Name: Kiana Asadzadeh
CandNo: 277215

Contents

1. Introduction 2
2. MTx's Conceptual and hardware design and proof of concept 4
3. Data 5
   I. Physical therapy exercises 6
   II. Data analysis 8
4. Feasibility Analysis 11
   III. K-Nearest Neighbors (KNN) 11
   IV. Decision Tree Classifier 11
   V. Support Vector Machine (SVM) 11
   VI. multi-template multi-match dynamic time warping (MTMM-DTW) 12
5. Socioeconomic background and acceptance of user experiences 16
6. Recommendation 18
7. Conclusion 19
8. References 19

Wearable Technologies Autonomous Systems sensor in physiotherapy

1. Introduction

One crucial kind of rehabilitation for people with a variety of conditions is physical therapy, Physiotherapy plays a pivotal role in the rehabilitation and improvement of patients' physical health [2,3]. In physical rehabilitation, a variety of sensor modalities are employed, such as inertial visual, strain, medical, physiological, kinetic, and environmental sensors, or some combination of these[10,13]. The advent of digital technology has significantly enhanced the effectiveness of treatment methods. Among these advancements, wearable technologies offer novel approaches to monitoring and facilitating patient recovery. Using wearable technologies is very common, especially in motion sensors. In physiotherapy nowadays, various wearable technologies are utilized, including vision-based systems such as cameras and body sensors.

the PRISMA-ScR framework, examining 7499 articles across four medical databases that involved wearables that measured vital signs and analyzed data quantitatively, excluding those not focused on wearables for outcome assessment. A wide range of studies focus on global health studies. Wearables were primarily worn on the wrist and cost less than €200. Five main applications are important to highlight wearables the first one is accuracy, including correlation analyses, method evaluations, population-based research, and big data explorations. (Figure 1, Figure 2) [20].

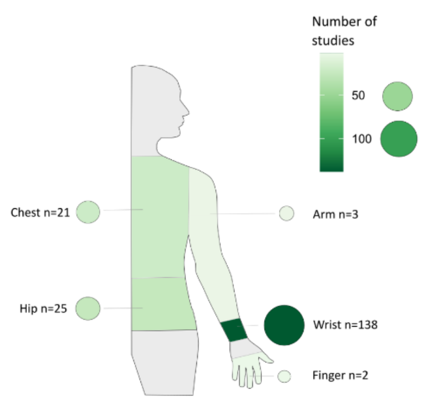


Fig 1. Wear locations of wearables and their frequencies.

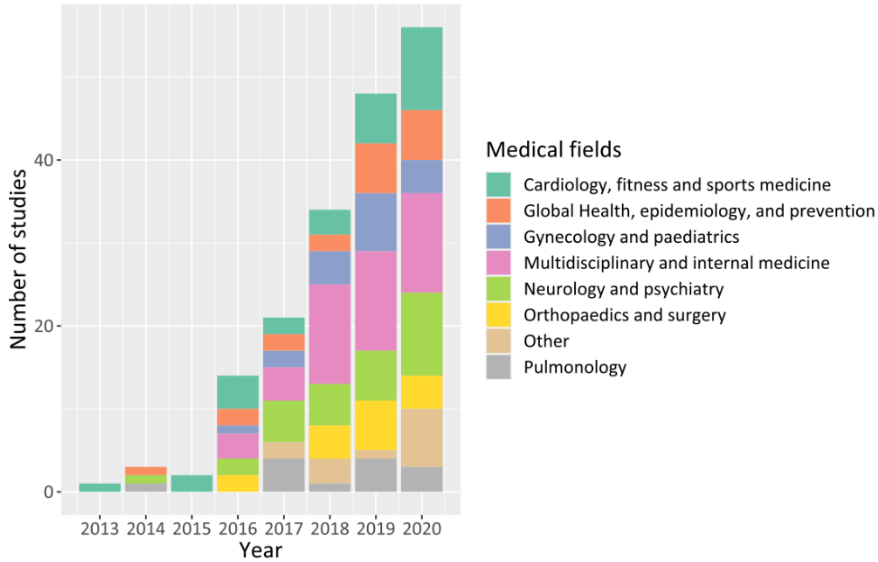


Fig 2. Studies per medical field.

In this essay, we discuss an autonomous system with an Xsens MTx sensor in terms of effectiveness and economic efficiency in physiotherapy and how we can enhance it. Our goal is to prepare a feasibility analysis, conceptual design, and concept for a wearable technology for this device. By examining outcomes, we seek to highlight the potential of wearable technologies in revolutionizing physiotherapeutic interventions.

This product proposes a completely autonomous system to detect sequential executions of one or more exercise kinds during an exercise session, classify the exercise type, evaluate each execution as correctly or incorrectly executed, and identify the error type and idle time intervals, if any. During the physical therapy session, the patient wears small, low-cost Xsens MTx sensor units. Xsens MTx sensors are lightweight and portable, allowing for home-based therapy. The patient first performs the exercises under the guidance of a specialist, who records reference templates. The patient can then execute the workouts anywhere if he wears the sensors appropriately.

The multi-template multi-match uses a dynamic time warping (MTMM-DTW) algorithm as a natural extension of DTW. Using MTMM-DTW, multiple template sequences of different durations can be searched in a test sequence of any duration based on the DTW dissimilarity measure. The system compares detected executions to templates recorded while under monitoring and measures the similarity and can provide statistical information about the exercise session at any desired level of detail to the specialist and provide feedback to the patient. The primary applicability of the system is to the rehabilitation of orthopedic patients [1]. I used clustering with KNN, SVM, DTW, and Tree decision to predict the activity with a high score.

2. MTx's Conceptual and hardware design and proof of concept

This wearable has inertial and magnetic sensors, each MTx equipped with tri-axial accelerometers, gyroscopes, and magnetometers, sampling data at 25 Hz. The MTx is a complete miniature inertial measurement unit with integrated 3D magnetometers, featuring an embedded processor capable of real-time calculation of roll, pitch, and yaw, in addition to outputting calibrated 3D linear acceleration, rate of turn (gyro), and (earth) magnetic field data. This device is designed for a variety of applications, including biomechanics, exercise and sports, virtual reality, animation, and motion capture. The orientation of this device is computed by the Xsens Kalman Filter for 3 degrees-of-freedom (3DoF) orientation, which uses signals from the rate gyroscopes, accelerometers, and magnetometers to compute a statistically optimal 3D orientation estimate of high accuracy with no drift for both static and dynamic movements. Later in part 3, we explain more about MTx for our use.

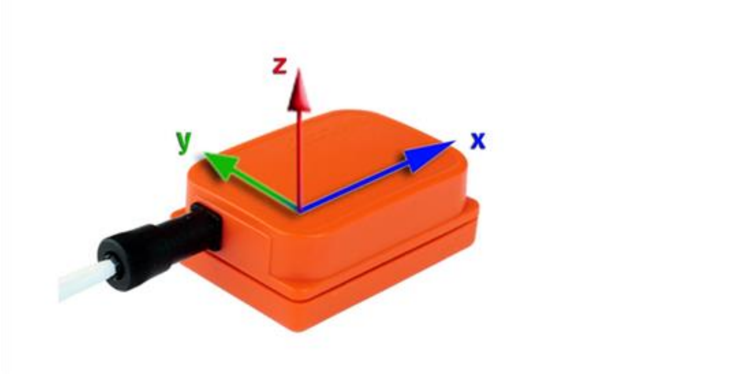


Fig 3: Xsens MTx unit.

The orientation output from the MTx can be presented in different formats: Unit Quaternions, Euler angles (roll, pitch, yaw), and Rotation Matrix. The orientation is the orientation of the sensor-fixed coordinate system (S) for a Cartesian earth-fixed coordinate system (G), with the output orientation described in terms of rotation between these two coordinate systems Fig 4.

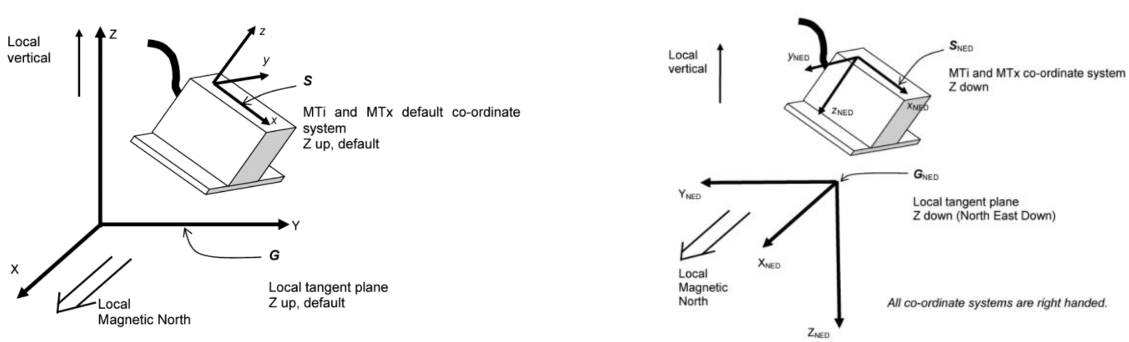


Fig 4: MT in the earth-fixed and NED convention coordinate system.

This device also comes with a development kit containing the measurement unit, a Calibration Certificate, a software license code, a USB-serial data and power cable, a Quick Setup Sheet, and documentation including user manuals and technical documentation to transmit data to other devices. The MTx offers versatility and precision for developers and researchers working in fields requiring accurate orientation and motion data [11].

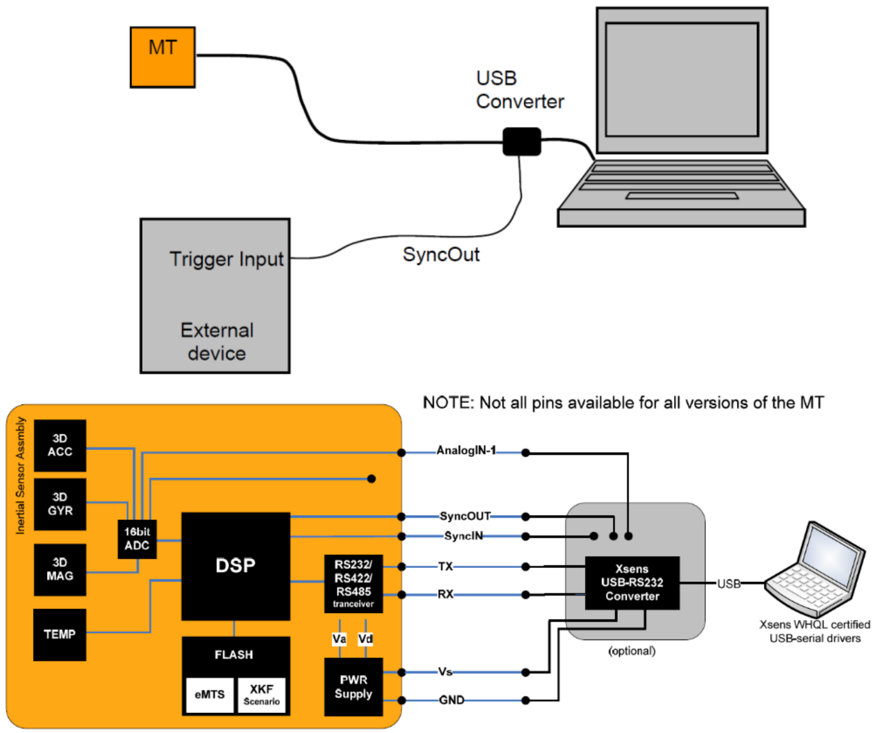


Fig 5: Transmit data to PC.

3. Data

The dataset was produced as part of a study on wearable motion sensors for automated detection of physical therapy exercise executions. A physical therapy specialist collaborates in determining the workouts and the trial protocol [22].

This dataset comprises data from wearable inertial and magnetic sensors during physical therapy exercises, focusing on eight types of exercises executed in three different manners (correct, fast, and low-amplitude) by five subjects. Each subject wore five MTx sensor units from XSens, each equipped with tri-axial accelerometers, gyroscopes, and magnetometers, sampling data at 25 Hz. Detailed methodology and the purpose behind the dataset are elaborated in referenced studies, with one emphasizing the automated detection and evaluation of these exercises. The collection process received ethical approval from Bilkent University, ensuring participant consent and anonymity. This dataset includes data from wearable magnetic and inertial sensors collected while performing physical therapy activities. Physical therapy exercises come in eight varieties, with three ways to perform them: accurate, rapid, and low-amplitude. Five individuals performed each exercise type execution type numerous times Table 1. Five MTx sensor units made by XSens were worn by five subjects. Three tri-axial sensors, measured at 25 Hz, are present in each unit: a magnetometer, a gyroscope, and an accelerometer. The collection includes time series data from simulated exercise sessions (including numerous exercise executions) and training sessions (containing time indices of the chosen templates)[18][16].

	Subject_ID	Sex	Age_(years)	Weight_(kg)	Height_(cm)
0	101	Female	55	73	169
1	102	Male	61	85	180
2	103	Male	23	95	180
3	104	Female	48	55	158
4	105	Male	53	98	175

Table 1: subject information

Fig 6 shows Sensor placement on the human body. (a) The first and (b) second configurations are designed for leg and arm exercises, respectively. The arrow perpendicular to the sensor unit indicates the z direction. The cable goes into the sensor unit in the direction of the x-axis. The y-axis can be easily determined given that right-handed coordinate systems are used [1]

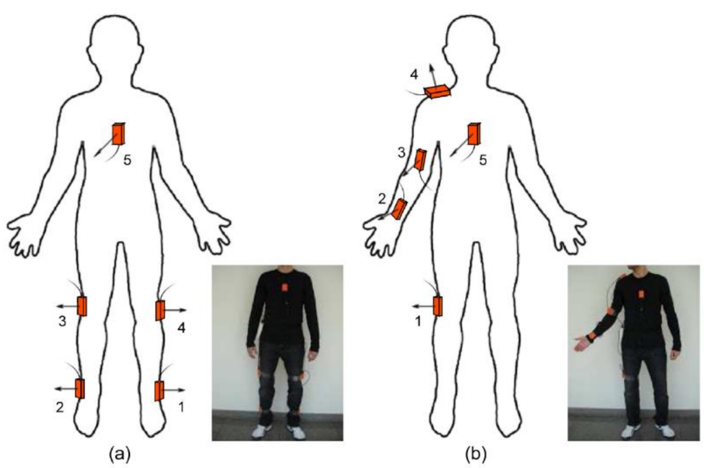


Fig 6: Sensor placement on the human body.

I. Physical therapy exercises

This study focuses on eight orthopedic rehabilitation exercises recommended by a physical therapy specialist, designed to be the most commonly assigned routines for patients. They must do all of them for 5 seconds.

1. Leg Raise (Sitting): Sit on a high flat surface, raise the right leg with a straight knee, and return to the starting position.

2. Upper Body Bend (Sitting): Sit upright on a stool, bend forward 30°, and revert to the initial posture.

3. Leg Raise (Lying on Back): Lie flat on your back, lift the right leg from the hip with both knees straight, and go back to the starting position.

4. Leg Raise (Lying on Side): Lie on the left side, elevate the right leg from the hip, keeping both legs straight, and return to the initial position.

5. Leg Raise (Lying Facedown): Lie facedown, lift the right leg from the hip with straight knees, and return to the starting pose.

6. Arm Curl (Sitting): Sit on a chair with a 1 kg weight in the right hand, extend the arm in front, then bend the elbow to raise the weight, and lower it back.

7. Lateral Arm Raise (Standing): Stand with a 1 kg weight in the right hand, lift the arm to the side until it's horizontal, and lower it back down.

8. Forearm Raise (Lying Facedown on Raised Surface): Lie facedown with the right arm hanging over the side, raise the forearm to straighten the elbow, and return to the start[1].

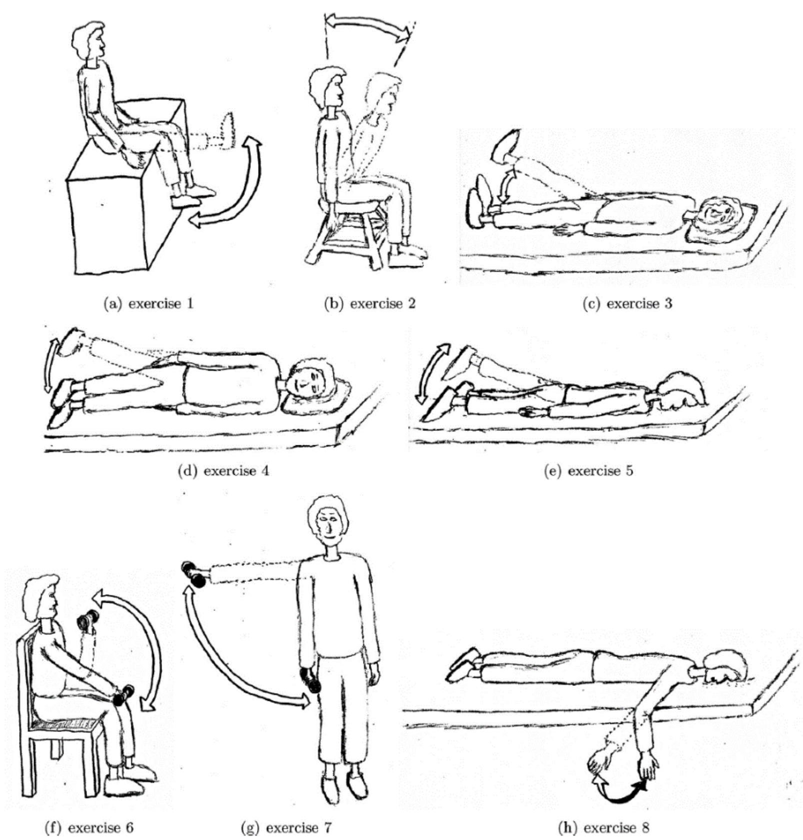


Fig 7: The eight physical therapy exercises.

II. Data analysis

This section aims to show more information about the data that further will be used for the model. As a result of 5 subjects, 8 exercises, and 5 units I had 200 files for my train data and 200 for my test overall 400 data. Each file had 10 columns, 'acc_x', 'acc_y', 'acc_z', 'gyr_x','gyr_y', 'gyr_z', 'mag_x', 'mag_y', 'mag_z', 'time_index' I additionally added 3 columns that I neede for my data analysis 'Subject_ID', 'activity_id', and 'unit'. I put each in one data frame by using different libraries such as Pandas and NumPy. I also manually created a data frame with details about subjects including ID, sex, age, weight, and height as a result in Table 2.

I handled missing values by filling in missing "time_index" data using a backward fill method and dropping any rows still containing NaN values.

	Subject_ID	activity_id	unit	acc_x	acc_y	acc_z	gyr_x	gyr_y	gyr_z	mag_x	mag_y	mag_z
0	1	1	1	-9.665799	-1.677241	0.615063	-0.014956	0.004388	0.010589	0.587318	0.455106	-0.094949
1	1	1	1	-9.665806	-1.684737	0.622513	0.000607	-0.003094	-0.007589	0.587428	0.455621	-0.093364
2	1	1	1	-9.628410	-1.699724	0.585751	0.006007	0.000557	-0.004879	0.588389	0.454722	-0.094907
3	1	1	1	-9.628372	-1.684836	0.600733	-0.003085	-0.000281	-0.000340	0.588673	0.455759	-0.092664
4	1	1	1	-9.643291	-1.639893	0.585661	-0.002932	-0.006807	-0.013043	0.589193	0.453927	-0.093143

Table 2: X train data frame

Fig 8 shows that there are relationships between different sensors and activity IDs.

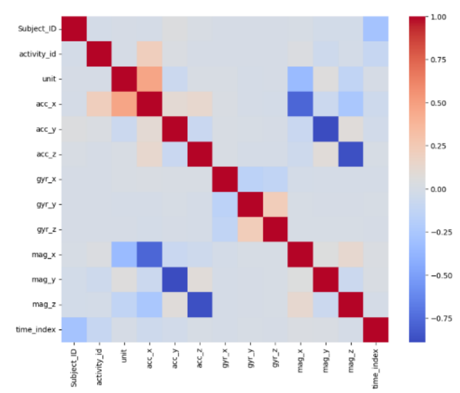


Fig 8: the heat map that shows the relationship between features.

Fig 9 shows that activity 7 has more frequency in acc_x and Fig 10 shows that subject one has the most participation in exercises.

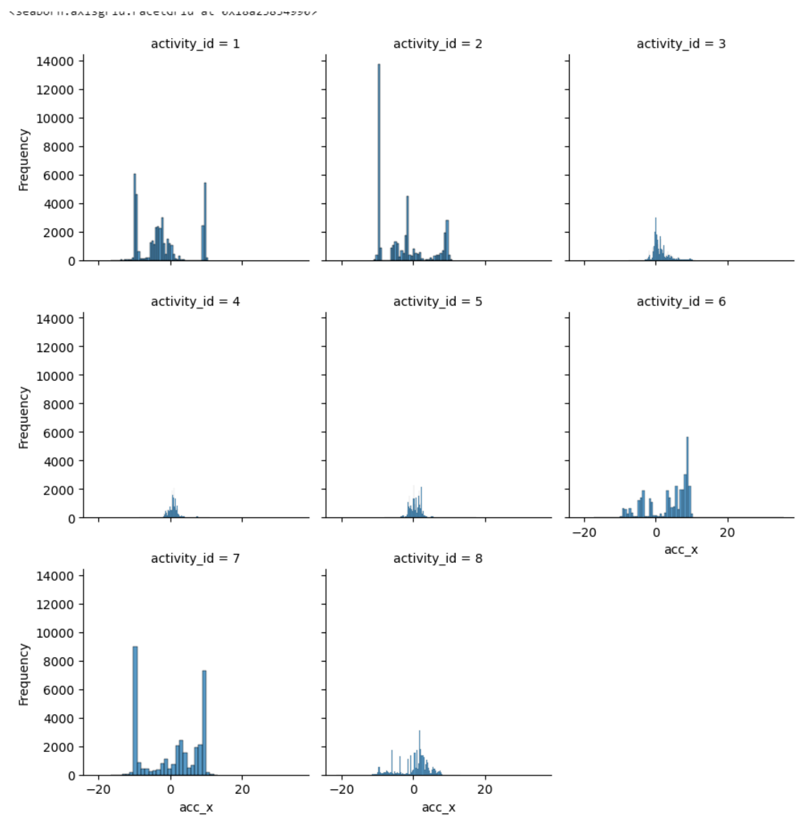


Fig 9: the plot shows the frequency of acc x for each activity.

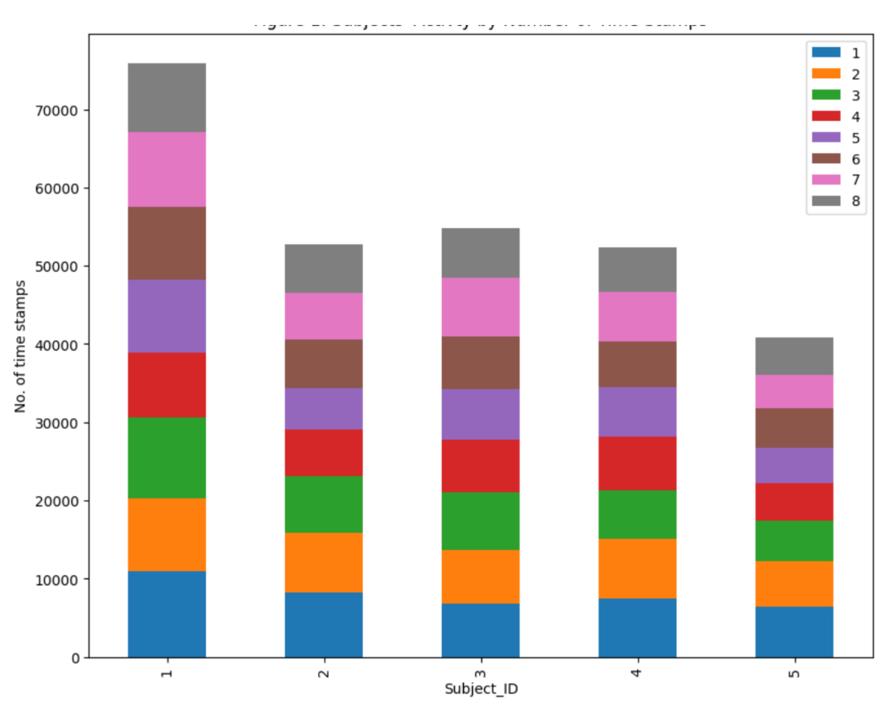


Fig 10: the plot shows the time of the activity that each subject has done.

Fig 11 and fig12 show that exercise one has the most frequency compared to other exercises.

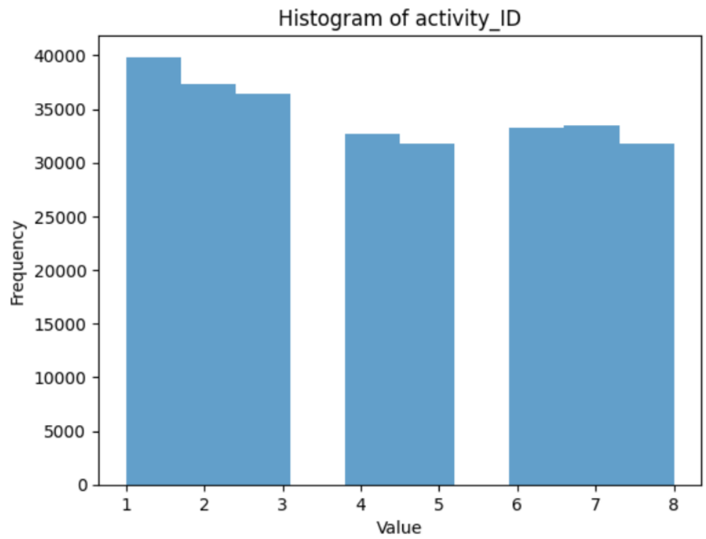


Fig 11: the bar shows the frequency of each activity ID

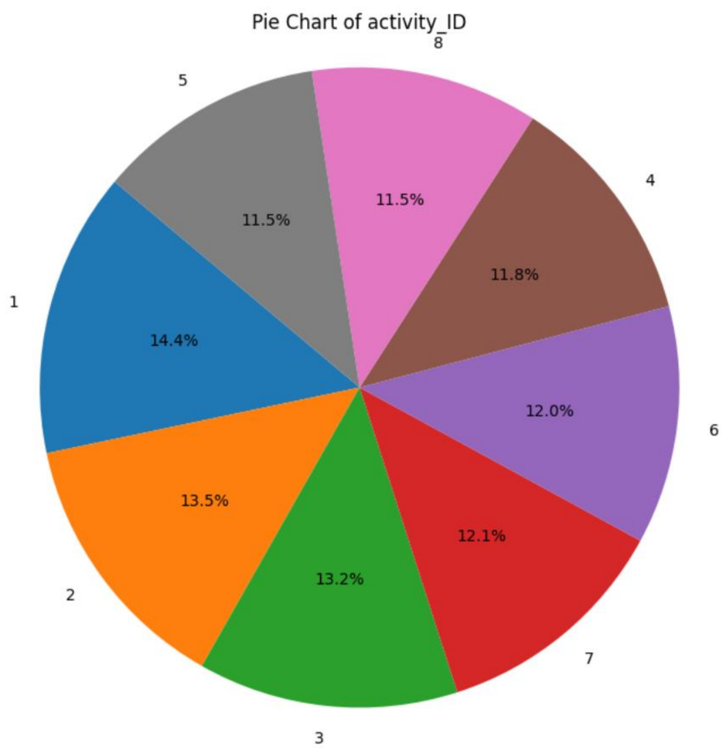


Fig 12: the pie chart shows the percentage of each activity.

4. Feasibility Analysis

For predicting activity ID I split my dataset into features (`X_train`, `X_test`) and labels (`y_train`, `y_test`). for my X_train I use data like acceleration, gyroscope, magnetometer readings, and subject information features, my target label is activity ID. I standardized my X train` and `X test` using `Standard Scaler` from Sklearn. This normalization ensures that the model isn't biased towards variables on larger scales. I use three models for prediction here is a brief explanation of each. The whole code is provided in the attached Jupiter pdf file. As a result, all the models predict the activity ID perfectly with the highest 0.99 score.

III. K-Nearest Neighbors (KNN)

I initialized a KNN model, I chose K=4 by getting help from the Elbow Method for the KNN algorithm and trained the model using the training data (`X train`, `y train`). The result calculated a metrics accuracy score of 0.998 and a metrics accuracy score of 0.977 evaluating the KNN as a good model performance.

IV. Decision Tree Classifier

I initialized a Decision Tree Classifier with the entropy criterion and a maximum depth of 11. The result calculated metrics accuracy f1 score of 0.99 evaluating the Decision Tree as a good model performance.

V. Support Vector Machine (SVM)

I initialized an SVM model with the Radial Basis Function (RBF) kernel. The result calculated metrics accuracy f1 score of 0.99 evaluating the SVM as a good model performance Fig 13.

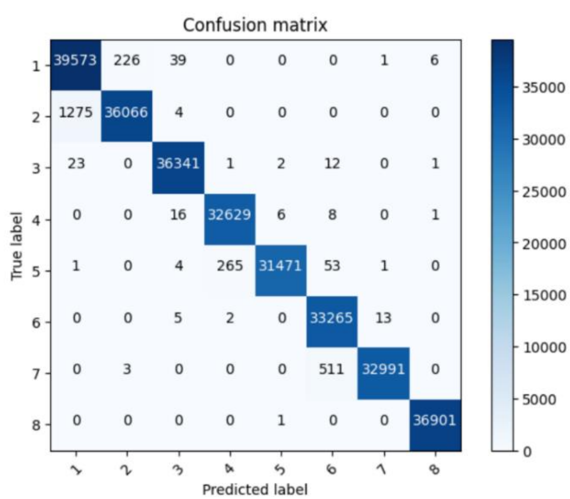


Fig 13. Confusion matrix

VI. multi-template multi-match dynamic time warping (MTMM-DTW)

Based on DTW distance, the technique offers a quantitative measure of similarity between an exercise execution and previously recorded templates, even though it permits some distortion (warping) in time. It can recognize and categorize the different exercise kinds by detecting multiple occurrences of multiple exercise types in a sequence recorded during a physical therapy session, count the exercises, assess whether they were performed correctly or wrongly, and pinpoint the type of error if any [1]. Fig 14 is an explanation of how the algorithm works.

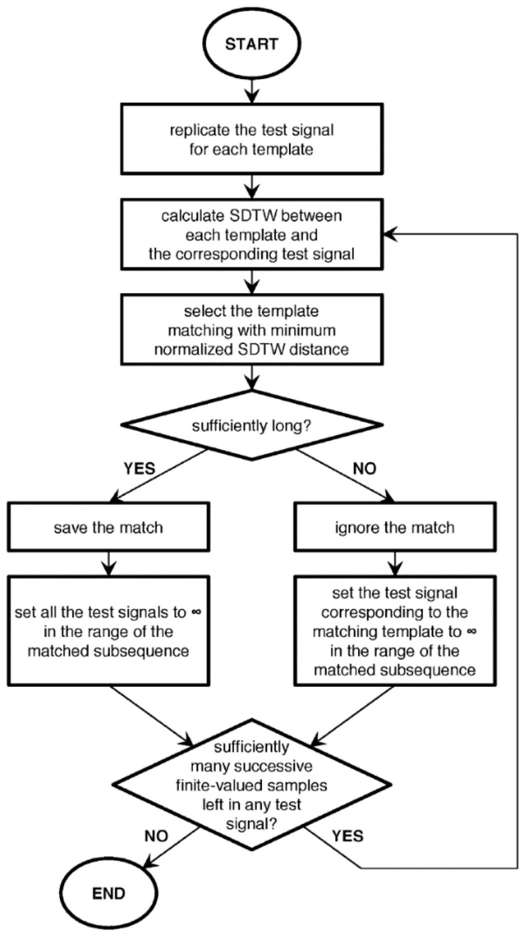
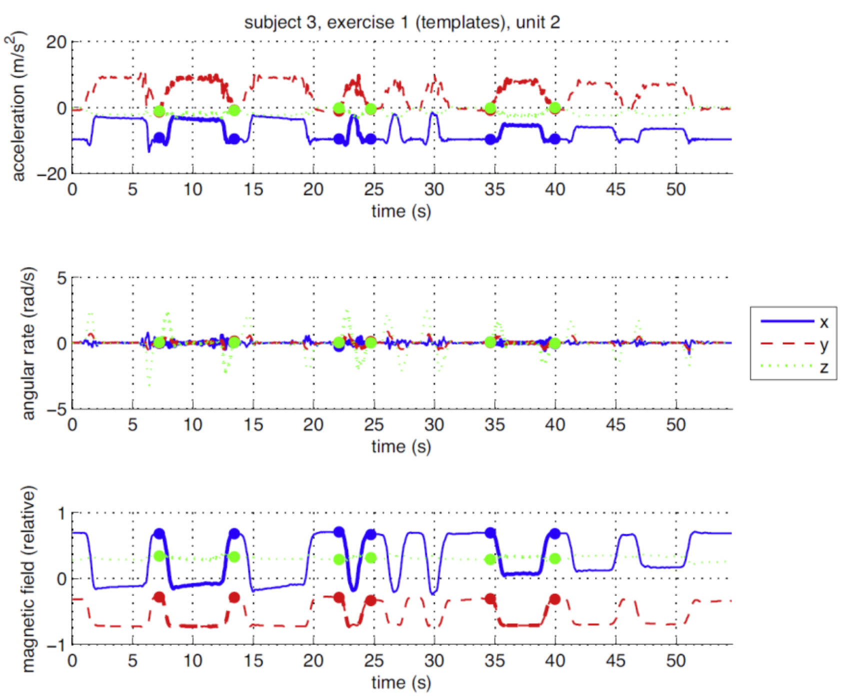


Fig 14: The flowchart of the MTMM-DTW algorithm.

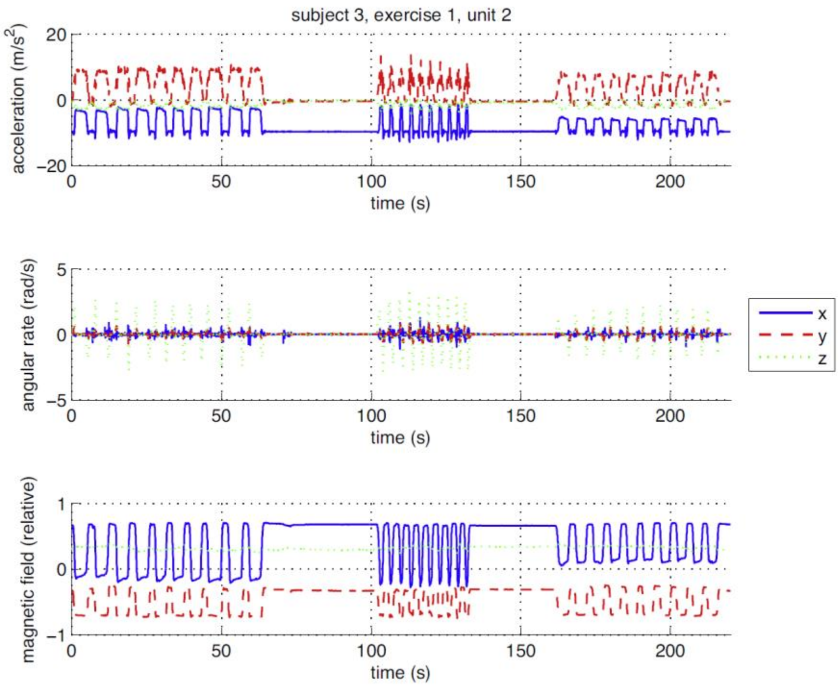
The MTMM-DTW algorithm enhances the classic DTW approach to address the complexity of monitoring physical therapy exercises more effectively. Unlike standard DTW, which compares single sequences, MTMM-DTW can recognize multiple exercise patterns and their instances within a lengthy recording session. This is crucial for distinguishing between different types of exercises and their repetitions, and for evaluating the correctness of each performance.

MTMM-DTW operates by allowing some flexibility in the time alignment of exercise sequences, which accommodates natural variations in patient performance speed and style. The algorithm works by matching exercise templates—pre-recorded correct executions of exercises—to segments within the session's data. It quantitatively measures similarity and identifies the exercise type, counts occurrences, and assesses execution quality, noting errors when they occur. An important feature of this algorithm is its ability to handle data that includes idle periods where no exercise is performed. The MTMM-DTW method not only detects and classifies exercises but also provides a statistical breakdown of the session, indicating portions of active exercise versus rest. To validate its effectiveness, experiments were conducted with subjects performing a series of exercises while wearing motion sensors. The algorithm demonstrated high accuracy in classifying exercises and identifying execution types. Moreover, it could detect exercises with minor variations in execution, which is essential for personalized therapy assessment. This capability makes MTMM-DTW particularly valuable in rehabilitating settings where accurate, real-time feedback on patient performance is crucial for recovery.

Fig 15 shows the recording of the templates and the experiment for exercise 1 performed by subject 3. (a) The three templates (highlighted with thick lines) for correct, type-1 error, and type-2 error execution types of exercise 1, (b) the experiment consisting of 10 repetitions of exercise 1 for the three execution types and two idle periods in between. Only the sensor outputs of unit 2, the most important one for this exercise, are shown [1].



(a)



(b)

Fig 15: Recording of the templates and the experiment for exercise.

Table 3 shows the three execution types (A: correct, B: type-1 error, C: type-2 error) of all eight exercises (1–8) summed up for all five subjects. The number of MDs and FAs are shown in an additional column and row, respectively. The elements in the 3×3 blocks on the diagonal correspond to correct exercise type classifications classes estimated 8C8B8A7C7B7A6C6B6A5C5B5A4C4B4A3C3B3A2C2B2A1C1B1AMD.

		Estimated classes																								
		1A	1B	1C	2A	2B	2C	3A	3B	3C	4A	4B	4C	5A	5B	5C	6A	6B	6C	7A	7B	7C	8A	8B	8C	MD	total
True classes	1A	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50
	1B	2	39	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50
	1C	0	0	50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50
	2A	0	0	0	44	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	50
	2B	0	0	0	3	45	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	50
	2C	0	0	0	7	4	30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	50
	3A	0	0	0	0	0	0	43	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	50
	3B	0	0	0	0	0	0	3	43	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	50
	3C	0	0	0	0	0	0	0	6	34	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	50
	4A	0	0	0	0	0	0	0	0	0	41	7	0	0	0	0	0	0	0	0	0	0	0	0	0	2	50
	4B	0	0	0	0	0	0	0	0	0	1	49	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50
	4C	0	0	0	0	0	0	0	0	0	5	6	17	0	0	0	0	0	0	0	0	0	0	0	0	22	50
	5A	0	0	0	0	0	0	0	0	0	0	0	0	42	4	1	0	0	0	0	0	0	0	0	0	3	50
	5B	0	0	0	0	0	0	0	0	0	0	0	0	5	21	0	0	0	0	0	0	0	0	0	0	24	50
	5C	0	0	0	0	0	0	0	0	0	0	0	0	5	7	25	0	0	0	0	0	0	0	0	0	13	50
	6A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	48	2	0	0	0	0	0	0	0	0	50
	6B	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	45	0	0	0	0	0	0	0	2	50
	6C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	1	40	0	0	0	0	0	0	2	50
	7A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	49	1	0	0	0	0	0	50
	7B	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	47	0	0	0	0	0	50
	7C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	10	1	39	0	0	0	0	50
	8A	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50	0	0	0	50
	8B	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	37	0	7	50
	8C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	2	39	0	50
	FA	4	6	0	0	16	3	1	4	1	1	2	0	9	2	4	5	4	0	1	2	0	6	0	3		74
	Total	56	45	59	54	70	34	47	55	37	48	64	17	61	34	30	63	52	40	63	51	39	71	39	42	103	1274

Table 3: Cumulative confusion matrix

As a result in Table 4 and 5, we log a total of 1200 exercise executions in the test set and 120 in the reference set. There are additional idle time periods in the test sequences. The suggested algorithm's accuracy is 88.65% for combined exercise and execution type classification and 93.46% for exercise classification alone. The system exhibits a false alarm rate of 4.91% and misses 8.58% of the exercise executions. This is because some idle time intervals are mistakenly identified as workout executions. In order to assess the system's resilience to unfamiliar exercises, leave-one-exercise-out cross-validation has been utilized. As a result, there is less than 1% false alert rate, indicating that the system is resilient to unidentified motions. The suggested technique can be utilized to give the patient feedback and evaluate how well a physical therapy session went [1].

	Exercise type								Total
	1	2	3	4	5	6	7	8	
Number of detected executions	160	142	135	127	115	149	151	146	1125
Number of actual executions	150	150	150	150	150	150	150	150	1200
	Percentage (%)								Overall (%)
Accuracy of exercise classification	97.01	90.71	91.92	91.35	83.07	96.36	99.26	94.84	93.46
Accuracy of exercise and execution type classification	93.54	84.29	87.93	85.67	77.01	92.74	94.73	89.57	88.65
Sensitivity	100.00	92.67	88.67	84.00	73.33	97.33	100.00	95.33	91.42
Specificity	89.15	95.65	96.56	98.29	94.44	95.65	98.83	94.97	95.09
MD rate	0.00	7.33	11.33	16.00	26.67	2.67	0.00	4.67	8.58
FA rate	10.85	4.35	3.44	1.71	5.56	4.35	1.17	5.03	4.91

Table 4: Experimental results summarized per exercise type.

		Estimated classes									Total
		1	2	3	4	5	6	7	8	MD	
True classes	1	150	0	0	0	0	0	0	0	0	150
	2	0	139	0	0	0	0	0	0	11	150
	3	0	0	133	0	0	0	0	0	17	150
	4	0	0	0	126	0	0	0	0	24	150
	5	0	0	0	0	110	0	0	0	40	150
	6	0	0	0	0	0	146	0	0	4	150
	7	0	0	0	0	0	0	150	0	0	150
	8	0	0	0	0	0	0	0	143	7	150
	FA	10	19	6	3	15	9	3	9		74
Total		160	158	139	129	125	155	153	152	103	1274

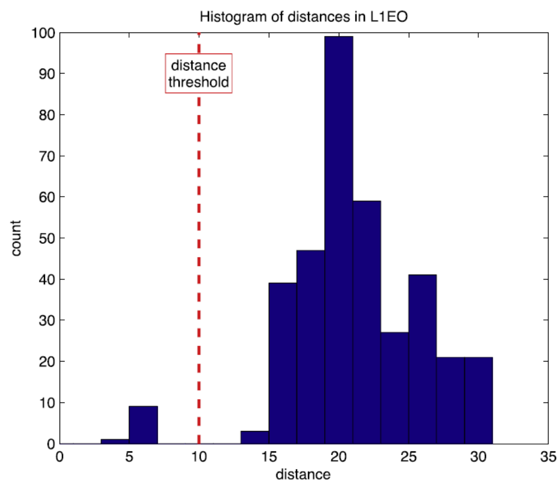
Table 5: Cumulative confusion matrix with MDs and FAs.

To assess the system's capability to handle unexpected movements, a "leave-one-exercise-out" cross-validation was conducted. This test showed a low false alarm rate of only 0.83%, highlighting the algorithm's effectiveness in distinguishing between known exercises and irregular or incorrect movements that were not part of the trained set. This indicates strong potential for the algorithm's application in diverse real-world scenarios where deviations from expected movements are likely [1].

Fig 16 shows (a) the number of FAs for each exercise of each subject in L1EO in tabular form. (b) Histogram of the normalized DTW distances of all the detections in L1EO. Detections with DTW distances below the threshold are considered FAs.

		exercise								
	FAs	1	2	3	4	5	6	7	8	total
subject	1	0	0	0	0	0	0	0	0	0
	2	8	0	0	0	0	0	0	0	0
	3	0	0	0	0	0	0	0	0	0
	4	0	0	0	0	0	0	0	0	0
	5	2	0	0	0	0	0	0	0	0
	total	10	0	0	0	0	0	0	0	10

(a)



(b)

Fig 16: Number of FAs and normalized DTW distances

5. Socioeconomic background and acceptance of user experiences

To receive physical therapy, patients are typically required to exercise at a hospital or rehabilitation facility under the guidance of a specialist who will prescribe them one or more exercises, even when a specialist is managing only one patient, this kind of process is challenging and time-consuming for him, and it becomes impossible when he is overseeing multiple patients. [4]. Patients typically must continue exercising at home without any feedback after learning how to do the exercises correctly [5]. Even in hospitals, specialists are unable to monitor every patient constantly during their exercise sessions due to their frequent switching between several patients or other obligations, which can lead to incomplete, erroneous, and frequently subjective feedback[6,7]. Evaluating the exercises and determining the efficacy of an exercise session is a crucial part of physical therapy and the length of the exercise session in its entirety, or the duration of the patient's physical activity [9]. An automated method would be extremely beneficial to both specialists and patients to lower the risk of over-exercising, the system generates a warning anytime key parameters surpass predetermined thresholds.

First, let us compare other wearable technology products that can be used for physical rehabilitation.

- **camera systems**

Automatic monitoring of patients undertaking physical therapy exercises should not limit their independence, intrude on their privacy, or degrade their quality of life. A frequent strategy is to deploy cameras around the area, which intrudes on privacy and typically has a significant installation cost. The key advantage of this method is that the person does not need to wear or carry any sensors or equipment on their body. This approach may also alleviate issues with sensor misplacement on the body, while some vision-based systems require the wear/pasting of special tags or markers. This strategy may be okay when the person always conducts exercises at the same area; however, when the exercises are conducted in other places, e.g. indoors and outdoors, this approach becomes unsuitable. wearable sensors are superior to camera systems in these respects.

- **MyHeart system**

The MyHeart system [14] uses strain sensors to measure the precision of arm movements for post-stroke rehabilitation. Healthy volunteers wearing tight-fitting clothing with printed strain sensors simulate how post-stroke patients could complete each of the seven exercise kinds correctly and incorrectly while under the supervision of a physician or therapist. An exercise is judged correct if the similarity between the recorded signal and a pre-recorded template, as determined by the open-end DTW, exceeds a certain level. The technology delivers real-time feedback to the patient and has an average categorization accuracy of 85%. The biggest downside of the system is the difficulty in putting on the garment for a post-stroke patient, even with assistance.

- **M-Physio platform**

The m-Physio platform [17] classifies physical rehabilitation exercises using an accelerometer. A smartphone with a tri-axial accelerometer is attached to the patient's leg or arm, depending on the type of exercise he is doing. The patient initially completes the exercises correctly under the observation of a specialist, who notes the reference templates. The signals captured during test exercises are compared to reference templates using the standard DTW algorithm. One disadvantage of the m-Physio platform is that it requires the determination of four parameters during the activity-capture phase: the minimum and maximum time of each workout, the accelerometer's sampling frequency, and the degree of signal smoothing applied. The specialist determines the values through trial and error, which can easily affect system performance. When using the system, the patient must touch the screen to signal the start and finish of each exercise execution, which is another disadvantage because some patients (e.g., elderly, crippled, and/or stroke patients) may be unable or forget to touch the screen on time. For each execution, the system delivers feedback such as correct, wrong, or too short/long in time. The patient's statistics are uploaded to a central database, allowing the specialist to monitor his development remotely via a web interface.

- **Xsens MTx with an automated algorithm**

In earlier studies, exercise executions were typically clipped manually and considered in isolation; the subject was required to mark each execution by pressing a button or do each exercise when prompted by the system via a sound or on-screen message. Sequential executions and idle time intervals are not considered.

This product proposes a completely autonomous system to detect sequential executions of one or more exercise kinds during an exercise session, classify the exercise type, evaluate each execution as correctly or incorrectly executed, and identify the error type and idle time intervals, if any. The patient does not need to click a button to indicate the start or conclusion of an execution or to pick the sort of exercise he wants to undertake. The system compares detected executions to templates recorded while under monitoring and measures the similarity.

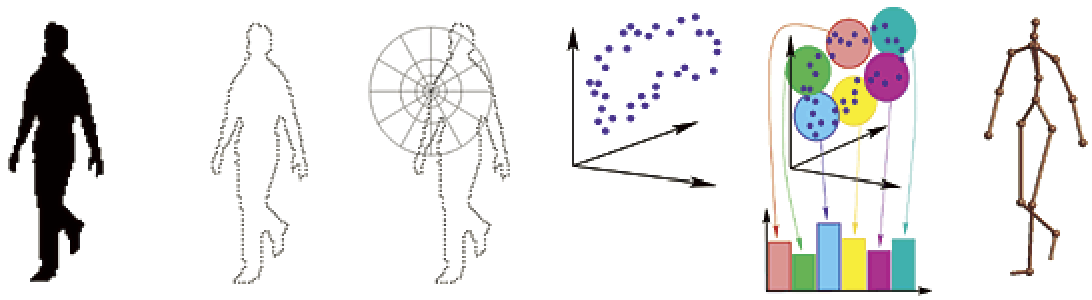
During the physical therapy session, the patient wears small, low-cost motion sensor units. The sensors are lightweight and portable, allowing for home-based therapy. It easily integrates changes in exercises or sensor configurations without needing extensive reprogramming. It accommodates any sensor configuration, which can be modified as required without affecting the system's functionality. Although initially tested in a controlled setting, the system shows promise for real-world clinical applications, especially in orthopedic and potentially neurological rehabilitation.

These wearable technologies can help patients reach their rehabilitation goals by allowing for more efficient and successful physiotherapy sessions. This efficiency can result in significant cost reductions in healthcare, including human time, facility resources, and administrative fees associated with traditional physiotherapy procedures.

6. Recommendation

The user may complain about the importance of the placement of sensors since it is sometimes hard for them to recognize if they place it correctly. My suggestion is they can set up a camera that shows the place of sensors on their body by laser light so they know exactly the placement of sensors.

Human Pose Estimation (HPE) is a computer vision task aimed at identifying key points on the human body, such as limbs and joints, to determine a person's current pose and track movements in real time. Fig 17 [21][19] shows step-by-step illustration: (a) Input silhouette extracted using background subtraction. (b) Sampled edge points. (c) Local shape contexts are computed on edge points. (d) Distribution in shape context space. (e) Soft vector quantization to obtain a single histogram. (f) Three-dimensional pose obtained by regressing on this histogram.



(a) (b) (c) (d) (e) (f)

Fig 17. Step-by-step illustration.

Another suggestion is to provide a user-friendly app for smartwatches that shows feedback on activities including lengthening, shortening, and exertion levels [12].

7. Conclusion

In conclusion, this essay has demonstrated that wearable technologies have the potential to revolutionize physiotherapy practices. Through enhanced accuracy in monitoring and the ability to provide real-time feedback, these technologies empower patients, ensuring more engaged and effective rehabilitation sessions. Despite these promising advancements, challenges such as sensor placement accuracy and user interface accessibility remain. Future research should focus on addressing these limitations to enhance user experience and integration into everyday clinical practice. By overcoming these hurdles, wearable technologies can significantly improve the quality and effectiveness of rehabilitation, offering a more personalized and proactive approach to patient recovery.

8. References

[1] García-de-Villa, S., Jiménez-Martín, A., & García-Domínguez, J. J. (2022). A database of physical therapy exercises with variability of execution collected by wearable sensors. *Scientific Data*, *9*(1), 266–266. https://doi.org/10.1038/s41597-022-01387-2

[2] Nizam Uddin Ahamed. (2012). Biosensors assisted automated rehabilitation systems: A systematic review. International Journal of Physical Sciences, 7(1). https://doi.org/10.5897/IJPS11.1521

[3] B.G. Steele, B. Belza, K. Cain, C. Warms, J. Coppersmith, J. Howard, Bodies in motion: monitoring daily activity and exercise with motion sensors in people with chronic pulmonary disease, J. Rehabil. Res. Dev. 40 (September–October (5 Suppl. 2)) (2003) 45–58.

[4] Milenkovic, M., Jovanov, E., Chapman, J., Raskovic, D., & Price, J. (2002). An accelerometer-based physical rehabilitation system. Proceedings of the Thirty-Fourth Southeastern Symposium on System Theory (Cat. No.02EX540), 57–60. https://doi.org/10.1109/SSST.2002.1027005.

[5] Tormene, P., Giorgino, T., Quaglini, S., & Stefanelli, M. (2009). Matching incomplete time series with dynamic time warping: an algorithm and an application to post-stroke rehabilitation. Artificial Intelligence in Medicine, 45(1), 11–34. https://doi.org/10.1016/j.artmed.2008.11.007

[6] P. Fergus, K. Kifayat, M. Merabti, A. Taleb-bendiab, A. El Rhalibi, Remote physiotherapy treatments using wireless body sensor networks, in: Proc. Int. Conf. Wireless Communications and Mobile Computing: Connecting the World Wirelessly, New York, U.S.A., 21–24 June, 2009, pp. 1191–1197.

[7] Winters, J. M., Yu Wang, & Winters, J. M. (2003). Wearable sensors and telerehabilitation. IEEE Engineering in Medicine and Biology Magazine, 22(3), 56–65. https://doi.org/10.1109/MEMB.2003.1213627

[8] Arrowsmith, C., Burns, D., Mak, T., Hardisty, M., & Whyne, C. (2022). Physiotherapy Exercise Classification with Single-Camera Pose Detection and Machine Learning. Sensors (Basel, Switzerland), 23(1), 363-. https://doi.org/10.3390/s23010363.

[9] Choquette, S., Hamel, M., & Boissy, P. (2008). Accelerometer-based wireless body area network to estimate intensity of therapy in post-acute rehabilitation. Journal of Neuroengineering and Rehabilitation, 5(1), 20–20. https://doi.org/10.1186/1743-0003-5-2031.

[10] Brutovsky, J., & Novak, D. (2006). Low-cost motivated rehabilitation system for post-operation exercises. 2006 International Conference of the IEEE Engineering in Medicine and Biology Society, Supplement, 6663–6666. https://doi.org/10.1109/IEMBS.2006.260915

[11] Xsens Technologies B.V., Enschede, The Netherlands, MTiand MTx User Manual and Technical Documentation, 2014,http://www.xsens.com.

[12] Burns, D. M., Leung, N., Hardisty, M., Whyne, C. M., Henry, P., & McLachlin, S. (2018). Shoulder physiotherapy exercise recognition: machine learning the inertial signals from a smartwatch. *Physiological Measurement*, *39*(7), 075007–075007. https://doi.org/10.1088/1361-6579/aacfd9

[13] M. Kirilly, Sensor-Based Skill Assessment for Health and Fitness Applications, M.Sc. Thesis, Dept. of Media Technology, Technische Universität München, Munich, March 2011.

[14] T. Giorgino, P. Tormene, G. Maggioni, C. Pistarini, S. Quaglini,Wireless support to poststroke rehabilitation: MyHeart'sneurological rehabilitation concept, IEEE Trans. Inform.Technol. B 13 (November (6)) (2009) 1012–1018.

[15] Brooks, D. A., & Howard, A. M. (2012). Quantifying Upper-Arm Rehabilitation Metrics for Children through Interaction with a Humanoid Robot. Applied Bionics and Biomechanics, 9(2), 157–172. https://doi.org/10.1155/2012/978498

[16] Yurtman, A., & Barshan, B. (2014). Detection and evaluation of physical therapy exercises from wearable motion sensor signals by dynamic time warping. 2014 22nd Signal Processing and Communications Applications Conference (SIU), 1491–1494. https://doi.org/10.1109/SIU.2014.6830523

[17] I. Raso, R. Hervás, J. Bravo, m-Physio: personalizedaccelerometer-based physical rehabilitation platform, in:Proc. Fourth Int. Conf. Mobile Ubiquitous Computing,Systems, Services and Technologies, Florence, Italy, 25–30October, 2010, pp. 416–421.

[18] Yurtman, A., & Barshan, B. (2014). Automated evaluation of physical therapy exercises using multi-template dynamic time warping on wearable sensor signals. Computer Methods and Programs in Biomedicine, 117(2), 189–207. https://doi.org/10.1016/j.cmpb.2014.07.003

[19] Chen, Y., Tian, Y., & He, M. (2020). Monocular human pose estimation: A survey of deep learning-based methods. Computer Vision and Image Understanding, 192, 102897-. https://doi.org/10.1016/j.cviu.2019.102897

[20] Huhn, S., Axt, M., Gunga, H.-C., Maggioni, M. A., Munga, S., Obor, D., Sié, A., Boudo, V., Bunker, A., Sauerborn, R., Bärnighausen, T., & Barteit, S. (2022). The Impact of Wearable Technologies in Health Research: Scoping Review. JMIR mHealth and uHealth, 10(1), e34384–e34384. https://doi.org/10.2196/34384

[21] Agarwal, A., & Triggs, B. (2006). Recovering 3D human pose from monocular images. IEEE Transactions on Pattern Analysis and Machine Intelligence, 28(1), 44–58. https://doi.org/10.1109/TPAMI.2006.21

[22] Yurtman,Aras and Barshan,Billur. (2022). Physical Therapy Exercises. UCI Machine Learning Repository. https://doi.org/10.24432/C5JK60.