Utilizing Neural Networks to Predict Freezing of Gait in Parkinson's Patients

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ABSTRACT

With the appropriate mathematical models, data from wearable devices can be used to help Parkinson's patients live safer and more independent lives. Inspired by this idea, the purpose of this study was to determine the viability of neural networks in predicting Freezing of Gait (FoG), a symptom of Parkinson's disease in which the patient's legs are suddenly rendered unable to move. A class of neural networks known as layered recurrent networks (LRNs) was applied to an open-source FoG experimental dataset donated to the Machine Learning Repository of the University of California at Irvine. The independent variables in this experiment – the subject being tested, neural network architecture, and down sampling of the majority classes – were each varied and compared against the performance of the neural network in predicting impending FoG events. It was determined that single-layered recurrent networks are a viable method of predicting FoG events given the volume of the training data available, though results varied between patients.

Keywords

Parkinson's Disease; Freezing of Gait; Machine Learning; Wearable Devices.

1. INTRODUCTION

One common result of Parkinsonian Gait is "Freezing of Gait" (FoG), which refers to the patient having difficulty initiating movement or continuing it once it has begun. Though there are several methods of mitigating the severity of a FoG episode once it has begun, the lack of a viable method of prediction means that patients and caregivers may not have adequate time to prepare for the onset of such an episode [4]. To overcome this challenge, this study proposes using layered recurrent networks (LRNs) as a method of predicting FoG before its onset to improve the effectiveness of such therapeutic techniques. The LRN was chosen because of its noise-tolerance and ability to recognize patterns over time in large datasets. The LRN model used is shown in Figure 1.

In this study, LRNs of varying configurations were applied to three subjects chosen from the Machine Learning Repository [4] to obtain a preliminary indication of whether LRNs are a viable method of predicting FoG events.

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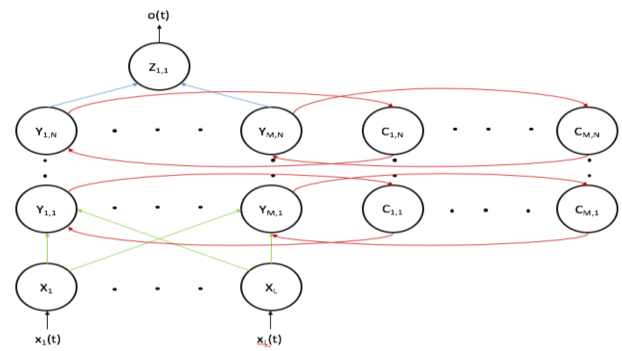

Figure 1. Layered Recurrent Network (LRN) Model

2. RELATED WORK

The effectiveness of neural networks in predicting the onset of Parkinsonian symptoms has not been extensively explored; however, previous publications have proposed other methods of predicting FoG. Such studies include analyzing skin conductance [6], motion data [7], and EEG data [1] using a variety of methods. Though previous studies have attained reasonable success in this area, neural networks provide the benefit of adaptability to each patient's unique symptom presentation while other methods require varying degrees of tailoring to account for human factors.

3. METHODS

In the dataset used for this study, motion data was captured from each subject using three accelerometers with different placement (shank, thigh, and torso). Any FoG events that occurred were then manually time-stamped into the dataset by an independent observer.

In this study, three subjects were chosen at random and only the data from the three-axis shank accelerometer was used. For each subject, neural networks were trained using the first half of their dataset. In this training period, each time-stamp where FoG occurred was shifted 1,000 samples (approx. 5 seconds) toward $t = 0$ such that the networks were trained to recognize the precursor symptoms of each FoG event. Once these networks were trained, they were tested using the second half of the dataset to yield the results shown in the following section. For each subject, several different neural networks were tested. The parameters that were varied include (1) N - number of hidden layers, (2) M - number of hidden units per layer, (3) f_0 - number of samples included in backpropagation through time (BPTT) algorithm, and (4) D - down sampling factor[1] [5]. This resulted in 48 different trials summarized in Table 1.

Table 1. Experimental Parameters

N	M	f_0	D
1	3	100	1
3	5	1000	3

4. RESULTS

After these trials were performed, the precision and recall for each network configuration were calculated. The precision is the percentage of FoG warnings by the trained network that correctly predicted a FoG event while the recall is the percentage of FoG events that were predicted by the trained network. Only the configurations which yielded statistically-significant precision and recall values are shown in the Table 2. Table 3 indicates the number of FoG events present in each dataset used for training and testing.

Table 2. Precision and Recall Values

				Subject 1		Subject 2		Subject 3	
f_0	D	N	M	P%	R%	P%	R%	P%	R%
100	1	1	3	-	-	100	11	-	-
100	1	1	5	-	-	100	4	-	-
100	3	1	3	-	-	89	30	57	27
100	3	1	5	-	-	96	16	62	25
1000	1	1	3	-	-	100	5	-	-
1000	3	1	3	42	47	100	2	-	-
1000	3	1	5	-	-	100	10	-	-

Table 3. Number of FoG Events per Dataset

	Subject 1	Subject 2	Subject 3
Training	18	9	39
Testing	5	15	26

Higher precision indicates that the network better identified FoG-specific patterns while higher recall indicates that it identified a wider range of FoG events. The values for precision and recall depend on how the network output is interpreted. In this study, the decision rule used to interpret the output was optimized using the receiver operating characteristic (ROC) of each network, thus maximizing precision and recall together. In certain applications, however, it may be more beneficial to bias the output toward one or the other. In the case of FoG, failing to predict an event may have more severe consequences than a false alarm.

5. CONCLUSION

5.1 Discussion

These results suggest that LRNs may be a viable method of predicting FoG events. The data shows that FoG events were predicted up to 47% of the time for Subject 1, 30% for Subject 2, and 27% for Subject 3 while the corresponding network precision was 42%, 89%, and 57% respectively. As listed in Table 2, the most effective networks (highlighted) were those that were both small and utilized down sampled data. This may indicate that larger networks – which detect more nuanced patterns – require either more computation time or more extensive datasets to provide comparable predictive power. Based on the results, LRNs may be used in the future to assist Parkinson's patients in their daily lives.

5.2 Future Work

Future work should integrate other data modalities such as skin conductance, medication cycles [2], and physical location [3] as well as incorporate a greater number of subjects. The effect of processing the raw data before training should also be examined along with the effect of training the networks over several different subjects rather than training each network independently. Furthermore, the implication of using a fixed time-shift when training the networks was that they could not learn longer-term predictive patterns; these should be addressed in future work. Finally, exploring different types of neural networks and methods of counteracting class imbalance may also improve these results.

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7. REFERENCES

[1] A. Handojoseno, J. Shine, T. Nguyen, Y. Tran, S. Lewis and H. Nguyen, "Analysis and Prediction of the Freezing of Gait Using EEG Brain Dynamics", IEEE Trans. Neural Syst. Rehabil. Eng., vol. 23, no. 5, pp. 887-896, 2015.

[2] J. D. Schaafsma, Y. Balash, T. Gurevich, A. L. Bartels, J. M. Hausdorff, and N. Giladi, "Characterization of freezing of gait subtypes and the response of each to levodopa in Parkinson's disease," Eur J Neurol European Journal of Neurology, vol. 10, no. 4, pp. 391–398, 2003.

[3] J. Nonnekes, A. H. Snijders, J. G. Nutt, G. Deuschl, N. Giladi, and B. R. Bloem, "Freezing of gait: a practical approach to management," The Lancet Neurology, vol. 14, no. 7, pp. 768–778, 2015.

[4] M. Bachlin, M. Plotnik, D. Roggen, I. Maidan, J. Hausdorff, N. Giladi, and G. Troster, "Wearable Assistant for Parkinson's Disease Patients With the Freezing of Gait Symptom," IEEE Transactions on Information Technology in Biomedicine IEEE Trans. Inform. Technol. Biomed., vol. 14, no. 2, pp. 436–446, 2010.

[5] N. Chawla, K. Bowyer, L. Hall and P. Kegelmeyer, "SMOTE: Synthetic Minority Over-sampling Technique", Journal of Artificial Intelligence Research, vol. 16, pp. 321-357, 2002.

[6] S. Mazilu, A. Calatroni, E. Gazit, A. Mirelman, J. M. Hausdorff, and G. Troster, "Prediction of Freezing of Gait in Parkinson's From Physiological Wearables: An Exploratory Study," IEEE Journal of Biomedical and Health Informatics IEEE J. Biomed. Health Inform., vol. 19, no. 6, pp. 1843–1854, 2015.

[7] S. Mazilu, E. Gazit, D. Roggen, J. Hausdorff, and G. Tröster, "Feature Learning for Detection and Prediction of Freezing of Gait in Parkinson's Disease," in Machine Learning and Data Mining in Pattern Recognition, vol. 7988, a calatroni, Ed. New York, NY, 2013, pp. 144–158.

[1] A down sampling factor of 3 indicates that one out of every 3 data points in the raw data were used in neural network training.