

Foot Strike Detection in Pathological Gait Using Random Dilated Shapelet Transform Classifier

Meghna Desai^{1*} and Dr. Viral Kapadia²

Department of Computer Science and Engineering
Faculty of Technology and Engineering
The Maharaja Sayajirao University of Baroda

¹meghna.desai-cse@msubaroda.ac.in and ²viral.kapadia-cse@msubaroda.ac.in

Abstract Accurate Automated foot strike detection for pathological gait is a known research problem. Sequence to Sequence LSTM has been used in research for foot strike event detection in pathological gait for heel strike patients. Kinematics produced from three-dimensional gait analysis or sensor data is used as input for event detection. Deep learning models require a larger dataset and are complex to train. Shapelets are short subsequences of time series that better represent a class. Shapelet based algorithms are fast to train, interpretable and can be trained for a dataset of modest size. We propose to use Random Dilated Shapelets transform combined with Rule based Detection Algorithm in order to detect foot strike for patients with heel strike foot contact pattern. The resultant model is interpretable, efficient and has an accuracy of more than 90%.

Keywords: Foot Strike, Gait, Pathological Gait, Automated Event Detection, Shapelets, Random Dilated Shapelet Transform

1. Introduction

Three-dimensional gait analysis (3DGA) is carried out for patients with pathological gait in gait analysis laboratories. Experts manually mark foot strike and foot-off events by visually reviewing the trials. Accurate automated foot strike detection for pathological gait is a known research problem. The outcome of this research can be used further to expedite the diagnosis of the underlying gait deformity, evaluate the effects of intervention, and evaluate the effectiveness of the rehabilitation process for patients. It is also helpful in the design of devices that support or enhance a suffering person's gait.

A category of automated event detection approaches uses kinematics generated from 3dGA or applied sensors for event detection. Research has employed marker data values to create simple algorithms [1], algorithms designed based on the threshold of velocities or other kinematics of markers [1,2,3,4,5,6], and machine learning approaches [7,8,9,10,11] for automated event detection.

2. Literature Review

Recently researchers have used Feed Forward Neural Networks [7], Sequence to Sequence Long

Short-Term Memory Networks [8,9,10,11] for automated foot strike detection. Most researchers using LSTM networks have used a relatively large dataset with multiple foot strike patterns [8,9,10,11]. Time Series datasets obtained from 3DGA trials of multiple patients are used to train the sequence-to-sequence LSTM as a binary classifier. The dataset is highly imbalanced as the number of frames labelled as event frames (FS occurred) is much less than that of non-event frames. This makes training the classifier difficult. A number of false positives are also obtained, which are tackled in particular research using Peak detection[8]. LSTM networks require a large amount of data to train the model, and they are prone to overfitting; training them is computationally expensive and the method has less interpretability[12].

Time series shapelets for time series classification were proposed in 2009 [20]. Shapelets are short subsequences present in a time series that better represent the occurrence of a class or event. Classification techniques using shapelets are fast, interpretable, and computationally efficient [20]. Shapelets Transform for Time Series Classification have been used for various research problems like Traffic Event Detection [17], detection of

earthquake events and strong velocity pulse in ground motions, identification of thunderstorms and vortex-induced vibration in bridges, detection of plunging breaking waves [18], Unsupervised Anomaly Detection [19], Orientation and defect identification method for nanostructure surface imaging[23].Shapelets have also been utilized successfully in human activity recognition and Human Gait Recognition [25,26] and Classification [24]. Gait trials in laboratories generate time series data containing various kinematics. Preliminary investigations of the dataset using visualization showed that distinct shapelets can be useful to distinguish foot strike events from other gait phases.

In this paper we propose to use a shapelets based classifier, Random Dilated Shapelet Transform to automate Foot Strike event detection for patients with pathological gait. Random Dilated Shapelet Transform classifier was introduced in 2021 and extends shapelets to be non-contiguous subsequences of time series data if the dilation parameter is greater than 1 [21]. Random Dilated Shapelet Transform classifier extracts three features the distance vector, location of best match and the shapelet occurrence feature in order to discriminate between the instances of different classes[27].

3. Dataset and Methods

The dataset contained kinematic data collected from walking trials of patients with pathological gait (mainly CP patients) in a three-dimensional gait analysis laboratory at Jupiter Hospital located in Thane, Mumbai. The foot contact pattern of individuals with pathological gait is usually divided into 3 types: (1) Heel Strike, (2) Front foot strike including toe walkers, and (3) Mid-foot strike [12,13,14,15,16]. Data from only those patients whose foot contact pattern was heel strike were used to create the datasets and the model in this research.

Data from multiple gait trials of 90 patients containing various kinematic information, including three-dimensional joint angle data, three-dimensional marker data, the linear velocity of markers, linear acceleration of markers, and sagittal velocity of foot markers, was used as input

during the training of the shapelet based classifiers. Table 1 shows the approximate number of patients and the number of trials considered during dataset creation. Each foot of the patient was considered separately when calculating the number of trials in the dataset. Training, validation, and test set samples were mutually exclusive at the patient level.

Two different window and interval sizes were used in the experiments. One method of creating windows was a window size of 11 with an interval size of 6 for creating windows of both classes. Another method of creating windows was window size of 15 and interval size of 8 for windows containing all non-event frames and windows size of 15 with interval size of 4 for windows containing event frame and representing data of desired class. Considering each foot independently, 160-foot strike events were used in the training dataset. Windows containing event data were created by randomly picking a few frames before the occurrence of the event and after the occurrence of the event. For training, testing and validation datasets, windows not containing event data were created by selecting the starting frame randomly between 46 to 50 frames above the event occurrence frame and going up to 70 to 75 frames after the event occurrence frame. Data from multiple trials of 10 patients was used to generate 24 windows of the desired class and approximately 100 windows of the non-desired class in the validation dataset. The model on which the best validation results were obtained was used for testing. The test dataset contained data from 40 patients with 194 windows of the desired class and more than 1900 windows representing instances of the undesired class. The number of windows containing the event frame for each individual event was more than one, to account for different locations within the window where the event frame could occur in a real-life scenario after the model gets deployed. So, the starting frame was randomly selected 7 to 12 frames above the event frame and randomly between 5 to 8 frames after the event occurred. Similarly the last frame in the window was randomly chosen some frames below the event frame and multiple windows containing the event frame were generated for training, validation and testing. The interval size

for windows of the desired class was also 4 so that shapelets representing event frames at any position in the window could be extracted; so, the number of trials and a number of windows containing event frames are not the same either for either training, validation or testing. The dataset was highly imbalanced as the number of non-event-based windows was about 80 to 85% more than the event-based windows. Only force plate detected events (gold standard) were used in this research as ground truth and chosen for training, validation and test events.

Table 1. Dataset Information

DataSet	Number of patients approximately	Number of trials considering both feet separately
Training	45	160
Validation	10	24
Test	35	122

Two models were trained , Shapelet Transform [22] classifier using TSlearn python library [28], and Random Dilated Shapelet Transform [21] classifier using Aeon toolkit version 0.11.1 [29]. RDST Classifier provided better results, so further study was conducted using RDST classifier with different combinations of classifier configuration parameters as listed in Table 2. Figure 1 stepwise summarizes the methodology followed. Initially, the models were trained using one selected kinematic feature, Heel Sagittal Velocity, as recommended in previous research[12,13,14,15,16]. Prominent changes are observed in plantarflexion of the ankle, flexion/extension of the hip and knee angles at Foot contact. The models then trained used all four features as input to improve classification scores and tackle false positives.

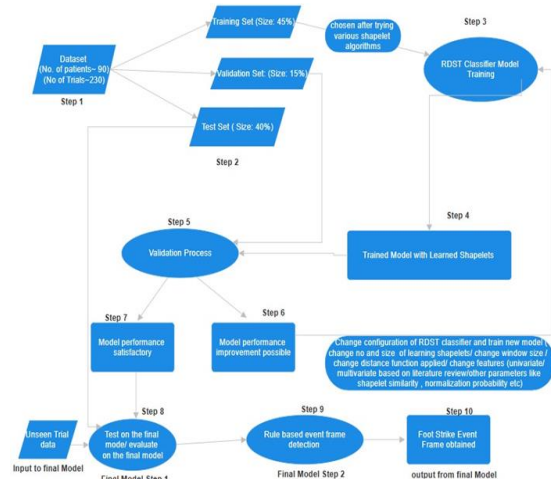


Figure 1. Methodology applied in the research

Table 2. Combinations of these parameters were used train the RDST classifier.

Model Configuration options	Different combinations of the parameters listed below were attempted when training on the dataset to learn a suitable model
Shapelet Algorithms	Shapelet Transform , Random Dilated Shapelet Transform
Window Size for creating shapelets	<p>Window Size 11 with interval size 6 for non-event windows and window size 11 with interval size 6 for event-based windows (windows containing event frames)</p> <p>Window Size 11 with interval size 6 for non-event windows and window size 11 with interval size 4 for event-based windows (windows containing event frames)</p> <p>Window Size 15 with interval size of 8 for non-event windows and window size 15 with interval size 4 for event windows (with randomization of 7 to 12 frames before the event frame and 4 to 8 frames after the event frame in the window)</p>

Number of Shapelets and Shapelets sizes	Number of maximum shapelets were tried from 7 to 50 Shapelet sizes tried were from 6 to 12
Features Selected	Heel Sagittal Velocity Ankle Joint Angles Hip Joint Angles Knee Joint Angles
Time series-based distance functions used with RDST classifier	Amerced Dynamic Time Warping Euclidean Distance Manhattan Distance Dynamic Time Warping Shape Dynamic Time Warping Minkowski Shape based distance Time Warp Edit Weighted Dynamic Time Warping

The windows that are identified with the binary classifier model to contain the event frames are then input to the rule-based detection algorithm, which exactly returns the event frame from the frames in the window. The algorithm is mentioned in Table 2.

Rule Based Algorithm for event frame detection from selected window

Algorithm 1

```

1: eventframe=0
2: count = 0
3: for each frame fi in window
4:   HSagVel = HeelSagittalVelocity at fi
5:   if HSagVel > HeelSagittalVelocity at (fi + 1)
6:     count := count + 1
7:   else if (HSagVel > HeelSagittalVelocity at (fi + 1)) and
           (count < 3)
8:     count :=0
9:     continue
10:  else if (HSagVel > HeelSagittalVelocity at (fi + 1)) and (count >3)
11:    for each frame fj in timeseries T
12:      if HeelSagittalVelocity at fj == HSagVel
13:        eventframe = fj
14:        return eventframe
15:  end for

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16: return eventframe
17: end for

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Algorithm 1 keeps a count of three or more consecutive increments in the Heel Sagittal Velocity when looking at all time points in the window, and the time point at which the first decrement after three or more than three increments is seen is considered to be the event frame. If no such pattern is found, the algorithm returns unsuccessfully. The algorithm has been formed after looking at many trials in the dataset where the shapelets also exhibited a similar pattern in the data.

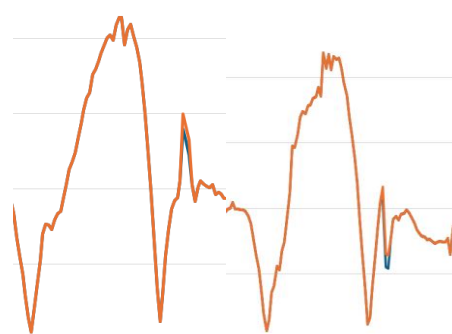


Fig 1 1(a) 1(b)

Figure 1 shows the plot of sagittal heel velocity of 2 patients. The blue point shows the frame where the foot strike occurred.

4. Results

The following parameters were used to configure the final model of Random Dilated Shapelet transform classifier: Number of maximum shapelets =40, distance = “amerced dynamic time warping”[30], lengths of shapelets = {7,8,9,10,11}, class weights ratio 0.2:0.8 for common class: rare and desired class and proba_normalization = 0.6 (This is a probability value between 0 to 1, where 1 indicates that all shapelets will use a z-normalized distance). Different distance functions were used for shapelet distance calculation the best results were obtained using amerced dynamic time warping distance for time series. There were four input features to the final model, Heel Sagittal Velocity, flexion/extension of hip joint angle, flexion/extension of knee joint angle, plantarflexion/dorsiflexion of ankle joint angle. The final model has an accuracy of 96.5% and an F1 score of 0.897 on the test dataset.

5. Discussion

On analyzing the results, the model fails to identify 17 windows of the desired class out of 193 windows in the test dataset. The true events were 82 out of which 193 windows were created to account for different positions at which event frame could occur in the window. So actually, the model fails to identify 5 true events out of 82. The time point values of velocity in most of the windows of the desired class that were misclassified, in general, were seen to be much higher compared to all the other windows that were correctly classified. Moreover, another observation was that the position of the event frame in the misclassified windows was not the problem as mostly all the misclassified windows of the desired class were misclassified each time, whether the event frame location was in the centre or towards the end of the window. So it can be inferred that the shapelets representing those events could not be learnt correctly. In two cases when the windows of the desired class were misclassified, the values of all the time points were almost the same, with a maximum difference of about 0.7 between two non-contiguous time point values in Heel Sagittal Velocity and a minimum difference of 0.01. This could mean that the speed of the patient was extremely slow or almost stagnant, at least around the foot contact event, and so the shapelet could not be identified. Out of 1940 windows representing the non-event class or undesired class 22 windows were misclassified, but the rate of false positives is highly reduced. The results can still be improved by further investigation and more empirical tests.

Finally, Heel Sagittal Velocity values of the output window from the final RDST model were input to Algorithm 1, which identified and returned the actual event frame. The final event frame returned is 94% of times within 20 ms of the original event frame in the test dataset. The sampling rate of the frames is 100 frames/second in the original dataset and hence the final event frame is 94% times within + or - 2 frames of the event frame.

Direct comparison of the results of this research with any other research is not exactly possible as most of the recent research done using machine learning had data sampled at 150 frames per second, and the data available for this research

was sampled at 100 frames per second. Also, to the best of our knowledge, no other research work has yet used a random dilated chaplet transform classifier for automated gait event detection. Moreover, research done using machine learning has considered all foot contact types of patients together, in this paper on patients with heel strike foot contact type are considered.

[8] defines an evaluation framework with formulae for coverage and time. Coverage is related to frequency of detecting the event and Time is the average error in milliseconds from the ground truth

. A coverage value of 94% and average time in number of frames between true and predicted events of 9.36 ms was achieved on the test set. Our model hence achieves comparable coverage and a slight better value for average error time for identified foot strike events.

6. Conclusion

The model shows high efficiency in identifying the foot strike event for patients with pathological gait and heel strike pattern for foot contact. Training the random dilated shapelet classifier with a dataset of modest size is fast, and the methodology applied is interpretable which is important in healthcare applications. There is a possibility of even better results by using an ensemble model by combining the shapelet transform and other machine learning classifiers like random forest or long short-term memory networks. There is also a future scope to apply different combinations of kinematic features to the model for even more accurate classification. Shapelets transform can also be explored for other foot strike patterns for automated foot strike and foot off detection using appropriate kinematic features.

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