A RGB-D Sensor Based Tool for Assessment and Rating of Movement Disorders

Vitoantonio Bevilacqua[1(✉)], Gianpaolo Francesco Trotta[2], Claudio Loconsole[1], Antonio Brunetti[1], Nicholas Caporusso[1], Giuseppe Maria Bellantuono[1], Irio De Feudis[1], Donato Patruno[1], Domenico De Marco[1], Andrea Venneri[1], Maria Grazia Di Vietro[3], Giacomo Losavio[3], and Sabina Ilaria Tatò[3]

[1] Department of Electrical and Information Engineering, Polytechnic University of Bari, Bari, Italy
{vitoantonio.bevilacqua,claudio.loconsole, antonio.brunetti}@poliba.it, gbellantuono@gmail.com, irio.defeudis@gmail.com, patrunodonato87@gmail.com, domy.sy@gmail.com

[2] Department of Mechanics, Mathematics and Management, Polytechnic University of Bari, Bari, Italy
gianpaolofrancesco.trotta@poliba.it

[3] Medica Sud S.R.L., Viale della Resistenza n.82, Bari (BA), Italy
giacomolosavio@libero.it

Abstract. The assessment of tremor features of subjects affected by Parkinson's disease supports physicians in defining customized rehabilitation treatment which, in turn, can lead to better clinical outcome. In the standard assessment protocol patient performed many exercises that are useful to physicians to rate disease. But the rating is subjective since is based on an observational evaluation. In this paper, we introduce a novel method for achieving objective assessment of movement conditions by directly measuring the magnitude of involuntary tremors with a set of sensors. We focused on one of the standard tasks of the Unified Parkinson's Disease Rating Scale: finger-to-nose maneuver. During the task, data related to patient finger position are stored and then some tremor's features are extracted. Finally, we employ a Support Vector Machine to measure the relevance of the extracted features in classify healthy subjects and patients.

Keywords: Parkinson disease · Finger-to-Nose maneuver · Kinect sensor · Support vector machine · Classification

1 Introduction

Parkinson's disease (PD) is a neurodegenerative condition. Unfortunately, no treatment is currently available. Nevertheless, many studies proved that different therapies may increase the quality of life of patients, reducing instability, gait disorders, and motor impairment, which are just some of the symptoms.

V. Duffy and N. Lightner (eds.), *Advances in Human Factors and Ergonomics in Healthcare and Medical Devices*, Advances in Intelligent Systems and Computing 590, DOI 10.1007/978-3-319-60483-1_12

The Unified Parkinson's Disease Rating Scale (UPDRS) [1] is a tool that supports the assessment of the course of PD over time. In 2007, the Movement Disorder Society (MDS) published a revision of the UPDRS, known as the MDS-UPDRS that consists in four parts: Part I (non-motor experience in daily living), Part II (motor experience in daily living), Part III (motor examination), and Part IV (motor complications).

In this paper, we specifically focus on improving part III. Usually, during motor examination, the patient realizes a set of different physical exercises. Simultaneously, physicians realize an observational assessment to identify and rate dyskinesia (chorea or dystonia). However, subjective evaluation affect the quality of results. Therefore, in this paper, we introduce a system for providing physicians with quantitative metrics, which would render the assessment of disease severity more objective. To this end, we designed a system, based on the use of a sensor embedded in a commercial device (i.e., Kinect®), which extracts the features of tremors during the finger-to-nose task inspired by the MDS-UDPRS scale.

2 Related Works

The aim of several recent studies is to objectify the measurement of disorders to overcome current limitations of assessment protocols and disease rating scales [2], in which qualitative evaluation affects accuracy.

Other studies focus on adherence to motor rehabilitation, and they aim at motivating PD patients to adhere to the exercise routine in order to improve the outcome of the treatment [3] [4].

The assessment of the severity of movement disorders in PD is essential for the development of new treatments and for improving the quality of life of patients. Hence, the scientific community working on PD is fostering the idea that a new objective method should be developed to increase accuracy, render results reproducible, and lower the assessment cost. In this regard, wearable and infrastructure-based systems, such as, Myo® and Kinect®, are among the most used devices for experimenting novel protocols [5].

Moreover, serious games and, in particular, approaches based on Augmented Reality and on Virtual Reality (AR/VR), are gaining increasing interest in the community, because they relief patients from the stress of being examined; also, being engaged in interaction with VR prevents anxiety, frustration, and other side effects which might affect performance [6].

In this paper, we introduce and present the evaluation of a system which objectively measures patient's performance in finger-to-nose sessions. Specific features are extracted to discriminate patients and healthy subjects using machine learning techniques. Particularly, we take into consideration amplitude and frequency of tremors. In addition to their subjective assessment, physician could use our proposed system (or the features considered by our analysis) for assessing disease severity with higher accuracy.

3 Materials and Methods

3.1 Participants

In this study, 17 subjects were recruited: 6 PD patients and 11 Control volunteers.

Coherently with the MDS-UPDRS scale, in which responses of each hand are evaluated separately, we realized independent acquisitions for each subject's hand. In the former, where only right hand is observed, 1 female and 5 male patients aged 58–80 years (average 73.8, sd 8.08) and 2 females and 9 male volunteers aged 21–33 years (average 25.63, sd 3.66) were recruited. In the latter, where only left hand is observed, a patient hasn't been considered because he didn't show any phenomena observed on the hand.

3.2 Acquisition System

Our objective is the implementation of a simple and intuitive system, which, regardless of its simplicity, can assess and classify movement disorders which are typical of PD. To this end, our system extracts significant parameters during the execution of exercises. We consider tremor's amplitude and frequency, and we collect them with high accuracy (up to one millimeter) in very short time intervals. As a result, we expect our system to be more reliable than the human eye.

Our system is based on the following hardware:

- Kinect One®

Acquisition and analysis software was developed using the following tools:

- Unity3D®
- MATLAB®

Kinect® is equipped with an RGB camera, a double depth infrared sensor consisting of an infrared laser scanner and an infrared camera. The RGB camera has a resolution of 640 × 480 pixels while the infrared uses a 320 × 240 pixel matrix. Kinect® was attached to a telescopic bar along the vertical axis to enable users to change its orientation and position so that it can recognize movements. According to Microsoft, Kinect® can simultaneously track movements of up to 4 people, both standing and sitting. As Kinect® primarily a gaming console intended for entertainment purpose, it is ideal combining experimental acquisition with potential integration of VR [7].

The Kinect® sensor is placed at a height of 80 cm above patient's head. So, from a raised position it can capture patient's location and the hand involved in the experiment. In addition, Kinect® was preferred to normal RGB cameras because it captures 3-dimensional information, using a depth sensor. Also, it has an infrared camera, which involves realizing calculations using a different wavelength than traditional RGB camera. Finally, it is a relatively low-cost technology, which makes the whole system extremely cheap.

In this paper, we mainly focus on one specific exercise to evaluate and characterize the disease:

- Kinetic tremor of the hands.

Kinetic tremor of the hands is evaluated with the finger-to-nose test, which measures smooth, coordinated movement of the upper limbs by having each of the examinees touch the tip their nose with their index finger (Fig. 1). In one variation of the test, examiners hold their finger at about 1 m away from the patient, who is instructed to touch the examiner's finger, and then, to reach their own nose. The finger-to-nose test is repeated 3 times and should be performed slowly enough not to hide any tremor that could occur with very fast movements of the arm. Then, the test is repeated with the other hand, so that they can be rated separately. The tremor can be detected throughout the movement or when the target (nose or finger) is reached [8]. The greatest detected amplitude is evaluated to identify the presence of conditions.

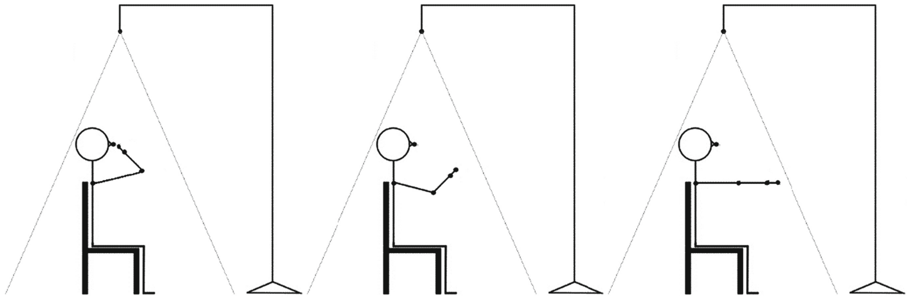

Fig. 1. Example of the exercise execution

For the experiment, we mainly used the infrared sensor of the Kinect®. In every experiment, it was possible extrapolate all features required for the classification by means of a reflector marker placed on a patient's finger.

Example of typical trajectory during the exercise for PD and Control are shown in Fig. 2.

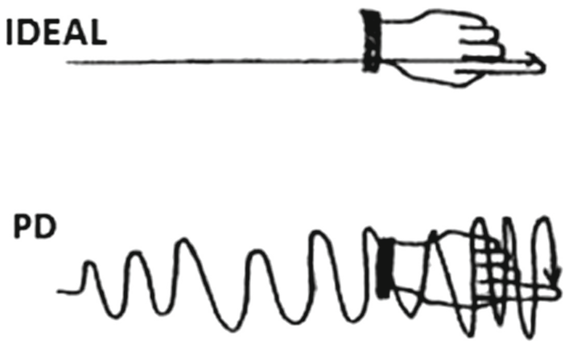

Fig. 2. Example of trajectory difference between PD and ideal

3.3 Features

We extracted several significant features which are useful for evaluating tremor. Usually, medical specialists observe them without any support tool, i.e., they adopt a qualitative and subjective approach in their evaluation.

All the features analysed by our system regard tremor, and they include:

- average amplitude;
- maximum amplitude;
- frequency.

During the finger-to-nose experiment, we acquire a cloud of points each representing the spatial position of the marker over three axes (X, Y, and Z), extracted from images captured at a frame rate of 30 FPS (frame per second). Subsequently, we utilize MATLAB to extract the features of interest from the cloud of points. Specifically, we applied linear regression to find the reference line for the specific test. Then, we evaluate the amplitude of tremor, which is calculated as the distance between the reference line and the trajectory of the index finger. This is calculated point by point in each frame. A typical fluctuation pattern of a PD patient is shown in Fig. 3.

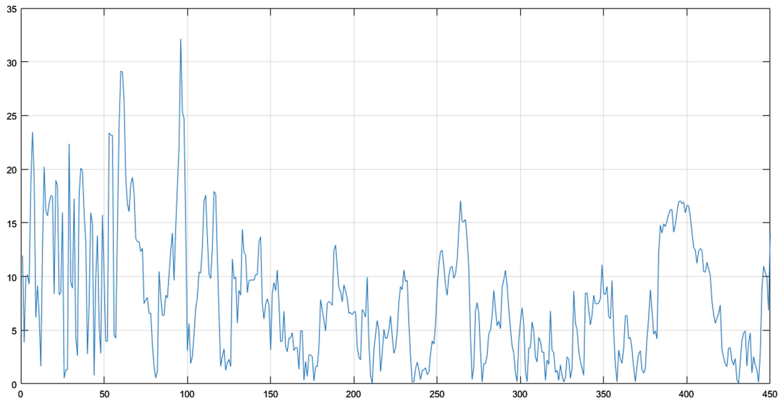

Fig. 3. Fluctuation pattern of a PD patient

Specifically, we use Principal Components Analysis (PCA) to fit linear regression [9]. PCA minimizes perpendicular distances from the data to the fitted model. This is the linear case of Orthogonal Regression, or Total Least Squares. This method can be appropriately utilized when there is no natural distinction between the predictor and response variables, or to accommodate for errors in variable. This contrasts with the usual assumption on regression, that predictor variables are measured without any errors, whereas only the response variable can have an error component.

Figures 4 and 5 show an example of a cloud of points extracted from subject's movement and the respective fit line.

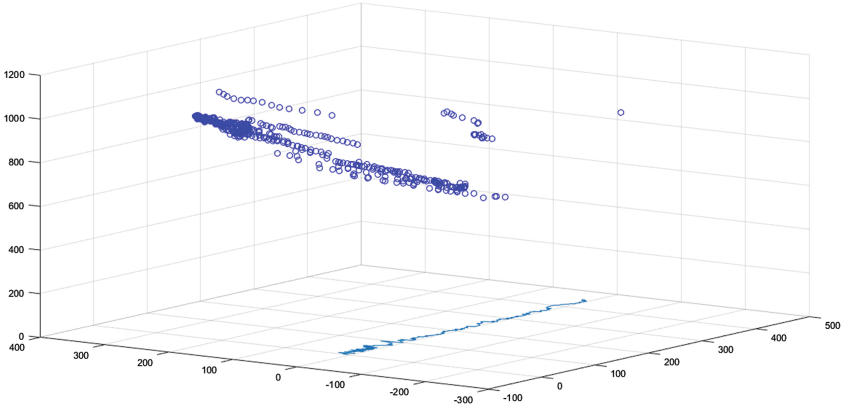

Fig. 4. Cloud of points representing the trajectory of the index finger

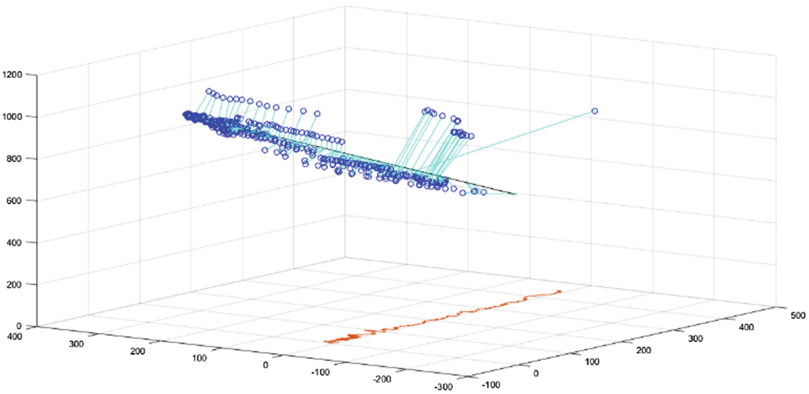

Fig. 5. Reference line of the trajectory of the index finger

We consider frequency as a third feature. In particular, we use the average frequency of tremor in every second. We calculate the peaks of the amplitudes during the task by means of the reference line obtained using linear regression, as described previously. We consider each peak as starting point of a tremor. Consequently, we are able to calculate the number of tremors during the exercise and the medium frequency of tremors per second.

During the experiment, we detected some errors in tracking the marker. They are due to light conditions, which can interfere with the infrared sensor of the Kinect® acquisition system. Also, they might be caused by reflective objects in the field of view of Kinect®. Interferences produce detection mistakes, as shown in Fig. 6. Therefore, we filter the selected data with a low-pass filter to remove peaks of amplitude over 20 cm. We choose this threshold because it is twice as much as the maximum severity of the MDS-UPDRS. Therefore, a fluctuation over this threshold is considered as an error of the acquisition system.

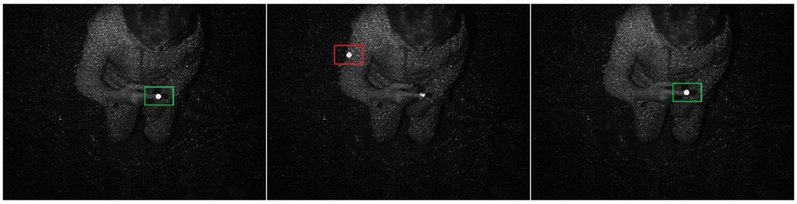

Fig. 6. Example of acquisition: correct tracking (1st and 3rd image) VS tracking error (2nd image)

We designed a SVM classifier [10] to discriminate PD patients from control subjects. SVM is a binary classifier whose goal is to find the best linear decision surface that separates the training features space. SVMs have very good generalization capability because they can be extended in order to separate a space of non-linear input features. Figure 7 shows the performance of our classifier.

(a)

		True Class	
		PD	Controls
Predicted Class	PD	4	0
	Controls	2	11

(b)

		True Class	
		PD	Controls
Predicted Class	PD	4	0
	Controls	1	11

Fig. 7. (a) Confusion Matrix for right hand acquisition (b) Confusion Matrix for left hand acquisition

4 Results

We designed different types of SVM classifiers. However, cubic SVM achieved the best results. To avoid data overfitting, we used 5-fold cross-validation. As the dimension of the dataset is relatively small, we realized multiple tests to obtain more reliable results.

The SVM approach on right hand yielded an average accuracy close to 82%; indeed, for left hand, it yielded an average accuracy close to 89.5%. This showing the existence of a good separation between the two classes for each case. The confusion matrix of the best SVM model is showed in Fig. 7(a) and (b), and the performance indexes are reported in Eqs. (1), (2), and (3):

$$Accuracy_{right} \quad \frac{TP + TN}{TP + TN + FP + FN} = 0.88 \qquad Accuracy_{left} \quad \frac{TP + TN}{TP + TN + FP + FN} = 0.93 \tag{1}$$

$$Sensitivity_{right} \quad \frac{TP}{TP + FN} = 0.66 \qquad Sensitivity_{left} \quad \frac{TP}{TP + FN} = 0.8 \tag{2}$$

$$Specificity_{right} \quad \frac{TN}{TN + FP} = 1 \qquad Specificity_{left} \quad \frac{TN}{TN + FP} = 1 \tag{3}$$

However, due to the low number of instances in the dataset, we suggest to further investigate the reproducibility of our findings.

5 Conclusion

In this paper, we present a novel method to increase objectivity in assessing the severity of Parkinson's disease. Our method is based on the performance in the execution of specific exercises realized by patients during medical examinations. We aim at supporting physicians with quantitative data about patients' movements which, in turn, are an indicator of the severity of the disease. To this end, we extract a dataset consisting of three features involved in the finger-to-nose test, and we leverage SVM to classify healthy subjects and patients. The finding of our evaluation of the method showed an average accuracy of 82% for test on the right hand and an average accuracy of 89.5% for test on the left hand, proving the relevance of selected features. Nevertheless, future work will include detailed investigation of our results in additional studies involving a larger group of subjects. Furthermore, more accurate sensors (e.g., Kinect® v2) might mitigate issues caused by the conditions of the examination environment.

References

1. Berganzo, K., Tijero, B., González-Eizaguirre, A., Somme, J., Lezcano, E., Gabilondo, I., Fernandez, M., Zarranz, J.J., Gómez-Esteban, J.C.: Motor and non-motor symptoms of Parkinson's disease and their impact on quality of life and on different clinical subgroups. Neurología. **31**, 585–591 (2016)
2. Nakamura, T., Nishimura, N., Asahi, T., Oyama, G., Sato, M., Kajimoto, H.: Kinect-based automatic scoring system of TWSTRS-severity. Mov. Disord. **29**, 1–483 (2014)
3. Palacios-Navarro, G., García-Magariño, I., Ramos-Lorente, P.: A kinect-based system for lower limb rehabilitation in Parkinson's disease patients: a pilot study. J. Med. Syst. **39**, 103 (2015). doi:10.1007/s10916-015-0289-0
4. Espay, A.J.: At-home training with closed-loop augmented-reality cueing device for improving gait in patients with Parkinson disease. J. Rehabil. Res. Dev. **47**, 573–582 (2010)
5. Mario, A., Jorge, B., Daniel, M., Pedro, V.: 3D sensors, a new paradigm for assessing Parkinson's disease. Mov. Disord. **30**, 1–703 (2015)

6. Bevilacqua, V., Brunetti, A., Trigiante, G., Trotta, G.F., Fiorentino, M., Manghisi, V., Uva, A.E.: Design and development of a forearm rehabilitation system based on an augmented reality. In: Italian Workshop on Artificial Life and Evolutionary Computation, vol. 587, 127–136. Springer, Cham (2015)
7. Microsoft, cur. Kinect. (2010). https://developer.microsoft.com/en-us/windows/kinect/develop
8. Goetz, C.G., Tilley, B.C., Shaftman, S.R., Stebbins, G.T., Fahn, S., Martinez-Martin, P., Poewe, W., Sampaio, C., Stern, M.B., Dodel, R., Dubois, B., Holloway, R., Jankovic, J., Kulisevsky, J., Lang, A.E., Lees, A., Leurgans, S., LeWitt, P.A., Nyenhuis, D., Olanow, C.W., Rascol, O., Schrag, A., Teresi, J.A., van Hilten, J.J., LaPelle, N.: Movement disorder society-sponsored revision of the unified Parkinson's disease rating scale (MDS-UPDRS): scale presentation and clinimetric testing results. Mov. Disord. **23**, 2129–2170 (2008)
9. Petráš, I., Bednárová, D.: Total least squares approach to modeling: a matlab toolbox. Acta Montanistica Slovaca Ročník **15**(2), 158 (2010)
10. Bevilacqua, V., Pannarale, P., Abbrescia, M., Cava, C., Paradiso, A., Tommasi, S.: Comparison of data-merging methods with SVM attribute selection and classification in breast cancer gene expression. BMC Bioinform. **13**(7), S9 (2012)