Gait Recognition with Smart Devices Assisting Postoperative Rehabilitation in a Clinical Setting

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***Abstract*—Postoperative rehabilitation is a vital program that re-establishes joint motion and strengthens the muscles around the joint after an orthopedic surgery. This kind of rehabilitation is led by physiotherapists who assess each situation and prescribe appropriate exercises. Modern smart devices have affected every aspect of human life. Newly developed technologies have disrupted the way various industries operate, including the healthcare one. Extensive research has been carried out on how smartphone inertial sensors can be used for activity recognition. However, there are very few studies on systems that monitor patients and detect different gait patterns in order to assist the work of physiotherapists during the said rehabilitation phase, even outside the time-limited physiotherapy sessions, and therefore literature on this topic is still in its infancy. In this paper, we are presenting a gait recognition system that was developed to detect different gait patterns including walking with crutches with various levels of weight-bearing, walking with different frames, limping and walking normally. The proposed system was trained, tested and validated with data of people who have undergone lower body orthopedic surgery, recorded by Hirslanden Clinique La Colline, an orthopedic clinic in Geneva, Switzerland. A gait detection accuracy of 94.9% was achieved among nine different gait classes, as these were labeled by professional physiotherapists.**

***Keywords*—Activity recognition, feature extraction, machine learning, pattern recognition, smart devices, wearable computers, wearable sensors.**

I. Introduction and Related Work

The role of physiotherapy following an orthopedic surgery is to assist the patient return to normal activities of daily living. Doctors and physiotherapists help the patient achieve this by prescribing suitable exercises that will establish the rehabilitation goals. There is a significant body of evidence coming from systematic reviews and controlled trials that dictate the best practices in physiotherapy [1]. Proper evaluation guarantees the effectiveness of physiotherapy [2] for a wide variety of medical conditions, including recovering after a lower body orthopedic operation.

Gait refers to a person's manner of walking and is influenced by age, personality, mood and sociocultural factors [3]. Several reasons including a lower body operation may lead to either temporary or permanent gait disorders. Any such disorder is typically thoroughly investigated by the physiotherapist who then suggests a specific treatment to the patient. There are various tools at the disposal of the physiotherapists, and many robotic solutions are being created in order to help people walk or to act as an aid during a physiotherapy session [4]. These robot-assisted gait solutions may be used as an excellent companion to conventional therapy and improve the independence and the gait capacity of the patient [5].

Activity recognition (AR) has emerged as a key research domain in computer science. The approaches for AR can be roughly divided into two categories: the camera-based ones [6], where gestures and activities are inferred from still images or videos using computer vision techniques, and the inertial sensor-based ones, where one or more body-worn sensors are used [7]. Any AR system includes many variables such as the definition of the classes of interest, the experiment design, the sensors, the data handling procedure and the performance evaluation. These variable components can be implemented in a variety of ways [8] having an impact on the overall performance of the system.

The increased availability of inertial sensors due to the omnipresence of smartphones and particularly smartwatches has enabled AR to become an essential context-awareness tool for mobile and ubiquitous computing. Sensors in modern consumer electronics provide reasonably accurate recordings when compared to research monitors [9]. This is why these devices prove to have clinical utility, although they continue to be underutilized in the healthcare industry [10].

Besides recognizing daily activities, inertial sensors have been used in gait pattern analysis. In most studies accelerometers are attached to the legs or feet, but gait patterns can be also extracted from data recorded from sensors attached to the upper body [11]. Common smartphone accelerometers have been used to detect different gait events [12]. In a similar manner, smartwatches that contain inertial sensors can be used for gait recognition. Unlike smartphones, smartwatches tend to be worn in the same location and the same orientation and can be even used for gait-based biometrics based on the accelerometer and the gyroscope data [13].

Various recovery programs have been developed to improve the recovery time after surgery [14]. Wireless monitoring of mobility after a major operation has the potential of improving services provided by healthcare professionals [15]. With the

This work was supported by the Commission for Technology and Innovation CTI, of the Swiss federal government, (CTI grant 18566.2 PFES-ES) in the frame of the Recover@home project.

TABLE I
CLASSIFICATION OF GAIT PATTERNS FOR RECOGNITION

Category	Class
No aid	Limping Walking
Crutches	Unladen Rolled out Laden 10kg Laden 20kg According to pain
Frame	Without wheels With wheels

proposed system, we incorporate smartwatches into the routine care of patients who have undergone a lower body operation in order to monitor their gait patterns. Doing so will enhance the patient-physiotherapist relationship, respect the patients' autonomy regarding their healthcare and provide a remote monitoring solution to the physiotherapist in charge.

The rest of the paper is organized as follows. In Section II we discuss the system that we have developed. We present the data acquisition tools, the features that we engineer for machine learning and the classifiers that we train. In Section III we present the experiment that we have conducted and we evaluate the performance of the overall system. Finally, we conclude our work in Section IV.

II. SYSTEM OVERVIEW

1) Gait Classification: The physiotherapists of Hirslanden Clinique La Colline, an orthopedic clinic in Geneva, Switzerland, compiled a list of the gait patterns of interest to our system. The patterns include walking with crutches with various levels of weight-bearing, walking with different frames, limping and walking normally. Table I includes the list of all the 9 gait patterns that our system should detect.

2) Workflow: The developed system comprises three components, the smartwatch, the smartphone and the web server. Fig. 1 presents the flow of data in the proposed system. The system is meant to be used during the rehabilitation phase, the time that the patient is undergoing physiotherapy, of someone that has had a lower body surgery. During physiotherapy sessions in the clinic, any patient is walking while wearing a smartwatch that tracks wrist movements. At the same time, the physiotherapist is labeling on a smartphone any physiotherapy session with the observed gait pattern of the patient. All these data from multiple patients and physiotherapy sessions are uploaded to the web server, where a user-independent machine learning model is trained.

During everyday life, through the rehabilitation phase, the patient is wearing a given smartwatch. Throughout the day, the smartwatch is passively recording gait sessions of unknown gait patterns when the patient is moving. These recordings are uploaded from the smartwatch to the web server. Using the trained machine learning model, those new recordings are classified into the predefined gait patterns. Using the web server, the physiotherapists can monitor how each patient's gait pattern is evolving, even between physiotherapy sessions.

3) System Implementation: Wrist movements of the patients are recorded using the three-axis accelerometer and the three-axis gyroscope of an Android smartwatch running Wear OS. The accelerometer sensor provides a three-dimensional vector representing acceleration along each device axis, excluding gravity. The gyroscope sensor measures the angular velocity of each axis of the device. Recordings can be made either on-demand during a physiotherapy session when the physiotherapist can provide the ground truth with the observed gait pattern, or by transparently monitoring the movement of the user throughout the day and saving only sessions where prolonged movement or steps are identified.

At the end of every on-demand recording, sensor data are sent from the smartwatch to the connected Android smartphone. The smartphone is used by physiotherapists to label each recording during a physiotherapy session with the identified gait pattern. The recordings that are produced during the monitoring phase of the system during the whole rehabilitation program, naturally have no ground truth label and are directly sent from the patient's smartwatch to the web server.

Every recording is saved to the web server. On every upload of a new recording, the web server is extracting the features that will be later used for machine learning. Training of the selected user-independent machine learning classifier is run periodically when enough new labeled recordings from multiple users have been obtained. On the other hand, the server exposes an API with which the unknown gait patterns of the non labeled recordings can be predicted. The physiotherapist can query the server in order to monitor what is the dominant detected gait pattern of a specific time and how it evolves during the rehabilitation program.

4) Feature Engineering: The accelerometer and the gyroscope sensors of the smartwatch that we have used did not provide a constant sampling rate throughout the recordings. This is why the raw sensor data were resampled with a constant sampling frequency of 60 Hz. This frequency was selected for this study as it is higher than the 20 Hz commonly required to assess daily living [16] and also lower than what typical off-the-shelf inertial measurement unit components can achieve. Features forming the feature vector used for machine learning were derived from these time series data.

Both time and frequency domain features were computed for both sensors over a selected time window. The time domain features include the mean, the standard deviation, the median, the skewness, the kurtosis, the 25th and the 75th percentile, and the squared sum of the components under the 25th and the 75th percentile. Those were derived from the resultant vector computed by the three, x, y and z, components that each sensor provides.

For the frequency domain features, a Fast Fourier Transform (FFT) was performed after normalization on the windows, and the features were computed per axis. Those features include the maximum frequency, the sum of heights of frequency components below 5 Hz and the number of peaks in the spectrum below 5 Hz, as it was noticed that most of the signal

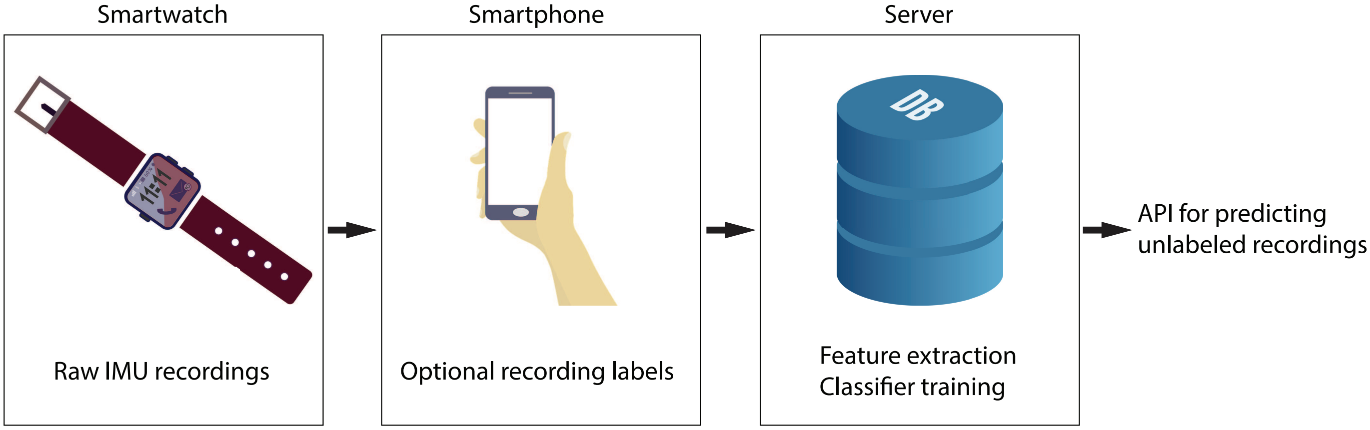

Fig. 1. Summary of the implementation of the gait recognition system.

TABLE II
EXTRACTED FEATURES PER SENSOR USED IN MACHINE LEARNING

Domain	Features	No of features
Time (resultant vector)	Mean Standard deviation Median Skewness Kurtosis 25th percentile 75th percentile Sq. sum of < 25th perc. Sq. sum of < 75th perc.	9
Frequency (per axis)	Maximum frequency Sum of 5 Hz Number of peaks	9

strength lied between 0-5 Hz. The selection of the features was based on a feature importance analysis presented in a previous work of ours [8]. All the features extracted for this study are summarized in Table II.

III. Experiment and Evaluation

Physiotherapists of the Hirslanden Clinique La Colline recorded wrist movements of patients walking soon after they have undergone a lower body orthopedic surgery. During all recordings, the physiotherapist was in close proximity to the patient, in order to guarantee the correct ground truth annotation and the cleanliness of the data. In total, 48 recordings from 33 different patients were made over a period of 4 months. The recordings amount to a total time of 155 minutes of labeled gait patterns.

The classifiers that we have evaluated are Light Gradient Boosting Machine (LGBM) [17], Logistic Regression (LR), Support Vector Machines (SVM), Random Forest (RF), Decision Tree (DT), Extra Trees (ET) and k-Nearest Neighbours (kNN). Each recording is segmented into multiple time windows. The features were computed over a time window of 5s with a step size of 1s, so there was a 4s overlap between consecutive windows. This value for the time window was identified in a previous work of ours [8] as a good candidate since it is large enough to contain useful information regarding

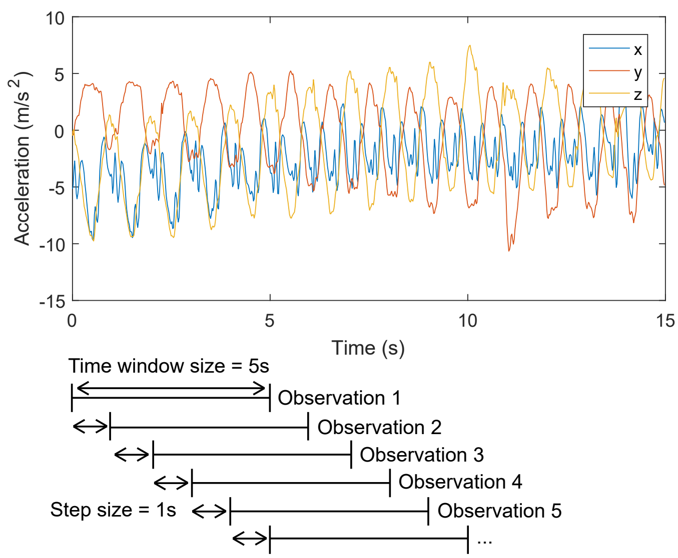

Fig. 2. An example of the segmentation of a data recording.

the activity and small enough to increase the number of the produced segments during segmentation. The segmentation of any given recording is depicted in Fig. 2. The constructed dataset contained in total 9089 observations.

Unfortunately, the acquired dataset was imbalanced. The reasons were either lack of availability of patients with a gait pattern belonging to one of the minority classes or no consent from the patient. Fig. 3 presents the observation count of the available dataset. To cope with the problem of the imbalanced dataset and to optimize the performance of the classification algorithms, the random minority over-sampling with replacement method was used [18].

We have used Matlab for feature extraction and Python and the Scikit-learn module [19] for machine learning. To evaluate the performance of our system, we split the available dataset into a training set (80%) and a test set (20%) in a stratified fashion. The minority classes of the training set were randomly over-sampled with replacement. The 10-fold cross-

TABLE III
CONFUSION MATRIX AND PERFORMANCE METRICS OF THE LGBM CLASSIFIER

		Predicted class									Precision	Recall	F1-score
		L	W	CU	CRU	CL10kg	CL20kg	CP	FN	FW			
True class	Limping (L)	155	0	0	0	0	0	5	0	0	0.981	0.969	0.975
	Walking (W)	3	66	0	0	0	0	8	0	0	0.971	0.857	0.91
	Crutches unladen (CU)	0	0	36	0	0	1	0	0	0	1	0.973	0.986
	Crutches rolled out (CRU)	0	0	0	43	1	2	5	0	0	1	0.843	0.915
	Crutches laden 10kg (CL10kg)	0	0	0	0	81	3	14	0	0	0.976	0.827	0.895
	Crutches laden 20kg (CL20kg)	0	0	0	0	0	377	23	0	0	0.938	0.943	0.94
	Crutches pain (CP)	0	2	0	0	1	19	899	0	0	0.937	0.976	0.956
	Frame without wheels (FN)	0	0	0	0	0	0	6	44	0	1	0.88	0.936
	Frame with wheels (FW)	0	0	0	0	0	0	0	0	24	1	1	1

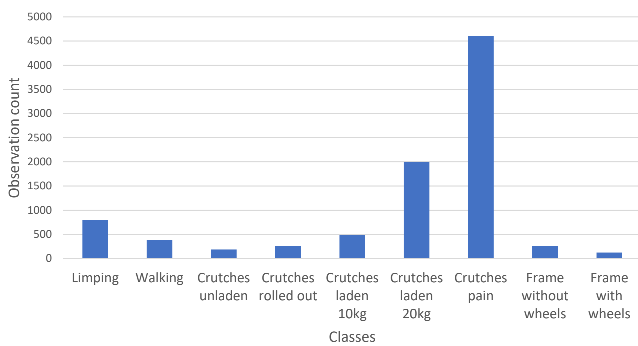

Fig. 3. Observation count of the available dataset of all gait pattern classes.

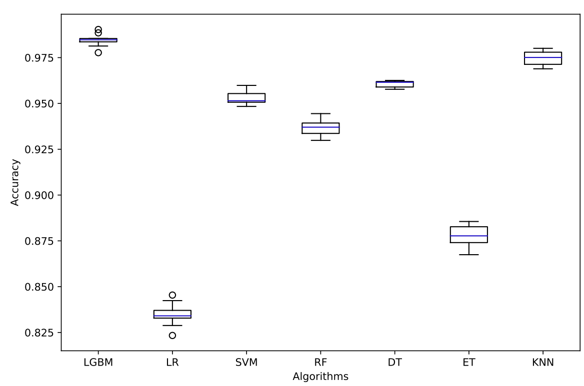

Fig. 4. Box plot of multiple classifiers trained for gait recognition.

validation scheme was used on the training set to train the model, the performance of which was evaluated on the test set. Fig. 4 presents the box plot for all trained classifiers. Different classifiers naturally perform differently. This is due to the nature of the problem, the characteristics of the dataset and the capacity of each classifier in terms of the variety of functions it can fit. Table III presents the confusion matrix for the LGBM classifier, the best performing classifier.

We have achieved an accuracy of 94.9% with the LGBM classifier on the previously unseen test set. From the confusion matrix, it is worth noting that the misclassified observations belonging to one of the crutches classes were most of the times predicted to belong to another crutches class. Although misclassified per se, these kinds of observations may still provide physiotherapists useful information regarding the gait patterns of the patients.

IV. CONCLUSION

This paper presented a machine learning based, gait recognition system that assists physiotherapists with the postoperative rehabilitation phase of patients who have undergone a lower body operation. The architecture of the system comprising a smartwatch, a smartphone, and a web server was presented. The performance of the system was validated with labeled data recorded by physiotherapists of the Hirslanden Clinique La Colline, an orthopedic clinic in Geneva, Switzerland. Gait patterns of patients were recorded soon after they have undergone various types of a lower body operation. The predicted performance of the system reached an accuracy of 94.9% with the best performing classifier among nine different gait classes. The innovation of the proposed system lies in the fact that it enables physiotherapists to monitor the evolution of the gait pattern of a patient under rehabilitation, throughout the day and not only during the defined and time-limited physiotherapy sessions.

ACKNOWLEDGMENT

The authors would like to thank the Hirslanden Clinique La Colline, an orthopedic clinic in Geneva of Switzerland and especially the physiotherapists' team for being responsible for the acquisition of gait pattern data that were used to evaluate our system.

REFERENCES

[1] A. M. Moseley, R. D. Herbert, C. Sherrington, and C. G. Maher, "Evidence for physiotherapy practice: a survey of the physiotherapy evidence database (pedro)," *Australian Journal of Physiotherapy*, vol. 48, no. 1, pp. 43–49, 2002.

[2] C. G. Maher, C. Sherrington, R. D. Herbert, A. M. Moseley, and M. Elkins, "Reliability of the pedro scale for rating quality of randomized controlled trials," *Physical therapy*, vol. 83, no. 8, pp. 713–721, 2003.

[3] W. Pirker and R. Katzenschlager, "Gait disorders in adults and the elderly," *Wiener Klinische Wochenschrift*, vol. 129, no. 3-4, pp. 81–95, 2017.

[4] C. T. Valadao, F. Loterio, V. Cardoso, T. Bastos, A. Frizera-Neto, and R. Carelli, "Robotics as a tool for physiotherapy and rehabilitation sessions," *IFAC-PapersOnLine*, vol. 48, no. 19, pp. 148–153, 2015.

[5] M. Belas dos Santos, C. Barros de Oliveira, A. dos Santos, C. Garabello Pires, V. Dylewski, and R. M. Arida, "A comparative study of conventional physiotherapy versus robot-assisted gait training associated to physiotherapy in individuals with ataxia after stroke," *Behavioural neurology*, vol. 2018, 2018.

[6] R. Bodor, B. Jackson, and N. Papanikolopoulos, "Vision-based human tracking and activity recognition," in *Proc. of the 11th Mediterranean Conf. on Control and Automation*, vol. 1, 2003.

[7] L. Bao and S. S. Intille, "Activity recognition from user-annotated acceleration data," in *International Conference on Pervasive Computing*. Springer, 2004, pp. 1–17.

[8] A. I. Kyritsis, M. Deriaz, and D. Konstantas, "Considerations for the design of an activity recognition system using inertial sensors," in *2018 IEEE 20th International Conference on e-Health Networking, Applications and Services (Healthcom) (IEEE Healthcom 2018)*, Ostrava, Czech Republic, Sep. 2018.

[9] Y. Bai, G. J. Welk, Y. H. Nam, J. A. Lee, J.-M. Lee, Y. Kim, N. F. Meier, and P. M. Dixon, "Comparison of consumer and research monitors under semistructured settings." *Medicine and science in sports and exercise*, vol. 48, no. 1, pp. 151–158, 2016.

[10] G. Appelboom, E. Camacho, M. E. Abraham, S. S. Bruce, E. L. Dumont, B. E. Zacharia, R. DAmico, J. Slomian, J. Y. Reginster, O. Bruyère *et al.*, "Smart wearable body sensors for patient self-assessment and monitoring," *Archives of Public Health*, vol. 72, no. 1, p. 28, 2014.

[11] M. Yang, H. Zheng, H. Wang, S. McClean, and D. Newell, "igait: an interactive accelerometer based gait analysis system," *Computer methods and programs in biomedicine*, vol. 108, no. 2, pp. 715–723, 2012.

[12] H. K. Chan, H. Zheng, H. Wang, R. Gawley, M. Yang, and R. Sterritt, "Feasibility study on iphone accelerometer for gait detection," in *Pervasive Computing Technologies for Healthcare (PervasiveHealth), 2011 5th International Conference on*. IEEE, 2011, pp. 184–187.

[13] A. H. Johnston and G. M. Weiss, "Smartwatch-based biometric gait recognition," in *Biometrics Theory, Applications and Systems (BTAS), 2015 IEEE 7th International Conference on*. IEEE, 2015, pp. 1–6.

[14] A. Nicholson, M. Lowe, J. Parker, S. Lewis, P. Alderson, and A. Smith, "Systematic review and meta-analysis of enhanced recovery programmes in surgical patients," *BJS*, vol. 101, no. 3, pp. 172–188, 2014.

[15] D. J. Cook, J. E. Thompson, S. K. Prinsen, J. A. Dearani, and C. Deschamps, "Functional recovery in the elderly after major surgery: assessment of mobility recovery using wireless technology," *The Annals of thoracic surgery*, vol. 96, no. 3, pp. 1057–1061, 2013.

[16] C. V. Bouten, K. T. Koekkoek, M. Verduin, R. Kodde, and J. D. Janssen, "A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity," *IEEE Transactions on Biomedical Engineering*, vol. 44, no. 3, pp. 136–147, 1997.

[17] G. Ke, Q. Meng, T. Finley, T. Wang, W. Chen, W. Ma, Q. Ye, and T.-Y. Liu, "Lightgbm: A highly efficient gradient boosting decision tree," in *Advances in Neural Information Processing Systems*, 2017, pp. 3146–3154.

[18] G. Lemaître, F. Nogueira, and C. K. Aridas, "Imbalanced-learn: A python toolbox to tackle the curse of imbalanced datasets in machine learning," *Journal of Machine Learning Research*, vol. 18, no. 17, pp. 1–5, 2017. [Online]. Available: http://jmlr.org/papers/v18/16-365

[19] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg *et al.*, "Scikit-learn: Machine learning in python," *Journal of machine learning research*, vol. 12, no. Oct, pp. 2825–2830, 2011.