Conference Paper

Segmentation and Feature Extraction of Human Gait Motion

Nicholas de Boer*, Hamid Abdi, Michael Fielding, and Saeid Nahavandi

Institute for Intelligent Systems Research and Innovation, Deakin University, Australia

Abstract

This paper presents segmentation and feature extraction of human gait motion. The methodology of this paper focuses on segmenting 'XYZ' position curves, in reference to time of gait motion based on the velocity or acceleration of the movement. The extracted features include amplitude, time, and equally spaced sample data, maximum and minimum for each segment. The results can be used for reconstruction of a viable dataset that is critical for simulation and validation of human gaits. We propose a method to enables the fitting of the same curve with limited data. Such data sets may prove valuable for studying impairments and improving simulations of rehabilitation tools, and statistical classification for researchers worldwide.

Keywords: Human gait, simulation, gait analysis, biomechanics, feature extraction

Corresponding Author:
Nicholas de Boer; email: nicholas.deboer@deakin.edu.au

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1 Introduction

Understanding of human gain mechanism is of interest to many areas from medicine [1] to engineering [2]. Deep knowledge of human gait behaviour is critical for robotic rehabilitation and assistive robotics due to the human-machine interactions [3]. For instance, in lower limb robotics rehabilitation, the robotic system is expected to work in tandem to humans enhancing stability, control, and patient gait motion profile. For such reasons, understanding of gait mechanism is critical, different approaches have been used for analysis of gait motions including biomechanics [4], motion capture [5] and inertial measurements [6].

One approach is to use real gait data for analysis of gait motions. Thus having access to gait data is a critical matter. However there is limited available human gait data sets that can be used for patients with impairments or even with no impairments. This is because gathering real data can be time consuming, costly, and involves ethical considerations. This is an improvement as it allows researchers to gain access to extended data sets, and apply a quanatative approach to gait analysis.

Currently significant research is being conducted into GaitID, its aim is to identify people in a similar way to a fingerprint of retina scan [7]. However most of the vision and datasets available for this have varied gait parameters. For example, subjects may not be walking in the same way, with the same stance, or even in the same direction. Additionally the data of these types of datasets is not for laboratory research, but rather every day application. Thus tracking points are not used, so data that could be used may not be as accurate and difficult to interpret when compared to marker based motion capture data.

Goldman and McKenzie demonstrate the ability to generate raw data with specified characteristics. Using applied statistics a random set of data can be constructed, however, creation of real-world data sets, via simulation is not a common occurrence [8].

The aim is to extract features from a dataset of a single subject. Using the proposed segmentation technique to separate the data into sections to assist in usability of the data. Using the segments and extracted features, the original data can be recreated, and a slight variation of the data also will be recreated as an example application.

Previously attempts had been made to use gait motion data set for a robotic rehabilitation simulation which failed to obtain a useful data set. The data segmentation will contribute a novel way to generate difficult to acquire data, in a simple yet effective simulation adding small variations to the newly simulated dataset. This may allow researchers to take smaller samples of subjects and extrapolate/generate the required amounts of data for simulation. This will help for accurate simulation of human gait relevant systems for efficient use of resources [9].

This paper proposes using a single patient's gait data, over a specified set of gait cycles for segmentation and feature extraction. Using segmentation and feature extraction on the data, it could be prepared for use as a sample for the creation of a larger dataset [10]. The challenges faced were finding an effective way to separate the data into segments for individual analysis and curve fitting (with different parameters) for further study. The contribution of this paper is a method and relevant MATLAB code for segmentation and feature extraction of the original gait data. This can be used for any 'XYZ' gait motion data. In addition, this paper presents the ability for new gait motions to be simulated.

The remainder of this paper is organised as the following: Section 2 reviews at the principals of biomechanics of human gait. Section 3 describes the process of segmenting the data for feature extraction, and the extrapolation and manipulation of a new data set. The discussion and conclusion of the results in sections 4 and 5 respectively.

2 Gait motion kinematics and biomechanics

A person's gait can be analysed by using several different key indicators, which can be measured. All of the key indicators can be broken up into spatial (distance) or temporal (time) measurements [11]. The basic properties of human gait are as follows.

Step length is the distance between the initial points of contract from one foot, to the point of initial contact of the opposite foot. Stride length that is defined by the distance between successive initial points of contact of the same foot. There are 2 steps in a stride. Cadence or walking rate is measured in steps per minute, based on the step length beginning and end [12]. Velocity is derived from the cadence and step length. It is traditionally expressed in either metres or feet per second. Walking base is the sum of perpendicular distances between step initial points of contact between both feet. Foot or toe out is the angle between the line of progression and the midpoint between the first and second toes [11].

There are several methods for visually capturing human gait locomotion, both based on marker and marker-less technology, both including both single and multiple camera system [14]. In 2008 Goffredo proposed a single camera system for biometric recognition of a human. The results were clustered to identify 3 different users based from their physical parameters and gait characteristics [15].

Using accelerometers based systems are not necessarily a novel concept, having been conceptualised in the 1950's for effective quantisation and analysis of gait attributes. During that time period the sophistication of accelerometer sensors wasn't at a level for application as a wearable, portable system [16]. It was not until the 1990's until accelerometers sensors had evolved sufficiently to satisfy the general requirements for gait feature extraction and quantification [17].

The Institute for Intelligent Systems Research and Innovation has a 12 camera Natural Point vision based motion capture systems. It has been used previously for human motion capture [18]. The difficulty of using this system is that may require human ethics approval that is a lengthy process.

3 Methodology and Results

This papers proposes using feature extraction for a single patient's gait data, over a specified set of gait cycles for data set generation. The methodology outlined in this work, and the resulting features and segments extracted, has the potential to be used in a generation of a dataset. The key concept which is developed in this paper, is the ability to extract features that can be use in variety of applications from limited data.

The original dataset was recorded on a MoCap vision system using markers place at the previously mentioned measurement points [19]. The dataset is for a humanoid female with 1 step on both sides, at a medium to brisk pace.

3.1 Gait Segmentation

The data is first separated into X, Y and Z variables for both left and right hips, knees and ankles. This data is then separated based on the rate of change (velocity) of the previously mentioned measurement points.

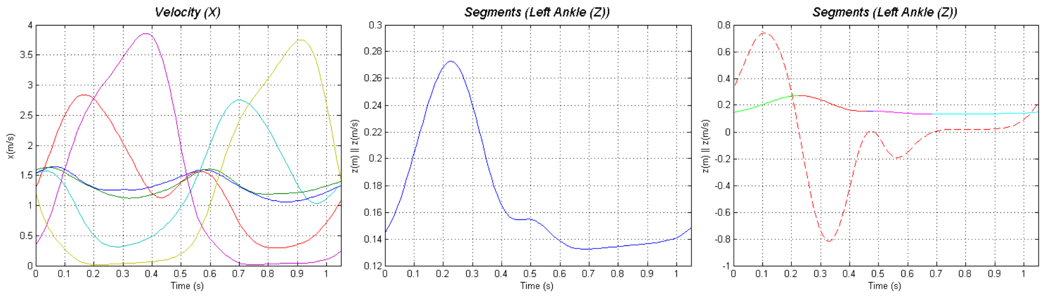

Figure 1: (L) SPATIAL AND TEMPORAL DATA (C) PRE -SEGMENTED DATA FOR LEFT ANKLE (R) SEGMENTED DATA FOR LEFT ANKLE.

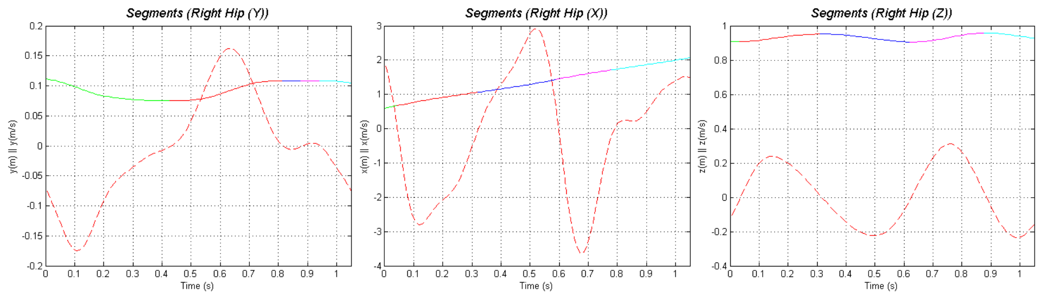

Figure 2: FINAL SEGMENTS OF THE RIGHT HIP FOR 'XYZ'.

When the velocity changes from positive to negative a new section is started, which continues until the beginning of the next segment. Using these generated segments, the data is able to be more easily analysed and critical points can be easily measured.

The first section (in this case green) is from the beginning of the measured data, to the point where the velocity changes from positive to negative. The process is repeated until the final time index is reached.

The exception to this is X velocity because of the nature of human gait the velocity in the X direction almost always positive. Alternatively for the segmentation of the X variables acceleration was used in a similar way to velocity. Following the segmentation of the various data points, the sections are measured for amplitude and time, yielding some points upon which the data can be statistically varied.

3.2 Results

Using the technique described in Section 3, the segmented data (Figure 3) was delivered. Whilst all of the graphs have not been included in this paper due to size constraints, the methodology and one example segmentation and extracted features has been provided below, with a table of the selected features. The full data set and results are available on request to the corresponding author.

Left Hip					Right Hip			
		X	Y	Z		X	Y	Z
Stage 1	Time (s)	0.0749	0.4708	0.0856	Time (s)	0.0535	0.4387	0.0428
	Max (m)	0.6871	0.2913	0.9067	Max (m)	0.6692	0.1117	0.91
	Min (m)	0.5788	0.254	0.897	Min (m)	0.5963	0.0749	0.9076
	Amp (m)	0.1083	0.0373	0.0097	Amp (m)	0.0729	0.0368	0.0024
Stage 2	Time (s)	0.1819	0.428	0.2675	Time (s)	0.2782	0.3852	0.2782
	Max (m)	0.9612	0.2893	0.9511	Max (m)	1.0634	0.1086	0.9517
	Min (m)	0.7056	0.254	0.8969	Min (m)	0.6876	0.0749	0.9077
	Amp (m)	0.2556	0.0373	0.0542	Amp (m)	0.3758	0.0337	0.044
Stage 3	Time (s)	0.321	0.1712	0.2247	Time (s)	0.2675	0.0642	0.3103
	Max (m)	1.4211	0.2894	0.9511	Max (m)	1.4316	0.1086	0.9518
	Min (m)	0.9753	0.2836	0.9127	Min (m)	1.076	0.1083	0.9053
	Amp (m)	0.4458	0.0373	0.0384	Amp (m)	0.3555	2.73E-04	0.0465
Stage 4	Time (s)	0.2889		0.2782	Time (s)	0.1926	0.0642	0.2568
	Max (m)	1.8181		0.9566	Max (m)	1.7138	0.1085	0.9577
	Min (m)	1.439		0.9127	Min (m)	1.4496	0.1083	0.9053
	Amp (m)	0.379		0.0439	Amp (m)	0.2642	1.96E-04	0.0525
Stage 5	Time (s)	0.2033		0.214	Time (s)	0.2782	0.1177	0.1819
	Max (m)	2.0663		0.9567	Max (m)	2.0799	0.1085	0.9578
	Min (m)	1.83		0.9274	Min (m)	1.7272	0.104	0.9264
	Amp (m)	0.2364		0.0294	Amp (m)	0.3527	0.0045	0.0314

Figure 3: SELECTED FEATURES FROM LEFT AND RIGHT HIPS.

4 Discussion

Initially when conducting the segmentation of the data, there was an issue with the translational measurement (X Plane) some issues with the methodology of using velocity as markers for the segmentation of the data. After checking the graph that acceleration could potentially be an alternative to using velocity in this case, the full set of key points and graphs was able to be generated.

The potential applications for using this innovative method of feature extraction for human gait are: for rehabilitation robotics, medical diagnosis, simulation and extrapolation of data sets from limited data.

4.1 Applications

This process has characterised a full step gait motion profile into a series of feature parameter values. The same methodology could be applied for larger groups of people, to ascertain a general variance for a specific disability or feature. Alternatively this data can be used to generate different gait motion profiles by adding some systematic permutation into the parameter values of the features. The value of the change for each parameter could be based on scaling of time or acceleration for whole gait data as well as for individual segment. Following on from this, for a large scale application rather than qualitatively assessing the gait of a subject, it can be segmented and the specific features extracted, and compared against other extracted features from similar patients.

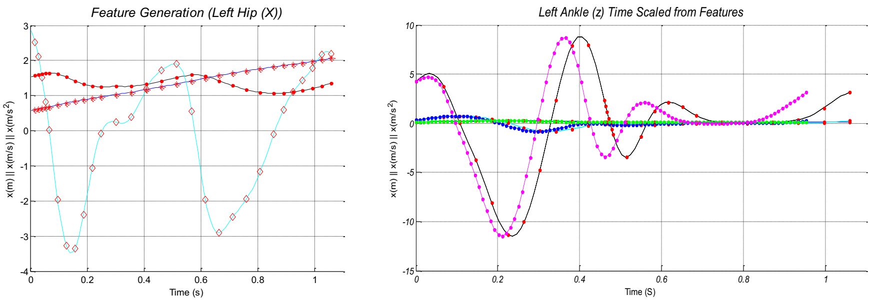

Figure 4: (L) EXTRACTED FEATURES FOR LEFT HIP, WITH RECREATED CURVES (R) LEFT ANKLE TIME SCALED DATA.

4.1.1 Time scaling

In this method the time of the motion profile or different segments are scaled, hence the motion can be considered as a faster gait (time scaling parameter less than one), shown in Figure 2, and slower motion (scaling greater than one). By varying the length of segments you can adjust the speed of the simulated gait profile.

5 Conclusion

The aim of this paper was to use feature extraction, to facilitate novel applications for small amounts of data. The methodology is based on the segmentation of the gait data using the velocity or acceleration to segment the extraction points. Each component of the position have been divided up to five segments for each stride and each section consists of nine feature points. As shown in this paper, this goal was achieved and the features were illustrated and a modified set of data was produced.

Using the results of this body of work, future work has been planned to include several key steps to the generation and validation of a larger scale dataset, and use within Rehabilitation Robotics Simulations. Following this, it is aimed to utilize this methodology to provide application based validation. Future work may include access to this larger database of simulated gait data.

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