An Effective Methodology for Movement Evaluation in Patients with Parkinson's Disease

Michele Calì[1], David Durand[2] and Jérôme Bosche[2]

[1]University of Catania, Department of Electric, Electronics and Computer Engineering, michele.cali@unict.it
[2]Modeling, Information and Systems (MIS) Laboratory, University of Picardie Jules Verne, Amiens, France, david.durand@u-picardie.fr; jerome.bosche@u-picardie.fr

Corresponding author: Michele Calì, michele.cali@unict.it

Abstract. Analyzing pathological movements can substantially help neurologists in the diagnosis and treatment improvement for patients with Parkinson's disease (PD). A linkage between the intensity and characteristics of moving and walking disorders and the stage and types of PD can be actually established. The main aim of this study is to develop an effective methodology that allows to evaluate, in real time and / or in deferred time, movements and posture of PD patients in their usual living environments. For this purpose, a wearable suit with Inertial Measurement Unit (IMU) sensors was designed; it has made it possible to acquire linear and angular signals of displacement, velocity and acceleration of the most relevant body points of the patients. The filtered and integrated signals were then used to animate a human parametric multibody model that virtually reproduces in real time and / or in deferred patient's movements and posture. Serving as the patient's "avatar", the multibody model enables the neurologist to carry out an accurate assessment of the patient's movements and posture (freezing, festination, postural balance) as well as to measure disease progression and response to interventions. If compared to traditional 3D video-based motion analysis systems, the proposed method has the advantage of providing a more accurately measurable patients movements analysis and comparison performed in their usual living environments in real-world conditions.

Keywords: Parkinson's disease movements, Human parametric multibody model, 3D posture analysis, Motion recognition algorithms, Inertial Measurement Unit sensors.
DOI: https://doi.org/10.14733/cadaps.2023.S6.25-36

1 INTRODUCTION

Tremor is one of the most important motor phenotypes of dystonia traced in over 80% of patients with neurological diseases [2],[3],[11]. Capturing the movements of these patients it can be realized through computer vision analysis [8], by using motion capture tools (mocap) [13] or adopting standard and depth cameras [1],[4]. A recent study has emphasized a technique developed using embedded sensors such as the Inertial Measurement Unit (IMU), composed of accelerometers, gyroscopes and sometimes magnetometers, for the detection of the body's movements [18].

Since 2013 Prof. Yoneyama from Mitsubishi, Prof. Mitoma from Tokyo Medical University and Prof. Watanabe from Hosei University have focused their attention to algorithms elaborated to process acceleration gait with the aim of studying Parkinson's disease [16]. More recently two of the authors of this manuscript have developed algorithms in a Matlab environment to filter the signals coming from IMU sensors placed on the patients' bodies so to be able to identify and analyze the movements of interest in Parkinson's disease (PD) [9].

Convolutional Neural Networks (CNN) has revealed to be one of the most efficient methods employed to characterize human movement as it involves image processing or also signal pre-processing associated with Recurrent Neural Networks (RNN) [6]. This method can turn out robust even with degraded data, such as noisy data or poor-quality sensors [17]. Specifically, the skeleton-based approach uses data from IMUs, where the person is represented as a raw data stream from these sensors, with quality improvement of the network and time performance. It is also true that an important technological advancement in real-time motion recognition is represented by Long-term Recurrent Convolutional Networks (LRCN) [5] where skeleton points are retrieved directly from video and data; which is considered an easier implementation compared to neural networks.

Differently, other recent studies advance the use of more synthetic modeling tools and a motion recognition approach based on the polytopic state-space representation as well as a Linear and Time-Invariant representation [10].

In the present study, data from IMU sensors was filtered and modelled in a matrix form by adopting the Ordinary Least Squares (OLS) method. The data thus processed was related to the movements of 17 points properly positioned on the body, allowing for the animation of a parametric multibody model that virtually reproduced the movements and posture of PD patients in their usual living environments. The neurologist was, therefore, able to carry out an accurate assessment of patients’ movements and posture (freezing, festination, postural balance) as well as to measure disease progression and response to therapies.

The proposed method provides in real time and / or in deferred time the measurable movement analysis of the patients performed in their usual living environments in real-world conditions without resorting to clinic visits and /or acquisitions with cameras. The quality and accuracy of the method was preliminary tested as part of an experiment including 5 movements, each performed by 14 student volunteers wearing the suit with IMU sensors.

This manuscript was structured as follows: in section II, the developed methodology was illustrated: the movements acquisition, the motion recognition algorithms and the developed parametric multibody model were described; in section III, the preliminary testing and the implementation of methodology on patient were reported; in section IV the main results obtained were discussed, while in section V the conclusions of the research were drawn.

2 METHODOLOGY

The analysis of the data available in the scientific literature and those that were collected at the Neurosurgery Department of the Hospital Center University of Picardie Jules Verne (Amiens, France) allowed the authors to establish the correct strategy for movement acquisitions, data filtering and the reproduction of the movements in the multibody avatar model. In particular, through the analysis conducted in this study the proper number and position of IMU sensors on the body patient were identified and the construction of patient-specific multibody models was carried out. The three phases of patient's movements data acquisition, signal filtering and movements implementation on multibody models are described hereafter in detail.

2.1 Movements Acquisition

The preliminary tests conducted on 14 student volunteers with a double acquisition (by adopting IMU sensors and RGB camera integrated with depth sensor and IR emiters) confirmed that 17 IMU sensors positioned in front and rear parts at the level of the main joints of the body guarantee the best compromise between the number of sensors and a high enough accuracy of signal acquisition. The Perception Neuron® IMU wireless sensors were selected among the most performing commercial IMU sensors (Table 1). Each sensor delivered signals obtained via triaxial accelerometer-gyroscope-magnetometer at the frequency of 125Hz to the computer which captured data through a transceiver. The signal data were then elaborated with commercial plugin (Unity3D®, Unreal®) and C++ API SDK and organized as a function of time in matrices exportable in .bvh, raw, .fbx formats easily implemented in commercial software for movement analysis (e.g. MotionBuilder®, Maya®, Blender®).

Characteristics	*Value*	*Characteristics*	*Value*
Weight [g]	15	Data output rate [Hz]	100/125/240
Size [mm]	12×13×4.3	Data format	.bvh; raw; .fbx
Accelerometer range [g]	± 32	Power [Wh]	3.9
Gyroscope range [dps]	2000	Operating autonomy [h]	40
Resolution [deg]	0.02	Latency [ms]	< 5
Frequency [MHz]	2400÷2483	Battery capacity [mAh]	280
Accuracy Roll [°]	0.7	Operating autonomy [h]	8
Accuracy Pitch [°]	0.7	Operating temperature [°C]	-10 - 50
Accuracy Yaw [°]	2	Magnetic Resistance	Full immunity
Internal processing rate [Hz]	800	Wireless Range [m]	10
Data output rate [Hz]	60/90/96/	Estimated cost [USD]	350

Table 1: IMU wireless sensor main characteristics.

The positions of the 17 sensors used in the analysis for the acquisitions are visible in Figure 1. The layout used for the acquisitions, and others similar, can be found in numerous scientific studies [4],[16],[18]. With this distribution the movements and proper PD vibrations of all parts of the body were captured with high accuracy. In some other scientific studies, the patient movements acquisition was completed adopting also a glove with several micro IMU wireless sensors (Figure 1 (a)) [16],[18].

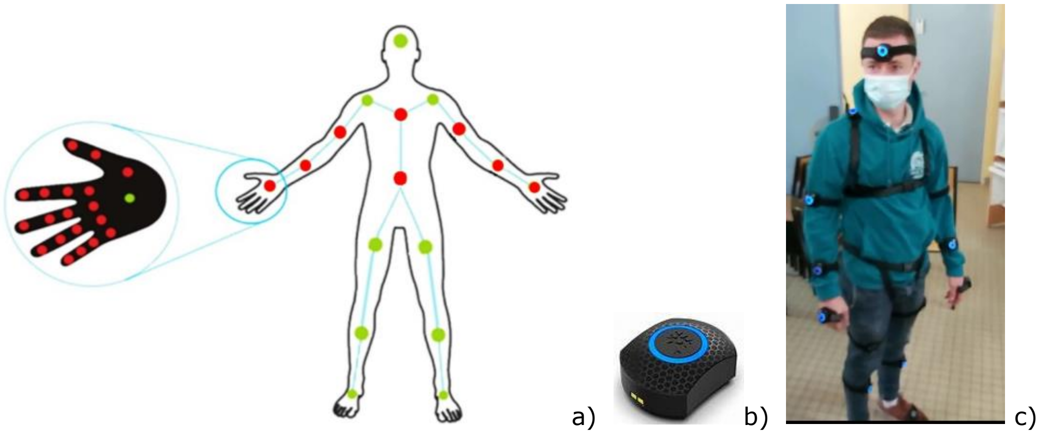

Figure 1: Positioning of IMU wireless sensors on the patient: (a) front (green) and rear (red) placement; (b) Perception Neuron IMU wireless sensor; (c) experimental acquisition.

Sensors delivered 16 signals for each skeleton point which are: 3D position, 3D speed, 3D acceleration, 3D angular velocity and the orientation quaternion representation. Some skeleton points were interpolated, such as neck and a few vertebra points. The signals were registered at a frequency of 125 hertz.

In this study, 14 volunteers' students were preliminary monitored, they were asked to perform 5 specific movements: walk [M_1], stand up (hands on shoulders) [M_2], long steps [M_3], trembling [M_4], freezing [M_5].

Only 6 signals out of the 16 delivered for each skeleton point were considered, namely those relating to the angular velocity and to the longitudinal acceleration in 3D space. Filtering and integrating these signals as described below, a proper movement dataset associated with 6 vectors of $\bar{\boldsymbol{k}}$ samples was created. This is resumed in Equation 1 and in Equation 2 for each movement *i* (*i* ∈{1,….,5}) and each person *j* (*j* ∈{1,….,14}). In particular, the 3 vectors relating to the angular velocity $V_{i,j}$ were showed in Equation 1, while the 3 vectors relative to the longitudinal acceleration $\Gamma_{i,j}$ are showed in Equation 2.

$$\begin{array}{lllll} \boldsymbol{v}_{x_{i,j}} & v^1_{x_{i,j}} & v^2_{x_{i,j}} & v^3_{x_{i,j}} \dots \dots v^k_{x_{i,j}} \dots \dots v^{\bar{k}-2}_{x_{i,j}} & v^{\bar{k}-1}_{x_{i,j}} & v^{\bar{k}}_{x_{i,j}} \\ \boldsymbol{v}_{x_{i,j}} & v^1_{y_{i,j}} & v^2_{y_{i,j}} & v^3_{y_{i,j}} \dots \dots v^k_{y_{i,j}} \dots \dots v^{\bar{k}-2}_{y_{i,j}} & v^{\bar{k}-1}_{y_{i,j}} & v^{\bar{k}}_{y_{i,j}} \\ \boldsymbol{v}_{x_{i,j}} & v^1_{z_{i,j}} & v^2_{z_{i,j}} & v^3_{z_{i,j}} \dots \dots v^k_{z_{i,j}} \dots \dots v^{\bar{k}-2}_{z_{i,j}} & v^{\bar{k}-1}_{z_{i,j}} & v^{\bar{k}}_{z_{i,j}} \end{array} \tag{1}$$

$$\begin{array}{lllll} \boldsymbol{a}_{x_{i,j}} & a^1_{x_{i,j}} & a^2_{x_{i,j}} & a^3_{x_{i,j}} \dots \dots a^k_{x_{i,j}} \dots \dots a^{\bar{k}-2}_{x_{i,j}} & a^{\bar{k}-1}_{x_{i,j}} & a^{\bar{k}}_{x_{i,j}} \\ \boldsymbol{a}_{x_{i,j}} & a^1_{y_{i,j}} & a^2_{y_{i,j}} & a^3_{y_{i,j}} \dots \dots a^k_{y_{i,j}} \dots \dots a^{\bar{k}-2}_{y_{i,j}} & a^{\bar{k}-1}_{y_{i,j}} & a^{\bar{k}}_{y_{i,j}} \\ \boldsymbol{a}_{x_{i,j}} & a^1_{z_{i,j}} & a^2_{z_{i,j}} & a^3_{z_{i,j}} \dots \dots a^k_{z_{i,j}} \dots \dots a^{\bar{k}-2}_{z_{i,j}} & a^{\bar{k}-1}_{z_{i,j}} & a^{\bar{k}}_{z_{i,j}} \end{array} \tag{2}$$

For each volunteer and each specific movement ($\bar{\iota}$, $\bar{\jmath}$) the 6 movements vectors calculated for the 17 skeleton points were implemented in the equivalent body points of the multibody parametric model so concurring in the reproduction of the specific movement.

According to the 6 signals generated by the associated sensors the linear matrix representation for each movement *i* and for each person *j* can be expressed as follows:

$$\Gamma_{i,\,j} = A_{i,\,j}.V_{i,\,j} + B_{i,\,j} \qquad \forall\,\{\mathrm{i},\,\mathrm{j}\} \in \{(1,..,5) \times (1,..,14)\} \tag{3}$$

Where: $\Gamma_{i,\,j} = \begin{bmatrix} a_{x_{i,j}} \\ a_{y_{i,j}} \\ a_{y_{i,j}} \end{bmatrix} \in \mathbb{R}^{3\times k}$ and $V_{i,\,j} = \begin{bmatrix} v_{x_{i,j}} \\ v_{y_{i,j}} \\ v_{y_{i,j}} \end{bmatrix} \in \mathbb{R}^{3\times k}$

$A_{i,\,j} \in \mathbb{R}^{3x3}$ and $B_{i,\,j} \in \mathbb{R}^{3x1}$ to be determined. The unknown coefficients $A_{i,j}$ and $B_{i,j}$ (parameters) of the linear models expressed in (3) were determined in four steps using the Ordinary Least Squares method (OLS) [15]. Three explanatory variables were considered to describe the behavior of $\Gamma_{i,\,j}$: v_x, v_y, v_z.

Step 1: Find a_{11}, a_{12} and a_{13}, the unknown parameters of the first line of $A_{i,\,j}$ that best fits the data (a_x, $V_{i,\,j}$) while minimizing e_1, the average of the sum of squared errors. In other words, solve the following optimization problem:

$$min\ \frac{1}{k} e_1^T \cdot e_1 \ \text{ such as } \ a_x{=}a_{11} \cdot v_x + a_{12} \cdot v_y + a_{13} \cdot v_z{+}{+}e_1\ a_{11}, a_{12}, a_{13} \tag{4}$$

The solution of which is:

$$[a_{11}, a_{12}, a_{13}]^T = \left(V_{i,j} V_{i,j}{}^T\right)^{-1} \cdot V_{i,j} \cdot a_x^T \tag{5}$$

Step 2: In the same way as in step 1 we can find a_{21}, a_{22} and a_{23}.

Solution:

$$[a_{21}, a_{22}, a_{23}]^T = \left(V_{i,j} V_{i,j}{}^T\right)^{-1} \cdot V_{i,j} \cdot a_y^T \tag{6}$$

Step 3: Always in the same way of step 1 we can find a_{31}, a_{32} and a_{33}.

Solution:

$$[a_{31}, a_{32}, a_{33}]^T = \left(V_{i,j} V_{i,j}{}^T\right)^{-1} \cdot V_{i,j} \cdot a_z^T \tag{7}$$

Step 4: Generate $B_{i,\,j}$ such as:

$$B_{i,j} = \begin{bmatrix} \frac{e_1}{k} & \frac{e_2}{k} & \frac{e_3}{k} \end{bmatrix}^T = [b_1\ b_2\ b_3]^T \tag{8}$$

2.2 Movements Signal Filtering and Integrating

The second phase of the proposed methodology consisted in the fine-tuning of algorithms for the profilation of 5 studied movements. Motion recognition algorithms were developed by specifically following an approach that consists in comparing the movement to be recognized and the models contained in the database. The most similar database movement model (MSM) was then identified and the corresponding movement was associated with the movement to be recognized. It was assumed that the models specific to the recognition of the person performing the movement were not to be included in the training database. Fine-tuning (filtering and integration) was carried out using the signals acquired by 14 volunteers wearing the suit with IMU sensors as it will be described in more detail in the following section 3.

This approach can be achieved, for any person *p* performing the movement *m*, by respecting the following steps.

Step 1: Concatenation: Generate $M_{i,j}$ ∀ {i, j} ∊ {(1,..,5) ×(1,.., 14)} corresponding to the concatenation of $A_{i,j}$ and $B_{i,j}$ such as:

$$M_{i,j} = \begin{bmatrix} a_{11i,j} & a_{12i,j} & a_{13i,j} \\ a_{21i,j} & a_{22i,j} & a_{23i,j} \\ a_{31i,j} & a_{32i,j} & a_{33i,j} \\ b_{1i,j} & b_{21i,j} & b_{3i,j} \end{bmatrix} \tag{9}$$

Step 2: Resemblance: Compute the resemblance index $r_{i,j}$ ∀ {i, j} ∊ {(1,..,5) × (1,.., 14)} & (j≠p) such as:

$$r_{i,j} = (M_{i,j} - M_{m,p}) \times (M_{i,j} - M_{m,p})^T \tag{10}$$

Step 3: Selection: Determine the smallest resemblance indexed $r_{i*,j*}$ such as:

$$r_{i^*,j^*} = min\,(\mathrm{r_{i,j}}) \tag{11}$$

Finally, MSM = *i**.
Algorithms were tested by exploiting the eigenvalues of *Ai,j* with the number of parameters of the matrix $M_{i,j}$ reduced such as:

$$M_{i,j} = [\mathrm{eig}\,(A_{i,j}) \quad b_{1i,j} \quad b_{2i,j} \quad b_{3i,j}] \tag{12}$$

2.3 Patient Multibody Model

Using the wide database of 3D human scans (CAESAR) [14] a parametric articulated multi-body model able to faithfully reproduce the acquired movements of patients was developed. The model consists of 16 parts, connected to each other through six spherical joints, one translational joint, one planar joint and one revolute joint (Table 2) with frictions and motion actuators located at the point at which the IMU Sensors were positioned on the patient (Figure 2). The choice of articulation constraints was carried out in such a way that we can faithfully reproduce the PD characteristic movements. The virtual patient model has 28 degrees of freedom overall.

The translational and rotational displacements measured as a function of time by each IMU Sensors were applied as motion actuators in the corresponding markers through time-histories contained in matrix form in the files .fbx.

A parameterization of the model was performed by introducing 3 parameters: the total height; the total weight and the waist circumference. The model lends itself to a more refined parameterization, like the one carried out by some of the authors in their previous works [12], [15], but in the current phase of the research this was not deemed necessary.

The mass and intertie values of the individual parts were given based on average values and regression equations and considering as input only the height, the weight and waist circumference of the subject.

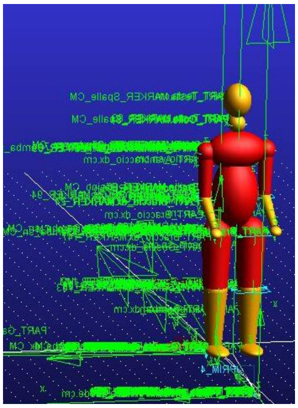

Figure 2: Parametric Multibody model.

Part	*Neck*	*Shoulder*	*Arm*	*Forearm*	*Hand*	*Pelvis*	*Thigh*	*Tibia*	*Foot*
Head	S	–	–	–	–	–	–	–	–
Neck	–	P	–	–	–	–	–	–	–
Shoulder	P	–	S	–	–	T	–	–	–
Arm	–	S	–	S	–	–	–	–	–
Forearm	–	–	S	–	S	–	–	–	–
Hand	–	–	–	S	–	–	–	–	–
Pelvis	–	T	–	–	–	–	S	–	–
Thigh	–	–	–	–	–	S	–	R	–
Tibia	–	–	–	–	–	–	R	–	S
Foot	–	–	–	–	–	–	–	S	–

R = Revolute, P = Planar, S = Spherical, T = Translational

Table 2: Joints between main parts of multibody model.

Setting the parameters on the anthropometric values of the patient studied and implementing acquired and filtered movements data in the homologous points of the multibody model, an accurate assessment of Parkinson patients' movements and posture (freezing, festination, postural balance) was carried out, and contextually disease progression and response to therapy were measured.

3 PRELIMINARY TESTING AND IMPLEMENTATION ON PATIENTS WITH PD

To validate the methodology, evaluate its accuracy and fine-tuning algorithms preliminary tests were performed. 14 volunteers wearing the suit with IMU sensors performed the 5 characteristic PD movements: walk [M_1], stand up (hands on shoulders) [M_2], long steps [M_3], trembling [M_4], freezing [M_5].

These calibration tests made it possible define the algorithms of filtering and integrating motion signals described in section 2.2. Furthermore, calibration tests made it possible to perfectly measure the accuracy of the method in the recognition of the 5 pathological movements.

In detail to verify the accuracy of the algorithms, the analysis of the movements was limited to a period of only 700 seconds. Table 3 shows the overall score obtained in the 70 scenarios analyzed. The global precision involved by our approach is 92.86%. The table shows that movements 1, 3 and 5 were identified with 100% accuracy.

Movement Identified\ Predicted	*M_1*	*M_2*	*M_3*	*M_4*	*M_5*
[M_1] – Walk	**100**	0	0	0	0
[M_2] - Stand up (hands on shoulders)	7.1	**78.8**	0	0	14.2
[M_3] - Long steps	0	0	**100**	0	0
[M_4] - Trembling	0	0	1	**85.7**	0
[M_5] - Freezing	0	0	0	0	**100**

Table 3: Accuracy matrix evaluation for 70 scenarios.

In Table 4, as an example, were reported the mass and principal moment of inertia values assigned to the multibody model to reproduce the movements of one of the 14 volunteers visible in Figure 3.

Part	*Mass [kg]*	*I_x, I_y, I_z [kg×m ^{2}]*		
Head	6.0	0.035	0.315	0.019
Neck	1.0	1.251 E-003	1.25 E-003	1.24 E-003
Shoulder	13	0.651	0.473	0.318
Arm	1.8 × 2	0.0133	0.0133	2.29 E-003
Forearm	1.8 × 2	0.0157	0.0157	0.0135
Hand	0.5× 2	5.935 E-004	5.935 E-004	4.672 E-004
Pelvis	13.4	0.135	0.130	0.0472
Thigh	8.6 × 2	0.146	0.416	0.031
Tibia	3.8 × 2	0.150	0.143	0.017
Foot	1.6 × 2	0.050	0.042	0.014
Total	69.6			

Table 4: Mass and inertia values in the parts of multibody model.

Specifically, the patient visible in Figure 3 had the total height of 1.76 m, the total weight of 69.6 kg and the waist circumference of 1.1 m. Figure 3 shows a comparison between the images captured in a video made with Microsoft Azure Kinect DK ver. 3 devices and the images reproduced in the multibody environment with the patient parametric model.

Finally, the methodology has been definitively applied to process the signals acquired by 20 patients at the University Hospital Center of Amiens; the 5 characteristic pathological Parkinson's movements were identified and evaluated. The acquisitions were repeated 3/4 times for each patient and evaluated along the 3 main axes of inertia associated with the patient (Figure 2).

Among the main results obtained, were reported below (Figures 4) the comparison between the average accelerations measured on the forearm, through direct acquisitions (with piezoelectric accelerometers) and those acquired with IMU sensors that, after being filtered and integrated, were reproduced in the multibody model. In particular in Figure 4 were reported the average values of the accelerations measured along the 3 main axes (x, y and z) of inertia on the forearm for a period of 700 seconds.

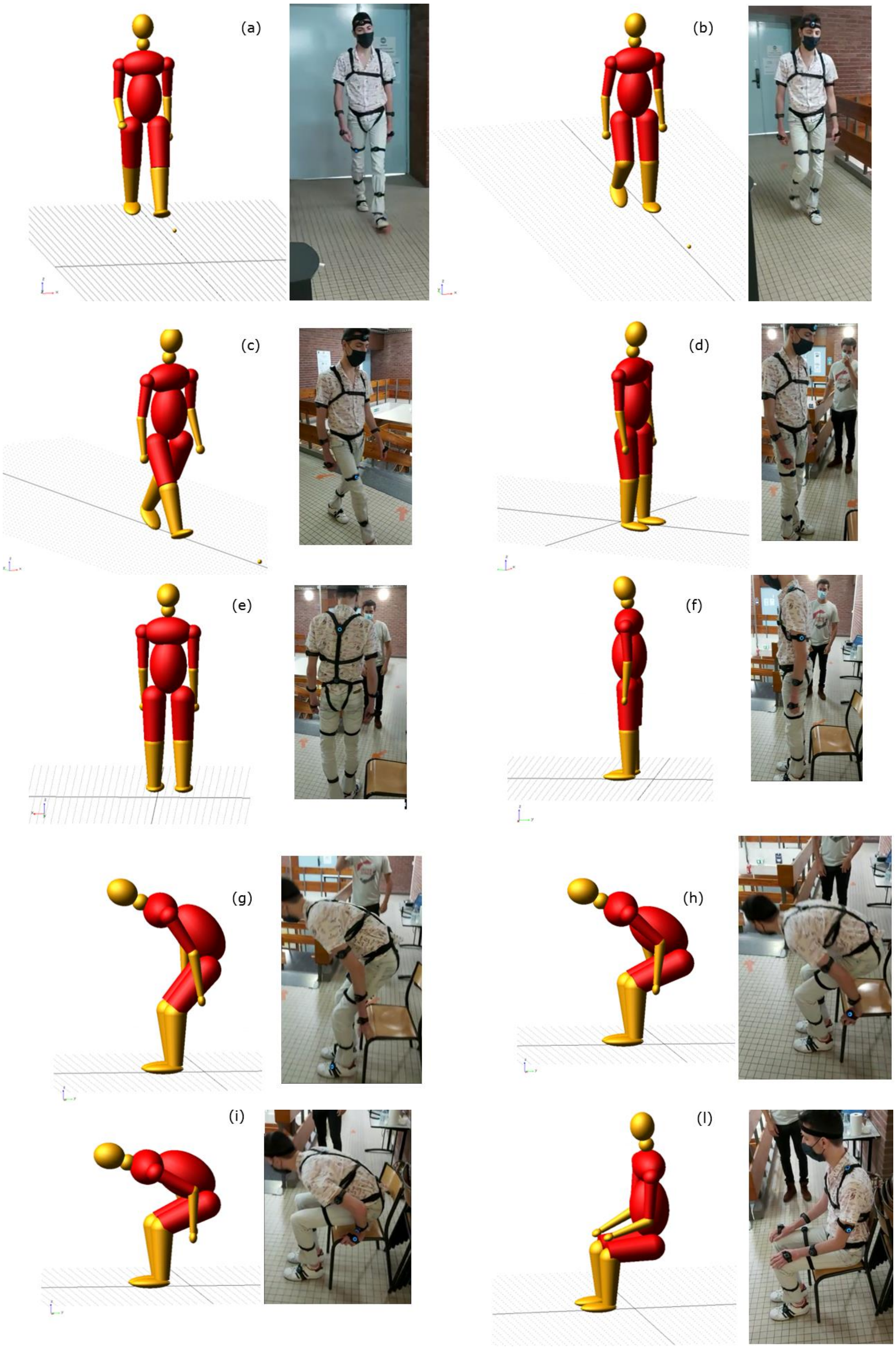

Figure 3: Comparison between video captured images and patient's multibody model frames at the same time steps: a) 0s; b) 2s; c) 4s; d) 6s; e) 7s; f) 9s; g) 10s; h) 11s; i) 11.5s; l) 12s.

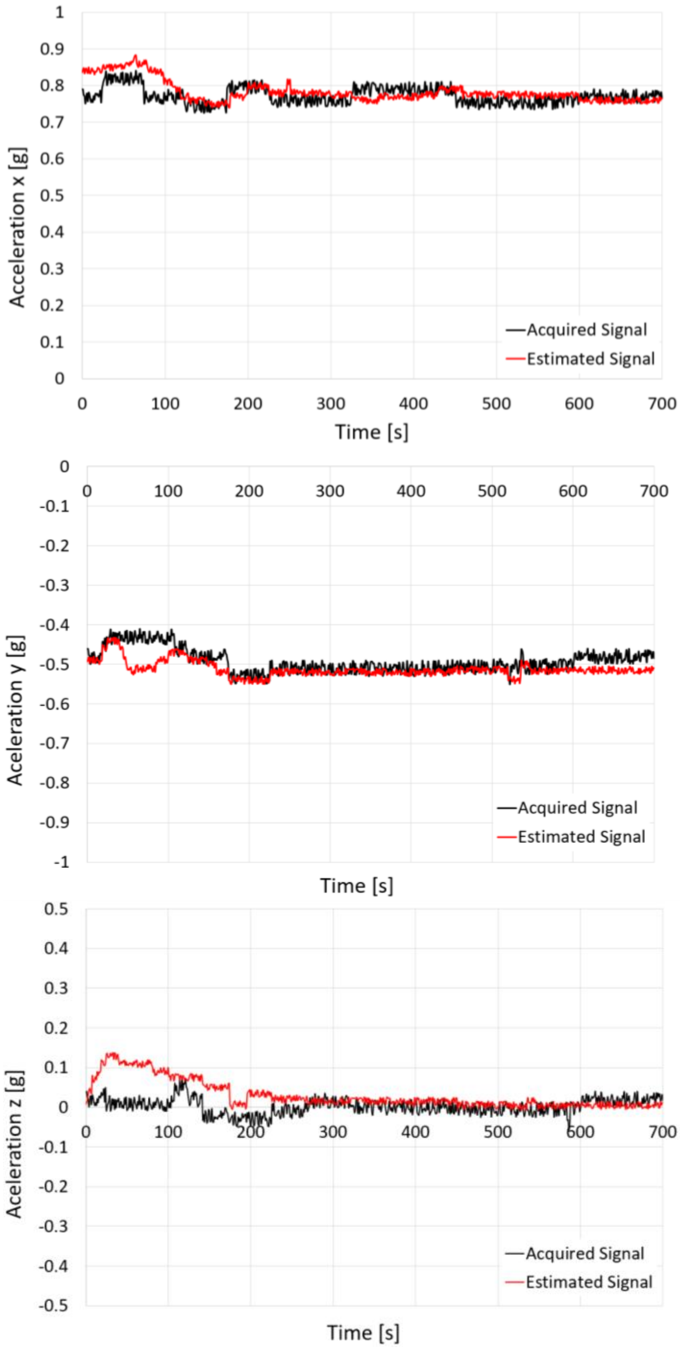

Figure 4: Comparison between measured and estimated acceleration signals on forearm.

The values acquired experimentally with piezoelectric accelerometers (black signal in Figure 4) were compared with values estimated with IMU sensors after filtered and integrated as described in sections 2.2 (red signal in Figure 4).

In Figure 5 the trembling movement of the hand is shown. Also, in this case the values were those obtained after filtering and integrating signals acquired 4 times for the patient. The correspondence between the estimated and acquired signals has a maximum error of less than 3%.

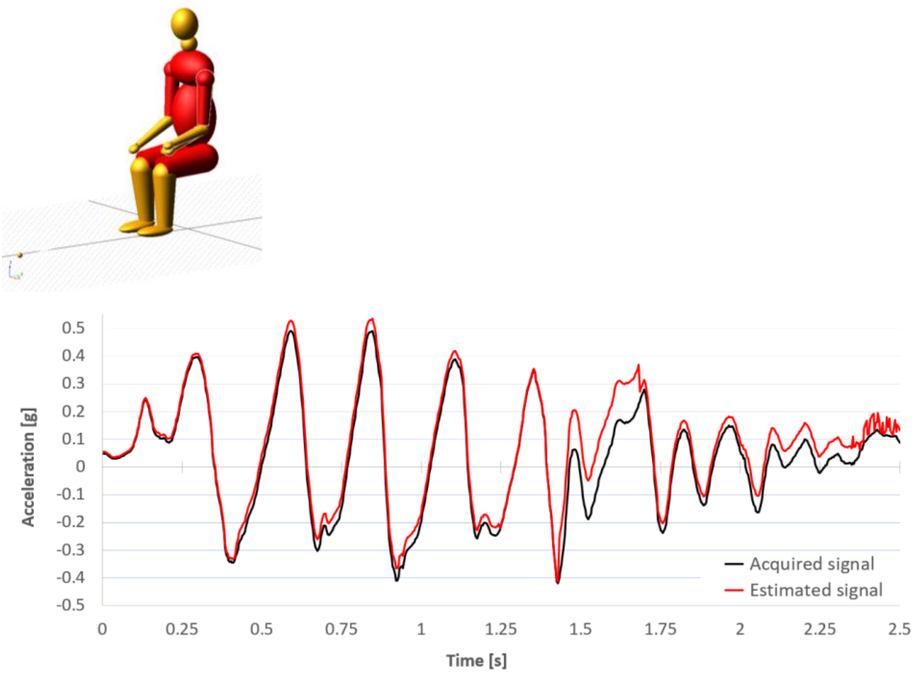

Figure 5: Comparison between measured and estimated acceleration signals on left hand.

4 DISCUSSION OF RESULTS

The proposed methodology led to a global estimation accuracy of over 90%. We can add that with this approach, the five movements were systematically recognized.

The proposed approach is based on signal selection. This means that each interpreted movement of the dataset involved one or more parts of the body and its representative IMUs sensors. According to this, we managed to determine, owing to a simple data analysis type PCA, which sensor was the most relevant for each movement. Table 5 shows the most relevant sensor that was seen be associated with each specific movement.

We want to highlight how the developed methodology is able to monitor and study the movements of patients during sleep, monitoring and measuring agitated dreams, movement stiffness and motor slowdown.

Movements	*Most relevant sensors*
[M_1] – Walk	Feet
[M_2] - Stand up (hands on shoulders)	Forearms
[M_3] - Long steps	Spine
[M_4] – Trembling	Hands
[M_5] – Freezing	Feet

Table 5: Most relevant IMU sensors for each studied movement.

Using patient multibody model, the patient's observation point can be changed as desired. The reproductions of the patient's movements through the animations of the multibody model have the considerable advantage of being able to be observed from neurologists a different speed, from any angle and with infinite levels of detail.

Authors received several positive feedbacks about the method effectiveness from neurologists of University Hospital Center of Amiens. In particular Neurologists found interesting to be able to accurately measure the magnitude of patients' movements and vibrations. The proposed methodology, according to neurologists, can be used for rehabilitation purposes also in other kinds of health problems in which it is possible to carry out neurological rehabilitation with greater effectiveness.

5 CONCLUSION

This paper presented an effective methodology suggested as an important strategy for the recognition of some pathological movements specific to Parkinson's disease. A wearable suit equipped with 17 IMU sensors positioned at the level of the main joints of the body was developed. The suit acquired the information considered as necessary to analyze the movements and posture which were characteristic of PD patients in their usual living environments. The signals collected by the suit, properly filtered and integrated, were employed to animate a parametric multibody model that virtually reproduced the patients' movements. The experimental clinical use of the suit at the University Hospital Center of Amiens enabled to identify and evaluate 5 more characteristic pathological Parkinson's movements. We can state that the main key contribution of this work can be indicated in two aspects: 1) the development of an effective non-invasive methodology that allows the neurologist to carry out an accurate assessment of Parkinson's disease, observing the graphic animations of pathological movements from any angle and with infinite levels of detail and contextually to measure disease progression and response to therapy; 2) the development of algorithms that allow to identify Parkinson's characteristic movements from a limited database acquired with IMU sensors. Differently from the traditional three-dimensional video-based motion analysis systems, the proposed method can be relevant for assuring a more easily measurable and comprehensive kinematic and kinetic analysis of patients' movement in normal living conditions.

ACKNOWLEDGEMENTS

The authors wish to thank Dr. Michel Lefranc of the University Hospital Center of Amiens and student volunteers of the University of Picardie who participated to the experimental acquisitions.

Michele Calì, https://orcid.org/0000-0001-8753-8804
David Durand, https://orcid.org/0000-0001-8086-8886
Jérôme Bosche, https://orcid.org/0000-0001-7894-5563

REFERENCES

[1] Barnachon, M.; Bouakaz, S.; Boufama, B.; Guillou, E.: Ongoing human action recognition with motion capture, Pattern Recognition, 47(1), 2014, 238-247. https://doi.org/10.1016/j.patcog.2013.06.020

[2] Bhatia, K.P.; Bain, P.; Bajaj, N.; Elble, R.J.; Hallett, M.; Louis, E.D.; et al.: Consensus Statement on the Classification of Tremors, The Task Force on Tremor of the International Parkinson and Movement Disorder Society. Mov Disord 33(1), 2018, 75–87. doi:10.1002/mds.27121. https://doi.org/10.1002/mds.27121

[3] Defazio, G.; Ercoli, T.; Erro, R.; Pellicciari, R.; Mascia, MM.; Fabbrini, G.; et al.: Idiopathic Non-task Specific Upper Limb Dystonia, a Neglected Form of Dystonia, Mov Disord 35(11), 2020, 2038–45. doi: 10.1002/mds.28199. https://doi.org/10.1002/mds.28199

[4] Devanne, M.: 3d human behavior understanding by shape analysis of human motion and pose, Ph.D. Thesis, Université Lille 1-Sciences et Technologies, 2015. https://doi.org/10.1002/mds.28199
[5] Donahue, J.; Anne Hendricks, L.; Guadarrama, S.; Rohrbach, M.; Venugopalan, S.; Saenko, K.; Darrell, T.: Long-term recurrent convolutional networks for visual recognition and description, Proceedings of the IEEE conference on computer vision and pattern recognition, 2015, 2625-2634.
[6] Ji, S.; Xu, W.; Yang, M.; Yu, K.: 3D convolutional neural networks for human action recognition, IEEE transactions on pattern analysis and machine intelligence, 35(1), 2012, 221-231. https://ieeexplore.ieee.org/document/6165309
[7] Kleinbaum, D. G.; Kupper, L. L.; Nizam, A.; Rosenberg, E.i S.: Applied Regression Analysis and Other Multivariable Methods, Cengage Learning, 2013. https://ieeexplore.ieee.org/document/6165309
[8] Lord, S.; Godfrey, A.; Galna, B.; Burn, D.; Rochester, L.: Patterns of daily ambulatory activity are different in early Parkinson's disease compared with controls, Proceedings of the 16th international congress of Parkinson's disease and movement disorders, Suppl. 1, 2012, p. 1565.
[9] Moreau, P.; Durand, D.; Bosche, J.; Lefranc, M.: A motion recognition technique based on linear matrix representation to improve Parkinson's disease treatments, 9th International Conference on Systems and Control (ICSC IEEE), 2021, 237-242. https://ieeexplore.ieee.org/document/9666608
[10] Moreau, P.; Durand, D.; Bosche, J.; Lefranc, M.: A motion recognition algorithm using polytopic modeling, International Conference on Control, Decision and Information Technologies (CoDIT'20) IEEE, Vol. 1, 2020, 679-686. https://ieeexplore.ieee.org/document/9263883
[11] Pandey, S.; Sarma, N.: Tremor in Dystonia, Parkinsonism Relat Disord 29, 3–9, 2016. doi: 10.1016/j.parkreldis.2016.03.024. https://doi.org/10.1016/j.parkreldis.2016.03.024
[12] Pascoletti, G.; Huysmans, T.; Conti, P.; Zanetti, E. M.: Evaluation of a Morphable Anthropomorphic Articulated Total Body Model, International Conference on Design, Simulation, Manufacturing: The Innovation Exchange, Springer, 2021, 761-772. https://doi.org/10.1007/978-3-030-91234-5_77
[13] Regazzoni, D.; Rizzi, C.: Digital human models and virtual ergonomics to improve maintainability, Computer-Aided Design and Applications, 11(1), 2014, 10-19. https://doi.org/10.1080/16864360.2013.834130
[14] Robinette, K. M.; Blackwell, S.; Daanen, H.; Boehmer, M.; Fleming, S.: Civilian American and European surface anthropometry resource (caesar), final report. volume 1. summary. Sytronics Inc Dayton Oh, 2002.
[15] Sequenzia, G.; Oliveri, S. M.; Fatuzzo, G.; Calì, M.: An advanced multibody model for evaluating rider's influence on motorcycle dynamics, Institution of Mechanical Engineers, Part K: Journal of Multi-body Dynamics, 229(2), 2015,193-207. https://doi.org/10.1177/1464419314557686
[16] Yoneyama, M.; Kurihara, Y.; Watanabe, K.; Mitoma, H.: Accelerometry-based gait analysis and its application to Parkinson's disease assessment: detection of stride event, IEEE Transactions on neural systems and rehabilitation engineering, 22(3), 2013, 613-622.
[17] Yue-Hei Ng, J.; Matthew, J.; Hausknecht, J.; Vijayanarasimhan, S.; Vinyals, O.; Monga, R.; Toderici, G.: Beyond Short Snippets: Deep Networks for Video Classification, CoRR, 2015.
[18] Zebin, T.; Sperrin, M.; Peek, N.; Casson, A. J.: Human activity recognition from inertial sensor time-series using batch normalized deep LSTM recurrent networks, 40th annual international conference of the IEEE engineering in medicine and biology society (EMBC), 2018, 1-4. https://ieeexplore.ieee.org/document/8513115