Postoperative rehabilitation exercise recognition for knee replacement surgery

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Introduction

Total Knee Arthroplasty (TKA) is a common medical procedure used to address advanced knee osteoarthritis, with postoperative recovery being a crucial aspect of patient care. However, current practices for TKA recovery vary widely and lack standardization, often relying on clinicians' intuition. This project aims to develop a clinician-based design platform to enhance the efficiency and usability of TKA postoperative recovery by utilizing motion tracking technology and machine learning algorithms.

Literature Review:

The current rehabilitation practices for Total Knee Arthroplasty (TKA) vary widely across clinical sites, lacking standardization [1]. Literature suggests that the content and goals of therapy are largely based on clinicians' experience and intuition [2,3,4,5,6]. There are several challenges that can impede the effectiveness of rehabilitation plans. One of the most significant challenges is the lack of consistency in the plans themselves, which can lead to confusion and ineffective treatment [4]. Another challenge is the inadequate supervision of rehabilitation exercises, which can cause serious complications such as thrombosis and necrosis [7]. Patients may also have reduced rehabilitation compliance due to poor nutrition management, emotional management, and pain management [8]. During inpatient rehabilitation, due to the crowding of medical resources, medical staff are unable to care for each bed and supervise all patients' exercise frequency and posture, resulting in low exercise efficiency, delayed recovery, and even thrombosis, which can lead to delayed outpatient rehabilitation treatment [9,10].

To address these challenges, a number of strategies can be employed. First, a consistent and standardized postoperative rehabilitation plan should be developed and followed. This plan should be tailored to the individual patient's needs and should be regularly evaluated and adjusted as necessary. It is also important to provide effective supervision of rehabilitation exercises, including regular monitoring of the patient's progress and the provision of feedback and guidance. Additionally, patients should be provided with adequate support for nutrition management, emotional management, and pain management. Finally, doctors should be given the necessary resources and support to manage patients in a timely and effective manner. This project aims to address this gap by introducing a data-driven approach to postoperative rehabilitation, facilitating personalized treatment plans tailored to individual patient needs.

Goal:

The primary goal of this project is to develop a clinician-based rehabilitation monitoring platform that maximizes the efficiency and usability of TKA postoperative recovery. Specifically, the project aims to:

1. Utilize motion tracking technology, such as Inertial Measurement Units (IMUs), for accurate monitoring of knee joint motion during rehabilitation exercises.
2. Employ machine learning algorithms to analyze motion data and classify different rehabilitation exercises accurately.
3. Provide clinicians with actionable insights derived from the analysis of motion data, enabling personalized rehabilitation plans for TKA patients.

Methods

Hardware Built up:

Setting up the ESP32 with a TCA9548, an I2C bus multiplexer, to connect three JY901 inertial measurement units (IMUs) facilitates simultaneous data collection from multiple sensors. This system enables efficient data acquisition via a single I2C bus communication, streamlining the process of motion data collection.

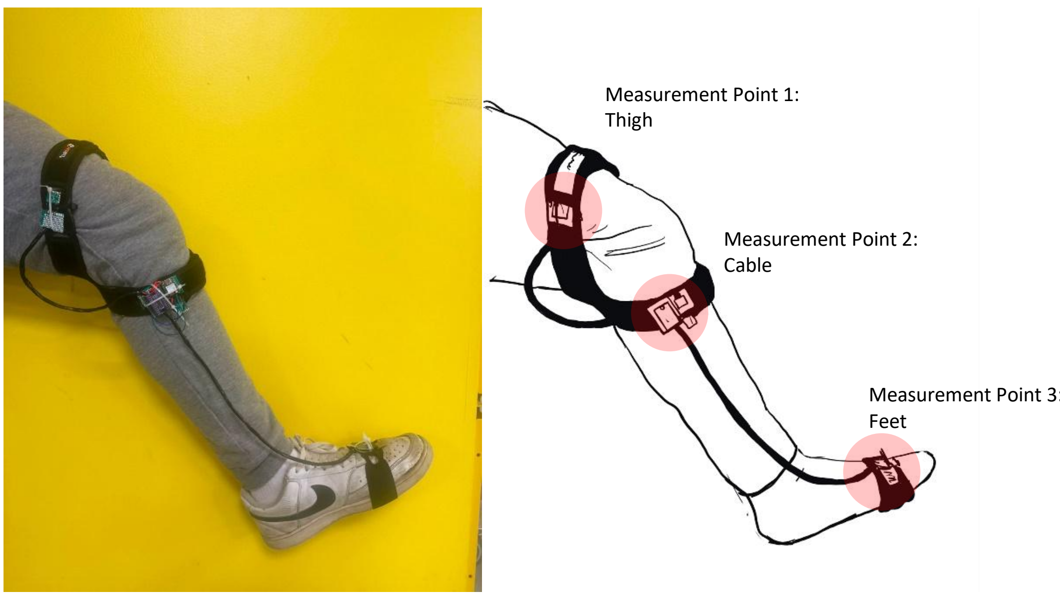

Figure 1. Hardware details and three points of measurements.

Data Collection:

In this project, motion data is collected using Inertial Measurement Units (IMUs) placed on specific points of the patient's body, including the thigh, calf, and foot. IMUs are devices equipped with accelerometers and gyroscopes that measure acceleration and angular velocity, respectively, along multiple axes. Placing IMUs on these body parts allows for the precise monitoring of knee joint motion during rehabilitation exercises.

1. Number of Participants: 6 individuals
2. Duration of Each Action: 20 seconds per action
3. Action1: Ankle Pump Exercise, Action2: Straight Leg Raise, Action3: Side Leg Raise
4. Ground Truth: Camera (Video) + Timestamp

Figure 2. Three actions data collection

Ethical Considerations:

Ethical Considerations： In conducting this research, we adhered to strict ethical guidelines, ensuring all experimental data was anonymized and handled with confidentiality. Informed consent was obtained from all participants. These measures underscore our commitment to upholding the highest ethical standards in our work.

Data Analysis:

Once the motion data is collected from IMUs, it undergoes thorough analysis. The data is first segmented into intervals corresponding to each rehabilitation exercise, such as ankle pumps, straight leg raises, and side leg raises. This segmentation ensures that each exercise's motion data is isolated and processed separately.

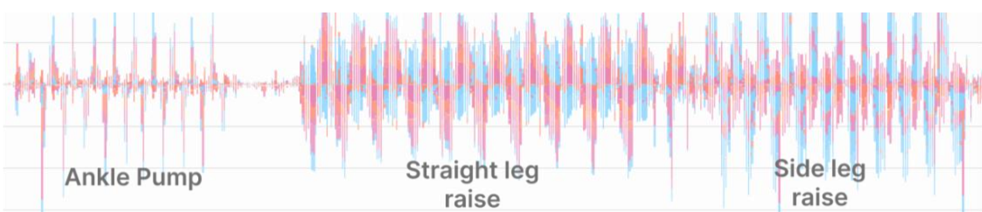

Figure 3. Data visualization and slicing

Data preprocessing：

In the data processing stage, several techniques are employed to ensure the accuracy and reliability of the collected motion data. The process involves applying appropriate filtering techniques to remove noise and enhance data quality. One of the key techniques utilized is the Moving Average Filter, which smoothens the data by averaging out fluctuations and outliers over a specific time window. This helps to mitigate the effects of sensor noise and movement irregularities, resulting in cleaner and more accurate motion data.

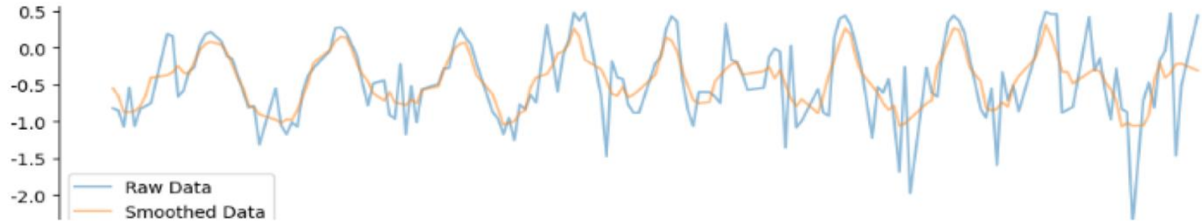

Figure 4. Dataprocessing

Data Segmentation:
Instead of dividing the data into non-overlapping 2-second intervals, the moving window segmentation approach is employed. This approach ensures continuous coverage of the exercise movements by collecting data every second, with each 2-second segment overlapping with the previous segment by 1 second.

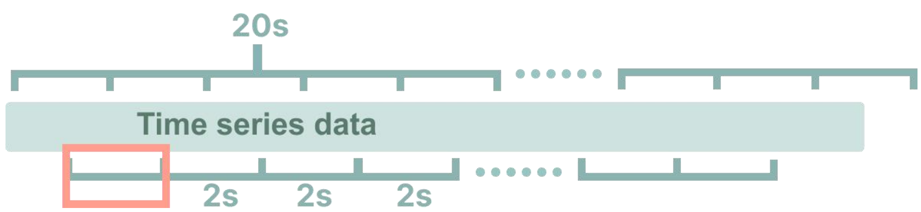

Figure 5. Moving window segmentation

Feature Engineering:
Feature engineering techniques are then applied to extract relevant features from the segmented motion data. Before model training, the multidimensional motion data collected from IMUs is flattened from 2 second time series data (19 data*18 axis) into a 1-dimensional feature (1*256 axis) vector within each 2-second interval. This flattening process allows for efficient representation of the motion data, facilitating further analysis and model training. 7 features are computed for each 2-second interval, including Skewness, Average Kurtosis, Minimum, Maximum, Root Mean Square (RMS), and Standard Deviation. These features provide insights into the characteristics of each exercise's movement pattern and help distinguish between different exercises.

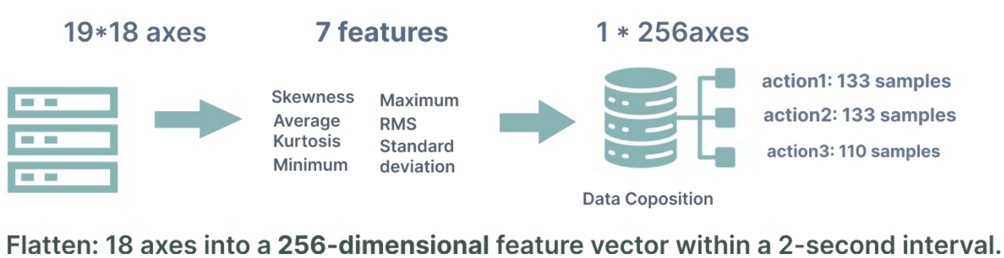

Figure 6. Flattening feature engineering

Model Training:

After completing data preprocessing, the collected motion data is utilized for model training using various machine learning algorithms. The dataset contained 376 samples of different digital signals, each with a length of 128 data points. We then divided the dataset into training and testing sets with a ratio of 80:20, utilizing K-fold cross-validation with 5 folds to ensure robustness and generalizability.
These algorithms include Decision Tree, Random Forest, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Logistic Regression. In selecting the machine learning algorithms for our platform, we prioritized versatility, accuracy, and computational efficiency. The choice of algorithms like Decision Trees, Random Forest, and SVM was informed by their proven track records in handling classification tasks within the domain of motion data analysis. Decision Trees offered a straightforward, interpretable model structure, making them ideal for initial experimentation[11]. Random Forest was selected for its ability to manage overfitting while handling high-dimensional data effectively[12]. The key advantage of the KNN algorithm in motion recognition is its simplicity and intuitiveness, with no need for a training phase and the ability to flexibly adapt to different datasets by adjusting its nearest neighbors[13]. SVMs were chosen for their robustness in dealing with non-linear data[14]. Each algorithm is trained on the preprocessed motion data to classify the different rehabilitation exercises accurately. The performance of each model is evaluated based on its accuracy in classification.

Deployment:
The trained model has been deployed on an ESP32 microcontroller, enabling real-time recognition of postoperative rehabilitation exercises directly on the device. This deployment allows for immediate feedback during rehabilitation sessions, aiding clinicians in monitoring patients' progress and ensuring adherence to the prescribed exercises.

Results

Data Collection and dataset:
The hardware setup for data collection includes IMUs placed on the patient's body to capture motion data during rehabilitation exercises. The dataset comprises samples for each exercise, and preprocessing results in 18 feature vectors. After signal processing, the dataset consists of:
Action 1: 133 samples
Action 2: 133 samples
Action 3: 110 samples

Model training：
The model training results demonstrate the performance of different machine learning algorithms in classifying rehabilitation exercises based on motion data collected from IMUs. The accuracy percentages achieved by each algorithm are as follows: Decision Tree (96.5%), SVM (94.4%), Logistic Regression (94.4%), KNN (94.7%), and. Above all, decision tree has the best accuracy.

ALGORITHM	ACCURACY	PRECISION	RECALL	F1-SCORE

DECISION TREE	96.5%	0.967	0.966	0.966
SVM	94.4%	0.948	0.944	0.944
LOGIC REGRESSION	94.4%	0.946	0.944	0.944
KNN	94.7%	0.951	0.946	0.946

Table 1. The classification performance metrics of each algorithm. The results indicate that the Decision Tree algorithm achieved the highest precision, recall, and F1-score among the three algorithms.

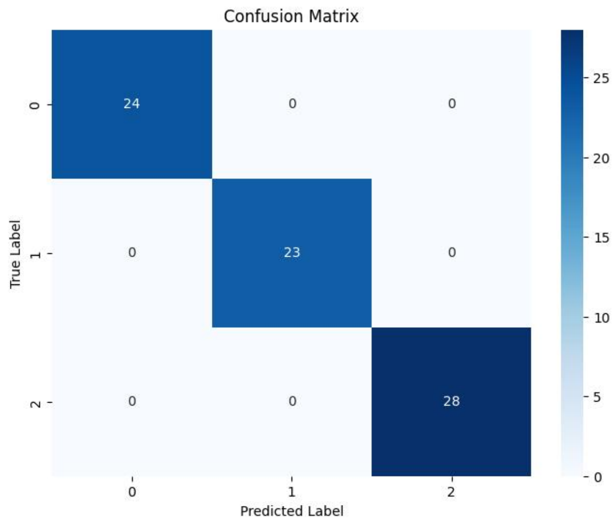

Figure 7. The confusion matrix indicates that the model's predictions for each class are entirely accurate.

Deployment：

The deployment phase was a key part of the project, and by integrating the model into wearable devices, such as smart knee braces or motion sensors, patients can receive personalized guidance and support throughout their recovery process, enhancing the effectiveness of postoperative rehabilitation for knee replacement surgery. This immediate feedback is essential to promote active patient participation, allowing patients to adjust their exercise posture and intensity based on the immediate assessment provided by the model. Demolink： https://youtu.be/5-mJ2uz3CA8

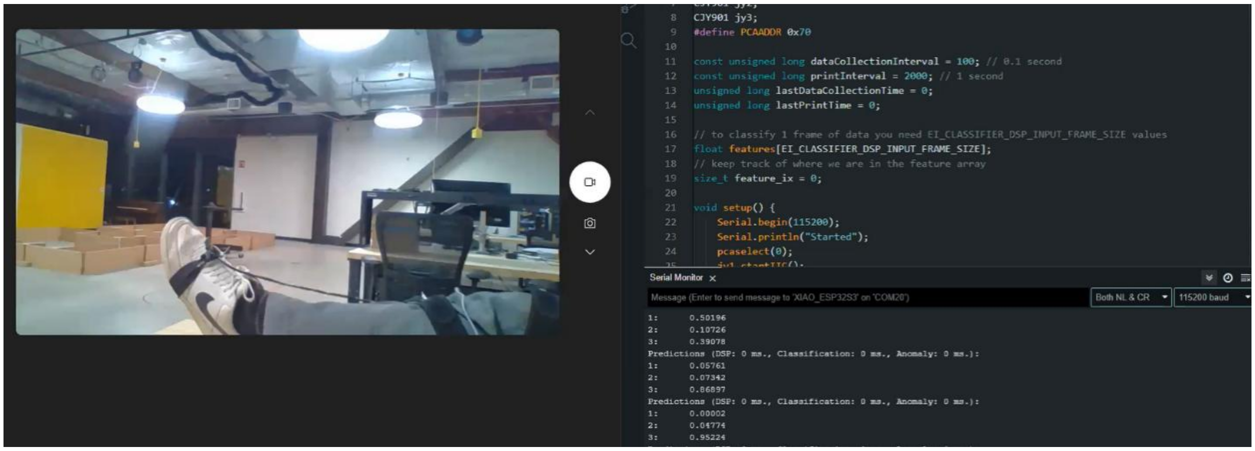

Figure 8. Deployment of the model on Seeeduino Xiao.

Discussion

Model Comparison:

Our findings suggest that Random Forest emerges as a highly effective method for signal classification in this study. The implementation of normalization techniques is crucial in standardizing input data across different models, thereby influencing their performance. Notably, Random Forest may outperform other models due to its capability to handle non-linear relationships and high-dimensional feature spaces effectively. However, further investigation is warranted to delve into the underlying reasons behind its superior performance and to validate its effectiveness in clinical settings.

Contribution:

1. Technological Application: We have successfully integrated 3 Inertial Measurement Units (IMUs) and machine learning algorithms to develop an innovative method to monitor and recognise rehabilitation exercises. The method is innovative in its ability to accurately identify specific rehabilitation exercises in real-time, including ankle pump exercises, straight leg raises and lateral leg raises, which is essential for the development of individualised rehabilitation plans.

2. Impact on Clinical Practice: The main contribution of this project lies in bridging the gap between clinical practice and data-driven approaches. By leveraging motion tracking technology and machine learning algorithms, the platform provides clinicians with actionable insights derived from motion data analysis. This enables personalized rehabilitation plans tailored to individual patient needs, ultimately improving patient outcomes and standardizing TKA rehabilitation practices.

3. Interdisciplinary Collaboration: Our study demonstrates the great potential for interdisciplinary collaboration between engineering, physiotherapy, data science and medicine. By working together as a team, we were able to develop a more comprehensive

understanding of the technical needs and clinical challenges of the rehabilitation process, leading to the development of more effective rehabilitation support tools.

Limitations:

1. Small Sample Size: Our study was limited by a relatively small sample size of only six individuals for data collection. While our findings provide valuable insights, the generalizability of the results may be constrained. Future studies with larger and more diverse participant pools could offer a broader understanding of postoperative rehabilitation exercises for knee replacement surgery.

2. Limited Exercise Variability: We focused primarily on three specific rehabilitation exercises (Ankle Pump Exercise, Straight Leg Raise, and Side Leg Raise), which may not encompass the full spectrum of exercises typically performed during TKA rehabilitation. Expanding the study to include a wider variety of exercises, such as hip lifts, quadriceps isometric stretching exercises, knee flexion and extension and knee hyperextension, can provide more comprehensive support for the rehabilitation process. Including a wider range of exercises would offer a more comprehensive representation of the diverse movements encountered in clinical practice.This will allow the platform to be better adapted to the specific needs of individual patients, which in turn will optimise rehabilitation outcomes.

3. Stability and Robustness Considerations:
   Our study faces limitations concerning the stability and robustness of the proposed clinician-based design platform for postoperative rehabilitation after knee replacement surgery. Firstly, variations in hardware setups could impact system accuracy and reliability, highlighting the need for robustness to hardware differences. Secondly, assumptions about exercise performance introduce uncertainty about system stability in real-world scenarios. Furthermore, limited clinical validation undermines the platform's real-world applicability and effectiveness. Addressing potential biases in data collection is crucial for maintaining system stability and validity. Finally, the narrow scope of the recognition system restricts its robustness in addressing the comprehensive needs of postoperative rehabilitation. By addressing these considerations, future research can enhance the reliability and real-world applicability of the proposed platform.

Future Work:

Despite the promising results, several challenges and areas for future work need to be addressed. Firstly, wearable devices used for motion data collection should prioritize patient comfort and meet clinicians' requirements to ensure widespread adoption in clinical settings. Additionally, further research is needed to expand the range of recognized movements, catering to the diverse needs of Total Knee Arthroplasty (TKA) patients. Comparing model performances with normalization techniques can provide insights into model selection for future applications. Furthermore, incorporating peak detection techniques into the platform can improve the granularity and precision of motion analysis, providing clinicians with more detailed insights into patients' progress. This enhancement can contribute to refining postoperative rehabilitation strategies and optimizing patient outcomes. Last, we will conduct interviews in the future with more professional rehabilitation teams, doctors, and TKA rehabilitation patients, determine all the standard rehabilitation actions required for rehabilitation, and allow doctors to formulate suitable rehabilitation plans according to the patient's own situation.

Conclusion

In conclusion, by leveraging motion tracking technology and machine learning algorithms, the platform facilitates personalized rehabilitation plans tailored to individual patient needs, ultimately improving patient outcomes and standardizing TKA rehabilitation practices. Future research should continue to refine the platform and address challenges to ensure its successful implementation in clinical practice.

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Appendix

Code : ShunxiWu/513-final (github.com)