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RESEARCH ARTICLE

An Intelligent Hierarchical Cyber-Physical System for Beach Waste Management: The BIOBLU Case Study

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ABSTRACT Nestled at the confluence of nature grandeur and human civilization, beaches command an influential presence that resonates throughout the environment, society, and culture. However, climate change and pollution overhang the beach health and need to be properly dealt with. Proactive measures involve education, responsible waste management, sustainable infrastructure, and environmental regulations, while reactive ones focus on immediate response and cleanup efforts. Nevertheless, continuous monitoring and cleaning are challenging due to various factors such as beach characteristics, hidden waste, weather conditions and, consequently, high costs. To overcome such challenges, this paper proposes an autonomous system for beach cleaning adopting an Intelligent Hierarchical Cyber-Physical System (IHCPS) approach and Information and Communication Technologies. The proposed beach waste management (BeWastMan) solution integrates an Unmanned Aerial Vehicle for the beach aerial surveillance and monitoring, a ground station for data processing, and an Unmanned Ground Vehicle to collect and sort waste autonomously. The research findings contribute to the development of innovative and fully automated approaches in beach waste management, and demonstrate the feasibility and effectiveness of the BeWastMan IHCPS by a real case study, developed in the frame of the BIOBLU project.

INDEX TERMS Intelligent cyber-physical systems, multi-robot systems, unmanned aerial vehicles, computer vision, unmanned ground vehicles, beach waste management.

I. INTRODUCTION

Coastal regions and their associated beaches hold immense significance for our life, due to their ecological, social, economic, and cultural impact. They provide habitats for diverse species, contribute to biodiversity, and act as natural buffers against coastal erosion. Beaches are popular tourist destinations, offering recreational opportunities and cultural value. They support the tourism and hospitality industry, creating jobs and stimulating the economy. Beaches also play a role in fishing, aquaculture, and carbon sequestration, while filtering water and maintaining water quality. Understanding and preserving the importance of beaches is essential for the sustainable coastal management and the community and environment well-being.

Beaches can become polluted due to marine debris, coastal runoff carrying pollutants from urban and agricultural areas, sewage and wastewater discharge, oil spills, improper

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waste disposal, recreational activities, and shipping/boating activities. These sources contribute to the contamination of beaches and can harm marine ecosystems. Recently, the Legambiente Beach Litter 2023 survey,[1] monitored 38 beaches in 15 Italian regions, reporting on average 961 litter items (72.5% plastic) per 100 mt of coastline.

It is crucial to address these sources of pollution through improved waste management, proper sewage treatment, and public awareness to preserve the cleanliness and ecological integrity of beaches. Given the current levels of pollution of our seas and beaches, the mitigation of the effects caused by human-generated debris (mainly plastic) has now become a critical and urgent issue to be addressed.

To keep beaches clean is often among the hardest to achieve goals for local governments, municipalities, and volunteers [1], [2]. Proactive and reactive solutions are vital to such a purpose. Proactive measures include raising awareness through education, promoting responsible waste management, implementing sustainable infrastructure, and enforcing environmental regulations, to reduce pollution sources, prevent beach pollution and preserve the pristine condition of coastal environments. In addition to proactive measures, reactive solutions focus on immediate response and cleanup efforts. This involves organizing beach cleaning initiatives, establishing waste collection and sorting systems, developing contingency plans for accidental spills, and implementing regular monitoring and surveillance programs. By swiftly removing litter, debris, and other pollutants from beaches and effectively managing cleanup operations, the impact of pollution can be minimized, ensuring cleaner and healthier beach ecosystems. Combining proactive and reactive strategies provides a comprehensive approach to combat beach pollution, promoting the well-being of coastal environments and preserving their beauty and ecological integrity.

Focusing on reactive solutions, continuously monitoring and cleaning beaches is very challenging due to several issues such as i) the landform, with sandy, rocky, or even mixed beaches; ii) the flatness or steepness of the ground (which makes them hard to reach); iii) the type of waste, e.g. liquid, toxic or dangerous; iv) the presence of people, animals or obstacles (e.g., boats, large rocks, etc.); v) (partly or fully) hidden or buried waste; vi) weather conditions (e.g. tides, rain, snow, wind), to name a few.

Information and communication technologies (ICT) can support beach waste management. More specifically, Cyber-Physical Systems (CPS), leveraging on technologies such as IoT, Edge-Fog-Cloud computing, Big Data management and artificial intelligence (AI), may play a key role in making beaches more interconnected and intelligent by their cyber counterpart able to live monitor and manage the beach. CPS such as Unmanned Aerial Vehicles (UAV) and Unmanned Ground Vehicles (UGV) equipped with high-resolution cameras and GPU, ensure real-time video streaming and processing, allowing small areas (e.g. beaches) to be monitored, quickly detecting waste items and geolocalizing them into waste maps.

On such premises, this paper proposes an autonomous system for beach waste management (BeWastMan), adopting an Intelligent Hierarchical Cyber-Physical System (IHCPS) approach. The BeWastMan IHCPS is therefore a CPS composed of three CPS: a UAV for beach monitoring, a Ground Station (GS) for data management and processing, and a UGV for waste collection and sorting, able to autonomously manage themselves and interact with each other through AI-based/intelligent algorithms. The UAV captures high-resolution videos and sensor data, probing the physical system (i.e. the beach). Such a data stream is thus processed by the GS to detect and locate beach waste items, implementing the IHCPS cyber system. The UGV is then deployed to collect and sort the waste items detected by the GS in a geolocalized map, closing the IHCPS loop by ensuring a minimally invasive and environmentally friendly approach.

Thereby, the main contributions of this work are:

1) *Fully autonomous system* - BeWastMan introduces a completely autonomous system, founded on cutting-edge autonomous technologies - namely, the UAV, GS, and UGV - designed for the automated management of beach waste. This system functions as an Intelligent Hierarchical Cyber-Physical System (IHCPS). Within this framework, the UAV is responsible for conducting aerial surveillance and monitoring, the GS operates as a central hub for data processing and decision-making, and the UGV independently traverses the beach environment to collect waste materials.
2) *Hierarchical CPS methodology* - Embracing the IHCPS methodology offers a methodical framework for the management of beach waste, guaranteeing the replicability of the BeWastMan solution across various contexts and domains.
3) *Edge-to-Cloud computing continuum* - The proposed approach harnesses the potential of an edge-to-Cloud computing continuum. This methodology empowers both real-time and time-sensitive applications by processing data at the edge, such as on the UAV for enhancing inspections through speed adjustments or on the UGV for addressing obstacles or emergencies. Concurrently, it enables the storage and processing of historical data in the Cloud, a feature beneficial for activities like ongoing training of diverse beach sediment models. This dual-pronged approach not only fine-tunes system performance but also enhances its scalability.
4) *Resilience and adaptability* - To ensure comprehensive and efficient waste collection across a diverse range of scenarios and beach environments, all components within the BeWastMan solution prioritize resilience and adaptability. The UAV employs an adaptive video

[1] https://www.legambiente.it/rapporti-e-osservatori/rapporti-in-evidenza/indagine-beach-litter/

capture process, dynamically adjusting its speed in response to prevailing environmental conditions and detected items. Meanwhile, the GS leverages continuous video streaming instead of video frame samples to significantly improve the precision of waste detection and geolocalization. Similarly, the UGV conducts thorough searches for detected items within target areas rather than fixed points, and it seamlessly collaborates with the GS when recognized items cannot be collected.

5) *Suitability to different beaches* - The BeWastMan design takes into account diverse beach typologies, encompassing sandy, rocky, and mixed beaches. The proposed architecture and technologies exhibit adaptability, enabling deployment across a wide spectrum of beach environments, ensuring effective waste management across various coastal regions.
6) *Minimally invasive nature* - The proposed BeWastMan solution emphasizes a minimally invasive approach through the aerial survey mission performed by the UAV and the precise pick-and-place operations executed by the UGV. This approach is intentionally designed to minimize the environmental footprint of the waste management process on the beach. Through robotic mechanisms and other non-disruptive techniques, the system endeavors to ensure a gentle cleaning process and to preserve the natural integrity of the beach.
7) *Real-world case study validation* - This paper encompasses the implementation and validation of the BeWastMan architecture in a case study derived from the BIOBLU project. This comprehensive assessment serves to validate the feasibility, functionality, and performance of the BeWastMan IHCPS in a real-world scenario, offering tangible evidence of its practical applicability and effectiveness.

These contributions collectively enhance the understanding and advancement of autonomous beach waste management, providing valuable insights and effective solutions for maintaining cleaner and healthier coastal environments.

Details are provided in the remainder, structured as follows. Section II describes the problem and provides an overview on the related works. Section III introduces the proposed solution and the BeWastMan IHCPS. Then, the UAV, the GS, and the UGV design are detailed in Sections IV, V, and VI, respectively. The BIOBLU project case study, implementing the BeWastMan IHCPS, is detailed in Section VII, while the results obtained by the experiments on the BIOBLU case study are reported and discussed in Section VIII. Section IX closes this paper with some remarks and discussion.

II. PRELIMINARY CONCEPTS

A. PROBLEM DESCRIPTION

In operational terms, beach cleaning is a multifaceted undertaking, involving a series of tasks, as illustrated in FIGURE 1 and described below:

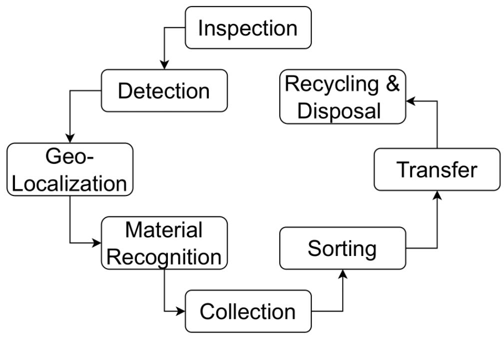


FIGURE 1. Beach waste management process.

T.1 *inspection* - the beach is monitored to discover waste items;

T.2 *detection* - waste items are detected and investigated to identify their geometric properties and features (size, height, length, volume, weight) useful for collection;

T.3 *geolocalization* - once detected, the waste items are geolocalized, whether or not it is possible or easy to collect them (e.g., too big/heavy or in not easy to access areas);

T.4 *material recognition* - detected waste material is recognized and classified for sorting;

T.5 *collection* - waste items are collected if the system is able to perform the collection, otherwise, a further waste collection process has to be enforced;

T.6 *sorting* - once detected, collected, and properly classified, waste sorting is performed by placing the items in the proper bins based on their materials;

T.7 *transfer* - collected and sorted waste is transferred to the recycling station;

T.8 *recycling and disposal* - once reached the recycling and disposal station, waste containers are emptied.

On a regular basis, beach cleaning prevents waste accumulation as discussed in [3] and [4], proposing beach clean-up programs and waste management strategies. However, currently this process is mainly implemented manually [5], with high costs impacting on regularity. Its automation may be a significant improvement to such a purpose, although challenging. Main issues and challenges to be dealt with in beach waste management automation are:

C.1 *inaccessibility* - namely the limited access to some areas;

C.2 *dynamic environment* - the beach environment may change suddenly (due to e.g. the weather, tides, wind, light);

C.3 *beach sediments* - which can differ, such as sand, gravel, shingle, pebbles, rocks, and cliffs;

C.4 *eco-friendliness* - minimizing the impact of waste management on the beach environment and ecosystem;

C.5 *completeness and accuracy* - most of (hopefully all) the beach waste objects should be detected, geolocalized and then (if possible) collected, sorted and further managed.

B. RELATED WORK

To automate the beach waste management process is an open problem, partially addressed in some recent works discussed in the following, but never, to the best of our knowledge, considered and tackled as a whole. Some of the reviewed works implement multiple beach waste management tasks, which makes it difficult to sharply categorizing them in only one task.

1) INSPECTION

Several works in the literature aim at automating beach inspection, usually by exploiting UAV. Drones have been adopted for different maritime application domains, mainly in the context of people safety to search and rescue castaways. Some works involving UAV in municipal solid waste management are reviewed in [6], mainly dealing with landfill-related issues, such as gas emission monitoring and waste volume estimation.

Authors in [7] discuss on the potential of using UAV for beach waste inspection. The findings support the incorporation of UAV into routine beach waste monitoring programs, offering a cost-effective and accessible sampling method by overcoming, at the same time, the limitations of labor-intensive visual surveys to quantify and characterize beached waste. The comparison with visual census demonstrates that the UAV-based quantification is three times faster.

In [8], a DJI Phantom 4 PRO quadcopter equipped with a 20 MP camera is used for marine waste detection and recognition. Binary image segmentation is proposed to detect the waste on the beach from RGB channels spectral profiles, providing high geolocalization accuracy. Similarly, a DJI Phantom 3 quadcopter equipped with a 12 MP camera is exploited in [9] for waste detection and multi-class recognition based on machine learning. A DJI Phantom 4 quadcopter equipped with a 12.4 MP camera is used in [10] for environment mapping and waste detection through CNN. In [11], two quadcopters, namely a DJI Inspire 2 and a Phantom 4 PRO, equipped with 20.8 MP and 20 MP cameras, respectively, have been used in different scenarios for aerial image acquisition. A commercial software has been used for mission planning at different flight altitudes and for the environment mapping, enhanced with RTK GPS and ground control points. Beach litter detection is obtained through object segmentation.

Related work mainly identify UAV as the most effective solution for beach inspection, nowadays a de-facto standard in such applications. Existing UAV technologies and devices are usually well-equipped and customizable providing ready made solution for beach inspection.

2) WASTE DETECTION, GEOLOCALIZATION, AND RECOGNITION

The problem of waste detection and recognition-classification represents a major challenge [12] in beach waste management. As a consequence to the adoption of drones to beach inspection, the mainstream approach for waste detection, geolocalization and classification is based on images, videos and their processing. Computer vision and machine learning have been thus applied, as in [13] where a vision-based robotic prototype for the classification and collection of construction waste is addressed by using R-CNN (Region-Based Convolutional Neural Network) and Mask R-CNN models.

The solution implemented in [14] proposes litter detection from low-altitude UAV imagery acquired by a calibrated onboard camera, adopting a YOLO-based architecture. Similarly, in [15] an end-to-end semantic segmentation algorithm based on the U-Net architecture is implemented to detect and recognize three types of plastic (OPS, Nylon and PET) in rivers and lakes by using high-resolution orthophotos from a UAV.

In [16] a beach waste detection and monitoring based on aerial images and Convolutional Encoder-Decoder model is proposed. The authors used orthophotos and a pre-trained neural network algorithm for waste detection by removing the fully connected layer for semantic segmentation. This model demonstrates excellent performance in detecting irregularly shaped waste, such as Styrofoam, and targets with diverse colors.

These computer vision and ML-based approaches offer promising solutions to address the problem of waste detection and classification in an efficient way. It is still a challenge, however, to integrate these solutions with physical waste collection systems to achieve a completely automated and reliable solution.

3) WASTE COLLECTION, SORTING, TRANSFER, AND DISPOSAL

The most widely used approach for waste collection in sandy beaches consists in sifting the sand through a sieving system composed of a set of meshes connected to a vibrating system. Such a system is usually mounted on human-driven tractors [17], [18] where the operator usually follows predetermined paths to cover the area of interest. All the solutions proposed in [19], [20], [21], [22], and [23] share the same sieving-based sand cleaning method with remotely controlled vehicles. The use of unmanned vehicles allows the design of small-sized solutions, which are suitable for areas with numerous obstacles and limited maneuvering space as is the case of crowded beaches, while the operator remotely drives the vehicle by continuously maintaining a visual feedback of it. This makes the beach cleaning process safe but also strictly bound to human intervention.

Autonomous robotic solutions [24], [25] use GPS receivers for localization and range sensors to avoid obstacles, mainly implementing blind techniques, i.e. without preliminary inspection. The autonomous beach cleaning process relies on the coverage path planning of the area of interest [26], while sieving the sand. At the end of the collection process, the ground vehicle reaches a recycling station where the collected waste is disposed. The main limitation of such an approach is its inefficiency, in terms of both duration and, hence, power consumption of the cleaning operation.

Other important limitations of all sieving-based solutions are: i) they cannot be employed on rocky, shingle or pebble beaches, and ii) invasiveness, as they imply the alteration of soil shape and composition (including natural elements such as marine life, shells, seaweed, small plants, insects, etc.), regardless of the presence of beached waste. To the best of our knowledge, no autonomous solutions deal with other types of beaches (apart sandy ones) and implement beach waste sorting.

4) AUTOMATIC WASTE MANAGEMENT APPROACHES

An effective approach in waste management automation is to combine computation, communication, and control with physical processes by the integration of the cyber and physical worlds into Cyber-Physical Systems (CPS) [27]. These are often referred to as *intelligent* CPS, thanks to the adoption of AI-based algorithms [28].

Different works demonstrated the CPS effectiveness in urban waste management applications [29]. In [30], an IoT (Internet of Things) and Cloud-based CPS for efficient solid waste management in a smart city scenario is implemented by developing a route optimization technique using smart dustbins and real-time road traffic information. In [31] a CPS solution for wastewater collection and treatment within buildings has been implemented. In the beach context, [32] proposes an autonomous maritime eco-CPS equipped with a computer vision system for pollution detection in the coastal and marine environment.

Although these CPS-based technologies are widely used in many areas, the automation of beach waste management is still a big challenge. The CPS approach may be promising in such context, framing the solution into the interaction between two or more CPS. Adopting UAV for inspection and robots for detection, collection and sorting is poorly investigated and poses a challenge in this research area [33].

III. THE PROPOSED SOLUTION

The main goal of this work is to develop an automatic system to monitor and keep clean beaches, automating the workflow shown in FIGURE 1 while addressing the challenges listed in Section II-A.

To address challenge C.1 concerning obstacles that may limit access to parts of the beach, the aerial view, as demonstrated by the related work, is the best way to detect and locate waste. This implies to i) split detection and collection/sorting activities into two separate sequential steps; ii) introduce further inspection and geolocalization steps to enable (offline) collection and sorting; and iii) adopt drones for the aerial image-video capture. Computer vision algorithms then process images and videos collected by the drones to detect, locate and classify the waste, generating a geolocalized waste map. Based on such a map, an autonomous UGV collects and sorts the waste from the beach.

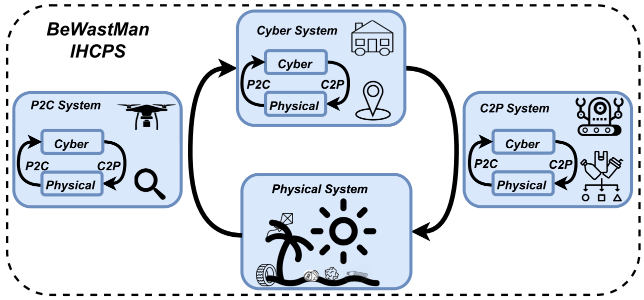


FIGURE 2. Beach waste management IHCPS reference architecture: the *BeWastMan* framework.

To cope with challenge C.2, i.e. the continually changing nature of the considered environment, a dynamic and self-adapting solution is required. From a methodological perspective, this solution can be framed into a cyber-physical system (CPS) probing the *physical system*, namely the beach, with the drone, feeding a *cyber system* to detect and localize waste into a map then provided to the ground robot to enforce on the physical system-beach waste collection, sorting, and transfer actions, thus closing the CPS feedback loop in a timely manner, while allowing prompt adaptation to changes of the environment conditions.

Adopting the CPS approach, the *BeWastMan* solution framework is identified, grouping the waste management tasks into 3 stages: i) inspection; ii) detection and geolocalization; and iii) material recognition, collection, sorting, transfer, recycling and disposal. Thereby, as shown in FIGURE 2, the physical system to be monitored and controlled is the beach, the cyber system is essentially deployed in the GS, processing the information coming from the UAV, i.e. the geotagged video stream, which acts as a physical-to-cyber (P2C) or *sensing* system. The obtained results are forwarded to the UGV to enforce on the physical system the beach cleaning policy, acting as a cyber-to-physical (C2P) or *actuation* system. The main benefit of a hierarchical CPS, as also argued in [34], lies in its capacity to offer a greater degree of flexibility compared to a flat solution. Within the BeWastMan IHCPS framework, the UAV, GS, and UGV operate as autonomous entities, capable of independently, dynamically, and swiftly addressing challenges and issues. The higher-level CPS serves to coordinate and orchestrate their activities.

More specifically, the UAV system flies over the beach to perform inspection, autonomously managing the mission by tuning the speed when waste items are detected through a waste detection model deployed onboard. To such a purpose, multiple frames and videos, instead of single images, are exploited, thus improving the detection accuracy of challenge C.5. Furthermore, different models have to be trained to deal with different beach sediments and conditions (e.g. light, weather) to tackle challenge C.3.

The UAV system interacts with the GS which plans and coordinates the mission and supports all the other components with computing (storage, networking and processing) and energy resources and facilities. The GS is also tasked at processing the UAV data streams, detecting and geolocalizing beach waste items from redundant videos to improve the overall precision (C.5).

It thus triggers the UGV that autonomously reaches the geolocalized points to collect the detected waste items by means of a robotic arm equipped with a gripper (working on any beach sediment for challenge C.3, while reducing the impact on the environment for C.4) and sort it in its onboard bins. Once waste collection and sorting is completed, the UGV first reaches the recycling station to dump the onboard bins and eventually parks in the GS charging station.

Thereby, all such components are CPS, since they continuously probe their own physical system, elaborate the obtained input, and consequently actuate on the former to manage the overall system, thus enabling a further layer of self-adaptation to address changes and fluctuations of C.2. As a consequence, overall the BeWastMan system is a *hierarchical* CPS (HCPS), i.e., a CPS composed of CPS interacting with each other autonomously for the beach waste management mission. Furthermore, adopting artificial intelligence techniques for processing the sensed input (e.g. video stream, telemetry, energy, weather and environment parameters), it is an intelligent HCPS (IHCPS).

Enforcing the principles of separation of concerns and modularity, each individual low-level CPS component of the BeWastMan IHCPS (i.e. UAV, GS, and UGV) is responsible for carrying out its own specific sub-mission within the overall BeWastMan mission. These sub-missions should be implemented mostly independently, with minimal or no interaction with the other CPS, to avoid jeopardizing the overall mission in the event of any failures. To such a purpose, it is possible to abstract and generalizes the main goals and (sub-)tasks of the UAV, GS and UGV CPS within the BeWastMan IHCPS into the management of:

- ST.1 *mission* - planning, coordinating, and implementing the specific CPS sub-mission;
- ST.2 *safety and security* - planning and enforcing policies to ensure the specific CPS safety and security;
- ST.3 *energy* - planning and enforcing policies to optimize the specific CPS energy management.

IV. THE UAV P2C SYSTEM

A. MISSION: INSPECTION

The UAV is tasked to fly over a specific area of a target beach of the BeWastMan mission, capturing georeferenced images and/or videos through its camera, acting as a CPS [35] to improve the inspection/video capturing quality. Captured images are indeed pre-processed onboard (edge computing) the UAV to detect waste online, in a timely manner, through machine learning-based computer vision algorithms. If a potential waste object is detected, the UAV autonomously modulates its speed to capture more detailed images/videos to improve the detection and geolocalization steps performed by the GS.

The waste detection performed onboard the UAV, which is a resource constrained device, has to provide results in a timely manner to allow slowing down the drone while the object is still in the field of view, speeding up otherwise. To such a purpose, a fast waste detection has to be performed on the UAV based on low-res videos and lightweight models, while the actual waste item detection and geolocalization is then performed offline by the GS, as detailed in Section V.

Specifically, the workflow of the BeWastMan UAV sub-mission starts with the i) *drone initialization*, checking the charge of the batteries and all useful components for the flight; then performs the ii) *mission planning*, using the drone route planning and scheduling software; and finally implements the iii) *beach inspection mission*, where the drone takes off, reaches the area of interest of the beach and captures aerial images/videos on the planned route, live processed by the drone to improve the overall inspection mission by speed tuning as discussed above.

B. PHYSICAL

Both fixed-wing and multi-rotor UAV are suitable for the beach waste management. However, the latter, thanks to their easier speed control, better fit with the speed tuning maneuver required by the BeWastMan mission. Moreover, multi-rotors are usually preferred with high-speed wind [9].

A BeWastMan UAV has to be equipped with processing facilities (a *companion computer*), for both video capturing, local processing and transmission to the GS and its high-level sub-mission management. Another crucial hardware component is the *flight control unit* (FCU), which is a microcontroller-based low-level autopilot in charge of drone initialization, stabilizing the drone during the flight and translating the high-level commands provided by the companion computer into either propeller speeds for multi-rotors, or surface control actuators and motor speed for fixed-wing vehicles.

For interacting with the GS a proper communication device is needed. Based on the distance to be covered and the required bandwidth, Wi-Fi and/or radio communications can be adopted. The minimal hardware equipment for a UAV also includes power supply management, namely batteries and DC-DC converters. Solar panels could be used as an autonomous power source for fixed-wing vehicles, useful in long-endurance missions. The type, size and placement of solar panels may depend on the power requirements of the fixed-wing drone and on its structure. Finally, an RC receiver for the remote control of the UAV must be included, as a backup for safety reasons.

C. P2C

Besides the main hardware components described in the previous Section, the BeWastMan UAV must be able to capture high-resolution geotagged images, operating under harsh conditions (e.g., humidity, sand, and wind). Specifically, the BeWastMan UAV should be equipped with: i) *inertial sensors*, i.e., a combination of accelerometers, gyroscopes, and magnetometers that acquire information about the UAV orientation, speed, and acceleration, crucial for low-level stabilization (particularly critical in windy conditions), navigation and control; ii) a *GPS receiver* required for navigation and control, particularly crucial for the BeWastMan inspection mission to reach specific areas of the beach and to geotag the acquired images; iii) *barometers*, to probe the atmospheric pressure, a parameter used in the UAV altitude assessment; iv) *ultrasonic sensors*, estimating the distance to the ground or other obstacles to maintain a stable hover and avoid collisions.

Other specific sensing devices suitable for a BeWastMan UAV are the *multispectral/hyperspectral* imaging sensor as well as a *high-resolution RGB camera* to capture and save multiple spectral/detailed images of the beach or a specific waste item and to identify and monitor changes in the landscape, the beach ecosystem composition and health. *Gimbal stabilizer* can be adopted to stabilize the cameras for high-quality stable images.

D. CYBER

The UAV cyber system plays a key role in BeWastMan, supporting the inspection (sub-)mission (through waste detection) while enforcing stabilization, to ensure proper UAV operation, and communicating with the GS for further data processing. Furthermore, mechanisms for enhancing drone energy resource management, security, and safety are provided. More specifically, the BeWastMan UAV cyber system can be implemented as a dashboard including different *software modules*, i.e. the tools to manage and visualize the drone functionalities (cameras, telemetry data, energy, processing and storage facilities).

The main module is the *mission and flyover management*, which must be programmed in advance with the flight route and related parameters to let the drone performs all the planned activities. It also ensures the safety and reliability of the UAV by taking care of in-flight stabilization and emergency systems.

The *energy module* provides facilities for the management and optimization of energy resources to maximize the flight autonomy. This involves the design of energy-efficient flight paths to reduce power consumption.

These modules are usually provided by the UAV manufacturer, allowing some customization to meet the BeWastMan mission requirements. Customization could include modifying the software features to meet specific mission needs, such as adding or removing sensors or cameras to/from the UAV to capture images or video of specific areas of the beach or to focus on specific details. For example, if the mission requires capturing a portion of the beach in details, the software could be customized to integrate a camera with wider field of view and/or zoom and image processing pipeline.

To such a purpose, indeed, an onboard *waste detection module* is specifically conceived by the BeWastMan framework for improving captured data (video and telemetry) quality to be delivered to the GS. As discussed above, such a module performs live waste detection, in an edge computing fashion, to control the drone flight by adapting its speed when a waste object is detected and the quality of the image is low, eventually allowing zooming into the image. An adaptive speed-tuning algorithm can also allow to reduce the UAV inspection mission time, slowing down when waste items are detected, speeding up otherwise.

Thereby, the detection module is interacting with the mission and energy modules, sending them commands for controlling the flight, enforced if the battery level is enough to perform the mission. More specifically, at this stage, considering the (energy, processing) resource-constrained UAV and the need to accomplish the mission within strict time/energy bounds, a low-resolution video stream with a reduced number of frames per second (fps) is processed by the UAV detection algorithm. This approach allows for faster processing and reduces the computational burden on the limited resources of the UAV allowing to meet the time constraints and successfully perform waste detection tasks.

To optimize energy management, flight data could be directly saved into the internal memory of the UAV, properly equipped with a built-in data storage system, such as an on-board memory card or hard drive, which automatically records flight data during, e.g., the return-to-home (RTH) process. This can save the energy to transmit flight data to the GS in real-time, sending only required data in batches when convenient (e.g. using wireless connectivity such as Wi-Fi in proximity to the GS).

E. C2P

As discussed above, in BeWastMan, the UAV could autonomously act on the mission by enforcing a speed-tuning maneuver in the case of waste detection. Thereby, a more detailed video and image acquisition can be obtained by simultaneously acting on the UAV motors, slowing down when detecting waste while speeding up otherwise, and camera, zooming-in/out accordingly.

The UAV actuation can also be exploited to improve the energy management of the UAV itself. A return-to-home policy allows the drone to automatically return to the take-off point in the event of low battery levels and low RC transmitter signal strength. Besides energy management, RTH procedures ensure both safety and security of the UAV. This capability can be especially valuable for missions that require prolonged flights, such as environmental monitoring applications.

V. THE GROUND STATION CYBER SYSTEM

A. MISSION: PLANNING, COORDINATION, DETECTION AND GEOLOCALIZATION

The GS is the brain of the BeWastMan system, planning and coordinating the beach cleaning mission. It hosts the main (computing and energy) resources and facilities to gather information from the UAV system, process it to detect and identify the properties of beach waste (e.g. size, location), and

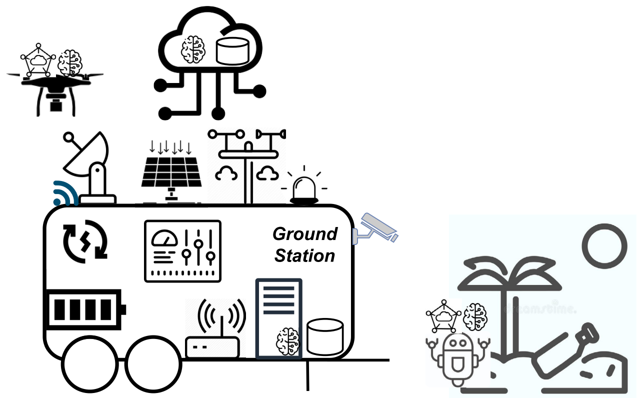


FIGURE 3. The BeWastMan ground station architecture.

provide a geolocalized waste map to the UGV robot for waste collection. It implements the cyber part of the BeWastMan IHCPS, mainly focusing on processing activities. To properly support and interact with the UAV and the UGV systems, the GS has to operate in proximity to the beach. As a consequence, a vehicle able to move the GS facilities, as well as all other BeWastMan system equipment, i.e. the aerial and the ground vehicles, is required.

Once the GS reaches a place nearby the beach, its focus is mainly on planning, coordinating and supporting the BeWastMan cleaning mission, including UAV and UGV tasks, with a system providing all required facilities, as shown in FIGURE 3. To reduce the risk of failures and optimize the overall resource management, the GS probes and monitors the beach area (e.g. light, weather conditions, waves, tides) and its unmanned vehicles (e.g. position, charge) to avoid, prevent and mitigate potential issues. In the case of issues, it could enforce specific policies adapting the BeWastMan system configuration. Therefore, all the GS components and modules can be framed into the CPS framework, implementing the tasks: i) supporting BeWastMan mission planning and coordination, ii) implementing beach waste item detection and geolocalization, ii) ensuring safety and security, and iv) managing energy of the GS vehicle and the BeWastMan equipment (including the drone and the UGV when stored in, at rest).

B. PHYSICAL

From the physical viewpoint, the main facilities provided by the GS to properly implement the aforementioned tasks can be grouped into the categories detailed below.

1) COMPUTING

The GS computing facilities include storage, processing and networking facilities and solutions to support the UAV data elaboration and the UGV mission acting as the BeWastMan cyber system. To such a purpose, it combines local (edge, fog) computing resources, able to provide a feedback in a timely manner, with global, ubiquitous resources, allowing to persistently store related data, to further process them, and to remotely access the obtained result, mainly exploiting Cloud facilities. In this light, the BeWastMan system implements an edge-fog-cloud computing continuum approach, as shown in FIGURE 3 and detailed in the following.

a: STORAGE

The GS storage components should mainly store and provide data from the UAV. Both local, temporary, and long-term storage should be provided to enable different processing patterns (e.g. real-time, stream, complex event, batch, historical). This requires a *local storage system* on the GS able to manage from GB to TB of data (video) streams in a timely manner, for example a *network attached storage (NAS)* system. Data archival and support for historical data processing can then be provided by specific *Cloud data services*, ensuring data persistence and availability, while allowing remote ubiquitous access and data sharing.

b: PROCESSING

The GS storage components mainly support the collected data processing, i.e. the beach waste detection and feature identification (e.g. localization, size), basically applying computer vision to the geotagged video streams from the UAV. It also supports further computational activities on historical data (e.g. machine learning model training, prediction, decision making, analytics) for planning and coordination. As a consequence, similar requirements to the storage ones can be identified, differentiating between local processing, to provide a feedback to the UGV in a timely manner, and remote processing, to optimize the mission planning and coordination. The former requirements can be addressed by a *local processing system* equipped with a multi-core CPU and a (many-core) GPU able to support machine learning-based computer vision algorithms and their processing locally, interacting with the NAS, in a *fog computing* fashion. On the other hand, more complex/batch computations on historical data, such as machine learning model training, can be performed remotely on *Cloud virtual servers* interacting with data services. Coupled with the onsite computation performed onboard the UAV and the UGV, in an *edge computing* fashion, the BeWastMan solution overall identifies an effective edge-fog-cloud computing continuum pattern for the beach waste data storage and processing activities.

c: NETWORKING

The GS also provides networking facilities to the BeWastMan system. On the one hand, the GS should be able to interact with the UAV and the UGV, through a dedicated (wireless) local network (e.g. a WiFi router, or even by 4G/5G networks). To support the UAV video streaming a bandwidth of at least 8 Mbps for full HD images at 30 Hz is required, but the higher the better to improve the image quality and the detection accuracy. Another relevant parameter is the coverage range, which can span few hundreds to one thousand meters, exploiting new technologies (WIFI 6) and specific devices (e.g. outdoor access points or extenders).

To meet all storage and processing requirements, an Internet connection is also required, enabling data and task offloading to the Cloud. To such a purpose, the GS is equipped with a 4G/5G router giving Internet access to all processing and storage devices.

2) ENERGY

The GS is also tasked at energy management and provisioning to all the BeWastMan system devices, starting from internal networking, storage and processing devices, till the UAV and the UGV. Specifically, any solution for energy generation, harvesting, storing, provisioning and optimized management can be integrated into the GS. Indeed, it could be equipped with solar panels or electrical generators for *production*, to allow the GS some energy autonomy or independence. As a consequence batteries, inverter, transformers, UPS and similar devices for *storing* the produced energy have to be included in the design of the GS, properly planning its capacity and other related metrics based on the absorption of the BeWastMan devices. This also requires advanced policies to manage the energy resources thus generated and collected, considering the BeWastMan system devices to be powered (GS, UAV and UGV), the source availability (sunlight, fuel, mechanical, etc.), the environment (e.g. weather), and the mission parameters (e.g. beach area, duration).

C. P2C

The GS is based on a sensing system able to probe the external environment to provide relevant information for its management, promptly adapting itself and the overall system to changes and fluctuations, thus addressing challenge C.2 described in Section II-A. This is done by equipping the GS with a set of sensors specifically conceived for probing its status, i.e. the GS P2C system.

Specifically, starting from the mission planning and coordination, the GS has to monitor the physical (computing and energy) resources as well as the external environment to properly manage the overall system mission. To such a purpose, computing resource utilization (e.g. CPU, RAM, storage, bandwidth) as well as energy ones (e.g. battery level) are continuously monitored and their values collected and then processed by the GS cyber system. Furthermore, external environment conditions should also be probed by specific device such as weather stations, light sensors, microphones and cameras.

Cameras are mainly used for mission planning and coordination, but also for safety and security purposes, as part of a surveillance system including internal and external cameras, presence and intrusion detectors, burglar alarms and door sensors and lockers.

To monitor the energy status (accumulator and device battery levels), it must also include energy-related sensors (and actuators), also exploiting environmental and weather sensors to optimize the energy management by, e.g., triggering and switching between solar panels and generator sets.

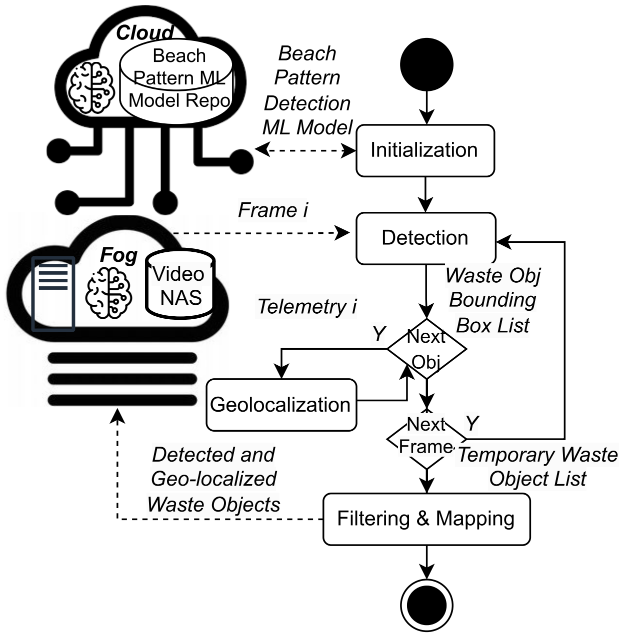


FIGURE 4. Ground station waste detection and geolocalization workflow.

D. CYBER

The cyber part of the GS provides and implements the software facilities and tools to support the BeWastMan mission, mainly concerning waste detection and geolocalization from the UAV videos, as well as other tools to support and plan the overall BeWastMan mission. Other GS tasks are related to the energy management, providing tools to optimally manage the energy based on the (UAV, GS and UGV) demand and the offer (e.g. batteries, solar panels, generators), as well as the GS security and safety management, mostly implementing proximity and environment surveillance, by elaborating the GS onboard camera videos.

The waste detection and geolocalization workflow is shown in FIGURE 4 and is mainly composed of four stages: the *initialization* step identifies the beach pattern and selects the corresponding ML model, triggering the frame by frame *detection* loop, which first detects waste objects in each frame, and then enters the *geolocalization* nested loop on such objects to geolocate them.

Thus, a temporary list of detected waste objects is identified, with multiple instances of the same objects (detected in different frames) or even other objects (e.g. stones, driftwood, shells) wrongly classified as waste. The last step is therefore focused on *filtering & mapping* activities, identifying and removing outliers from such a list while improving the accuracy of geolocalization, as detailed in the following.

1) INITIALIZATION

The *initialization* step performs preliminary activities to the waste detection and geolocalization, mainly concerning the beach pattern identification, considering sediment type, morphology, light, weather, and other relevant parameters that may affect image processing. To this purpose, image samples from the UAV video to be processed are extracted and then elaborated for the identification of the specific beach pattern, through an ad-hoc ML model such as those proposed in [36] and [37].

Once the beach pattern is identified, the GS queries the Cloud to obtain the most suitable ML detection model available on its repository for analyzing the beach video. On the Cloud, indeed, detection and recognition models for different beach patterns are provided and updated by a specific training process in a continuous learning fashion. Videos, as well as ML models, are therefore collected, catalogued and stored into specific sections or folders of the Cloud BeWastMan repository and continuously improved.

The detection model thus identified is then loaded from the Cloud by the GS (fog) server, setting up the input parameters and the environment to run the inference process on the video to be processed.

2) DETECTION

In BeWastMan *waste detection* is implemented by applying computer vision techniques to beach videos sampled by the UAV. The proposed approach identifies three complementary stages for detection: i) onboard the UAV (on the edge) for improving the capturing process meanwhile, in real-time (see Section IV-D); ii) in the GS (on a fog server) to carefully detect and geolocalize the waste on a beach map to be delivered to the UGV; and iii) remotely (on the Cloud, as discussed above), exploiting the video dataset to train and improve the beach pattern detection ML models adopted for inference on the GS (continuous learning).

In general, image processing techniques such as those reviewed in Section II-B2 can be used in beach waste detection. Specifically, ML models like CNN, R-CNN or Mask R-CNN are usually adopted, often exploiting one of the different public implementations and tools (such as YOLO, Mediapipe, OpenCV), providing facilities for customizing such models to the problem at hand. It is however necessary to train such models, starting from specific datasets of beach waste images and videos, taking into account the selected beach patterns. Data filtering, pre-processing, augmentation, object annotation and labeling, integration and formatting may be required for further processing on ML model training and testing. This is performed offline on specific Cloud remote servers able to gather and store waste images and videos, also coming from drone beach inspection and UGV collection missions, continuously processing incoming data streams to improve the corresponding ML models. Detection models are then deployed into the UAV and the the GS, while recognition ones on the UGV for inference.

As discussed above and in Section IV-D, the BeWastMan UAV implements live object detection on the video stream, to improve the inspection phase and the whole mission. On the other hand, the BeWastMan GS fog server performs more advanced and accurate waste detection by processing the high resolution video frame by frame offline. This allows for a more detailed detection process, exploiting the GS processing capabilities to infer advanced features of detected object such as size, shape, color, texture, and contextual information. These additional data help in achieving more accurate and detailed detection results. Each detected object is located in a bounding box and inserted into a list including all the detected objects of the considered frame, then sequentially processed by the geolocalization loop.

3) GEOLOCALIZATION

The *geolocalization* step aims at identifying the georeferenced locations of the detected waste items to enable the UGV robot collect them. The bounding box pixel coordinates provided by the detection object list are thus transformed into geographic information coordinates (GPS *latitude* and *longitude*) exploiting the equations of coordinate systems and map projections [38], [39] also considering the image metadata and UAV telemetry.

To determine the latitude and longitude of a detected waste object, the parameters included in the tuple of Definition 1 are exploited.

Definition 1: Given an image i (i.e. a beach video frame) with a detected waste item w to geolocalize, a *geolocalization problem* glp, aiming to obtain the GPS projection coordinates of the waste object $\mathrm{gps}_w = \{\mathrm{lon}_w, \mathrm{lat}_w\}$, is defined by the 7-tuple

$$\mathrm{glp} = \{\mathrm{px}_c, \mathrm{fl}, \mathrm{gps}_c, \mathrm{hagl}, g, \mathrm{px}_w, \phi\}$$

where:

- $\mathrm{px}_c = \{x_c, y_c\}$ is the image i center pixel coordinates;
- fl is the camera focal length (in mm);
- $\mathrm{gps}_c = \{\mathrm{lon}_c, \mathrm{lat}_c\}$ is the GPS coordinates of the frame i center;
- hagl is the UAV height above the ground level;
- g is the yaw gimbal orientation with respect to true north;
- $\mathrm{px}_w = \{x_w, y_w\}$ is the waste item w center pixel coordinates in the frame;
- ϕ is the reference latitude of the beach, e.g. the latitude of a specific hotspot located within the beach.

The goal is to solve the geolocalization problem, finding $f(\mathrm{glp})$ such that $\mathrm{gps}_w = \{\mathrm{lon}_w, \mathrm{lat}_w\} = f(\mathrm{glp})$. To such a purpose, the pixel coordinates $\mathrm{px}_w = \{x_w, y_w\}$ are first aligned to north by applying a rotation $\mathbf{R}$ equal to the yaw value g, given by the matrix of Eq. (1), then translated to the center of the frame according to Eq. (2), where x'_w and y'_w are the coordinates of the waste object rotated with respect to the center of the frame.

$$\mathbf{R} = \begin{pmatrix} \cos g & -\sin g \\ \sin g & \cos g \end{pmatrix} \quad (1)$$

$$\begin{pmatrix}\Delta x'_w\\ \Delta y'_w\end{pmatrix} = \begin{pmatrix}x'_w - x_c\\ y'_w - y_c\end{pmatrix} = \mathbf{R}\begin{pmatrix}x_w - x_c\\ y_w - y_c\end{pmatrix} = \mathbf{R}\begin{pmatrix}\Delta x_w\\ \Delta y_w\end{pmatrix} \tag{2}$$

To obtain the $\text{gps}_w = \{\text{lon}_w, \text{lat}_w\}$ coordinates, the principal radius of the spheroid ($a = 6,378,137$ m), the inverse flattening ($\text{if} = 298.257223563$), and the quadratic eccentricity ($e^2 = (2 - 1/\text{if})/\text{if}$) are exploited to compute the radius of curvature along the parallel n by Eq. (3), the radius of the parallel r by Eq. (4), and the meridional radius of curvature m by Eq. (5).

$$n = \frac{a}{\sqrt{1 - e^2 sin(\phi)^2}} \tag{3}$$

$$r = n\cos(\phi) \tag{4}$$

$$m = \frac{a(1-e^2)}{(1 - e^2 sin(\phi)^2)^{(3/2)}} \tag{5}$$

For each frame, the distance between the frame center and the detected waste object is quantified using Eqs. (6) and (7) from Eq. (2).

$$d_{x'_w} = \frac{\text{hagl}\Delta x'_w}{\text{fl}} \tag{6}$$

$$d_{y'_w} = \frac{\text{hagl}\Delta y'_w}{\text{fl}} \tag{7}$$

Thereby, the $\text{gps}_w = \{\text{lon}_w, \text{lat}_w\}$ coordinates of a detected waste object are obtained by Eqs. (8) and (9).

$$\text{lon}_w = \text{lon}_c + \frac{180 d_{x'_w}}{\pi r} \tag{8}$$

$$\text{lat}_w = \text{lat}_c + \frac{180 d_{y'_w}}{\pi m}. \tag{9}$$

4) FILTERING AND MAPPING

Once all video frames are processed by detection and geolocalization algorithms, the results are gathered into a list of all the geolocalized detected objects. As stated above, since frames are spatially overlapped, the same object can be detected in multiple frames and thus replicated in such a list. On the other hand, detection errors may occur, wrongly classifying other objects (e.g. stones, shells, woods) as waste. A way to deal with such a "noise" can be based on exploiting the number of occurrences (i.e. the frequency) of each item. Low frequent items are likely outliers, while dense item *"clusters"* can confirm the presence of a waste object and can be profitably exploited to improve its geolocalization.

On this premise, the *filtering & mapping* step aims at improving the accuracy and effectiveness of waste object detection and geolocalization in BeWastMan. To such a purpose, the *clustering* approach is adopted in the analysis of the detected waste object list, to identify clusters and outliers as well. Among the clustering methods, *K-means*, *DBSCAN* (Density Based Spatial Clustering of Applications with Noise), and HDBSCAN (an updated version of DBSCAN), are the most widely used in unsupervised ML approaches [40]. Briefly, K-means enforces partitional clustering, minimizing intra-group variance, while HDBSCAN aims to enable the creation of variable density clusters based on a hierarchical decision tree approach displaying clusters as high-density areas separated by low-density areas.

The (spatial) clustering is therefore an essential step in the BewastMan process, analyzing the waste object list to improve both the detection and the geolocalization accuracy by filtering the outliers and thus extracting the filtered item GPS coordinates through the cluster points (mapping), respectively. Specifically, a cluster is identified as a waste item and thus the cluster centroid is an estimate of the waste object position, improving the geolocalization accuracy by averaging on the cluster item coordinates. A proper clustering method can also deal with issues due to multiple (close) objects, considering the number of cluster items (larger implies multiple items) and other item features (such as size, shape, color).

To obtain efficient waste management the BeWastMan generates two maps by the UGV mission: i) the *full map* encompasses all the detected objects, providing a comprehensive overview of waste items distribution within the area of interest, thus including also oversize items that cannot be collected by the UGV, to however alert the authorities; ii) the *UGV map* is a subset of the full map, only including items that are viable for collection by the UGV based on the waste size and other spatial properties. However, this does not ensure the UGV is really able to collect all the items in the UGV map, due to obstacles or other accessibility issues on the beach, therefore a feedback to the GS about collected items is provided by the UGV at the end of its waste collection and sorting mission. Based on this feedback, the full map is updated removing collected waste items, thus obtaining a waste maps including the items that cannot be collected by the BeWastMan system, alerting authorities for further activities.

E. C2P

The GS is a self-adapting CPS, aiming to optimize its own tasks. More specifically, to support mission planning and coordination, the processing system is kept fully operating, by offloading tasks to the Cloud when given thresholds on resource utilization are overwhelmed (fog-Cloud computing continuum). Furthermore, it monitors the light, weather and visibility conditions of the beach, by mainly exploiting its weather-pollution station and surveillance system. The GS thus acts on its PTZ (pan, tilt, zoom) cameras to capture the area of interest and the drone or the robots during their (sub-)mission. To secure the GS equipment, the surveillance system is exploited, by acting on the cameras triggered by the audio/video anomalies and presence detectors. Alerts or alarms can be triggered in the case of lock/door issues or even to the other indoor (e.g. smoke, presence) detectors.

Energy management policies are enforced by the GS acting on switches, which can control the (solar panels, fuel) generators, inverters, and power plugs. The latter can be thus selectively switched off based on their absorption, continuously monitored by the system, according to the specific energy management policy adopted, e.g. based on device (UAV, UGV, computer, NAS, routers, etc.) priorities.

VI. THE UGV C2P SYSTEM

A. MISSION: COLLECTION AND SORTING

Once received the geolocalized waste map by the GS, the main objective of the UGV is to enforce the waste collection and sorting on the beach as the BeWastMan IHCPS actuator. Based on such a map, the UGV plans a path to reach all the detected waste objects, collect them through a robotic arm equipped with a suitable gripper, sort the waste in its onboard bins, and dump these into the recycling station. The collection task performed by the UGV in BeWastMan differs from and outperforms state-of-art solutions as it is:

- *Fully autonomous*: a fully automated workflow is implemented to such a purpose. It starts with a path planning algorithm to optimize the collection of waste on the beach, thus minimizing the mission time and reducing the robot's energy consumption. Full autonomy includes the local recognition of the waste through the onboard camera and the automatic pick and place of the waste with the robotic arm and its gripper. Once the mission is completed, onboard bins are autonomously dumped by the UGV at the recycling and disposal station.
- *Cross-terrain*: by means of the robotic arm equipped with a gripper, the UGV can collect objects of different sizes and shapes, such as plastic bottles, cans and other waste. The all-wheel drive platform offers a good navigation performance compared to tracked vehicles, as demonstrated by the preliminary tests reported in Section VII-A3. These solutions, including the custom recognition models trained on different beaches sediments and characteristics by the specific GS Cloud service, make the robot versatile and suitable for cleaning multiple types of beaches, thus addressing the C.3 challenge of Section II-A.
- *Eco-friendly*: the waste item pick and place through the manipulator and the wheel-based traction ensure a low impact cleaning process on the beach surface and composition (challenge C.4), only collecting the identified waste, as opposed to the mainstream sieving-based approaches with tracks. This is also achieved by performing an efficient waypoint-based mission rather than the full-coverage missions adopted by sieving systems, thus reducing the energy required to carry out the mission and thus the environmental footprint.

B. PHYSICAL

From the physical viewpoint, the BeWastMan UGV must include hardware designed to operate in maritime environments, posing greater challenges compared to generic outdoor environments. The presence of sand, tiny rocks and sediments, combined with the exposure to strong wind, water splashing, salt, and high humidity, represents a challenging operating condition for a robotic system. Thus, the robot chassis and all the electro-mechanical components must have a proper ingress protection against solid particles, saltiness and water.

A beach cleaning robot must be able to cope with the challenges of moving on a deformable, uneven surface like a beach. In BeWastMan, an all-wheel drive robot combined with wide tires is selected, as it is suitable to overcome dunes on beaches without sinking, while ensuring partial damping on more compact and harder beaches, such as those made up of stones or large pebbles. Furthermore, wheeled platforms represent a good trade off between invasiveness on the beach surface, compared to tracked vehicles, and the robustness and the payload needed to carry the robotic arm and the waste containers, compared to legged vehicles.

Beach cleaning robots are mainly battery powered. Internal combustion engines have also been adopted, especially in manually operated platforms, as they ensure long operating time. However, the latter are not eco-friendly solutions as they introduce exhaust emissions and noise pollution. Thus, in BeWastMan the electric traction is selected for the low environmental and acoustic (silent) impact, since batteries can be recharged from renewable sources, addressing challenge C.4.

Finally, a reliable and robust connection of the UGV with the GS is required for audio/video streams and telemetry data transmission. Such a connection can be on wireless WIFI and/or through 4G/5G networks to ensure redundancy on the communication link.

C. P2C

The BeWastMan UGV must include *exteroceptive* sensors that provide useful information of its surroundings, thus ensuring the safety of the vehicle itself. The data acquired from such sensors can be used to avoid obstacles and to identify optimal trajectories over the beach, in terms of traversability and reduced power consumption [41]. The most common exteroceptive sensors are range sensors, especially LIDAR (Light detection and ranging sensors), also called laser scanners, which can acquire large distance measurements thanks to their laser emitting source. They can be 1D, 2D, and 3D, depending on how the laser beam is deflected to acquire a single point distance, a 2D array of distances or a point cloud, respectively. The latter can be used for building a 3D model of the surrounding area, thus enabling local trajectory optimization through traversability assessment (e.g. in the case of sand dunes, terrain depressions, etc.).

The BeWastMan robot has to be equipped also with a GPS receiver to locate itself, track its path during the beach cleaning mission from the GS to the recycling station and back following the geolocalized waste detected by the UAV. The GPS can also be used for geofencing, namely to define those areas excluded from the cleaning procedure. This can be helpful to ensure the safety of the vehicle by excluding the areas too close to the water or dangerous.

Another exteroceptive sensor required for the BeWastMan approach is a vision sensor to locally recognize the waste on the beach and to collect it. Both Red-Green-Blue (RGB) and Red-Green-Blue and Depth (RGB-D) cameras can be used, where RGB-D ones allow depth measurements through structured light or stereo vision thus providing a local point cloud of the area framed by the camera. Other types of vision sensors can be used, such as thermal or hyperspectral cameras. However, for each type of camera a suitable processing algorithm, on the cyber side, has to be designed and developed.

The UGV must be also equipped with *proprioceptive* sensors to acquire information on the internal state of the robot, to ensure the safety of the robot during the mission and to properly navigate within the environment. Among them, the Inertial Measurement Unit (IMU) acquires the orientation and the attitude of the robot, allowing to know the robot heading to properly navigate and plan the pick and place maneuver with the arm. In turn, the robotic arm, besides mandatory joint encoders for kinematic control, must be equipped with force/torque sensors, i.e., a collaborative robotic arm, to let the BeWastMan UGV be safely employed also in presence of people in the surroundings.

Other sensors that can be included in the beach cleaning UGV include environmental sensors, such as temperature, humidity, and wind sensors that can be used to monitor the weather conditions on the beach.

D. CYBER

The cyber part of the UGV includes the software needed to ensure the communication, sensor data processing, and control of the robot. Specifically, it must be able to implement the workflow shown in FIGURE 5. This includes the management of the different mission tasks, namely path planning (according to the waypoint list received by the GS), waypoint routing, waste object picking through the arm, and bin dumping.

1) PATH PLANNING AND ROUTING

Concerning path planning, the robot must follow an optimized route minimizing the mission time and the energy consumption. Since the UGV has to sequentially visit all the waypoints (WP) provided by the GS one by one, the path planning problem falls into the well-known Traveling Salesman Problem (TSP) [42], [43], [44]. Although TSP is known to be an NP-hard problem, estimating a waypoint list in the order of tens detected waste items, the global

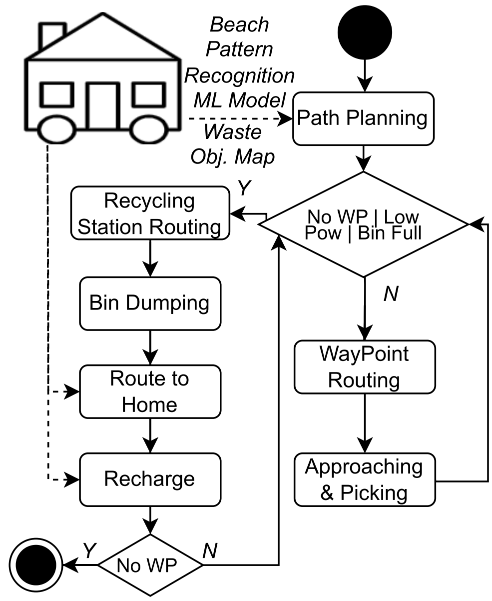


FIGURE 5. **UGV waste collection and sorting workflow.**

path processing time on a single board computer has been (experimentally) observed to be bounded in at worst few minutes. However, in the case of a larger number of waypoints, the mission can be split into sub-missions that can be processed sequentially, overlapping the planning of the next sub-mission with the enforcement of the current one in a dataflow/pipeline model, thus ensuring each single sub-mission can be safely carried out within the battery run time. Furthermore, although TSP could be solved by the GS, having high processing power, we opted for deploying it in the UGV since to implement a self-contained and independent solution that could be even run on a list of geolocalized points provided by an operator, without the need to set up the whole BeWastMan framework.

The outcome of the TSP algorithm is used for global path planning, i.e. as a reference path to be tracked during the whole cleaning mission. Such outcome is essentially the shortest path between the set of waypoints, visiting each waypoint only once and finally returning to the starting point. The use of this algorithm in BeWastMan is viable since there is no need to follow a specific order in reaching the points of interest, thus significantly improving the efficiency of the mission (compared to full-coverage approaches) by reducing mission time, length and, consequently, the energy consumption.

The only point which is enforced to be reached as a final waypoint before moving back to the GS for storage and recharging is the recycling station, to dump the onboard containers. Since the recycling station is expected to be placed in the close surrounding area of the GS, the TSP algorithm is applied to the waypoints, including the GS, but initially excluding the recycling station. After that, the recycling station waypoint is added to the path planned by the TSP algorithm as the last point to be reached before going back to the GS. This avoids that waste items close to both the ground and the recycling station may result in a path driving the UGV to the recycling station before visiting all the remaining waypoints, i.e., the spots where the UAV detected the waste.

2) APPROACHING AND PICKING

To properly approach the waste object, once visualized by the UGV camera, a proximity waste recognition step is necessary. Specifically, the UGV employs advanced computer vision algorithms and machine learning models to perform more detailed multiclass recognition. In contrast to the waste detection carried out by the UAV and the GS, the UGV recognition process identifies the waste material type and orientation. To such a purpose, the UGV can use tools like TensorFlow or PyTorch, paired with OpenCV library for real-time image and video processing.

As for detection models, multiple recognition models are trained by the GS Cloud services based on the beach pattern. Therefore, the GS initially sends to the UGV the specific model that should be adopted by the latter for waste item recognition. Specifically, the recognition algorithm deployed in the UGV heavily relies on high-resolution, detailed images or video feeds to classify 4 waste materials: paper, glass, plastic, and metal. It adopts ML models like CNN or R-CNN, similar to detection ones described in Section V-D2, but implementing multiclass classification. Furthermore, the UGV models have to also estimate the waste item orientation, which is critical for successful waste removal. The orientation and position estimation of the waste through the camera can be supported by depth estimation if an RGB-D camera is used. Tools like TensorFlow, PyTorch, and OpenCV can be adopted for recognition model training and image processing.

Once the waste has been recognized and localized by the UGV, waste collection is performed by the robotic arm and gripper control. Specifically, the relative pose of the item with respect to the vehicle is considered, along with the current robotic arm configuration and the vehicle heading, and a classical inverse kinematic problem is solved to plan the arm actuation, including gripper control.

To address the C.2 challenge, the UGV cyber system must also manage the case the identified object is out of the camera field of view once the waypoint has been reached, even if the camera is pointed towards the ground. In this case, a visual scan of the surrounding area is performed to look for the item by slowly rotating the arm.

To ensure an accurate and complete waste collection process, as per challenge C.5, the UGV during the collection mission must establish a feedback loop with the GS, communicating whether it was able to collect the item or not, e.g. when the item is not detected even by the preliminary surrounding check, if the item weight exceeds the arm payload, or it is unreachable due to the presence of obstacles. This feedback helps to identify areas where manual intervention or alternative collection methods may be required.

If the UGV reaches the waypoint and recognizes the object as not waste, the waypoint is removed from the list and the UGV proceeds with the following waypoint. Finally, the dumping of the containers is performed controlled by a microcontroller unit acting as an intermediate layer between the onboard computer and the actuators.

E. C2P

The UGV within the BeWastMan solution represents the C2P system, since it allows the interaction with the physical system, i.e. the beach. To this end, the minimal hardware required for the vehicle motion and the arm actuation, are the wheels and joint motors, respectively. In BeWastMan, the gripper plays a crucial role, since it allows picking up the waste objects from the ground. Grippers are usually equipped with one or more motors, for opening and closing fingers. Grippers can be of different types, such as pneumatic, hydraulic or electric, and their design depends on the type of object to be grasped. It is important that the actuation of the gripper is precise and controllable, to avoid damage to or slipping of the gripped objects. Tactile sensors may be integrated to detect the shape and consistency of the objects to be grasped and to guarantee a firm and stable grip.

The waste containers on board are dumped using proper mechanisms and actuation. Linear actuators could be employed, which are usually composed of an electric or hydraulic motor which provides a linear force to move the piston within the cylindrical case. Once in proximity of the recycling station, the linear actuator is activated to lift one side of the container while the other side is hinged on the robot chassis, thus tilting it down and allowing the waste to fall into the compactor. Since the UGV may carry separate containers for sorting different types of waste, in proximity of the recycling station the UGV has to perform pre-programmed maneuvers to empty all the containers.

VII. CASE STUDY

The BeWastMan IHCPS has been implemented in real-world scenario case studies developed within the BIOBLU project (“robotic BIOremediation for coastal debris in BLUE Flag beach and in a maritime protected area”). As testbeds, the beaches of two protected areas have been selected: Baia del Tono in Milazzo, Italy, and Ramla Bay in Malta, where the final validation and testing of the BeWastMan IHCPS implementation has also been performed. Baia del Tono is a medium-grained shingle beach shown in FIGURE 6a, while Ramla Bay is a fine sand beach shown in FIGURE 6b. The BeWastMan system implemented in the BIOBLU case studies is described in the following, adopting and applying the guidelines above detailed.

A. PHYSICAL SYSTEMS

1) UAV

Based on the design choices discussed in Section IV, in the BIOBLU case studies, we opted for a commercial UAV

(a) Medium grained shingle beach in Milazzo.

(b) Fine sand in Gozo.

FIGURE 6. The two types of beaches considered for the BIOBLU project.

FIGURE 7. The UAV - Mavic 2 enterprise advanced used in our case study.

implementing most of the features above specified by the BeWastMan framework. As most of the works reported in Section II-B1, a DJI aerial platform has been chosen, specifically the Mavic 2 Enterprise Advanced drone (in FIGURE 7), providing features meeting the BeWastMan UAV requirements. It is equipped with a stabilized 3-axis gimbal, hosting a 48 MP 1/2-inch CMOS sensor camera able to capture 4K video at 30 frames per second. In addition, the Mavic 2 is provided with 360∘ obstacle avoidance and an RTK navigation system.

Its battery ensures a maximum flight duration of approximately 30 minutes, depending on weather conditions and payload. The excellent flight duration allows us to cover a wide beach area and complete the automatic takeoff and landing maneuvers on the GS. Furthermore, an intelligent battery management system, together with the automatic recharge device, allows the drone to return to its base and recharge autonomously through the specific (optional) module. This is a drone-in-a-box configuration that includes a specially designed housing that keeps the UAV protected from external agents, such as dust and humidity during recharge or transport. Furthermore, the box is equipped with weather sensors, presence detectors, and alarm systems to ensure the safety of the equipment and people in the surroundings. Table 1 describes the Mavic 2 main characteristics.

TABLE 1. UAV features.

Takeoff weight (without accessories)	909 g
Maximum takeoff weight	1100 g
Flight autonomy	31 minutes
Max Speed (no wind)	72 km/h
Precision positioning system	RTK
RTK Positioning Precision (RTK FIX)	1cm+1ppm (H) 1.5cm+1 ppm (V)
High-resolution camera	1/2' CMOS, effective pixels: 48 MP
Lens FOV	84°
Digital zoom	32×
Max image size	8000 × 6000
Operating Temperature	-20 ÷ 40 °C
Max altitude	6000 m
Sensing System	Omnidirectional Obstacle Sensing

2) GROUND STATION

As discussed in Section V, the GS is the brain of the BeWastMan system, offering processing and information management capabilities, as well as hosting-parking and energy facilities to both the UAV and the UGV, as shown in FIGURE 8 and FIGURE 9. Following the design choices of Section V, the BeWastMan GS implementation is based on the chassis of a car trailer, equipped with 4 off-road tires with independent suspension, allowing it to drive on uneven terrains. The GS has an external size of 4 × 2 × 2.2 m (L×W×H), which guarantees the space needed to accommodate a desk with two laptop units, even when the UGV is recharging inside the GS. The design features a rear-assisted tailgate that can be opened and closed for robot loading and unloading and a side access door for operators. On the right-hand side, there is a retractable awning covering a 72" LED monitor that allows the operators to check the mission status. A stainless steel automated hangar is placed on the GS roof to store drone. It also includes a charging station.

The GS is composed of hardware and software designed to receive, store, analyze, and display the information collected by the drone. The managed data is related to flight information, such as the position and altitude of the drone, as well as data related to the environment, such as temperature, pressure, and humidity. The computing equipment of the GS includes a 19" rack cabinet which contains an ethernet gigabit switch and a 16 TB NAS for temporary storage of the BeWastMan mission data. The external WiFi network is generated by a dual frequency antenna (2.4 - 5 GHz)

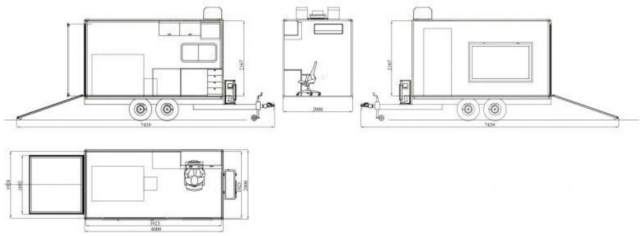


FIGURE 8. Design of the BIOBLU ground station.

fixed on a pneumatic telescopic pole. The GS is equipped with two laptop units, one High-performance Computing (HPC) computer for real-time waste detection, processing, and management and the other for the automatic flight route management. All the laptops and the other components on board are linked to the local network and powered by the GS grid connected to the power grid.

3) UGV

The UGV employed for the BeWastMan implementation is shown in FIGURE 11. The platform has four steerable wheels, an all-wheel drive system, and a six Degrees Of Freedom (DOF) robotic arm. The mobile base is capable of smooth movement on the ground with slight steering of the wheels, allowing for easy alignment with the compactor during bin dumping.

A scheme outlining the main hardware components of the robotic system is shown in FIGURE 13. The software integration is based on ROS [45], a popular open-source framework for robotic systems development.

Based on the design guidelines of Section VI, an off-road wheeled platform has been selected by the inspection of the two test beaches. These are two scenarios with sediments of different granularity requiring a solution to address challenge C.3 successfully. Preliminary qualitative tests have been performed with two platforms with different types of traction, i.e. tracked and all-wheel drive traction in Baia del Tono and Ramla Bay.

During this trial, the tracked UGV was able to move smoothly over the beach, regardless of the sediment granularity. However, the use of tracks resulted in a large amount of sand and shingle displaced in direction changes, as shown in FIGURE 10, thus significantly altering the natural morphology of the beach and failing in addressing challenge C.4. On the other hand, the all-wheel drive robot shown good performance in both types of sediments while navigating in an agile and reliable way without considerably defacing the terrain.

The UGV is equipped with a Real-Time Kinematics (RTK) GPS receiver for geolocalization with centimeter-level accuracy and an inertial measurement platform. The robot is equipped with a Velodyne Ultra Puck, a 32-channel 3D laser scanner with a 360° horizontal and a 40° field-of-view (FoV). The Velodyne is installed in the upper-rear section of the vehicle, which generates a point cloud of the surrounding

TABLE 2. ZED2i features.

Video Output	2.2K 1080p 720p WVGA
Depth Range	0.2 - 20 m
Motion Sensors	Accelerometer and Gyroscope
Position Sensors	Barometer and Magnetometer
Pose Update Rate	Up to 100Hz
Field of View	110° (H) × 70° (V) × 120° (D)
Connectivity	USB 3.0
Dimensions	175 × 30 × 33 mm
Weight	124 g

TABLE 3. 2FG7 gripper features.

Max payload force fit	7 kg
Max payload form fit	11 kg
Total stroke	38 mm
Max gripping force	140 N
Max gripping speed	450 mm/s
Operating temperature	0 ÷ 60 °C
Motor	Integrated electric BLDC
IP classification	IP67
Dimensions [L × W × D]	144 × 90 × 71 mm
Weight	11 kg

environment up to 200 m. This helps to detect any obstacle during waypoint navigation.

The robotic arm mounted on the top of the robot, as shown in FIGURE 12, is the UR10e manipulator, which can lift up to 10 kg and has a workspace radius of about 1.3 m. It is a collaborative manipulator, which makes it safe even when accidentally working in proximity of people, as could occur on beaches.

The ZED2i stereoscopic camera with IP67 protection against water and solid particles is used to locally recognize the waste. The technical specifications of the selected camera are displayed in Table 3. Stereoscopic vision is exploited for depth estimation, which is crucial to properly plan the pick and place maneuver, as further detailed in Section VII-B3.

An OnRobot 2FG7 gripper featuring IP67 protection is used in the BeWastMan BIOBLU implementation (FIGURE 14a) since it has to operate close to the ground with dirty and potentially damp objects. It also offers force sensing that allows the robot to understand whether the item has been grasped or not.

The 2FG7 gripper has a total stroke of 38 mm, with a grip width ranging from 35 to 73 mm and the original fingers mounted as shown in FIGURE 14a. Further technical details of the chosen gripper are reported in Table 3.

To overcome the limited grip width range, a custom tool, shown in FIGURE 14b, has been thus designed and realized. Through a set of lever mechanisms, this tool exploits

(a) (b)

FIGURE 9. **Overview of the BeWastMan implementation for the BIOBLU project, including the UGV, the GS, and the UAV.**

the translational stroke of the 2FG7 and achieves a grip width ranging from 0 to 160 mm. To achieve a firm grip, the tool consists of five staggered aluminum claws divided between the two fingers (three on one and two on the other) for effective grasping. The elongated J-shape and the adopted material of the claws allow the tool to sink into the ground while preventing dust or grains of sand from causing mechanical problems to the proposed structure. The tool body is made using 3D printed ABS (Acrylonitrile-Butadiene-Styrene), while the lathed mechanical joints were made up of aluminum. The rotational joints have been designed with minimal clearance to enhance their protection against solid particle ingress.

An aluminum frame supports the two bins used for waste collection. The waste containers on board the platform are dumped using linear actuators. Once in proximity of the recycling station, the linear actuator is activated to lift one side of the container while the other side is hinged on the aluminum frame, thus tilting it down and allowing the waste to fall into the compactor.

The GPS-RTK antenna, 3D laser, and WiFi antenna are mounted on a vertical aluminum profile at the rear of the robot, as shown in FIGURE 12.

B. CYBER SYSTEMS

This section reports the details of the software developed for the BeWastMan IHCPS adopted in the BIOBLU case studies. According to the design criteria presented in Section III, the BeWastMan software covers multiple aspects.

To manage the UAV mission a software called the Unmanned Ground Control System (UGCS) is used for planning and monitoring the UAV flight. Referring to Section II-A, the UGCS software (shown in FIGURE 15) is a key component in the GS for the inspection task (T.1), allowing the coordination and control of the UAV through its flight planning interface, as well as the definition of waypoints, and other parameters (maximum speed, accelerations, etc.) for the missions on the two beaches.

Concerning waste detection and recognition through video processing two fundamental steps are required: i) the manual creation and management of dedicated waste datasets, and ii) the development of the waste detection model for task T.2 (by the UAV and the GS), the geolocalization method (task T.3 by the GS), and the material recognition model for task T.4 (by the UGV). Finally, tasks T.5 to T.8 are managed by the software onboard the UGV.

The following subsections detail the main software modules developed in the BIOBlU project for implementing the BeWastMan IHCPS.

1) WASTE DATASET

To ensure a proper generalization capability of the models, we used a dataset combining four public and continuously updated datasets, namely *UAVVaste* [14], *TACO* [46], *TrashNet* [47], and *Drinking Waste Classification* [48]. UAVVaste includes 772 images of waste in urban and natural environments, such as roads, parks, and lawns, acquired by a low-altitude aerial survey with a UAV. TACO (Trash Annotations in Context) holds 1900 high-resolution trash images taken in various environments, manually labeled and segmented according to a hierarchical taxonomy to train and evaluate object detection algorithms. TrashNet contains 2492 images of waste, mainly paper, glass, plastic, and metal, taken at different exposure and lighting. From the Drinking Waste Classification dataset, we considered 544 images of waste taken with a 12 MP cell phone camera and manually


(a) A tracked vehicle.

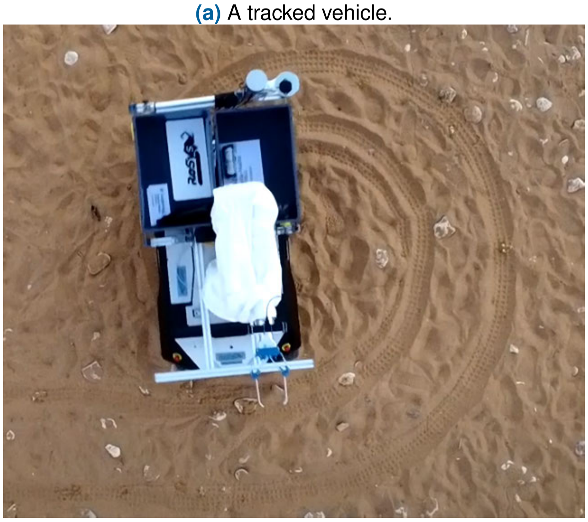

(b) The UGV adopted for the BeWastman implementation.

FIGURE 10. Comparison of the impact of the rotation maneuver on a sandy beach.

FIGURE 11. The UGV during testing in Gozo.

labeled, specifically, aluminum cans, glass bottles, plastic bottles, and paperboard.

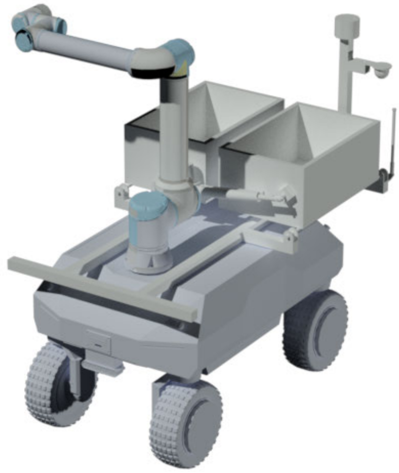


FIGURE 12. 3D visualization of the platform.

TABLE 4. ROBOFLOW data specifications.

Pre-processing	Augmentation
Auto-Orient Stretch resizing to 416×416	90° Rotate: Clockwise, Counter-Clockwise, Upside Down Rotation: between -15° and +15°

TABLE 5. Images in the BIOBLU training, validation and testing dataset overall.

Dataset	Images #	After augmentation
TACO	1900	4488
TrashNet	2492	5929
UAVVaste	772	1853
Drinking Waste	544	1298
Total	**5708**	**13568**

The above datasets have been pre-processed integrated, and merged through the ROBOFLOW platform [49] for training and testing the detection and material recognition models. Specifically, data pre-processing, filtering, labeling (for both the waste detection and the multiclass material recognition), and augmentation (random rotations, flipping, and image resizing) have been applied to the datasets. Table 4 shows all the specifications applied to the four datasets.

Table 5 describes the list of images used for the BIOBLU project, obtained after data augmentation, with 13568 images for the training and testing phase of the detection and recognition models.

For the training and testing phases of the detection and recognition models, we split the final dataset into a training set, validation set, and testing set, using the proportions of 85%, 10%, and 5%, respectively. The final dataset is available at the following open access repository[2].

[2]https://universe.roboflow.com/bioblu/merged_datasets

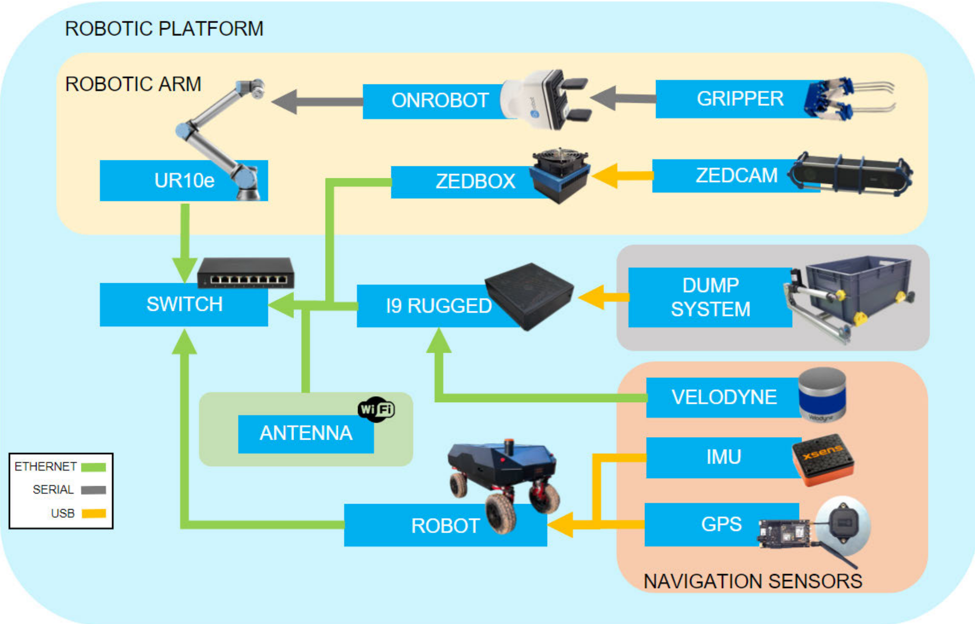
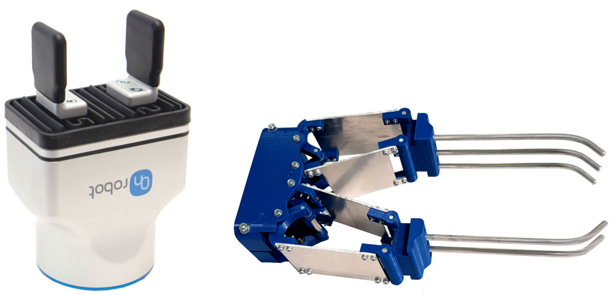


FIGURE 13. **Diagram of the UGV hardware connections. The arrow color represents the type of the link. Ethernet connections are green, serial connections grey, and USB connections orange. The yellow block represents the components of the robotic arm, while the cyan area depicts the complete robot system.**



(a) OnRobot 2FG7 (b) The custom tool

FIGURE 14. **The gripper and the attached custom tool designed and realized for waste picking.**

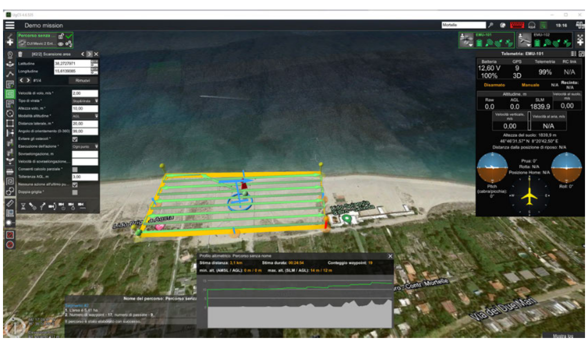


FIGURE 15. **UGCS software used for flight planning.**

2) WASTE DETECTION, GEOLOCALIZATION, AND MATERIAL RECOGNITION

According to Section V-D2, the model chosen for the waste detection and recognition phases is YOLO (you only look once) version 5 [50]. For the BIOBLU project case study, we implemented the waste detection on the GS to obtain information on object sizes and contextual details such as geolocalization information (described below).

To evaluate the performance of YOLOv5 object detection and recognition models, the following metrics have been used [51]:

- *Mean Average Precision (mAP)*, that evaluates the overall precision of object detection models across all classes in the dataset, considering both precision and recall at different *Intersection over Union*(IoU) thresholds;
- *Precision, Recall, and F1 Score*, the commonly used metrics to evaluate the performance of classification models, so, to correctly identify true positives and avoid false positives or negatives.

In the GS, the HDBSCAN method has been used to improve the detection and geolocalization accuracy. This approach discussed in Section V-D4 allowed the effective filtering of detected items in the video stream, as it can handle clusters of various densities and shapes while identifying noise and outliers in the data. The geolocalization accuracy has been evaluated in terms of Root Mean Squared Error (RMSE), which measures average errors in distance predictions with respect to ground truth GPS positions acquired with high-accuracy instrumentation.

For the local (UGV-side) waste recognition, the multi-class classification model YOLOv5 OBB (Oriented Bounding Boxes) [52] has been used. YOLOv5 OBB enables oriented bounding box (OBB) annotation to also take into account the current rotation of the objects detected in the acquired image frame. YOLOv5 OBB has been used in the testing and evaluation phase of waste recognition by the UGV in real-time.

3) WASTE APPROACHING AND PICKING

Once the rotated bounding box prediction is provided by YOLOv5 OBB on the ZED2i video stream, it is crucial to translate this output in pixel units within the image frame into a full pose, i.e. position and orientation, in the 3D space, to properly control the arm and the gripper to collect the item. In the current implementation, as we have two bins on board, we collect only plastic, metallic and glass items, dropping paper as it is biodegradable. The collected waste items are divided between glass and the other materials.

We assume to have the camera vertically pointing towards the ground. Thereby, the rotation provided by YOLOv5 OBB is approximately similar to the rotation of the item with respect to the gripper. Moreover, the Z Cartesian coordinate in meters with respect to the camera optical frame of the bounding box center is derived through the ZED2i stereoscopic depth estimation. In details, we apply the bounding box to the depth map provided by the camera, which is an image whose pixels represent the estimated distance in meters along the camera optical axis. By taking the average value of the pixels included in the bounding box we get an approximate distance estimation along the axis of the item above the ground. Once the Z coordinate is known, we can obtain the other bounding box coordinates X and Y by applying the central projection camera model [53] Eq. (10):

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = K^{-1} \begin{bmatrix} xZ \\ yZ \\ Z \end{bmatrix} \tag{10}$$

where

$$K = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix} \tag{11}$$

Namely matrix K of Eq. (11) is the matrix projecting 3D points in the camera coordinate frame (X, Y, Z) to 2D pixel coordinates (x, y) using the focal lengths (f_x, f_y) and principal point (c_x, c_y), which are estimated by the camera calibration.

At this point, (X, Y, Z) coordinates of the item are obtained, as well as its orientation with respect to the gripper. Thus, the collection task is performed through classical inverse kinematics. Specifically, we used the UR10e control implementation available for the MoveIt framework [54]. To avoid accidental collisions with the object to be grasped, the gripper is first aligned and rotated above the object, and after that the gripper goes vertically down to collect it. Finally, the item is released in either one of the two bins according to the recognized material.

TABLE 6. Waste detection performance on the GS.

P	R	F1	mAP_0.5	mAP_0.5:0.95
73.54%	39.18%	51.12%	40.53%	23.40%

FIGURE 16. Example of image acquired by the UAV during beach inspection and the related waste detection performed by the GS at Ramla Bay in Gozo, Malta.

VIII. EXPERIMENTAL RESULTS

A. DETECTION

The BeWastMan detection phase, performed by the the GS, adopts an ML model to detect waste items on the video captured by the UAV. In the training step, *yolov5l* pre-trained weights have been used as a starting point for fine-tuning the detection model on our dataset, with the number of epochs set to 600 and batch size set to 64. Default settings have been used for all the other hyperparameters.

Table 6 reports the experimental results for the waste detection training, including precision (P), recall (R), mAP_0.5, and mAP_0.5:0.95 metrics. The precision is 73.54% of the waste detected by the YOLOv5, while the recall is 39.18%. This indicates that the model is able to detect a high percentage of the total waste present in the beach. Also the the metric mAP_0.5 of 40.53% denotes a good average precision of the algorithm with 0.50 as IoU threshold.

The mAP_0.5:0.95 metric of 23.40% shows a fine average precision of the algorithm at different IoU thresholds from 0.5 to 0.95. Overall, the obtained results indicate that the model has an acceptable accuracy based on the higher precision, recall, and F1-score values for waste detection and bounding box assignment. The mAP values show that the algorithm performance depends on the IoU threshold, which can be useful in optimizing the algorithm for the specific use case.

FIGURE 16 shows a sample frame acquired by the UAV during beach inspection, and the related waste item properly detected.

B. GEOLOCALIZATION AND CLUSTERING

The *geolocalization* and *clustering* steps are carried out by the GS to estimate the position of the waste detected by the specific process from the UAV data captured during the beach

TABLE 7. Waste geolocalization performance with HDBSCAN in the two areas.

Areas	N. of Objects	RMSE_tot	Avg Distance (m)
Milazzo	7	$3.1047{\cdot}10^{-6}$	0.81
Gozo	6	$2.6345{\cdot}10^{-6}$	0.72

inspection. As discussed in Section V-D3, a transformation from pixels to GPS coordinates is required, following the workflow of FIGURE 4 combining the data acquired by the UAV and the detection performed by YOLOv5.

HDBSCAN is used for clustering items detected multiple times in different frames, to remove outliers and improve the position estimates. To such a purpose, different tests for hyperparameters tuning have been performed in the BIOBLU case study adopting a grid search tuning technique to find the optimal values.

Specifically, the HDBSCAN hyperparameters include: i) *min_cluster_size*, set to 10, represents the minimum number of points required to form a cluster; the ii) *metric* (*haversine*) is the distance metric used for clustering; and the iii) *algorithm* (*Prim - balltree*) is the algorithm used for clustering by constructing a minimum spanning tree (MST) of the data. Moreover, the *epsilon* ϵ parameter is used to convert the distance from kilometers to radians in the haversine formula, generally adopted to calculate the great-circle distance between two points on a sphere (approximating the Earth surface). The value of ϵ is set to $1.571 \cdot 10^{-7}$ radians, corresponding to approximately 1 meter. This means that items distant less than 1 meter are considered within the same cluster.

The clustering *silhouette coefficient*, i.e. a measure of the quality of a clustering approach, is 0.7890 in Milazzo and 0.8989 in Gozo (the lower the better). These results reveal that the clusters are clearly defined and well separated, indicating the effectiveness of the clustering approach in creating distinct clusters, slightly better in the Gozo case.

To validate the waste geolocalization, i.e., to estimate the geolocalization error, the ground truth positions of some waste items in the two beaches has been collected as baseline to measure the root-mean-square error (RMSE) between the clustering results and the effective position.

Table 7 shows the clustering results on the two different beaches in terms of number of detected objects, the total root mean square error (RMSE_tot) and the average distance between the position estimated by HDBSCAN and the ground truth (GT).

Comparing the two beaches, the total RMSE is different, with a slightly higher value for Milazzo than Gozo. Some possible reasons may be the difference in the sediment color, since the Milazzo beach is darker than Gozo one, implying lower contrast of waste items. Another possible reason is the lighting conditions and brightness of the images, captured in different times (late morning in Gozo, late afternoon in Milazzo). Such results are also validated by the most relevant information for the clustering approach, which is the average

TABLE 8. Waste recognition performance.

P	R	F1	mAP_0.5	mAP_0.5:0.95
55.40%	34.10%	42.21%	34.40%	18.50%

FIGURE 17. UGV waste localization and recognition on the field (Ramla Bay in Gozo, Malta).

distance between data points, shown in the last column. In fact, even in this case, we can see that the average distance is slightly lower in Gozo (0.72m on 6 waste objects) than in Milazzo (0.81m on 7 waste objects).

Based on such results, however, it is important to highlight that the optimal value of ϵ may vary and depend on other factors like the density and distribution of the waste items, and the specific requirements of the application and case study.

C. RECOGNITION, COLLECTION, AND SORTING

For the material recognition model training, the started point is the *yolov5n.pt* model, setting the maximum number of epochs to 200 and the batch size to 48. As for the GS detection model training, default settings are used for all other hyperparameters. Table 8 reports the evaluation metrics for the recognition task performed on the UGV camera video stream in real time. FIGURE 17 shows a sample frame acquired by the ZED2i onboard UGV and the output of the recognition model tested in Ramla Bay in Gozo, Malta.

Table 8 results show that the model has an acceptable precision value (55.40%) and the relatively low recall (34.10%) highlights missed positive instances. The F1 score indicates a balanced performance (42.21%), while the mAP_0.5 and mAP_0.5:0.95 metrics provide insight on the waste recognition model at different IoU thresholds (34.40% and 18.50%, respectively). The results demonstrate acceptable performance for a challenging 4-class classification problem related to the waste material recognition.

Further tests have been performed on the robotic arm and the gripper to assess the waste item pose estimation for the collection and sorting task. Bottles and cans with varying shapes have been used. A picking and sorting sequence is shown in FIGURE 18. First, the UGV reaches the point of interest (FIGURE 18a) and the arm points the camera orthogonal to the terrain in front of the vehicle to

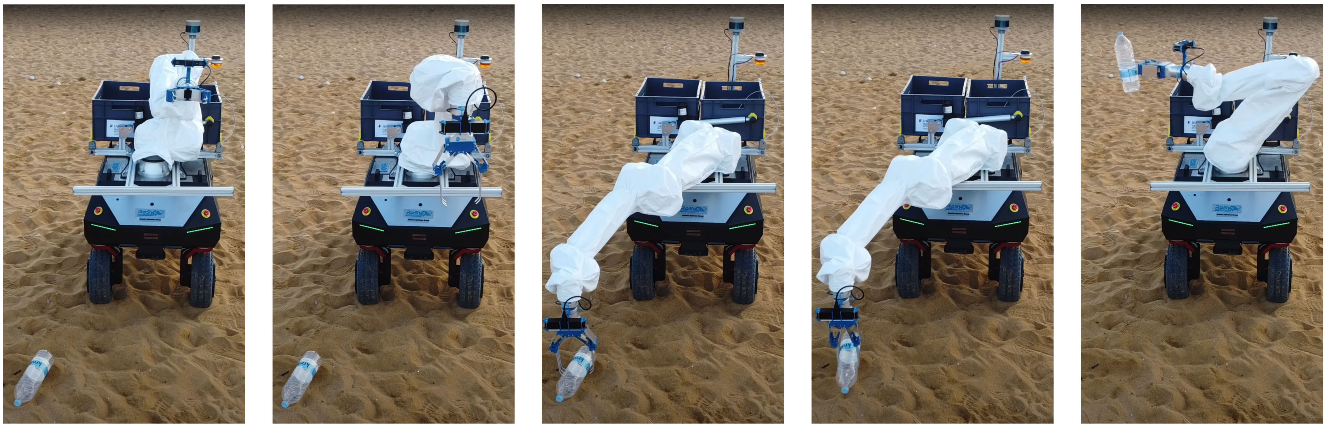


FIGURE 18. A sequence of the picking up and sorting task for a plastic bottle.

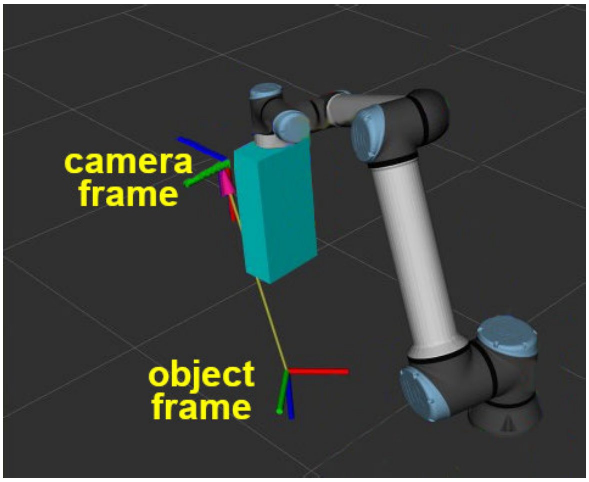


FIGURE 19. The waste object frame obtained from YOLOv5 OBB with respect to the camera frame. The cyan box represents the volume of the gripping mechanism.

carry out waste recognition (FIGURE 18b). Once the waste object is recognized, its pose is estimated as described in Section VII-B3 and a reference frame is attached to the object with respect to the camera frame as shown in FIGURE 19. The arm trajectory for approaching the object is planned and executed (FIGURE 18c), and the gripper tool is closed to grasp the item (FIGURE 18d). Finally, the waste is lifted up from the ground and placed into its corresponding container (FIGURE 18e).

The video below[3] provides a more detailed overview of the UGV and the whole picking and sorting process. videos showing an overview of the BeWastMan IHCPS implementation adopted in the BIOBLU project can be found at this link.[4]

The waste detection and recognition models are available at the link.[5]

[3]https://www.youtube.com/watch?v=dNyUeop_Ihc
[4]https://youtu.be/1LuQTZDqqIc
[5]https://github.com/gcicceri/BIOBLU_project

IX. CONCLUSION

In this paper, an intelligent hierarchical cyber-physical system (IHCPS) for fully autonomous eco-friendly beach waste management (BeWastMan) has been proposed, designed, and implemented. The BeWastMan IHCPS is grounded on the integration and interaction of three CPS: a UAV for aerial inspection of the beach, a GS for mission coordination and waste detection, and a UGV for waste recognition, collection, sorting, transfer, and recycling. The presented results showcase the effectiveness of the proposed approach, substantiated by a real case study implemented as part of the BIOBLU project. Such a validation through the implementation and testing of the BeWastMan IHCPS provides concrete evidence of its feasibility and performance in real-world scenarios.

The proposed approach differs from those available in the literature by proposing an autonomous solution that streamlines the waste collection and sorting processes, reducing the reliance on manual-huma intervention and improving the overall system efficiency, adaptable and robust to diverse coastal environments and scenarios. Furthermore, an efficient data processing is proposed, thanks to edge-to-cloud computing continuum, which improves the performance and scalability of the system. Versatility, adaptability and high accuracy is enforced by multiple specific models continuously trained on different beach patterns. Finally, the sustainability of the solution is ensured by a minimally invasive approach through the aerial survey and the pick-and-place, which ensures that the cleanup process has minimal impact on the beach environment during waste collection.

As a future development the plan is to address more specific aspects of the BeWastMan implementation. Concerning local waste recognition by investigating and benchmarking different classification methods for the collection through the gripper, based on either classical image processing or deep-learning. Other case study including multiple beaches, obstacles, and other alternative scenarios will be taken into account and possibly further developed.

From a methodological viewpoint, the next step in the CPS direction will be to implement the *beach digital twin* concepts, i.e. a way of continuously monitoring, surveillance and geolocalizing beach waste in real time. This could impact on the BeWastMan IHCPS design, for example by including some fixed cameras probing in real-time the beach rather than using a drone. To such a purpose, all the BeWastMan solution (i.e. the GS, the UGV, detection and recognition models) here implemented could be easily reused and adapted.

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