Real-time Streaming of Gait Assessment for Parkinson's Disease

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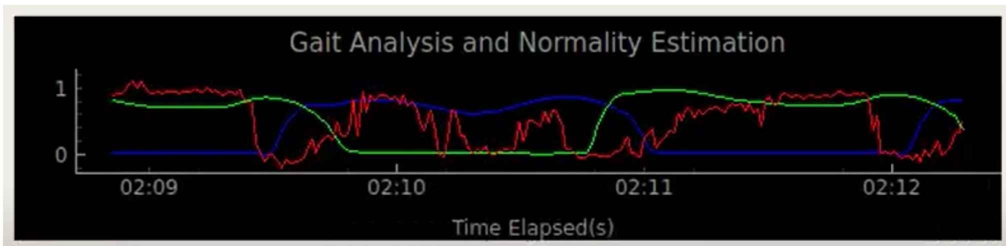

Figure 1: A real-time streaming data analysis of the normality of the gait of a patient with idiopathic Parkinson's disease. The green line represents the pressure exerted by the left foot. The blue line represents the pressure exerted by the right foot. The red line is an estimate of the normality of the gait, where low scores represent an abnormality at that point in the gait.

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. Real-time assessment and visualization of sensor data can be valuable to physicians monitoring the progression of these conditions. We present a system that utilizes the attention based bi-directional recurrent neural network (RNN) presented in [2] to evaluate foot pressure sensor data streamed directly from a pair of sensors attached to a patient. The demonstration also supports indirect streaming from recorded sessions, such as those stored in a FHIR [1] enabled electronic medical records repository, for post-hoc evaluation and comparison of a patient's gait over time. The system evaluates and visualizes the streamed gait in a real time web interface to provide a personalized normality rating that highlights the strengths and weaknesses of a patient's gait.

CCS CONCEPTS

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

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KEYWORDS

Parkinson's Disease; Gait; Diagnostics; Neural Networks; Web Streaming; FHIR; Electronic Medical Records

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1 INTRODUCTION

The personalized analysis of human gait is a complex task directed at both immediate analysis of a patient's gait characteristics as well as long term analysis of gait degeneration over time. In a clinical setting, a practitioner needs access to real time results generated by a sensors attached to a patient. These data are used to assess neuromuscular and gait issues. Web streaming enables real-time assessment of the condition and avoids the need for specialized hardware for signal processing and assessment. The data can also be stored in electronic health records (EHRs). These data are also archived to a repository for later analysis and comparison against previously recorded patterns.

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 a 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 6,500 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.

We demonstrate a system for streaming and processing of sensor data. Our system supports physicians looking to assess the condition and progression of conditions like Parkinson's Disease, both in real-time and historically from recorded sessions. Our system consists of two main components: 1) a stream sender which can simulate either sensors to stream data live or gait data stored in an EHR, and 2) a stream reader which listens for data, assesses the normality of the gait data, and plots both the gait and the assessment in real-time. In the demonstration, we show our system both simulating the live acquisition of streaming gait data and the replay of a recorded session from an EHR. The gait normality is indicated by the red line and the right and left foot pressures are shown by the green and blue lines, respectively. In Figure 1, there is a high normality when weight is on the left foot, but low normality during transition from the left to right foot, and varied normality while pressure is on the left foot. With no similar system yet existing, our system demonstrates clear clinical impact.

2 RELATED WORK

2.1 Streaming Electronic Health Care Data

Henry et al. [5] demonstrate the use of two open standards, FHIR and RDF, combining both to integrate data from disparate sources in real time. The system combines multiple sources to stream data containing blood pressure, temperature, and laboratory values for analysis and a streamed sepsis analysis result for a specific patient.

Saripalle et al. [9] evaluate the issues related to data from wearable devices to an individual's electronic health record. The effort leverages the HL7 FHIR standard to design an interoperable entity that integrates activity and associated data with an EHR. The described effort comprises HL7 FHIR Java-based implementation, REST web service, and OpenEMR, and is tested using wearables.

2.2 Analysis of Gait

Moore et al. [7] profile different vertical linear acceleration and analyze the power spectra to differentiate general classes of gait. By comparison of the walking and freezing-of-gait (FOG) power spectra, a power spectra threshold is identified. If this threshold is exceeded a FOG warning is raised. Eleven patients with idiopathic PD were used for both analysis and testing in this study.

Jovanov et. al. [6] disclose a wearable system for real-time gait monitoring to recognize FOG episodes based on the Moore [7] power spectra analysis. Signals from five experiments, four from simulated freezing gait events and one actual patient, are analyzed to establish the feasibility of real-time inertia based FOG detection.

Flagg et al. [2] propose the application of an attention based bi-directional recurrent neural network (RNN) to medical gait data to identify and rate the normality of gait patterns from streaming data and to inform clinicians of specific gait abnormalities. The neural network learns to generalize normal and idiopathic gait characteristics from large data sets (166 and 64 patients) to assess the normality of the gait from unseen subjects. We utilize the network as described herein and in US Patent App. 16/889,642 [8] for gait analysis in this demonstration.

3 DATA SETS

To simulate streaming of clinical data within a research context, data from several sources were considered. These sources provide the raw data and may either be used as a data stream to simulate clinical streaming or as a data file simulating an electronic medical record, as shown in Figure 2.

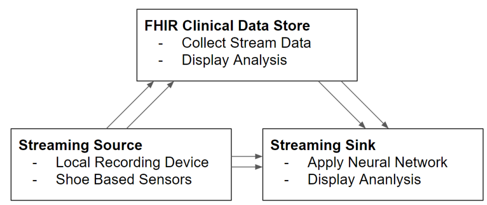


Figure 2: Streaming Network Design

Gait in Neurodegenerative Disease Database (GaitNDD). The data streamed to the application are from the publicly available gait data set for the pathophysiology neurodegenerative diseases [4]. The data are based on 64 subjects with Parkinson's disease, Huntington's disease, ALS, and no idiopathic gait symptoms walking independently for five minutes. The data were obtained through force-sensitive resistors placed under each subject's foot.

Gait in Parkinson's Disease (GaitPDB). This publicly available data set contains measures of gait from 93 idiopathic Parkinson's disease patients and 73 healthy 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. The data set provides an aggregation of these sensor data into left and right foot pressure readings taken 100 times per second. [3].

4 SYSTEM IMPLEMENTATION

4.1 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 3.

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.

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 matching the GRU hidden state size and an output of one dimension is used as the attention layer. This layer is applied to each of the hidden vectors and creates a single value representing the weight of the contribution strength of each hidden vector. This weight is multiplied against each hidden state to modify the strength of the hidden state with respect to predicted value. The weighted hidden states are summed to create the final output of the GRU.

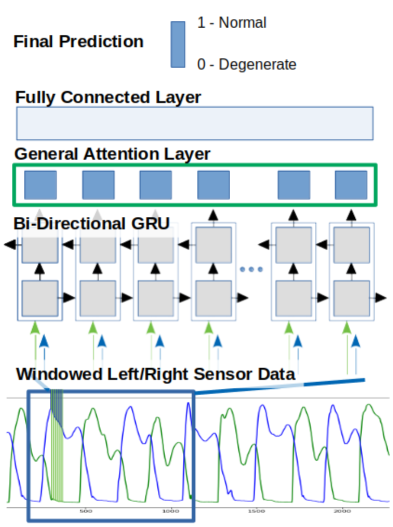


Figure 3: Bi-Directional GRU with General Attention.

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 other data 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 differences between normal and degenerate cases to train an accurate model.

4.2 Network Implementation

The PyTorch implementation utilizes an initial three layered bi-directional GRU with 256 neurons per hidden layer. A dropout of 0.3 is used by the GRU to reduce overfitting. The input data have 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.

4.3 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 [0,1] over the stream. 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: a Gated Recurrent Unit (GRU), a general attention layer to summarize the GRU output, and a final fully connected layer.

4.4 Streaming Sender

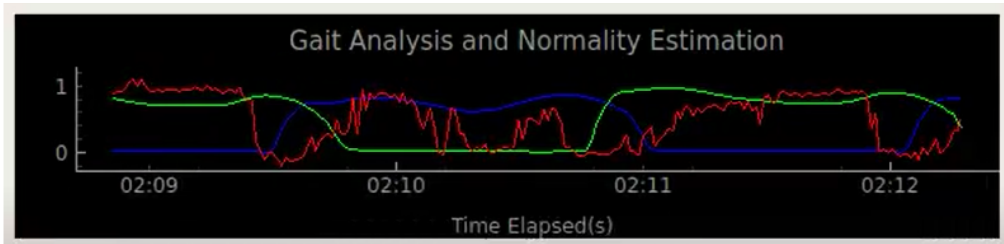
For this demonstration, the data from the two disclosed data sets may be used as source data. The data are loaded into the sender, either as a partial record or as a complete record, based on the size of the data. The sender then establishes a UDP socket to send messages to any number of receivers. Each message is formatted as a JSON object that contains the two foot pressures.

The sender may be initialized with a specific rate at which it sends the data. When the sender is acting as a live data source, the data are sent out at the specified rate to the socket. To simulate data from repository the sender listens to a socket for an incoming file name. Once the file name is received, the file is loaded data and is sent in the same manner as with the live data scenario. If the file is not available, an error message is created, and no data are sent.

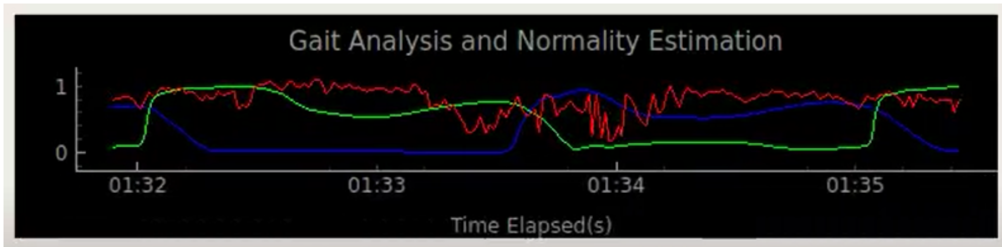
4.5 Streaming Receiver

The receiver listens to a UDP socket for incoming data. If the data are in the proper JSON format, the receiver begins collection and analysis of the data. The receiver immediately begins displaying foot pressure readings. Since a window of data is required to perform normality analysis, a static value of 0.5 for the normality is initially displayed. Once there is enough gait data received to fill the required window for the neural network, the windows are evaluated by the neural network, and normality estimates are produced and displayed along with the gait data.

The incoming rate of data may be specified when the receiver is started. If the data are arriving slower than this rate, the data are displayed as they are received. If the data are streamed faster than they can be displayed, they are buffered and displayed as quickly



(a) Streaming Parkinson's - Note the low normality estimates (red)



(b) Streaming Control - Note the higher normality estimates (red)

Figure 4: Interface for viewing streaming data. The green lines represent the left foot. The blue lines represent the right foot. The red line is the estimate of the normality for the gait.

as the plot of the data may be refreshed. To this end, the size of the window may be specified to allow for a smaller or larger plot size and faster or slower maximum display rate.

5 DEMONSTRATION

Demonstration at the conference will highlight the ability to work with multiple data sources and perform normality analysis on their gaits. Two scenarios will be explored 1) live streaming of gait data and 2) the ability to load gait data from a repository. Based on user interest, various gait patterns from the data sets will be loaded and streamed. These patterns will be received, processed by the neural network, and evaluated for normality. The resulting normality ratings of the streamed data may be reviewed for issues such as cyclical abnormalities and gait characteristics.

The streaming receiver display shown in Figure 4 provides examples from two different gait sources. The Parkinson's gait shown in Figure 4(a) shows a high normality while pressure is on the left foot. At other instances in the gait, particularly the transfer to the right foot, display low normality. The Control gait shown in Figure 4(b) shows consistently high normality with minor fluctuations at the transfer to the left foot.

6 CONCLUSION

Automated gait analysis provides pre-clinical and clinical decision support for the identification of abnormalities within a subject's gait. Using sensor data from a wearable device, we demonstrate this assessment using a recurrent neural network architecture with attention. While this style of network is known, the application of normality analysis has considerable impact on a subject's prognosis and improves 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. These 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 to patients with neurogenerative diseases and provides a continuous monitoring paradigm for patients.

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