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Time series classification using a modified LSTM approach from accelerometer-based data: A comparative study for gait cycle detection

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ABSTRACT

Background: Gait event detection (GED) is an important aspect in identifying and interpret a user's gait to assess gait abnormalities and design intelligent assistive devices.
Research question: There is a need to develop robust GED models that can accurately detect various gait instances in different scenarios and environments.
Methods: This paper presents a novel method of detecting heel strikes (HS) and toe offs (TO) during the user's gait cycle using a modified Long Short-Term Memory (LSTM) networks approach. The method was tested on a database from Movement Analysis in Real-world Environments using Accelerometers (MAREA) (n = 20 healthy subjects) that consisted of walking and running in indoor and outdoor environments with accelerometers positioned on waist, wrist and both ankles. Modifications include oversampling, composite accelerations and optimizing the LSTM network architecture were made.
Results: Performance of our modified model was found to be better than six state-of-the-art GED algorithms, with a median F1 score of 0.98 for Heel Strikes and 0.98 for Toe Offs in the scenario of steady walking in an indoor environment, and a median F1 score of 0.94 for Heel Strikes and 0.68 for Toe-offs in the scenario of walking and running in an outdoor environment.
Significance: This paper highlights the potential of the single proposed model to be an alternative to the six GED models in gait detection under various conditions.

1. Introduction

Gait analysis is a well-known practice to support and standardize the researcher's, clinician's and therapist's decisions in assessing gait abnormalities and identifying changes due to orthopedic or physiotherapeutic interventions [1]. Some aspects of gait analysis are in identifying the freezing of gait (FoG) [2–4] and building control strategies for improving gait movements [5,6]. In the context of clinical gait analysis, it is important to be able to accurately detect events in order to make correct interpretations about a user's gait, which can then be applied to a wide variety of assistive devices [7,8]. One example is functional electrical simulation where action potentials are generated in subcutaneous efferent nerves during the swing phase of the paretic foot by applying tiny electrical pulses via skin electrodes or implanted electrodes [9].

To this end, the development of gait event detection (GED) algorithms using various sensing modalities has been an active area of research for many years [10]. In particular, algorithms have been developed using accelerometer data as they are miniature, inexpensive and low-powered devices [10,11] as compared to foot switches and foot pressure sensors, which have been shown to be more accurate but are disadvantaged by a shorter lifespan due to shock forces generated by gait.

A key limitation of accelerometer data is that they suffer heavily from noise due to mechanical vibrations. Furthermore, human gait is dynamic in different environments, often involving varying gait speeds, changing walking surfaces and varying surface inclinations [12]. These additional factors make gait event detection from accelerometer readings an evolving challenge.

2. Literature review

According to Vu et al. [5], a large set of techniques is available for improving the performance of event and phase detection. More common among these techniques are: kernel-based discriminant regression [13], threshold-based methods [6,14–16], time-frequency

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analysis [17,18], peak heuristic algorithms [17,19,20], combinations of these [21] and deep neural networks [22].

Khandewal et al. previously evaluated the performance of six state-of-the-art accelerometer based GED algorithms in detecting Heel-strikes (HS) and Toe-offs (TO) in different scenarios using the Movement Analysis in Real-world Environments using Accelerometers (MAREA) database from Halmstad University [12]. The six algorithms used methods such as defining reference signals [23], applying thresholds within sliding windows [24], dividing strides into faster and slower strides and applying separate calculations to each group to detect the events [25], wavelet transforms and Gaussian mixture models [26], piecewise linear segmentation [27], and a combination of techniques incorporating domain knowledge, wavelet transform and Gaussian distribution fitting [18]. It was found that the performance of the algorithms was inconsistent and varied with changing environments and gait speeds and that all GED algorithms displayed better performance for detecting heel strikes as compared to toe offs. Such models also required complex preprocessing to filter out the noise and segment the user's gait before any analyses could be performed.

Several approaches based on machine learning in recent years [28–30] were able to differentiate gait patterns and provide new insights into the nature of human gait control without substantial preprocessing of the data. It has also been said that deep learning algorithms are best suited for gait-phase detection using inertial measurement unit signals as they perform well on signals that have a medium signal-to-noise ratio. In a recent study by Vu et al., an exponentially delayed fully connected neural network was shown to predict the full gait cycle within a 1% interval [5].

With advances in deep learning and the increasing use of recurrent neural networks such as long-short-term memory (LSTM) models for event detection in various fields [31,32], our study investigates if such methods can be applied as an alternative to the six algorithms to detect HS and TO events under different conditions.

Furthermore, as compared to the other algorithms which are rule or statistics-based and require time series feature extraction, the use of LSTM architecture with memorizing and forgetting gates simplifies the data preprocessing step [33]. Another advantage of LSTM network is their ability to retain information from past outputs to predict the current output. This is often useful for time series data as the current output mainly depends on what has happened in the past [34–37].

3. Materials and methods

3.1. Overview of proposed modified LSTM approach

The proposed flow process and the modified LSTM approach are presented in Fig. 1(a) and (b) respectively.

3.2. Database

The MAREA database from Halmstad University consists of labeled gait events such as toe-offs and heel strikes at both right and left ankles [12]. The database comprised of accelerometer data of 20 subjects walking or running under indoor and outdoor conditions. 10 scenarios were chosen for evaluation, and for each subject and scenario, median filtering and scaling was applied to the accelerometer data. The processed data was then used as input to train the model for detecting HS and TOs.

Ten different scenarios were employed to test the performance of Khandelwal's and our GED algorithms in different environmental settings, namely indoor walk, indoor run, indoor walk and run, treadmill walk, treadmill run, treadmill walk and run, treadmill slope, outdoor walk, outdoor run and outdoor walk and run. The motivation behind this is to observe the changes in performance across different scenarios with the use of the proposed modified LSTM model.

Data for each subject and scenario was split into training and testing datasets with the first 70% of the total timesteps as training and the last 30% of timesteps as test data.

3.3. Data preprocessing

A recent study showed that GED methods are generally more accurate when using ankle data than when using waist data [38]. Hence, to reduce the number of accelerometers needed, only the data from accelerometers that were attached to the left and right feet of the subjects were used in this study.

Due to the relatively few positive samples for heel strikes and toe-offs, an oversampling approach was adopted, where the time steps just before and after the actual heel strikes and toe-offs were also labeled as positive examples.

3.4. Composite acceleration and median filtering

To enhance the performance of the model, a few modifications were made in the data processing steps. Firstly, four composite accelerations were formed from the root sum of squares of the individual accelerations, namely:

$$a_{c1} = \sqrt{{a_x}^2 + {a_y}^2} \tag{1}$$

$$a_{c2} = \sqrt{{a_y}^2 + {a_z}^2} \tag{2}$$

$$a_{c3} = \sqrt{{a_y}^2 + {a_z}^2} \tag{3}$$

$$a_{c4} = \sqrt{{a_x}^2 + {a_y}^2 + {a_z}^2} \tag{4}$$

where a_x, a_y, a_x, are the acceleration the along the X, Y and Z axes respectively; and a_{c1}, a_{c2}, a_{c3} and a_{c4} are the four composite accelerations. This gave rise to four additional features for each foot or an additional 8 features for the LSTM model.

Median filtering with a rolling window of 3 timesteps was used to remove noise from the data. Data were scaled to a range of 0 to 5 using Min-Max scaling before being used as inputs to the LSTM model.

3.5. Modified-LSTM network architecture

The first layer is a feedforward layer which consists of accelerometer data on the left and right ankles, in three directions x, y and z. The second layer, or LSTM layer, consists of LSTM node units. Inputs from the LSTM layer are fed into a feedforward dense layer with relu activation function, which is connected to another extra LSTM layer and feedforward layer with relu activation function. The output then is then fed to a dropout layer with dropout rate of 0.5, another dense layer, and lastly to one output node with sigmoid activation that gives the probability of the event (left foot HS, left foot TO, right foot HS and right foot TO), occurring for each timestep. If the output value was above 0.5, it was taken that a heel strike or toe off had occurred inside the predicted values. The extra LSTM layer allows for the introduction of more hyperparameters.

Our model was trained on i7 8th generation Processor and RTX 2080 GPU using jupyter notebook with Python 3.

3.6. Hyperparameters

The hyperparameters need to be predefined before model building, which greatly affects the performance of the trained model in terms of both accuracy and complexity

In using an LSTM network architecture to determine which foot should receive output stimulation, Tang et al. [33] found that the optimal condition was a look back window of 3 timesteps, 2 features (total acceleration of left and right foot), and 44 LSTM nodes. Their model used similar parameters, with 6 features (acceleration of the left and

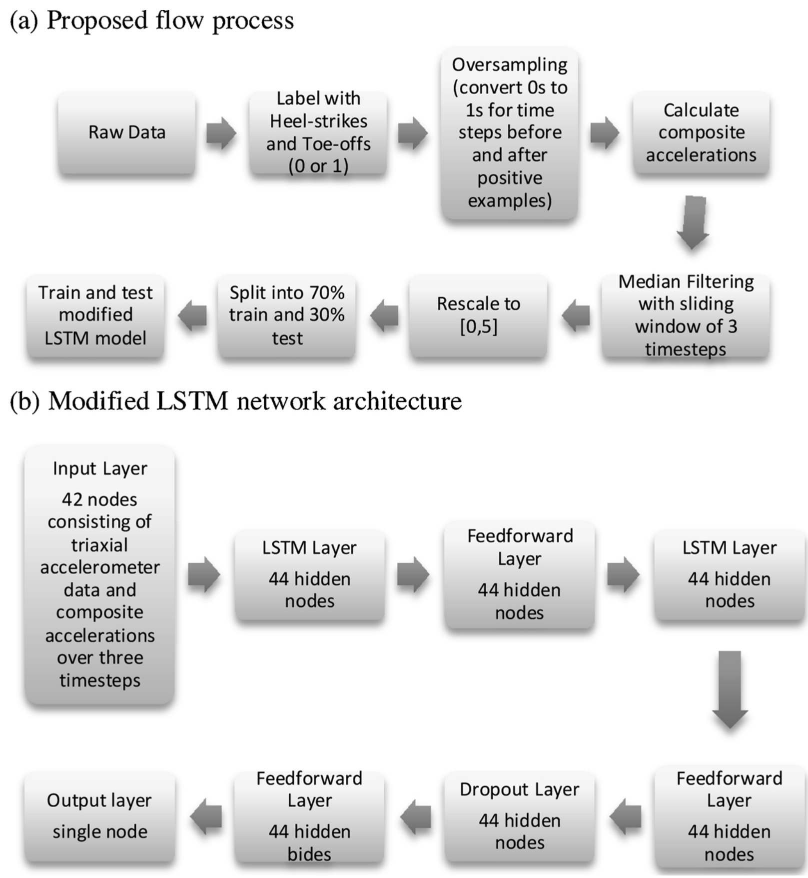

Fig. 1. Novel proposed process flow (a) and the modified-LSTM network architecture (b).

right feet along the X, Y and Z axes), 3 timesteps and 44 LSTM nodes.

Each dataset was split into 70% training and 30% testing. The training set was further divided into 67% training and 33% validation data. The training was done with a batch size of 20, the number of epochs as 50, with early stopping applied when the validation loss started to increase beyond 5 training epochs. The model was built in Python version 3 using the Keras and Tensorflow packages.

3.7. Statistical analysis

A temporal tolerance of ± 5 samples was used to match the gait events with those detected by the algorithms.

The results were evaluated based on the F1 score, defined as

$$F_1 = 2\frac{Precision\ \times\ Recall}{Precision\ +\ Recall} \tag{5}$$

where

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{6}$$

and

$$Recall = \frac{True\ Positives}{True\ Positives\ +\ False\ Negatives} \tag{7}$$

To evaluate the accuracy, the mean absolute error (MAE) was computed by finding the mean of the absolute difference (in time) between the true positives and the corresponding events. 3-fold cross-validation under the following scenarios was further performed on the modified LSTM model to better measure model performance:

1 training on first 70% and testing on last 30% of data
2 training on 1 st 35% and last 35%, testing on middle 30% of data
3 training on 1ast 70% and testing on first 30% of data

4. Results

Fig. 2 shows the F1 scores for detecting the HSs and TOs in five different scenarios, defined earlier, as well as three additional scenarios of indoor run, treadmill run and outdoor run for both the original (Fig. 1a) and modified LSTM (Fig. 1b) models. Each colored boxplot consists of the F1 scores from all subjects collected for a given scenario, for either a heel strike or toe-off event. Overall, the new model performed better with an increase in recall with only a slight compensation in precision. Variability of F1 scores across subjects also decreased. The new model also led to a concurrent mild reduction in the F1 score for the treadmill walk scenario. Tables 1 and 2 show the Average Precision, Recall and F1-score for each of the scenarios using the original and modified LSTM models.

On the whole, the average HS detection precision, recall and F1 score for the original (modified) LSTM models was between 0.68-0.91 (0.69-0.94), 0.78-0.99 (0.95–1.00) and 0.77-0.93 (0.79-0.96) respectively. The mean TO detection precision, recall and F1 score was between 0.04-0.88 (0.06-0.87), 0.15-0.96 (0.29-0.97) and 0.06-0.90 (0.10-0.90) respectively. The best performance was in the detection of heel strikes under walking conditions. Fig. 3 shows the MAE in detecting HSs and TOs under the various scenarios for both the original (a) and modified (b) models. The MAE was less for heel strikes than for toe-offs. Overall, the proposed modified model showed superior performance compared to the six state-of-the art algorithms studied by Khandelwal et al. (Table 3) [12].

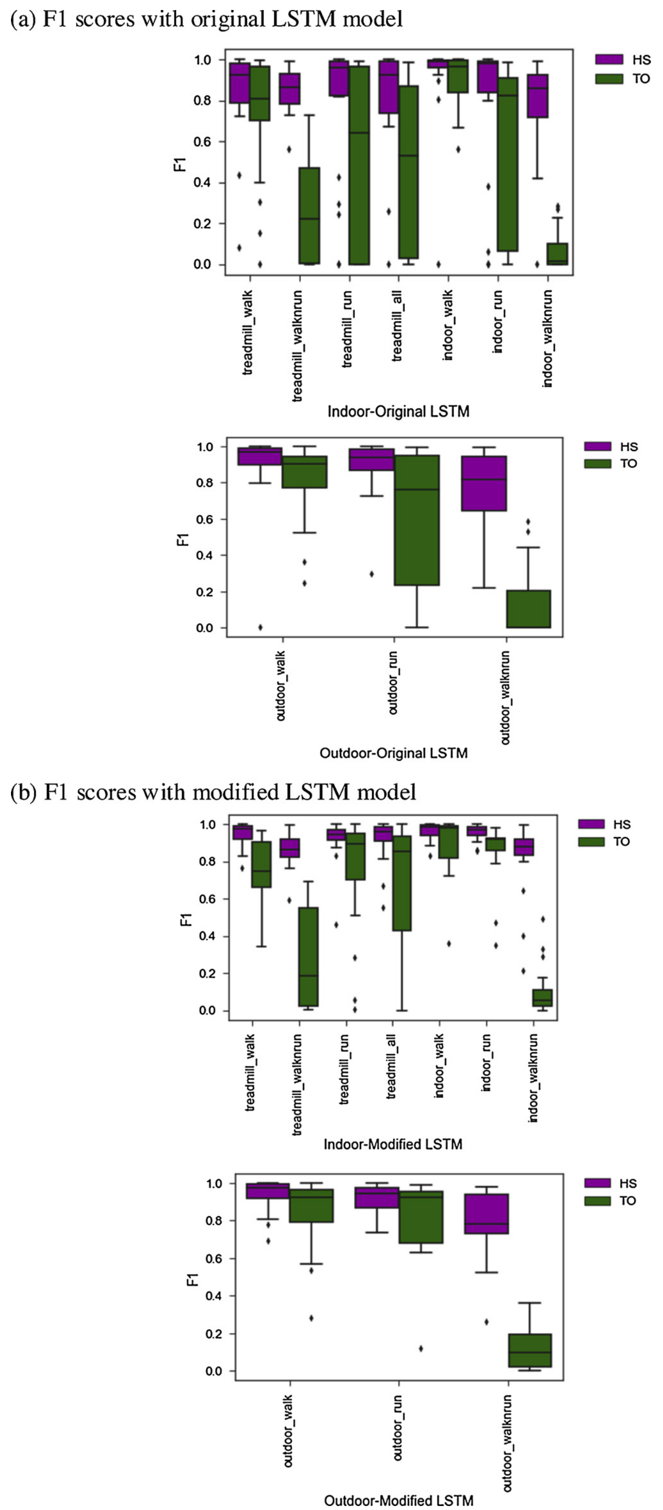

Fig. 2. F1 Scores for Heel Strikes and Toe-off Detection under Indoor and Outdoor scenarios for original (a) and modified LSTM models (b).

Table 1
Average Precision (P), Recall (R) and F1-score for each scenario using original LSTM Model Approach.

Environment	Scenario	Heel Strikes		
		P	R	F1
Indoors	Treadmill Walk	0.85	0.92	0.84
	Treadmill Walk + Run	0.76	0.99	0.85
	Treadmill Run	0.82	0.78	0.78
	Treadmill All	0.86	0.82	0.82
	Indoor Walk	0.91	0.94	0.93
	Indoor Run	0.86	0.81	0.81
	Indoor Walk + Run	0.71	0.91	0.78
Outdoors	Outdoor Walk	0.88	0.91	0.89
	Outdoor Run	0.90	0.88	0.88
	Outdoor Walk + Run	0.68	0.92	0.77
		Toe Offs		
Indoors	Treadmill Walk	0.67	0.86	0.74
	Treadmill Walk + Run	0.21	0.44	0.28
	Treadmill Run	0.48	0.57	0.51
	Treadmill All	0.59	0.49	0.48
	Indoor Walk	0.88	0.96	0.90
	Indoor Run	0.61	0.61	0.60
	Indoor Walk + Run	0.04	0.15	0.06
Outdoors	Outdoor Walk	0.88	0.82	0.80
	Outdoor Run	0.59	0.62	0.57
	Outdoor Walk + Run	0.09	0.26	0.13

Table 2
Average Precision (P), Recall (R) and F1-score for each scenario using the Modified LSTM Model Approach.

Environment	Scenario	Heel Strikes		
		P	R	F1
Indoors	Treadmill Walk	0.90 (0.93)	1.00 (0.99)	0.94 (0.96)
	Treadmill Walk + Run	0.77 (0.89)	1.00 (0.99)	0.86 (0.93)
	Treadmill Run	0.90 (0.92)	0.96 (0.98)	0.92 (0.95)
	Treadmill All	0.89 (0.90)	0.97 (0.99)	0.92 (0.94)
	Indoor Walk	0.94 (0.95)	1.00 (1.00)	0.96 (0.97)
	Indoor Run	0.92 (0.92)	1.00 (0.99)	0.96 (0.94)
	Indoor Walk + Run	0.77 (0.85)	0.95 (0.98)	0.83 (0.90)
Outdoors	Outdoor Walk	0.90 (0.90)	0.99 (0.98)	0.94 (0.94)
	Outdoor Run	0.87 (0.89)	0.99 (0.99)	0.92 (0.93)
	Outdoor Walk + Run	0.69 (0.78)	0.97 (0.96)	0.79 (0.85)
		Toe Offs		
Indoors	Treadmill Walk	0.66 (0.80)	0.95 (0.94)	0.75 (0.84)
	Treadmill Walk + Run	0.20 (0.57)	0.52 (0.77)	0.28 (0.63)
	Treadmill Run	0.73 (0.79)	0.86 (0.94)	0.77 (0.85)
	Treadmill All	0.64 (0.65)	0.71 (0.83)	0.65 (0.71)
	Indoor Walk	0.87 (0.90)	0.96 (0.99)	0.90 (0.93)
	Indoor Run	0.78 (0.83)	0.97 (0.98)	0.86 (0.89)
	Indoor Walk + Run	0.06 (0.50)	0.29 (0.72)	0.10 (0.56)
Outdoors	Outdoor Walk	0.77 (0.81)	0.96 (0.97)	0.84 (0.87)
	Outdoor Run	0.78 (0.84)	0.92 (0.95)	0.81 (0.87)
	Outdoor Walk + Run	0.09 (0.49)	0.40 (0.76)	0.13 (0.56)

Note: values in bracket refer to median precision, recall and F1 when evaluated using 3-fold cross-validation.

5. Discussion

5.1. Evaluation of results

In the study, the six algorithms demonstrated good performance for the scenario of steady walking in a controlled indoor environment with a combined median F1 score of 0.98 for heel strikes and 0.94 for toe-offs. They exhibited significantly decreased performance when evaluated in other lesser controlled scenarios such as walking and running in an outdoor street, with a combined median F1 score of 0.82 for heel strikes and 0.53 for toe offs.

Similar to the GED methods featured in the study by Khandelwal et al., the modified LSTM method showed better performance in detecting heel strikes than toe offs. It is postulated that this may be due to the peaks and sudden changes in acceleration that tend to happen during heel strikes but not in toe-offs, hence it is easier for the LSTM model to learn the patterns for detecting HSs.

F1 scores were not consistent across different environment and activities, however, applying the modified LSTM model to purely walking or purely running scenarios achieved much better performance than

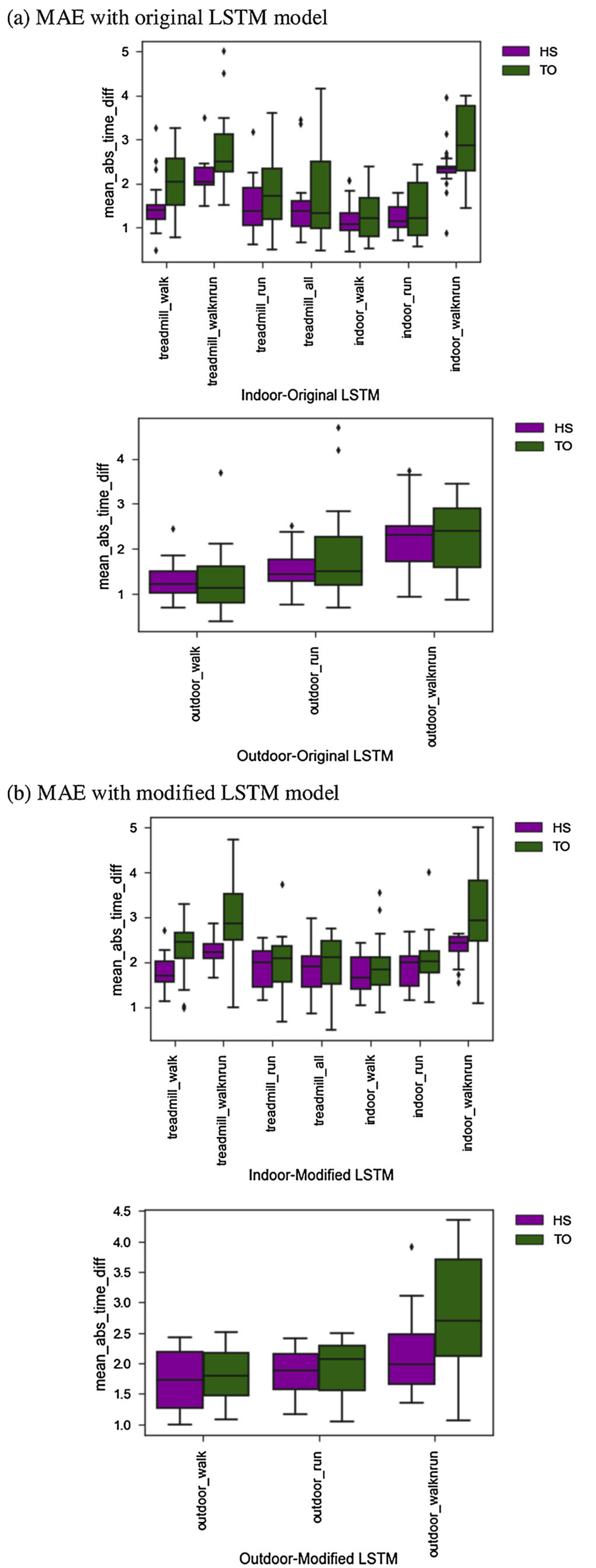

Fig. 3. Mean Absolute Error for heel strikes and toe-off detection under indoor and outdoor scenarios for original (a) and modified (b) LSTM models.

Table 3
Comparison with overall performance of six existing algorithms by Khandelal et al (Median F1 Score).

	Indoor, Steady Walking		Outdoor, Walking and Running	
	Heel Strikes	Toe Offs	Heel Strikes	Toe Offs
Original LSTM Model	0.99	0.97	0.93	0.53
Modified LSTM Model	0.98	0.98	0.94	0.68
Overall Performance of Six Existing Algorithms	0.98	0.94	0.82	0.53

applying it to scenarios with a mixture of walking and running activities. This shows that the modified LSTM algorithm from one activity cannot be extended to other contexts where speed and acceleration are different.

5.2. Observations

In many cases, time steps that were closer to the real heel strike (or toe off) were also predicted as heel strikes (or toe offs) by the modified LSTM model. One way to make our algorithm more precise (that is, to reduce the false positives) is to specify a model that recognizes predicted heel strikes as true heel strikes only when they are found near other predicted heel strikes; as these are more likely to be true heel strikes.

In addition, applying median filtering helped to remove the noise in the data. In particular, the model missed many heel strike and toe offs in its prediction before median filtering was applied. This issue then improved with the application of median filtering.

Interestingly, rescaling the variables to a range of (0,5) produced better predictions than rescaling them to a range of (0,1). It could be the fact that subtle differences in acceleration could only be captured with a larger range of values despite the black-box nature of the neural network model. The reasons behind this are still unclear.

On the whole, the improvement in F1 scores under the new model shows that the data preprocessing steps were crucial for the subsequent performance of the models. However, the choice of data preprocessing is important as well. Um et al. proposed a method of data augmentation for convolution neural networks in the classification of the motor state of Parkinson's Disease patients [39] but when the same data augmentation techniques were applied to our model, the acceleration signals were distorted such that the final LSTM model was unable to detect the events in the test set.

The use of only readings from the accelerometer positioned on the left and right feet also produced good results, hence one of the advantages of the models is that a reduction in the total number of sensors leads to an equally good outcome in predicting heel strikes and toe-offs.

In theory, a deep learning model should be able to derive patterns directly from the three-dimensional accelerations, given the many layers of a neural network, rendering the use of composite accelerations superfluous. However, our rationale for using the composite accelerations is that the current neural network architecture may not be sophisticated enough to pick up patterns related to composite accelerations in a short span of training time, hence we feed the composite accelerations in directly to the model.

Researchers have made use of computational methods of event detection that rely on data from reflective marker systems where the position of the heel or marker is tracked through multiple frames. In particular, Zeni et al. [40] considered two algorithms to detect HS and TOs during treadmill walking. These comprised the coordinate-based algorithm that identified the HS and TOs from the maximal displacement of the heel and toe from the sacrum marker, and the velocity-based algorithm that looked at changes in the direction of velocity to do so. In recent work by Kidziński et al., researchers studied a GED algorithm that employed LSTM-based artificial neural networks on marker data to detect heel-strikes and toe-offs [41]. The LSTM model was shown to have a substantial advantage over coordinate and velocity-based algorithms. Similarly, our study suggests that deep learning techniques could be more adept at picking out gait events that such computational methods may have missed.

5.3. Limitation

A limitation to this study would be the small sample size of 20 subjects (11 for indoor activities and 9 for outdoor activities).

5.4. Future works

Future works would include further fine-tuning of the hyperparameters, which may potentially improve model performance. A grid search could be performed to find the optimal set of parameters given the LSTM architecture. LSTM are also well suited for multi-label classification tasks [42–44], hence another possible area of study would be to see if an LSTM to that predicts all HS and TO simultaneously will have better performance than one that predicts only one event at a time. Transfer learning techniques can also be considered in future works to achieve better results on the current dataset.

5.5. Source codes for reproducing results

The source code is freely available at https://github.com/nwaynwaylily/Time-series-classification-using-a-modified-LSTM-approach-from-accelerometer-based-data.

6. Conclusion

Our proposed novel approach using a modified LSTM had better performance compared to the existing GED methods, but also faced the same limitations. These limitations include the inability to adapt to large differences in gait speeds, and the poorer performance in detecting TO events.

However, the median F1 score for predicting heel strikes was more than 0.8, thus while the LSTM model cannot be used for applications that require very accurate predictions on HS and TO from accelerometer data, it can be applied to cases where a larger margin of error can be tolerated but faster processing is needed, for example in pedometers.

When training and testing on smaller subsets of scenarios, the performance was shown to improve, suggesting that more complex deep learning algorithms that can learn the scenario and apply the appropriate algorithm accordingly may achieve even better performance. This is an area that researchers may wish to explore in the future as computing capabilities increase. Moreover, human gait involves significant subject-based variability and the model trained on a particular subject's data may not generalize well to other patients. One way to extend the usefulness of the current model is to apply a secondary deep learning filter to a single patient's gait to optimize the results for a particular individual. Nonetheless, this research will serve as a stepping stone toward the development of more advanced algorithms for gait event detection. Potential applications of the proposed machine learning approach would be for humanoids and other bi-pedal assistive robotics, in order to achieve closer resemblance to human gait.

Declaration of Competing Interest

None.

Acknowledgments

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