Gait Analysis using LSTM*

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ABSTRACT

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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

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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

2.1 Foot Velocity Algorithm

The Foot Velocity Algorithm (FVA) proposed by O'Connor et al. [2] belongs to a category of algorithms that use heuristics such as the velocity and acceleration of heel and toe markers to detect motion events. There are other examples of such algorithms, notably the one developed by Hreljac and Marshall [1]. These algorithms are quite similar, we will therefore restrict the discussion to the FVA.

The FVA takes as its input the location of the heel and toe markers as a function of time. After passing the data through a simple low pass filter, a new virtual marker representing the foot center is created by taking the mean of the heel and toe markers. Finally, the velocity of this virtual marker is calculated. Due to the quasi-periodic nature of walking, the graph of the velocity signal exhibits a repeating pattern in which the toe off event is marked by a global maximum and the heel strike by a local minimum. This makes it possible to first detect the toe off event for each cycle and then, in a second step, go through all the possible candidates for the heel strike. By using a constraint on the heel strike time, one of the candidates is selected as the heel strike event.

The FVA is easy to implement as it does not require preprocessing beyond simple signal processing and because it does not require any training. This makes it a popular choice in practice. That said, the FVA has several problems. First, it makes questionable assumptions about the relationship between the marker location and the gait cycle. For instance, it is not clear that the marker velocity peaks exactly coincide with the events to be identified. Secondly, the algorithm is very sensitive to a threshold that has to be applied in order to restrict the search for heel strike candidates. The value of this threshold has to be manually tuned for each subject and, if not chosen correctly, the algorithm fails catastrophically. Finally, the accuracy of FVA is bad when compared to more sophisticated methods such as neural network and LSTM (cf. Section 7).

2.2 Neural Network

description

preprocessing (dimensionality reduction)

baseline2

- 3. LSTM
- 4. DATA
- 5. NETWORK ARCHITECTURE
- 6. NETWORK TRAINING
- 7. RESULTS
- 8. CONCLUSION AND FUTURE WORK

References

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