Leveraging walking inertial pattern for terrain classification

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Abstract— **The goal of this work is to illustrate how measurements collected during walking by inertial sensors embedded in the shoes' sole can be used to reveal the underlying terrain type. The final aim is to enable the automatic, real time adaptation of the actuated bottom cushioning of the innovative Wahu shoe for the sake of safety and comfort. For this purpose, the gait patterns of the normal walk of different healthy subjects on four different surface types, with different hardness and friction, are collected offline and represented through the three accelerations' time history. These signals are pre-processed and segmented into two different ''elementary" items, a ''walk" object, made of a sequence of subsequent steps, and a ''mean step" object. In both cases, time and frequency attributes are computed and the most explicative selected through a principal component analysis. A cubic SVM classifier is then trained with the experimental data from multiple walking trials and its performance investigated on different validation sets. Confusion matrices show that the complete ''walk" segment performs much better in terms of prediction power and this is encouraging for further development of the methodology in real time.**

I. INTRODUCTION

Real time recognition of the terrain on which vehicles or people move and walk has become a recent, sensor enabled capability, which can ensure greater efficiency in the motion and of course higher safety, thanks to the possibility of accordingly adapting driving style or walking trait, see for a comprehensive illustration [1]. In the field of vehicles, [2], including autonomous ones, [3], [4], the issue of preventive recognition of the type and quality of the terrain is of obvious importance because it implies, in many cases, the success of the vehicle's task, [5]. Here, the studies are numerous and within a frontier research path. Regarding moving people, several literature works, see for example [6], have addressed the issue of ground type and quality recognition, in particular its slipperiness or adherence, in the context of research related to the walking of individuals with different types of mobility pathologies or prostheses, [7]. Here, the goal is to make walking as quiet as possible. On the other hand, even when it comes to people practicing sports, soil condition prediction methods are essential for a more efficient exercise. The common denominator of all systems for automatic terrain recognition is the employment of sensors. Video cameras, laser or lidar sensors can be used, [8], [9], [10], while, at the other extreme, to reduce costs, increase miniaturization and decrease algorithmic complexity, even the simpler, but innovative, inertial sensors, [11], can be sufficient in some cases, by positioning them in locations of the body that mostly reflect the effect of the terrain on the person's gait. Subsequently, measurements gathered from the sensors are usually preprocessed so as to maintain their richest informative content which eventually will feed up an intelligent, computation algorithm that outputs an estimate of the terrain's type, quality and other related characteristics. One of the locations on the human body most correlated with an individual's walking is the foot, but detecting the outside soil typology by barefoot tests does not make sense. It is therefore necessary to develop a methodology for obtaining information on the type of terrain on which one is walking with a sensor suitably positioned in the shoe. This can be accomplished just by using inertial sensors, the only sensing units capable of being embedded in a shoe, being integral with the person during the whole walk and even being capable of finely measure the dynamic quantities related to the walk itself. In [12] an inertial sensor is embedded in the heel of a shoe and it is shown that the acceleration signals exhibit different characteristics according to the type of soil. Inspired by this, we devise a methodology to extract relevant information from acceleration signals with the purpose of terrain recognition.

The proposed approach is definitely new in the literature on sensor related features linked to the study of human walk and its environment, although the employed inertial sensors are exactly those that characterize the so-called wearables, electronic worn devices nowadays widely used for many different purposes, for example monitoring, notification, danger detection and others. These wearable devices are in fact able to track movement on real time basis and at a high frequency. Thereby, in this paper, we describe the experimental setup that makes us possible to register an individual's daily walking dynamic pattern. This obtained by wearing very common sneakers with inertial sensors suitably embedded in the shoe's sole. Subsequently, we illustrate the machine learning approach to concretely extract from acceleration data the required information employed to distinguish the type of terrain and apply the algorithm to validate it and discuss its performance on different subjects, demonstrating the offline feasibility of the terrain identification but also opening up the way to a possible future on board arrangement of ground recognition and the successive possible shoe adaptation for comfort and safety.

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II. Problem statement and experimental setup

The goal of this work is the identification of different ground surfaces an individual is walking on, by only using the measurements provided by an Inertial Measurement Unit (IMU) embedded in a shoe sole. The final task is to close the loop for an autonomous shoe sole actuation. In fact, the shoe prototyped by Wahu, a start-up company at *E-novia*, a company which supports enterprises in selected and strategic business areas, has the innovative feature of being able to change the morphology of its sole, in order to adapt to a particular terrain, Fig.1. For example, a rougher and uneven terrain would call for a shoe sole which provides more cushioning, whereas a hard and smooth one would require a flat sole. Furthermore, the actuation of the shoe could be decided to increase personal safety on more slippery terrains.

Fig. 1: The two actuation states of the shoe developed by *Wahu*

In the scientific literature, there are unfortunately no studies available on the description of the deformation of the shoe's sole during motion on different terrains and, consequently, on the derivation of a dynamic model of the shoe. This is mainly due to the fact that each footware producer usually makes its own tests to assess the properties of the shoes and their sole (see [13]). Therefore, in this study, a new black-box, machine learning approach is illustrated, making use of accelerations measured at the sole level to derive insight in the shoe-sole response to different ground surfaces and subsequently to get an automatic, intelligent classification of the most common walking terrains. In doing this, one can refer to [5] as a related research.

Since the actuated Wahu shoe is not yet available in its operable version, we have explored the sneakers market in order to identify an existing shoe model that could be used for experiments to collect the data and to validate the algorithm. The selected model is a commercial sneaker characterized by some bumps on the sole, which make it quite similar to the *Wahu* shoe, when the latter are set in *pumped mode* (see Fig. 2). One of the shoes, chosen for experimental trials, was then equipped with a miniaturized IMU LSM6DS3H, by ST Microelectronics) placed in the sole inside a tiny housing underneath the heel and glued. A key feature of the selected IMU platform is the possibility to mount it on a small and low power board, as the one which will be employed in the final *Wahu* product.

Fig. 2: The experimental sneaker's sole and, in red, the IMU position.

Through the sole incorporated IMU, accelerometer measurements along the three axes are collected: the x-axis is in the same direction of the forward motion, the z-axis is perpendicular to the floor, positive upwards, and the y-axis is placed to obtain a right-handed frame. All measurement campaigns are performed using a sampling frequency of $f_s = 200$ Hz and measured data are collected using a *Vector CANalyzer* and then imported in Matlab, where the data-driven algorithms are developed. The experiments were conducted considering four young adults each one of them had to walk wearing the chosen experimental sneakers on four different terrains.

Accordingly to [12], terrains with different hardness are considered. First, hard surfaces like *linoleum* and *asphalt* have been taken into account, then a softer but more irregular surface such as *trail*, that represents a sort of uneven ground like the typical one of mountain path or something like a flower bed (that is the place where we made the tests) and, the fourth surface was a slippery one made by *wet grates*. The terrains selection made according to the key of hardness finds its main motivation in the fact that usually, terrains characterized by high stiffness are more reliable and can be seen as 'safe' while, on the other hand, terrains like trail or wet grates represent a less safe situation in which we need the shoe in pumped mode to help the person who is walking. Finally, all experiments were performed walking straight forward, and, to make the algorithm robust to speed variations, at different speeds.

III. IMU based walk inspection on different types of terrain

In this Section, a preliminary analysis of the acceleration patterns on the different surfaces is performed, analyzing, for each terrain, the intra-subject variability and differences. Then, the two ways used to preprocess the measured data in order to find the most informative signals, from which to extract features for terrain identification, are described.

A. Preliminary analysis of walk-terrain patterns

The goal of the preliminar analysis is to verify the existence of different behaviors in the sole level accelerations on each of the four different terrains. To reveal, at a first visual inspection, the differences between the ground surfaces, all subjects' walk signals were resampled, to guarantee that they are composed by the same number of samples. and grouped for the same terrain Raw IMU accelerations are noisy and a preprocessing must be performed in order to correctly handle the data.

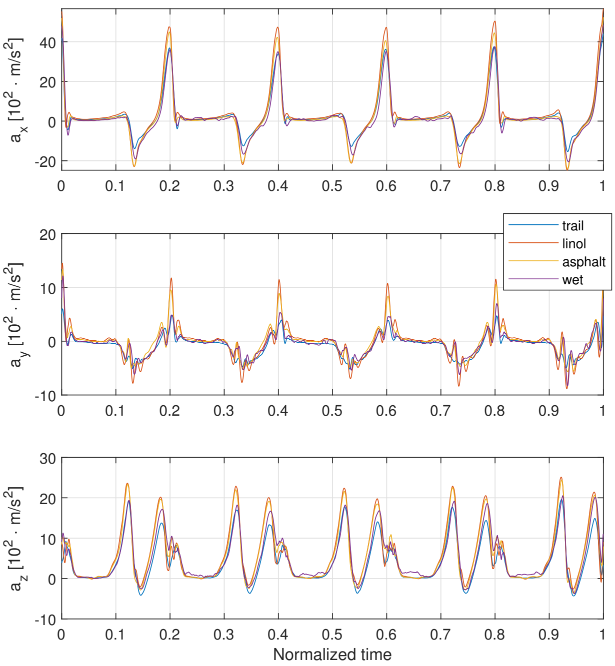

Fig. 3: Accelerations of the reference walks on the three axes for each terrain.

Noise reduction is carried out with a digital low-pass filter (Savitzky-Golay filter, see [14]). This filter performs a data smoothing operation based on a least square polynomial approximation of the signal. Therefore its two parameters are w, the width of the window of data considered when fitting, and p, the degree of the polynomial used for fitting. The parameters chosen for this experiment are $w = 15$, $p = 5$. With this choice the filtered signal is very close to the original one, but without the high frequency noise ($f > 30$ Hz) that affected the original measurement. Then, each one of the filtered, single accelerations is segmented in slots, each containing six consecutive steps. To highlight a single step, the positive peak (corresponding to the heel strike phase of the gait) in the acceleration along the x-axis is detected by imposing a suitable threshold on its height (peak value must be higher than a certain threshold), prominence (peak value must have a vertical drop of more than a certain threshold from the peak on both sides without encountering either the end of the signal or a larger intervening peak) and distance (peak values must be distant at least as much as a certain threshold from the previous peak). In this analysis these parameters were set this way: the minimum height at $20\ \mathrm{m}/(100 * \mathrm{s}^2)$ the minimum prominence at $10\ \mathrm{m}/(100 * \mathrm{s}^2)$ and the minimum distance at 80 samples $(0.4\ \mathrm{s})$

Furthermore a selection based on the walking pace is enforced. An estimation of the walking pace is done by taking into account the time passing between a step and another. A reference pace is considered (60 steps per minute), and if a walk is either too fast or too slow it is discarded (+/- 10 steps per minute). This is done to prevent walks with too different speeds from the others from joining the average. Finally, the "reference walk" for each terrain is defined by averaging sample-by-sample all the walks on the same terrain.

As shown in Fig. 3, some remarkable differences are present in the "reference walks" on different terrains. At a first inspection, each single-axis acceleration exhibits significant pattern differences, in particular in the number, location and characteristics of local maxima and minima. On the y-axis, these differences are more evident and can be extracted by an appropriate choice of features. The irregularities in the behavior on the three axes of the reference walks on the wet terrain are the expression of a more irregular way to walk on that terrain.

B. *IMU based shoe behavior featuring:* walk *and* average step

Once the differences in the accelerations on different terrains have been highlighted, it is necessary to describe define the best features to capture these patterns. However the ''elementary" signal considered from which to extract these features is yet to be determined. To do so, we followed two approaches: one which considers all the data relative to the last six steps and one which focuses only on the span of a step by superimposing and averaging these last six steps.

In the first approach, that we named *walk*, the basic ''objects" are the linear accelerations along the three axes of a continuous sequence of six steps, Fig. 5. The algorithm to build these elementary sequences, for each kind of surface, loads all the raw accelerations Fig. 4, filters the high frequency noise and splits the signals in series of six steps by automatically recognising the acceleration's peaks due to a heel strike. Then, we scale each signal over a fixed time axis, this operation guarantees that each signal is made up of the same number of samples. Finally, the *walk* signals are ready for the features' extraction phase.

In the second approach, each linear acceleration behavior is focused for what concerns a single step, then six different consecutive steps on the same ground surface are averaged sample-by-sample to form the *average step* acceleration behavior in the x, y and z directions, Fig. 6. The algorithm we use to build the *average step* loads all the raw acceleration signals collected during the experiments keeping only the ones that contain gaits in a specific range of pace. Signals are then split in steps. In particular, we are only interested on the so called *stance phase*, i.e. when the foot is in contact with the surface and we want to discard the *swing phase*, when the foot is not in contact. To perform this operation, we take inspiration from the method explained in [15] and we make it suitable for our setup. To understand how the method works, we have to mention that linear accelerations are quite constant and close to zero during *swing phase*

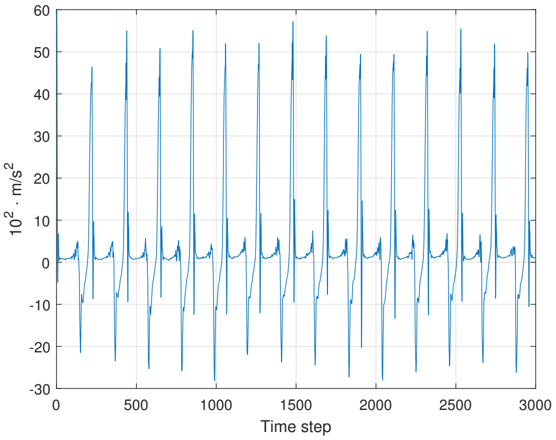

Fig. 4: An example of the raw signal a_x measured by the IMU

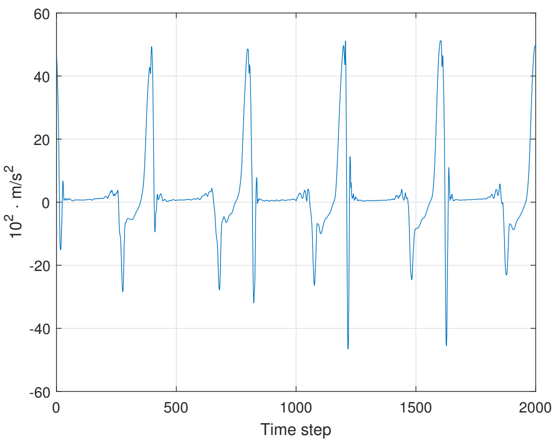

Fig. 5: An example of the elementary building-block *walk* for a_x

instead they vary a lot during the *stance phase*. We consider only the accelerations along axes x and z, because they clearly show the gait cycle, then we compute the variance of the squared norm of the signals from a sliding window of a certain dimension. The variance is a signal always positive that is close to zero during *swing phase* and much bigger during *stance phase*, by comparing it with a fixed threshold it is possible to distinguish the two phases. Once, we have obtained the *stance phase* for all the steps contained in the raw signals we scale each step over a fixed time axis, in this way every step is composed by the same number of samples. Finally, six consecutive single steps over the same surface are considered and averaged sample-by-sample to get the *average step* for the three linear accelerations.

IV. Gait Features Selection

For the first approach, also referring to [11], an initial, comprehensive set of 70 features is chosen, for each of the three accelerations (49 in the time domain and 21 in spectral domain). In addition to classical statistical entries, the entropy and power of the signal, its time domain zero-crossing rate and frequency domain band power ratio are included.
To reduce the dimensionality of the task, which means an easier application of the future onboard terrain detection algorithm, features selection with NCA (Neighborhood Component, Analysis) [16], is then carried out. Thanks to this method, the most informative features are reduced to 13, taken from both time and spectral domains. The new features set is reported in Tab I. As shown later on in this paper, the extended and compressed sets of features ensure the same classification performance, with the latter guaranteeing an important improvement in dimension reduction.

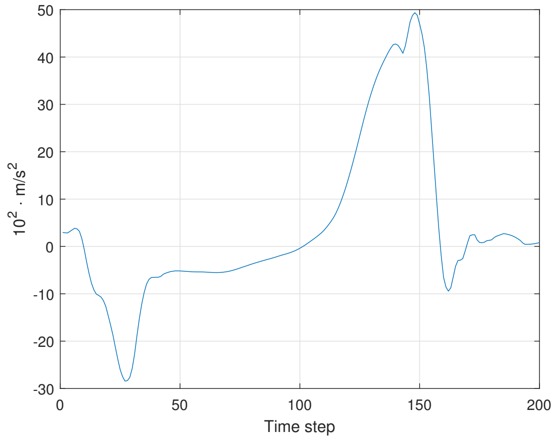

Fig. 6: An example of the elementary building-block *average step* for a_x

Time Domain			**Frequency Domain**		
Feature	Unit	Axis	Feature	Unit	Axis
mean	m/s^2	x, y	band power ratio	-	y
std. deviation	m/s^2	z			
median	m/s^2	x, z			
maximum	m/s^2	z			
entropy	-	-			
mean absolute deviation	m/s^2	z			
zero-crossing rate	-	y, z			

TABLE I: Features subset for the *walk* approach after selection with NCA

Conversely to the first approach, the *average step* approach focuses on building three accelerations' profile for a single step, (Fig. 6). Therefore, the generic signal associated to an average step is smaller in number of samples than the *walk* one. This difference has an impact on the choice of the features to be extracted. In fact, due to the smaller number of samples which the *average step* is composed of, it is impossible to extract meaningful features in the spectral domain. So, the extracted 18 features are all in time domain and are shown in Tab II.

Time Domain		
Feature	Unit	Axis
mean	m/s^2	x, y, z
std. deviation	m/s^2	x, y, z
norm	m/s^2	x, y, z
maximum	m/s^2	x, y, z
skewness	-	x, y, z
zero-crossing rate	-	x, y, z

TABLE II: Features extracted for *average step* approach

V. Automatic terrain classification algorithm

Once the features' selection phase is completed for both *walk* and *average step* approaches, the corresponding regressor vectors are clearly defined. Each input regressor is a vector containing the selected features for each *walk* or *average step* calculated from the real experiments.
The classification algorithm is firstly described and then the results on the experimental data will be commented and examined.

A. Machine learning based classification

The used classification algorithm is called Cubic Support Vector Machine (c-SVM), a supervised, discriminative classifier that iteratively generates separating surfaces, like any SVM algorithm, given the labeled training data, [17]). The reasons that drove the choice to c-SVM are multiple: firstly it has always provided good results in every test we made, compared to other classifiers as Decision Trees or Nearest Neighbor, secondly the cubic kernel has worked finer than the linear or Gaussian radial basis function ones, thirdly the training phase is faster and lighter (in terms of memory allocation) with respect to a standard feed forward neural network and lastly the prediction model is compact and shallow.

B. Classification algorithm training and validation

From both approaches, (*walk* and *average step*), training and validation phases have been conducted in the following scenarios:

1) Randomly split all the data in two subsets: one for the training phase (70%), one for the test phase (30%). With this scenario it is simply desired to assess the ability of the algorithm to correctly classify unseen data points contained in the validation dataset.
2) The second scenario is set out to verify the ability of the learning algorithm to classify correctly the data coming from a person that is not included in the training dataset. Thus, the procedure to built the training and validation regressors is slightly different. In fact, the training regressors are the data of three out four of the subjects, the fourth is used to build the validation regressor regressor.
3) The third situation evaluates the robustness of the algorithm with respect to data collected at different gait speeds. Therefore, in this case the training regressor contains the walks at faster pace (from 65 to 85 spm), while the validation regressor is formed by data at a slower pace (from 45 to 60 spm).

Before the training phase, a column-wise normalisation of the regressors is performed, because different features contain values of different order of magnitude that may undermine the performance of the classification algorithm. Finally, to ensure robustness, a 5-fold cross-validation is adopted.

VI. Experimental results and discussion

The algorithm just described is executed on a computer with Intel i7-8565U processor, 16 GB RAM and a Nvidia GTX 1050 GPU. The software used is MATLAB. Once the regressor is built (with the average step approach or the walk approach) and the machine learning algorithm is decided (always c-SVM), it is enough to train the latter with the former in order to construct the predictor. The hyper-parameters of c-SVM are shown in Table III and in each test the multi-class predictor has been trained using the *one-vs-one* method.
Then, the predictor is fed with the data that was separated before training and it tries to classify them. These results are compared with the true tags of the data. To show how well each predictor behaves we decided to use the confusion matrix, as it provides a quick visual representation of how well the predictor behaves for each surface.

		Box constraint	Kernel scale
Test 1	avg. step	1	4.6
	walk	1	4.0
Test 2	avg. step	1	4.6
	walk	1	4.0
Test 3	avg. step	1	4.6
	walk	1	3.0

TABLE III: Hyperparameters of Cubic SVM

The first test shows satisfying results for both approaches, with a very good performance for all the surfaces. Conversely, the second (Fig. 7) and third tests are able to display some issues with the classification. The approach that extracts the features from the walk performs better in all the tests. The single average step approach has its performance deteriorate heavily in the second and third tests. Hence, it is advisable to consider the whole walk for the classification. Another observation possible by looking at the tests with an external person as a validation set, is that there are classifications more difficult than others. In particular, it is very difficult to correctly assess whether the terrain is *asphalt* or *wet grates*. We believe that this is due to the fact that the two surfaces are intrinsically very similar and, except the moment when the subject is actually slipping, the accelerations recorded are also comparable. While this classification performs poorly, the identification of the *trail* surface does remarkably well, as perhaps it is the surface that distinguishes itself the most. Considering the test about the robustness with respect to different speeds these results are confirmed. Again the walk approach performs much better than the other one. Again the most difficult classification is

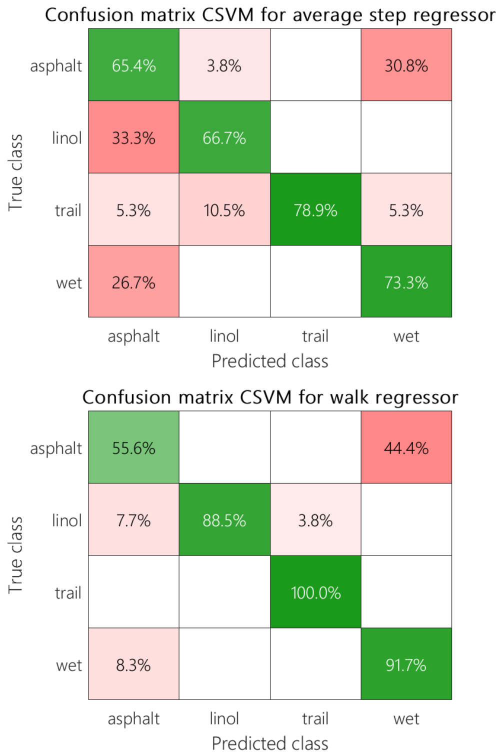

Fig. 7: Confusion matrices for the two approaches, considering the external person test.

the one regarding *asphalt* or *wet grates*. Furthermore we see no worsening of performance with respect to the basic case, so we conclude that the walking speeds are not very relevant in this classification problem.
Robustness is assessed by evaluating the performance while classifying a walk of a user not belonging to the data-set and while classifying walks at different speed. As stated above, the algorithm behaves robustly to these tests, especially for the *trail* classification.

VII. Conclusion and Future Work

This work investigates the feasibility of a terrain identification algorithm based on the xyz accelerations measured by an inertial sensor embedded in a shoe sole. The motivation of this research is to detect the different terrain conditions in order to adapt accordingly the sole cushioning in the innovative Wahu shoe. Data are collected on four different surfaces, with four different subjects walking both at their normal speed and at an accelerated pace. Afterwards, significant features are outlined and extracted from the original signals, previously cleaned up and suitably compressed into standard segments, a "single average step" and a sequence of a certain number of steps, called "walk". A cubic SVM classifier is then trained on data from multiple young adults walks and its performance evaluated on different test sets. Also the robustness of the terrain recognition with respect to different walking speeds is taken into account. It is possible to state that the approach that extracts the data from the ''walk" performs much better, particularly in the test trials. This, in turn, corresponds to the real situation the method will have to work at, that is classifing a terrain based on a generic, previously unknown, walk. Future work should focus on collecting more data from male/female individuals, in a broader range of age, walking on the same and on new kinds of terrain. Furthermore, from an algorithmic point of view, the possibility to employ also the IMU gyroscope measurements should be deepened to understand if a finer terrain detection could be obtained relying also on rotational velocities at the sole level. The study of an unsupervised classification algorithm could also be worth a further investigation to cluster together similar terrains that require the same shoe actuation. To end up, the developed terrain detection algorithm should be implemented in real time on a suitable processing unit combined with the inertial platform.

References

[1] C. Weiss, H. Tamimi, and A. Zell, "A combination of vision- and vibration-based terrain classification," pp. 2204–2209, 2008.
[2] S. Wang, S. Kodagoda, L. Shi, and H. Wang, "Road-terrain classification for land vehicles: Employing an acceleration-based approach," *IEEE Vehicular Technology Magazine*, vol. 12, no. 3, pp. 34–41, 2017.
[3] B. Sebastian and P. Ben-Tzvi, "Support vector machine based real-time terrain estimation for tracked robots," *Mechatronics*, vol. 62, 2019.
[4] F. Yandun, E. Gregorio, M. Zúñiga, A. Escolá, J. Rosell-Polo, and F. Auat Cheein, "Classifying agricultural terrain for machinery traversability purposes," *IFAC-PapersOnLine*, vol. 49, no. 16, pp. 457–462, 2016.
[5] M. Mei, J. Chang, Y. Li, Z. Li, X. Li, and W. Lv, "Comparative study of different methods in vibration-based terrain classification for wheeled robots with shock absorbers," *Sensors*, vol. 19, no. 5, p. 1137, 2019.
[6] P. Dixon, K. Schütte, B. Vanwanseele, J. Jacobs, J. Dennerlein, J. Schiffman, P.-A. Fournier, and B. Hu, "Machine learning algorithms can classify outdoor terrain types during running using accelerometry data," *Gait and Posture*, vol. 74, pp. 176–181, 2019.
[7] F. Zhang, Z. Fang, M. Liu, and H. Huang, "Preliminary design of a terrain recognition system," pp. 5452–5455, 2011.
[8] A. Milella, G. Reina, and J. Underwood, "A self-learning framework for statistical ground classification using radar and monocular vision," *Journal of Field Robotics*, vol. 32, no. 1, pp. 20–41, 2015.
[9] Y. Zou, W. Chen, L. Xie, and X. Wu, "Comparison of different approaches to visual terrain classification for outdoor mobile robots," *Pattern Recognition Letters*, vol. 38, no. 1, pp. 54–62, 2014.
[10] G. Reina and A. Milella, "Towards autonomous agriculture: Automatic ground detection using trinocular stereovision," *Sensors (Switzerland)*, vol. 12, no. 9, pp. 12405–12423, 2012.
[11] M. Z. U. H. Hashmi, Q. Riaz, M. Hussain, and M. Shahzad, "What lies beneath one's feet? terrain classification using inertial data of human walk," *Applied Sciences*, vol. 9, no. 15, p. 3099, 2019.
[12] M. J.-D. Otis and B.-A. J. Menelas, "Toward an augmented shoe for preventing falls related to physical conditions of the soil," in *2012 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pp. 3281–3285, IEEE, 2012.
[13] D. Chaffin, J. Woldstad, and A. Trujillo, "Floor/shoe slip resistance measurement," *American Industrial Hygiene Association journal*, vol. 53, pp. 283–9, 06 1992.
[14] R. W. Schafer, "What is a savitzky-golay filter?[lecture notes]," *IEEE Signal processing magazine*, vol. 28, no. 4, pp. 111–117, 2011.
[15] H. Fourati, N. Manamanni, L. Afilal, and Y. Handrich, "Position estimation approach by complementary filter-aided imu for indoor environment," pp. 4208–4213, 07 2013.
[16] W. Yang, K. Wang, and W. Zuo, "Neighborhood component feature selection for high-dimensional data.," *JCP*, vol. 7, no. 1, pp. 161–168, 2012.
[17] L. Wang, *Support vector machines: theory and applications*, vol. 177. Springer Science & Business Media, 2005.