it from the movement observed in the healthy group [38].

5 Conclusion

This study used machine learning models to extract key movement features from IMU sensor data, specifically targeting gait abnormalities in SSI patients. These abnormalities included changes in pelvic tilt. This study successfully identified movement disorders by analyzing the sensor independently. Furthermore, the accuracy of the machine learning models showed that the main features of the extracted gait could distinguish SSI patients from healthy individuals with more than 97% accuracy.

The obtained outputs show the potential of machine learning models, SVM model, in handling complex nonlinear relationships in motion data. The findings of this study can increase the results of treatment and rehabilitation and ultimately improve the quality of life of SSI patients. However, it is important to note that one of the limitations of this study is its exclusive focus on women. Future research should include larger data sets and examine both genders to explain the aforementioned differences.

Conflict of interest

No authors have any conflicts of interest to disclose. All authors have no financial or non-financial interests directly or indirectly related to this work.

Consent for publication

Not applicable.

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Table 4: P-values for comparisons between control, pre-op, and post-op across different parameters and sensor

Dataset	Parameter	Control vs. Post-op	Pre-op vs. Post-op	Control vs. Pre-op
Pelvic	med acc AP	< 0.001	< 0.001	< 0.001
	MAD acc AP	< 0.001	< 0.001	< 0.001

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