Unsupervised extraction and clustering of physical therapy exercise executions*

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1 Introduction

In certain types of physical therapy, patients need to repeatedly perform prescribed exercises at home. Incorrect execution of these exercises may prolong the recovery process and increase the chance of injury [3], so feedback is important. As physiotherapists cannot monitor each patient individually, an autonomous monitoring system that assesses the quality of exercise executions is of great value.

This thesis describes and implements an unsupervised framework that facilitates and partly automates physical therapy exercise evaluation. The resulting pipeline is evaluated on a physical therapy data set [6] containing motion data acquired by inertial and magnetic sensors.

2 Proposed Methodology

The input consists of a multidimensional time series that represents a patient performing a physical therapy session, containing correctly and incorrectly performed exercise executions. The proposed framework comprises two steps:

1. An **execution extraction** step, that finds individual executions of the performed exercise in the input session recording (Figure 1).
2. A **clustering** step, that groups the individual executions such that similarly performed executions are in the same cluster.

The output of the framework can be used to provide feedback on the exercise session in a time-efficient manner: An expert can label each cluster as correct and incorrect according to its representative execution (centroid), and the cluster labels can be propagated to individual executions in the session.

For the execution extraction step, a novel technique is developed, which is called Extraction of Repeated Subsequences (ERS). ERS aims to find multiple subsequences that approximately repeat in a long time series. As ERS is unsupervised, it cannot make use of pre-recorded templates or labels to find the

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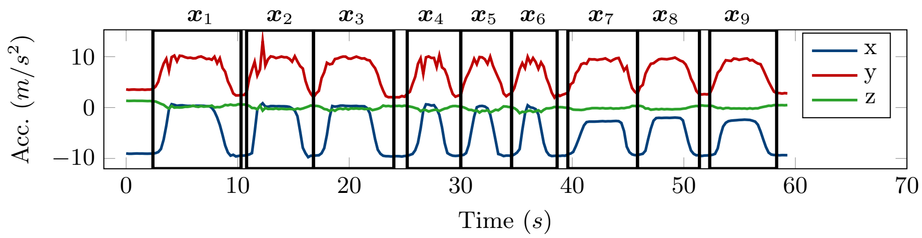

Fig. 1. Time series data representing a physical therapy exercise session and the subsequences $\boldsymbol{x}_i$ for $i = 1, \ldots 9$, representing individual exercise executions to be extracted.

exercise executions. Instead, ERS exploits the repetitive nature of the time series, while making limited assumptions on the shape and length of the exercise executions.

ERS is based on the audio thumbnailing procedure proposed by Müller in Section 4.3 of [2]. Both techniques calculate the same fitness measure defined for each subsequence of the input series. However, ERS reduces the computational cost in two ways. Firstly, it uses one single alignment matrix, obtained using the Local Concurrences algorithm [1], to calculate all fitness values. Secondly, it does not explicitly calculate the fitness measure for each possible subsequence. In addition, ERS iteratively obtains multiple repeating subsequences by, in each iteration, finding the occurrences of the optimal subsequence that has not been considered in the previous iterations. This allows multiple executions of the (possibly) multiple exercise types present in the input time series to be found.

The second, clustering step simply clusters the extracted executions to provide an interpretable output to the physiotherapist. It is implemented using CLR, which is a technique that consists of k-medoids clustering using weighted, ψ-relaxed Dynamic Time Warping [4] as a pairwise dissimilarity measure.

3 Experimental Evaluation

Both ERS and CLR are evaluated using a publicly available physical therapy data set [6]. The ERS technique extracts the executions with an average Missed Detection Rate (MDR) of 10.75% and an average False Discovery Rate (FDR) of 22.57%. Compared to its supervised counterpart [5], ERS achieves similar results in terms of MDR but a considerably higher FDR. The latter turns out not to be a problem, as false discoveries tend to be identified as such in the ensuing clustering step.

The CLR technique ultimately clusters the extracted executions with an average Adjusted Rand Index value of 0.82. In combination with the low MDR of ERS, this is considered an excellent result, given the low level of supervision that the complete pipeline (ERS+CLR) requires. In the future, ERS can be evaluated on other data sets from physical therapy or data sets from other fields where it is useful to find repeating patterns in time series.

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