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Combination of Madgwick Filter and Machine Learning for Predicting Trunk Flexion Angle in Patient Handling by a Single Inertial Sensor

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Abstract

Low back pain is a major occupational health problem among caregivers, largely caused by excessive trunk flexion during patient-handling tasks. This study proposed and evaluated a method to predict trunk flexion angle during patient repositioning using a single inertial sensor without magnetic data. The method combined orientation estimates from a Madgwick filter with machine learning models to compensate for systematic errors in inertial sensing. Trunk flexion angles estimated by the proposed method were compared with those obtained from an optical motion capture system, and performance was evaluated using the root mean square error (RMSE). The results showed that the proposed approach substantially improved accuracy compared with the conventional Madgwick filter without magnetic data. Among the evaluated algorithms, the k-nearest neighbors (k-NN) model achieved the smallest RMSE of 2.34°, followed by the support vector machine (7.70°) and artificial neural network (12.5°) models, while the conventional method yielded an RMSE of 17.6°. The k-NN model demonstrated superior robustness to nonlinear errors and achieved accuracy within a biomechanically meaningful range for assessing lumbar load. These findings indicate that the proposed single-sensor, magnet-free approach can accurately monitor trunk flexion angle during patient handling and has potential for practical application in preventing lower back pain among caregivers.

Keywords:
Caregiver, Trunk Flexion Angle, Inertial Sensor, Madgwick Filter, Machine Learning

1. Introduction

Musculoskeletal disorders, especially low back pain, remain a serious occupational health problem among caregivers and healthcare workers. Patient handling tasks such as lifting, repositioning, and transferring patients repeatedly expose workers to excessive trunk flexion and high spinal loads. Longitudinal evidence shows that despite improvements in assistive devices and training, the prevalence of severe low back pain among caregivers continues to increase over time. This trend indicates that existing prevention strategies are insufficient to monitor and control biomechanical risk during daily work activities, particularly in real clinical environments where continuous assessment is difficult to implement [1].

Several ergonomic studies have clearly linked awkward trunk postures to low back pain among nurses and caregivers. Observational and questionnaire-based research shows that sustained trunk flexion and frequent bending significantly increase pain severity and injury risk. These findings emphasize that trunk flexion angle is a critical biomechanical indicator for evaluating patient handling safety. However, most studies rely on retrospective

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self-reports or manual observation, which lack precision and cannot provide real-time feedback to prevent injury during task execution [2].

Injury report analyses further confirm that patient care activities dominate occupational injury cases in healthcare facilities. Text mining studies reveal that improper lifting techniques and poor posture during patient handling are among the most frequently reported causes of injury. These reports highlight a systemic issue: caregivers often perform physically demanding tasks without continuous posture monitoring or objective risk assessment tools. This gap motivates the need for automated and quantitative methods to measure trunk posture during real-world patient handling [3].

Biomechanical laboratory studies demonstrate that modifying patient-handling techniques can significantly reduce spinal loading and trunk flexion. Controlled experiments using motion capture systems show that proper technique lowers compression forces at the lumbar spine. While these findings provide valuable ergonomic insights, they depend on complex laboratory setups with markers and cameras. Such systems are impractical for daily use in hospitals, nursing homes, or home care settings, limiting their applicability for continuous monitoring and prevention [4].

Recent advances introduce vision-based approaches to estimate trunk kinematics without physical markers. Computer vision and markerless optical motion capture systems successfully estimate trunk angles and provide real-time feedback to improve lifting techniques. These systems achieve high accuracy in controlled environments, but they require fixed cameras, stable lighting, and unobstructed views. Their performance degrades in crowded clinical settings, and their installation cost limits scalability for widespread healthcare deployment [5][6].

Wearable sensing technologies, particularly inertial measurement units (IMUs), emerge as a practical alternative for ergonomic monitoring. Systematic reviews confirm that IMUs offer portability, low cost, and suitability for real-world environments. Recent studies demonstrate that IMU-based systems can estimate spine and trunk angles with acceptable accuracy for clinical and ergonomic applications. However, many approaches rely on multiple sensors attached along the spine, which increases setup complexity and reduces user compliance in routine healthcare work [7][8][9].

Single-sensor solutions attract growing interest because they reduce the burden on users and simplify deployment. Validation studies show that a single IMU placed on the trunk can reliably measure lumbar motion under certain conditions. Nevertheless, raw IMU data suffer from noise, drift, and magnetic disturbances, which reduce accuracy over long durations. Orientation filters such as the Madgwick filter provide computationally efficient sensor fusion to estimate orientation, but magnetic distortion and task-specific motion patterns still challenge robust trunk angle estimation during complex patient handling tasks [10][11][12][16].

To address these limitations, recent research increasingly combines wearable sensors with machine learning models. Reviews in wearable health technologies show that machine learning improves robustness, personalization, and prediction accuracy by learning patterns from noisy sensor data. Machine learning models can compensate for sensor limitations and adapt to individual movement styles. However, their application to trunk flexion estimation during patient handling, especially using a single IMU combined with an efficient orientation filter, remains limited. This gap motivates the present study, which integrates the Madgwick filter with machine learning to predict trunk flexion angle accurately and efficiently using only one inertial sensor [18][19].

This study aimed to propose and evaluate a method for predicting trunk flexion angle during patient handling using a single inertial sensor without relying on magnetic data. The paper introduced a single-sensor trunk flexion estimation approach that avoided magnetometer dependence, integrated Madgwick filter outputs with machine learning models to compensate for systematic estimation errors, and compared multiple machine learning algorithms to identify the most effective approach for patient-handling tasks.

2. Related Works

Previous studies consistently reported that patient handling tasks exposed caregivers to a high risk of low back pain, mainly due to excessive trunk flexion and awkward postures. Iwakiri et al. analyzed long-term trends among caregivers in Japan and showed that severe low back pain remained prevalent despite ergonomic interventions, indicating that risky trunk movements persisted in daily practice [1]. Nourollahi et al. further confirmed that sustained trunk flexion and asymmetric postures strongly correlated with low back pain among hospital nurses [2]. These findings highlighted the need for objective and continuous trunk angle monitoring during patient handling rather than relying on observational assessment alone.

Several biomechanical studies investigated trunk motion during patient handling to understand injury mechanisms. Schibye et al. conducted a biomechanical analysis of different patient-handling techniques and demonstrated that trunk flexion angle significantly influenced spinal loading [4]. Similarly, Hye-Knudsen et al. quantified trunk motion characteristics across multiple patient-handling tasks and found large variations in flexion angles depending on task type and caregiver technique [13]. While these studies provided valuable insights, they relied on laboratory-based measurement systems that limited practical deployment in real clinical environments.

To overcome laboratory constraints, researchers explored vision-based approaches for estimating trunk kinematics. Greene et al. proposed a computationally efficient computer vision method to estimate trunk angle during lifting and achieved promising accuracy under controlled conditions [5]. Brandl et al. used markerless optical motion capture to provide real-time biomechanical feedback and demonstrated improvements in lifting technique [6]. However, these systems required multiple cameras, controlled lighting, and substantial computational resources, which reduced their feasibility for routine patient-handling monitoring in hospitals.

Wearable motion capture technologies gained attention as practical alternatives for ergonomic assessment. Salisu et al. reviewed motion capture technologies for ergonomics and concluded that inertial measurement units (IMUs) offered the best trade-off between accuracy, cost, and portability [7]. Michaud et al. and Pan et al. further showed that IMU-based approaches could estimate spinal posture with reasonable accuracy using multi-sensor configurations and biomechanical models [8], [9]. Despite these advantages, most approaches relied on multiple sensors placed along the spine, which increased setup complexity and reduced user compliance.

Several studies evaluated the validity of IMUs for lumbar motion measurement. McClintock et al. conducted a systematic review and reported that IMUs showed acceptable validity and reliability for lumbar spine motion in both healthy individuals and patients with low back pain [10]. However, the review also highlighted variability across sensor configurations and signal processing methods. In particular, magnetometer-based orientation estimation suffered from magnetic disturbances in indoor environments, such as hospitals, as demonstrated by De Vries et al. [12].

To address orientation estimation challenges, Madgwick proposed a computationally efficient sensor fusion filter that combined accelerometer, gyroscope, and magnetometer data [11]. Many ergonomic studies adopted the Madgwick filter due to its low computational cost and real-time capability. However, when researchers removed magnetometer data to avoid magnetic distortion, orientation accuracy degraded, especially during dynamic movements. Kitagawa et al. recently evaluated a single inertial sensor for trunk angle measurement during patient repositioning and reported systematic estimation errors when magnetic data were excluded [16].

Recent studies began to incorporate machine learning to enhance wearable sensor performance. Pan et al. demonstrated that learning-based models could estimate spine angles and even identify sensor placement automatically [8]. Reviews by Nurmi and Lohan and by Olyanasab and Annabestani emphasized that machine learning improved robustness and personalization in wearable biomedical systems [18], [19]. Nevertheless, most existing works focused on general movement analysis or rehabilitation and rarely targeted patient-handling tasks or trunk flexion estimation specifically.

In summary, prior research established the importance of monitoring trunk flexion during patient handling and demonstrated the potential of IMU-based systems. However, limitations remained in sensor count, magnetic sensitivity, and estimation accuracy. Few studies combined magnetometer-free orientation filtering with machine learning to compensate for systematic errors using a single sensor. This gap motivated the present study to integrate Madgwick filter outputs with machine learning models to improve trunk flexion angle prediction during patient handling tasks.

3. Proposed Method

An overview of the proposed method is presented in Fig.1. The proposed method predicts the trunk flexion angle using a combination of the Madgwick filter [11] (without magnetic correction) and machine learning based regression. The caregiver must be standing upright in the initial posture of the measurement because the trunk flexion angle is defined as the change in the flexion angle from the initial trunk posture.

The prediction process is shown in Fig.1. First, the trunk flexion angle was calculated via the Madgwick filter with 3-axis acceleration and 3-axis gyro data obtained from a single inertial sensor on the trunk. Second, the 3-axis acceleration, 3-axis gyro, and trunk flexion angle via the Madgwick filter were used as features of machine learning. The machine learning based regression model calculates the corrected trunk flexion angle using these features. From these processes, the proposed method predicts an accurate trunk flexion angle by using a single inertial sensor without magnetic data.

The angle of the inertial sensor is represented by a quaternion q at discrete time k. Angular velocity is measured by the gyroscope, and the gravity direction is obtained from the accelerometer. The Madgwick filter without magnetic correction updates orientation as follows:

$$q_k = q_{k-1} + \frac{1}{2} q_{k-1} \otimes \omega_k \Delta t - \beta g_k \tag{1}$$

where ω_k is the gyroscope angular velocity vector, Δt is the sampling period, β is the filter gain (this study: $\beta=0.0756$), and g_k is a correction term derived from the acceleration-based gravity direction. After the update, quaternion q_k is normalized to unit length. The trunk flexion angle is defined as the change in sagittal plane orientation relative to the initial upright posture. Using the quaternion q_k, the flexion angle θ_k is computed as:

$$\theta_k = \theta(q_k) - \theta(q_0) \tag{2}$$

where q_0 is the quaternion measured at the initial standing posture. The Madgwick-based flexion angle contains systematic errors. To compensate for these errors, machine learning regression is applied. The input feature vector x at time k is defined as:

$$x_k = [a_x, a_y, a_z, \omega_x, \omega_y, \omega_z, \theta_k] \quad (3)$$

where α is the acceleration vector, ω is the gyroscope angular velocity vector, and θ_k is the Madgwick-based flexion angle from equation (2). The corrected trunk flexion angle $\widehat{\theta_k}$ is obtained by the regression algorithm $f(x_k)$:

$$\hat{\theta}_k = f(x_k) \quad (4)$$

In this study, we evaluated the accuracy of the proposed method by comparing it with an optical motion capture system. Several useful algorithms exist in machine learning for wearable technology [18], [19]. The suitable regression algorithm depends on the target and the sensor of the measurement. Thus, a suitable regression algorithm should be explored experimentally. In this study, the accuracies of artificial neural network (ANN), k-nearest neighbors (k-NN), and support vector machine (SVM) were compared to explore the most suitable regression algorithm for the proposed method.

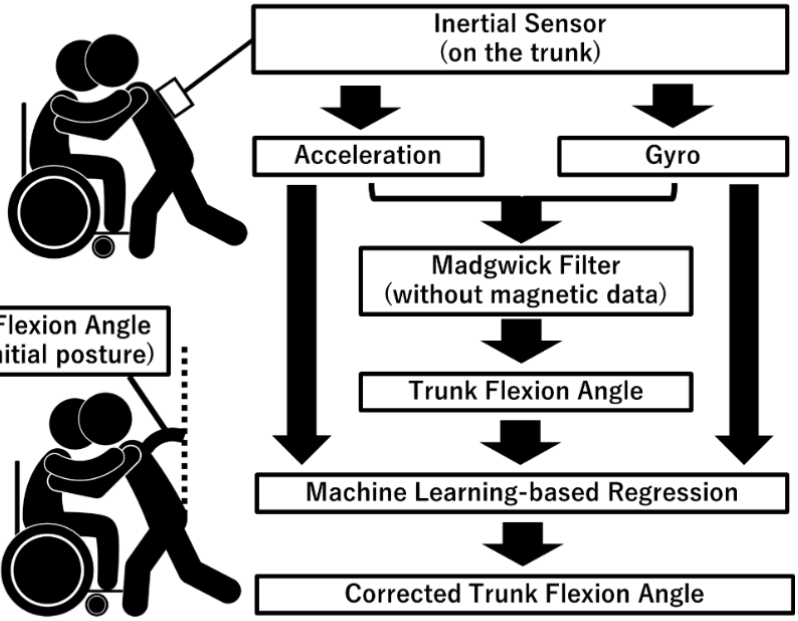

Fig. 1. Overview of the proposed method

Fig.1 illustrates the conceptual definition of trunk flexion angle used in this study. It depicts trunk orientation measured relative to an initial neutral posture rather than an absolute global reference. The simplified body representation emphasizes the trunk segment and its rotational relationship to a fixed reference point, which is consistent with biomechanical modeling of sagittal-plane motion during patient-handling tasks.

The upper illustration represents the initial posture, which served as the reference orientation for angle estimation. A small rectangular marker on the trunk indicates the placement of a single inertial sensor used to capture motion data. This reference posture established the baseline for subsequent flexion angle calculation and reduced dependency on external alignment or magnetic information. The lower illustration shows a forward-flexed trunk posture during task execution. The trunk flexion angle was defined as the angular deviation from the initial posture to this flexed position. This representation aligns with the study objective of estimating trunk flexion using a single inertial sensor without magnetic data, while supporting the proposed method for evaluating posture-related biomechanical risk during patient handling activities.

4. Experimental Setup

In this experiment, we evaluated whether the proposed method could accurately predict the trunk flexion angle during patient handling by a single inertial sensor without magnetic data. In addition, ANN, k-NN, and SVM were compared to determine the most suitable machine-learning algorithm for the proposed method.

The sensor data during patient handling for this experiment were measured in our previous study [16]. The participants were young people (n = 10). The characteristics of the participants are shown in Table 1. The experimental procedures were conducted in accordance with the Ethics Committee for Human Research of the National Institute of Technology, Hachinohe College (approval numbers: R4-2 and R7-1). The participants were asked to perform 10 trials of patient repositioning motions for the doll (height 140 cm, weight 4.8 kg, HB0141F, Avice, Inc., Tokyo). The patient repositioning motion is shown in Fig.2.

A single inertial sensor (SS-MS-SMA16G15, Sports Sensing Co. Ltd., Fukuoka) on the trunk measured the 3-axis acceleration and 3-axis gyro data during each patient repositioning. These inertial data were used as features in the proposed method. An optical motion capture system (OptiTrack, Flex3, Natural Point Inc, Corvallis, OR) was used to measure the ground truth of the trunk flexion angle during each patient recognition. The sampling rate of these devices was 100 Hz.

Feature extraction, including angle calculation using the Madgwick filter, was performed using MATLAB R2024a. The training and testing of the machine learning (ANN, k-NN, and SVM) were performed using WEKA [20]. The parameters of ANN, k-NN, and SVM are listed in Tables 2, 3, and 4, respectively. The 10-folds cross validation was performed for training and testing. The root mean square error (RMSE) of the trunk flexion angle between the proposed method and the optical motion capture system was calculated as a performance metric. Small RMSE values indicate small prediction errors for the proposed method. The RMSE values of the trunk flexion angle were compared for ANN, k-NN, and SVM models.

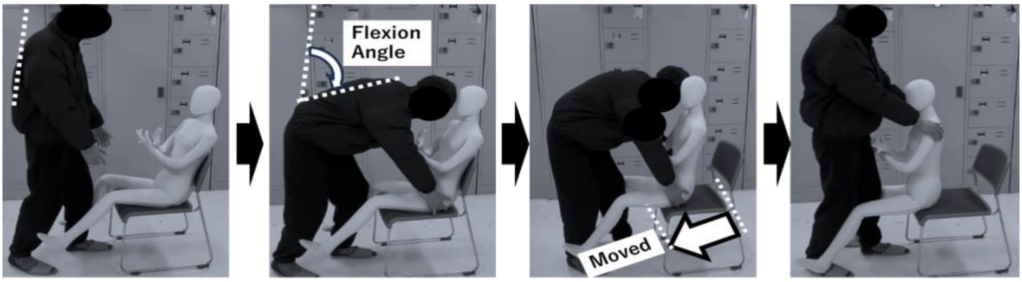

Fig. 2. Patient repositioning in the experiment

Table 1. Characteristics of the Participants

Characteristic	**Value (Mean ± S.D.)**
Gender	Male (all)
Age [years]	19.5 ± 0.81
Height [cm]	172 ± 5.96
Weight [kg]	64.4 ± 8.50

Table 2. The Parameters of Artificial Neural Network (ANN)

Parameter	Value
Batch Size	100
Number of Input Layers	1
Number of Hidden Layers	1
Number of Output Layers	1
Number of Nodes / Neurons at Input Layers	7
Number of Nodes / Neurons at Hidden Layers	7
Number of Nodes / Neurons at Output Layers	1
Activation of Hidden Layers	Sigmoid
Activation of Output Layers	Linear
Training	Back Propagation
Loss Function	Mean Squared Error (MSE)
Momentum	0.2
Learning Rate	0.3

Table 3. The Parameters of k-Nearest Neighbors (k-NN)

Parameter	Value
Batch Size	100
k	1
Distance	Euclidean Distance

Table 4. The Parameters of Support Vector Machine (SVM)

Parameter	Value
Batch Size	100
c	1.0
Kernel	Linear Kernel

5. Results and Discussion

In this part, we present the RMSE values of the trunk flexion angle between the proposed method and the optical motion capture system. Table 5 presents the RMSE values between the conventional Madgwick filter (without magnetic data) and optical motion capture.

Table 5. RMSE between Inertial Sensor and Optical Motion Capture System

Method and Algorithm (without magnetic data)	RMSE [degrees]
Proposed Method using ANN	12.5
Proposed Method using k-NN	2.34
Proposed Method using SVM	7.70
Conventional Madgwick Filter [16]	17.6

These RMSE values show that the proposed method can accurately predict the trunk flexion angle during patient repositioning compared to the conventional Madgwick filter without magnetic data. The k-NN-based model showed the smallest RMSE, indicating superior robustness against nonlinear errors in inertial sensing. SVM achieved moderate accuracy, while ANN showed overfitting tendencies with limited training data. In addition, the proposed method using k-NN or SVM could predict the trunk flexion angle with a smaller than 10 degrees. A previous study indicated that lumbar loads are changed by a 5 to 10 degree change of trunk angle [17].

According to these findings, the proposed method can be used to monitor trunk flexion angles using a single inertial sensor without magnetic data to prevent lower back pain among caregivers. The proposed method using k-NN could predict the trunk flexion angle with a smaller than 5 degrees. In addition, the RMSE of k-NN was the smallest in 3 algorithms. These results suggest that k-NN is a suitable algorithm for machine learning in the proposed method. Because k-NN directly exploits local similarity in the feature space without requiring complex model training, it is well-suited for activity recognition tasks with strong intra-class similarity and inter-class separability. In contrast, the RMSE of the proposed method using ANN was larger than 10 degrees. These results show that ANN may be unsuitable for the proposed method.

The accuracy of the proposed method can be improved by modification of machine learning. For example, hybrid and ensemble machine learning models might be useful for improving the proposed method [21], [22]. Additionally, recent machine learning algorithms using time series data-based features might improve the accuracy of the proposed method [23], [24]. In the future, machine learning algorithms will be modified for the proposed method.

The limitation of this study was that the proposed method was tested only for patient repositioning. There are various patient-handling motions, such as assisting sit-to-stand, related to lumbar loads in caregivers [4]. Thus, the proposed method should be tested and improved for various other patient handling motions. Furthermore, the participants were limited to young males. There are differences in patient handling techniques and strategies between males and females [25]. In addition, patient handling motions are also changed by the experience of caregivers [26]. Based on these differences, the proposed method should be tested on a larger population. Additionally, the simulated patient was a doll in the patient repositioning of the experiment. In the future, the proposed method will be tested in various fields and setups to evaluate its performance. In this study, other conditions of the proposed method, such as sensor placement, were not compared. In the future, these conditions will be compared for the implementation of the proposed method.

6. Conclusion

This study proposed and evaluated a trunk flexion angle prediction method for patient handling using a single inertial sensor without magnetic data. The results demonstrated that integrating the Madgwick filter output with machine learning substantially improved estimation accuracy compared with the conventional Madgwick filter alone. Among the evaluated algorithms, the k-NN-based model achieved the lowest RMSE of 2.34°, which was markedly smaller than that of the conventional method (17.6°) and other machine learning models. This level of accuracy is biomechanically meaningful, as previous studies reported that lumbar loads change significantly with trunk angle variations of 5–10°. The SVM-based model also achieved acceptable performance with RMSE below 10°, while the ANN-based model showed inferior accuracy, likely due to overfitting under limited training data conditions.

These findings indicate that the proposed method can reliably estimate trunk flexion angle during patient repositioning and has practical potential for monitoring posture-related biomechanical risk in caregiving tasks. The superior performance of k-NN suggests that algorithms exploiting local similarity in the feature space are well-suited for inertial-sensor-based trunk motion estimation, especially under nonlinear error characteristics and limited datasets. Furthermore, the ability to achieve high accuracy without magnetic data enhances robustness in clinical and workplace environments where magnetic disturbances are common.

Despite these promising results, this study has several limitations. The evaluation focused only on patient repositioning tasks, involved a small and homogeneous participant group, and used a simulated patient. Other patient-handling activities, different sensor placements, broader populations, and real clinical settings were not examined. Future work should extend the proposed method to diverse patient-handling motions, larger and more varied populations, and real-world environments. In addition, advanced machine learning approaches, including hybrid, ensemble, and time-series-based models, may further improve accuracy and generalizability. Overall, this study provides a solid foundation for single-sensor, magnet-free trunk flexion monitoring aimed at preventing lower back pain among caregivers.

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