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Feature Selection using Random Forest Classifier for Foot Strike Event Detection in Toe Walkers

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Abstract

Automated Gait event identification of Foot Strike (FS) and Foot Off (FO) in pathological gait data, can be time saving in comparison to conventional manual annotations done currently. Identification of FS and FO allows breaking walking trials into gait cycles and hence aids in comparison of gait parameters like joint angles, forces and moments across gait cycles. Automated Gait Event Detection is also useful in development of wearable sensor devices and robotic systems that assist gait. Researchers have proposed several automatic gait event detection algorithms based on kinematic parameters and systematic study of the literature suggests specific parameters to have higher contribution in identification of FS event in all common pathological gait patterns. We used Random Forest Classifier Feature selection technique to identify high contributing features in FS event in toe walking pediatric pathological gait dataset and the results suggest high similarity in selected features by the machine learning technique with those suggested by popular event detection algorithms based on kinematic parameters for pathological gait. Hence we conclude that RFC feature selection is suitable for feature selection in toe walkers gait dataset for event detection purpose.

Keywords

Feature selection, foot off, foot strike, pathological gait.

INTRODUCTION

Gait refers to a person's manner of walking. Normal gait is a repeated cycle of rhythmical, alternating movements of the body which results in its forward movement [1]. Normal gait consists of two phases. These phases are further divided into a total of 8 subphases. The first subphase of a normal gait cycle is called stance phase, it occupies 60% of the complete gait cycle during which some part of the concerned foot is in contact with the ground. The further division of stance phase is done into Initial Contact (foot / heel strike), loading response (foot flat), Midstance, terminal stance, Pre-swing (toe off/ foot off). The second subphase of a normal gait cycle is called swing phase, it occupies 40% of the total gait cycle, during which the concerned foot is not in contact with the ground and the body weight is borne by the other leg and foot. The further division of swing phase is done into Initial swing, mid swing and late swing.

Pathological gait is an altered gait pattern which can occur due to deformities in limbs, weakness, injuries, ageing or medical conditions like cerebral palsy, parkinsons disease, stroke, multiple sclerosis or other impairments. Gait abnormality can have tremendous impact on the patients especially on the quality of life, can cause severe injuries [2].

Gait analysis is an assessment of the way a person walks or runs from one place to another. 3d Gait analysis is done in gait laboratories for people with impaired gait, especially CP children. The results of the 3D Gait analysis are used to diagnose gait issues, track the progression of disease, measure the improvement in gait due to intervention/ rehabilitation/ therapy given to patient. Gait Event Detection is essential for gait analysis. During gait analysis the gait variables at joint angles, forces and moments observed at specific events during a gait cycle are compared, so gait cycle determination becomes a primary task. Gait cycles can be determined from walking trials by the detection of Initial Contact (IC/FS/HS) and toe off/Foot Off (TO/FO) events. However, Gait Event detection is a highly time-consuming process in 3d Gait Analysis [3] [4]. Force plate measurements calculated from ground reaction forces are considered the gold standard in the task of gait event detection [3] [4] [5]. Force plates are not always installed in gait laboratories and in case of pathological gait like CP it is not always applicable as force plate strikes may not be clear and that results in false force thresholds many times. The cost of installation and maintenance of force plates in the laboratory restricts the number of cycles available for measurement and in pathological or pediatric gait clean force plate hits may not be possible due to simultaneous multiple steps on same force plate or if gait is assisted by devices like croucher or walker [6] [7]. In the case of pathological gait, manual gait event detection of IC and FO is required, which is time consuming and can result in human error due to visual inspection of gait events.

Accurate and efficient automated gait event detection can make gait analysis process comparatively fast and error free, aid in calculating spatio temporal parameters and is also required for development of wearable sensor devices and robotic systems that assist gait. The different types of quantitative data collected/computed during gait analysis includes kinematic, kinetic, oxygen consumption and electromyography. Kinematic parameters of walking gait include displacement of the body, orientation of the body, joint angles and spatio-temporal data. Most of the automated gait event detection (AGED) algorithms are based on kinematic parameters [3] and this paper will also focus on automated gait event detection methods based on kinematic parameters. For performance evaluation most of the gait event detection algorithms use either force plate data (if available) or manual identification of gait events performed through visualization of markers trajectory as ground truth data. The literature review suggests some highly important kinematic features in detecting IC in pathological gait patients. In this paper we apply machine learning based feature selection technique and check its applicability to feature selection for kinematic gait data obtained from 3d instrumented gait analysis by comparing the same with information derived from literature review.

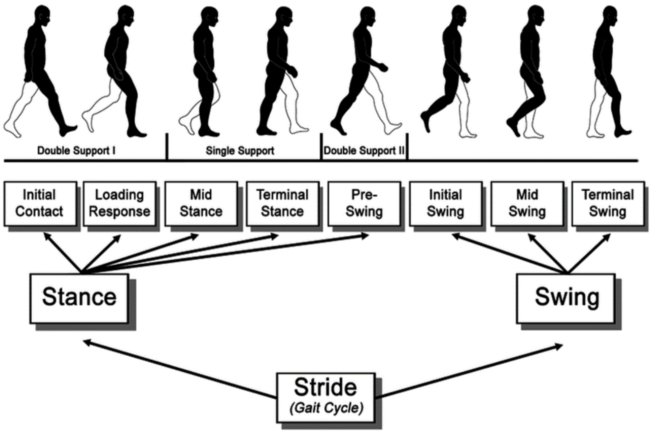

Figure 1. Gait Cycle phases and sub phases according to [8]

LITERATURE SURVEY

Researchers have used different kinematic parameters and proposed algorithms for IC detection, most of which show good accuracy for normal gait [6]. Comparing the performance of different algorithms, which use different kinematic parameters for gait event detection, on same pathological dataset can provide a basis for comparison, determination and recommendation of the most suitable technique. Researchers [3] [5] [9] have compared these algorithms on pathological datasets of subtle sizes and based on those results recommended the approach that can be used for AGED in pathological gait. [3] identified four gait patterns and classified each child participant in one of the patterns, then compared the results obtained by implementing nine published kinematic AGED algorithms [10] [11] [12] [13] [14] [15] [16] [17] [18] on a pediatric gait database (primarily CP pathologies) with more than 750 total manually annotated events. For FS they recommended the kinematic features sagittal resultant velocity [12], horizontal position [11] [18] or vertical/horizontal acceleration [13] [14] depending on whether the participant's terminal swing was observed to be more horizontal or vertical. For TO/FO, their recommendation was horizontal position [11] [18] and Sagittal Velocity [12] for all classified gait patterns. They also recommended algorithm determined by [12] in case when only one algorithm was preferred in common for IC and FO event detection across all identified gait patterns**.**

Another research classified the participants into 3 gait patterns namely Toe walkers, Flat IC and Heel IC, and compared the results obtained by implementing five kinematic AGED algorithms (one modified) [11] [12] [16] [18] on pediatric gait dataset of 90 children which was already rated with visual and force-plate mechanisms[9]. The recommendations given for IC included Sagittal Velocity of the heel for Heel IC pattern and Sagittal Velocity of the toe marker configurations for Toe Walkers and Flat IC groups [9]. Sagittal velocity of the hallux marker configuration for FO/TO was also recommended [3].

One more study classified seven CP participants in 2 gait patterns and collected kinematic and kinetic data for a total 202 steps with 202 FS and 194 FO events detected using force plate [5]. The FS and FO events were detected by implementing five AGED algorithms [11] [12] [13][14] [18] on this dataset and the results were compared with those obtained by the detection of these same events using the force plate. They concluded that AGED algorithm for IC and FO algorithm determined by [12] was recommended in children with Spastic Cerebral Palsy (SCP) when force plates were not available.

Recently researchers have also applied machine learning and deep learning techniques for AGED in pathological patients. In one study the researchers trained a multilayer feed forward neural network using the kinematic data obtained from cohort of 50 pathological subjects from which 29 walked barefoot and 21 shod/braced [19]. They used kinematic parameters sagittal plane position, velocity and acceleration of the heel and toe markers, foot-floor angle, angular velocity and angular acceleration to describe each frame of motion capture data. PCA was applied for dimensionality reduction. The trained multilayer feed forward neural network's event detection method was validated using kinematic data of 40 pathological patients. The comparison of results obtained from the neural network method with that of ground truth results obtained from force plate was in agreement within 1 to 2 frames in most of the cases, which assured the applicability of neural networks trained using kinematic gait data for AGED task [19].

[6] used three-dimensional coordinate and velocity based kinematic parameters obtained from 3d gait analysis in a gait laboratory to train and validate an LSTM model for AGED of FS and FO. They used a pediatric pathological gait dataset consisting of 18153 walking trials with 9092 annotated FS events was used to train and validate the constructed LSTM model(s).The best performing model identified FS with an average error of 10 milliseconds and FO events with an average error of 13 milliseconds. The applicability of deep neural networks for AGED using kinematic gait data was determined [6].

[20] used 3d position and velocity of markers on the heel, toe and lateral malleolus to train and validate a bilateral LSTM for AGED of FS and FO. A pediatric pathological gait database of 226 children with 1156 trials having manually annotated gait events was used to train and validate the Deep

Event recurrent network. They also compared the results of their deep learning model with the results from AGED obtained by implementing the same dataset on [18] [12] [14] [6] [20] and based on results obtained recommended their proposed deep event model for AGED of FS and FO.

EXPERIMENTS

When the heel is unable to contact the floor at the explicit beginning of stance phase or the absence of first heel rocker is defined as toe walking [21] [22] [23] [24][25]. Toe walking is observed to be a common disorder in hemiplegic children and diplegic children with Cerebral Palsy [21] [22] [23] [24][25]. Gait Analysis results in collection of high number of kinematic parameters. Systematic review of literature reveals specific kinematic parameters to have high contribution in identifying the FS event in gait cycle for all common gait pathological patterns.These features/parameters are listed in Table1. Gait event identification is basically a classification problem and machine learning, deep learning may be suitably applied for the same [6] [19] [20]. We attempt to carry out Feature selection using machine learning to the gait dataset because large number of kinematic parameters are collected from gait analysis. The purpose of this paper is to check the suitability of a well-known feature selection technique Random Forest Classifier, to the paediatric pathological gait dataset collected from 19 toe walking patients.The resultant important features in order of ranks assigned by Random Forest Classifier are compared to features listed in Table 1.

Table 1

Significant Gait Kinematic Parameter in FS detection in Pathological Gait derived from Literature Survey
Sagittal Heel Velocity
Sagittal Velocity Toe 5
Toe and Heel Marker Longitudinal (Z Component) Position and Velocity
Linear Velocity of Heel Marker (X Component)

DataSet

A retrospective study was conducted on the dataset consisting of 23 kinematic features (listed in Table 2) from 115 walking trials of 19 patients from a paediatric toe walking gait analysis dataset. The dataset was determined from the 3d gait analysis of the patients carried out at gait laboratory Jupiter Hospital, Thane, India.

Experiment Details

Feature Selection was carried out using sci-kit learn library. The csv file containing the gait data consisted of 93422 frames marked with 590 FS events manually annotated by the laboratory engineer. Table 2 lists the ranks given to the features/ gait parameters by the feature selection algorithm. Figure 2 shows the plot of obtained feature importances using mean decrease in impurity.

Table 2. Ranks of Features by Random Forest Classifier

Column Number in dataset	**Description of Parameter**	**Rank Given by Random Forest Feature Selection**
Feature 0	Knee Angle X Component	10
Feature 1	Knee Angle Y Component	21
Feature 2	Knee Angle Z Component	7
Feature 3	Linear Heel Velocity X Component	9
Feature 4	Linear Heel Velocity Y Component	8
Feature 5	Linear Heel Velocity Z Component	6
Feature 6	Linear Toe 5 Velocity X Component	3
Feature 7	Linear Toe 5 Velocity Y Component	19
Feature 8	Linear Toe 5 Velocity Z Component	14
Feature 9	Linear Toe 2 Velocity X Component	4
Feature 10	Linear Toe 2 Velocity Y Component	15
Feature 11	Linear Toe 2 Velocity Z Component	20
Feature 12	Linear Toe 1 Velocity X Component	16
Feature 13	Linear Toe 1 Velocity Y Component	17
Feature 14	Linear Toe 1 Velocity Z Component	12
Feature 15	Sagittal Velocity Heel	1
Feature 16	Sagittal Velocity Toe 5	2
Feature 17	Sagittal Velocity Toe 2	11
Feature 18	Sagittal Velocity Toe 1	13
Feature 19	Vertical Acceleration Heel (Z Component)	5
Feature 20	Horizontal Acceleration Heel (X Component)	22
Feature 21	Jerk Heel (Z Component)	23
Feature 22	Jerk Heel (X Component)	18

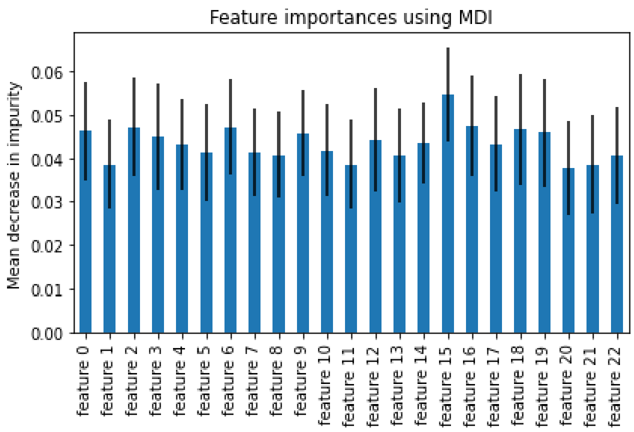

Figure 2. Feature importances using mean decrease in impurity

COMPARISION OF RESULTS

The most important features resulting from the input features given to the algorithm for feature selection are Sagittal Heel Velocity and Sagittal Toe 5 Velocity as per Table 2. The other important features in order are X Component of Linear Velocity of Toe 5 and Toe 2. Comparing these obtained results to the list of features/ gait parameters identified as important contributors in determining the FS from the research reviewed in literature, it is observed that Sagittal Heel Velocity , Sagittal Toe 5 Velocity are the common parameters determined by both methods.

CONCLUSION

The experiments performed on the gait dataset of toe walkers and the analytical results achieved show a high similarity in the prominent features derived. The literature review has suggested Sagittal Heel Velocity and Sagittal Toe Velocity as important features and the same features have been rank highest by the feature selection technique using Random Forest Classifier for determining FS event in toe-walkers. Hence we conclude that random forest classifier feature selection technique suits the data of toe walkers. And the selected features can further be used to classify FS gait event in toe walkers using suitable algorithms.

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