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Gait Based Vertical Ground Reaction Force Analysis for Parkinson's Disease Diagnosis Using Self Organizing Map

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ABSTRACT

The aim of this work is to use Self Organizing Map (SOM) for clustering of locomotion kinetic characteristics in normal and Parkinson's disease. The classification and analysis of the kinematic characteristics of human locomotion has been greatly increased by the use of artificial neural networks in recent years. The proposed methodology aims at overcoming the constraints of traditional analysis methods and to find new clinical ways for observing the large amount of information obtained in a gait lab. Self organizing maps (SOM) also called Kohonen maps are a special kind of neural networks that can be used for clustering tasks. The results are shown in the terms of sensitivity, specificity, accuracy, error rate from the two groups of features which are the Mean Coefficient of Variation and Mean Sum of Variation and Mean Max and Mean Standard deviation of the Ground Reaction Force. Results showing the potential of this technique for distinguishing between population of individuals with normal gait and with gait disorders of different causes of disease.

Introduction

Human gait is a difficult spatiotemporal process involving structures and function of the neuro musculoskeletal system of human body. Every human has different gait. The only similarities between individuals are such that a typical pattern of normal human gait can be found. In addition, this pattern feels change due to the influence of diverse factors and particularly under certain pathological conditions, where the gait efficiency reduces with the following increase of energy expenditure that this implies Parkinson Disease is characterized by symptoms such as tremor, rigidity, and bradykinesia, being a highly complex neurodegenerative disorder. The factors causing Parkinson's disease are the interaction between genetic and environmental factors, only about 10% cases are genetically based. The symptoms reflect the gradual loss of neurons in particular areas of brain (Vim - Ventrointermediate nucleus, GPi – Globus Pallidus intern and STN – Subtalamic nucleus). It is a chronic neurological disease; define by tremor, slow motion and stiffness. The disease affects the dopamine producing by neurons. The neurons do not produce dopamine any more or produce very low level of this chemical mediator, necessary on movement coordination. According to the number of affected neurons, the disease can progress quickly or slowly. We can obtain the kinematic, kinetic and EMG variables that characterize normal and abnormal gait patterns through computer analysis which is realized in gait laboratories. To obtain an accurate diagnosis of the considered abnormal gait, we need to know the information of the data processing and analysis. The trained personal spends many hours for the accurate diagnosis of raw

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data. Moreover, the difficulty to find new ways of linking information in complex locomotion disorders such as PD through traditionally used algorithms hinders the task of defining more precisely the underlying cause of this disorder and its effect on locomotor activity(3). To quickly discriminate between normal and abnormal gaits we can apply the clustering techniques based on artificial neural network (ANN). In this regard, numerous studies show the high probability of success in achieving this classification from different types of supervised and unsupervised ANN [10, 11, 12, and 13]. The aim of this paper to distinction between the normal and abnormal gait with the help of an unsupervised ANN, as is the case of self organizing maps or Kohonen maps. For verifying the above statement in the next section the input variable used to differentiate normal and PD inter subject gait patterns are defined. In the next section the SOM structures and classification has shown. At the end the result and brief conclusion is over there.

Materials and Methods
Human Gait Database
To analysis the Parkinson's disease in gait, a database corresponding to 70 normal individuals and 70 patients with idiopathic Parkinson's disease is used as classifier of inter-subject gait variability. Table 1.Shows all the data summery.

Table1. Parkinson's Disease Gait Data Base Summery

Category	Control Object	Parkinson's Disease
Total (no)	73	93
Female	33	35
Male	40	58
Age(year)	37-86	36-84
Height(m)	1.5-1.9	1.45-1.95
Weight(kg)	47-101	50-105
HoehnYahr(0-5)	0	2to3
UPDRS	0-3	13-70
UPDRSM	0-3	5 TO 44
TUAG	6.23-13.4	7.27-36.34
Speed(m/s)	0.91-1.54	0.36-1.42

Table 2. Classification of severity level of PD according to modified Hoehn

Stage	Signs and symptoms
0	No signs of disease.
1	Unilateral symptoms only.
1.5	Unilateral and axial involvement.
2	Bilateral symptoms. No impairment of balance.
2.5	Mild bilateral disease with recovery on pull test.
3	Balance impairment. Mild to moderate disease. Physically independent.
4	Severe disability, but still able to walk or stand unassisted.
5	Needing a wheelchair or bedridden unless assisted.

Among other variables, this database has demographic information such as the weight, height, Unified Parkinson's Disease Rating Scale (UPDRS), Unified

Parkinson's Disease Rating Scale Motor (UPDRSM), Timed Up And Go (TUAG), speed and scale of the analyzed subject and a commonly used system, like as the Hoehn & Yahr scale, for describing how the symptoms of Parkinson's disease progress (Hoehn and Yahr, 1967) [1, 6]. According to the original scale, the natural progression of Parkinson's disease is developed through five stages of ever increasing severity. Since then, stage zero has been added (corresponding to individuals with traditional gait), and stages 1.5 and 2.5 have been proposed, resulting in a modified scale as is indicated in Table2. In contrast to normal cases, pathological cases here considered correspond respectively to 40 and 20 cases of stages 2 and 2.5 based on the modified Hoehn and Yahr scale. These stages are associated to patients that show an altered gait with bilateral symptoms however while not loss of body balances [1, 6]. As well, the database includes kinetic data for each foot that were acquired during a gait test of about two minutes on level ground at normal self-selected cadence for each test participant, that has been digitalized and recorded at one hundred samples per second [1]. Underneath each foot there are eight sensors that measure force (in Newtons) as a function of time and together represent the plantar pressures distribution for each foot. The database also contain two signals that replicate the sum of the eight detector outputs for every foot, corresponding to the vertical component of the ground reaction force (GRF) for both feet. Besides, to minimize the effects of start-up and to match the length of the vector data for all samples due to this only 70 CO and 70 PD has taken. Figure 1 displays the vertical component of GRF during a gait cycle (GC) for each foot, obtained for a subject with normal gait and a Parkinson's patient from the mentioned database.

Normal and Abnormal Gait and VGRF
Depending on the condition of analyzed subject, the choice of ANN input variables is based on typical inter-subject differences observed in the size and shape of the curve representing the temporal variation of the vertical component of GRF. Indeed, as displayed on Figure 1(a) for a case of normal gait, such curve has 2 peaks. The first one happens during heel strike with the ground at the beginning of stance phase, whereas the second peak is because of the upward force exerted by ground during toe off at the end of the same phase [3]. Besides, the stance and swing phases pass between 0 - 60 and 60 - 100% gait cycle, respectively. In contrast, the curve shown in Figure 1(b) for the case of Parkinson's disease patient some times, shows a reduction in the peaks height of GRF, in similar kind to what occur in old individuals. Also of note is the variation of taken time for stance and swing phases for PD patients with respect to normal individuals (in this case 70 and 30% of GC, respectively), so as to ensure as far as possible, the body stability throughout locomotion. Later stages of Parkinson's disease are described by a gait with small

shuffling steps and a single narrow peak of vertical component of GRF, therefore reducing considerably the

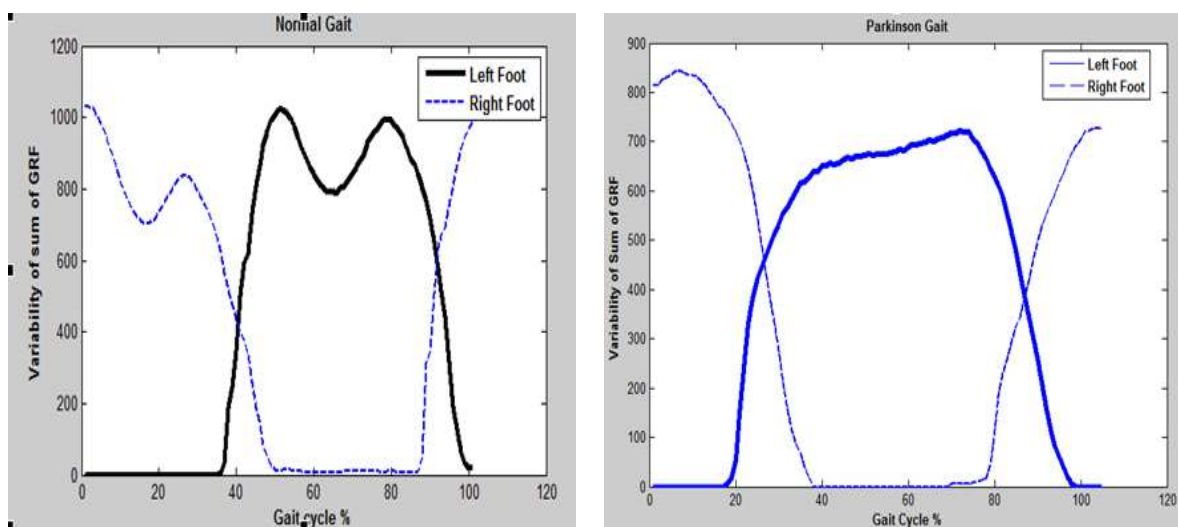time needed for swing section [8].

Figure 1. Vertical component of ground reaction force (GRF) for both feet during a gait cycle (GC). a) Normal gait (b) Parkinson's gait. For normal gait stance phase (0-60% GC) begins at left heel strike (HS) and ends with toe off (TO)

Swing phase takes between 60 and 100% GC. Notice how these percentages vary for Parkinson's gait. The determined variations in Figure 1 between kinetic patterns for traditional and Parkinson gaits are consistent with the general conclusion declared by Crowther [7]. A stable movement pattern is a behavioral state that is reproducible and independent of others and equates to low variability. Higher gait variability due to injury, disease, or aging, indicating that the related neuromuscular system is less stable. Particularly in Parkinson's disease patients, different researches have shown increased gait variability, both intra- or within-subject and inter- or between-subject, that is joined to Associate in nursing inflated risk of falls in such patients [24].

Features of Gait Based VGRF
Mean coefficient of variation and Mean sum of variation and Mean standard deviation and Mean Max of GRF has selected for input variables. These selected inputs give the fast differentiation of normal and Parkinson's gait patterns by ANN. Such parameters characterize the inter-subject gait variability throughout the considered temporal signal. Mean standard deviation of GRF signal during consecutive stance phases, its maximum value (which defines the mean peak GRF intensity for successive stance periods), the mean coefficient of variation (CV) of GRF, and the mean sum of GRF over successive stance phases (as an approximation of the

mean value of the area under the curve through these consecutive phases).   In Figure 2 the inter-subject variability for GRF signal during successive stance phases, the variability exhibited by the mean coefficient of variation of GRF for the right and left legs is depicted. These 70 normal (on the left) and the 70 abnormal (on the right) curves shown respectively. The inter-subject variability of mean sum of GRF through consecutive stance phases for the right and left legs is represented for the same normal (on the left) and pathological (on the right) cases in Figure 3. Both Figures 2 and 3 on the left show the inter-subject variability values for normal gait exhibit not only a lower magnitude but also a minor temporal variability with respect to abnormal gait (Figures 2 and 3 on the right). This shows the practicability of utilizing these indexes as descriptors of inter-subject gait patterns through ANN.

The following feature of vertical component of GRF characteristics for both feet is finally selected:

• Inter-subject variability for GRF signal during successive stance phases, the variability exhibited by the mean coefficient of variation of GRF for the right and left legs.

• Coefficient of variation (CV) is defined as the ratio of the standard deviation to the mean.
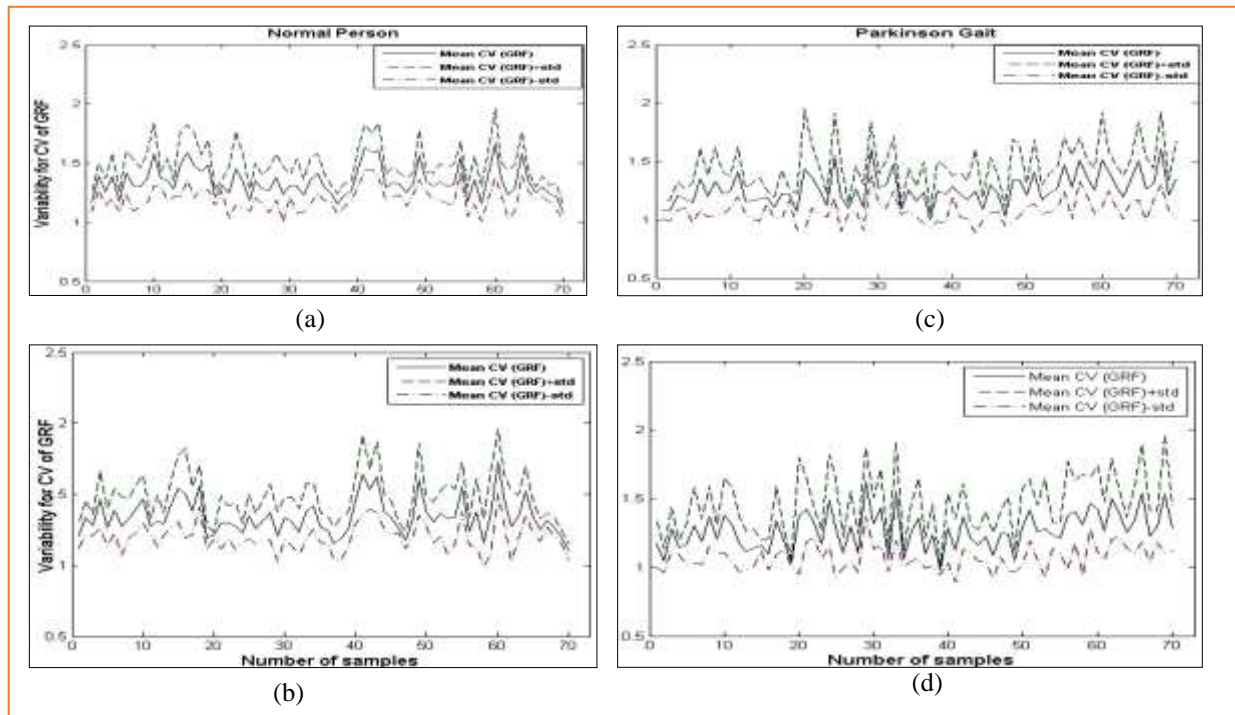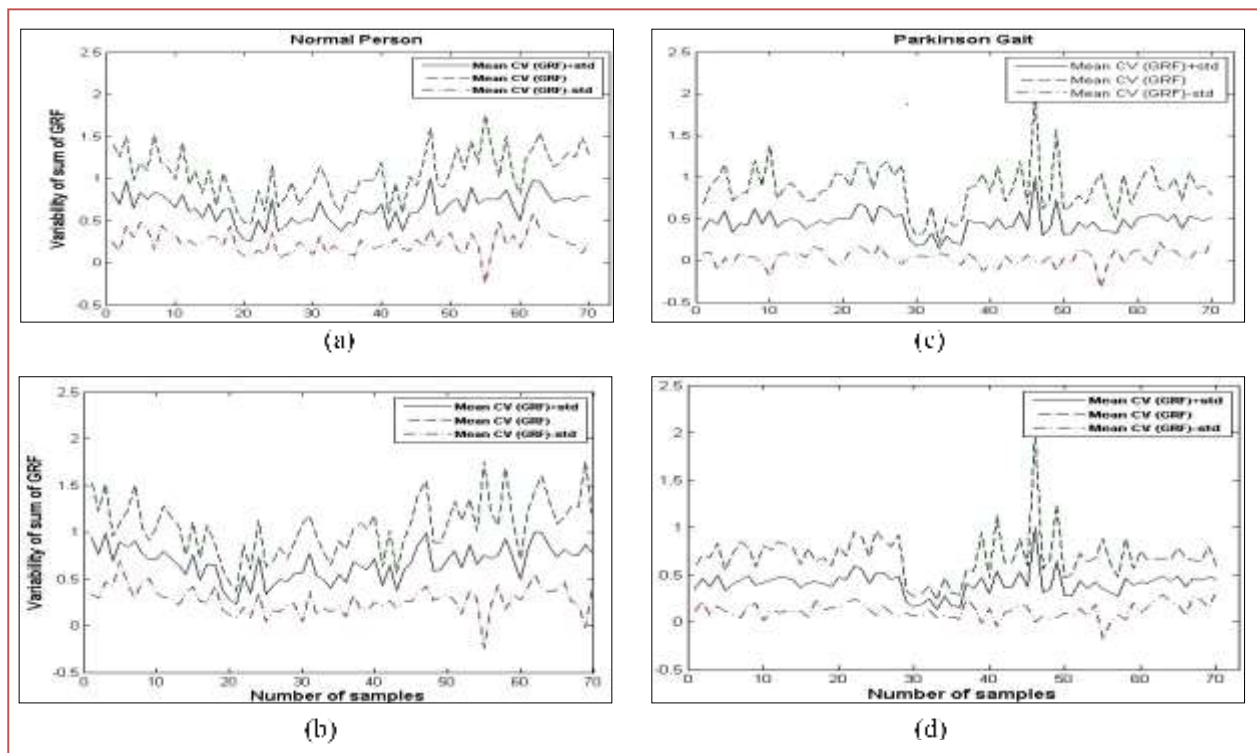
$$c_v = \frac{\sigma}{\mu}$$

Figure 2. Inter-subject variability evaluated by the MCV of GRF during consecutive stance phases of gait cycle, corresponding to 70 normal subject and 70 Parkinson's patients analyzed. (a) Left foot for normal individuals; (b) right foot for normal individuals; (c) left foot for Parkinson's patients; (d) right foot for Parkinson's. In each figure, the visualized values represent the mean coefficient of variation (MCV) of GRF during successive stance phases (mean CV (GRF)) and its corresponding standard deviation (Std).

Figure 3. Inter-subject variability evaluated by the mean sum of GRF during consecutive stance phases of gait cycle, corresponding to 70 normal subjects and 70 Parkinson's patients analyzed. (a) Left foot for normal individuals; (b) right foot for normal individuals; (c) left foot for Parkinson's patients; (d) right foot for Parkinson's. In each figure, the visualized

values represent the mean sum of GRF during successive stance phases (mean sum (GRF)) and its corresponding standard deviation (Std).

The inter-subject variability of mean sum of variation of GRF through consecutive stance phases for the right and left legs is represented for the same normal and pathological cases.

Mean of the sum of two random variables *X* and *Y* is the sum of their means

$$\mu_{x+y} = \mu_x + \mu_y$$

Other two features are Mean standard deviation of the GRF and Mean Max of the GRF.

Variables were normalized by their respective maximum values, so that they have the same rank, in this case between 0 and 1. Finally, the ANN input data are composed by normal and pathological cases randomly chosen.

Self organizing map

ANN is chosen for the classification of gait data between normal and Parkinson. The ANN is chosen to classify the gait data between the normal and abnormal by the SOM (Self Organizing Map).Self Organizing Maps learn to classify input vectors according to how they are groups in the input space. A SOM map is defined by an array of neurons (connected by a neighborhood relationship that defines the structure of the network) of a single layer, which represents filters or processors selectively tuned by input data simultaneously presented to all network nodes. Consequently, the neurons transform the input signals in a probability distribution encoded by positions on a map structured according to its topology [22, 23]. From a training process based on unsupervised competitive learning, the SOM group the input data (of *n* dimension) in network nodes (each of which also has dimension *n*) in terms of their similarity, projecting them on a smaller map output in where the input data characteristics are distributed in a gradual and order form [23]. Thus, SOMs allow for two tasks on the input data: to reduce their dimensionality and to visualize similarities. In this case and bearing in mind that the objective of this work only aims to assess the usefulness of ANN as differentiating normal and Parkinson's gaits, a 2 × 2 structure was chosen.

(a). Generation, Training and Visualization of the Artificial Neural Network

SOM implementation was done through *newsom* function, which generates an ANN. After defining the ANN (with the values specified for the topology and distance function), the arrangements for the input data (an array of 140 samples of 4 elements each) were established. The number of samples for training, validation and testing was distributed in 105, 18 and 17, equivalent to 75%, 12.5% and 12.5% of samples, respectively. For training the Matlab® *train* function based on the function NET.trainFcn and training parameters NET.trainParam was used. Where: *NET*: generated SOM map; *X*: input vector (in this case, 105

samples of 4 elements each), *T:* target vectors (in this case, do not apply), *net*: new ANN generated from training, *tr*: training register is used. In this training for fine tuning, the steps are increasing and iterations are constant. Finally, after the training phase, the network produces an output suitable to all input samples through *sim* Matlab® function.

Results and Discussion

Both types of input data are given to the Som. They are the MCV and MSV of GRF during consecutive stance phases of the analyses gait signal. The small hexagons represent the neurons, while the lines within the big hexagons connect neighboring neurons in this figure. Additionally, the colors of the regions containing these lines indicate the distance between the neurons. The dark and light colors represent the large and small distance, respectively. As well, the dark segment dividing the two dimensional maps show that the Kohonen map grouped the input data into two different regions, corresponding to individuals with normal Parkinson gait. In this result there is diagram of SOM Topology, SOM Neighbor Weight Distance, SOM Neighbor Connections, SOM Weights and SOM Weight Positions with sample Hits. The sample hits figure is shown that is the distribution between normal and pathological cases.

Table3. Mean Coefficient of Variation and Mean sum of GRF

Mean Coefficient of Variation and Mean Sum of GRF					
Steps	**100**	**200**	**300**	**400**	**500**
Sensitivity	67.24	78.18	78.57	94	98.03
Specificity	55.31	66.00	65.30	69	66.66
Accuracy	65.00	71.66	72.13	73.43	73.52
Error Rate	38.01	27.61	27.61	19.04	18.09

Table4. Mean Max and Mean Standard of GRF

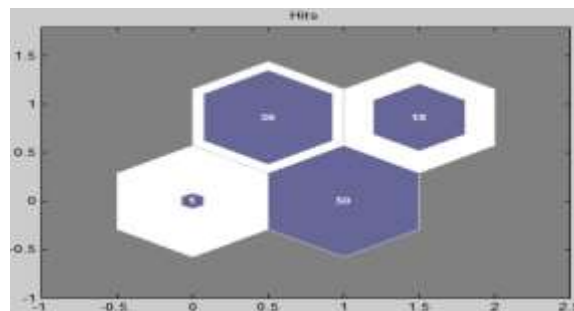| Mean Max and Mean Standard of GRF					
Steps	**100**	**200**	**300**	**400**	**500**
Sensitivity	91.30	93.33	94.44	94.44	94.44
Specificity	66.10	84.44	86.27	88.23	88.23
Accuracy	67.74	88.88	87.97	89.47	89.47
Error Rate	22.00	10.4	9.5	8.0	8.0

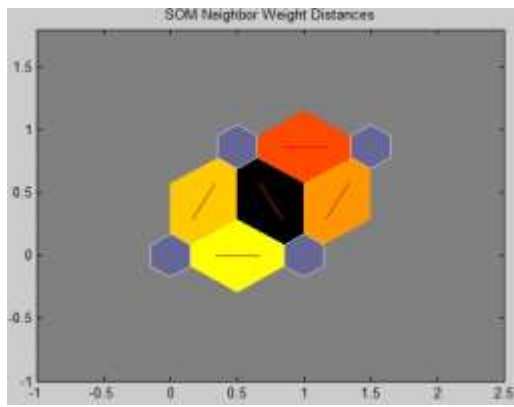**Figure 4.** Sample Hits of MCV and MSV

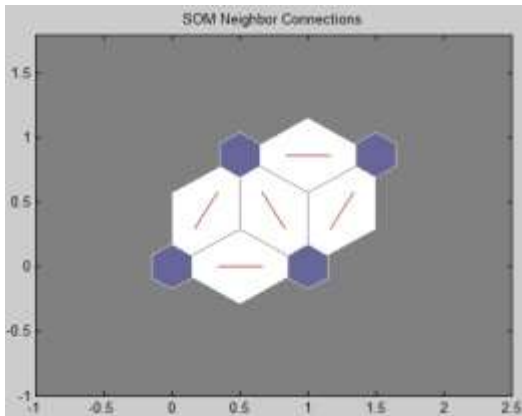**Figure 5.** SOM Neighbor Distances of MCV and MSV

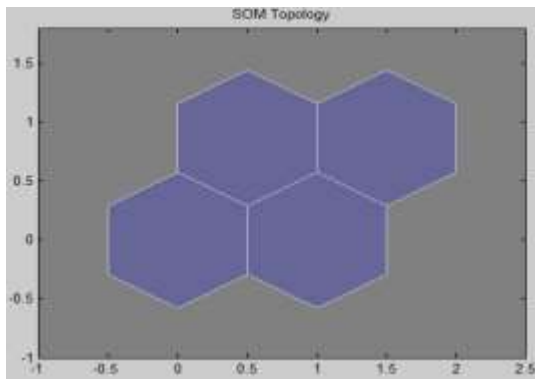**Figure 6.** SOM Neighbor Connections of MCV and MSV

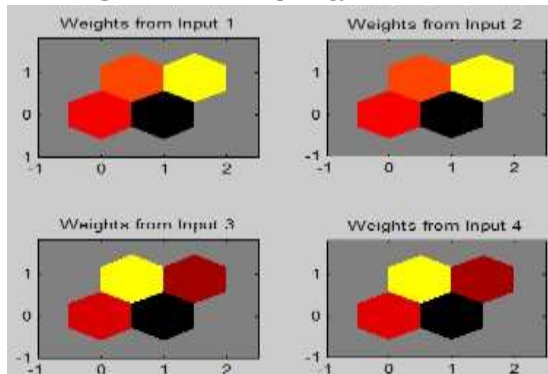**Figure 7.** SOM Topology of MCV and MSV

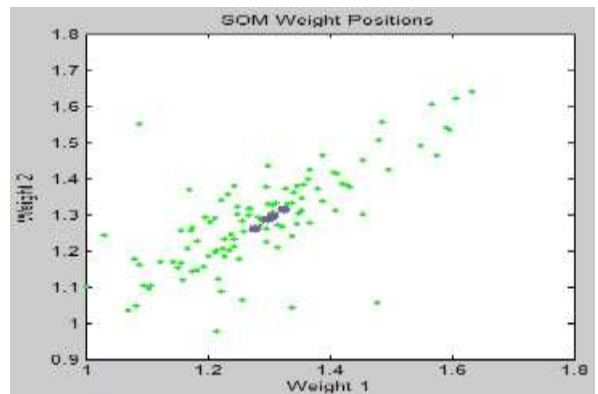**Figure 8.** SOM Weight of MCV and MSV

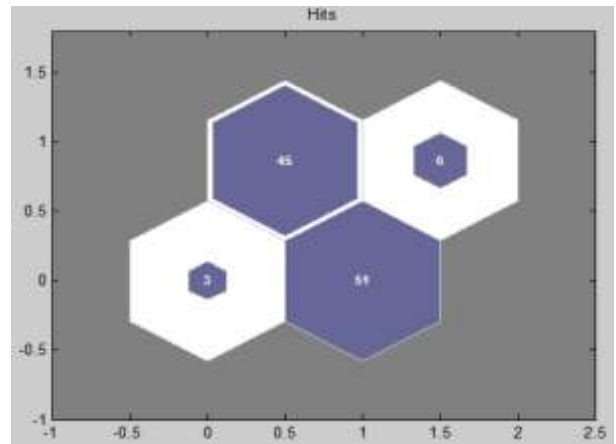**Figure 9.** SOM Weight Positions of MCV and MSV

Figure 10. Sample Hits of Mean Max AND Mean Std

In the Table 3 and Table 4, the SOM training result is shown. The result is in the term of sensitivity, specificity, accuracy and error rate. In this the epochs is constant and steps is increasing due to increase in the steps the sensitivity, specificity, accuracy is increasing and the error rate is decreasing. If we compare the result of both the input MSV and MCV and Mean Max and Mean std GRF we find that the error rate is minimum in the Mean Max and Mean std GRF.Figure 9, indicates the weight adjustment of input variables made by the SOM map in function of the spatial distribution of the samples presented during training. Additionally, the dark spots represent the neurons in the SOM. Also, there exists a correlation between dark and light areas shown in figure 5 and the distances between neurons in figure 9. The figure 8 shows the weight map for every element of the input vector (in this case, 2 elements for every leg) that characterizes the influence degree of every input on every network neuron. Dark colors are indicative of bigger weight and so, bigger influence in shaping the clusters. Furthermore, if the connection patterns of two inputs are very similar, it can be assumed that the inputs are extremely correlated. Such is the case of weights for inputs 1 and 2 and for the inputs 3 and 4, representing respectively, the Mean CV, Mean Sum, Mean Max and Mean Std of GRF for left and right feet.

Discussion

In the literature there are previous works oriented to classification of kinematic and kinetic gait patterns through ANN. About this, the work by Chau [10] provides an excellent review on the Parkinson gait analysis. An automatic classification of Parkinson patients into groups with a SOM map was obtained using the vertical component of Ground Reaction Force under each foot, with results considering the clinical classification of the patients [11]. Supervised ANN is used to differentiate gait patterns from hip and knee joint angles in the sagittal plane from other research group [12]. The same cluster used then a SOM map to reduce the complexness of 3-dimensional joint kinematic and kinetic data, projecting them in a 2-dimensional map [13]. Also, in a very previous work a classification of traditional and Parkinson's gait supported a multilayer perceptron ANN was achieved from the power spectral density of Ground Reaction Force for the left leg as input variables [14]. These examples show the relevance of ANN as an objective tool that will enhance decision making. In this work, a series of test were performed with different input variables for the SOM. The result in Table 3 and Table 4 of the Mean Max, Mean Std Deviation, MCV and MSV of GRF is given. By the table we can see that the increase of the steps increases the sensitivity and specificity of the system. In the first case Mean Max and Mean Std the sensitivity and specificity is 94.44% and 88.23% but in the case of MCV and MSV the sensitivity is 98.05% and 66.66%. Different hypothesis has been postulated for the reason of gait variability. One of them proposes that it is due to the complex neuromusculoskeletal system of the human, what determines an even more complex functional system that is inherently variable, each at intervals and among people [15]. In addition, in keeping with Bernstein's theory, effective organization of the multiple degrees of freedom of the neuromusculoskeletal system may be a requisite for healthy functional and steady locomotion patterns [16], manifested by tiny fluctuations of gait parameters throughout free walking. Nevertheless, insure neuromuscular pathologies like as Parkinson's Diseases, such fluctuations are accumulated as a result variability in stride length and walking speed during ambulation at self-selected cadence, determining an inability to maintain a gradual walk with small stride-to-stride fluctuations [17, 18, 19]. Other analysis works additionally show the importance of the integrity of cerebellum and basal ganglia structures, typically affected in Parkinson's disease patients, in adequately regulating force and timing control in motor activities like as locomotion [20, 21]. Figures 2 and 3 explain the greater inter-subject variability observed in the right for PD patients and on the left for normal gait. But in the Figure 5 and 10, this differential gait attribute is reflected in the sensitivity and specificity index of well classified pathological samples. With respect to the clinical relevance of these issues, such changes in variability of gait parameters for Parkinson's disease patients may be a predictor of the extent of degradation of brain structures that regulates force and timing control for an economical gait. In this sense, it is proposed here to estimate a reference range of traditional gait that can be used then to compare the degree of gait impairment in the considered pathological condition. During this manner it may be quickly viewed in a first approximation, how the pathological condition divert from normality. Furthermore, bigger inter-subject variability in Parkinson's disease patients would indicate an increased level of postural instability. As it is visualized in Table 1, the changed Hoehn and Yahr scale is based on the 2-fold idea that the severity of overall Parkinson's pathology relates to bilateral motor involvement and the degree of gait balance. Summing up and in step with these examples and observations, the results here obtained reveal the maximum chance of success in achieving differentiation between traditional and Parkinson's gait patterns. In this sense, the sensitivity, specificity of the utilized descriptors played a important role not only in minimizing the dimensionality of the input data, but also in finding similarities.

Conclusion

The clustering of normal and Parkinson gait patterns SOM is used. The Self Organizing Map work as a software tool that reduces the amount of data with minimal loss of information content in kinetic data analysis. Input values can be classified as belonging to their specific clusters after the learning phase and in general hidden structures of the input data set can be detected. SOM map indicates that the VGRF contains relevant information for differentiating quickly and objectively normal and Parkinson gait patterns from the biomedical point of view. This shows that the used combination of input variables and also the form of ANN is possible for clustering of gait patterns and to urge the classification mechanically, while not shaping a biomechanical model of the human body to process the information. As well, the clinical relevancy of this application of ANN is said with the fact that changes in gait variability with respect to traditional gait might be a predictor of the degree of walking impairment within the considered pathological condition. The obtained results is expected to come up with new descriptors to spot more accurately the mechanical and neurological behaviors of human body throughout Parkinson's gait, both intra-and inter-subject in future work. Such descriptors may be parameters to spot the marked body imbalance or the raised variability between steps, typically seen in patients with Parkinson's illness.

References

Physiobank, 2009. Physiological signal archives for biomedical research. [Internet]. PhysioNet: MIT; Cambridge. [Cited 2011 Mar 20]. Available from: http://www.physionet.Org/physiobank/ database /gaitdb/

National Parkinson Foundation http:// www. Parkinson. Org.

Simon, S.R., 2004. Quantification of human motion: gait analysis -benefits and limitations to its application to clinical problems. Journal of Biomechanics. 37(12):1869-80.Pmid: 15519595.http:// dx .doi .org /10 .1016/j. jbiomech. 2004.02.047

Geman, O., Ungurean, I., Popa, V., Octavian Turcu, C., Găitan. N.C., Gait in Parkinson's Disease-signal processing and modeling. 11th International Conference on development and application system, Suceava, Romania.

Rodrigo, S.E., Lescano, C.N., Rodrigo, R.H., 2012. Application of Kohonen maps to kinetic analysis of human gait. Engenharia Biomedical Brazilian Journal of Biomedical Engineering. Volume 28, Número 3, p. 217-226.

Hoehn, M.M., Yahr, M.D., 1967.Parkinsonism: onset, progression, and mortality. Neurology. 17(5):427-42. PMid: 6067254.

Crowther, R.G., Spinks, W.L., Leicht, A.S., Quigley, F., Golledge, J., 2008. Intralimb coordination variability in peripheral arterial disease. Clinical Biomechanics. 23(3):357-64. PMid: 18061322. http://dx.doi.org/10.1016/j.clinbiomech.2007.10.009.

Koozekanani, S.H., Balmaseda, M.T., Fatehi, M.T., Lowney, E.D., 1987. Ground reaction forces during ambulation in Parkinsonism: pilot study. Archives of Physical Medicine and Rehabilitation. 68(1): 28-30. PMid: 3800620.

Sanchez Lacuesta, J.J., Prat Pastor, J.M., Hoyos Fuentes, J.V., Viosca Herrero, E., Soler Gracia, C., Comín Clavijo, M., Lafuente Jorge, R., Fabregat, A., Vera, P.P., 1999. Biomecánica de la marcha humana normal y patológica. Valencia: Instituto de Biomecánica de Valencia.

Chau, T., 2001. A review of analytical techniques for gait data. Part 2: neural network and wavelet methods. Gait & Posture. 13(2):102-20. http://dx.doi.org/10.1016/S0966- 6362(00)00095-3

Köhle, M., Merkl, D., 1996. Identification of gait patterns with self-organizing maps based on ground reaction force. In: ESANN'96: Proceedings of the European Symposium on Artificial Neural Networks; 1996 Apr 24-26; Bruges, Belgium. Bruges. p. 73-8.

Barton, J.G., Lees, A., 1997. An application of neural networks for distinguishing gait patterns on the basis of hip-knee joint angle diagrams. Gait & Posture. 5(1):28-33. http:// dx.doi.org/10.1016/S0966-6362(96)01070-3

Barton, J.G., Lees, A., Lisboa, G., Attfield, S.,2006. Visualisation of gait data with Kohonen self-organising neural maps. Gait & Posture. 24(1):46-53. http://dx.doi.org/10.1016/j. gaitpost.2005.07.005

Battistella, M.E., Lescano, C.N, Rodrigo, R.H., Rodrigo, S.E., 2009. Registrador de presiones plantares en condiciones dinámicas. Memorias del XVII Congreso Argentino de Bioingeniería y las VI Jornadas de Ingeniería Clínica. Rosario, Argentina. 2009. p. 150-3.

Bates, B.T., James, C.R., Dufek, J.S., 2004. Single-Subject Analysis. In: Stergiou N, editor. Innovative tools for human movement research. Human Kinetics, p. 3-28.

Bernstein, N., 1967. The coordination and regulation of movement. London: Pergamon Press.

Hausdorff, J.M., 2005. Gait variability: methods, modeling and meaning. Journal of Neuro Engineering and Rehabilitation. 2:1-9. PMid: 16033650 PMCid: 1185560. http://dx.doi. org/10.1186/1743-0003-2-19.

Hausdorff, J.M., Lertratanakul, A., Cudkowicz, M.E., Peterson, A.M., Kaliton, D, Goldberger, A.L., 2000. Dynamic markers of altered gait rhythm in amyotrophic lateral sclerosis. Journal of Applied Physiology. 88:2045-2053. PMid: 10846017.

Hausdorff, J.M., Schaafsma, J.D., Balash, Y, Bartels, A.L., Gurevich, T., Giladi, N., 2003. Impaired regulation of stride variability in Parkinson's disease subjects with freezing of gait. Experimental Brain Research. 149(2): 187-94. PMid: 12610686.

Davie, C.A., 2008. A review of Parkinson's disease. British Medical Bulletin. 86(1):109-127. PMid: 18398010. http:// dx.doi.org/10.1093/bmb/ldn013

James, C.R., 2004. Considerations of Movement Variability in Biomechanics Research. In: Stergiou N, editor. Innovative Tools for Human Movement Research. United States of America: Human Kinetics. p. 29-62.

Haykin, S., 2005. Self-organizing Maps. In: Haykin S, editor. Neural Networks. A Comprehensive Foundation. Delhi: Pearson Education. p. 465-505.

Kohonen, T., 2001. Self-organizing maps. Berlin: Springer; http://dx.doi.org/10.1007/978-3-642-56927-2

Hausdorff, J.M., Cudkowicz, M.E., Firtion, R., Wei, J.Y., Goldberger, A.L., 1998. Gait variability and basal ganglia disorders: stride-to-stride variations in gait cycle timing

in Parkinson's disease and Huntington's disease.   Movement Disorders. 13(3):428-37. PMid: 9613733.

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