Streaming Gait Assessment for Parkinson's Disease

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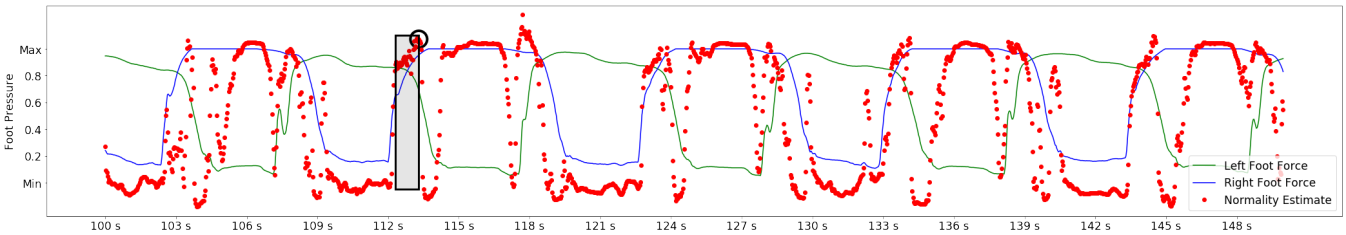


Figure 1: Analysis of the normality of the gait of a patient with Parkinson's disease.

ABSTRACT

Patients with progressive neurological disorders such as Parkinson's disease, Huntington's disease, and Amyotrophic Lateral Sclerosis (ALS) suffer both chronic and episodic difficulties with locomotion. These difficulties result in falls and injuries which negatively affect a patient's quality of life. Decision support within the health domain attempts to characterize the patient's current gait with respect to recent and long term gait characteristics to monitor disease degeneration and suggest preventative intervention. We propose the application of an attention based bi-directional recurrent neural network (RNN) to medical gait data collected from wearable mobile sensors to identify and rate the normality of gait patterns from streaming data and to inform clinicians of specific gait abnormalities. Experimental results with respect to multiple data sets demonstrate the effectiveness of streaming gait analysis to augment traditional health care diagnostic methods, automatically classify a patient's mobility, and provide monitoring of patients outside of the clinical environment.

CCS CONCEPTS

• **Applied computing** → **Health care information systems**; **Health informatics**; • **Computing methodologies** → *Causal reasoning and diagnostics*; *Neural networks.*

KEYWORDS

Neural Networks, Parkinson's Disease, Gait, Diagnostics

1 INTRODUCTION

Human gait is controlled by a complex set of interactions between multiple organ systems. Keeping balance while standing on two feet with relatively small surface area requires very complex and delicate interactions between the musculoskeletal system on the one hand, the peripheral nervous system (PNS) and the central nervous system (CNS) on the other. This task becomes even more complicated considering that while walking the whole body stands only on one foot while the other foot is lifted and has to be put back on the ground in synchrony with the other foot.

Patients with Parkinson's disease or Parkinsonism (a set of similar neurodegenerative disorders) are increasingly at risk of falling for a variety of mechanisms involved. By freezing of the upper body during a walk, they would be thrown forward and given their slowed postural reflexes they would fall; they develop rapid, small, shuffling steps and a tendency to run (festination). As the disease progresses, movements are further impaired leading to stiffness and episodic immobility known as "freezing of gait" (FOG) [16]. A recent multi-study, multi-regional estimate for individuals over the age of 45 suggests there are 572 individuals with Parkinson's disease per 100,000 people [13] or over 1.5 million individuals with Parkinson's disease in the United States today.

It is important to provide a continuous assessment of the quality of the patient's gait to assign both an instant assessment of the normality of a patient's gait in a clinical setting and an historical context by which changes in the gait may be assessed over time. The medical group associated with this study, MedStar Hospital and the Georgetown University Department of Neurology, supports over 6500 Parkinson's patients and provides care for all manner of neurological conditions that involve gait stability, including stroke service, neuromuscular disorders, and movement disorders which affect gait such as Parkinson's, dystonia, tremors, and cerebellar abnormalities. In conjunction with the diagnosis and management of such conditions using traditional methods, we developed a neural network for automated gait analysis that provides a diagnostic tool for pre-clinical assessment and improved diagnosis. As a means of continuous monitoring, our neural network for automated gait

analysis provides historical insight and long term monitoring for decision support and preventative intervention.

Figure 1 shows an example of the analysis of a gait for a Parkinson's disease patient. The gray box indicates the one second window of data used to estimate the gait normality of the window, where the normality is indicated by the point located in the upper right corner. The cross-over from right to left foot shows a strong similarity to the cross-over of a normal gait.

Any deterioration in the structures involved in this process may result in gait abnormality. As a result, gait abnormalities may present in many different ways. For example, peripheral neuropathy as a very common condition (affecting 2.4% of the population, but by age rising up to 8%) can interfere with gait stability by interfering with signal transduction (in particular deep positional sensation carried by thick myelinated nerves) to the CNS. Patients with severe peripheral neuropathy may not feel their position in space fast enough to correct their position and fall during walking.

Previous attempts to automatically distinguish degenerate gait from normal gait are hindered by two factors. First, previous research treats degenerate gait as always degenerate and normal gait as always normal. Degeneration of gait is a gradual progression, resulting in only a portion of the gait suffering from abnormalities. Events such as FOG are episodic and occur at random intervals. The progression gait degeneration provides indicators that may not be apparent from a single clinical session with a subject.

Second, publicly available data sets focusing on Parkinson's disease gait provide both raw sensor data as well as information derived from this raw sensor data. These data include analysis and derived signals that are simply not available without further offline processing of the raw data, which is not appropriate for a streaming or online context. Some efforts automatically extract these parameters in real-time [14] for the purpose of monitoring and analysis, and while an improvement over offline analysis, is still only an abstraction of the raw sensor data.

Given the goals of automatically classifying a patient's mobility and monitoring patients outside of the clinical environment we validate the following hypotheses:

H1: Streaming gait analysis can rate the level or normality within an individual's gait pattern.

H2: Streaming gait analysis can identify specific portions of an individual's gait pattern that suffer from degeneration.

H3: Streaming gait analysis can categorize degradation in an individual's gait pattern over time.

2 RELATED WORK

2.1 Non-Clinical Gait Analysis using Neural Networks

The re-identification of an individual is typically framed as a video gait analysis problem. Sequential frames of a video are used to classify individuals. Recent work utilizes bi-directional RNNs both with [12] and without [22] attention mechanisms. Other re-identification techniques focus on gait analysis from multiple sensors placed on the body (foot, thigh, and lower back) [26].

The authentication is performed using an RNN to process the raw features and a CNN to perform the final authentication [5]. Attention based RNNs are also used to study video gait silhouettes [11]. Silhouettes are generated from a video sequence, and view-independent features are then generated for the gait. In this context, gait irregularities refer to individually identifiable gait features within a video sequence but not specific degeneration of any type.

Finally, EEG signals used for authentication [19] were employed based on a 1D Convolutional Long Short-Term Memory Neural Network (1D-Convolutional LSTM). The network decodes the EEG using four levels of 1D convolutions prior to feeding the resultant vectors into the LSTM.

Analysis of activity context and activity recognition spans the gamut of neural network implementations [2, 17]. The analysis is usually derived from accelerometer and gyroscope data from cell phones worn on the subject at a specific location. These data sets [1] typically include walking (on both horizontal and inclined surfaces), descending and ascending stairs, jumping, running or jogging, sitting and standing. Activities of daily living include running or ascending stairs. Hammerela[7] explores deep, convolutional, and recurrent approaches across three representative data sets that contain movement data captured with wearable sensors to different tasks. These data sets only focus on asymptomatic or Non-Parkinsonian subjects.

Attention-based gait recognition is approached as a WiFi reflectance problem [23] where spectrograms are generated from the signal reflection from eleven walking subjects. Multiple WiFi access points determine signals and feed parameters into bi-direction RNN with attention. The research describes an encoder-decoder format for the network, but then claims the decoder has no input, reducing the network to an RNN with attention. Other systems [25] analyze gaits and brainwaves of seven participants using an encoder-decoder network with attention. The decoder does not generate a sequence of output, so it is unclear what data is fed into the final fully connected network, other than the attention vector.

2.2 Clinical Gait Analysis

Jovanov[10] discloses a wearable system for real-time gait monitoring to recognize FOG episodes. They recorded signals from five experiments, four from simulated freezing gait events, and one from the real patient and analyzed feasibility of the real-time detection.

Joshi[9] presents the automatic noninvasive identification of Parkinson's disease based on spatio temporal gait variables. The authors use wavelet transform and a support vector machine (SVM) to produce efficient classification based on a representation of spatio temporal gait variables to identify Parkinson's gait.

Shetty[18] focuses on the specific gait characteristics which would help differentiate Parkinson's Disease from other neurological diseases (Amyotrophic Lateral Sclerosis (ALS) and Huntington's disease) as well as healthy controls. A range of statistical feature vectors are considered from the time series gait data which are then reduced using a correlation matrix. These feature vectors are then individually analysed to extract the best seven feature vectors which are then classified using a Gaussian radial basis function kernel based support vector machine (SVM) classifier.

Wu[21] uses stride interval parameters to form a feature vector in the pattern classification experiments. The results evaluated with the leave-one-out cross-validation method demonstrated that the

least squares support vector machine with polynomial kernels was able to provide an accurate classification.

2.3 Clinical Gait Analysis using Neural Networks

In research relating to gait analysis, a form of testing referred to as "all-training, all-testing" is utilized. This simply refers to training on all of the data and using the validation set in lieu of the testing set. For smaller data sets, a testing method called "leave one out" is used, where all but one sample is used for training and validation, and the held-out sample is used for testing. In research where this method is used there is no strong definition of what is left out. In several related papers, [27] and [28], a bi-directional RNN is utilized for analysis of gait data. The foot pressure signals are used in conjunction with derived data relating to swing and stance. This research compares each of three degenerative conditions to the control gait using both the "all-training, all-testing" and "leave one out" testing methodologies. These results are indicative of neural network overfitting and use both raw and derived data not available in a streaming context.

A cross-correlation-based feature extraction and Elman's recurrent neural network (ERNN) based classification [3] is used to partition healthy and pathological gaits, followed by partitioning of pathological gaits into Parkinson's disease, ALS, and Huntington's disease. The research uses a 50% training and a 50% testing split and suffers from the issues raised in the "all-training, all-testing" methodology. The research notes a direct visual analysis of foot pressure measurements "reveals that it is impossible to differentiate between healthy and pathological subjects without any ambiguity." The inability to visualize gait abnormality is a result of the methodology used, which is addressed by this paper.

For predicting FOG experienced by patients with Parkinson's disease [20], an LSTM with a 50% training and a 50% testing split is used to create an overall FOG identifier. Transfer learning applies a new layer of the network which is trained on a portion of a held-out subject's data and then tested on another portion of that subject's data to identify the user.

A multi-layered artificial neural network was constructed to classify control, Parkinson's disease, ALS, and Huntington's disease using "One-versus-one", "one-versus-rest", and "control-versus-pathological" analysis. The research includes an overview of the results obtained by previous papers using the "Gait in Neurodegenerative Disease Database" data set.

Other classification utilizes a three layer Radial Basis Function (RBF) activation based neural network [24]. The authors feature vector sequences for all the 93 Parkinson's disease patients and 73 healthy controls and then extract all of the subject's gait features as a time series provided as the input of the RBF neural network.

Mohammadian[15] proposes a deep normative modeling as a probabilistic novelty detection method, in which a model of the distribution of normal human movements is recorded by wearable sensors to detect abnormal movements in patients with Parkinson's disease and ALS. The problem is framed as a novelty detection framework where a movement disorder behavior is treated as an extreme of the normal range or, equivalently, as a deviation from the normal movements.

3 DATA SETS

3.1 Gait in Neurodegenerative Disease Database (GaitNDD)

This publicly available data set focuses on the pathophysiology neurodegenerative diseases to improve the "ability to measure responses to therapeutic interventions."[8] Control subjects (n = 16) are considered to have the optimal normal gait while subjects with Parkinson's disease (n = 15), Huntington's disease (n = 20), or Amyotrophic Lateral Sclerosis (n = 13) are considered to have abnormal gaits. The subjects in this data set with Parkinson's disease were professionally assessed and ranked on the Hoehn and Yahr scale. Subjects were required to walk independently for five min, did not require an assistive device for mobility, and were free from other gait affecting pathologies. The study was approved by the Massachusetts General Hospital Institutional Review Board and made publicly available through PhysioNet on December 21st, 2000.

The data for this data set were obtained through force-sensitive resistors placed under each subject's foot. Stride-to-stride measures of footfall contact times were derived from these signals. The data are divided into subjects in the control group, with Parkinson's disease, with ALS, and with Huntington's disease.

To simulate a streaming data scenario, we only use the force sensor readings. The additional derived signals were not used as part of the data for analysis.

3.2 Gait in Parkinson's Disease (GaitPDB)

This publicly available data set contains measures of gait from 93 subjects with idiopathic Parkinson's disease and 73 control subjects. The database includes the vertical ground reaction force from eight foot pressure sensors recorded for subjects as they walked at a self-selected pace for approximately two minutes on level ground. [6] These data were collected at the Laboratory for Gait Neurodynamics, Movement Disorders Unit of the Tel-Aviv Sourasky Medical Center and made available on February 25th, 2008.

The data also includes two additional data points that reflect the sum of the left and right foot pressures. To simulate a streaming data scenario, we only use the summed force sensor readings to match the two force readings provided by the GaitNDD data set. The additional force sensor readings and the derived signals are not used as part of the data for analysis. Additionally, this data set includes 214 total trials with Parkinson's participants and 92 total trials with control participants.

4 EXPERIMENTAL METHODS

4.1 Gait Sensors and Normalization

The GaitNDD and GaitPDB data sets provide left and right binary foot pressure signals which are appropriate incoming data in a streaming context. Only the force sensor data from each data set are used. The initial ten seconds of the time series include some standing and non-walking measurements and data before this point are not used in these experiments.

Each stream of data, comprising left and right foot pressures, is individually normalized within a ten second window to a range from 0 to 1. As the window is passed over the data, a ten second moving average is computed and used to normalize the streaming

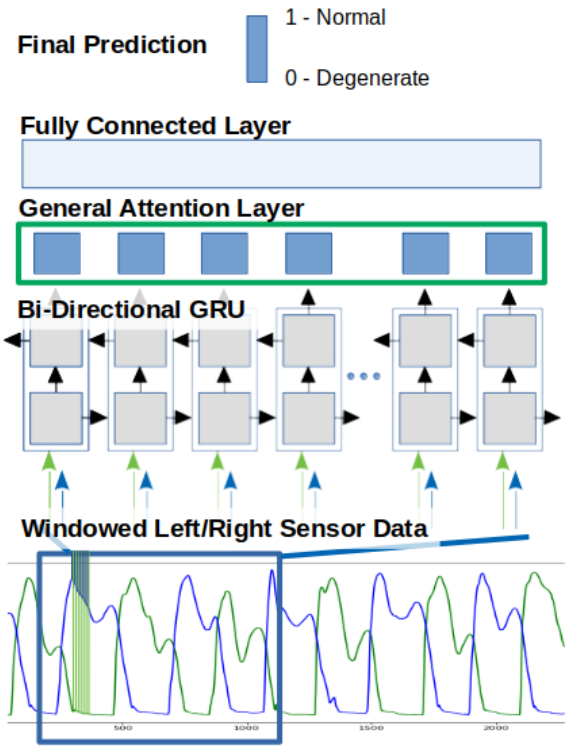


Figure 2: Bi-Directional GRU with General Attention.

data. Any incoming data that exceeded the [0,1] bounds are clipped to the maximum or minimum value. These normalized data are then used as the input to the neural network.

The model used to identify normal patterns within a subject's gait contains three layers: 1) A Gated Recurrent Unit (GRU), 2) A general attention layer to summarize the GRU output, and 3) A final fully connected layer.

4.2 Network Design

A Gated Recurrent Unit (GRU) is a variant of the Long Short Term Memory (LSTM) RNN structure. Internally, the GRU uses an update and reset gate to determine which information should be passed to output. These gates determine how much information from previous data should be saved as well as how the saved data are combined with the incoming data to produce the output. In this manner, the output of previous time steps is combined with the current input. The full model is shown in Figure 2.

As the data arrive at the model, one second (30 left/right data points) of samples are grouped into a window and passed to the GRU. Preliminary studies have shown a one second window provides optimal results with these gait analysis methods. A sliding window is used for this analysis, however other windowing methods such as discrete windows could also be used. Each data point passed to the GRU produces an output which is fed into the next iteration of the GRU along with the next data point. These outputs are generally considered hidden states since they are part of the process of generating the final output, which is referred to as the context. In the case of a bi-directional GRU, there are two hidden states for each input: one generated by a forward pass over the window and one generated by the backward pass over the window. We follow the common convention of concatenating the forward and backward results into a single vector.

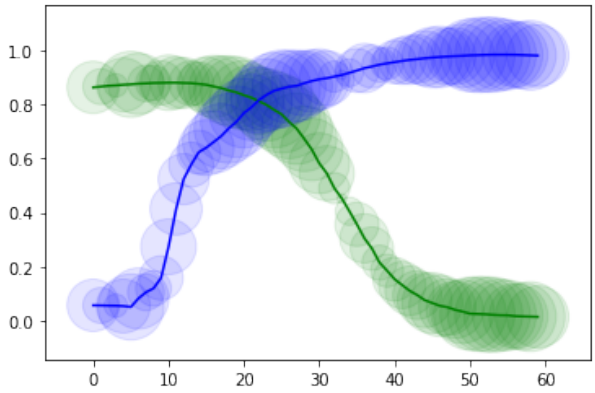


Figure 3: General Attention Applied to Incoming Data Points. The radius of the circles denote the amount of attention paid to that point in the gait. Note the increased attention at the crossover point where the two foot pressures are equal and the balance shifts from one foot to the other.

Once the GRU has processed the incoming data and created a hidden state for each incoming sample, a general attention mechanism is applied. A single fully connected layer with an input dimension that matches the hidden state size of the GRU and an output of one dimension is used as the attention layer. This layer is applied to the hidden vectors and creates a single value representing the strength or attention of the hidden state that matches the corresponding input. This value is multiplied against the hidden state to increase or decrease the strength of the hidden state with respect to the attention. These modified hidden states are summed to create the final output of the GRU with respect to the general attention vector. Since the left and right sensor values are combined together by the GRU, the attention is applied at each time step, rather than to a particular sensor reading, as shown in Figure 3.

The final GRU output with applied attention is then fed into the final fully connected layer. This layer outputs a value relating the normality of the data within the window where [1] is completely normal and [0] is completely degenerate. The ground truth for this value is determined by the file from which the data came: data specified as Control are assigned a target value of [1] and data other files (ALS, Parkinson's disease, and Huntington's disease) are assigned a target value of [0]. Although our premise is that gait is not a binary assignment of normal/degenerate across an entire subject's data set, the use of binary classification labels to train the model provides enough insight into difference between normal and degenerate cases to train an accurate model.

GaitNDD

	Control	Parkinson's	Huntington's	ALS
Total	16	15	12	13
Train	12	4	4	4
Test	4	4	4	4

GaitPDB

	Control	Parkinson's	Huntington's	ALS
Total	73	93	-	-
Train	57	57	-	-
Test	16	16	-	-

Table 1: Parkinson's Gait Databases, distribution of training, validation, and testing files.

4.3 Training/Validation/Testing

As shown in Table 1, for all data sets used, a full training, validation, and testing split is implemented as follows:

For the GaitNDD data set, an equal number of control (12 files) and other files (4 Parkinson's disease, 4 ALS, and 4 Huntington's disease) are selected at random for the training set to provide a balance of control and abnormal training input. In order to balance the normal and abnormal cases, the data selection is constrained by the number of normal gaits within the data set. Using an 80/20 split, the first 80% of the data for all of the selected training files are used as the training set and the final 20% of the data are used for the validation set. Since gait patterns are repetitive, this creates over-fitting in the validation set. Dropout in the GRU is used to lessen the impact of the over-fitting. Due to the limited amount of data available within the data sets, it was not feasible to use disjoint sets of subjects for the training and validation.

For the testing set, four files from each category are selected at random from the files not included in the training set. From these files, the final 20% of the data for all of the selected testing files are used for testing to match the data split used for the validation set, with the understanding that the entire testing set could be used for testing. Due to the repetition of the gait within the sessions, the use of the final 20% of the testing data did not alter the results when compared to the use of the entire testing set.

For the GaitPDB data set, an equal number of control (57 files) and idiopathic Parkinson's disease (57 files) are selected at random to provide a balance of control and abnormal training input. Using an 80/20 split, the first 80% of all of the selected training files is used as the training set and the remaining 20% of the data is used for the validation set. Dropout, again used in the GRU, is used to lessen the impact of the over-fitting.

For the testing set, 16 patients with idiopathic Parkinson's disease and 16 control patients are selected at random from the files not included in the training set. From these files, the final 20% of the data are used for testing to match the data split used for the validation set, with the understanding that the entire testing set could be used for testing. The use of the final 20% of the testing data did not alter the results when compared to the use of the entire testing set.

4.4 Implementation

The PyTorch implementation utilizes an initial three layered bi-directional GRU with 256 neurons in each hidden layer. A dropout of 0.3 is used by the GRU to reduce overfitting. The input size is two, with one channel for the left signal data and one channel for the right signal data. The hidden vectors for each batch contained one hidden layer for the forward RNN and one for the backwards RNN, and are subjected to a general attention vector of size 512. The attention vector, after application to each context vector, was normalized using softmax and the results are summed to form a single feature vector of 512. This is passed to a fully connected layer with an output size of one. The learning rate is selected as 0.0001 and the cross entropy loss function is used for training. The training batch size is selected as 1024 and the models were trained for 20 epochs.

5 EVALUATION

Our evaluation of gait abnormalities focuses specifically on the labeling of individual points within a gait based on the 'normality' of that point. The model is designed to distinguish between normal and degenerate points within the data. This classification is applied at three distinct levels of focus.

First, an entire gait sequence is reviewed and the overall gait pattern is classified as either normal or abnormal (one of Parkinson's disease, ALS, or Huntington's disease in the case of the GaitNDD data set) or the gait is classified as either normal or abnormal (Parkinson's disease in the case of the GaitPDB data set). This may be applied by practitioners in a clinical setting to aid in the diagnosis of neuromuscular disease.

Additionally, specific portions of the gait sequence may be analyzed to identify traits specific to an individual's gait. This involves review of a portion of the gait to identify cyclic irregularities such as repeated pressure abnormalities in an otherwise normal gait or portions of a degenerate gait that are not as strongly effected by the neuromuscular disease.

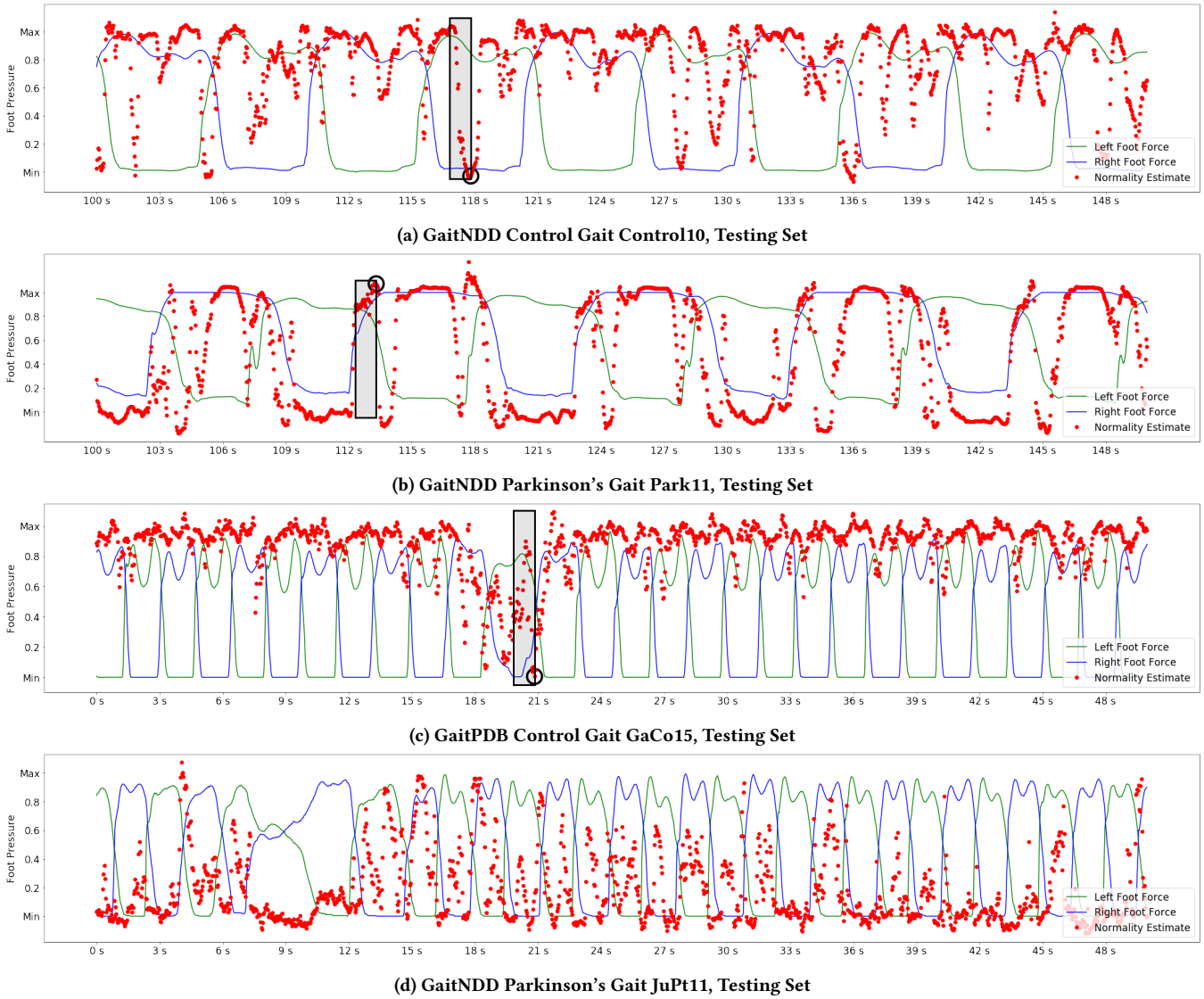
Finally, tracking the normality of a gait over time allows degeneration to be identified. Long term changes in gait are reflected in the normality as viewed on an hourly, daily, and weekly time frame. Since the data sets do not include long-term tracking of gait, the degeneration of gait over time is simulated by combining different gaits and noting the change in the average normality of the gait.

5.1 Identifying abnormal gait

The model predicts the normality of a specific point within a gait based on a sliding window. Within a streaming context, new data points are received and the sliding window of data points is updated. The updated window is used to predict the normality of the gait at the new data point. The resulting stream of normality predictions is collected to evaluate the overall gait of the subject for monitoring and diagnosis.

In the case of the GaitNDD data set, the first 10 seconds of data included non-gait-events such as standing (high pressure on both feet) and general shifting of balance. The data used for analysis of overall gait quality begins after this initial 10 second window.

To evaluate the quality of the model when applied to this data set, the normality ratings of each data point within the session is



(a) GaitNDD Control Gait Control10, Testing Set

(b) GaitNDD Parkinson's Gait Park11, Testing Set

(c) GaitPDB Control Gait GaCo15, Testing Set

(d) GaitNDD Parkinson's Gait JuPt11, Testing Set

Figure 4: Normality of Gait Patterns. The blue and green lines indicate the foot pressure exerted by the left and right foot, respectively. The red dots show the confidence of the normality of each sampled window within the gait.

collected and the average normality over the gait session is calculated. A threshold is established to determine the classification of this number. As optimal normal prediction is [1] and the optimal degenerate prediction is [0], the threshold is determined by identifying the threshold that provides the highest overall precision over the validation set, in this case 0.45. This average normality is then assigned to a grouping of normal (normality $\geq$ threshold) or degenerate (normality $<$ threshold).

Gait abnormalities are distributed across the entire session; thus, initial attempts to use a non-binary classification for Parkinson's patients resulted in a lower precision and created difficult in identifying normal subjects. In the initial test, assessed subjects were assigned predicted normality values based on the inverse of the Hoehn and Yahr scale where a patient with a low score was given a more normal prediction (HY assessment of stage one was given a predicted value of 0.8) and a higher score was given a more abnormal prediction (HY assessment of stage four was given a predicted value of 0.2). Using this gradation of predicted values for subjects with Parkinson's disease drove the average control patient's predictions toward the threshold since lower stage Parkinson's patients experience only minimal degradation.

The mean squared error (MSE) is included as an additional measure of classification performance. It is the average difference of the correct (Target) classification value and the value predicted (Pred) by the model. The MSE is calculated over all predictions for the gait session and provides a means of comparing not only the specific subject's classification accuracy but also the accuracy of the predictions over an entire class of subjects. This method is

particularly useful where the predicted value for a subject lies on a scale between normal [1] and abnormal [0]. A macro-average of the MSE for the training and testing sets is provided for each class.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Target_i - Pred_i)$$

Table 2 shows the results of the final classification of the GaitNDD data set. For this data set, any control subjects are considered correctly classified if the average normality is above the defined threshold, and all other subjects were considered correctly classified if their average normality was below the threshold. The table shows the number of correct classifications for both the validation and the testing set. As seen with previous papers that use the "all testing, all training" methodology, correct classification of all subjects within the validation set is easily achieved with this model. The testing set shows a high accuracy for classifying the degenerate cases but is only able to correctly classify half of the control cases.

	GaitNDD		GaitPBD	
Class	Testing	MSE	Testing	MSE
Control	2/4	0.1795	16/18	0.1169
Parkinson's	4/4	0.1655	16/18	0.1009
Huntington's	4/4	0.0857	-	-
ALS	3/4	0.1230	-	-
All Files	13/16	0.1384	32/36	0.1089

Table 2: Analysis of the GainNDD and GaitPDB data sets. The testing columns indicate the number of subjects correctly classified. The mean squared error (MSE) between the value predicted by the model and the target value.

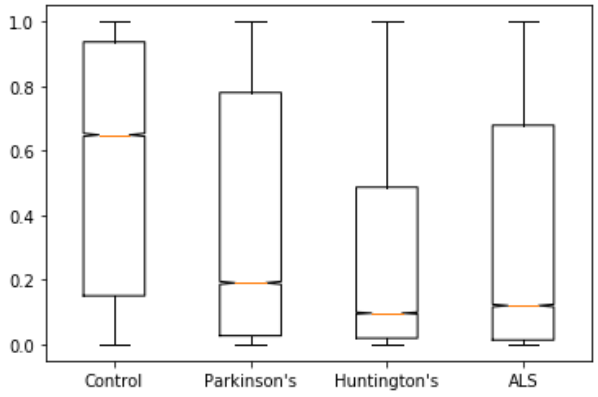


Figure 5: Distribution of normality estimates by gait type. Since all gaits are a combination of normal and abnormal estimates, this box plot shows the distribution of estimated normality for each class within the GaitNDD data set.

To evaluate the quality of the model when applied to the GaitPDB data set, the data is divided into two classes: control and Parkinson's disease. Control sessions are considered normal and given a ground truth of [1]. Parkinsons's disease sessions are considered degenerate and given a ground truth of [0]. Again, a threshold is determined based on the maximum precision obtained over the validation set to distinguish normal and degenerate sessions.

Table 2 shows the results of the final classification of the GaitPDB data set. For this data set, any control subjects are considered correctly classified if the average normality is above the defined threshold and Parkinson's disease subjects were considered correctly classified if their average normality is below the threshold. The table shows the number of correct classifications for both the validation and the testing set. The larger data set allows for a higher testing set prediction accuracy. The MSE is calculated using the same method as the GaitNDD data set.

Subject	Normal	Abnormal	Total	Abnormal/All
control10	14466	2853	17319	0.1648
control16	10837	6482	17319	0.3743
control2	8440	8879	17319	0.5127
control7	11089	6230	17319	0.3598
Average	**44832**	**24444**	**69276**	**0.3528**
park15	1974	15345	17319	0.8860
park3	8533	8786	17319	0.5073
park5	7166	10153	17319	0.5862
park6	820	16499	17319	0.9526
Average	**18493**	**50783**	**69276**	**0.7331**
hunt10	3300	14019	17319	0.8095
hunt14	10943	6376	17319	0.3682
hunt2	7992	9327	17319	0.5385
hunt8	11392	5927	17319	0.3422
Average	**33627**	**35649**	**69276**	**0.5146**
als2	4883	12436	17319	0.7180
als4	5105	12214	17319	0.7052
als5	2405	14914	17319	0.8611
als7	5357	11962	17319	0.6907
Average	**17750**	**51526**	**69276**	**0.7438**

Table 3: GaitNDD Testing Set.

Similar to the supervised ground truth novelty estimate utilized by Mohammadian[15], the percentage of abnormal estimates for the GaitNDD testing set is shown in Table 3. This details the trend observed in individual gaits, where the normal gaits include a set of abnormal points and abnormal gaits include a set of normal points. This distribution of points, shown in Figure 5, illustrates the distribution of estimates across classes. A majority of points within the control set are above the 0.45 threshold and a majority of the Parkinson's, Huntington's, and ALS estimates are below the 0.45 threshold. That being said, the points within one standard deviation of the classifications show significant overlap. As a diagnostic tool, the goal is to provide both an overall classification and to identify specific points within the gait that indicate abnormality.

5.2 Identification of specific gait abnormalities

In addition to the overall classification of gait behavior, assessing the normality of specific portions of a subject's gait provides deeper insight into the subject's overall gait characteristics. This information may be used for diagnosis and in a clinical review of the

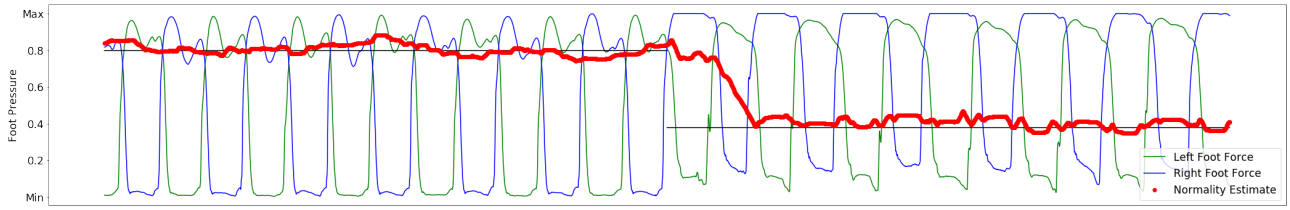


Figure 6: Simulated Gait Degradation. The red line shows the moving average of the gait normality. The black lines show the average gait normality of the first and second sections with a discontinuity at the point of simulated gait degradation.

gait reveals repeating patterns within the gait as well as episodic abnormalities, such as FOG.

In Figure 4(a), the control gait chosen from the GaitNDD testing set exhibits a recurrent degradation after the transfer to the left foot just after the point where the right foot (blue) lifts (reduces pressure) and the left foot (green) steps down (increases pressure) just before the 118 second mark. This is repeated again at the 102 second, the 128 second, and the 148 second marks. This signal within this subject's gait is regular and repeating (not episodic). Repeated abnormalities on a single side of a transfer may not indicate an abnormality beyond an injury. Other possible causes could include imbalances such as a strong and weak side related to handedness.

In Figure 4(b), the GaitNDD Parkinson's testing gait seems to have shuffling gait issues and maybe even some festination (a tendency to speed up in parallel with a loss of normal amplitude of repetitive movement, e.g. *marche a petits pas*). The transfer from the right foot (blue) to the left foot (green) exhibits some hesitation characterized by a jagged transfer. This shows that there is hesitance in the transfer from the left foot to the right foot. While the session shows low normality over a majority of the gait, a highly regular gait interval is indicated by the gray window which covers the transfer from the left foot (green) to the right foot (blue).

In Figure 4(c), a normal gait from the GaitPDB data set shows a stumble or inconsistency between 18 and 21 seconds. This is an episodic variation that is not exhibited in the surrounding steps. The system identifies this as a portion of the gait with low normality.

in Figure 4(d), no window is used since the abnormality from seven seconds to tweleve seconds is clearly identified by the system. While there is a generally low abnormality across the data set, this particularly low normality could indicate a stumble or hesitance in transition from the left foot (green) to the right foot (blue).

5.3 Simulation of Degradation

The publicly available data sets limit the scope of the data to a single subject during a single clinical session and do not include long-term degradation data. Long term activities of daily living data sets are limited to only normal candidates. To simulate long-term degradation, the testing files from the GaitNDD database are spliced to create a transition between two different gaits.

First, two files are chosen at random and are considered the beginning sequence and the ending sequence. A single point is chosen at random within each of the files. The nearest transition from left foot to right foot, where the pressure for each foot is approximately equal, is then selected in each file as the point at which to splice the files. The data from the beginning sequence (starting after 10 seconds) to the splice point in the beginning sequence is added to the new time series. The data from the ending sequence from the ending splice point onward are concatenated to the new time series. The point at which the two time series are joined is recorded as the splice point.

To identify the transition point, there are four cases: a control to control splice, a degenerate to degenerate splice, a control to degenerate splice, and a degenerate to control splice. We generate a random set of 40 transition files, 10 from each of the above cases. The average normality for the beginning sequence is used as the threshold for identifying changes to the gait. A change in long term gait is defined as a change of average gait normality (over the one second window) of 25%.

As shown in Figure 6, changes in normality are identified around the splice point. In the cases where the average normality of the beginning sequence is within 20% of the average normality of the ending sequence, the system is able to identify the gait degradation. When the difference in average normality is less than 20% the system is not able to consistently identify the degradation. While not a long term analysis, it does demonstrate the ability to evaluate changes to a patient's gait.

6 CONCLUSION

Automated gait analysis provides decision support and aids in the diagnosis of neurodegenerative diseases. The pre-clinical and clinical assessment of the overall normality of a subject's gait using sensor data from a wearable device can improve the initial diagnosis of Parkinsonian gait. We demonstrate this assessment using a recurrent neural network architecture with attention. While this style of network is known, the application of normality analysis could have a considerable impact on a subject's prognosis and improve their overall quality of life.

Streaming data from a wearable device makes it possible to monitor disease degeneration and suggest preventative intervention over an extended period of time. This data may also act as an indicator that more serious clinical review is in order. Moving to an approach that rates the normality of the gait gives doctors the flexibility to review a subject's gait in a clinical setting, identify specific issues within a subject's gait, as well as provide long term monitoring for continued gait degradation. This enables doctors to increase the quality of care they provide to patients with neurogenerative diseases and provides a continuous monitoring paradigm for patients.

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