An Online System for Tracking the Performance of Parkinson's Patients

Andreas Kuhner[1] Tobias Schubert[1] Christoph Maurer[2] Wolfram Burgard[1]

***Abstract*— An objective performance measure for movement tasks is widely regarded as having utmost relevance for the therapy of movement disorders. Existing systems typically rely on human experts, which is known to produce substantial inter- and intra-rater variability. Present solutions are either based on simple features or invasive motion capture techniques. They typically work on a specific motion task only and fail to generalize to other tasks. In addition, they often require manual offline pre- and post-processing. In this paper we present a novel approach to compute a continuous and objective performance measure online during a patient session, without tedious and time-consuming pre- or post-processing steps. Our approach is able to generalize between different motion capture devices and different motion tasks. It runs on live motion data extracted with a non-invasive marker-less off-the-shelf vision-based tracking system as well as on data extracted from an inertial measurement unit suit. In the experiments we show that our approach is competitive with an offline approach as well as with the Unified Parkinson's Disease Rating Scale. Our approach is robust with respect to motion execution speed and it outperforms the offline approach regarding movement task generalization. We show promising results to track the current state of a Parkinson's subject online during a therapy session.**

I. INTRODUCTION

In the first few years of our life we have tediously learned and optimized first simple and later more and more complex motions. We extended our skill database by additional motion patterns like swimming, biking or dancing. However, the older we get the more of our abilities we lose. Besides other reasons this might be caused by neurological disorders.

In this work we have a closer look at subjects who are influenced by the neurological disorder Parkinson's disease (PD) which typically starts to develop at the age of 60 and can lead to severe motor impairments. However, due to therapy, medication and other interventions, like Deep Brain Stimulation, the quality of life can be improved again. Affected people undergo many therapies which involve continuous performance tracking. The disease progression is currently qualified using various tests like the Unified Parkinson's Disease Rating Scale (UPDRS) [11], where the Parkinson's patients perform full body motion tasks. An expert is measuring the decline in stiffness, smoothness and agility in each limb and body part which creates the UPDRS measure to keep track of the movement capabilities. However, each human expert has a subjective view on each patient due to a distinct experience and diverse knowledge base. The state-of-the-art performance measure in Kuhner *et al.* [8] does not require any human rater and, as such, is objective. The method is capable to distinguish between subjects with and without Parkinson's and gives a real valued performance score. Unfortunately, the algorithm in Kuhner *et al.* [8] requires tedious and time-consuming pre- and post-processing of the motion data. Thus, the therapy process and the progression of Parkinson's disease can not be tracked online. Furthermore, the algorithm does not generalize well to other tasks than walking.

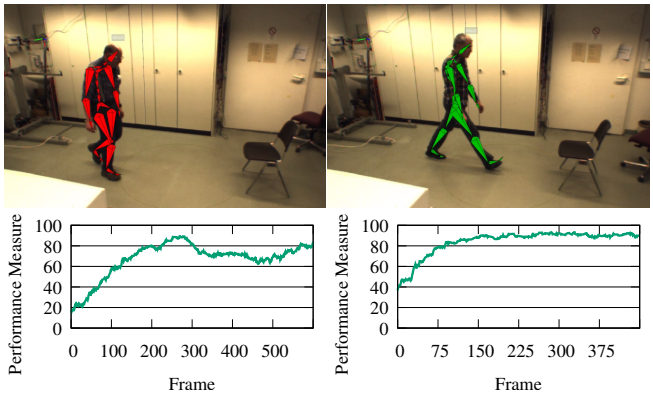

Fig. 1. The commercial The Captury system extracts the trajectory of a subject and our algorithm computes an online performance measure where a high value represents movement similar to a healthy subject. The pictures show the computed skeletons of a Parkinson's patient (left) and a healthy subject (right) in one of the camera frames. The respective graphs below the pictures depict the course of the motion quality during the exercise timed-up-and-go on the way back to the chair.

In this paper we present an online performance measure, which does not require any offline pre- or post-processing of the data and generalizes well over different motion tasks. We developed a system which consists of two parts: In an offline step we train our machine learning algorithm on motion capture data and in the online part we compute the performance measure continuously from a tracked subject. Our experimental evaluation shows, that the trained algorithm produces a reliable measurement score independent of the used motion capture device. We test this with two different motion capture systems, the commercial vision-based marker-less motion capture system Captury Live from The Captury (www.thecaptury.com, [16]) and the XSens motion capture suit.

In Fig. 1 we see a Parkinson's patient (left) and a healthy subject (right) being tracked with Captury Live and their respective live performance measures below each picture.

[1] These authors are with the Department of Computer Science, Albert-Ludwigs University of Freiburg, Germany. [2] This author is with the University Hospital in Freiburg, Germany. This research was supported by the German Research Foundation (DFG, grant number EXC 1086). kuhnera@informatik.uni-freiburg.de

II. RELATED WORK

Online tracking of movement quality is quite complex. Therefore, many studies have been conducted on the feasibility of tracking systems involving a minimal amount of sensors. Gonzáles *et al.* [7] evaluated two systems: The first with two acceleration sensors mounted on the ankles and, the second, an RGB-D camera with 3D pointcloud processing. They compared both systems with the GaitRite electronic walkway. Their aim was to track the inherent gait variability among ten test subjects and found that the inertial units can be competitive while the vision-based system lacks some consistency among subjects. Parisi *et al.* [14] and Chang *et al.* [4] deploy inertial measurement units to extract gait parameters and analyze them with various techniques. Lebel *et al.* [9] focuses on joint orientations and the usability of their raw signal produced by inertial measurement units. By training an artificial neural network on the data of 20 subjects they classified good from bad joint orientation sequences with a sensitivity and specificity above $83\,\%$. All of the just mentioned competitive approaches use a small number of inertial measurement units. In contrast, we deploy full body capture devices to track the skeleton motion of the whole body which enables us to qualify the complete movement and to compute a one dimensional score.

Gait detection is crucial in order to evaluate the state of a subject. Papageorgiou *et al.* [13] tackles this problem with a walker for elderly people equipped with a Hokuyo laser scanner to extract the foot motion. Data combined with a Hidden Markov model enables the estimation of different gait parameters. Altilio *et al.* [1] takes a closer look on feature selection which is important for motion evaluation. They compared multiple machine learning techniques with different feature subsets. Their findings show that step length, swing speed as well as cadence and stride provide non redundant data. Their main focus lies on classification. Our approach is not restricted to gait and proposes a real valued score instead of a binary classification value.

Systems based on inertial measurement units are always obtrusive and a patient might feel restricted. To circumvent this, Cunha *et al.* [5] deploys a Microsoft Kinect to track the movement of a subject to analyze relevant events, which is completely non-invasive. Funaya *et al.* [6] investigates the accuracy of the Microsoft Kinect SDK to apply the device in studies of balance disorders and observes that the precision of the system fulfills the requirements of standard balance tests. Okada *et al.* [12] tries to improve posture among Parkinson's patients while using the Microsoft Kinect for visual feedback. The aim was to increase the bending flexibility in the anterior angle which was achieved with significant improvements. Along that line we developed a system which relies solely on a marker-less vision-based system (Captury Live) to track the motion of a subject through space. This system uses up to 12 RGB Cameras and thus allows to capture complicated motion tasks with occlusions.

III. SYSTEM

Therapists have to continuously rate patients. However, the inter- and intra-rater consistency is not very high due to different knowledge bases. To overcome this limitation we employ a system which tracks a person with a motion capture device and computes an objective performance measure without offline pre- or post-processing of the data.

First, in Sec. III-A we describe the advantages of using a vision-based motion capture device in the context of medical studies. In Sec. III-B we describe the randomized architecture of our algorithm. In Sec. III-C we elaborate on the matching of data from different motion capture devices. Finally, we present the live system which is capable to track the performance quality of a subject.

A. Marker-less Motion Capture System

Typically, patients are burdened with many diagnostic examinations and therapeutic interventions during a hospital stay and, depending on the disease, are weakened due to drug regimens. Hence, a non-invasive system is desirable.

Motion tracking is a wide research field with different approaches. So far, the most promising results came from systems which either use inertial measurement units or attach highly reflective markers to subjects. However, both systems are tedious to set up. For marker-based systems which have been automatized over the last years, see [10, 15], the attachment of markers to patients is still invasive while suit systems require sensors across the whole body.

Marker-less vision-based systems overcome the limitation of the previously mentioned motion capture devices by working on RGB data without the use of any sensor which makes the system less obtrusive.

In this work we use a marker-less vision-based motion capture system. The commercial system from The Captury is a good solution due to its easy setup time and its accuracy allows medical studies. We installed the system in a room to get a tracking volume of roughly $28\,\mathrm{m}^2$ where a patient can execute a couple of exercises like timed-up-and-go, a circular walk and functional reach. After an initialization gesture the subject can easily be tracked. The system uses 12 RGB cameras which run with a frequency of 120 Hz. The setup involves calibrating each single camera (intrinsic calibration), the cameras to each other (extrinsic calibration) and the extraction of the background. Those calibrations can be stored and used later which makes the system perfect for a static hospital environment. A patient steps into the system and, after a short skeleton calibration, one can either record or use the data in an online fashion.

The following section explains the improved performance measure.

B. Randomized Architecture

Therapists of motion disorder diseases track the movement quality state of a patient during motion. However, this introduces inter- and intra-rater variability due to different experience and leads to a subjective opinion. To solve this

challenge we invented an objective performance measure in [8].

In Balasubramanian *et al.* [2] the center out motion task of stroke patients was analyzed with several smoothnes metrics. This includes the Normalized Mean Absolute Jerk, Speed Arc Length, Root Mean Square Jerk, Dimensionless Jerk, Log Dimensionless Jerk and Spectral Arc Length. We use all of them together with the Joint Activity from Kuhner *et al.* [8] which represents the distance between two motion trajectories and combine them using a Random Forest [3] with probability distributions.

Besides, the performance measure should also be applicable for full body motion tasks. It is well known that the structure of a Random Forest and its Decision Trees can heavily influence the generalization capabilities of the algorithm. Hence, we applied two enhancements to the construction of Decision Trees in Kuhner *et al.* [8]. Therein, each Decision Tree received a randomly chosen subset of the training data S, consisting of a randomly chosen subset of features F. To decide which feature was used in a respective node the best separating threshold δ_i^{best} was calculated for all present feature $f_i \in F$ and the overall best feature with the corresponding threshold was chosen. In our approach we change two parts: First, we do not compute the best separating threshold but sample a threshold δ_i^{rand} from a uniform distribution in the range of $[\delta_i^{min}, \delta_i^{max}]$:

$$\delta_i^{rand} \sim \mathcal{U}(\delta_i^{min}, \delta_i^{max}). \tag{1}$$

Second, we choose the feature f_i in a node which maximizes the information gain:

$$IG(S_i) = H(S_i) - \sum_{v \in \{L,U\}} \frac{|M_v|}{|S_i|} \cdot H\left(M_v\right), \tag{2}$$

where S_i is the set of samples of feature f_i and $H(S_i)$ represents the entropy:

$$H(S_i) = -\sum_{c \in C} \frac{|S_i^c|}{|S_i|} \cdot \log \frac{|S_i^c|}{|S_i|}, \tag{3}$$

with the class index $c \in C = \{h, pd\} = \{$healthy, Parkinson's patient$\}$, S_i^c is the set of samples of feature f_i and of class c and M_L, M_U are defined by

$$\begin{aligned} M_L &= \{x < \delta_i | x \in S_i\}, \\ M_U &= S_i \setminus M_L. \end{aligned}$$

In the experiments we show that these changes allow for better generalization and allow to score motions which the algorithm has not seen before.

The following section presents our live system which is capable to track the performance quality of a patient online.

C. Live System

A motion performance measure requires robustness with respect to the used motion capture device. Therefore, we need an automatic pre-processing method which matches motion trajectories from different devices. In the experiments we align data from the vision-based to data from an inertial measurement suit. Anyhow, our alignment is not restricted to data from these devices. The motion data from The Captury is typically noisier than our motion capture suit data. We take this into account through an online smoothing as preprocessing step. We use Gaussian smoothing

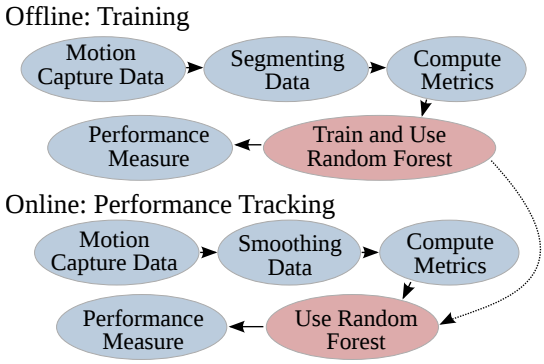

Fig. 2. Offline step: We first use motion capture training data to learn our Random Forest and compute the probability distributions. Online step: After a pre-processing smoothing step, we compute the metrics on the live data, then, propagate the metrics through the trained Random Forest with probability distributions, which leads to the final performance measure.

$$\hat{x}_i = \sum_{j=-N}^{N} w_j x_{i+j}, \tag{4}$$

where x_i is motion data of frame i, N denotes the window size and w_j are normally distributed weights

$$w_j \sim \mathcal{N}\left(0, \sigma^2\right), \tag{5}$$

with standard deviation σ. We optimize the parameters N and σ by comparing motion capture suit data to the vision-based data. Let

$$err_{\sigma,N} = \frac{1}{|X|} \sum_{x \in X} \left| P(\mathbb{S} = h \mid x^{suit}) - P(\mathbb{S} = h \mid \hat{x}_{\sigma,N}^{vis}) \right|, \tag{6}$$

be the error between both systems depending on our performance metric $P(\mathbb{S} = h \mid x)$: The likelihood to be healthy given the motion data. Thereby, X is the set of subject samples. We minimize this term with a breadth search over the parameter space.

In Fig. 2 we see an overview of the system and its two components. First, in the offline step, we compute the Random Forest and its respective probability distributions with segmented timed-up-and-go data from our motion capture suit. A whole sequence of such a try is split into its standing up, forward walking, turning, walking back and sitting down phase. We choose this kind of task because this set of different motion patterns represent everyday movements.

Yet, to avoid any offline pre-processing we do not segment the motion data during the online performance tracking. To compute the current performance we take the last n frames of data, smooth it accordingly and calculate the performance measure. Hence, our performance metric has to generalize sufficiently to deal with distinct motion patterns.

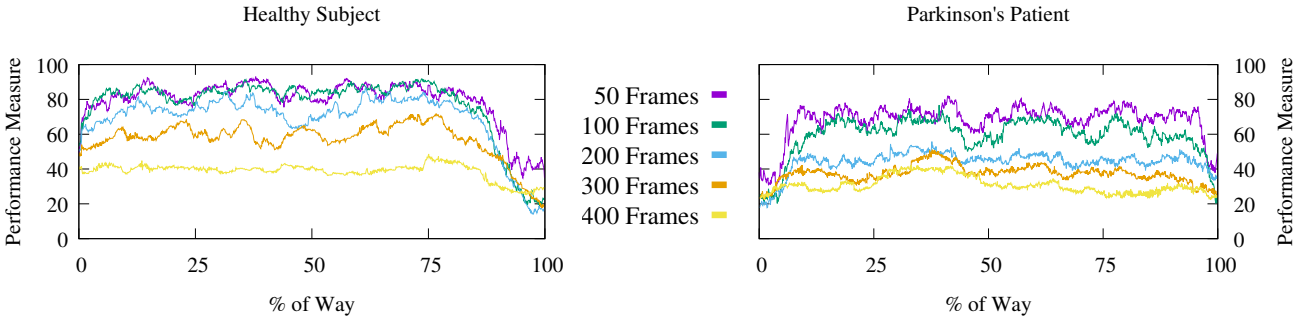

Fig. 3. Performance tracking for a healthy subject (left) and a Parkinson's patient (right). High values correspond to a healthy subject while low values represent Parkinson's patients. Different segment lengths are compared to each other. The test subject does not move during start and end of the motion. Hence, the performance measure drops to low values.

	Healthy	**PD w/o Stim.**	**PD w Stim.**
# of TUG Subjects	25	14	20
# of TUG Data Sets	97	56	137
# of FR Subjects	26	12	19
# of FR Data Sets	26	12	36
# of HC Subjects	26	15	20
# of HC Data Sets	155	81	219

TABLE I. The number of subjects and data sets. We have for each subject at most 4 data sets of a timed-up-and-go (TUG), 6 of a functional reach (FR) and 1 of a hand coordination task (HC). However, Parkinson's patients with stimulation can be present in different stimulation settings and each Parkinson's patient can be both in the stimulated and non-stimulated set. We take for training only the group of healthy subjects and Parkinson's patient without stimulation.

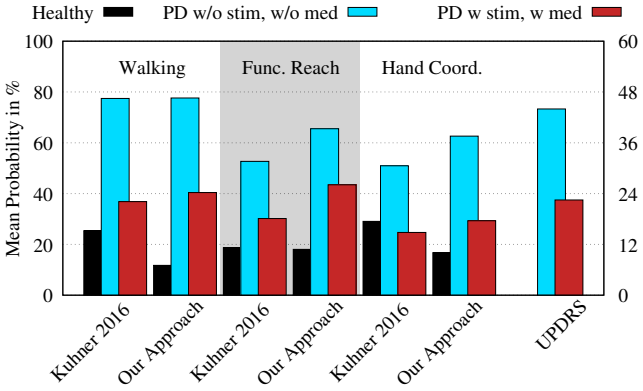

Fig. 4. The graph shows the comparison of Kuhner *et al.* [8] to our approach on the same data set (Table I). We compare three motion tasks (walking, functional reach and hand coordination) and take the mean over all subjects in each group (healthy, Parkinson's patient without stimulation and medication and Parkinson's patient with stimulation and medication). The Unified Parkinson's Disease Rating Scale (UPDRS) verifies our results.

IV. EVALUATION

Our system has two main components. The first one is the offline part where we train our Random Forest with motion capture data. Here, we use data from the motion capture suit because of its higher precision compared to the vision-based system. Our training dataset consists of 59 recording sessions. See Table I for more information. The data from the motion capture suit is first segmented into smaller sequences which represent important everyday movements like standing up, walking, turning or sitting down. These sequences compose the training data on which our Random Forest is finally trained. However, this introduces several challenges for the online part: First, in a pre-processing step, we segment our offline data into sequences while our online data is continuous. Hence, the system has to be robust against different kind of unknown motions. Second, in the case we use live data from the marker-less vision-based system we need to apply the smoothing described in Sec. III-C.

A. Performance Improvement

In the first experiment we compare our approach to Kuhner *et al.* [8] where we enhanced the structure of the Random Forest to better generalize over different motions. In Fig. 4 one sees the comparison. We improved the separation quality in the walking as well as functional reach task and correctly score healthy subjects during the hand coordination task with a lower performance measure than Parkinson's patients with stimulation which Kuhner *et al.* [8] does not.

B. Segment Length

The first challenge to deal with is the used time segment length to compute each metric. In the offline case we have segments of data which represent everyday movements. However, we deploy a live system and continuously track the performance of a subject. Therefore, waiting for a meaningful segment is not applicable. Thus, we compute our performance measure on a fixed time interval.

In this experiment we focus on the optimal segment length. In Fig. 3 we see two example graphs from a healthy subject (left) and a Parkinson's patient (right) with different lengths of segments. Overall, we reach the most promising results with 200 frames which corresponds to the mean segment length of the training samples. Here, the healthy subject reaches a score around 75 while the Parkinson's patient is around 45 which is the biggest gap between both subjects.

This section was about one of three parameters to choose. The next section deals with consistency among different systems. Therein two smoothing parameters are chosen.

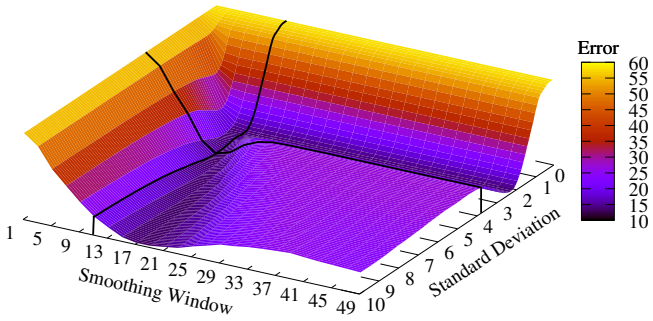

Fig. 5. The graph shows the error reduction through optimized smoothing parameters. Dark colors represent a low error while bright colors depict a high error. The x-axis shows the standard deviation and the y-axis the window size. The error ranges from 10 (dark colors) to 60 (bright colors).

Subject	**Suit Data** $\mu \pm \sigma$	**Vision-Based System** $\mu \pm \sigma$	**Diff.** $\mu \pm \sigma$
H	84.5 ± 3.81	75.4 ± 2.91	9.05 ± 1.11
PD	36.2 ± 1.99	41.2 ± 2.62	5.06 ± 0.67
PD DBS	59.5 ± 1.02	59.3 ± 0.14	0.72 ± 0.17

TABLE II. Evaluation of different motion capture systems: The XSens motion capture suit and the vision-based system The Captury. We compare three subjects. A healthy subject (H) and a Parkinson's patient with (PD DBS, UPDRS of 20) and without (PD, UPDRS of 50) Deep Brain Stimulation. The mean of both systems are close to each other with an overall mean difference of 4.94 and standard deviation of 0.65.

C. Consistency over Different Systems

We deploy two systems to record data: For training we use motion capture suit data due to its higher precision and for live tracking we collect data from a marker-less vision-based system which is less invasive. Typically, this data is noisier than data from the suit. To deal with this challenge we apply a smoothing parameter optimization to transform the data from the vision system into a similar motion capture suit data shape. Fig. 5 shows results of the optimization over the parameter space. We compute the error by comparing simultaneously recorded data from both motion capture suit and vision-based system. Typically, short smoothing windows and low standard deviations generate a high error and lead to an identity function: $x_{post} = x_{pre}$. On the other hand, a high standard deviation and a long smoothing window eliminates each interesting feature of the signal. The best results (black values) were achieved with a standard deviation of $\sigma = 3.8$ and a overall smoothing window length of $11 = 2N + 1$, hence, $N = 5$. In Table II we show the results of a direct comparison between motion capture suit and vision-based system with optimized parameters. The overall mean difference between suit and vision-based system is 4.94 with a standard deviation of 0.65. Summarized, both systems map the current state of a subject to appropriate and similar values without the need to offline pre- or post-process the used data.

The next section describes how the continuous measure compares to segmented data.

Subject	**Seg. Performance** $\mu \pm \sigma$	**Cont. Performance** $\mu \pm \sigma$	**Diff.** $\mu \pm \sigma$
H1	90.4 ± 1.01	90.2 ± 0.56	1.23 ± 0.42
H2	89.7 ± 0.98	85.5 ± 0.83	4.21 ± 0.98
H3	83.7 ± 1.57	82.3 ± 2.89	1.34 ± 1.33
H4	86.7 ± 1.98	90.2 ± 0.77	3.52 ± 1.53
PD1	44.5 ± 3.02	50.1 ± 2.86	5.62 ± 0.65
PD1	59.8 ± 2.96	55.2 ± 10.1	7.21 ± 3.36
PD2	39.6 ± 2.23	53.6 ± 1.68	14.0 ± 3.23
PD2 DBS	74.5 ± 2.11	78.2 ± 1.67	3.74 ± 1.23

TABLE III. Performance measure of various subjects from segmented data as well as continuous data. All values are in the interval $[0, 100]$ where 0 represents a very bad Parkinson's patient and 100 a healthy subject. H1 to H4 represent healthy subjects while PD1 and PD2 are Parkinson's patients.The UPDRS of the first day for PD1 is unknown. At the second day the patient had an UPDRS score of 51.5. PD2 was measured once with stimulation (PD2 DBS, UPDRS 20) and one time without (PD2, UPDRS 50), where both measurement were taken within 20 min. Shown are mean and standard deviation values of the performance and difference between segmented and continuous data.

D. Segmented Data vs. Continuous Data

In an offline scenario one can manually pre-process data to find interesting segments like standing up or walking. In the online case we have to continuously compute the performance measure on data generated in the last few seconds. As shown in Sec. IV-B, $n = 200$ is a suitable number of back-tracked frames. We recorded the exercise timed-up-and-go which consists of different everyday movements where the continuous data starts with standing up and ends with sitting down. In between, we calculate a continuous performance measure and, to compare both variants with each other, take mean and standard deviation from both. Table III shows the results. The difference between segmented and continuous data is smaller for healthy subjects than Parkinson's patients. Overall, we have a mean error of 5.1 with a standard deviation of 4.2. The performance measure is in both cases verifiable through the UPDRS where low UPDRS values correspond to high values of our performance measure.

E. Performance Measure Robustness

In the following we want to show that our proposed performance measure is robust to the variance in the movement execution. Therefore, we ask the subjects to increase their movement speed during a circular walk. We can show that the performance score is not only influenced by changes in speed, which is an important aspect in the diagnoses of Parkinson's disease, but by other features as well. Fig. 6 shows the performance and speed change. We see that increasing the speed increases the performance measure as well. However, even while walking at the same speed the healthy person has a higher score compared to the Parkinson's patient. Fig. 7 shows the same results. We removed the start and end segment to avoid data without movement. Parkinson's patients have a lower score even with the same mean speed. In the overlapping region between 0.8 m/s and 0.95 m/s, healthy subjects get roughly a score of 82 while Parkinson's subjects get roughly a value of 70.

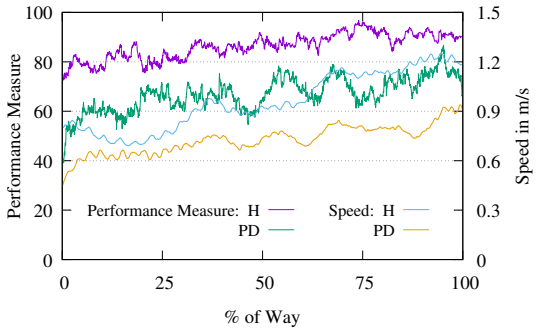

Fig. 6. The robustness of our score compared to mean speed. The left side shows our performance measure (purple, green curve) while the right side corresponds to mean speed in m/s (blue, orange curve).

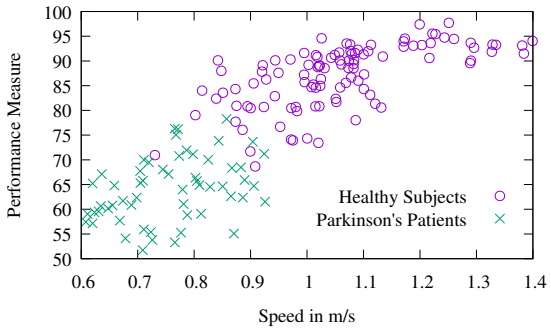

Fig. 7. The graph shows the performance measure plotted against the mean speed. Purple circles represent healthy subjects and green crosses Parkinson's patients.

The results show that we can transfer data from the vision-based system to the motion capture suit and that the system can compute a live and continuous performance measure.

V. CONCLUSIONS

In this paper we proposed a novel live system without tedious and time-consuming pre- or post-processing of data to objectively track the performance of Parkinson's patients. Our approach is able to generalize over different motion tasks and motion capture devices. In the experiments we show that we can track the current state of a Parkinson's subject online during a therapy session. This is a further step towards a closed loop system to adjust parameters of a deep brain stimulator for Parkinson's patients which, well tuned, improves the motion abilities to a former state.

ACKNOWLEDGMENT

The authors thank Sabine Ahrendt for a steady stream of Parkinson's patients.

REFERENCES

[1] R. Altilio, M. Paoloni, and M. Panella. Selection of clinical features for pattern recognition applied to gait analysis. *Medical & Biological Engineering & Computing*, pages 1–11, 2016.

[2] S. Balasubramanian, A. Melendez-Calderon, and E. Burdet. A robust and sensitive metric for quantifying movement smoothness. *IEEE Transactions on Biomedical Engineering*, 59(8):2126–2136, 2012.

[3] L. Breiman. Random forests. *Machine learning*, 45(1):5–32, 2001.

[4] H.-C. Chang, Y.-L. Hsu, S.-C. Yang, J.-C. Lin, and Z.-H. Wu. A wearable inertial measurement system with complementary filter for gait analysis of patients with stroke or parkinson's disease. *IEEE Access*, 4:8442–8453, 2016.

[5] J. P. S. Cunha, A. P. Rocha, H. M. P. Choupina, J. M. Fernandes, M. J. Rosas, R. Vaz, F. Achilles, A. M. Loesch, C. Vollmar, E. Hartl, et al. A novel portable, low-cost kinect-based system for motion analysis in neurological diseases. In *Proceedings of 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 2339–2342, 2016.

[6] H. Funaya, T. Shibata, Y. Wada, and T. Yamanaka. Accuracy assessment of kinect body tracker in instant posturography for balance disorders. In *7th International Symposium on Medical Information and Communication Technology (ISMICT)*, pages 213–217, 2013.

[7] I. González, I. H. López-Nava, J. Fontecha, A. Muñoz-Meléndez, A. I. Pérez-SanPablo, and I. Quiñones-Urióstegui. Comparison between passive vision-based system and a wearable inertial-based system for estimating temporal gait parameters related to the gaitrite electronic walkway. *Journal of Biomedical Informatics*, 62:210–223, 2016.

[8] A. Kuhner, T. Schubert, M. Cenciarini, C. Maurer, and W. Burgard. A probabilistic approach based on random forests to estimating similarity of human motion in the context of parkinson's disease. In *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 1851–1856, 2016.

[9] K. Lebel, P. Boissy, H. Nguyen, and C. Duval. Autonomous quality control of joint orientation measured with inertial sensors. *Sensors*, 16(7):1037, 2016.

[10] J. Meyer, M. Kuderer, J. Müller, and W. Burgard. Online marker labeling for fully automatic skeleton tracking in optical motion capture. In *Proceedings of IEEE International Conference on Robotics and Automation (ICRA)*, pages 5652–5657, 2014.

[11] Movement disorder society task force on rating scales for Parkinson's disease. The Unified Parkinson's Disease Rating Scale (UPDRS): status and recommendations. *Movement disorders: official journal of the Movement Disorder Society*, 18(7):738, 2003.

[12] Y. Okada, T. Shibata, T. Tamei, Y. Orito, H. Funaya, C. Obayashi, K. Ikeda, M. Hiyamizu, and S. Morioka. In-home posture evaluation and visual feedback training to improve posture with a kinect-based system in parkinson's disease: A case study. *Movement Disorders*, 29:256, 2014.

[13] X. S. Papageorgiou, G. Chalvatzaki, K.-N. Lianos, C. Werner, K. Hauer, C. S. Tzafestas, and P. Maragos. Experimental validation of human pathological gait analysis for an assisted living intelligent robotic walker. In *Proceedings of 6th IEEE International Conference on Biomedical Robotics and Biomechatronics (BioRob)*, pages 1086–1091, 2016.

[14] F. Parisi, G. Ferrari, M. Giuberti, L. Contin, V. Cimolin, C. Azzaro, G. Albani, and A. Mauro. Inertial bsn-based characterization and automatic updrs evaluation of the gait task of parkinsonians. *IEEE Transactions on Affective Computing*, 7(3):258–271, 2016.

[15] T. Schubert, K. Eggensperger, A. Gkogkidis, F. Hutter, T. Ball, and W. Burgard. Automatic bone parameter estimation for skeleton tracking in optical motion capture. In *Proceedings of IEEE International Conference on Robotics and Automation (ICRA)*, pages 5548–5554, 2016.

[16] C. Stoll, N. Hasler, J. Gall, H.-P. Seidel, and C. Theobalt. Fast articulated motion tracking using a sums of gaussians body model. In *Proceedings of IEEE International Conference on Computer Vision (ICCV)*, pages 951–958, 2011.