Proof of Concept for the Use of Small Unmanned Surface Vehicle in Built Environment Management

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Abstract

Unmanned surface vehicles (USVs) are remotely-operated robotic agents that can safely deploy and maneuver on the surface of bodies of water. Although, there is an established body of literature on large, complex and expensive USVs in structural health monitoring, comparing the solutions provided with the current available UAVs and their scale, cost, and applications, shows that USVs are not yet developed at this scale. The goal of this study is to provide a proof of concept for applications and development of USV devices (small, low cost, and versatile) similar to the current available UAVs. These devices can be used for monitoring the construction progress, facility management or in other words it can basically stretch over the lifecycle of the facilities.

This paper first presents a discussion on different adaptations of the UVs and their definitions and applications. This is followed by a literature review on different health monitoring algorithms and methods to establish the body of knowledge in the area of automation of the health monitoring. This includes some related examples of small, low cost UAVs that are used to automate the health monitoring system. These are reviewed briefly to show how such systems can provide the basis for development of a similar USV. Next, deployment and use of various USVs is discussed. To provide a proof of concept for such a USV device an experiment is conducted with a small-scale commercial USV mounted with a camera to visually assess the health of a retention pond in Gainesville, Florida. The paper concludes with a discussion of the feasibility of the device and testing the possibility of automating the health assessment process using image-processing techniques.

INTRODUCTION

The conventional structural inspection procedure has been a visual inspection by an experienced and trained human inspector, which can be time-consuming and costly. It could also put human life in danger where the inspection environment is hazardous, or it may be at an inaccessible location or awkward to access location for people. For example, inspection of bridges and structures over water bodies can be hazardous to humans due to the tides, currents, waves, and strong winds. Using USVs would mitigate any risk to human life. Furthermore, inspection methods including routine tactile examination would require personnel to get close to the structure which causes additional risks, and in some cases the components may not be accessible. Again, using USVs and appropriate equipment would mitigate such issues. Using automated structural inspection systems, that integrate robotic systems and new advanced technologies, such as thermal cameras, improves the efficiency and reliability of visual inspection (Jahanshahi and Masri 2013). Using fully or semi-autonomous robots in structural inspection systems are believed to make the inspection process of civil structures cheaper, safer, and more reliable than the conventional visual practice. The increasing availability of low-cost commercially available robots has led to a massive growth in using such systems (Torok et al. 2013).

Recent Developments in technology (especially in low powered computing components, high capacity batteries, and affordable advanced sensing technologies) have led to the rise of commercially available unmanned vehicles (UVs). The rapid growth in the development of different robotic devices has resulted in a lack of consensus on the nomenclature of UVs. UVs can be broadly categorized as vehicles that operate without direct human physical contact (Gogarty and Robinson 2012). Table 1 presents the general terms used by the majority of the literature which categorizes the UVs based on their operating environment.

Table 1. Unmanned vehicles devices and their operating environment

Device name	Operating environment
Unmanned Ground Vehicle (UGV)	ground and solid surfaces
Unmanned Aerial Vehicle (UAV)	above the ground
Unmanned Underwater Vehicle (UUV)	underwater
Unmanned Surface Vehicle (USV)	water surface
Unmanned Marine Vehicle (UMV)	includes both USV and UUV

Another distinctive feature that can be used to categorize UVs is the degree of autonomy. This ranges from fully autonomous (where humans define the overall mission objective, but control is implemented using artificial intelligence) through to full but remote manual control by a human operator. As with many technological advancements, UV development started in the form of military applications. However, nowadays they are more widely available to the public and often used in research and development for a variety of applications. The first nonmilitary implementation of unmanned vehicles occurred within the agriculture industry (for spraying, cultivating and harvesting crops) and for deep water mapping and discovery (Gogarty and Robinson 2012).

UVs have been extensively used in search and rescue missions (Murphy, 2014), primarily because of their ability to access remote, confined and hazardous areas without putting human life in danger. The promise of autonomous operation makes UVs potentially a highly versatile and valuable tool for many other applications and thus is becoming a focus for research and development. However, the technology is not currently very mature for applications such as autonomous infrastructure health inspection. The research in this area is divided into two complementary categories: first, developing useful applications, and second, developing fully autonomous artificial intelligence controllers.

UVs with sensing and collision avoidance technologies through computer vision are a recent step toward developing autonomous infrastructure inspection systems. As Table 1 shows, USVs are one type of UV that operate on the surface of the water. USVs have been used in several missions with different tasks including mapping and monitoring piers, bridges and marine structures (Sakuma et al. 2017). One of the advantages of USVs' over UAVs is that small USVs can reach locations where it is hard for UAVs to navigate.

Schiaretti et al. (2017) reviewed 60 prototypes of autonomous surface vessels and concluded that there is a gap in the knowledge concerning the different applications and appropriate environments in which to use USVs. The goal of this paper is to provide a proof of concept for the viability of small, low cost and versatile USVs. The ultimate aim is to achieve fully autonomous robotics agents through ultra-low powered computing components capable of deep learning implementations coupled with reinforcement learning.

RELATED WORK

The main goal of this paper is to explore the viability of using a small and low-cost USV as a stand-alone robotic agent and also as a cooperative agent with UAVs. First, early adaptations of the UVs and their definitions and application are discussed. This is followed by a review of literature concerning different health monitoring algorithms and their automation. Next, some related examples are considered that utilize small and low-cost UAVs to automate the health monitoring system. These systems are briefly reviewed to show how they may provide the basis for development of a similar USV. Finally, a review is presented on the development of various USVs and the possibility of cooperative use of UAVs and USVs.

UVs can be controlled autonomously by a computer, remotely by an operator, or a combination of the two methods. Implementing UVs for inspection, progress monitoring and search and rescue is much less costly and less risky compared to the current human intervention methods (Jahanshahi and Masri 2013). Mobility, autonomy, and sensing are identified as the crucial challenges in developing a robot for infrastructure inspection (Lattanzi and Miller 2017). The Three Mile Island disaster where a nuclear meltdown happened on March 28, 1979, was one of the earliest deployments of an inspection conducted by UVs (Lovering 2009). Lattanzi and Miller (2017) identified the ever-growing commercially available unmanned vehicles as a platform for the development of nondestructive evaluation technologies. They have also mentioned increasing level of UVs' autonomy and the need for appropriate frameworks for analyzing the massive amount of data developed by these devices as the main challenges. Human-robot interaction, better inspection algorithms, real-time hazard and risk identification, early deterioration detection, collision avoidance are among the UVs' features that need further research and development.

Numerous researchers have worked on non-destructive crack detection methods using image processing (Jahanshahi and Masri 2013). However, using autonomous vehicles for conducting real-time crack detection can be challenging due to the motion blur and lack of high-quality data. This issue has been partially solved by advancements in the development of better cameras and three-axis camera stabilizers which drastically reduce the loss of data due to motion blur. Aldea and Le Hégarat-Mascle (2015) discussed limitations of minimal cost path analysis and on image percolation algorithms for crack detection using a UAV and proposed a new strategy to cope with the motion blur. Identifying a crack is essential in health monitoring. However, that is just the start of the health monitoring process. The width and depth of the crack, location and its progress over time are also crucial details that studies such as Jahanshahi and Masri (2013) have tried to address. While most analysis has been concerned with 2D image processing, there have been efforts using 3D inspection techniques. For instance, Torok et al. (2013) have proposed a method for developing a 3D model of a target structure to identify cracks and damages using a new 3D crack detection algorithm. The proposed algorithm can detect structural damages regardless of the 3D mesh building process. They have also proposed a platform for deploying this system through a robotic platform. The result of their investigation shows that the 3D crack detection is viable and useful in post-disaster structural health assessment. Hallermann and Morgenthal (2013) discussed the application of UAVs for the assessment of the existing structures and checked the viability of their method on an industrial chimney and a historical tower. Ellenberg et al. (2014) have shown that present red-green-blue cameras available on commercial UAVs are able to detect cracks in structures which are identifiable via human visual inspection. Sakuma et al. (2017) have proposed a framework to conduct pier inspection using a UAV.

One of the first research-oriented USVs was developed at the MIT sea grant college program in 1993 (VANECK et al. 1996). Subsequently, the release of the US Navy's master plan in 2007 highlighted the promising future of USVs (Navy 2007). Different uses of large USVs in hydrographic survey, seafloor mapping, bathymetry, mine countermeasures (Subhan and Bhide 2014), surveillance and reconnaissance are explored thoroughly within the literature (Yan et al. 2010). The Charlie project (Caccia et al. 2007) is an example of the whole process of design, development, and test of a fully or semi-autonomous USV for coastal and protected waters applications. One of the main findings of this experiment was the importance of rules of engagement and development of capable fully autonomous navigation systems which avoid a collision and follow the provided rules of engagement. ROAZ (Ferreira et al. 2009) is another example of design and test of a catamaran as an autonomous USV for risk assessment in the marine environment. The navigation system used in ROAZ is reported effective in path following and trajectory maneuvers. Han et al. (2015) have proposed an autonomous navigation and mapping algorithm for a USV and demonstrated its viability in an experiment by mapping the structures under a bridge. Challenges in developing a USV application include achieving a suitable level of intelligence, accuracy in control, attaining high stability, and keeping the development costs as low as possible (Manley, 2008). A proof of concept system developed and tested by Von Ellenrieder and Wampler (2016) was used to collect underwater and waterline information using multiple sensors for bridge inspection. The proposed USV and 60 USVs reviewed by (Schiaretti et al. 2017) were found to be very effective, especially for deployment in a harsh environment. However, the

USVs mentioned in these studies are large, expensive vessels. This shows the opportunity to develop a small and cheap but relatively capable USV that can be deployed in water bodies where there are minimal environmental challenges.

Murphy et al. (2011) have deployed a USV and two UUVs for inspection of a bridge after Hurricane Ike. Deployment of two USVs after hurricanes Wilma (2005, Florida) and Ike (2008, Texas) for littoral structural inspection showed the viability of disaster assessment via USVs (Steimle et al. 2009). Furthermore, the experiments showed that the loss of GPS, rough waves and atmospheric challenges such as fog could cause a problem for autonomous navigation systems. Also, transmitting a significant amount of data over the current wireless network is not very effective for long distances. After hurricane Wilma 2005, cooperative use of USV and UAV was tested by Murphy et al. (2008) for disaster assessment. Their experiment consisted of checking structures such as sea walls for damage concurrently but independently and also cooperative and coordinated inspection by the two platforms. Their study suggests that a USV is a better option to perform close-range inspection compared to a UAV.

Most of the USVs discussed in the literature are large and usually expensive. Being large is a common thread as it is a requirement for being stable in rough waters. However, there is quite a large number of instances where the water body is not that active, and deployment of small and low-cost USVs is viable and more helpful compared to the existing USVs. Applications of small and low-cost USVs are mostly unexplored. In this paper, authors provide proof of concept for the viability of small, low cost, and versatile USV as a stand-alone robotic agent and also as a cooperative agent with UAVs.

PROOF OF CONCEPT

To provide proof of concept for such a device a feasibility study was conducted at a retention pond in Gainesville, Florida, that is designed for capturing and treating stormwater from an 89-acre area in downtown Gainesville and runoff from an adjacent creek. This trial provides the opportunity to test the small, low-cost USV in a practical situation. The robotic system used in this study is a remote-controlled small-size USV, which is commercially available and mounted with a WIFI enabled waterproof camera shown in figure1 along with the landscape of the retention pond. The USV's length is 43 centimeters, and its weight is 1.3 kilograms. The USV is remotely controlled, and the camera is controlled via a smartphone. The operator can use the video feed and visual tracking of the USV to remotely direct it to the desired place or follow a predefined path. The USV is remotely directed toward the concrete walls to capture video and pictures from the wall's surface. A smartphone is used to control the red-green-blue camera connected via WIFI connection. Two rounds of data collection are conducted (one with close vicinity of the concrete surface and one with a more wide-angle view) to make sure the quantity and quality of data are satisfactory for future analysis.

Figure 1. USV during the experiment and USV setup

The goal of this experiment was to provide a proof of concept for small, low cost, and versatile USV applications primarily focused on structural health monitoring and maintenance of structures adjacent to water bodies. The ultimate goal is stretching the application of such a device over the whole lifespan of the built environment from monitoring the construction work to facility management and possible disaster relief efforts. The Data captured through this device can be used for visual inspection, automatic environment detection, and crack detection.

RESULTS AND DISCUSSION

The main issue under investigation in this study is examining the possibility of having small, low cost USVs (similar to available commercial UAVs) and providing a proof of concept for such a device in built environment management. Also, in regards to the data analysis, many studies in structural health monitoring use proprietary software with computationally expensive algorithms which should be run on the gathered data sometime after the inspection via the UV (regardless of its type). The approach proposed and used in this paper uses an open source software and machine learning algorithms that can be trained once and implemented in the device to provide real-time data analysis in place. An autonomous USV should be able to navigate on its own and ideally automatically run analysis on the captured data as it is not possible to send all the data over the air across long distances. As an early step toward this goal, the following provides the results and discussions of using this device for visual inspection, automatic environment detection, and crack detection.

Figure 2 shows an example of the findings from visual inspection from the testing of the small USV in the retention pond. It is visible that the aggregates are exposed in the highlighted section of the structure, which might be of concern for the longevity of the structure.

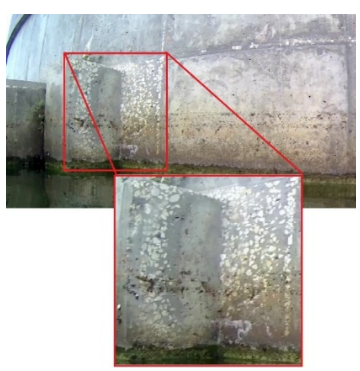

Figure 2. Example of visual inspection result

Real-time analysis of the surrounding environment and automatic detection of the surrounding objects through computer vision can support the autonomous navigation. It can also be used to detect structural components and help the device to run health monitoring algorithms on the detected segments automatically. The first step is analyzing the pictures and determining a way to automate the segmentation process. This task can be undertaken using machine learning algorithms for classification. In this study trainable Weka segmentation plug-in (Arganda-Carreras et al. 2017) from the ImageJ (Schneider et al. 2012) software which is an open source image processing platform was used for classifying different sections of the captured data. The Weka segmentation is chosen because it is an open source, free, and portable platform which provides many machine learning algorithms for pixel-based segmentation in an easy to use manner. It can be used in conjunction with other open source libraries to provide light solutions to complex problems. This new approach can provide low cost, customizable, and versatile solutions depending on the target environment for automating the monitoring and maintenance of the built environment compared to the expensive proprietary software and conventional computationally expensive image processing algorithms. A random forest algorithm was trained to segment three elements in the pictures, air, concrete, and water. One advantage of machine learning algorithms compared to conventional image processing algorithms is that training (which is computationally expensive) can be done once off-site and then deployed for real-time use. Figure 4 shows the training samples and the probability map of the concrete detection result for the training sample. The first step to conduct the segmentation is to define the different classes for extracting the desirable features and associate desirable features to each class. Three classes are defined: concrete, air, and water. From a representative sample picture (shown in figure 3) sections of each target area are selected to extract Gaussian blur, Sobel filter, Hessian, Difference of Gaussians, membrane projections, and many more features and convert them to a set of vectors of float values. Based on the extracted features and associated classes, the random forest algorithm is trained. The result of applying the trained algorithm to the whole picture is shown in figure 3.

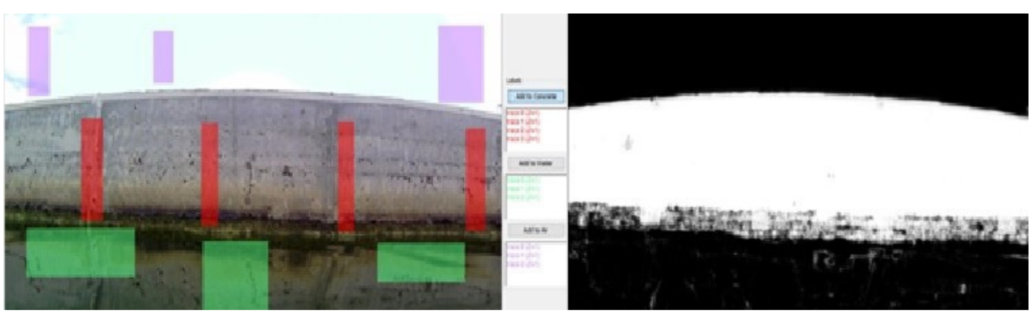

Figure 3. Random Forest training

Figure 4 shows three samples from applying the trained random forest classifier to new sample pictures. The result shows a visually acceptable detection accuracy. This automatic segmentation can help in autonomous navigation and automation of the diagnostic algorithms on the structures in real time.

Figure 4. Sample results from applying classifier on different pictures

After segmentation (isolating the concrete from the background), the robot can apply health monitoring algorithms to check for any desired problem in the structure. Figure 5 shows a sample problem detected visually and automatically. As this retention pond was recently constructed, there were not much visible cracks and health problems. However, the identified issues is enough to provide proof of concept for the viability of the proposed device.

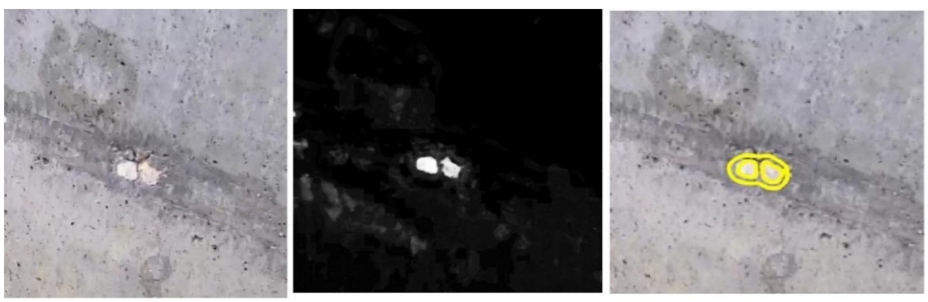

Figure 5. Sample results from automated health monitoring

Another application which is beyond the scope of this paper and could be explored is the cooperative use of USVs and UAVs as they can complement each other's weaknesses. A successful scenario would be using a UAV to gain a generalized view of the area and identify the locations that need close-in inspection by the USV.

CONCLUSION

This paper briefly reviewed the early adaptation of the UVs and their definitions and application, different health monitoring methods and their limitations, and examples of small, low-cost UAVs used in automated health monitoring systems. Combined with the review of the literature related to the development of the USVs, it is shown that there is an opportunity for development of small, low cost, and versatile USVs to make such devices more accessible. A proof of concept is provided for such a device, and its possible applications using a small USV mounted with a camera. First, the implications of the device for remote visual inspection was explored. Then, using a random forest classifier, the feasibility of real-time segmentation of the surrounding area was validated, which can be useful for both autonomous navigation and automation of structural health monitoring. Furthermore, using segmentation and edge detection computation the feasibility of running algorithms such as crack detection on the data collected by the USV was demonstrated. As a result, it is shown that with further development and testing such a device can be used for monitoring construction progress and facility management, in other words it is relevant to the complete lifecycle of a facility.

The amount of data captured in these surveillance exercises is massive and transmitting it via current wireless systems is not viable for long distances. One solution proposed in this paper is using computationally light machine learning algorithms to achieve real-time in-place analysis within the UV. As a result, the robot only transmits the log or the critical findings during a large-scale inspection. This system is feasible by implementing ultra-low powered computing components in the design of the robot for processing the data in real-time.

Further development and tests of small-scale USVs with different sensors such as sonar and thermal cameras for health monitoring or floor mapping are among the many ways this study can be extended. Also, implementing these devices with autonomous pathfinding capabilities is critical to achieving fully autonomous robotic inspection agents. The ultimate aim of this study is to help to build a more accessible intelligent robotic agent for built environment management.

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