IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 26 June 2023, accepted 7 July 2023, date of publication 11 July 2023, date of current version 20 July 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3294276

RESEARCH ARTICLE

Robotic Monitoring of Habitats: The Natural Intelligence Approach

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This work was supported in part by the European Union's Horizon 2020 Research and Innovation Program (Natural Intelligence) under Grant 101016970, in part by the Ministry of University and Research (MUR) as a part of the PON 2014-2021 "Research and Innovation" resources—Green/Innovation Action—DM MUR 1062/2021, and in part by the Italian Ministry of Education and Research (MIUR) in the framework of the FoReLab project (Departments of Excellence).

ABSTRACT In this paper, we first discuss the challenges related to habitat monitoring and review possible robotic solutions. Then, we propose a framework to perform terrestrial habitat monitoring exploiting the mobility of legged robotic systems. The idea is to provide the robot with the Natural Intelligence introduced as the combination of the environment in which it moves, the intelligence embedded in the design of its body, and the algorithms composing its mind. This approach aims to solve the challenges of deploying robots in real natural environments, such as irregular and rough terrains, long-lasting operations, and unexpected collisions, with the final objective of assisting humans in assessing the habitat conservation status. Finally, we present examples of robotic monitoring of habitats in four different environments: forests, grasslands, dunes, and screes.

INDEX TERMS Environment monitoring and management, legged robots, field robots.

I. INTRODUCTION

Today climate change is threatening life on Earth as we know it. For instance, Earth's average surface temperature is increasing [1]. This includes the temperature of the ocean alone [2], which inevitably leads to the rising of the sea level [3]. Climate change is expected to continue through the current century [4], and its magnitude will be related to the quantity of heat-trapping gases globally emitted in the atmosphere [5].

The associate editor coordinating the review of this manuscript and approving it for publication was Binit Lukose.

FIGURE 1. The quadruped robot ANYmal C equipped with the adaptive feet SoftFoot-Q performing a habitat monitoring mission.

Tackling this issue is currently one of the top priorities for humanity, and most of the world governments are trying to solve it.[1,2,3,4] For instance, the European Union (EU) response to this challenge is the European Green Deal.[5] This is a set of deeply transformative policies among which the conservation of habitats and species stands out for its crucial role. On this topic, the idea of the European Green Deal is to enhance the habitat and species conservation by expanding the land and the sea areas covered and protected by the Natura 2000 Network (N2000N [6]),[6] with a major focus on the biodiversity-rich ones. The objective is to be able to take on time the right measures to ensure nature preservation. To this end, repeatable, consistent, and affordable monitoring techniques are necessary to assess the conservation status of the natural and semi-natural habitats.

The relevant areas composing the N2000N are currently monitored mainly by human operators, especially in the case of terrestrial habitats. The reasons behind this are primarily two: i) highly specialized operators possess the expertise and knowledge to perform the assessment of the conservation status of a habitat, ii) human beings have the physical intelligence to traverse (for hours) extremely unstructured and previously unknown environments such as natural scenarios.

Yet, these tasks are usually costly and extremely time-consuming, especially with the increasing number of ecosystems in danger. For these reasons, the goal of this paper is to enhance human capabilities in monitoring the vegetation of terrestrial habitats through the employment of robotic platforms (see, e.g., Fig. 1). However, despite the tremendous advancements made by robotics in recent years, a deployable solution is still not present. Most of the robotic solutions are applied to aquatic habitats [7], [8], [9]. In the case of terrestrial habitats, locomotion is a major issue [10]. Ground robots usually fail to move over really irregular and unstructured terrains [11]. On the contrary, aerial robots can be successfully applied for habitat monitoring (e.g [12]), but they require frequent recharges [11] due to their limited autonomy [13].

vIn this paper we discuss how enabling robots to perform terrestrial habitat monitoring could substantially mitigate the burden on the human workforce. The solution we propose is to empower robots with the Natural Intelligence [14], which emerges emerges from the interaction of the environment, body, and mind of the robot. The role of robot intelligence has already been investigated in literature starting from the seminal works by Brooks [15], [16]. In [17], the Author distinguishes between the intelligence embedded into the robot body, i.e., physical intelligence, and the one present into the robot brain, i.e., computational intelligence. The synergy between physical and computational intelligence has been widely studied as the embodied intelligence paradigm [18], [19] especially under the name of morphological computation, which is the concept of transferring computation load from a controller onto the robot's body, reducing the required controller complexity [20]. In the context of embodied intelligence, the interaction between the robot body and brain and the environment plays a crucial role [21]. Based on this idea, in [11], the Author proposes the robot ecology paradigm, for which environmental constraints drive the robot behavior. In [22], the Authors propose the concept of physical artificial intelligence, which is the theory and practice of designing simultaneously the robot structure, morphology, actuation, sensing and control.

With the term Natural Intelligence we aim at stressing even further the role of the environment and its synergy with the robot body and mind. Indeed, the environment gives the specifications and models the robot body and mind design. For the robot body, we propose the employment of a legged system to increase traversability and battery duration. However, this is not sufficient. The robot structure should indeed embody also a certain degree of physical intelligence [17], [21]. This can be obtained, for instance, through articulated soft-robotics powered mechatronics [23] strengthened by bio-inspired feet for adaptive and resilient locomotion and terrain perception, novel robust-by-design articulated soft robot structures, and long-lasting operation capabilities thanks to the efficient exploitation of robot dynamics. On the other hand, the mind of the robot should focus on the computational intelligence [17]. For instance, it should address autonomous navigation in natural environments, autonomous detection and identification of plant species and natural habitats, and effective physical robot-environment interaction through bio-inspired anticipatory control and environment-aware impedance planning.

To summarize the contribution of this paper is a novel concept to perform terrestrial habitat monitoring employing legged robotic systems. The ultimate goal is to help humans in the assessment of conservation status of the environment

[1] https://www.un.org/en/climatechange/cop26

[2] https://www.awe.gov.au/environment/biodiversity/conservation/strategy

[3] https://www.whitehouse.gov/briefing-room/statements-releases/2022/06/09/fact-sheet-tackling-climate-change-and-creating/

[4] https://unfccc.int/sites/default/files/resource/China%E2%80%99s%20Mid-Century%20Long-Term%20Low%20Greenhouse%20Gas%20Emission%20Development%20Strategy.pdf

[5] https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1576150542719&uri=COM%3A2019%3A640%3AFIN

[6] https://ec.europa.eu/environment/nature/natura2000/index_en.htm

through the autonomous acquisition and interpretation of natural data. This approach has been already tested in four different habitats, which are continental grasslands, forests, dunes, and screes.

This paper is organized as follows. In Sec. II, we introduce habitat monitoring, explaining what it is, where it is performed, who performs it, and how expert human operators execute it. In Sec. III, we summarize the current State of the Art for robotic environmental monitoring, focus primarily on habitat monitoring and summarizing also the challenges introduced by it. In Sec. IV, we present the approach we propose to achieve this ambitious task, i.e., the empowerment of robots with the Natural Intelligence, which is the combination of the environment, the body, and the mind of the robot. In Sec. V we experimentally show four examples of robotic habitat monitoring in four different natural environments. Finally in Sec. VI, we draw the conclusions.

II. HABITAT MONITORING

Monitoring, i.e. periodical and repeatable assessment of a given set of key indicators is an essential instrument for management and conservation of the ecosystems. Monitoring of natural habitats has three main functions: i) to provide information on the differences of the current environment status if compared to a reference status; ii) to assess the effect of actions aiming at preserving the habitat status; iii) to assess the effects of perturbations and disturbances [24]. The Habitat Directive (92/43/EEC) [25] introduced a formal definition of the concepts of "natural habitats", "typical species", and "favorable conservation status of a natural habitat". The scientific community and the EC guidelines [26] agreed that the structure and functions, can be measured via the assessment of its vegetation or of the typical species.

A. WHERE TO DO HABITAT MONITORING?

The "Nature Directives" (Directive 79/409/EEC, later amended to Directive 2009/147/EC), i.e. the Birds and the Habitats Directives 92/43/EEC established special protection areas and special areas of conservation that together compose N2000N, a network that today covers about 18% of the European land, and that should be extended to 30% by 2030 according to the EC Biodiversity Strategy. Today N2000N affects 9 bio-geographical regions: Alpine, Boreal, Mediterranean, Atlantic, Continental, Pannonian, Black Sea, Macaronesian, and Steppic. The Habitat Directive requires members States to implement surveillance of the conservation status of habitat and species of community interest. Data of N2000N sites are generally updated once a year,[7] while every 6 years a report for the complete habitat and species distribution (inside and outside N2000N) is required. The last report has been presented in 2019 (concerning the period 2013-2018).

[7]https://www.eea.europa.eu/data-and-maps/data/natura-12

B. WHO MONITORS THE HABITATS?

The European Environment Agency (EEA) coordinates the European efforts and activities on four environment-related topics. Among these topics, nature and its biodiversity preservation are one of the most prominent. The European Topic Centre on Biological Diversity (ETC/BD) assists, provides information and builds capacity for reporting on biodiversity in Europe. The ETC/BD collaborates with a broad range of European partners, especially with national centres focusing on biodiversity and ecosystem assessments. This collaboration serves as the conduit with local and regional data suppliers. The national collected data are then used to determine the state of Europe's ecosystems, and therefore to aid in the evaluation, creation, and implementation of novel EU policies. The European directives are thus forwarded to each European State, and each country has its own decision-making process. For instance, in Italy, this role is played by the governmental organization Istituto Superiore per la Protezione e la Ricerca Ambientale (ISPRA) which edited the "Manuals for Monitoring of Species and Habitats" [27]. Responsible for the monitoring activities are the 20 Italian administrative regions that in the majority of the cases subcontract these to other entities (Universities or consultancy companies) that have the expertise to perform the monitoring in the field.

C. HOW TO MONITOR?

The methodological foundations of habitats monitoring according to the European guidelines [26], [28] are presented in [29]. Even if every habitat has its own specific physiognomy, structure and characteristics, and therefore its own specific parameters indicating its conservation status, there are standard steps that constitute the habitat monitoring procedure.

Sampling: monitoring vegetation and hence habitats can be suitable performed through phytosociological relevés [30]. Relevés should be located in homogeneous vegetation stands (sampling plots). Homogeneity is defined in terms of structure and species distribution, which can be determined employing a stratified random sampling scheme [31], [32]. Permanent plots are suggested to achieve a repeated sampling at habitat-specific fixed time periods [33]. For complex vegetation mosaics such as coastal dunes, the transect is the preferred solution to identify the vegetation and environmental heterogeneity [34], [35].

Sampling Plot Size: habitats and vegetation are inherently scale-dependent units, which are influenced by species size, ecological and physical heterogeneity, growth patterns and interactions among plant individuals [36], [37], [38], [39], [40]. The sampling plot size can be a compelling topic for some habitat types, e.g., due to the risk of pseudo-turnover when monitoring annual-rich plant communities [41], [42]. In [43], it is suggested the adoption of fixed-dimension sampling plots in vegetation analysis based on four typical size for four vegetation macro-typologies.

Distribution Mapping: thanks to their vegetation-based character, the habitat spatial distribution is appropriately defined by distribution maps of the plant communities [44]. Each habitat's spatial pattern of occurrence is essential for determining its conservation status, and for evaluating the potential distribution and the inherent vulnerability. The interpretation and definition of each habitat can be performed though intrinsic and extrinsic features such as physiognomy, structure, and floristic composition of the plant community for the former ones, and discontinuity w.r.t. the surrounding vegetation for the latter ones [45]. Specific patterns of spatial occupancy were determined for each habitat, w.r.t. the three primary types proposed by [40], i.e., areal, linear and point.

Typical Species: in [26] it is proposed the concept of ''typical'' species, which is decidedly distant from the one used by the phytosociological school (from [46] to [47]). Indeed, it does not focus directly on the species diagnostic value, but rather on identifying taxa, which can be employed as synthetic indicators of the conservation status of a habitat. Given these observations, the monitoring Manual identifies three main classes of ''typical'' species (sensu Habitat Directive) depending on each habitat structure and species abundance, and it adopts three solution models [48].

D. CHALLENGES

There are still certain challenges that need to be resolved before existing monitoring activities can provide policymakers in the EU with comparable, reliable, cost-effective, and sizable data sets about the state of habitat conservation. The primary causes of these problems are that highly experienced human operators are now the only practical option for habitat monitoring. On the one hand, the human element adds a significant amount of subjectivity to the monitoring processes, which reduces the comparability and consistency of relevés. On the other hand, the increasing number of habitats in danger, joined to the fact that, for each habitat monitoring activities are confined to a limited period during the year lead to the necessity of a larger number of professional surveyors. However, the high skill requirements that are listed in the Manual [27] for each habitat as well as the low human rate of relevés per day and data processing per day (usually one to few) make habitat monitoring extremely cost-intensive. This is exacerbated even further by the fact that experienced botanists who are elderly or with limited mobility may no longer perform on field habitat monitoring due to the challenging terrains or to the potentially unfavorable weather conditions, reducing the number of available surveyors. As a result, the generation of a consistent and large enough data set about habitat conservation status is lacking, and it will require huge European investment (20 BE/year).[8]

Robotic environmental monitoring could improve and enhance human monitoring capabilities, with no goal of substituting them. For instance, robots could be used as a tool by a proper number of botanists to simultaneously perform multiple surveys leading to a general increment on the total number of surveys performed per habitat per year. Unfavorable weather conditions or personal limited mobility would not hinder the capability of experienced plant scientists in performing surveys. Finally, with standardized monitoring algorithms and metrics, surveys performed by botanists with different backgrounds, skills, and experience would be easily comparable obtaining a common baseline for a worldwide habitat conservation status analysis.

[8]https://ec.europa.eu/commission/presscorner/detail/en/fs_20_906

III. ROBOTIC HABITAT MONITORING:STATE OF THE ART

Robotic environmental monitoring is a topic which is gaining more and more attention in recent years [49]. Within this field, several different applications can be identified, ranging from wildlife monitoring [50], [51], [52] to pollution localization and tracing [53], [54], [55], from radiation localization [56], [57] to environmental DNA surveillance [58], [59], from wildfire detection [60], [61] to habitat monitoring [9], [62]. The variety of technologies employed for these applications is also extremely broad, and it includes, for instance, sensor networks [63], [64], [65], remote sensing [66], [67], [68], and autonomous vehicles [53], [69], [70].

In this paper, we focus on habitat monitoring through the adoption of autonomous robots. This field is of paramount importance to acquire quantitative and reliable data on the biodiversity conservation status [71]. Literature proposes several solutions in this regard, especially for aquatic habitats [7]. For instance, autonomous surface vessels have been used for monitoring water bodies [72] and invasive aquatic plant species [9], while Autonomous Underwater Vehicles (AUV) have been used to monitor the Peruvian coastline [73] or eelgrass habitats [74].

In the case of terrestrial habitat monitoring, Unmanned Aerial Vehicles (UAV) are commonly used [7], [10] thanks to their broad commercial availability and to their excellent mobility even in unstructured scenarios. An example of such application is [12], where the Authors employ UAVs to monitor coastal cliffs. Conversely, in [75] UAVs are used for tree detection and species classification. It is worth mentioning that UAVs are typically used for studies and surveys which rely on data taken above the tree canopy [76], [77], while they are rarely and hardly used for studies on the ground flora, i.e., flora below the tree canopy. The biggest disadvantage of the UAV technology is the flight time, which is strictly related to the battery endurance, and it is often only tens of minutes long [7], [11], [13], [78], [79], while it can reach hours only for high-altitude UAVs at the cost of very high operational complexity [61].

To obtain a reliable robotic environmental monitoring platform, battery endurance is of paramount importance. For instance, in [80] the Authors propose the SlothBot, a robot purposefully designed for long-term environmental monitoring applications. Indeed, this system is able to ''*survive*'', i.e., to outlast a single battery charge [11], on the field, thanks to its ability to recharge through solar radiation and its efficient mobility. The major advantage and main limitation of this system is that it is a wire-traversing robot. This allows to greatly reduce energy consumption. However, it also requires a pre-mounted wired infrastructure to operate. Therefore, it cannot be applied to habitat monitoring, which requires the random selection of the to-be-sampled area.

On the other hand, autonomous ground robots are able to carry large batteries, but they may fail in moving in extremely unstructured terrains [11]. Depending on the task and on the type of terrain, different locomotion system may be used [10]. For instance, caterpillar solutions are very common in forestry [10], [81]. However, tracks may damage plants and other organisms.

In [82], the Authors propose WAMOT, a mobile wheeled-robot for environmental monitoring. This system is able to traverse fields with tall grasses [83] and also irregular terrains [84]. Furthermore, the Authors directly tackle the problem of energy efficiency [85]. However, this system mainly targets grass fields and forests, limiting its applicability.

Legged systems promise to be the best trade-off between battery endurance and mobility over challenging terrains. However, their application to habitat monitoring is still understudied [7], [10] despite the fact that in recent years several quadrupedal robots were commercialized, e.g. Spot,[9] Unitree GO1,[10] and ANYmal[11] The main step towards this direction is the Environmental Hybrid Robot (EHR) [86], which presents both legs and wheels and its goal is the monitoring of the Amazon rain forest.

IV. THE PROPOSED APPROACH FOR ROBOTIC HABITAT MONITORING

The approach we propose to bring robots out of the factories to be operational in the real words is to confer to the robot a Natural Intelligence. In this context, Natural Intelligence can be identified as the interaction of three elements: environment, body, and mind (see Fig. 2).

A. THE ENVIRONMENT

The environment first sets the requirements to be matched by the robotic devices and then—through field testing—provides feedback to guide robots development.

The goal of habitat monitoring is the evaluation of the conservation status of a habitat. Such an evaluation is currently carried out by human operators on the basis of a series of parameters. Towards robotic environmental monitoring, the main challenge is to obtain and assess robot mobility in natural environment. The first step toward deploying robots in natural environments is the survey of the habitat. Indeed, this defines the requirements for the robotic devices and the challenges that should be tackled.

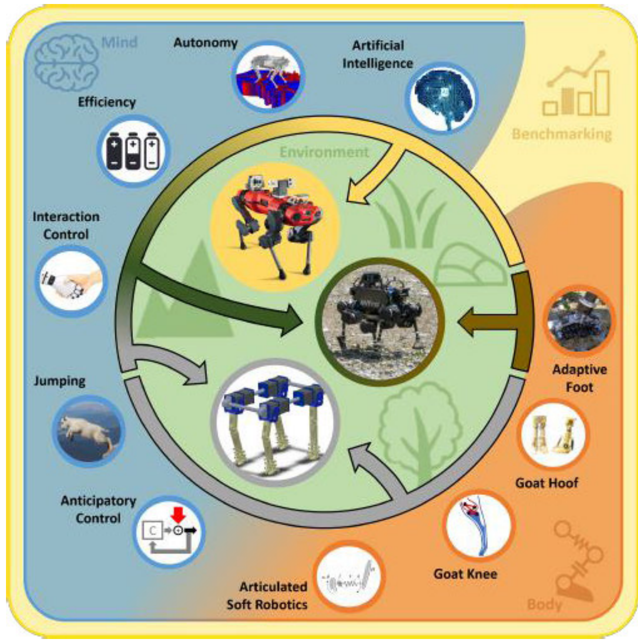


FIGURE 2. The proposed approach for robotic habitat monitoring combines environment, body and mind to confer a Natural Intelligence to robots.

1) CONSERVATION STATUS EVALUATION OF HABITATS

Several are the key indicators of the conservation status of a habitat, and each specific habitat requires different parameters to assess it. However, it is possible to divide these parameters into three main categories:

- *Vegetation cover*: The vegetation cover represents the percentage of the surface of a given area that is covered by vegetation. The vegetation cover can be measured by taking into account all the species that are present in a plot. Moreover, for some habitats, it is also relevant a more detailed analysis of the vegetation clusters reporting data on the cluster size and distribution.
- *Typical species*: Each habitat presents typical species, which reflect favorable structure and functions of the habitat type. Other species, such as alien invasive, may indicate that the habitat is threatened. Therefore, it is important to recognize the presence of these two groups of species together with their coverage.
- *Physical parameters*: Depending on the habitat it is important to collect a series of parameters pertaining to relevant physical properties of the environment such as (but not limited to): temperature, humidity, light conditions, and stability of the ground.

In this context, the main Key Performance Indicators (KPIs) are the accuracy with which the parameters are collected and the time required to perform the parameter collection.

2) CHARACTERISTICS RELEVANT FOR ROBOT MOBILITY

The ability of a robot to successfully move in the environment depends on several characteristics of an environment itself. In particular, there are:

[9] https://www.bostondynamics.com/products/spot
[10] https://shop.unitree.com/
[11] https://www.anybotics.com/anymal-autonomous-legged-robot/

FIGURE 3. The SoftFoot-Q [87], a compliant foot designed to be robust and to adapt to the terrain.

- maximum terrain slope;
- terrain friction;
- terrain stiffness;
- sink likelihood;
- presence and size of obstacles or gaps.

A quantitative evaluation of these features is an essential first step towards the realization of robots able to perform environmental monitoring. Furthermore, cost of transport can be regarded as an additional KPI, which is of paramount importance for the mission success. Indeed, the target is to realize a robotic solution able to perform at least a monitoring mission with the onboard energy capacity.

Tab. 1-4 illustrate a few examples of analysis of the environment for four different habitats: continental[12] grasslands, continental forests, Mediterranean coastal dunes, and Alpine screes, respectively. Information reported on these tables are taken from literature [26], [27], [29], while the terrain characteristics are directly taken from on site sampled measurements.

B. THE BODY

The robot body should enable the execution of long missions over challenging terrains. For this reason, the robotic platform we adopted is a legged system to achieve a trade-off between battery duration and mobility over irregular terrains. The body embeds also technologies able to robustly interact with natural environments. Walking on rough, uneven terrain may destabilize the robot or even preclude the system locomotion. Adaptive end-effectors already proved their unmatched capability in grasping irregular objects also with limited feedback information. On the other hand, adaptiveness is a key feature also for locomotion tasks that involve unstructured environments such as natural habitats (Fig. 3). Locomotion in such scenarios is a challenging task due to the slope steepness that can also change in a highly discontinuous way, terrain roughness, slippage (e.g. moving objects, leaves, humidity, etc..), and also the possibility to sink in the ground, e.g., because of sand. These pose a challenge for slip resistance and reduction of the magnitude and variability of collision forces. Both slippage and punctuated state transitions due to collision forces are high-frequency processes, taking counteraction requires high bandwidth computation and actuation.

Additionally, moving around in an unstructured environment inevitably leads the robot to endure forceful interactions. These interactions may damage the robot or destabilize it. To avoid this scenario, the robot actuation and body should be designed with shock absorption properties to mitigate the force exchanged during the interaction and to filter disturbances. However, in extreme scenarios, it is unrealistic to require a robot not to fall or slip. Therefore, the robot body must be designed in order to be resilient to potential disruptive impacts, for instance, introducing compliant elements into the robot structure. This is the case of soft robots [23], and, in particular, of articulated soft robots, which are systems with elasticity lumped at the joints.

C. THE MIND

The mind includes algorithms for planning and controlling the robot motion and autonomy in extreme environments. Autonomous navigation through natural environments with legged systems is one of the biggest challenges in robotics as it combines understanding of a complex, unstructured environment with a dynamic, highly non-linear control problem of locomotion over rough terrain. For example, vegetation like bushes or tall grass seems untraversable when looking only at its geometric appearance from lidar or depth camera. Moreover, mud, water, loose sand, or gravel have properties that are difficult to predict or model as they often move or deform during interactions. Learning traversability could be a solution to cope with different terrains. Indeed, this allows determining optimal navigation paths from experience with the real robot. However, when walking over unpredictable terrain, successful traversal can never be guaranteed hence haptic perception should be adopted to realize fall recovery systems for rough terrains.

A compliant behavior is mandatory when moving in natural environments, because several obstacles such as rocks, fallen branches, and wet grass may impair the robot. A compliant body - like the one of articulated soft robots - could help achieve this goal, but to really capitalize on these new hardware resources requires solving quite substantial challenges in robot control. First, the introduction of compliant elements results in sensibly more complex dynamic behaviors, making it quite hard to even recover the performance that we had in classic rigid robots. Second, physical intelligence needs to be properly dealt with and exploited by controllers able to reason on the new physical resources. In analogy to how the central nervous system controls the animal body, generating anticipatory actions via the integration of model-based and learning strategies could lead to precise yet compliant motions. Furthermore, control algorithms to perform highly dynamic tasks such as jumping and landing, and able to cope with external disturbances could also be realized.

[12] It refers to the EU N2000 continental biogeographic region.

TABLE 1. Habitat analysis: Continental grasslands.

6210 Semi-natural grasslands and scrubland facies on calcareous substrates	
One of the species-richest and wide distributed habitats, its existence is strongly connected with grazing. Pattern of spatial occupancy: the habitat is of areal type	
Conservation Status Key Indicators	
Structure and functions	Vegetation cover; clumps size and distribution
Typical species	Indicators of Favourable Conservation Status (FCS): Orchid species, especially in important Orchid sites; early warning species of not-FCS: Asphodelus macrocarpus, Pteridium aquilinum, Brachypodium rupestre, Brachypodium januense
Physical parameters	Bare soil, rock, stones, slope
Monitoring Mission	A sampled field relevé is required to measure vegetation cover, estimate bare soil, rock, stones, detect the occurrence of typical species and early warning species, and estimate their abundance. The relevé has to be accomplished in randomly placed macro-plots (10x10m size). The number of macro-plots depends on the overall habitat surface. Within each macro-plot the habitat surface should be estimated. One plot will be positioned in each macro-plot for vegetation cover assessment. The minimum homogeneous area of the relevé is 4 m$\times$4 m.
Monitoring KPIs	Number macro-plot relevés (including data interpretation) per person day
Robot Mobility KPI	
Maximum slope	25°
Friction	$\sim$0.58 (Softfoot Q on grass)
Penetrability	Min 1-2 kg/cm^2 (on grass)
Sink likelihood	Low
Obstacles/gaps	None (obstacles extremely rare and small if present)

TABLE 2. Habitat analysis: Continental forests.

9210 Apennine beech forests with Taxus and Iles	
This habitat is characterized by a stratification of different levels of vegetation at different heights. Pattern of spatial occupancy: the habitat is of areal type	
Conservation Status Key Indicators	
Structure and functions	Vegetation cover; cluster size and distribution
Typical species	Fagus sylvatica, brushes, rocks, dead wood
Physical parameters	Light conditions
Monitoring Mission	A sampled field relevé is required to measure vegetation coverage. The minimum homogeneous area of the relevé is 200 sqm. A relevé should be made every 100 ha. An important parameter here is the percentage of typical species over the found species. Diameter and Height of typical species should be recorded
Monitoring KPI	Number of relevés (including data interpretation) per person day
Robot Mobility KPI	
Maximum slope	30°
Friction	$\sim$0.47 (Softfoot Q on leaves)
Penetrability	Min 0.5-1.5 kg/cm^2 (on leaves)
Sink likelihood	Low
Obstacles/gaps	Frequent obstacles (0.1-1) x (0.5-3) - diameter x length – m (typically horizontal dead wood)

TABLE 3. Habitat analysis: Mediterranean coastal dunes.

2110 Embryonic shifting dunes, and 2120 Shifting dunes along the shoreline with Ammophila arenaria.	
Pattern of spatial occupancy: the habitat may be of areal (small extension), linear or point type	
Conservation Status Key Indicators	
Structure and functions	Vegetation cover; area, shape, and connections among patches
Typical species	Achillea maritima and Agropyrum junceum (2110); Ammophila arenaria (2120)
Physical parameters	Bare soil percentage, elevation and inclination of the dune, soil stability, sand deposition, tracks of mechanical disturbances
Monitoring Mission	A field relevé is required to measure habitat surface, vegetation cover, and patches. The relevé has to be accomplished in contiguous plots (1 m $\times$1 m size) along a permanent transect normal to the shoreline. The number of transects is proportional to the length of the shoreline, the inter-transect distance should be not less than 200 m. The number of plots per transect should be proportional to the habitat area
Monitoring KPI	Number of transect relevés (including data interpretation) per person day
Robot Mobility KPI	
Maximum slope	40° (sand friction angle)
Friction	$\sim$0.58 (Softfoot Q on sand)
Penetrability	Min 0-1.5 kg/cm^2
Sink likelihood	High
Obstacles/gaps	None (obstacles extremely rare and small if present)

Energy efficiency is also a crucial feature for the mind of robotic systems applied to monitoring activities. Indeed, field missions are typically a time-consuming activity, which may require a full working day of an operator in the case of a relevé to monitor natural habitats [27]. Robots equipped with short-lasting batteries may dramatically increase the

TABLE 4. Habitat analysis: Alpine screes.

8110/8120 Alpine screes	
Fixed and mobile screes with pioneering and persistent vegetation. Pattern of spatial occupancy: the habitat may be of areal, much less frequently, linear or point	
Conservation Status Key Indicators	
Structure and functions	Vegetation cover; size and distance among patches; debris mobility;
Typical species	Forbs, graminoids, woody species, mosses, rocks
Physical parameters	Soil stability
Monitoring Mission	A sampled field relevé is required to measure vegetation coverage. The minimum homogeneous area of the relevé is 16-20 sqm. A relevé should be made every 2-5 ha. An important parameter here is the evaluation of the debris mobility.
Monitoring KPI	Number of relevés (including data interpretation) per person day
Robot Mobility KPI	
Maximum slope	60°
Friction	∼0.58 (Softfoot Q on dry rocks). This value can depend on humidity
Penetrability	None
Sink likelihood	Low
Obstacles/gaps	Gaps (0.1-0.5) - length – m

FIGURE 4. ANYmal C robot performing a benchmarking test on the EUROBENCH facility.

mission duration due to the necessity of several recharge phases. Moreover, in some cases power generators may not be available or even allowed.

Finally, the mind includes techniques for identifying and classifying the typical species and assessing the habitat conservation status. The interpretation of habitats, with a specific focus on the conservation status of natural habitats, is of paramount importance. To this aim, following the required standards of the European Directives, robots should collect both quantitative and qualitative data. Quantitative data concern vegetation structure, including total plant cover (i.e. estimation of live plant vs. bare ground and litter cover), vegetation patchiness (occurrence of patches of plants, their dimension, arrangement, connection), plant vertical development (occurrence of different vertical layers: trees, shrubs, grasses, and forbs). An example of quantitative data assessment though segmentation algorithms and convolution neural networks can be found in [88]. Qualitative data involve species identification through the recognition of diagnostic parts (usually flowers and, to a lesser extent, leaves), image capture, and comparison with reference images, with the possibility of improving the identification skills through a learning process.

D. BENCHMARKING AND STANDARDIZATION

A fourth vital component to obtain a concrete solution to the problem of habitat monitoring is benchmarking and standardization. Benchmarking is the process of evaluating systems by comparing them with a common standard or point of reference. Due to their capacity to communicate concisely and synthetically the essential characteristics of a system, benchmarks are widely established in numerous industry sectors, including mobile phone technology, electrical appliances, automobiles, and internet connections. Unfortunately, a generic, widely used, and comprehensive benchmarking methodology for robotics is still lacking. Several efforts have been made to benchmark robotic platforms in different areas [89], [90], [91]. However, in the field of robot locomotion, benchmarking is typically approached through competitions [92], [93] (e.g. European Robotics League, Robocup, DARPA Robotic Challenge, RockIn). Competitions are excellent to generate public awareness and stimulate development but, from a performance evaluation perspective, they fail to quantify the system abilities on a fine-grained level [94]. Measuring aspects like stability, naturality, smoothness of motion, or control, actuation, and structural properties of the machine is of utmost importance to identify its criticalities and increase performance. And currently, there are no solutions able to address these aspects on a rigorous and scientifically sound way [93]. This is even more pronounced in the case of specific applications such as robotic monitoring of natural habitats, which completely miss benchmarking methods, protocols, testbeds, and pre-standards for assessing the robot abilities.

To fill this gap, the European project EUROBENCH[13] [95] is currently creating the first European framework for benchmarking legged locomotion. The framework includes a wide range of testbeds able to replicate realistic situations such as slopes, irregular terrains, stairs, as well as various types of disturbances, like pushes or moving surfaces. The framework

[13] https://eurobench2020.eu/

FIGURE 5. Photo-sequence of the ANYmal C robot walking on a 25° slope in the beech forest scenario.

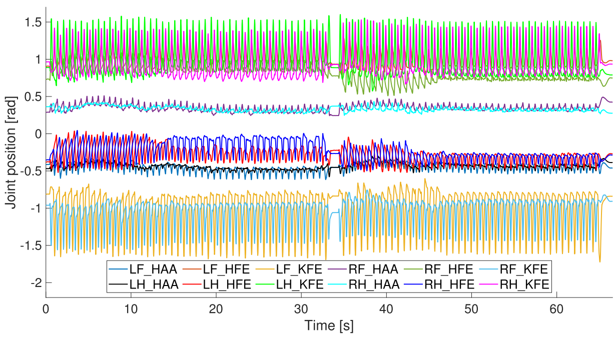


FIGURE 6. Joint evolution of the ANYmal C robot walking on a 25° slope in the beech forest scenario. The joints in the figure are named using the following taxonomy. The first letter indicates the side Left (L) or Right (R), while the second indicates Front (F) or Hind (H). The other three letters indicate Hip Abduction/Adduction (HAA), Hip Flexion/Extension (HFE) and Knee Flexion/Extension (KFE).

also includes benchmarking software composed of several algorithms able to automatically score the performance level of different legged systems, thanks to a unified database with a standardized data format. The framework is currently focused on bipedal robotic technologies, but we are working towards including other types of legged modalities, such as quadrupedal robots (Fig. 4).

V. EXAMPLES OF ROBOTIC MONITORING OF HABITATS

In this section, we provide examples of robotic habitat monitoring using the proposed approach. The platform chosen to validate the method is the ANYmal C robot [96] produced by ANYbotics AG.[14] ANYmal is a quadrupedal robot, which weighs ∼50 kg, it is ∼0.6 m tall when in stand configuration (Fig. 1), and its body has a size equal to ∼ 1.05 m×0.52 m. Each one of four limbs of the robot is composed of 3 joints enabling hip abduction/adduction, hip flexion/extension and knee flexion/extension. Between the hip and the foot there are two links, namely thigh (hip-knee) and shank (knee-foot), which are each ∼0.3 m long. All 12 joints are actuated by identical ANYdrives [96], which are compact Series Elastic Actuators [97]. Therefore, each joint presents a mechanically elastic element between the joint and the gearbox output. The compliance purposefully introduced in its 12 joints makes ANYmal C an articulated soft robot [23]. The shank can be easily removed and replaced to swap between the classic ball point feet, and the adaptive SoftFoot-Q [87].

The robot proprioception is demanded to an inertial measurement unit (IMU) and to joint encoders. Thanks to the spring inserted in the ANYdrive actuator, the joint torque can also be robustly estimated through the measurement of the spring deflection. Joint torque, together with joint position, velocity, and acceleration, are then also exploited to estimate the contact force at the feet thanks to the kinetostatic duality. The robot exteroception is achieved through cameras and a LiDAR sensor. The latter is a LiDAR Velodyne VLP-16 puck lite, and it is used to scan the environment and create a 3D map of it. The cameras equipped on the robot are six: two wide angle FLIR Blackfly BFS-GE-16S2C-BD2 cameras mounted on the front and the back of the system, and four Intel RealSense D435 cameras mounted on each side of the robot. The latter are RGB-D cameras, and we used them to acquire full HD RGB images of the habitat. These sensors both enable the robot autonomous locomotion and also the capability to acquire data for habitat surveys.

The onboard computation is demanded to three computers: locomotion computer, navigation computer, and application computer. The first two computers execute tasks related to motion control and to path planning and following. Both computers are equipped with an Intel core i7 8850H processor (6 cores, 12 threads), 2×8 GB 2666 MHz DDR4 memory, and a 240 GB Solid State Disk (SSD). Conversely, the application computer is composed of an Intel Core i7 7600U processor (2 cores, 4 threads), 2 × 8 GB 2133 MHz DDR4 memory, and a 240 GB SSD. The application computer is used to execute the monitoring tasks, in particular the data acquisition. At the moment, the analysis of the acquired data is performed offline, not during autonomous monitoring missions. This is done to reduce power consumption, considering the fact that corrective actions are usually taken by national or local government at a political level at the end of multiple field monitoring campaigns, as described in Sec. II.

The employed controller is trained by reinforcement learning [98]. In particular, simulations are used to train a policy, exploiting the privileged information such as contact states, contact forces, terrain profile, friction coefficient and disturbances. Then, a student policy is trained with the goal of imitating the policy trained at the previous step. The student

[14]https://www.anybotics.com/

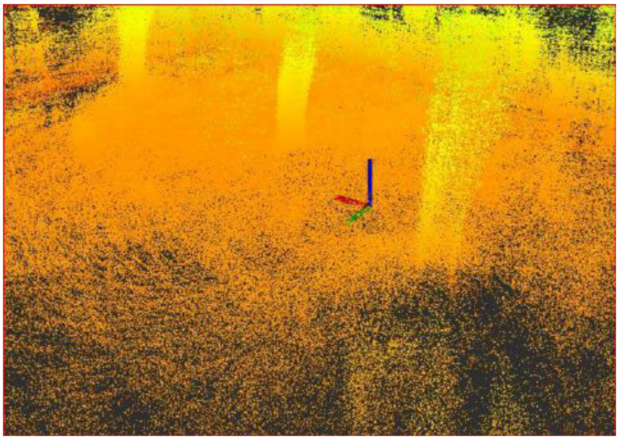


FIGURE 7. Point cloud of the first autonomous mission in grasslands. This 3D map was created by the robot using the LiDAR sensor.

policy has access only to the command vector and the history of the proprioceptive measurements such as base velocity and orientation, and joint states. The result is a controller that outputs desired joint positions, with which it is able to drive the robot over many different challenging terrains with a maximum velocity of 1 m/s. The ANYmal C robot while using this controller presents a power autonomy of 2-4 h according to the producer specification.[15]

In the following, we present four different experiments performed in different environments.

A. LOCOMOTION IN FORESTS

The first experiment aims at showing the ability of the robot in locomoting in a beech forest environment. As depicted in Tab. 2, this habitat is characterized by the of steep slopes and frequent ground obstacles, e.g. fallen branches and rocks. The terrain is typically covered by leaves that increase slippage. We tested the robot autonomously moving up and down a 3 m long slope. The inclination of the slope is (almost) constant and equal to 25° Fig. 5 shows the robot performing half of the task, i.e. walking up the slope. The joint evolution is reported in Fig. 6. This test was repeated five times, with an average completion time equal to 72 s, and an average power consumption of 1.5% of the total battery charge.

B. AUTONOMOUS MISSION IN CONTINENTAL GRASSLANDS

The second tested environment is continental grasslands, whose characteristics are reported in Tab. 1. In this scenario, the robot was equipped with the SoftFoot-Q adaptive feet [87], as depicted in Fig. 1. Two autonomous habitat monitoring missions were performed in two different scenarios with slightly different terrains.

Among the conservation status key indicators reported in Tab. 1, we focus on vegetation cover. Therefore, the goal of the mission is to employ the robotic system to estimate the vegetation cover of the grassland area under analysis. As described in Tab. 1, the monitoring mission for measuring this kind of indicator is performed on macro-plots with size 10 m$\times$10 m. In particular, one plot is positioned in each macro-plot for vegetation cover assessment with minimum homogeneous area of the relevé equal to 4 m$\times$4 m.

The first step is to acquire through the LIDAR sensor a point-cloud map of the area to enable the robot to autonomously move in the environment. For instance, Fig. 7 shows the acquired point cloud for the first mission. We then employed the ANYmal robot to acquire information on the sampled area, in particular, we acquired 16 images of the ground on a 4 m$\times$4 m grid. Fig. 8(a) shows a few examples of the acquired images. Then, these images have been processed to extract information about the vegetation. This can be done by properly selecting the cluster of green pixels in each figure. Fig. 8(b) shows the results. The vegetation in the images are represented by white spaces. From this data, we can roughly estimate the percentage of vegetation cover with a proportion between the number of white pixels and the total number of pixels. With this method, the estimated vegetation cover in the figures (from left to right) is 50%, 53%, and 58%, respectively, and the average among all the data acquired is 53%.

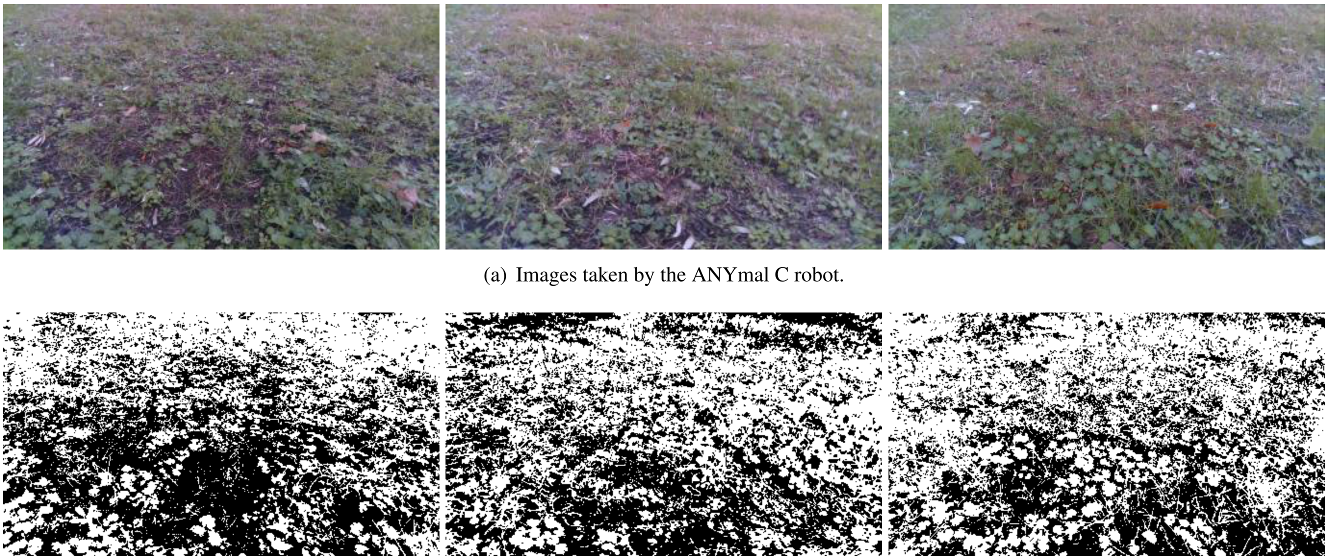
Currently, habitat monitoring is performed by expert plant scientists who go on the field and, among the various executed tasks, estimate the vegetation cover. Since this is the standard procedure for vegetation cover estimate, we employed it as a benchmark for the robot performance. asking to a plant scientist to perform the vegetation cover estimation on the images taken by the robot. The human estimation of the vegetation cover in the Fig. 8(a) (from left to right) is 50%, 55%, and 60%, respectively, and the average among all the data acquired is 55%.

Analogously, we performed a second autonomous mission on a 4m$\times$4m grid. Fig. 9 shows the photo-sequence of the mission, which was successfully performed by the robot in less than 180s, with a power consumption of 3%. Each subfigure represents one of the spot where the robot took pictures of the ground. Please refer to the video attachment for the complete experiment.

C. AUTONOMOUS MISSION IN DUNES

In this experiment we test the robot behavior in the dune habitat. As described by Tab. 3, the typical procedure to monitor this habitat is a relevé with contiguous plots (1 m$\times$1 m size) along a permanent transect normal to the shoreline. In particular we performed one mission to monitor the vegetation cover of the embryonic-2110 and white dune-2120. The mission procedure is similar to the one in Sec. V-B, but a transect is performed instead of a grid. The environment is also very different. The presence of the sand extremely increases the sinking likelihood, and the inclination of the embryonic dune is usually not negligible (in the case under analysis was approximately 15°). After the initial 3D map creation, the autonomous mission is started: the robot moves along a 12 m

[15] https://www.anybotics.com/anymal-legged-robot/?from=mergeek.com



(a) Images taken by the ANYmal C robot.

(b) Vegetation cover estimation.

FIGURE 8. Monitoring mission to estimate Vegetation cover in a Continental Grassland scenario. (a) Images taken by the ANYmal C quadruped robot employed as testbed. (b) Estimation of the vegetation cover.

FIGURE 9. Photo-sequence of the ANYmal C robot performing a habitat monitoring mission in continental grasslands.

long transect, taking images and videos every 1 m. Fig. 10 shows the robot at meter 4, 8 and 10 from the mission starting point. Fig. 11 shows the estimated robot motion during the mission execution. The accuracy of the starting point is 3.4 m. The robot starts on the blue cross in figure and ends its motion over the yellow star. Totally, the mission lasts for 220 s, with a power consumption of approximately 5% of the total battery charge. Please refer to the video attachment for the complete experiment.

D. AUTONOMOUS MISSION IN SCREES

In the last experiment we test the robot behavior in the scree habitat, performing an autonomous mission to acquire data on a 7 m×2 m grid, similarly to the missions executed in

FIGURE 10. Photo-sequence of the ANYmal C robot performing a habitat monitoring mission in embryonic and white dunes.

FIGURE 11. Map of the robot motion while performing the habitat monitoring mission in embryonic and white dunes. The blue cross indicates the starting point, while the yellow star indicates the final point.

Sec. V-B and Sec. V-C. As described by Tab. 4, this habitat is challenging even for humans due to the extremely steep slopes and moving ground. The tested scenario was characterized by ~30° terrain inclination, with the ground covered by moving rocks and stones. The experimental setting was close to a ravine and in the presence of sustained wind of approximately 30km/h. This working condition can be challenging and dangerous also for human beings, especially in the case of elderly or limited mobility people. After the initial 3D map creation, the autonomous mission is started: the robot moves over the grid taking images and video from the cameras, as depicted in Fig. 12. Totally, the mission lasts for 127 s, with a power consumption of approximately 2% of the total battery charge. Please refer to the video attachment for the complete experiment.

E. DISCUSSION

We presented a total of five experiments performed in four different habitats: forests, grasslands, dunes, and screes. As described by Tab. 1-4, each habitat is characterized by different challenges, which hinder the robot locomotion. Grasslands can be considered the less demanding environment among the four tested. Obstacles are sparse and rare, and sinking likelihood is low. Slopes are also usually gentle. From a locomotion perspective, the main challenges are two: potential holes, and the vegetation itself. Holes and gaps are usually produced by wild animals while building their dens, or searching for food. A typical example for the latter are the ones produced by wild boars. The presence of the vegetation can also hinder the robot locomotion, for instance wet grass may increase slippage and tall grass may impair the robot motion. In the case of forest habitats, locomotion is more demanding. Obstacles are very frequent, both in the form of trees or shrubs, and in the form of ground obstacles, e.g., stones and dead wood. The presence of leaves also increases slippage. This issue, together with the presence of slopes that may reach 30° inclination, poses a challenge for the robot locomotion. Dune habitats are among the most challenging scenarios. Dune inclination is usually variable, and it can reach very steep values. Obstacles are rare, but sinking is very common. Finally, Alpine screes require a non-negligible locomotion effort, both for humans and robots. Terrain inclination is among the steepest ones, and the ground is covered by unstable debris, which may move at each step.

The experimental tests validated the robot ability to move over these four types of terrains. These presented different slope inclinations, different sinking likelihoods, different friction coefficients, and different ground mobility. These four factors are generally the main barriers to a proper robot locomotion, and they may even hinder human locomotion. For instance, these monitoring scenarios may require a huge effort for people who are elderly or with limited mobility. This is particularly relevant for the scree experiment, which represents a perilous set for humans due to the ground instability, strong wind gusts, and the proximity to a ravine. Nevertheless, in all the tested scenarios the robot was able to successfully complete the commanded tasks.

During the experimental tests, mission duration and battery consumption have also been measured. Tab. 5 summarizes the results obtained during the tests for each habitat. From these results, it is shown that the robot is able to perform multiple monitoring missions within a single battery charge. This holds true even in the case of demanding scenarios, like the autonomous relevé in the dune habitat (Sec. V-C), which required approximately 5% of the total battery charge despite the slope and sinking terrain. Given the results of Tab. 5, we can estimate that the robot is able to perform multiple autonomous missions for a total of 1.2-1.8 h operation time depending on the specific habitat. This estimate is lower than the producer specifications, but it does not include robot idle time, which may extend the total battery duration. However, the estimated operational time is way larger than the one of

FIGURE 12. Photo-sequence of the ANYmal C robot performing a habitat monitoring mission in Alpine screes.

TABLE 5. Summary of duration and power consumption of the tests in the four environments.

Habitat	Duration [s]	Power Consumption [%]
Forest	72	1.5
Grassland	180	3
Dune	220	5
Scree	127	2

commercial drones which stands in the range 0.3-0.5 h [78]. Nevertheless, future work will be devoted also to the improvement of the robot energy efficiency.

The robot exteroception in natural environments has also been successfully tested. Indeed, the LiDAR sensor allows the perception of the surrounding, and therefore it enables the robot autonomous navigation. Analogously, the Real Sense cameras enables the acquisition of the habitat information. Pictures are then analyzed to assess the habitat conservation status, e.g., though vegetation cover estimation. This analysis was benchmarked though vegetation cover estimation performed by a plant scientist. Results show that human and robot analysis are very similar validating the applicability of the proposed method.

Finally, each to-be-monitored habitat requires a different survey scheme in agreement with the Habitat Directive (92/43/EEC) [25]. In case of robotic monitoring, this translates into different monitoring plans and thus area coverage. For instance, in grasslands, the relevé is performed over a 4m×4m grid, while in dunes the relevé is a 12 m long transect. In both cases the robot was able to successfully acquire the plot data.

VI. CONCLUSION

In this paper, we discussed the importance of robotic environmental monitoring of habitats, and the challenges related to this operation. Robotics could indeed enable continuous monitoring of the ecosystems, but several steps forward must be performed to achieve such an ambitious goal. Indeed, irregular and rough terrains, long-lasting operations, and unexpected collisions are just a few examples of the challenges to be tackled. Natural Intelligence, identified as the combination of body, mind and environment, could fill this gap. Examples of robotic monitoring of habitats are presented in four different environments: forests, grasslands, dunes, and screes. Future work will focus on improving the robot ability in evaluating the habitat conservation status. Additionally, we will present a benchmarking platform to evaluate the robot locomotion capabilities.

ACKNOWLEDGMENT

The authors would like to thank Riccardo Mengacci, Andrea Timperi, Mathew Jose Pollayil, and Giuseppe Alfonso with Centro di Ricerca "Enrico Piaggio," Università di Pisa, and Huy Mahn with Kingston University.

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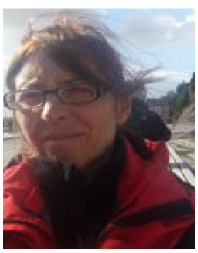

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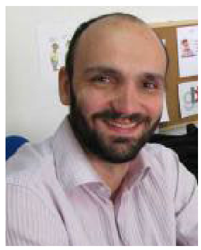

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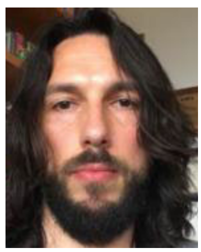

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Open Access funding provided by 'Università di Pisa' within the CRUI CARE Agreement