
Extracting Gait Spatiotemporal Properties from Parkinson's Disease Patients

Albert Samà*, Andreu Català⁺, Cecilio Angulo⁺ and Alejandro Rodríguez-Molinero*

CETpD -Technical Research Centre for Dependency Care and Autonomous Living
Neàpolis Building. Rambla de l'Exposició, 59-69 Vilanova i la Geltrú, Barcelona. Spain

*albert.sama@estudiant.upc.edu, {andreu.catala,cecilio.angulo}@upc.edu,
arodriguez@fhcsaa.cat*

⁺Universitat Politècnica de Catalunya - UPC

*Fundació Hospital Comarcal Sant Antoni Abat de Vilanova i la Geltrú

Abstract

This report presents an application of Machine Learning, specifically the use of Support Vector Regression, for the automatic computation of spatiotemporal properties during gait in patients with Parkinson's Disease.

1 Introduction

The Parkinson's disease (PD) is a frequent chronic progressive syndrome in the elderly population. Current available PD treatments either stimulate brain dopamine receptors or increase dopamine synthesis. In the long-term, especially from the fifth year of disease on, onset of motor complications is often observed. Such motor complications arise as a consequence of a reduction in the duration of the effect of the medication. This motor complications affects spatiotemporal properties during the gait of patients [8]. Length and speed of the steps change due to the effects known as dyskinesia and or akinesia, thus, and on-line measurement of these properties during gait may help to predict these situations and therefore warn the patient (e.g., minimizing risk of falling) or a remote health care system. Recently several approaches using inertial sensors have been developed with the aim of measure these types of gait properties [1, 2, 4, 5, 6]. The gait characteristics may be obtained using gyroscopes tied at legs using a double inverted pendulum model [1, 5], nevertheless wearing these devices on the legs during daily life activity seems a drawback, leaving the application scope of this method to clinical environments. In the case of accelerometers, they are usually positioned at the dorsal side of the trunk near the L3 region of the subject, since it is the CoM location. In this position, 3D CoM acceleration, velocity and displacement can be estimated [2, 4]. However, to the best of our knowledge, there is no a user-friendly wearable device/location, that patients may use outside the hospital. Here we propose a method, based on SVM-regression, to extract spatiotemporal properties from accelerations obtained from a single accelerometer positioned at the lateral side of the waist, with the advantage of being a wearable system the patients may use during their daily life, without danger of hurt or damaging the device.

2 Gait Analysis

Gait analysis based on signals obtained from a tri-axial acceleration sewed to a belt is performed in order to obtain two main parameters: step length and step velocity. The sensor can be situated at any of both lateral sides of the waist. Accelerations signals obtained from the lateral side of the waist differ from standard signals obtained from the region near L3. Fig. 1 shows anterior-posterior acceleration on normal gait obtained by the sensor from both sensor locations. Signal obtained from the L3 region is similar to reported on the literature [4], where negative peaks of the anterior-posterior acceleration are due to the end of the single support phase and the beginning of double

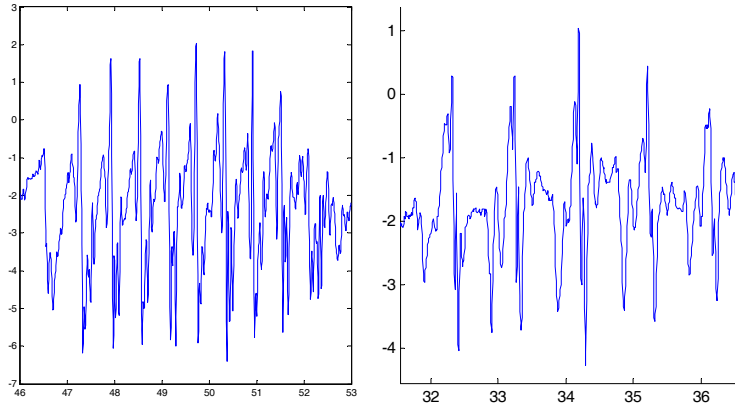


Figure 1: Forward acceleration obtained on L3 region (left) and lateral side of waist (right)

support phase. These peaks are preceded by a positive peak, produced in the feet-floor contact. On the other hand, when the accelerometer is located in the lateral side of the waist, the negative peaks are also observed, but not all positive peaks appear. Only those contacts generated by the foot of the side where the sensor is located produce positive peaks.

Next, we present the methodology for the gait analysis wearing the sensor in this position, from where step length and velocity will be estimated.

2.1 Subjects and conditions

The local ethics committee approved the study, and subjects' participation was informed consent. Four male and one female participated in the experiments. They were asked to walk several times over a plain surface of 6 m. length, while tri-axial accelerometer recorded the signal obtained. Two methods were used in order to obtain real step velocity and step length. First, subject's shoe sole were painted to leave footprints over a 6-meter-length paper placed over the ground, so that step length was provided. The process was recorded by a video-camera in order to obtain step duration time and velocity. The video-camera was also used on the second method, in order to obtain the velocity and length of steps: Visual markers were placed on the ground along the 6 meter every 15 cm.

2.2 Data acquisition

In the experiments, accelerations of the lateral side of the waist were measured by two orthogonally mounted biaxial differential capacitor MEMS accelerometers ADXL203 which provide tri-axial measurement. This analogical sensor has a measuring range of $\pm 1,7G$ and the sampling rate is 190 Hz. The accelerometers are mounted on a printed circuit board that holds a DSPic and a SD module to write the measurements on a file. When standing in anatomical position, the orientation of the accelerometer was conform ISB recommendations, i.e. positive X values correspond to anterior acceleration, positive Y values to upward acceleration and positive Z values to the acceleration to the right. Raw data was low-pass filtered before any analysis using a second-order zero-lag Butterworth filter with a cut-off frequency of 15 Hz.

2.3 Problem Formulation.

Biomechanics characteristics of gait allow to automatically identifying steps from the acceleration signals [3]. Fig 2. shows the automatic detection of the segments of signals of interest, i.e. the segment of acceleration correspondent to a step. Let us define as $a_{i,x}(t)$, $a_{i,y}(t)$, $a_{i,z}(t)$ to the accelerations signals provided by the sensor during the i^{th} -step, i.e. the segmented signal. Thus, the

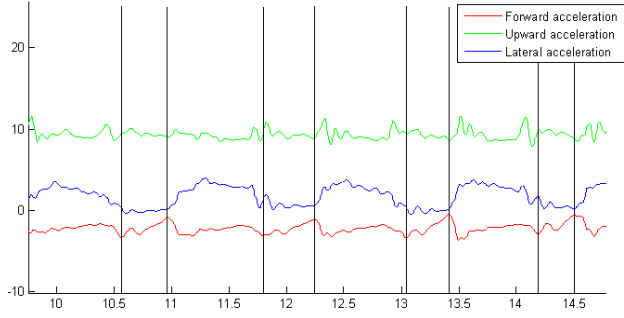


Figure 2: Automatic detection of steps

module of the acceleration signal is given by

$$r_i(t) = \sqrt{a_{i,x}^2(t) + a_{i,y}^2(t) + a_{i,z}^2(t)}. \quad (1)$$

Let us also define as $\bar{r}_{i,j}$ to a given stationary property of the signal correspondent to the i^{th} -step, e.g. the mean

$$\bar{r}_{i,1} = \frac{1}{n} \sum_{t=0}^T r_i(t), \quad (2)$$

where n is the number of samples during the step. For notation simplicity we will drop the identification of the step, leaving the index to identify the property. As first approach we decide to use three representative properties to characterize the step signal: the mean (2), the sum of the absolute value of the components

$$\bar{r}_2 = \sum_{t=0}^T (|a_x(t)| + |a_y(t)| + |a_z(t)|), \quad (3)$$

which is related to the well-know Energy Expenditure Indicator IAA, and the mean of the absolute values of the time-step increments

$$\bar{r}_3 = \frac{1}{n-1} \sum_{t=1}^T |r(t) - r(t-1)|. \quad (4)$$

Additionally, the length and velocity of a given step, measured directly from the experiments are denoted using l, v correspondingly. The problem at hands consists in finding the maps, $f(\cdot)$ and $g(\cdot)$ such that,

$$l = f(\bar{r}_1, \bar{r}_2, \bar{r}_3) \quad v = g(\bar{r}_1, \bar{r}_2, \bar{r}_3). \quad (5)$$

A machine learning technique is used in order to extract this relationship from the experimental data. The technique used in our work has been ϵ -Support Vector Regression [7], as it is able to establish non-linear relations between input and output.

3 Results

ϵ -Support Vector Regression is performed based on the features extracted. In order to evaluate its prediction capacity, a set formed randomly by 80% of the steps is used to train ϵ -SVR, and the rest is used to establish MSE error rate. One hundred times the experiment is repeated to establish significant values. A three degree polynomial kernel is compared against linear regression under same training and evaluation sets in each repetition.

Results for step velocity are summarized on Table 1. The mean MSE of ϵ -SVR is significantly lower than the error obtained on linear regression. A mean RMSE error of 14.67 cm/s is obtained when using ϵ -SVR for predicting new step velocities. Features used when predicting step velocity are (2), (3), (4). Features used on predicting step length are the same used on step velocity combined

Table 1: Summary of results

VELOCITY		LENGTH	
Regression	Mean MSE (cm/s ²)	Regression	Mean MSE (cm/s ²)
Linear Regression	301.5	Linear Regression	605.5
ϵ -SVR	214.37	ϵ -SVR	340.9

with duration time of the step. Results are summarized on Table 2. MSE value for ϵ -SVR is much lower than obtained on linear regression. However, an RMSE value of 18.4 cm. is obtained, which is greater than obtained by velocity. This means step length is more difficult to estimate than step velocity using these features.

4 Conclusions

A new user-friendly wearable location for accelerometer sensors has been proposed and evaluated on estimating step length and velocity through a machine learning approach. Step length and velocity regression has been performed using few features obtained from acceleration signals which necessarily are independent from gravity. Results show good prediction performance for both measures. Step length has worse performance, pointing that other features may offer better results. This gait analysis has the advantage to be able to work without extracting gravity. A real-time implementation of the analysis on a low-cost processor then could be obtained, since low power-computing is required. As part of our feature work, a real-time implementation in our sensor would be fundamental on supervising applications. Other machine learning techniques can be tested so as new approaches to the problem could be found. For instance, locally weighted regression could provide a better performance results. An important gait characteristic on determining gait properties is Center of Mass, which been determined by our sensor would be a significant enhancement.

Acknowledgments

This work was supported by the Spanish Ministry of Science and Innovation (PI08/90756).

References

- [1] Salarian A., Russmann H., Vingerhoets F. J. G., Dehollain C., Blanc Y., Burkhard P. R., Aminian K. (2004) The Gait assessment in Parkinson's Disease: Toward an Ambulatory System for Long-Term Monitoring (2004). IEEE Transactions on Biomedical Engineering 51(8), pp. 1434-1443.
- [2] Meichtry A., Romkes J., Goblete C., Brunner R. and Miller R. (2007) Criterion validity of 3D trunk accelerations to assess external work and power in able-bodied gait. Gait & Posture 25, pp. 25-32.
- [3] Zijlstra W., Hof At L. (2003) Assessment of spatio-temporal gait parameters from trunk accelerations during human walking. Gait & Posture 18, pp. 1-10.
- [4] Brandes M., Zijlstra W., Heikens S., van Lummel R., Rosenbaum D. (2006) Accelerometry based assessment of gait parameters in children. Gait & Posture 24, pp. 482-486.
- [5] Aminian K., Najafian B., Blab C., Leyvraz P. -F. and Robert Ph. (2002) Spatio-temporal parameters of gait measured by an ambulatory system using miniature gyroscopes. Journal of Biomechanics 35(5), pp. 689-699.
- [6] Seon-Woo L., Kenji M., and Kiyoshi K. (2005) Detection of Spatio-Temporal Gait Parameters by Using Wearable Motion Sensors. Proceedings of the 2005 IEEE Engineering in Medicine and Biology 27th Annual Conference Shanghai, China, September 1-4, 2005.
- [7] Smola A. J., Schlkopf B., (2004). A tutorial on support vector regression. Statistics and Computing 14(3), pp. 199-222.
- [8] Lord S., Rochester L. (2008). Concurrent validity of accelerometry to measure gait in Parkinsons Disease. Gait & Posture 27(2), pp. 357-359.