

Wearable microdevices for muscle activity and human gait sensing in Parkinson's Disease

L. Mazzetta ^a, A. Manoni ^a, A. Zampogna ^b, A. Suppa ^{b,c}, M. Pessione ^d, F. Irrera ^a

^a Dept. of Information Engineering, Electronics and Telecommunications, Sapienza University, Rome, Italy

^b Dept. of Human Neurosciences, Sapienza University, Rome, Italy

^c IRCSS NEUROMED Institute, Pozzilli, Italy

^d STMMicroelectronics, Agrate Brianza, Italy

e-mail: fernanda.irrera@uniroma1.it

Keywords: Wearable sensors, smart microdevices, muscle activity, gait disorders, Parkinson's Disease.

The new technologies involving the use of sensors are becoming increasingly important in healthcare. This is the case of wearable and implantable microdevices detecting abnormal and/or unforeseen situations by monitoring physical and/or physiological parameters. Patients affected by the Parkinson's Disease (PD) can benefit mostly from the technological advancements in this field, manifesting a variety of symptoms in the motion sphere, which in principle can be detected by inertial sensors and electromyography. Our wearable smart device monitors in free-living condition both the motion features and the activation pattern of leg antagonist muscles during the freezing of gait (FOG), an impairing symptom of the PD causing injuries and falls. This is an advancement of the state-of-art knowledge of the PD pathophysiology and can allow new therapeutic strategies as dedicated proprioceptive muscle manipulation. Fusion of inertial and electromyography signals allows distinguishing for the first time the trembling FOG (TFOG) phenotype. In the TFOG, the patient has a lack of postural adaptation and an abrupt inclination of trunk, often causing forward falls. Studying the daily occurrence and duration of the TFOG in free-living condition is the first step to foresee the concrete fall risk of a patient.

Our miniaturized devices are positioned on the tibialis anterior (TA) and on the gastrocnemius (GC), as displayed in Fig.1. They integrate a surface electromyography (sEMG) sensor and a gyroscope (gyro). We used the z-axis gyro component and the TA sEMG trace for the signal fusion. In this way, our system distinguishes the TFOG from the shuffling FOG (SFOG) phenotype. Furthermore, it assesses the type of activity of the antagonist leg muscles (stretching or contracting). The results of this study can be used by neurologists to evaluate the tendency to TFOG and the fall risk, and to adopt therapeutic strategies for overcoming TFOG as dedicated proprioceptive muscle manipulation [1].

The flow-chart of the signal processing for calculating the FOG phenotype index (PI) is displayed in Fig.2. First, we calculated the product of the normalized sEMG and gyro traces (Fig.3a, for one TA). During shuffling a periodic series of negative peaks is present in the product, since sEMG maxima correspond to gyro negative minima. On the contrary, during the trembling the product varies randomly around zero. Then, we low pass filtered the product at 2 Hz by means of a FIR filter (Fig.3b). In Fig.3c, we see that the two legs traces are in antiphase in the shuffling interval while they are randomly varying in the trembling one. Subtraction of the two traces gives a sinusoidal curve only in the shuffling interval and a value randomly varying around zero in the trembling interval (Fig.3d). The PSDs outline these features (Fig. 4).

We calculated the ratio between the maximum value of the PSD and its geometric mean in the frequency interval below 1.5 Hz. This quantity is our PI. The PI values obtained range from 9.2 ± 1.29 in TFOG to 166.82 ± 2.28 for SFOG. Following [2,3], the muscle activity intensity and type can be identified. In particular, the positive sign of LP filtered signal is related to contraction, negative to stretching. In Fig.7 traces of the antagonist TA/GC muscles are shown.

As one can see, during TFOG, TA exhibits repeated contraction and stretching of appreciable intensity while the GC remains only slightly stretched.

In conclusion, our wearable system can be very useful in remote home assistance of patients in free living conditions. This study opens new insights into the pathophysiology and therapeutic strategies.

[1] M.P. Pereira et al., Park. Relat. Disord. 29 (2016) 78 -82.

[2] P. Gentile et al., Euroensors2017 Proceedings 1 (2017) 600.

[3] I. Mazzetta et al., Sensors 18 (2018) 1748.

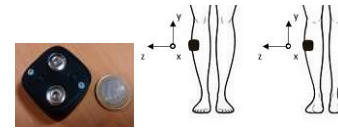


Figure 1 View of the device (left) and positioning on a leg (right).

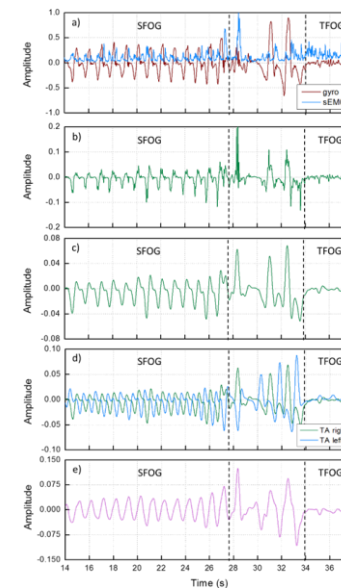


Figure 3 (a) an example of gyro (blue) and sEMG (red) traces recorded on the TA during shuffling and trembling FOG (with a few step attempts in-between); (b) product between the normalized sEMG and gyro traces; (c) low pass filtering at 2 Hz; (d) left and right; (e) result of the subtraction of the right and left leg traces.

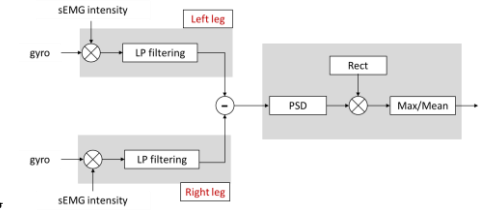


Figure 2 Flow chart of the algorithm implemented for the offline distinction of the FOG phenotypes.

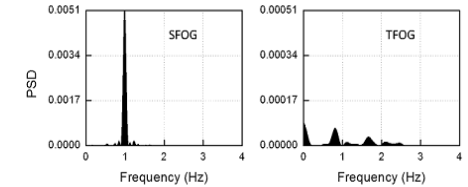


Figure 4 Power Spectral Density of shuffling and trembling traces reported in Fig 3e.

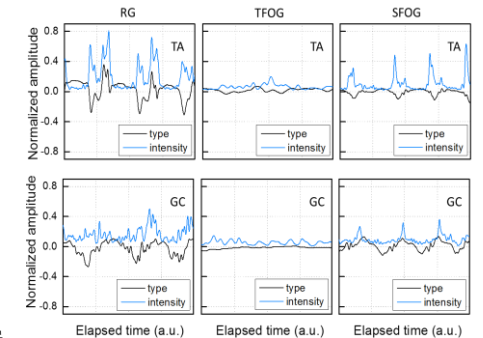


Figure 5 Examples of the traces of the muscle activation pattern *type* (black) and *intensity* (blue) recorded on the TA (top) and on the GC (bottom) during: (left) regular gait; (middle) Trembling FOG; (right) Shuffling FOG.