

Physical Therapy Modeling

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Introduction

When providing physical therapy, most physical therapists rely on their professional oversight and patient discretion to ensure proper execution of an exercise. After a few initial sessions with the patient, it is usually prescribed to continue these exercises at home. Although this has proven effective, it can result in a sub-optimal success rate due to time constraints of the therapist and lack of feedback for patients practicing at home.

It is clear to see that the standard practice does not ensure maximum utility from this method of rehabilitation. In this paper, we will explore some methods to evaluate physical therapy sessions based on motion sensors placed on the patient. This will allow us to provide consistent feedback to patients practicing at home and improve the effectiveness of physical therapy treatments.

We have three primary objectives. First, we want to be able to correctly identify the exercise a patient is doing. If we have sensors on a new subject, can we use data from previous subjects to determine what exercise the new subject is doing? Second, can we determine the quality of a rep? Exercises can be incorrectly performed by being too fast or with a limited range of motion, so we want to be able to detect these errors as well. Finally, do we need all of our data to be able to complete the first two objectives? Reducing the amount of sensors a patient has to wear improves ease of use as well as reduces the complexity of our algorithms.

Data

Our data was collected from the UC Irvine Machine Learning Repository with accompanying paper “Automated Evaluation of Physical Therapy Exercises Using Multi-template Dynamic Time Warping on Wearable Sensor Signals” [citation here](#).

The data set contains 5 sessions. Each session, a subject performs 8 different exercises while wearing 5 motion sensors on different parts of their body. Each sensor takes 9 measurements at 25 Hz while the subject is performing the exercise. In all directions (x , y , and z) the sensor calculates the acceleration ($\frac{\text{meters}}{\text{second}^2}$), angular rate ($\frac{\text{radians}}{\text{second}}$), and magnetic field (relative). This means that with 5 sensors and 9 measurements per sensor, there are 45 continuous measurements that describe a session. Figure 1 shows what these 45 measurements look like for the first exercise in the first session in our data set.

There are two data sets for each combination of subject, exercise, and sensor. A template session which contains 3 executions of each 3 execution types (correct, too fast, and low amplitude), and a test session which contains 10 executions of each 3 execution types.

Exercises in the Data

As mentioned previously, we have 8 different exercises in our data. The four lower body exercises are exercises 1, 3, 4, and 5. The four upper body exercises are 2, 6, 7, and 8. Diagrams of these can be seen in figure 2. There are also different sensor configurations for lower and upper body exercises shown in figure 3.

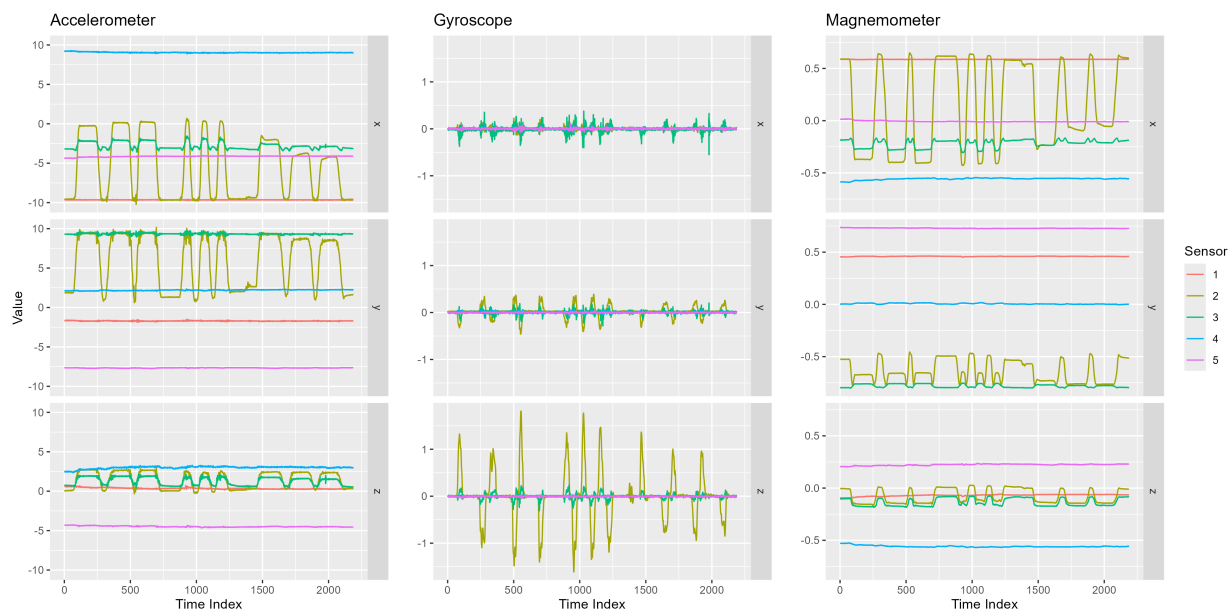


Figure 1: Example of data for a single session

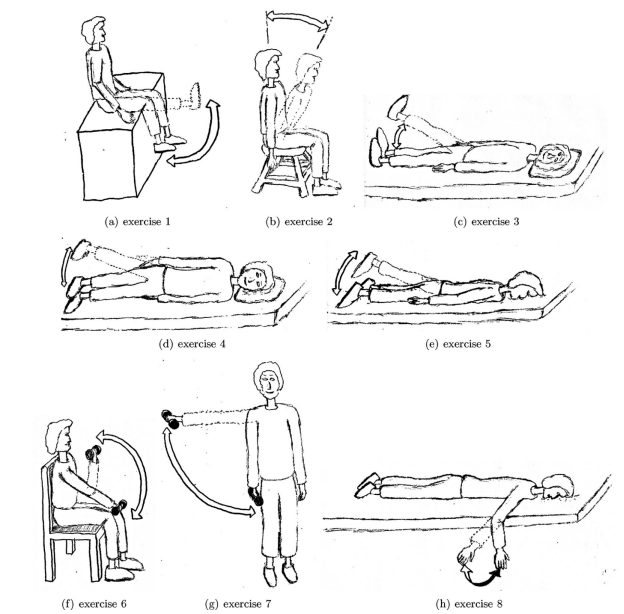
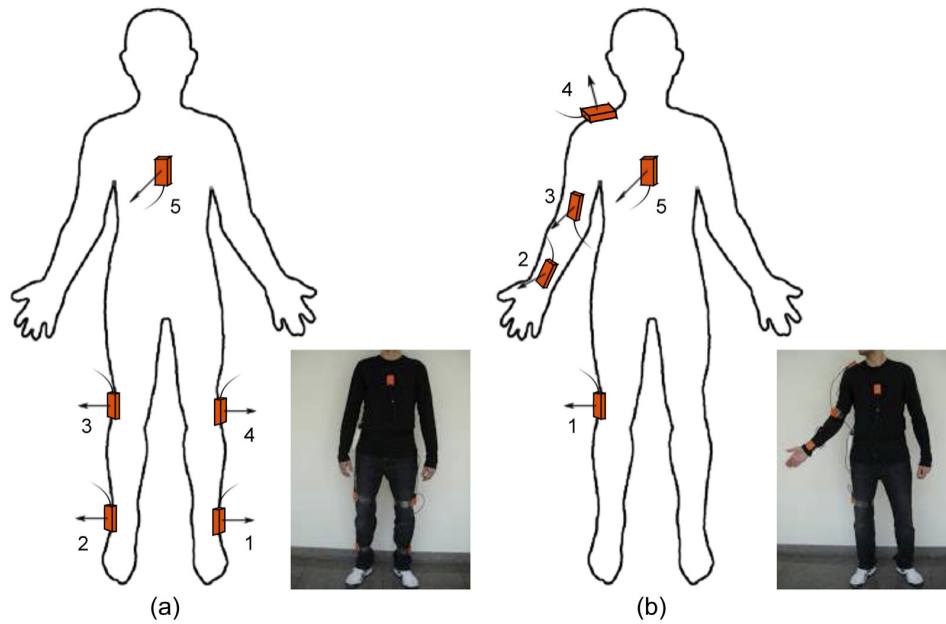


Figure 2: Diagram of the 8 exercises



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.

Figure 3: Diagram of sensor placement

Methods

Results

Limitations

Improvements

References