Causal Analysis of Inertial Body Sensors for Enhancing Gait Assessment Separability towards Multiple Sclerosis Diagnosis

Jiaqi Gong, John Lach
Department of Electrical and Computer Engineering
UVA Center for Wireless Health
University of Virginia
Charlottesville, VA, USA
{jgong, jlach}@virginia.edu

Yanjun Qi
Department of Computer Science
UVA Center for Wireless Health
University of Virginia
Charlottesville, VA, USA
yq2h@virginia.edu

Myla D. Goldman
Department of Neurology
UVA Center for Wireless Health
University of Virginia
Charlottesville, VA, USA
mdg3n@virginia.edu

***Abstract*—Gait assessment is a common method for diagnosing various diseases, disorders, and injuries, studying their impact on mobility, and evaluating the efficacy of various therapeutic interventions. The recent emergence of inertial body sensors for gait assessment addresses the limitations of visual observation and subjective clinical evaluation by providing more precise and objective measures. Inertial sensors have been included in an ongoing study at the University of Virginia Medical Center on Multiple Sclerosis (MS), a chronic autoimmune disorder of the central nervous system (CNS) that produces neurologic impairment and functional disability over time, with the goal of improving the ability to assess MS-affected gait and to distinguish between subjects with MS and those without MS.**

This work presents a gait assessment technique based on causal modeling to distinguish MS-affected gait and healthy gait. The approach in this work is based on the hypothesis that the strength of interaction between body parts during walking is greater in healthy controls that in MS subjects. The strength of interaction was quantified using a causality index based on the pairwise causal relationships between body parts as characterized by the Phase Slope Index (PSI) of inertial signals from pairs of body parts. In a pilot study with 41 subjects (28 MS subjects and 13 healthy controls), the approach developed in this paper provided better separability ($p < 0.0001$) compared with existing methods.

Keywords—inertial body sensors; gait assessment; multiple sclerosis; causality

I. Introduction

In recent years, performance in the 6-minute walk (6MW) is gaining popularity as an outcome measure in evaluating Multiple Sclerosis (MS), which is a chronic autoimmune disorder of the central nervous system (CNS) that results in neurologic impairment and functional disability over time [1]. Over the course of the disease, loss of functional ambulation occurs in almost all patients. Walking performance is, therefore, an important outcome to assess severity of disease, disease progression, and therapeutic efficacy. More recently there has been interest in the objectivity that inertial sensing provides over human observation.

There are many methods for gait assessment based on inertial body sensors using gait cycle detection [2], gait pattern recognition [3], etc. Often temporal gait features based on gait phase decomposition are used. These include gait speed [1, 4], stride length [5], joint angles [6], swing time [7], double stance time, single stance time [8] or other derived parameters [9]. Other systems for gait assessment include motion capture system based on computer vision techniques, such as Vicon, which provides 3D position tracking.

Despite the advances in MS research using gait assessment, the detailed impact of MS disease on gait performance is unresolved. For instance, the neurologic impairment and functional disability may result in left foot abnormality in one individual, but right arm abnormality in another. Since MS can affect different body parts in different individuals, separately investigating gait parameters in individual body parts may not work well for MS gait assessment.

In addition, human motion consists of not only the spatial-temporal evolution of individual body parts, but also the coordination and interaction between body parts. Johansson [10] showed that humans recognize motions by observing only a few tracked points and considering their interactions. The interactions among body parts contain rich information of body motion, even more than the separate spatial-temporal evolution of body parts. These interactions give a richer representation and quantification of the body motions.

Since the impact of MS disease on gait performance would result in the motion abnormality of any body part, comprehensive gait assessment of the whole body is needed for improving separability in MS diagnosis. According to the above analysis of human motion, we calculate the overall interactions between body parts to assess the comprehensive gait performance. The idea behind this paper is a hypothesis that these interactions between body parts are stronger in healthy controls than in MS subjects.

In this work, we propose a causality-based approach for quantifying these interactions between body parts with the goal of providing better separability in MS diagnosis compared with previous work. We evaluate our method on a data set of inertial

978-1-4673-7201-5/15/$31.00 ©2015 IEEE

body sensor data, including 121 data sessions, each of which contains time series data from 41 subjects (28 MS and 13 healthy control) performing the 6MW wearing 5 inertial body sensors (a 3-axis accelerometer and 3-axis gyroscope on both wrists, both ankles, and sacrum). We compare to state-of-the-art methods for the separability performance in MS diagnosis.

Organization of the rest of the paper is as follows. Approach for gait assessment using interactions among body parts is explained in Section II. The details of the experimental setup are provided in Section III. Results on the data set for motion assessment and experiments related to MS diagnosis are given in Section IV. Comparison with other related work is discussed in Section V, and we conclude the paper in Section VI.

II. CAUSALITY BASED APPROACH

Causal interactions among body parts occur inherently among motion patterns in an action and capturing such interactions will help in modeling and quantifying actions better. In this section we will formally introduce causality and use it to construct descriptors which will encode the interactions among body parts. In order to quantify the specified action (walking) regardless of the effect of other needless actions, such as body rotation, we perform a coarse-level segmentation to eliminate the needless actions. Pairwise causality matrix based on Phase Slope Index (PSI) [11, 12] is built for each data segment from coarse-level segmentation. At last, the average value of the significant PSIs in pairwise causality matrix is used as a metric so called causality index to represent the strength of the interactions between the body parts. Figure 1 illustrates an example of the proposed motion assessment approach.

A. What is Causality?

The idea behind that a signal is said to be "causal" to another comes from the understanding of the interacting system in a physical view. This was formalized by Nolte [11], and this interaction between a pair of signals is so called "Phase Slope Index". The central idea behind the PSI measure of causal influence is that the cause precedes the effect in time and thus the slope of the phase of the cross spectrum between two signals reflects the direction of influence.

Given two time-varying signals $x_i[t]$ and $x_j[t]$. The cross spectrum between them is defined as follows:

$$S_{ij}(f) = E\left[X_i(f)X_j^*(f)\right] \tag{1}$$

And the complex coherence is

$$C_{ij}(f) = \frac{S_{ij}(f)}{\sqrt{S_{ii}(f)S_{jj}(f)}} \tag{2}$$

The unnormalized PSI metric is defined using complex coherence as follows [13]

$$\widetilde{\Psi}_{ij} = Imag\left(\sum_{f\in F} C_{ij}^*(f)C_{ij}(f+\delta f)\right) \tag{3}$$

Where f is the frequency band of interest and δf is the frequency resolution. It is straightforward to show that $\widetilde{\Psi}_{ij}$ measures a weighted sum of the slopes of the phase between $x[t]$ and $x_j[t]$ over the band f [11]. This measure is normalized by its standard deviation to obtain a metric Ψ_{ij}that can be used to determine whether causal influence from $x_i[t]$ to $x_j[t]$ is significant:

$$\Psi_{ij} = \frac{\widetilde{\Psi}_{ij}}{std(\widetilde{\Psi}_{ij})} \tag{4}$$

The causal direction is estimated to go from $x_i[t]$ to $x_j[t]$ if Ψ_{ij} is positive. Nolte et al. [12] suggest that absolute values of Ψ_{ij} greater than 2 should be considered significant. We compute Ψ_{ij}using the MATLAB software available in [11].

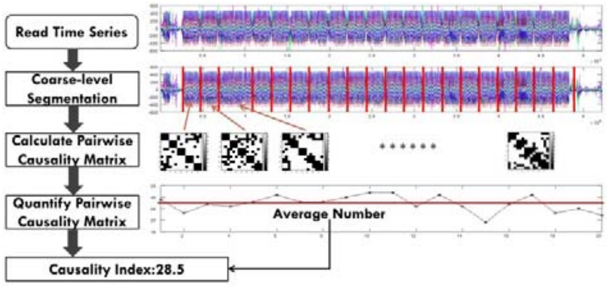

Figure 1: Illustration of causality based approach: The time series data is segmented in coarse level to eliminate the needless actions. The causal interactions between pairs of body parts are caculated resulting in a pairwise causality matrix (PCM) for each data segment. The average value of the quantifications of PCM so called causality index is used to quantify the strength of the interactions among body parts during the time series.

B. Coarse-Level Segementation

In order to get better quantification of the walking performance, we adopt a coarse level segmentation to eliminate the needless actions (body rotation in this application). When the subjects wearing inertial sensors on the lower limbs were asked to undergo an in-clinic 6MW, they are required to walk as far and as fast as possible up and down a 75-foot hallway, the actions merged in the data from inertial body sensors contained straight walking and body rotation. These two different actions have different coordination strategies in the body parts, which may affect the causality estimation.

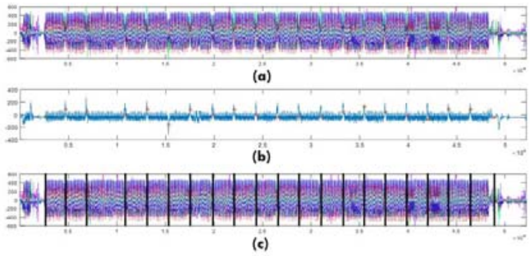

Figure 2: An example of coarse-level segementation: (a) original time-series data; (b) change point discovery and (c) 20 motion data segements were extracetd from the time series data in this example.

With considerations of human factors during the real-world deployment, such as mounting errors (from sensor displacement orientation) [14] and looseness of sensors [15], we adopted a robust segmentation method proposed in [16]. The method combined change point discovery and features based on linear dynamical system to robustly segment time series inertial data into different temporal scales.

978-1-4673-7201-5/15/$31.00 ©2015 IEEE

Figure 2 shows an example of one data session from one subject's 6MW. The segmentation method successfully cuts the time series data into 20 pieces and eliminates the needless actions. For more information about the segmentation method, we refer the reader to [16].

C. Pairwise Causality Matrix

Our hypothesis is that the strength of the interactions among body parts in healthy control subjects is greater than in MS subjects. In order to represent the interactions among body parts, we use the normalized PSI to construct a pairwise causality matrix of the inertial body sensors which are attached on different body parts, as described in the following, and then count how many significant PSI in the matrix as the strength of the interactions. The strength value will be used as a metric which we called the causality index to represent the interactions among body parts. This is the proposed gait assessment of the subject during the 6MW.

Let $x[t] \in R^{N*D}$ denote time series data session from inertial body sensors during 6MW where D is the signal dimension of each inertial body sensor and N is the number of inertial body sensors the clinics adopted to put on the subject's body. In other words, N is the number of the body parts the interactions among which we are going to investigate. The reason that we consider all the dimensions in the signal from each inertial body sensor is the uncertain orientation of the inertial body sensor during the real-world deployment of 6MW. It means we cannot eliminate any dimensional signal since the orientation of inertial body sensors is unknown. We therefore consider all the dimensional signals to discover the interactions between inertial body sensors.

After coarse-level segmentation, $x[t] \in R^{N*D}$ is segmented into $x^k[t], k \in [1,2..M]$, where M is the number of the data segments. Note that the segments do not overlap. Let $x_i^k[t] \in R^1$ and $x_j^k[t] \in R^1$ denote a pair of 1D signals in dimension i and j, respectively, where $i, j \in \{1,2,\ldots,N*D\}$. Now let Ψ_{ij}^k be the PSI computed using $x_i^k[t]$ and $x_j^k[t]$. Then the matrix Ψ^k is the pairwise causality matrix of the k segment of time series data $x^k[t]$. Otherwise, the diagonal D*D matrix in the ND*ND matrix Ψ^k are set to 0, because the self-causality cannot be counted as interactions. Figure 3 shows the graphic and matrix demonstration of the pairwise causality between body parts.

We judge the significance of the PSI according to the suggestion from Nolte et al. [11], and then count the number of significant PSIs in the pairwise causality matrix. Considering our hypothesis, the number of significant PSIs in the pairwise causality matrix is used to describe the strength of the interactions among body parts during the walking period of the k segment of time series data $x^k[t]$.

The binary pairwise causality matrix using significant threshold is given as below:

$$\Lambda^k = \Psi^k 1_{\{|\Psi_{ij}^k| \geq 2\}} \tag{5}$$

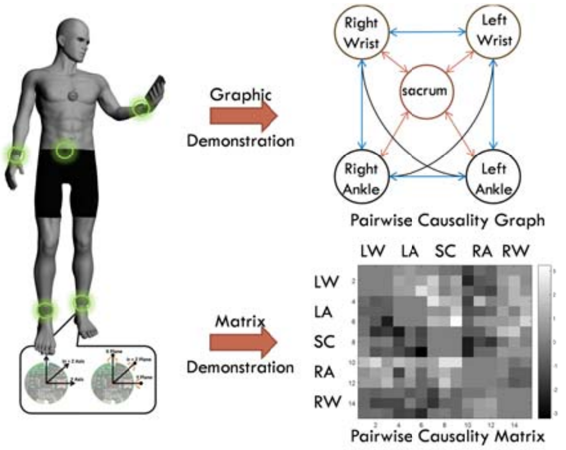

Figure 3: Illustration of pairwise causality in graph and matrix demonstrarion: the subject wears five inertial body sensors in left/right wrist, left/right ankle and sacrum, and the 3D gyroscope data from each inertial sensor is used to calculate the 15*15 pairwise causality matrix. Note that the diagonal 3*3 matrix are set to be 0, because the self-causality are not counted as interactions.

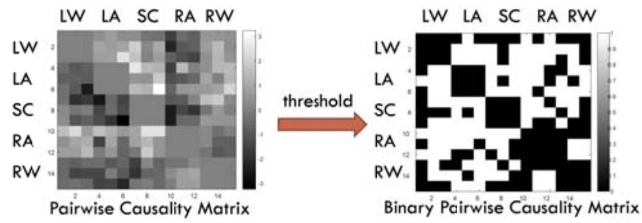

Figure 4: An example of binary pairwise causality matrix: threshold is suggested by Nolte et al. [11] to select the significant PSIs and then the significant PSIs is counted as a metric for describe the strength of the interactions between body parts in the data segment.

Where

$$1_{\{|\Psi_{ij}^k| \geq 2\}} = \begin{cases} 1, if\ |\Psi_{ij}^k| \geq 2 \\ 0, if\ |\Psi_{ij}^k| \leq 2 \end{cases} \tag{6}$$

Figure 4 gives an example of the determination of significant PSIs in pairwise causality matrix using the threshold suggested by Nolte et al. [11].

The strength of the interactions among all the body parts in the kth segment of data as follows:

$$\Theta^k = \frac{1}{2} \sum_{i,j(i \neq j)} \Psi^k 1_{\{|\Psi_{ij}^k| \geq 2\}} \tag{7}$$

D. Causality Index

Based on the calculation of pairwise causality matrix, we create a causality index for each data session to represent the average strength of the interactions among body parts during the 6MW. The causality index is defined as below:

$$\mathbb{C}(x[t]) = \frac{1}{M} \sum_k \Theta^k \tag{8}$$

Figure 1 illustrates the calculation process of causality descriptor for a time series data session as an example. This feature is used to separate the healthy control and MS subjects. In corresponding to our motivated hypothesis, if the causality indexes of healthy controls were larger than those of MS subjects, then the hypothesis get proved.

III. Experimental Setup

A. Description

41 study subjects (28 MS and 13 healthy control) wearing 5 inertial sensors (3 axes of accelerometers and gyroscopes on each sensor node) on the left/right wrists, left/right ankles and sacrum were asked to undergo an in-clinic 6MW. Figure 3 illustrates the locations of the inertial body sensors on the body.

Followed by a medical assistant with a measurement wheel, the distance walked was recorded in 1-minute epochs. Subjects were asked to walk as far and as fast as possible (without running) up and down a 75-foot hallway. The inertial sensor data was wirelessly transmitted to a laptop for post-processing.

The sampling rate of inertial sensors is 128Hz which is sufficient to capture the frequency band of the body motion in walking action. The operator of the data collection system is required to make timestamp annotations in order to indicate the beginning and end of the walking actions.

B. Acquisition and Preprocessing

132 data sessions were collected in 3 years and each subject performed at least once 6MW. All the data sessions are calibrated with the recorded calibration parameters that had been done before the data collection [14]. There is no general normalization in the data preprocessing. However, due to the technical issues of our custom data collection system and human factors in the real-world deployment, 11 data session failed in the calibration process; 6 of them have too much drop packets during the wireless transmission to the laptop for data collection, 3 of them have timestamp error due to the system operator's fault, and 2 of them lose the calibration parameters in the calibration records. Finally, 36 data sessions were collected from 13 healthy controls while 85 data sessions were collected from 28 MS subjects, successfully.

Current causality algorithms, including PSI and granger causality, always have restriction on the stationary properties of the input signal. As the discussion in [16], accelerometer data always merged with random spikes and other artifacts make its stationary property cannot meet well for the requirements of causality algorithms. In contrast, short-term calibrated gyroscope data basically meets the stationary requirements of causality algorithms. According to the initial test results of accelerometer and gyroscope data with different causality algorithms, we choose the calibrated gyroscope data as the target and PSI as the causality estimation method in our experiments. It means each data session contain 15 dimensional gyroscope data from the 5 inertial body sensors.

C. Setting Parameters

There are three parameters needed to be set up before running the proposed algorithm: frequency band and frequency resolution in equation (3) and threshold used to quantify the significance of PSIs in pairwise causality matrix.

Recently the discovery in causal relationship between the frequency band of motion and neurological signals had been reported [17, 18], however there is rare prior knowledge about which frequency band of body motion is dominated during walking and how this motion frequency gets impact from MS disease. In order to avoid the information loss, we therefore choose the all frequency bandwidth in the data (1-64Hz). The frequency resolution is chosen as 0.5Hz. As mentioned before, we adopt the suggestion from Nolte [11] to choose the threshold as 2.

IV. Results

Figure 5 shows the causality index calculated from 121 data sessions. The blue bars indicate the 36 data sessions are collected from healthy control subjects, while green bars indicate the data sessions collected from MS subjects. Apparently, the healthy control subjects have higher causality index than MS subject. More specifically, the outlier of the healthy control subject in the red circle shown in Figure 5 is the subject 39. From the clinic records, this healthy control subject got a surgery between the two moments of 6MW data collection. The impact on the gait performance of the subject from surgery should be considered in future research. Other outliers of MS subjects in black circle will be investigated in future personalized analysis combining other medical records or factors, which is not included in this paper.

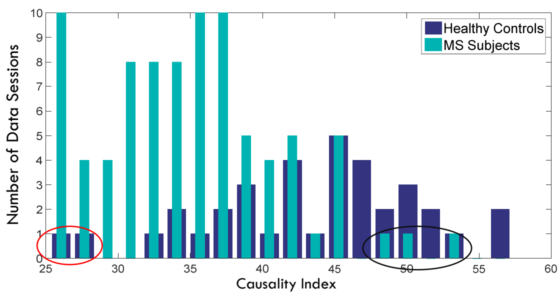

Figure 5: Experimental results of causality index caculated from 121 data sessions. The outlier of healthy control subjects in ellipse circle is subject No. 39. The clinic record shows the subject got a surgery between the moments of two data sessions.

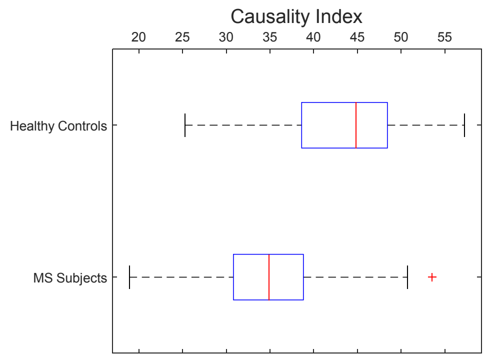

Figure 6: Comparision of causality index between healthy control and MS subjects.

Figure 6 illustrates the comparison of the causality index from the two groups: healthy control and MS subjects. The average value of the distribution in healthy control group is higher than in MS group.

We adopt two statistical evaluation methods, Cohen-D (Effect Size) [19] and t-test (p value), to compare the performance of different features in separability between healthy control and MS subjects in this dataset. Gait speed is the current clinically-used metric for gait assessment in MS diagnosis [1]. Chen et al. [9] reported a set of features extracted from gait cycle detection and the best of the features is the ratio between double stance time and single stance time (DST/SST). The reason for we compared to Chen et al is because we had access to their original data and code for identifying the various events. We selected these two features in the experiment of performance comparison. Effect size (p value) of gait speed, DST/SST, and causality index are 0.74 ($p<0.05$), 0.96 ($p<0.01$) and 1.12 ($p<0.0001$), respectively. The proposed causality index improves much in separability for MS subject diagnosis.

Apparently, it is reasonable to find a threshold in causality index calculated from inertial sensor data to assist the MS diagnosis which is the goal of this research. As you can see in Figure 5 and 6, the threshold in this pilot data can be set up at 40. However, in order to generalize the efficacy of the threshold in MS diagnosis, we need to collect more data and conduct more research in personalized analysis regarding of other factors as mentioned before.

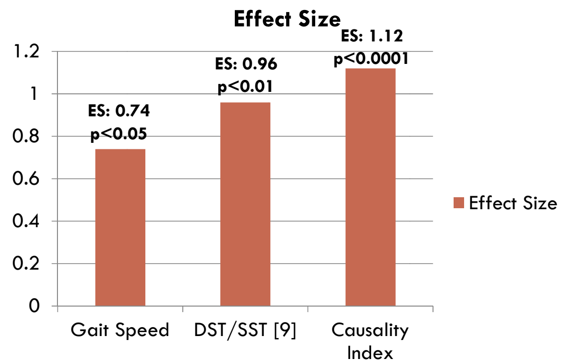

Figure 7: Performance comparision of different features in separability between healthy control and MS subjects in this dataset. Effect size (p value) of gait speed, ratio between double stand time and single stand time (DST/SST), and causality index are 0.74 ($p<0.05$), 0.96 ($p<0.01$) and 1.12 ($p<0.0001$), respectively.

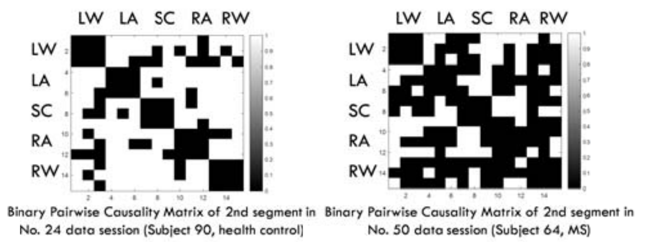

Figure 8: A comparision example of strength of interactions between inertial body sensors from healthy control and MS subject: the causality index on the left (66) is calculated from the 2^{nd} sement in No. 23 data session (subject 90, healthy control), while the causality index on the right (40) is calculated from the 2^{nd} sement in No. 45 data session (subject 64, MS subject).

As we know, gait speed is measured manually in clinics with man power and time consumption, while Chen et al. [9] requires the fine-level gait cycle detection to decompose the gait cycles in double stance time, single stance time and swing time that means it heavily relies on the accurate gait cycle detection and is fragile to noise. It is also a time-consuming method to reliably detect gait cycles in the real-world time series data. In contrast, the proposed causality index conducts coarse-level segmentation instead of gait cycle detection. It enhances the robustness of the method in real-world data processing. We implemented the proposed method in a commercial PC with Intel i7 CPU and 8G memory using MATLAB code. Each data session took 2 seconds to calculate the causality index. Therefore, the proposed method is a fast and robust algorithm to provide better performance.

Considering the motivated hypothesis, the experimental results can give a conclusion that it is proved: According to the performance of separability in healthy control and MS subjects, the strength of the interactions between body parts in healthy control is stronger than in MS subjects. Figure 8 illustrates an comparison example of strength of interactions between inertial body sensors from healthy control and MS subject.

V. Related Work

Similar to this work, a number of the causality based methods for motion assessment has been used in other research fields such as computer vision, motion capture system, music conducting. Narayan et al. [20] computed the feature interactions based on causality between pairs of trajectories of body parts from video for human action recognition. Jiang et al. [21] proposed an action classification method using 2D histogram on trajectory features. Saehoon [22] proposed a sparse causality graph to classify human actions using motion capture data.

Alessandro et al. [23] explored the interaction between music conductors and musicians using accelerometer equipped on the arms of the subjects.

Mohammad et al. [24] proposed a framework for mining causal relationships in time-series data with comparable experimental results using accelerometers and motion capture system.

All the above approaches are used to perform action classification or interaction exploration and most of them have been applicable in motion capture data or video. Although [23, 24] demonstrated the ability to process the causality relationship in accelerometer data, these methods had only few time series signals to deal with and the signals were known to be originating from specific joints in case of action recognition. We propose an approach to incorporate the advantages of causality measures in the data processing of inertial body sensors for MS diagnosis where such constraints cannot be fulfilled. First, the signals from inertial body sensors during the 6MW for MS diagnosis are in higher dimensions without the information of specific joints. Second, gait assessment in 6MW is a task of motion quantification in the same action (walking) rather than a task of classification from different actions. Compared with state-of-the-art methods, the proposed method has better separability in MS diagnosis and our motivated hypothesis is proved.

Based on the above considerations, the contributions of this paper are:

978-1-4673-7201-5/15/$31.00 ©2015 IEEE

1. An approach for incorporating the interactions among large number of inertial signals (i.e., 15-dimensional signal from 5 inertial body sensors) in a clinical deployment.
2. Strong evidence that the strength of interactions between body parts in healthy control subjects during 6-minutes walking is stronger than in MS subjects.

VI. CONCLUSION

This paper is motivated by the hypothesis that the strength of the interactions between body parts in healthy controls is greater than in MS subjects. In order to test the hypothesis, we developed a causality index, a technique that leverages causal modeling theory for quantifying the interactions between body parts through the time series data from inertial body sensors. The pairwise causality matrix is calculated to model all the interactions between body parts, and the causality index is used to assess the gait performance of the subject during 6MW. The novelty comes from the causality index incorporating the interactions among inertial body sensors as rich information into gait assessment. The main contribution comes from the proven hypothesis, which provides a new technical view in MS research. We have compared causality index to state-of-the-art algorithms for separability in MS research, with the causality index achieving better performance.

Future work focuses on personalized signal processing for high precision diagnosis, intuitional meaning extraction for clinicians, and deep leaning in causal relationship between the gait performance and clinic records.

ACKNOWLEDGMENT

Our thanks to Philip Asare for his input on this paper.

REFERENCES

[1] M. D. Goldman, R. A. Marrie, and J. A. Cohen, "Evaluation of The Six-Minute Walk in Multiple Sclerosis Subjects and Healthy Controls", Multiple Sclerosis, vol. 14, no. 3, pp. 383-390, 2007.

[2] J. Rueterbories, E. G. Spaich, B. Larsen, and O. K. Andersen, "Methods for Gait Event Detection and Analysis in Ambulatory Systems", Medical Engineering & Physics, vol. 32, no. 6, pp. 545-552, 2010.

[3] S. J. Preece, J. Y. Goulermas, L. P. Kenney, D. Howard, K. Meijer, and R. Crompton, "Activity Identification using Body-Mounted Sensors—A Review of Classification Techniques", Physiological Measurement, vol. 30, no. 4, pp. R1, 2009.

[4] B. C. Kieseier, and C. Pozzilli, "Assessing Walking Disability in Multiple Sclerosis", Multiple Sclerosis Journal, vol. 18, no. 7, pp. 914-924, 2012.

[5] C. L. Martin, B. A. Phillips, T. J. Kilpatrick, H. Butzkueven, N. Tubridy, E. McDonald, and M. P. Galea, "Gait and Balance Impairment in Early Multiple Sclerosis in the Absence of Clinical Disability", Multiple Sclerosis, vol. 12, no. 5, pp. 620-628, 2006.

[6] J. Favre, R. Aissaoui, B. M. Jolles, J. A. De Guise, and K. Aminian, "Functional Calibration Procedure for 3D Knee Joint Angle Description using Inertial Sensors", Journal of Biomechanics, vol. 42, no. 14, pp. 2330-2335, 2009.

[7] G, Chen, C. Patten, D. H. Kothari, and F. E. Zajac, "Gait Differences Between Individuals with Post-Stroke Hemiparesis and Non-Disabled Controls at Matched Speeds", Gait & Posture, vol. 22, no. 1, pp. 51-56, 2005.

[8] R. Sacco, R. Bussman, P. Oesch, J. Kesselring, and S. Beer, "Assessment of Gait Parameters and Fatigue in MS Patients during Inpatient Rehabilitation: A Pilot Trial", Journal of Neurology, vol. 258, no. 5, pp. 889-894, 2011.

[9] S. Chen, J. Gong, J. Lach, and M. D. Goldman, "Enhanced Multiple Sclerosis Gait Assessment using Inertial Sensors", Wireless Health Conference, Baltimore, MD, USA, Nov. 2013.

[10] G. Johansson, "Visual Perception of Biological Motion and A Model for Its Analysis", Perception and Psychophysics, vol. 14, no. 2, pp. 201–211, 1973.

[11] G. Nolte, A. Ziehe, V. V. Nikulin, A. Schlögl, N. Krämer, T. Brismar, and K. R. Müller, "Robustly Estimating The Flow Direction Of Information in Complex Physical Systems", Physical Review Letters, vol. 100, no. 23, pp. 234101, 2008.

[12] G. Nolte, A. Ziehe, N. Krämer, F. Poupescu, and K. R. Müller, "Comparison of Granger Causality and Phase Slope Index", Neural Information Processing Systems (NIPS) Workshop on Causality, Whistler, Canada, Dec. 2008.

[13] P. Rana, J. Lipor, H. Lee, W. Drongelen, M. H. Kohrman, and B. Veen, "Seizure detection using the phase-slope index and multichannel ECoG", IEEE Transactions on Biomedical Engineering, vol. 59, no. 4, pp. 1125-1134, 2012.

[14] S. Chen, J. S. Brantley, T. Kim, and J. Lach, "Characterizing And Minimizing Synchronization and Calibration Errors in Inertial Body Sensor Networks", 5th International Conference on Body Area Networks, pp. 138-144, 2010.

[15] S. T. Boerema, L. van Velsen, L. Schaake, T. M. Tonis, and H. J. Hermens, "Optimal Sensor Placement for Measuring Physical Activity With a 3D Accelerometer", Sensors, vol. 14, no. 2, pp. 3188-3206, 2014.

[16] J. Gong, P. Asare, J. Lach, and Y. Qi, "Piecewise Linear Dynamical Model for Actions Clustering from Inertial Body Sensors with Considerations of Human Factors", BodyNets: 9th International Conference on Body Area Networks, London, UK, Sep. 2014

[17] F. Protopapa, C. I. Siettos, I. Evdokimidis, and N. Smyrnis, "Granger Causality Analysis Reveals Distinct Spatio-Temporal Connectivity Patterns in Motor and Perceptual Visuo-Spatial Working Memory", Frontiers in Computational Neuroscience, vol. 8, pp: 146, 2014.

[18] C. Begliomini, L. Sartori, D. Miotto, R. Stramare, R. Motta, and U. Castiello, "Exploring Manual Asymmetries during Grasping: A Dynamic Causal Modeling Approach", Frontiers in Psychology, vol. 6, pp. 167, 2015.

[19] H. Hentschke, and M. C. Stüttgen, "Computation of Measures of Effect Size for Neuroscience Data Sets", European Journal of Neuroscience, vol. 34, no. 12, pp. 1887-1894, 2011.

[20] S. Narayan, and K. R. Ramakrishnan, "A Cause and Effect Analysis of Motion Trajectories for Modeling Actions", IEEE Conference in Computer Vision and Pattern Recognition (CVPR), pp. 2633-2640, 2014.

[21] Y. G. Jiang, Q. Dai, X. Xue, W. Liu, and C. W. Ngo, "Trajectory-Based Modeling of Human Actions with Motion Reference Points", European Conference on Computer Vision (ECCV), pp. 425-438, 2012.

[22] S. Yi, and V. Pavlovic, "Sparse Granger Causality Graphs for Human Action Classification", 21st International Conference in Pattern Recognition (ICPR), pp. 3374-3377, 2012.

[23] A. D'Ausilio, L. Badino, Y. Li, S. Tokay, L. Craighero, R. Canto, Y. Aloimonos, and L. Fadiga, "Leadership in Orchestra Emerges from The Causal Relationships of Movement Kinematics", PLOS ONE, vol. 7, no. 5, pp. e35757, 2012.

[24] Y. Mohammad, and T. Nishida, "Mining Causal Relationships in Multidimensional Time Series", Smart Information and Knowledge Management, pp. 309-338, 2010.