UAVs and GIS: An Innovative System for Monitoring Structures

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Abstract: - In the last years, Unmanned Aerial Vehicle (UAV) – systems have become relevant for multiple purposes in different fields of study. The purpose of this work is presenting an innovative experimental system for the assessment of the structural conditions of buildings and infrastructures through continuous monitoring stations based on the use of UAVs. This allows the automation in the monitoring of artifacts that present structural criticalities. The system consists in the acquisition, processing, and selection of images from a group of drones flying from wireless charging stations, whose data are then transmitted to a cloud platform which identifies defects and transmits them to an online Web-GIS platform. This will be the tool for viewing all elements that need maintenance. In addition to the improvement in the automation of data processing and in the precision of their selection, we will analyze an experimental procedure that uses different algorithms for damage detection.

Keywords: - UAV, Image classification, GIS, Image analysis, Segmentation, structures.

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1 Introduction

Structural cracks are nothing more than lesions that appear along the walls of a building. The causes that underlie this phenomenon can be different, some directly attributable to human action, others to external factors such as earthquakes or other natural events. Cracks can originate for structural or non-structural reasons: structural origins, poor quality of construction materials or structural failure of the land on which the building is built. These phenomena are the potentially most dangerous ones, which can give rise to important cracks on which to intervene promptly; non-structural origins normal phenomena of expansion or shrinkage of materials, also due to the action of atmospheric agents such as rain, humidity and snow. The nature of these cracks is of no particular concern.

The fissures that are identified in the artifacts are due to various causes: structural crises of foundations and pillars; subsidence of foundations or land; vibrations; weather conditions.

The cracks that can be observed on the outside of a building indicate an alteration of the static balance of the structure and are a signal that an analysis must be made on the nature of the causes that led to the cracking. In order to manage the building in complete safety, it is necessary to have information on the state of the cracks by carrying out periodic analyzes and monitoring.

To understand its seriousness, it is indispensable to check and estimate the extension of the phenomenon over time, first of all by observing the ways in which the lesions manifest and their nature.

Alongside the traditional crack pattern control systems of buildings, it is also possible to add monitoring through images. Until recently, conventional methods of acquiring the status of constructions relied on the work of operators who collected visual and quantitative data of the surface. The rapid development of robotic systems in recent years has allowed the application of UAVs for the acquisition of images in an automatic, safe, and inexpensive manner.

With the goal to help improve the acquisition of information on the conditions of our structures, the Geomatics Laboratory of the Mediterranea University of Reggio Calabria has developed the first prototype of continuous survey stations using drones and an online Web-GIS platform. The GIS is particularly useful to have a cartographic support that is accurate and precise for determining the path and to construct maps in which the obstacles are represented and georeferenced.

Therefore, the main novelty of this contribution is in the coordinated use of all these elements that through predictive systems provide results visualizable in the GIS.

2 Materials and Methods

The scope of this study is to improve the automation of data processing, the grade of accuracy in the automatic selection of data and to consent the transfer of geolocated data on an online Web-GIS platform. The system adopted allows the acquisition of data through a group of UAVs connected to a cloud or to a local network that are recharged through pre-established wireless bases.

Fig. 1: UAV used for inspection

The drones used are DJI Mavic 2 Pro, equipped with omnidirectional vision sensors and infrared sensors. To obtain more complex images, drones use advanced technologies such as:

- Hyper-lapse: a technique for time-lapse photography in which the location and the zoom level of the camera changes after each exposure.
- POI: Point of Interest, an intelligent flight mode with which the drone flies around a desired subject. On the automated flight, the drone keeps the object centered in the camera frame.
- ActiveTrack 2.0: it is a software that bases its functions on the combo of GPS system and visual recognition of space. An automatic function that allows the drone to locate its position, stabilize the flight and move easily between obstacles.
- Tapfly: it is a DJI mode with which the operator can choose to press a point on the real-time video to control the drone to automatically fly towards that destination.

Equally functional is the APAS (Assisted Piloting System) that allows to detect objects in the flight path in real time.

Mavic 2 Pro features an exclusive Hasselblad L1D-20c camera with a new one-inch CMOS sensor that features a larger sensing area than other systems on the market. It also allows for better performance in low-light environments thanks to a wider ISO range. The drone is enhanced with a 12-megapixel 1/2.3” sensor with a 4x zoom. Video resolution is 4K and in FHD. This allows for better quality shooting and camera stability.

Drones are recharged in pre-established platforms that allow not only the charging but also the processing and transfer of data collected along the path. For the research, we decided to use two platforms installed along the path. We realized a mini light-weight unattended drone system, including a C500 charging pad, a charging landing gear, a tailored Mavic 2/2 Pro battery, a canopy, an OC (Embedded AI-computer), a LS (local server), an CS (internet server), a T3 (HDMI camera monitoring), a Loudspeaker and a DJI Mavic 2 Pro.

So, when the drone in flight detects that the battery is running low, it looks for the nearest charging station. Having obtained the OK to land the drone, knowing GPS coordinates of the station, lands. Once landed, a subsystem recharges the onboard battery or swaps it. During the replacement, the drone is still powered through a special connector in order not to lose communications.

The methodology used involves three phases: the definition of flight plan of drones’ fleet; the analysis of images acquired during the flight; the geolocation of data on the WEB-GIS online platform. Its implementation, the functioning of the algorithms explaining how they interact with each other are shown below.

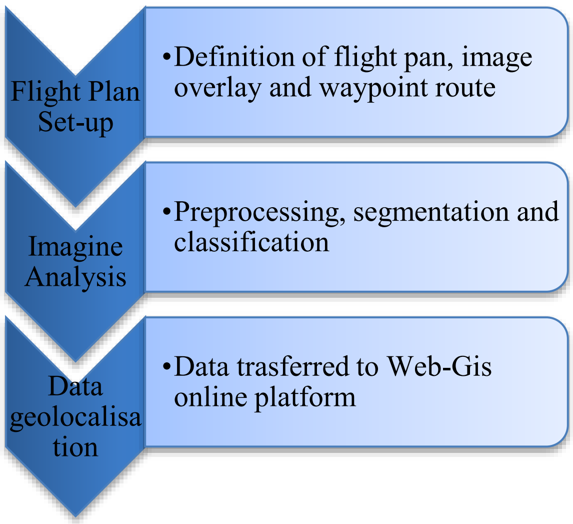

Fig. 2: Workflow for road safety assessment

The definition of the flight plan is established in terms of GSD (Ground Sampling Distance). It is defined as the range between the center points of two consecutive pixels of an image, measured on the real ground. There is an inverse proportionality relationship between the value of the GSD and the definition of an image. The higher the GSD value, the lower the image definition. Conversely, the lower the GSD value, the more defined the image. The designer decides the path of the drone and the definition required; in this case it was cm / pixel. Image capture time is also determined to avoid overlapping and to detect areas that are already processed. Subsequently, the image analysis phase takes place, which is divided into preprocessing, segmentation, and classification. Finally, the geolocation of the data on the Web-GIS platform takes place in order to associate each element of the GIS with coordinates referred to the data executed in the database.

The operations were tested in a limited area of Cardeto center (an urban area in the province of Reggio Calabria) where research activities have already been carried out by the authors. Fig 3.

Fig. 3: Test area – Cardeto – Reggio Calabria

2.1 Flight Plan Set-Up

The acquisition of images carried out by the fleet of drones follows a precise process: initially, a plan was established for the acquisition of the images, then the Ground Sampling Distance (GSD) was defined and finally the overlapping of the images was established. The image acquisition plan was set up in such a way that the UAVs acquired images during automatic flight along the waypoints positioned along the path. The drone software automatically calculates the image acquisition plan and mission settings through parameters: the flight height, overlap (%) and the area to be mapped.

The parameters for the flight conditions of the drones were set before departure. They are as follows: to obtain a GSD<1, and therefore a good accuracy of the acquired images, it was established that the maximum flight height did not exceed 10 meters for vertical flight; Flight plans were made with the drone's camera set with an inclination of 70°; the drone maintained a constant height during the flight and to do this, tests were carried out in order to control that no obstacle could compromise the safety of the mission. To optimize these conditions, an app, Flight Plan was used, which let us to change the various heights of the waypoints.

2.2 Image Analysis

Entering the heart of the research, in the image analysis process, different ad appropriate algorithms were used using the combination of different methodologies: Preprocessing (Sobel and Prewitt operator), Segmentation (Edge detector, Canny filter, Gaussian filter) and Classification (SVM). The aim is to improve the quality and precision of the images acquired.

In the *preprocessing* process, images taken by drones' camera are converted to grayscale, and images that had uneven background lighting were corrected to reach the same standards as those that had uniform illumination. In addition, the pixels that had an average intensity compared to those that had a higher intensity were removed and finally in order to eliminate noise from the images, two operators were used: Sobel and Prewitt. This first phase of the process is carried out to allow a better efficiency of the next process, namely that of segmentation.

To avoid attributing structural cracks to shadows or other noise elements, different algorithms are used: Edge Detectors, Canny and Gaussian filters.

Contour recognition plays a vital part in the field of extracting the features of an image as it is used to mark points in a digital image where the intensity of light changes abruptly. This generates images that contain less information than the original ones because it eliminates most of the details that are not relevant to the identification of the contours, while retaining the main information, such as the geometric shapes of the objects represented. The aim of segmentation is to simplify and change the image representation to something that is easier to analyze. It is seen as the process by which image pixels that have common characteristics are classified. We have obtained the most significant results with sophisticated nonlinear algorithms for calculating the size of the gradient such as the sum of the square of the response of a horizontal edge finder, and the square of the response of a vertical edge finder and Canny's algorithm. This procedure is an excellent edge detector among the traditional algorithms. According to this algorithm a border is identified by the relationship between the image and the filter, and the latter is chosen on the basis of three effectiveness criteria defined by Canny:

1) *Good detection capability*: the operator could not detective a real edge and could recognize a false edges;
2) *Good tracking ability*: the operator highlights the point that should be as close as possible to the center of the real edge;
3) *Uniqueness of response*: only one answer for a real edge.

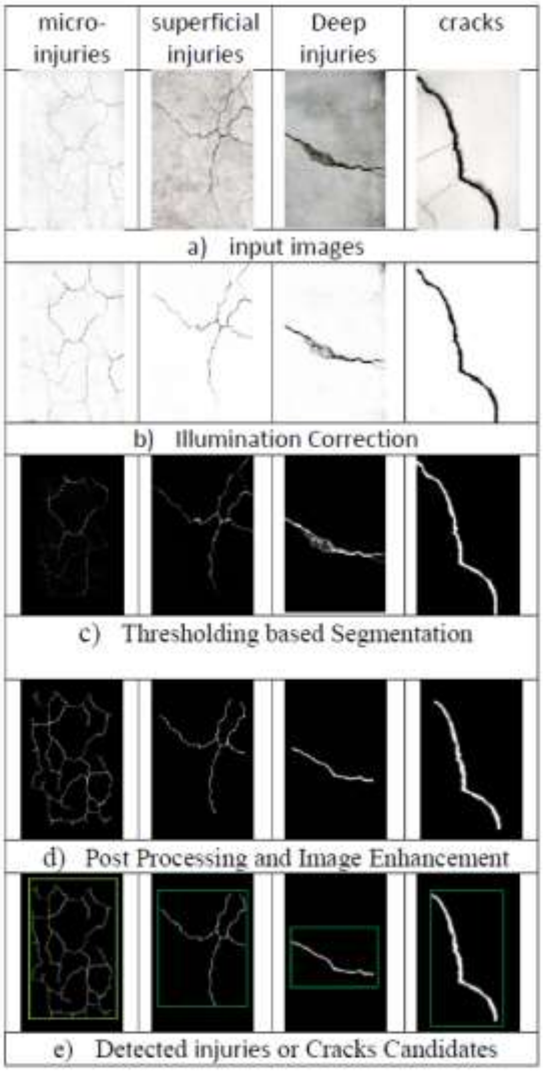

Fig. 4: Process crack detection

The segmentation process described above was used to detect distinct types of lesions, micro-injuries, superficial injuries, deep injuries, and cracks, present in common structures. In Fig. 4a, Images are shown as the drone captures them, before being processed. To speed up the processing time of the above algorithm, images have been resized to 512 x 512 pixels. In Fig. 4b, images are shown after a morphological operation with a disc-shaped filter, the non-uniform lighting has been adjusted. Subsequently, images were then processed using both Edge Detector and Canny algorithm and the automatic threshold value. The median filter with a rectangular element of 3x3 pixels was then applied, and regions with areas greater than 500 pixels were removed. At the end, the structures of cracks were enhanced through a morphological closure operation with a diamond-shaped filter with a radius of 5x5 pixels. In Fig. 4c, you can see the results of these operations. In Fig. 4d images are shown after removing the noise and finally the crack candidates are shown in Fig. 4e.

Following the above image analysis technique to segment and enhance image edges, crack detection was applied through SVM classification.

The classification process was carried out using the SVM method. Support vector machines is a supervised machine learning algorithm that can be used for both classification and regression. This type of method finds wide application in natural language processing, speech recognition but achieves maximum effectiveness in binary classification problems. A SVM model is a representation of data as space points, mapped in such a way that data belonging to two different categories are clearly separated with a space. New data are mapped in the space and the prediction of the category to which they belong is made on the basis of the side in which data relapse. So, to apply this model it was necessary to find a hyperplane that best divides a dataset in two classes. Initially, it must look for a linearly separable hyperplane or a decision limit that divides the value of one category from another and if there is more than one hyperplane, it must look for the one that can improve the strictness of the model. If a hyperplane does not exist, SVM uses a nonlinear mapping to transform the training data into a higher dimension, from two dimensions to three.

For the non-linear classification, we have used the Kernel method, implicitly mapping their entrances into a multi-dimensional feature space. In the case of using a linear kernel, the KSVM degrades to linear SVM. Kernel methods are so called for Kernel functions that are used to work in the characteristics' space without calculating data coordinates in the space. This operation is more efficient than the calculation of the coordinates and it is called "Kernel trick". Four SVMs with different Kernel functions are tested: LIN, HPOL, IPOL and GRB. The comparison was made through the confusion matrix.

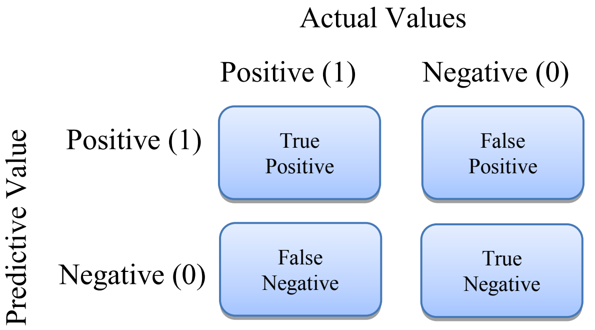

Fig. 5: Confusion Matrix

The classification of cracks with SVM was carried out as it follows.

First, the geometric features of the assigned components for SVM were calculated. Then, they were normalized to a range (0,1). For the reason we have explained, the Kernel with Radial Base Function was chosen as the Kernel trick, because the number of connected regions was not very large, and the size of the space transformed with RBF is infinite.

SVM parameters were found using grid search and to correctly identify the several types of cracks triple cross-validation was performed. That is, the training set was split into 3 subsets by testing each of them via the trained classifier on the two remaining different subsets.

This was led to ensure that the classifier can predict test data effectively with a good choice of the parameters. After this operation, using MATLAB LIBSVM Library, SVM was trained.

The results of the classification showed that the algorithm was precise regarding the classification of superficial injuries, deep injuries, and cracks, while those of micro-injuries were not classified correctly due to their more articulated shapes. This is due to disjoint parts with respect to the rest of the main body of the crack.

This procedure is not always accurate for the conditions of constructions because of the countless shapes of cracks: it requires the implementation of neural networks with different layers and many neurons. This leads to a considerable degradation of the performance of the software to be implemented [20].

For this reason, it was decided to adopt a modular approach: to use multiple neural networks, each of which recognizes a part of the crack. This first bottom-up approach is followed by another top-down one, during which, through a deterministic function, the various recognized parts are analyzed, and the object is identified which is unequivocally composed of the parts themselves.

Similarly, we have identified the various types of most significant defects in different structures in the area taken in consideration.

In our case study, the comparison results show that the used method DWT+PCA+KSVM with GRB Kernel performed best, reaching the best classification preciseness at 99.4%. The advantages of the SVM method were already known compared to other methods based on artificial neural networks [1], [2],[3],[4],[5],[6],[7],[8],[9]. In fact, SMVs have a simple geometric interpretation and represent an elegant and solid theory. In addition to having a compact representation of the dataset, they allow optimization in terms of time and are more performing systems than those previously adopted. It is therefore a real time analysis due to the speed of the process with which the images are processed. It turns out that through this procedure it was possible in a logical and linear way to recognize and classify the various types of cracks, [10], [11], [12], [13]. Some relevant studies can be also found in [14], [15], [16], [17], [18], [19].

2.3 Defects in GIS Data Localization (DLCGIS)

We proceeded with the automatic positioning on digitized cartography of the identified elements in support and further confirmation of the validity of the proposed methodology, also using a further methodology developed by the authors based on the use of GIS and Neural Network already tested in other applications related to the automated update of the road cadaster (from images captured by UAVs). In this regard, an automatic procedure was also used in the specific application under investigation, Data Localization GIS (DLCGIS), to locate and report defects. These algorithms are used to automatically save the positions of identified elements and alphanumeric data exporting later data acquired within the GIS, where the "historical" update is managed in the existing database, in order to verify the effectiveness of the infrastructure conditions. Once the defects have been identified, they are loaded into a special layer and "snapped" (moved and anchored) with a polyline present in the layer containing the cartography, [20], [21], [22]. Specifically, the procedure used works as shown in Fig. 6-9. The DLCGIS is divided into four software modules that each serve a specific purpose: the Plug-In module, the Kernel, the NNS module (Neural Network System), and the GIS I/O module.

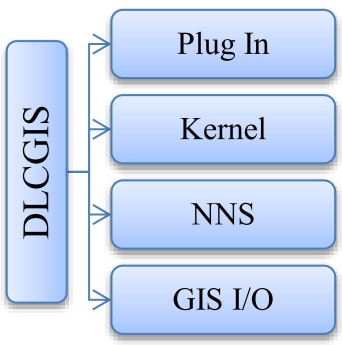

Fig. 6: Schematic representation of the four modules that compose the automatic defects classification application.

The Plug-In Module increases the number of objects that can be represented, recognized, and classified by assigning and identifying the type of border and the different shades of depth color within the parameter processing range (Fig. 7).

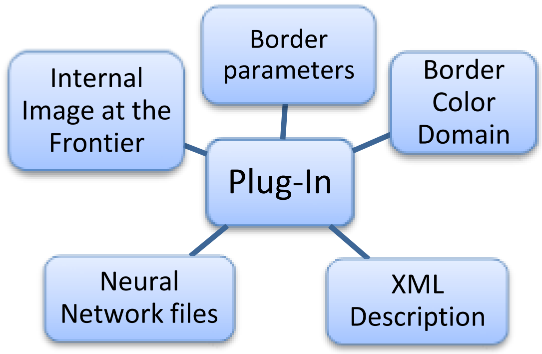

Fig. 7: A Plug-In valid for the application and the parameters that make it up.

The kernel, which interacts with users, coordinates the various modules, pre-processing and post-processing the modules' Input/Output data. On the detected and recognized elements, the application Kernel performs spatial adjustments (Simple and Intelligent Snapping). The Kernel exports to the GIS one or more specific layers containing the spatial and alphanumeric data of the identified elements through this module; the data refers to both "adjusted" and "unadjusted" elements.

Instead, the NNS (Neural Network System) module processes the Neural Network algorithm (the image is portioned and processed by different neural networks) trained to recognize the elements of interest.

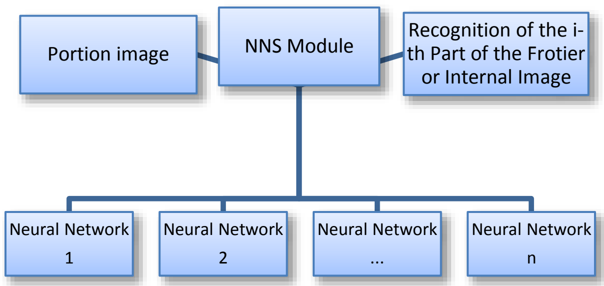

Fig. 8: The NNS Module computes the different models of the Neural Network.

Figure 9 depicts an example of the GIS Input/Output module. The GIS I/O module, in particular, is given in Input the files (polylines and polygons) in shp-dbf format, returning to Output a space database with the various attributes assigned to the objects.

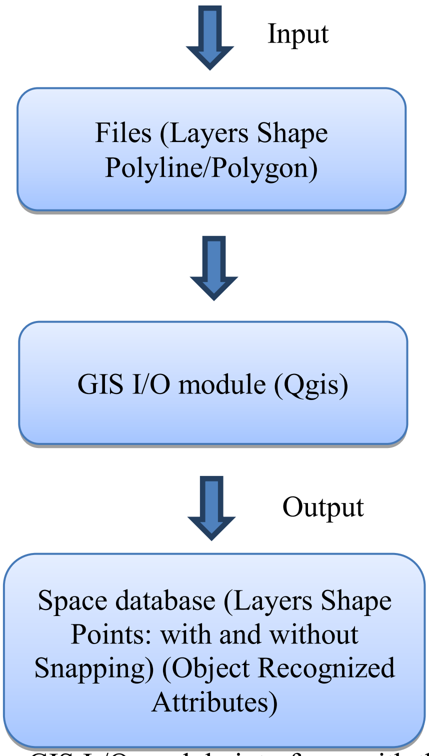

Fig. 9: The GIS I /O module interfaces with the GIS software using files in shp-dbf format.

The system was created as an example on a study area. Cardeto allows you to identify the presence or absence of structures with deep injuries and cracks (red) or micro-injuries and superficial injuries (blue) after selecting a graph (Fig. 10).

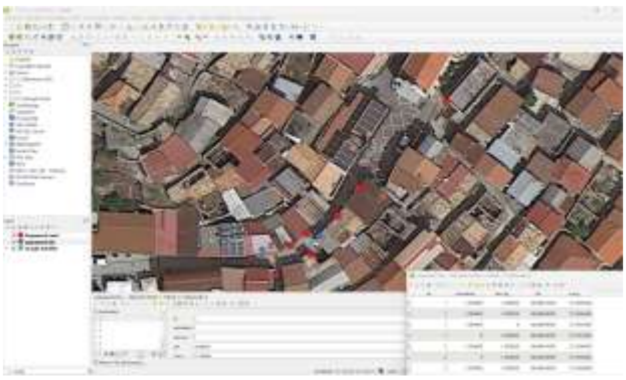

Fig. 10: On-screen display of the properties of structures. In red the structures with deep injuries and cracks

3 Discussion

The system we proposed and developed automates data acquisition, transmission, and updating in GIS. As previously stated, we programmed a fleet of automated drones that connected to the cloud and recharged at predetermined charging bases, collected in-flight data on the condition of the structures, and transmitted it to a cloud platform that provides real-time data feedback. This data is processed automatically in the cloud. Finally, DLCGIS was developed, allowing the acquired data to be localized.

All of this is done to reduce the time and cost of crack analysis while increasing its efficiency. This system has been designed to work in conjunction with other methods and tools for assessing and monitoring significant cracks in buildings. Aerial Laser Scanning is a popular nationwide method for mapping cracks and thus the instability of an artifact (ALS). [25] and [26] contain a synthesis of ALS. While the state of the art is multitemporal, ALS research in brief can be found from [23], [24], [25], [26], [27], [28], [29], [30].

By comparing the application system developed by us to what is reported in the bibliography, it is clear that there is a reduction in costs for data acquisition and management, as well as the ability to reduce time by one-third when compared to alternatives.

It should be noted that the Mobile Mapping System is one of the alternatives to UAVs (MMS). This system combines three major hardware components: optical sensors (laser scanners and/or digital cameras), navigation/positioning sensors (IMU/GNSS), and a control and synchronization activity. LiDAR (also known as Mobile Laser Scanning - MLS systems) is one of the most recent solutions, producing dense point clouds in real time. As a result, they enable high data acquisition speed with reduced time and costs, high spatial density of measured data (3D reconstruction), and remote acquisition, [31], [32], [33], [34], [35]. Although it is a valid proposal, the cost of data processing and management is higher than the solution we propose with UAVs.

The use of drones to automate monitoring processes eliminates the need for a large number of operators and allows access to areas that would otherwise be inaccessible with an MMS or other tools. In addition, we conducted a survey (the subject of future papers) on a viaduct using both an MMS and the UAV system. Finally, the findings of this study demonstrate the actual time and cost savings of this innovative system.

4 Conclusions

The Geomatics Laboratory of the Mediterranean University of Reggio Calabria has created an experimental prototype system for continuous structural surveying. The product system, which is still in development, sends a georeferenced dataset to a processing system, which already today allows the correct detection of the same dataset with a very satisfying result using classification algorithms.

The system has several advantages, the first of which is the automation of the image acquisition process and the speed with which data is available, allowing for the immediate identification of the most degraded areas. As a result, it enables more efficient and timely planning of infrastructure maintenance and management. Another benefit is the low cost. As a cost-effective system with maintenance functions, it can be an excellent tool for maintenance management based on data collected in the GIS.

Although the system has numerous benefits, it does have limitations. Even though drones were initially used only for military purposes, the National Civil Aviation Authority (ENAC) and the European Union Aviation Safety Agency (EASA) have recently expanded their use. However, the requirement to avoid flying in congested areas and to use an operator remains.

To overcome this limitation, one solution would be to install parachute systems in drones to avoid damage to property and people, as well as to provide a buffer zone under the trajectory of drones to warn users who cross it that they are in an area where drone flight is possible. The method used by UAVs offers an exciting opportunity to obtain information from captured data, which is extremely useful for civil applications.

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