Wearable Platform for Automatic Recognition of Parkinson Disease by Muscular Implication Monitoring

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Abstract – The need for diagnostic tools for the characterization of progressive movement disorders - as the Parkinson Disease (PD) – aiming to early detect and monitor the pathology is getting more and more impelling. The parallel request of wearable and wireless solutions, for the real-time monitoring in a non-controlled environment, has led to the implementation of a Quantitative Gait Analysis platform for the extraction of muscular implications features in ordinary motor action, such as gait.
The here proposed platform is used for the quantification of PD symptoms. Addressing the wearable trend, the proposed architecture is able to define the real-time modulation of the muscular indexes by using 8 EMG wireless nodes positioned on lower limbs. The implemented system "translates" the acquisition in a 1-bit signal, exploiting a dynamic thresholding algorithm. The resulting 1-bit signals are used both to define muscular indexes both to drastically reduce the amount of data to be analyzed, preserving at the same time the muscular information. The overall architecture has been fully implemented on Altera Cyclone V FPGA. The system has been tested on 4 subjects: 2 affected by PD and 2 healthy subjects (control group). The experimental results highlight the validity of the proposed solution in Disease recognition and the outcomes match the clinical literature results.

Keywords—EMG, Gait, FPGA, Parkinson Disease, Wearable Diagnostic

I. INTRODUCTION

Parkinson disease (PD) is a progressive neurological disease characterized by bradykinesia (slowness) or akinesia (absent movement), tremor, rigidity and postural instability [1]. The Centers for Disease Control and Prevention (CDC) rated the motor complications from PD as the 14th top cause of death in the United States [2]. Typically, these movement disorders are associated with a slow short-stepped, shuffling gait pattern. For this aim, analysis of the gait in response to medication, visual cues, attentional strategies, provide insight into the nature of the motor control deficit in Parkinson disease and the efficacy of current therapeutic interventions. Currently, the Unified Parkinson Disease Rating Scale [3] jointly with the Hoehn&Yahr (H&Y) [4] one, are used to assess the severity of gait and mobility complications, as well as the presence/absence of characteristic motor signs in term of independence and quality of life. Despite the widespread use of this scales, these metrics of judgment suffer of strong subjectivity from neurologists and caregivers, since the score assignment are left to visual inspection approaches. Then, subjectively extracted information are the current trends in daily clinician's diagnostic work and therapeutic decisions. With the aim of releasing the assessment of a serious disease such as Parkinson's from this kind of information, a new rising branch of bio-medical application was born, named Quantitative Gait Analysis (QGA).The QGA is a *systematic* study of human walking in terms of kinematics, and spatio-temporal parameters useful for the characterization of human movement. With the above-stated definition, QGA in clinical assessment can guide physicians to optimal decision making. In such cases, QGA can provide objective and progressive data about the gait deviation and functional deficits [5]. The QGA solutions can be divided in: (i) wearable systems (WS) and (ii) non-wearable ones (NWS). Among the NWSs, most of the systems utilizes a combination of commercial video recording system and inertial sensors for gait monitoring in PD [6, 7], or complex hybrid combinations of cameras and Kinect system [8]. These systems adopt image-processing approaches that are not suitable for low computational and real-time implementation. Other NWSs use floor sensors [9] to reach useful evaluation about the force exerted by the subject's feet on the floor when he/she walks. The major limitation of NWSs is that these solutions typically require the use of controlled research environment, in which the sensors are located and capture data on the gait. For NWS applications, the subject is typically asked to walk on a clearly marked walkway [10]. Differently, WSs make it possible to analyze data outside the laboratory and capture information about the human gait during the person's everyday activities. Wearable systems use a network of sensor (e.g. accelerometers, gyroscopic, magnetometers, active markers) located on the user body (e.g. feet, knees, leg, arms and waist) [11, 12]. The above-mentioned methods despite of their sensing capability, provide only a partial knowledge of the disease since the PD involves a deterioration of deep muscular activity before it becomes clearly visible through visual inspection techniques. Analyzing the muscular involvements represents, instead, a deep knowledge of motor activity allowing precise quantification of the progression of the disease. In this work, we propose a novel QGA wearable and wireless platform for PD early recognition, fully based on electromyography (EMG). The proposed architecture is able to define the real-time modulation of an "ad hoc" calculated muscular index, to characterize the gait. The system describes the muscular activity, acquired by 8 commercial EMG wireless electrodes, exploiting their single bit correspondent signals and, thus, define on them, some muscular indexes. The monitoring of these quantitative deep myoelectric parameters allows discriminating also an early stage of PD, as well as highlighting the difference between Controls and diseased people. Finally, if used in synchronized mode with EEG signals, the system is able to understand the presence of

an involuntary movement, which can be an unbalancing event (e.g. inducing fall) or muscular dyskinesia [13, 14]. The here proposed QGA platform has been tested on PD patients (n=2) and controls (n=2), provided in-vivo measures, in order to highlight the approach validity in the quantification of disease symptoms. The paper is organized as follows: Sec. II recalls a basic medical knowledge, extracts the typical clinical protocol for the gait assessment, and describes the algorithm for the EMG - 1-bit translation and the muscular indexes evaluation. Sec. III outlines the implementation on FPGA. Sec. IV is dedicated to the experimental results. Sec. V concludes the paper.

II. THE QGA PLATFORM

A. Clinical Description and Gait Analisys Protocol

The early symptom of Parkinson's disease is the disappearance of the anticipatory postural reflexes, which are usually activated when a disturbance, however slight, of the posture occurs. For this reason, the probability to reach postural instability trends increases in PD patients. Indeed, the PD is an extrapyramidal system impairment, which is the motion control system [15]. Therefore, when a lesion affects this system, in particular the nigrostriatal circuits, induces decrement in the movement control capability, plastic rigidity and lack of motor automatisms. For instance, missing accessory movements, such as the oscillation of the upper limbs in the course of walking, lead the patient to lose the control and then generates abnormality in the gait patterns. These gait drifts are typically linked to abnormal trunk's postures of the parkinsonian patients. Among them, the Pisa Syndrome (PS) - a sustained lateral bending of the trunk (at least 10°) - is a real clinical enigma, and its management remains a challenge [15, 16]. However, the lack of consistent diagnostic criteria leads to significant differences in frequency reports [17]. All of these cardinal features of the Parkinson's disease are strictly linked to the motor symptoms of the disease itself. In this work, the standardized clinical task adopted during the system validation is extracted from the Unified Parkinson Disease Rating Scale (UPDRS) Part III and IV guidelines [3]. In order to validate the proposed QGA platform ability in gait analysis and PD status recognition, subjects are asked to perform the protocolled task named *10-meter walk*. The protocol asks to the subjects under test to walk for 10 meters distance, 10 times with a comfortable walking speed [3]. This procedure is clinically defined to be suitably used as diagnostic procedure (sec.: III.10 "March", III.11 "Freezing", III.13 "Postural Assessment", III.14 "Bradykinesia" - UPDRS, IV and IV.3 " Motor Fluctuations") [3, 4].

B. The Implemented Solution

The system, outlined in Fig.1, uses 8 EMG electrodes positioned on the lower limbs. In particular, the muscle monitored by the surface EMG are: Gastrocnemius, Tibialis, Rectus and Biceps Femoralis of both the legs. The acquired signals undergo to a low-pass filtering that allows only the useful frequency EMG spectrum: about 250Hz [18]. At the FPGA platform front-end, the data are sampled at 500Hz with 16-bit resolution [19, 20]. The FPGA is then dedicated to the signal processing stage. As shown in Figure 1, the wireless body area

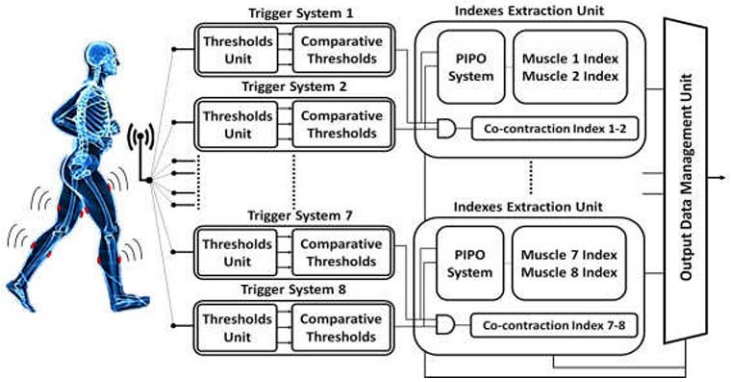

Fig. 1. Architecture of the implmented QGA system.

network sends data to the FPGA platform, which operates with a first block of triggering (Fig.1 – ith "Trigger System"). This block aims to create a unique correspondence between a 16-bit EMG sample and a Boolean value, as soon as the magnitude of the EMG represent an activation condition. Mathematically this correspondence is evaluable as in (1):

$$\begin{pmatrix} x_{1,1} & \cdots & x_{8,1} \\ \vdots & \ddots & \vdots \\ x_{1,16} & \cdots & x_{8,16} \end{pmatrix} \rightarrow (y_1 \quad \dots \quad y_8) \qquad (1)$$

where the matrix $\mathbf{X} \in \mathbf{R}^{16,8}$ represents the 16-bit samples present at the same time on the 8 EMG channels. The first column of X is the EMG sample dedicated to the first muscle. The Trigger system converts them into a 1-D vector $\mathbf{y} \in \mathbf{R}^8$. The generic y_i element represent the Boolean status of the first column of $\mathbf{X}$. The Boolean status starts when the detection of the contraction occurs, i.e. when the magnitude of the signal level overcomes the learned baseline. This block is realized exploiting the dynamic thresholding algorithm proposed in our previous works [19, 21]. As widely stated in [19, 21], the EMG is stored in M sample shift-registers, which realizes 1 sec lenght acquisition (about 500 samples). The average of the samples in the M shift register contributes to define the threshold. Similarly, the last N samples (~250ms of acquisition, and then N=128) of the M ones (with N≤M) are used to define a local average. The local average is compared with the threshold. The 1-bit EMG signal goes '1' whenever the local average is larger than the dynamic threshold. Similarly to [19, 21], four co-contraction signals are also generated. They consist in a square waveform that goes '1' when both agonist-antagonist 1-bit signals are both high. Once the 1-bit signal is generated downstream the ith "Trigger system", 8 dedicated computing blocks (one for each muscle) extract the muscular indexes, in order to recognize the cardinal PD abnormality in walking pattern. These blocks compose the "Indexes Extraction Unit" (Fig. 1) and are realized with counters driven by the system clock. The Indexes Extraction Unit generates a total of 32 parameters from the 8 trigger signals and 4 co-contraction ones. They are: (i) 4 agonist-antagonist muscles co-contractions, (ii) 4 numbers of co-contractions during a second of acquisition (512 samples), (iii) 8 contractions, (iv) 8 relaxation times and (v) 8 step duty cycles. The first two muscular indexes, allow compiling the UPDRS-III section related to instability. The last three parameters (contraction, relaxation and duty cycle) contribute to UPDRS Section III and IV. They allow the evaluation of the bradykinesia degree (i.e. slowness or abnormal muscular hyperactivity) and the Pisa Syndrome implications. In addition, they allow to objectively

assessing motor fluctuations in long period and the drug treatment impact.

III. THE QGA SYSTEM LEVEL DESIGN

This proposed QGA platform algorithm has been implemented by using VHDL coding in Quartus II software environment. The adopted hardware board is Altera Cyclone V SE 5CSEMA5F31C6N FPGA. The design plans 8 input bio-signals and 32 outputs. The inputs, coming from signal conditioning circuits and level shifter [22]. The 32 outputs values are functionally distributed on the available GPIO pins and, at the same time, made available in real time on four 7-segment dedicated display. The output parameters are: (i) 4 co-contraction time values defined by 11 bit (2ms time resolution – 500sps) (ii) 4 co-contraction/s defined by 3 bit (1co-contr./s resolution), (iii) 8 contractions and 8 relaxation times of 11 bit (iv) 8 duty cycles with 7 bit (1% resolution). The global system clock is set by an embedded PLL to 8.19209MHz driven by a 50MHz oscillator. A 500Hz clock manages both the ADC sampling rate for the input EMG data and the increment of the dedicated muscular counters. All the 8 EMG branches operate in parallel on FPGA [22]. Two global signals have been used as asynchronous Reset and Enable.

A. Dynamic Thresholding FPGA Implementation

The Trigger System implementation is proposed unaltered w.r.t. [22]. The acquired EMG samples are squared and then are used to feed two VHDL based finite state machines (FSM) designed to realize the global average, or threshold and the local one. These two FSM uses 2 dedicated RAM (512 samples and 128 samples for the Threshold and the local average, respectively) in a FIFO functionality to store the new arrived EMG data sample at the first address, and to pop out the last sample, previously inserted. This last sample is subtracted and the new sample is added to refresh the sum, before to divide the value for the register length. For instance, the sum obtained by the Threshold FSM is divided by $(512)_{10}$, while the Local Average FSM is divided by $(128)_{10}$ The FSMs overwrite the RAM word with the new data. Finally, a 64-bit comparator evaluates the Local Average w.r.t. the Threshold magnitude. The comparator provides a 1-bit EMG Trigger, used for the muscular computing.

B. The MIs Computing Branch on FPGA

Fig. 2 schematizes the operation process of a single muscle dedicated computing implementation. Eight similar branches are present in the architecture, one for each monitored muscle. It operates serially with the Trigger System block, analyzing the Trigger 1-bit signal. As shown in Fig.2, when the `Trigger` goes '1' a counter, named `Contra. Counter` is enabled to count and, thus, starts increasing its value by $(2)_{10}$ (due to the sampling rate), every time a `CLK_500Hz` positive edge occurs. `Relaxation Counter` operates with similar modality, but is fed by the `Trigger'`. When the step is over, both the counters makes available the reached value upstream a canalization system made up by the Parallel Input Parallel Output (PIPO) register.

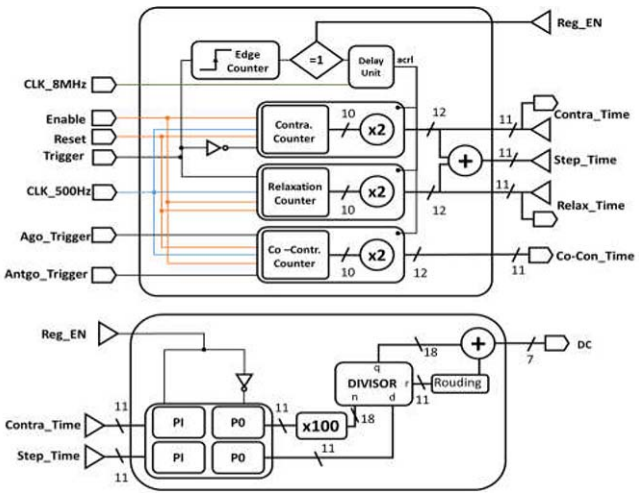

Fig. 2. Functional block diagram of a single Muscular Index extraction unit

Indeed, the `Contra Time` loop counter is not reset (because the Trigger signal work as a count enable), allowing the value to be available in parallel with `Relax Time`. The progressive bit parallel sum realizes the `Step Time`. When the second `Trigger` positive edge arrives all the extracted indexes are first stored in a sequence of parallel DFF which constitute the Parallel In (PI) and then canalized to the output (PO) by using 2 pulses driven by the 1 bit `Reg EN` signal. Furthermore, a delayed version (two `8MHz Clk` pulses) of `Reg EN` is used to resets the `Contra` and `Relaxation Counters`, allowing the data transfer before the asynchronous reset. After the `Reg EN` pulse on PO section, all the useful values (`Contra Time` and `Step Time`) are simultaneously statically present downstream from the PO, while the circuit upstream the PI section, is now reset and able to acquire. In other words, this approach isolates the counting section, generating a static calculation section for the duty cycle (`DC`). In the DC section, the acquired `Contra Time` is first multiplied for $(100)_{10}$ and then divided by the `Step Time`. The quotient in output represents the integer value of the `DC` (7-bit representation). The remaining of the divider block is defined as a binary subtraction between `Step Time` and `Contra Time`. It is also multiplied with $(100)_{10}$ and, thus, divided for the `Step Time`. If the quotient is higher than $(50)_{10}$ the `DC` is increased by one, otherwise it is left unaltered. This process halves the maximum error in DC assessment from 1% to 0.5%. Agonist and antagonist muscle triggers together contribute, through an AND gate, to generate the square co-contraction waveform. Then, similarly to `Contra./Relaxation Counters`, the co-contractions time is evaluated (`CoCon Time`) and returns its value when the step - in which the co-contraction is contained - end.

IV. RESULTS

This section is dedicated to the evaluation of the implemented QGA solution responses during a clinical walking test. A quantitative comparison between the PD parameters and Controls ones is here proposed, aiming to emphasize the system

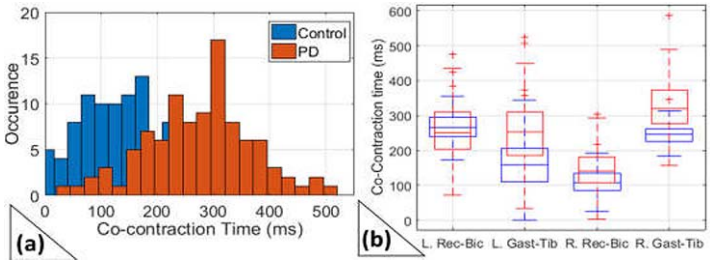

Fig. 3. QGA platform extracted co-contraction time in a sample of 100 co-contractions: (a) probability density function of co-contraction time in PD (red) and Controls (blue); (b) a statistical representation (Matlab boxplot) of co-contraction time values w.r.t. the evaluated muscle pair. Controls in blue, and PD in red.

TABLE I. PD MUSCULAR IMPLICATIONS

	L REC	L BIC	R TIB	R GAS	L TIB	L GAS	R REC	R BIC
Cocont. (ms), μ±σ	266±88		260±90		128±72		336±186	
Cocontr./s	1.53±0.66		1.1±0.09		1.1±20		1±0.16	
Contraction (ms), μ±σ	482 ±138	434 ±198	554 ±260	386 ±72	386 ±150	382 ±270	528 ±232	420 ±282
Relax (ms) μ±σ	338 ±204	382 ±156	362 ±132	596 ±138	632 ±298	572 ±206	336 ±174	536 ±88
DC (%)	58 ±6	53 ±4	60 ±6	40 ±3	38 ±10	40 ±8	61 ±6	44 ±8

TABLE II. CONTROLS MUSCULAR IMPLICATIONS

	L REC	L BIC	R TIB	R GAS	L TIB	L GAS	R REC	R BIC
Cocont. (ms), μ±σ	268±44		140±56		100±42		246±26	
Cocontr./s	0.68±0.05		0.25±0.12		0.25±0.08		0.59±0.05	
Contraction (ms), μ±σ	353 ±128	509 ±198	574 ±208	382 ±170	560 ±254	444 ±110	328 ±142	494 ±182
Relax (ms) μ±σ	982 ±498	788 ±361	632 ±282	868 ±392	950 ±266	980 ±230	982 ±438	812 ±368
DC (%)	26 ±3	39 ±5	48 ±6	31 ±2	37 ±7	31 ±5	25 ±3	38 ±8

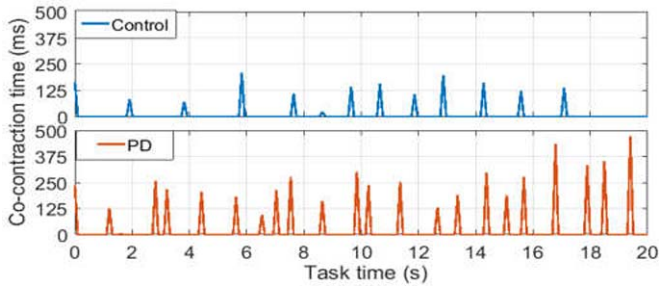

Fig. 4. Co-contraction time in 20s of task time. The y-axis of both subplots are normalized to the interval 0-500ms in order to emphasize the difference between PD and Controls values in magnitude and number of co-contractions/s.

ability in disease recognition. The subjects (n. 2 PD subjects under Levodopa and n.2 Controls) are asked to perform the 10-meter walk protocol [3] maintaining a natural and fluid walk in an in straight path of 10m for 4 times (40m total). The test is repeated for 10 times, wearing the EMG wireless sensors. Each test is interspersed by 10 min of resting state.

A. Experimental Results

The results are reported in Table I and II for PD and Controls, respectively. The tables report, starting from the top: the typical co-contraction time, the co-contraction/s, the activation/relax time and DC during a single step. All the time indexes are expressed as mean ± std. The results in tables quantify the clear differences between PD subjects and healthy Controls in terms of walking patterns. The features extracted and discussed in the following, can be easily used to diagnose or monitor the PD. The main results achieved are reported in the following:

1. Typical co-contraction times show an increase of 58ms (average value on all the four muscles couples) between PD and Controls. The greater incidence of co-contraction events concerns the right leg with Δt=+120ms on R.Gast and R. Tib, as well as a differece of 90ms on R. Bic – R. Rect. The co-contraction times are higher in PD than in healthy subjects during gait. The incidence on the right leg can be attributed to a trunk flexion in that direction.
2. The number of co-contraction/s is, on average (on all the 4 evaluated pairs), 1.17 co-contractions/s for the PD subjects. Differently, it reaches, on average, 0.44 co-contractions/s for Controls. Clearly, co-contractions are more frequent in PD than the healthy subjects during gait.
3. Considering the single muscle-based indexes, PD subjects shows contractions time that cover the 48.56% of the step time length. The healthy subjects returns a value of 33.62%. The PD outlines muscular hyperactivity.
4. The PD step duration is typically higher than the Control ones, due to the slow short-stepped trend of the PD [2]. The mean step time in PD subject (under Levodopa short-term effects – State ON of the treatment) is about 1047ms, while the Controls returns a value of 977 ms.

Fig. 3. shows the co-contraction time extracted by the QGA platform in a sample of 100 co-contractions. In particular, Fig. 3.a outlines with an histogram based PDF, the occurrence of particular co-contraction time values in PD (red) and Controls (blue). It is notable the shift of the PD linked PDF to higher co-contraction time values, according to the Table I and II. Fig. 3.b shows a boxplot, statistical representation of co-contraction time values, referred to all the evaluated muscle pair. Experimental results show that only the L.Rectus and Biceps pair does not provide a good discrimination between the groups. Fig.4 shows two acquisition of the same duration (20s) related to a PD and Controls 10-meter walks. On the y-axis are drawn the co-contraction time values with a normalized range between 0-500ms. It allows to emphasize the difference between PD and Controls values in magnitude and number of co-contractions/s.

V. CONCLUSION

In this paper, we have described the FPGA implementation of a QGA platform for the extraction of muscular implications features in ordinary motor action, such as gait. The platform has been used for PD recognition comparing datasets obtained by 2 subjects affected by PD and 2 healthy one (control group). The proposed architecture is wearable, wireless, and able to define the real-time modulation of muscular indexes to characterize the gait. The system is fully based on EMG acquisition, obtained by 8 nodes positioned on Gastrocnemius, Tibialis, Rectus and Biceps Femoralis of both the legs. The system exploits an algorithm for the dynamic thresholding of the signals, extracting muscular indexes [22]. The experimental results highlight the validity of the proposed solution to quantify PD symptoms: (i) the step time in PD is about 100ms higher than in controls, according with [2]; (ii) a muscular hyperactivity is detected, in Parkinson patients, according with [17]; (iii) the number of co-contractions during a walking task,

is higher in PD than in Control group [1]. The solution aims to be a diagnostic tool for the early detection of the disease, as well as a useful clinical support tool for monitoring the therapy impact. Future perspectives include the design and fabrication of an Application Specific Integrated Circuit (ASIC) [23-30], the use of biocompatible and flexible electronics in order to increase the wearability degree of the system [31, 32] and the optimization of the wireless network [33-36].

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