Sequence Labeling for Gait Analysis using LSTM[*]

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ABSTRACT

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[*]TODO give credit to lab and PI etc.

1. INTRODUCTION

In order to study human gait, it is necessary to divide the gait cycle into swing phase and stance phase. The transition between the phases is marked by two events: the subject's heel hitting the ground (heel strike) and the subject's toe lifting off the ground (toe off). It is paramount to accurately identify these events because otherwise, no meaningful comparison of different stride cycles is possible.

There are three basic approaches to event detection. The first approach uses visual inspection to manually label the events. Although quite accurate, the cost associated with this method is prohibitive for all but the smallest amounts of data. For this reason, it is not usually used as a stand-alone method but rather as a postprocessing step for automated event detection systems or as a means to generate small sets of hand-labeled test data. The second approach uses dedicated hardware such as force plates that measure ground reaction forces and foot switches that are pressed when the foot is in contact with the ground. Due to its high accuracy, hardware-based methods are considered to be state of the art for gait event identification. However, their usefulness is limited by the fact that many laboratories do not have access to the necessary equipment. Furthermore, there is a risk of affecting the gait because some of the devices require the modification of normal footware. The third approach consists in automatated event detection based on solely on the data. If succesful, this approach is superior to the other two because it scales easily, does not require additional equipment and does not pose a risk of affecting the gait.

Given these apparent advatages, it is not surprising that several data-based methods have been proposed in the literature. Although some of those methods achieve results that are accurate enough to be useful in practice, they also have drawbacks such as relying heavily on questionable heuristics or requiring an undue amount of data preprocessing. For this reason, we present a new approach to gait event detection using a Long Short-Term Memory (LSTM) recurrent neural network (RNN). We believe that our method is superior to existing approaches both in terms of accuracy and in terms of only requirying a small amount of training data and preprocessing.

This paper is organized as follows: Section 2 discusses some of the existing data-based methods for event detection; Section 3 gives a short overview over LSTM networks in general; Section 4 contains a description the dataset; Sections 5 and

6 describe the architecture and training of our network; Section 7 presents the experimental results and compares them to existing baselines; Section 8 concludes and shows possible paths for future work.

2. PREVIOUS WORK

[Overview; justify why we discuss oconnor and miller in detail]

2.1 Heuristic Approach

2.2 Neural Network

3. LSTM

4. DATA

5. NETWORK ARCHITECTURE

6. NETWORK TRAINING

7. RESULTS

8. CONCLUSION AND FUTURE WORK