A Comparison of Inertial Data Acquisition Methods for a Position-Independent Soil Types Recognition

Florentin Thullier*, Valère Plantevin*, Abdenour Bouzouane*, Sylvain Hallé† and Sébastien Gaboury*
*LIARA Laboratory, Department of Computer Science and Mathematics,
Université du Québec à Chicoutimi, Chicoutimi, Québec, Canada
$Emails$: $\{florentin.thullier1, valere.plantevin1, abdenour\_bouzouane, sebastien\_gaboury\}$ $@uqac.ca$
†LIF Laboratory, Department of Computer Science and Mathematics,
Université du Québec à Chicoutimi, Chicoutimi, Québec, Canada
$Email$: $shalle@uqac.ca$

***Abstract*—In a previous work, we presented a method to recognize different soil types based on inertial data generated by a user's gait through a wearable device. Although results we have obtained were encouraging, we judged that this method needed further evaluation. Thus, this paper aims at comparing our previous approach between several acquisition methods. The device was upgraded to a 9-axis IMU and a comparison of this wearable with a mobile phone was also offered. Both the features processing and the classification phases remain unchanged from our previous work to perform a proper comparison. Although this evaluation let us expose a slight improvement in the recognition rate, it allowed us to prove the reliability of our device since the performance obtained with the mobile phone was similar.**

***Index Terms*—Soil Types, Recognition, Wearable Object, Mobile Device, IMU, Position-Independent**

I. Introduction & Related Work

In the past few years, brand manufacturers have pushed the wearable technology in the forefront of the consumer electronics scene. As a result, in 2014, there was 15% of mobile devices users employing a wearable device in their daily lives [1]. These devices have, first, brought more sensors than the ones already embedded in current smartphones. Moreover, the increasing use of the Bluetooth Low Energy (BLE) technology [2] allowed a more efficient communication with mobile devices as regards energy consumption. In that sense, wearable devices become widely adopted in order to track activities since they present a convenient and portable way to record physiological data produced by their users. Hence, a considerable amount of data is collected each day and several statistical analyses are offered for monitoring carriers' daily activities [3]. Besides, according to recent advancements in machine learning, it is possible to say that existing activity tracking applications may be enhanced to become more ubiquitous.

The idea of recognizing soil-type, also known as terrain classification, through data produced by an accelerometer, firstly comes from the mobile robotics area. First of all, Vail and Veloso [4] experimented a surface detector using inertial data generated by a four-legged robot. Authors opted for a C4.5 decision tree, and they obtained an overall accuracy of 84.9% over a 10-fold cross-validation method.

Additionally, Bibuli *et al.* [5] suggested a terrain classification method for a four-wheels mobile robot equipped with several sensors, including inertial ones. Their artificial neural network trained with Discrete Fourier Transform components achieved at best an overall recognition rate of 82.7% for the x-axis of the gyroscope.

In the same way, Weiss *et al.* [6] proposed a comparison of terrain recognition for a four-wheeled robot between the Support Vector Machine (SVM) and several other classification techniques. Input data for the SVM algorithm were either a log-scaled Power Spectral Density, or a 128-point Fast Fourier Transform (FFT) features vector. Authors performed the experiment over different velocities of the robot (*i.e.* 0.2, 0.4 and 0.6 m/s) and they obtained most accurate results with SVM rather than other algorithms, such as Probabilistic Neural Network, k-Nearest Neighbors (k-NN), Naïve Bayes and C4.5.

Conversely, Kertész [7] recently introduced a rigidity-based surface recognition for a four-legged robot using features extracted through the FFT, then, classified with the Random Forest (RF) algorithm. Through a 10-folds cross validation method authors have obtained an accuracy of 96.2%.

Although such a related literature was relevant in understanding how to answer hypotheses we formulated, all of these methods are not suitable for soil-types-recognition in a human-walking context. However, such an idea may also be employed with human beings since several use cases of terrain classification in this context are noticeable to us. For example, we can mention the annotation of every subset of a full GPS trace with a given type of soil for hikers. Another example is related to health since such a recognition may be employed for fall prevention since it is known that it exists more risks when people are walking on certain types of soil. Based in such a postulate, a recent study suggested by Otis *et al.* [8] introduced a terrain discrimination analysis to reduce the risk of falling through a three-axis accelerometer embedded in a shoe. A clustering algorithm was employed in order to segment FFT-based discriminating features. This work claims a misidentification rate between 1% and 5% in a laboratory setup, while it rose up to 20% in real conditions.

The rest of the paper is structured as follows: section 2 details the suggested method for soil type recognition. Next, section 3 describes experiments we conducted. Section 4 and Section 5 expose and discuss results we obtained. Finally, section 6 draws a conclusion and provides future works.

II. Proposed Solution

A. Wearable Device

In order to test our approach and record several datasets, we have conserved the design of the wearable device introduced in [9]. It is based on the the *Arduino 101* board, with a dedicated proto-shield providing a SD card slot, on which a new 9-axis IMU (*LSM9DS1*) has been installed. Our decision in conserving this design was motivated, at first, by the capability of the *Arduino* board to communicate through BLE since it is embedded in many smartphones [2] and it offers a very low power consumption [10]. Secondly, this board offers a large amount of I/O that allows interfacing other hardware. Our custom firmware embedded on the device remains unchanged except that a computation process of the Euler angles was included in the *dataset formatting module*. The inertial data were further obtained at a stable frequency of 60 Hz.

B. Mobile Device

To compare our wearable device with a mobile phone, a dedicated application was developed to record the values of the embedded 9-axis IMU. Such a record was achieved on a *Huawei Nexus 6P* running *Android* 8.0 and a stable frequency of 60 Hz was also set for this setup. As for our wearable device, the three Euler angles were calculated and finally, all data were stored in the flash memory of the phone.

C. Features Extraction

The features' extraction process suggests conserving the same set of either time and frequency domain features from our previous work [9] that are all computed from a fixed non-overlapping time window over each raw signal. The conversion from the time domain to the frequency one was achieved through the FFT algorithm.

D. Classification

According to the literature in the field of activity recognition, as well as terrain classification in robotics, it is known that several of such algorithms achieve excellent results in classifying data from inertial sensors. This research retains the direct comparison between the RF and the k-NN algorithms. This choice was previously made, first because they belong to two distinct families of classifiers—respectively, the meta-classifiers and the lazy learning ones. Moreover, as non-parametric methods, these algorithms remain simple, flexible, powerful and efficient [11]. Indeed, their satisfying classification performance is, most of the time, reported in the literature [7], [4].

III. Experiments

A. Participants

Since our previous work, only six over the nine recruited participants were available. They were all the same university students, being all males from 23 to 30 years old. Their weights were placed between 65 kg and 110 kg (median: 85 kg), and their heights were between 172 cm and 192 cm (median: 181 cm) respectively. Moreover, we counted up 5 right-handed persons and 1 left-hander. All of them were healthy people without any motor function issues.

B. Requirements

In order to preserve the consistency of the experiment previously proposed, the 215 cm long and 90 cm wide box was reused at it was (filled with either gravel or sand). Nevertheless, because of the time of the year, the data collection was impossible to reproduce on the snow.

The management of the recording was synchronized to start and stop the data collection for the two devices at the same time. Moreover, the annotation of all the records was done similarly to our previous work through the same *Android* application [9], where each participant was anonymized by the same capital letter for every of their records.

C. Procedure

To perform the data collection, we attempted to get as close as possible to real use case situations. In that sense, we judge that the three most natural places where a user may wear the device are: a hand-bag, a backpack and inside the pockets of a jacket. Both the hand-bag and the backpack were ballasted with an extra weight (1 kg and 3 kg respectively) as they could be in real use case scenarios. Moreover, since we wanted to reduce variable noise that may occur due to arm balancing, a special attention was placed on preserving the jacket closed during each walk.

Once participants were introduced how to wear both devices, they were invited to perform six round trips on each soil types, for each given position.

IV. Results

A. Datasets

Through the recorded raw data, several datasets have been produced. Details about each of them are provided in Table I. In the same way as our previous work [9], each dataset was split in several subsets of 6×60 instances to obtain one sample per round trip. Thus, we obtained an average total of 5 samples for each participant, on each soil type, for each position of the device on which features were extracted for each device regrouped by the total number of axes.

Since it is known that the human gait is considered to be a behavioral biometric [12], we have constructed one particular dataset containing each soil type for each participant for the most accurate acquisition technique. These 6 datasets let us experience the user-independent assumption. Moreover, since we have exploited several positions, a dataset per soil types was created to test the position-independent hypothesis.

TABLE I
THE DETAILED LIST OF PRODUCED DATASETS WHERE THE NAME OF EACH DATASET IS EXPRESSED WITH THE BNF NOTATION.

Dataset	Description
soil_type_[wear|cell]_[6|9|12]	Instances are annotated only with the related soil type.
soil_type_people_[wear|cell]_[6|9|12]	Instances are annotated both with the related soil type and the participant's letter.
soil_type_position_[wear|cell]_[6|9|12]	Instances are annotated both with the related soil type and the location of the given device.

B. Results Obtained

The performance of the whole comparison provided here was evaluated through the same 10-folds cross validation method over the same parameter tuning for each classification algorithms that were employed in our previous work [9]. As recall, when using the random forest algorithm, the parameters that were selected to perform the comparison were $B = 150$ or $B = 300$ trees and for each case, $F = \lfloor \frac{1}{2}\sqrt{m} \rfloor$, $F = \lfloor \log_2(m) + 1 \rfloor$ or $F = \lfloor \sqrt{m} \rfloor$ random variables. With the k-NN algorithm, these parameters where $k = 1$ nearest neighbors as well as both the Euclidean and the Manhattan distance measure.

1) Wearable Device: This section exposes the results obtained when using every set of features samples extracted from every acquisition method for the wearable device. Nevertheless, results of our previous work were modified to handle the loss of participants as well as our impossibility to perform any records on the snow. This paper only presents detailed results in Tables II and III, with the parameters tuning that let us obtain the best overall recognition rate for the two different classification algorithms. When using the wearable device, optimal parameters are either $B = 300$ trees and a number of random variables equivalent to $F = \lfloor \log_2(m)+1 \rfloor$, or $k = 1$ neighbor and a Manhattan distance measure for the RF and the k-NN classifier respectively.

TABLE II
RESULTS OF RF CLASSIFICATION USING $B = 300$ TREES AND $F = \lfloor \log_2(m) + 1 \rfloor$ AS PARAMETERS FOR THE WEARABLE.

Dataset	Acc.	F1	k
soil_type_wear_6	0.87	0.87	0.83
soil_type_wear_9	0.92	0.92	0.88
soil_type_wear_12	0.90	0.90	0.84
soil_type_people_wear_6	0.88	0.88	0.88
soil_type_people_wear_9	0.91	0.91	0.91
soil_type_people_wear_12	0.91	0.91	0.91
soil_type_position_wear_6	0.92	0.92	0.92
soil_type_position_wear_9	0.92	0.92	0.92
soil_type_position_wear_12	0.92	0.92	0.91

Through such results, a significant overall improvement with the upgraded version of the wearable device is noticeable. As an example, a rise of the median F-Score from 86% with the 6-axis IMU to 92% with the new 9-axis IMU has been observed when only considering soil type recognition. Moreover, it is possible to observe that the performance gains when including the Euler angles is almost negligible in every case.

TABLE III
RESULTS OF k-NN CLASSIFICATION (WHERE $k = 1$), USING THE MANHATTAN DISTANCE FOR THE WEARABLE.

Dataset	Acc.	F1	k
soil_type_wear_6	0.92	0.92	0.90
soil_type_wear_9	0.93	0.93	0.89
soil_type_wear_12	0.90	0.90	0.85
soil_type_people_wear_6	0.89	0.89	0.89
soil_type_people_wear_9	0.92	0.92	0.91
soil_type_people_wear_12	0.90	0.90	0.89
soil_type_position_wear_6	0.87	0.87	0.86
soil_type_position_wear_9	0.91	0.91	0.91
soil_type_position_wear_12	0.87	0.87	0.86

2) Mobile Device: In the same way as for the wearable device, this section only exposes, in Table IV and V, results obtained when using optimal parameters for both classification techniques when applied on every set of features samples extracted from every acquisition method for the mobile device.

TABLE IV
RESULTS OF RF CLASSIFICATION USING $B = 300$ TREES AND $F = \lfloor \log_2(m) + 1 \rfloor$ AS PARAMETERS FOR THE MOBILE.

Dataset	Acc.	F1	k
soil_type_cell_6	0.92	0.92	0.88
soil_type_cell_9	0.92	0.92	0.88
soil_type_cell_12	0.92	0.92	0.87
soil_type_people_cell_6	0.91	0.91	0.91
soil_type_people_cell_9	0.92	0.92	0.91
soil_type_people_cell_12	0.91	0.91	0.91
soil_type_position_cell_6	0.92	0.92	0.91
soil_type_position_cell_9	0.92	0.92	0.92
soil_type_position_cell_12	0.92	0.92	0.91

TABLE V
RESULTS OF k-NN CLASSIFICATION (WHERE $k = 1$), USING THE MANHATTAN DISTANCE FOR THE MOBILE.

Dataset	Acc.	F1	k
soil_type_cell_6	0.92	0.92	0.87
soil_type_cell_9	0.92	0.92	0.87
soil_type_cell_12	0.92	0.92	0.89
soil_type_people_cell_6	0.89	0.89	0.89
soil_type_people_cell_9	0.90	0.90	0.89
soil_type_people_cell_12	0.89	0.89	0.89
soil_type_position_cell_6	0.90	0.90	0.89
soil_type_position_cell_9	0.89	0.89	0.88
soil_type_position_cell_12	0.91	0.91	0.90

These results demonstrate an excellent overall performance, for every dataset. Moreover, we observed that neither the acquisition method employed, nor the parameters tuning of the algorithms has affected the recognition rate since it stands truly similar in every case. Although the results appear to be slightly better than the ones obtained with the wearable devices, they remain mostly comparable.

C. Independence Hypothesis

Since our previous research have stated that the proposed soil types recognition method was position-independent, it is important to verify such a claim through these new results yet again. Results are shown in Figures 1 and 2. The evaluation metric used as the position-independent baseline is the kappa measure being 92% for both devices, as highlighted in Tables II and IV. Although preceding overall results were indeed accurate, it is possible to observe an excellent performance, for both devices, when the learning process is achieved separately for each position as it was in our previous work. Moreover, there is no specific position that is greater than the baseline value in any cases.

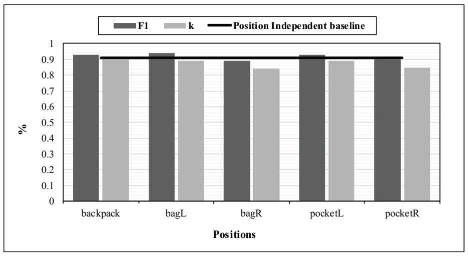

Fig. 1. Kappa and F-Score measures comparison for both dependent and independent positions with the wearable device.

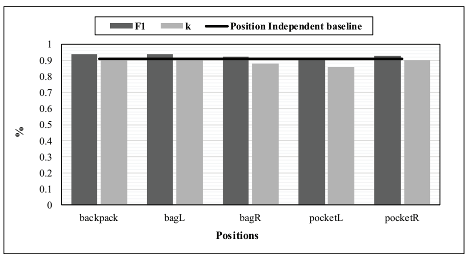

Fig. 2. Kappa and F-Score measures comparison for both dependent and independent positions with the mobile device.

Additionally, the user-independent hypothesis was also verified based on our new results. In the same way as the position-independent assessment, one dataset by participants were generated and annotated with the corresponding soil type for the same acquisition method and for each device. Figures 3 and 4 show the obtained results, where the first chart refers to the wearable device analysis and the second corresponds to the mobile phone one. Both of them were computed with the same parameters as the position-independence verification.

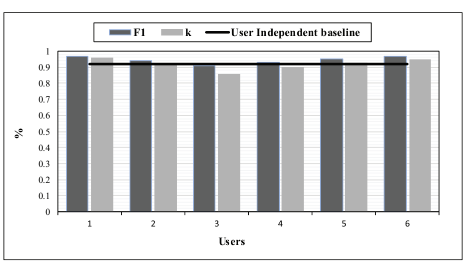

Fig. 3. Kappa and F-Score measures comparison for both dependent and independent users with the wearable device, where each letter refers to a given participant.

Yet again, when compared to results that were achieved for the position-independence, the performance remains excellent when learning each participant individually for both devices. However, unlike the position-independence appraisal, there are few of given sets where the kappa measure exceeds the baseline value (*i.e.* 91% for both devices). In our previous

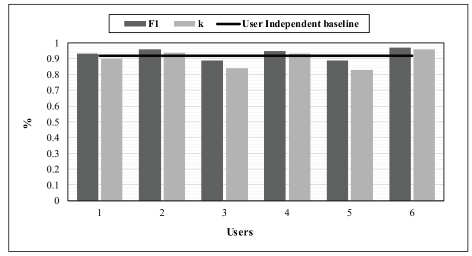

Fig. 4. Kappa and F-Score measures comparison for both dependent and independent users with the mobile device, where each letter refers to a given participant.

research we have stated that due to a few number of participants, the user-independence condition was not possible to be acknowledged accurately. This new evaluation strengthens this belief since the number of involved participants is even smaller.

V. Discussion

According to the results detailed in the previous section, it is possible for us to say that the upgraded version of our device has enhanced the results we obtained before. When it was a matter of classifying only soil types, the accuracy has increased from 87% to 92%, in the best case, using respectively 6 and 9-axis data from the wearable device. However, when considering the additional time required by the processing of the Euler angles and the negligible performance gains they offer—we can state that preserving only 9-axis data records will be sufficient to achieve a suitable and accurate recognition of soil types.

Then, through the comparison of our wearable device with a mobile phone, a slight gap on the overall performances between both devices only when considering a 6-axis acquisition method was noticed. Such a difference could be explained first, by a poor quality of the 6-axis IMU embedded in the *Arduino 101* board comparatively to the new *LSM9DS1*. The other hypothesis refers to a prior filtering of data generated by the inertial sensor of the mobile device that undoubtedly make these data less noisy.

Finally, as regards the position-independence, it is possible for us to affirm that both the wearable device and the mobile phone will truly recognize the current soil type, no matter where they are worn by the user. However, just as our previous work, the even smaller number of users that it was possible to recruit do not allow us to acknowledge the user-independence accurately.

VI. Conclusion & Future Works

To conclude, this work addresses further evaluation of the method for soil types recognition based on inertial data produced by the human gait that has been introduced in a previous research [9]. In this work, the wearable device was upgraded from a 6 to a 9-axis IMU. The three additional axes brought by the new *LSM9DS1* let us process the Euler angles to include a comparison between 6, 9 and 12-axis for data recorded by the wearable device. In addition to a direct comparison between different acquisition techniques for the same device, these acquisition methods were also compared for a mobile phone. The same feature extraction process was applied on every raw signal, where a set of features, which belongs to both time and frequency domain were classified by both the RF and the k-NN machine learning algorithms.

The assessment of our method was done through the same experiment as our past work except it involved only 6 of the 9 previous participants. Results obtained when considering only soil types have shown better performances for the 9-axis data records produced with the wearable device than the ones obtained earlier with the 6-axis IMU. Moreover, the reliability of our device has been proven since the performance with the mobile device was similar to the same acquisition technique. We also discovered that the location where the device was worn by the user does not affect the success rate of the recognition. In that sense, it was possible for us to confirm our method as a position-independent one. Conversely, as regards results observed for the verification of the user's independence condition, we were not able to designate our approach as a user-independent method due to an even smaller number of participants than before. In that sense, future works will now focus on determining—with a larger set of participants—if our proposed method for soil type recognition may become user-independent.

Acknowledgment

This work has been supported by the Natural Sciences and Engineering Research Council of Canada (NSERC), through the discovery grant of Sébastien Gaboury. Moreover, authors would like to acknowledge every member of the *LIARA laboratory* that were involved in our experiment.

References

[1] Nielsen, “Tech-Styles: are Consumers Really Interested In Wearing Tech on Their Sleeves?” Tech. Rep., 2014. [Online]. Available: http://bit.ly/1FwD4NR

[2] N. Taplett, “Bluetooth Smart Technology from Trend To Standard,” 2014. [Online]. Available: http://bit.ly/2l7SDJt

[3] M. S. Patel, D. A. Asch, and K. G. Volpp, “Wearable devices as facilitators, not drivers, of health behavior change,” *Jama*, vol. 313, no. 5, pp. 459–460, 2015.

[4] D. Vail and M. Veloso, “Learning from accelerometer data on a legged robot,” *Proceedings of the 5th IFAC/EURON symposium on intelligent autonomous vehicles*, 2004.

[5] M. Bibuli, M. Caccia, and L. Lapierre, “Path-following algorithms and experiments for an autonomous surface vehicle,” *IFAC Proceedings Volumes*, vol. 7, no. 17, pp. 81–86, 2007.

[6] C. Weiss, N. Fechner, M. Stark, and A. Zell, “Comparison of different approaches to vibration-based terrain classification,” *European Conference on Mobile Robots*, pp. 1–6, 2007.

[7] C. Kertész, “Rigidity-Based Surface Recognition for a Domestic Legged Robot,” *IEEE Robotics and Automation Letters*, vol. 1, no. 1, pp. 309–315, 2016.

[8] M. J.-D. Otis, J. C. Ayena, L. E. Tremblay, P. E. Fortin, and B.-A. J. Ménélas, “Use of an Enactive Insole for Reducing the Risk of Falling on Different Types of Soil Using Vibrotactile Cueing for the Elderly,” *PloS one*, 2016.

[9] F. Thullier, V. Plantevin, A. Bouzouane, S. Hallé, and S. Gaboury, “A Position-Independent Method for Soil Types Recognition Using Inertial Data from a Wearable Device,” in *14th IEEE International Conference on Ubiquitous Intelligence and Computing*. San Francisco: IEEE, 2017.

[10] C. Gomez, J. Oller, and J. Paradells, “Overview and Evaluation of Bluetooth Low Energy: An Emerging Low-Power Wireless Technology,” *Sensors*, vol. 12, no. 12, pp. 11 734–11 753, 2012.

[11] S. J. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*, 2010.

[12] F. Thullier, B. Bouchard, and B.-A. J. Ménélas, “Exploring Mobile Authentication Mechanisms from Personal Identification Numbers to Biometrics Including the Future Trend,” 2016.