Gaits Classification of Normal vs. Patients by Wireless Gait Sensor and Support Vector Machine (SVM) Classifier

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***Abstract*—Due to the serious concerns of fall risks for patients with balance disorders, it is desirable to be able to objectively identify these patients in real-time dynamic gait testing using inexpensive wearable sensors. In this work, we took a total of 49 gait tests from 7 human subjects (3 normal subjects and 4 patients), where each person performed 7 Dynamic Gait Index (DGI) tests by wearing a wireless gait sensor on the T4 thoracic vertebra. The raw gait data is wirelessly transmitted to a near-by PC for real-time gait data collection. To objectively identify the patients from the gait data, we used 4 different types of Support Vector Machine (SVM) classifiers based on the 6 features extracted from the raw gait data: Linear SVM, Quadratic SVM, Cubic SVM, and Gaussian SVM. The Linear SVM, Quadratic SVM and Cubic SVM all achieved impressive 98% classification accuracy, with 95.2% sensitivity and 100% specificity in this work. However, the Gaussian SVM classifier only achieved 87.8% accuracy, 71.7% sensitivity, and 100% specificity. The results obtained with this small number of human subjects indicates that in the near future, we should be able to objectively identify balance-disorder patients from normal subjects during real-time dynamic gaits testing using intelligent SVM classifiers.**

Keywords—Balance disorders; Fall risks; Gait analysis; Support Vector Machine (SVM); Wearable gait sensor; Wireless Gait Sensor

I. INTRODUCTION

The number of patients with balance disorders is increasing rapidly because of aging-related factors such as muscle and joint weakness with arthritis, inner ears degeneration with vestibular impairments, vision impairments caused by glaucoma and macular degeneration, diabetic peripheral neuropathy and other associated factors [1]. Elderly people with chronic balance disorders and/or dizziness are two to three times more likely to fall than those who do not experience these problems of the similar ages [2]. Walking is the most important method of human mobility; however, patients with balance disorders often have difficulties in walking and are of significant fall risks. Rehabilitation is crucial to recovering patients' mobility, while the diagnosis and evaluation of walking gaits are necessary to investigate the cause of the balance disorders for proper treatments. In recent years, sensors that measure inertial acceleration (i.e., the G-forces) and/or the angular velocity are used to analyze walking gaits [3 4]. By using the miniaturized accelerometers and gyroscopes similar to the inertial measurement unit (IMU) equipped in larger inertial navigation systems, these small sensors can be worn on the human body to detect an acceleration change and an angular rate change for effective gait analysis. An advantage of using the accelerator and gyroscope integrated circuit (IC) sensors is that they are of low-cost and with good reliability and can detect gait issues objectively. We have, therefore, designed a custom wireless gait sensor with a tri-axial accelerometer IC, 2 gyroscopes ICs, and a MSP430 microcontroller to sample the dynamic gait data of six degrees of freedom (i.e., x, y, z and θ_x, θ_y, θ_z). In previous work, we used this wireless gait sensor and demonstrated that it can detect falls with 99% accuracy vs. average daily activities (ADL) by using Back Propagation Artificial Network (BP ANN) and SVM classification algorithms [5, 6]. In this work, we use a smaller but similar wireless gait sensor specifically for gait analysis to detect patients and normal people by using various Support Vector Machine (SVM) classification algorithms. During the gait testing, this sensor is placed at the T4 vertebrate position of each subject.

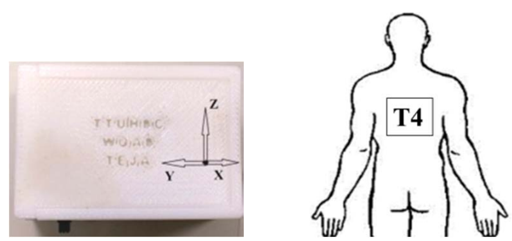

Fig. 1. Wireless gait sensor orientation and placement location at the T4 thoracic vertebrate.

II. SENSOR SYSTEM AND EXPERIMENTAL METHOD

A. The Wireless Gait Sensor

The wireless gait sensor orientation and placement location at the T4 thoracic vertebrate are shown in Figure 1. The custom-designed wireless gait sensor consists of a 3-axis linear accelerometer IC, a single axis gyroscope IC, and a dual axis gyroscope IC to measure 3-D human body translations and rotations during a gait pattern with the help of these Micro-Electrical and Mechanical system (MEMS) ICs. This wireless gait sensor system is supported by a Texas Instruments (TI) MSP430 microcontroller, and a wireless 2.4 GHz USB transceiver using the SimpliciTI™ protocol with a

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ICIS 2016, June 26-29, 2016, Okayama, Japan

range of ~12 meters (40 ft). The 2 AAA batteries used in our earlier wired sensor [6] were replaced by a single rechargeable Li-ion coin battery, providing a battery lifetime of ~40 hours continuous operation time with each recharge. The PCB, coin battery and the microcontroller are placed in a specially designed 3D printed box (2.2" x1.5" x0.8") with a total weight of 42 grams. The design of the box was done with a 3D modeling software Rhinoceros (Rhino) and printed using a 3D printer with acrylonitrile butadiene styrene (ABS) plastic. The box has a sliding lid and is shown in Figure 2.

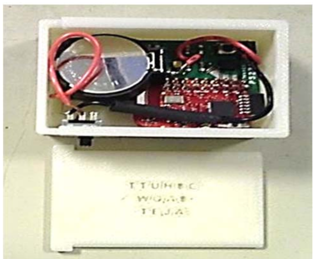

Fig. 2. An inside look of the wireless gait sensor used in this work (2.2" x1.5" x0.8")

The accelerometer data is sampled at 160 Hz and digitized to 8 bits, with its output scaled to ±6g at ΔV=(±6g)/V_{DD} for each axis. Note V_{DD} is 3.6 V when fully charged; however it is subject to change slightly based on the charging status of the battery, so we have tried to always fully charge the sensor before any gait measurement. The gyroscope data is also sampled at 160 Hz and digitized to 8 bits, with its output scaled to 300 per sec. (dps) at ΔV=(±300dps)/*So* (Note the typical *So*(sensitivity) value is 3.752 mV/dps for the accelerometer and 3.33 mV/dps for the gyroscopes). The sensor is carefully secured to the subjects during testing to avoid artifacts. The microcontroller and the transceiver unit enables the real-time transmission of the 6-dimensional gait data wirelessly to the nearby PC, where a LABVIEW™ program is used for designing the Graphical User Interface (GUI) . The DC values for the 6 signals is not constant as the battery charging state may be slightly different during the gait tests, and we did not want to perform sophisticated DC value calibration as the height of each subject is different; therefore, we are taking the *range* as the extracted feature values from the measured gait signals for analysis used in this work.

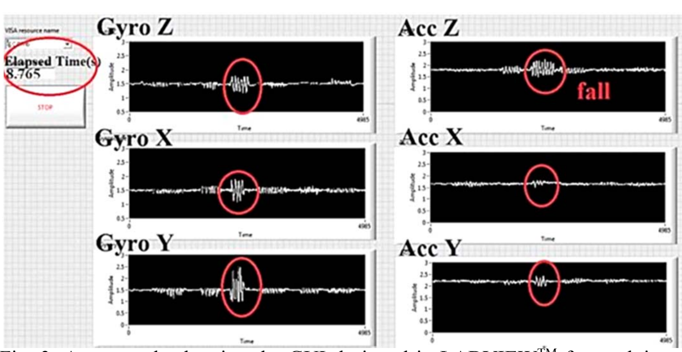

Fig. 3. An example showing the GUI designed in LABVIEW™ for applying our real-time gait sensor system, indicating a fall occurred after 8.765 sec as reported in [7]

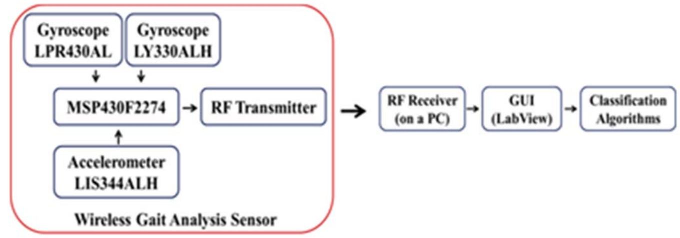

Fig. 4. A simplified block diagram of the wireless gait sensor and analysis system

For the supervised learning of classifiers, the following 6 features (R_ω: Range of angular velocity; R_A: Range of acceleration) as shown in Equations (1) and (2) were extracted from the raw data taken from gait sensor. They are used as input features for the SVM classifiers.

$$\begin{aligned} R_{\omega,x} &= \max(\omega_x) - \min(\omega_x), \\ R_{\omega,y} &= \max(\omega_y) - \min(\omega_y), \\ R_{\omega,z} &= \max(\omega_z) - \min(\omega_z) \end{aligned} \qquad (1)$$

$$\begin{aligned} R_{A,x} &= \max(A_x) - \min(A_x), \\ R_{A,y} &= \max(A_y) - \min(A_y), \\ R_{A,z} &= \max(A_z) - \min(A_z) \end{aligned} \qquad (2)$$

B. *Dynamic Gait Index (DGI) Tests*

The description of Dynamic Gait Index (DGI) tests [8] are shown in Table 1. All subjects (3 normal subjects and 4 patients) performed these DGI tests.

Table 1. Dynamic Gait Index (DGI) tests performed

No.	Description
1.	**Gait level surface** – walk with the normal speed up to 20 'mark
2.	**Change in Gait speed** - walk with normal pace up to 5'; walk fast for next 5'; walk slowly for next 5' and walk normal pace for last 5'
3	**Gait with horizontal head turns** - walk normal with horizontal head turns up to 20' mark
4	**Gait with vertical head turns** - walk normal with vertical head turns up to 20' mark
5	**Gait and pivot turn** - walk normally but at the end turn around like a pivot turn
6	**Step over obstacle** - walk normally, and when one comes across an obstacle, step over it, not around it
7	**Step around obstacles** - walk normally and when comes across first obstacle, walk around on the right side; when second obstacle comes, walk around on the left side

III. Support Vector Machine (SVM) Classifiers

A support Vector Machine (SVM) is an important discriminative classifier defined by a separating hyperplane. Under supervised learning, a SVM training algorithm builds a model that assigns new data into one category or the other, making SVM a non-probabilistic binary linear classifier. The SVM classifiers can be efficient for many applications, such as in patterns recognition and classification problems [9, 10].

A. *Linear Support Vector Machine (SVM)*

The optimization algorithm for linear SVM classification was proposed by Vapnik [11]. This algorithm finds the maximum-margin hyper-plane from given training data set D as described in Eq. 3:

$$\mathrm{D} = \{(\vec{x}_i, y_i) | \vec{x}_i \in \mathrm{i}^p, y_i \in \{-1,1\}\}_{i=1}^{n} \quad (3)$$

, where y_i is either -1 or 1 and n is the number of training data. Each $\vec{x}_i$ is a p-dimensional vector having the feature quantity R . Any hyper-plane can be written as:

$$\vec{w} \cdot \vec{x} - b = 0 \quad (4)$$

, where $\vec{w}$ is the vector to the hyper-plane. If the training data are linearly separable, the hyper-plane can be described as:

$$\vec{w} \cdot \vec{x} - b = 1 \text{ and } \vec{w} \cdot \vec{x} - b = -1 \quad (5)$$

The distance between these two hyper-planes is $2\|\vec{w}\|$, so the purpose is to minimize $\|\vec{w}\|$.

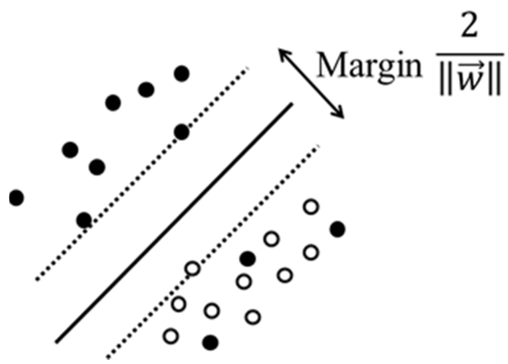

Fig. 5. Feature space of a Linear SVM

In general, it is hard to separate the training data linearly. When the training data are not linearly separable, the hyper-plane can be described as:

$$Min \qquad \frac{1}{2}\|\vec{w}\|^2 + C\sum_{i=1}^{l} \varepsilon_i \quad (6)$$

, where parameter C determines a trade-off between the error on the training set and the separation of the two classes. Here ε is a set of slack variable. The dual problems lie in maximizing the following function with respect to the Lagrange multiplier α:

$$\text{Max} \qquad \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) \quad (7)$$

$$\text{Subject to} \qquad 0 \le \alpha_i \le C \quad (i = 1, \dots, l)$$

$$\sum_{i=0}^{l} \alpha_i y_i = 0 \quad (8)$$

B. *Nonlinear Support Vector Machine (SVM)*

The SVM approach can be extended to a non-linear surface by using a kernel trick. B. E. Boser *et al.* proposed the nonlinear SVM classifiers by using the kernel trick. A non-linear function φ can move the original space into a higher dimensional space. The kernel functions used in this study are as followed:

・Polynomial function (Quadratic : d=2 and Cubic : d=3)

$$\mathrm{k}(x_i, x_j) = (x_i, x_j + 1)^d \quad (9)$$

・Radical Basis function(Gaussian function)

$$\mathrm{k}(x_i, x_j) = \exp\left(-\gamma\|x_i, x_j\|^2\right) \quad \gamma > 0 \quad (10)$$

In the non-linear SVM, the objective function is as followed:

$$\text{Max} \qquad \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j k(x_i \cdot x_j) \quad (11)$$

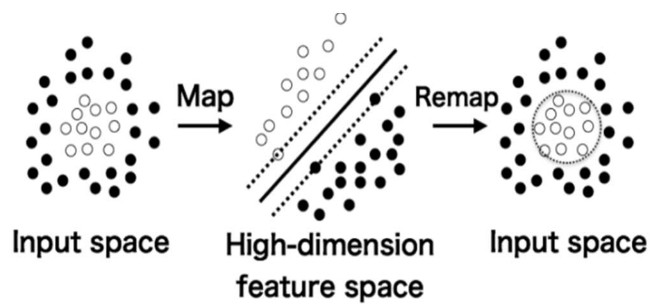

Fig. 6. Feature space of a Non-linear SVM

IV. CLASSIFICAON RESULTS

In this section, we will explain the gait data trends of normal subjects and patients. Moreover, we will present the results of classification by using 4 different types of SVM classifiers: Linear SVM, Quadratic SVM, Cubic SVM, and Gaussian SVM.

A. *The Clasiffication Trends between Normal vs. Patients*

We extracted the 6 features (R_ω: Range of angular velocity; R_A: Range of acceleration) from the raw data by using our wireless gait sensor. We compared the box plots to show Median, Range (highest to lowest values), and Inter quartile range (IQR) of each test. Figure 7 shows the box plots of DGI tests 1 to 7 for 3 normal subjects and 4 patients. Moreover, the average of STDEV, Range, Mean, Median, and IQR of DGI tests 2 and 7 is calculated and shown in Table 2 and 3. The training optimization time for each classifier is 0 sec when we ran them in MATLAB, so the gait classification is effectively performed *real time.*

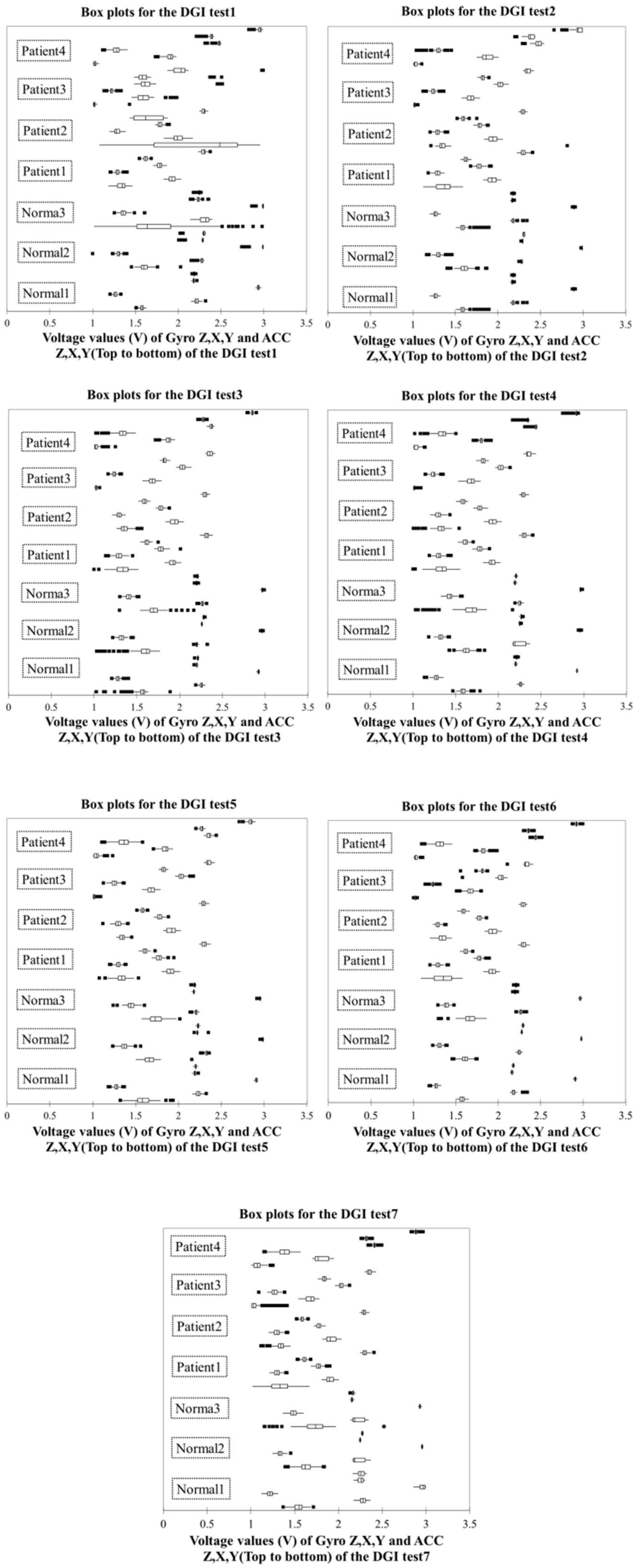

Fig. 7. Box plots of the 7 DGI tests for normal subjects and patients

Table 2. Average STDEV, Range, Mean, Median and IQR of DGI test 2 for normal subjects vs. patients

Average-STDEV-test 2						
	Gyro Z	Gyro X	Gyro Y	ACC Z	ACC X	ACC Y
Normal	0.0783	0.0202	0.0369	0.0051	0.0074	0.0076
Patients	0.0582	0.0570	0.0424	0.0375	0.0325	0.0270
Average-Range-test 2						
Normal	0.4130	0.1513	0.1855	0.0302	0.0410	0.0312
Patients	0.5559	0.2230	0.2623	0.2112	0.1825	0.1861
Average-Mean-test 2						
Normal	1.6048	2.2149	1.2785	2.9267	2.2080	2.2218
Patients	1.1907	1.8570	1.2795	2.0153	1.8551	2.4705
Average-Median-test 2						
Normal	1.5926	2.2708	1.3076	2.9728	2.2325	2.2445
Patients	1.1869	1.8528	1.2813	2.0146	1.8561	2.4686
Average-IQR-test 2						
Normal	0.0258	0.0976	0.0195	0.0293	0.0048	0.0053
Patients	0.0336	0.0484	0.0205	0.0255	0.0218	0.0260

Table 3. Average STDEV, Range, Mean, Median and IQR of DGI test 7 for normal subjects vs. patients

Average-STDEV- DGI test 7						
	Gyro Z	Gyro X	Gyro Y	ACC Z	ACC X	ACC Y
Normal	0.1088	0.0606	0.0395	0.0158	0.0167	0.0197
Patients	0.0860	0.0592	0.0531	0.0280	0.0264	0.0244
Average-Range-test 7						
Normal	0.7207	0.2011	0.2099	0.0683	0.0673	0.0820
Patients	0.4081	0.2228	0.2815	0.1678	0.1403	0.1311
Average-Mean-test 7						
Normal	1.6300	2.2414	1.3458	2.9470	2.2183	2.2318
Patients	1.2041	1.8253	1.3104	1.9982	1.8384	2.2458
Average-Median-test 7						
Normal	1.6359	2.2175	1.3447	2.9494	2.2208	2.2308
Patients	1.1937	1.8158	1.3104	1.9971	1.8380	2.4559
Average-IQR-test7						
Normal	0.0585	0.0551	0.0273	0.0131	0.0136	0.0156
Patients	0.0467	0.0043	0.0413	0.0141	0.0106	0.0121

In 7 box plots and 2 tables, the median value of the acceleration measured on the X and Z axes (i.e., ACC X, ACC Z) of normal subjects are quite different from those of patients. This is because walking gaits of normal subjects are different from that of patients, especially in decrease of speed, shortening of stride length and other associated factors. However, the median values of ACC Y of the normal subjects are not so different from those of patients. This is due to the fact that during the DGI tests, the Y axis is parallel to the walking direction, while the X and Z axes are vertical to walk direction. Moreover, when the STDEV is small, the walking is stable. In the box plots and tables, the average normal subjects' STDEV of Gyro X and Y, ACC X, Y, and Z are smaller than those of patients. However, the average normal subjects' STDEV of Gyro Z is larger than that of the patients. In every 7 tests, the STDEV of Gyro Z for the patient 1 and 2 are so different from those of patient 3 and 4. The values of the STDEV for normal and patients in DGI test 2 is shown in Table 4. Therefore, the average normal subjects' STDEV of Gyro Z is larger than that of patients'. Moreover, figure 8 to 11 show the box plots of DGI test 2, 3, 4, and 6 that group Normal subject as 1 group vs. patients as 1 group. From these points, the DGI tests 2, 3, 4 and 6 are better tests than the tests 1, 5, and 7 to differentiate patients from normal subjects.

Table 4. STDEV for 3 normal subjects and 4 patients in DGI test 2

STDEV of GYRO Z for DGI test 2 (in Voltage)						
Normal 1	Normal 2	Normal 3	Patient 1	Patient 2	Patient 3	Patient 4
0.0802	0.0746	0.0802	0.1021	0.0940	0.0155	0.0212

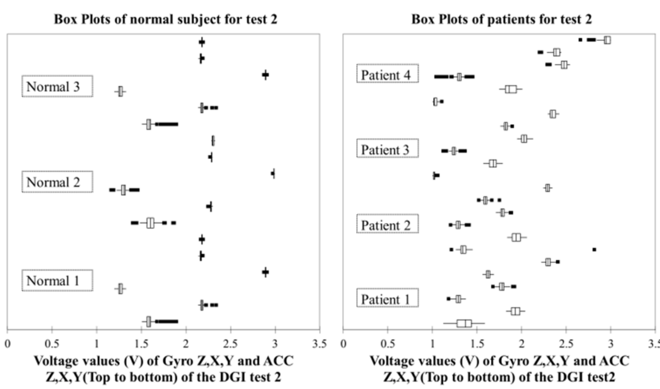

Fig. 8. Box plots of DGI test 2: normal subjects (Left) vs. patients (Right)

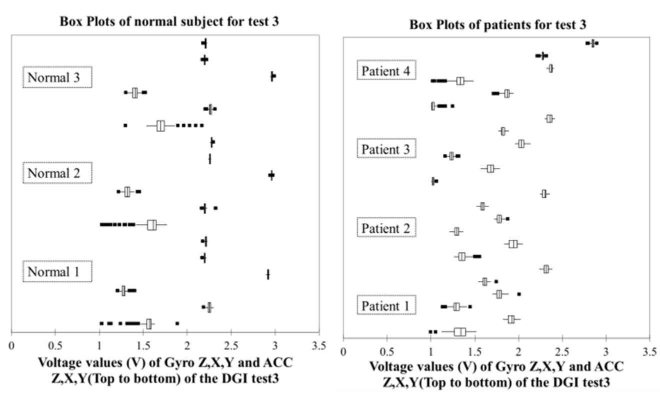

Fig. 9. Box plots of DGI test 3: normal subjects (Left) vs. patients (Right)

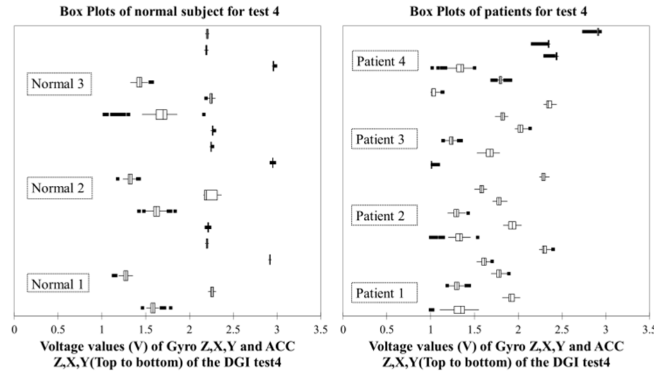

Fig. 10. Box plots of DGI test 4: normal subjects (Left) vs. patients (Right)

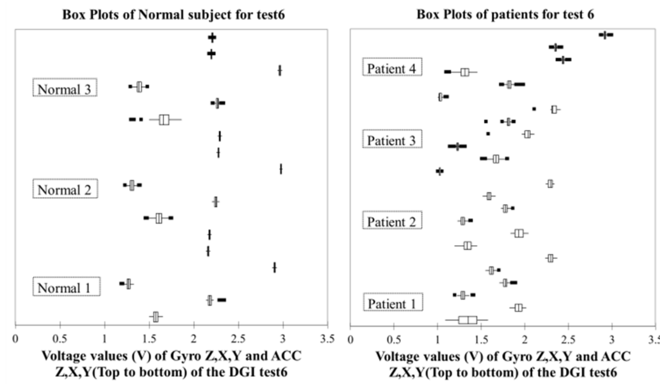

Fig. 11. Box plots of DGI test 6: normal subjects (Left) vs. patients (Right)

B. Support Vector Machine (SVM) Classification Results

In this work, we used 4 different types of SVM; Linear SVM, Quadratic SVM, Cubic SVM, and Gaussian SVM. The six features of the raw data from all the testing subjects are very important as they form the inputs for training the classification algorithms. The data was obtained using a 1.7 GHz PC with 4 GB of RAM, Windows 8 OS, and the SVM classification algorithms were implemented in MATLAB R2015b. The performance indicators such as sensitivity and specificity are calculated by using Eqs. 12 and 13.

$$Sencitivity = \frac{TP}{TP+FN} \tag{12}$$

$$Specificity = \frac{TN}{TN+FP} \tag{13}$$

The results of SVM classification are rather impressive. For Linear SVM, Quadratic SVM and Cubic SVM, they all achieved 98% accuracy, 95.2% sensitivity, and 100% specificity in this work. However, the Quadratic SVM obtained only 87.8% accuracy, 71.7% sensitivity, but 100% specificity. In this classification data, the normal subjects and patients' data are so clearly different; therefore, the first three types of SVM classifiers achieved the same results of classification. The Gaussian SVM, however, suffered from the fact that the data is not distributed anywhere close to a normal distribution, and therefore did not achieve excellent classification results. Moreover, the SVM algorithms in MATLAB2015b are so fast that we can achieve real-time gait classification to differentiate patients vs. normal subjects with the proper SVM algorithms.

Table 5. Comparison of SVM classification algorithms

	Sensitivity	Specificity	Accuracy
Linear SVM	95.2%	100%	98%
Quadratic SVM	95.2%	100%	98%
Cubic SVM	95.2%	100%	98%
Gaussian SVM	71.70%	100%	87.80%

V. CONCLUSION

Our custom wireless gait sensor was applied on human subjects for real time gait classification by using 4 different types of SVM classifiers with 6 simple features. Table 10 shows the results of SVM classification algorithms. The results show that Linear SVM, Quadratic SVM and Cubic SVM all obtained impressive results with 98 % accuracy, 95.2% sensitivity, and 100% specificity in this work. On the other hand, Quadratic SVM achieved only 87.8% accuracy, 71.7% sensitivity, and 100% specificity. These preliminary patient's results show that our low-cost wearable wireless gait sensor is able to differentiate patients against normal subjects with the simple but fast SVM algorithms. More test data on human subjects are needed to prove the classifiers' robustness for potential clinical use in the future.

REFERENCE

[1] Harris, G.F. and Wertsch, J.J., "Procedures for Gait Analysis", *Arch Physical Medicine and Biology*, 1994, 75(2), pp. 216- 225.

[2] Ko CW, Hoffman HJ, and Sklare DA. "Chronic Imbalance or Dizziness and Falling: Results from the 1994 Disability Supplement to the National Health Interview Survey and the Second Supplement on Aging Study". Twenty-ninth MidWinter Meeting of the Association for Research in Otolaryngology (ARO); National Institute on Deafness and Other Communication Disorders (NIDCD). Feb. 2006.

[3] Aminian, K., *et al.,* "Temporal feature estimation during walking using miniature accelerometers: an analysis of gait improvement after hip arthroplasty", *Med Biol Eng Comput*, 1999, 37(6): pp. 686-91.

[4] Yoshida, T., *et al*., "Gait Analysis for Detecting a leg accident with an accelerometer", in 1st Distributed Diagnosis and Home Healthcare (D2H2) Conference, pp.43-46,. 2006. Virginia, USA.

[5] Nukala, B.T., *et al*., "An Efficient and Robust Fall Detection System Using Wireless Gait Analysis Sensor with Artificial Neural Network (ANN) and Support Vector Machine (SVM) Algorithms", *Open Journal of Applied Biosensor*, 2014, 3, pp.29-39.

[6] Nukala, B.T.; Shibuya, N.; Rodriguez, A.I.; Tsay, J.; Nguyen, T.Q.; Zupancic, S, and Lie, D.Y.C. "A Wireless Gait Analysis Sensor for Real-Time Robust Fall Detection Using an Artificial Neural Network", Proc. IEEE Point-of-Care Technologies Conf. pp. 219-222, Oct. 8-10, Seattle, WA, 2014

[7] Jacob, J.; Nguyen, T.; Zupancic, S. and Lie, D.Y.C. "A Fall Detection Study on the Sensors Placement Location and a Rule-Based Multi-Thresholds Algorithm Using Both Accelerometer and Gyroscope", Proceedings of IEEE International Conference on Fuzzy Logics, Taipei, 27-30 June 2011, pp.666-671

[8] Perel, K.L.; Nelson, A.; Goldman, R.L.; Luther, S.L.; Prieto-Lewis, N. and Rubenstein, L.Z. "Fall Risk Assessment Measures: An Analytic Review", *Journals of Gerontology Series A—Biological Sciences & Medical Sciences*, 2001, 56, pp.761-766.

[9] Mao, Y.; Kanno, T.; Wei, D.; and Muroi, H. "Walking pattern analysis and SVM classification based on simulated gaits", Enginnering in Medicine and Biology Society, 20-15 Aug. 2008, pp.5069-5072

[10] Begg, R.K. and Owen B, "Support Vector Machines for automated gait classification", IEEE Transactions on Biomedical Engineering, May 2005, pp.828-838

[11] Cortes C. and Vapnik V*., "*Support-Vector Networks*", Machine Learning,* 20, 273-297 (1995)