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INTELLIGENT AUTONOMOUS INFORMATION ACQUISITION AND SCENE UNDERSTANDING OVER LARGE SPACE

S. S. Ge[1,2], G. Wang[1], Le Dong[1], B. B. Ren[2] , R. X. Cui[2]

[1]Institute of Intelligent Systems and Information Technology (ISIT), University of Electronic Science and Technology, Chengdu, China
[2]Department of Electrical & Computer Engineering, National University of Singapore
Email: samge@nus.edu.sg

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Abstract:
With the advances of technologies, the time is ripe for the development of an intelligent system for autonomous information acquisition and scene understanding (IASU) over large space. In this paper, we will present the basic structure, technologies investigated, technical fundamentals, and the scientific problems around its development. This topic is of academic interest and has potential for significant practical applications as well.
This could be achieved through the combination of satellite

Keywords: Information Acquisition/Recognition, Scene Understanding, Autonomous Systems, Decision Making.

1. Introduction

Much research has been obtained in autonomous systems, communication, pattern recognition, and scene reconstruction. By combining the above technologies together, we can handle emergence more efficiently, more effectively and at a larger scale as well as with a higher complexity over large space by seamlessly fusing them together.

There are many emergencies, including forest fires, hurricanes, floods, mining accidents, etc, that need our timely responses and prevention. Most of these disasters involve rescue teams, which are trained to perform search and rescue operations in extremely hostile environments. In all these emergences, time is one of the most important critical factors: the time to be able to identify the troubled area, the time to reach the scene, the time to find the targets, the time to transport the right tools/equipments to the place, etc. In the cases, with limited resources, we could also determine the most effective and efficient rescue operation in an optimal manner.

With the advances of modern technologies, several studies have fully demonstrated the benefits coming from the cooperation between heterogeneous set of machines: (i) the integration of data coming from complementary types of sensors and from different points of view makes the contents more informative and meaningful, and (ii) missions of high complexity and difficulty also call for the orchestration of heterogeneous set of machines for efficient operation in a timely manner.

As emergencies happen over large space, the system has to be able to cover the whole area of interests, and the resources could then be mobilized. As such, it should include the following three basic components:

(i) Remote sensing and monitoring capability:

This could be achieved through the combination of satellite remote sensing and collections of sensor networks.

(ii) Rapid response capability:

This demands a fleet of heterogeneous set of machines for rapid responses and real-time resources re-allocation.

(iii) Efficient operation capability:

This requires accurate information on the emergence, the targets, and on-site real time evaluation of the situation and scene reconstruction for efficient decision making.

When an emergence is being identified by a remote sensing and monitoring system which operates 7/24, an alarm, with a rough analysis of the situation, will be sent. Upon receiving the information, unmanned aerial vehicles (UAVs) and unmanned ground vehicles (UGVs), representing complementary vehicles, will be mobilized to the troubled area for detailed understanding, assisting on-site rescue operations, and reporting conditions that may be hazardous to the teams. With a better understanding of the scene, resources could be better utilized, operation would be more efficient, and resources could be updated as required.

One can imagine a scenario, as shown in Fig. 1, where the buildings collapsed in cities due to the earthquakes. The rescue mission under disaster environment is very complicated and dangerous for a rescue team. Search and rescue robots can not only improve the efficiency of rescue operations but also reduce the casualty of rescuers. They have a great potential to assist in searching ahead of rescue teams and reporting conditions that may be hazardous to the teams. For these reasons, there is a need to develop more effective surveillance, reconnaissance and rescue technologies and tools. This could be realized by the cooperation of UAVs and UGVs, and information technology and 3D reconstruction for actual situation evaluation

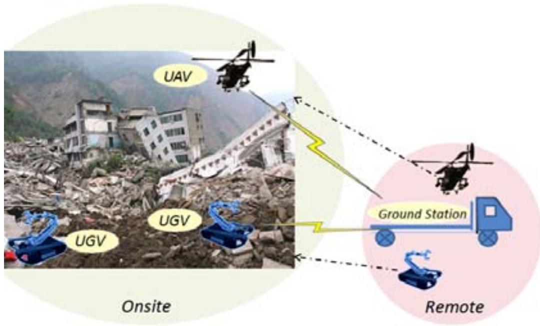

Fig.1: Scenario

In this article, we present an intelligent system for autonomous information acquisition, scene understanding, and real-time 3D reconstruction of area covered and to be covered. Its goals are to establish fundamental and enabling science and technology for building trustworthy networked information systems, to develop techniques for assessing trustworthiness of networked information systems, and to apply the developed techniques to critical applications.

2. Systems Architecture

To achieve the goal of autonomous information acquisition and scene understanding over large space and rapid responses in real-time, the system has three subsystems, (i) global information acquisition and monitoring system, (ii) rapid response and scene understanding, and (iii) real-time 3D reconstruction and supporting system.

The global information acquisition and monitoring subsystem are constructed as a distributed remote sensor system over large space, and it will monitor the whole area and send the information to the ground station as shown in Fig. 2. Based on the data sent by the remote sensors, the rapid response and scene understanding subsystem will analyze the situation of the interested area and give a detailed onsite scene understanding timely. In certain urgency, such as forest fires, hurricanes, floods, etc, the subsystem will make a real-time resource and task allocation, and arrange the demanded UAVs or UGVs to go to the area and do the onsite operation.

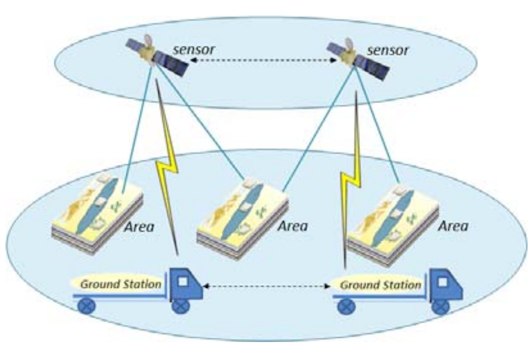

Fig. 2: Remote Sensing

The UGVs perform reconnaissance in unison within on-site disaster territory locally, while the UAVs explore the surrounding area and provide the global scene information. Then, both local and global information will be transmitted to the grand station (GS) where data association, scene understanding and the real-time 3D reconstruction are conducted to facilitate decision-making further.

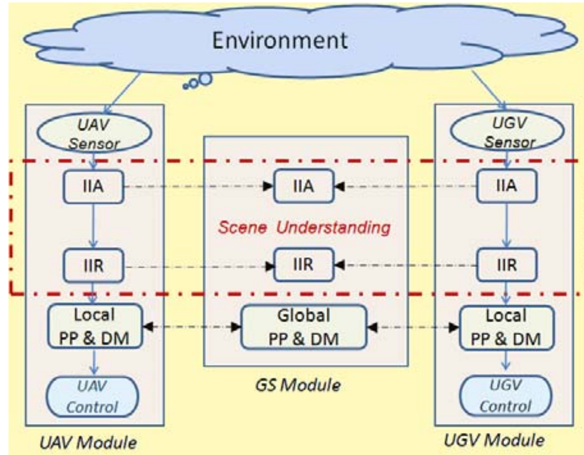

Fig. 3: The UAV, UGV, and GS modules

Physically, there are there modules in the whole system, namely, UAVs, UGVs, and GS. As shown in Fig. 3, each module includes three sub-modules , i.e., Intelligent Information Acquisition (IIA) module, Intelligent Information Recognition (IIR) module, Path Planning (PP) and Decision Making (DM) module, which work together to perform the information collection, processing and planning. Finally, both UAVs and UGVs have low-level control modules to steer vehicles to the desired positions.

3. Global Information Acquisition and Monitoring System

To provide a robust global information acquisition and monitoring system, different sensing/monitoring technology can be combined for area of interest over a large space.

There are two types of technology can be utilized for the purpose: (i) the remote sensing (RS) technology for the whole space, and (ii) the network of distributed vision and audio monitoring system for the area of interest.

RS technology can provide two kinds of information: (i) objects on the ground, and (ii) the elevation of the terrain.

The information about an object or scene can be acquired by electro-optical remote sensing technology without any physical contact with it [1]. Radiation reflected by objects at different wavelength is recorded as pixel's value in RS images. The radiance or reflectance of objects can be extracted from images, according to which the material of objects can be identified. The accuracy of identification mainly depends on quality of RS images, such as spectral and spatial resolution. Since hyperspectral image has high spectral resolution, many unknown sources can be uncovered by hyper spectral sensors which have been widely applied to identify earth objects in many fields such as geology, agriculture, environmental, forestry, water assessment and military [2]. Figure 4 shows a set of hyperspectral images of Cuprite, Nevada of America in ENVI database. There is spectrum information in each pixel of hyper spectral images, and we can identify the corresponding materials by the radiance or reflectance extracted from the pixel values.

Respect to the elevation information of the terrain, it can be obtained by Synthetic Aperture Radar interferomety (InSAR) technology. Through InSAR we can utilize the phase information of single look complex SAR data to obtain the corresponding 3-dimension information, which will help us get the elevation of the earth surface. InSAR has been a hot topic in Radar filed since last century. Recently, it has been widely used in remote sensing discipline

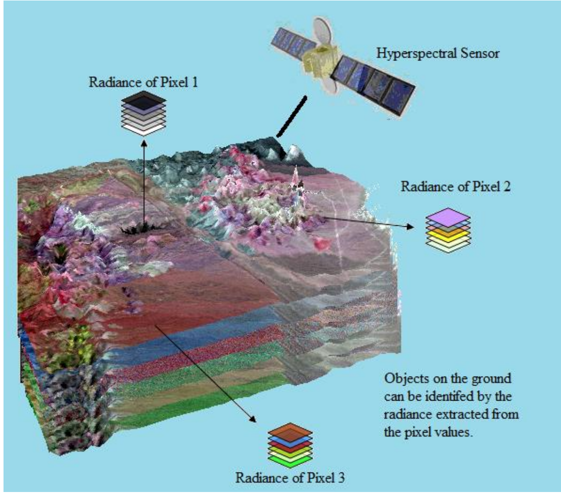

Fig. 4 Principle of imaging spectroscopy

3.1. Distributed Vision and Audio Monitoring Systems

For cities and area of interest, a network of distributed vision and audio monitoring system can be established.

Sensors having complementary features should be integrated together for improved system performance. In the context of the system framework, we shall emphasize the visual and audio monitoring systems individually and as a whole. Vision is the most informative modality, and it is organized in terms of space at the input stages but with limited range and angles. In an audio location system, the range of frequency and Interaural Time Difference can be chosen to detect movement of the desired source that cannot be "seen" by the vision system. Vision has been extensively studied in comparison with audio location systems. In reality, the two should be combined together for better performance.

For both vision and audio monitoring systems as individual or their fusion, neural networks have been frequently and successfully used in data compression and classification of complex data patterns. In our system, the highlight has been casted upon the fusion of audio and vision location systems using neural networks as individuals, and the complete monitoring system by combining vision and audio together – sensor fusion. Thus, the system developed can be tailored for different applications as standalone solutions, or as a whole for improved performance.

3.2. Intelligent Information Recognition (IIR)

The framework of intelligent information recognition consists of two parts, to which we refer as the global processing unit and the local processing unit. These two parts function in parallel and may also interact with each other via the adaptation on parameters [3].

The goal of the local processing is to sort out detail information in objects. To this end, we adopt saliency region/point detectors as the feature extraction tools [4]. There are numbers of the relevant methods satisfying our requirement. For saliency region detection, the state of the art methods include the saliency model [5] and the Spectral Residual Approach [6]. For the feature point extraction, one of the most popular methods is SIFT. The local image features, extracted from regions or points, are salient when they are statistically distinguishable from the background. We then use a Bayesian methodology for the pseudo restoration of the visual objects which might be blurred. Starting with a comprehensive model the probability posterior distribution is approximated by applying variational methods. This approximating probability distribution is used to define a more realistic particular model, with spatially dependent prior variances. The synthesizing comprehensive and particular model better captures the non-homogeneity of the image field, that leading to a better restoration, thus offering a favorable condition for the following local highlight detection. Given an initial approximate solution, the applied algorithm iteratively modifies the shape, the scale and the spatial location of a point and converges to a local structure.

In the global processing unit, visual context information is available early in the visual processing chain providing an efficient shortcut for object detection and recognition. The processing of the global scene information is performed in parallel to the processing of local image structure such as the detection of salient areas. The object together with its background is initially represented using a low-dimensional vector of global features computed from the same pool of low-level features used to compute local image saliency. The global scene features can then be used to predict the probability of presence of the target object in the scene, its location and scale.

There would be an interaction between the global and local processing. The global processing is a coarse feature extraction which performs recognition in a high-level and can filtering out the most irrelevant objects. The local processing, on the other hand, is a fine processing which can identify the appearance, location and scale of objects, and thus confine the region of global processing. Furthermore, there could be an interface between the system and people, and the recognition can be performed in a supervised and semi-supervised manner. Above all, the information recognition framework integrating both local and global processing naturally satisfies the principle of human intelligent system.

4. Rapid Response Systems (IAS)

4.1 Autonomous Control of Unmanned Vehicles

Ensuring stability in UAVs flight is a challenging problem for nonlinear control design and development. Unlike many classes of mechanical systems, which naturally possess desirable structural properties such as passivity or dissipativity, UAVs are inherently unstable without closed-loop control, especially during hover. In addition, the dynamics are highly nonlinear and strongly coupled such that disturbances along a single degree of freedom can easily propagate to the other degrees of freedom and lead to loss of performance or even destabilization.

Increasing effort has been made towards control design that guarantees stability for helicopter systems. Many techniques have been proposed for the motion control of UAVs, which range from feedback linearization to model reference adaptive control and dynamic inversion. The foregoing works require reasonably precise knowledge of the dynamic models in order to achieve satisfactory performance. In the control of UAVs, an important concern is how to deal with unknown perturbations to the nominal model, in the form of parametric and functional uncertainties, unmodelled dynamics, and disturbances from the environment. UAVs control applications are characterized by time-varying aerodynamical disturbances, which are generally difficult to model accurately. To deal with the presence of model uncertainties, approximation based techniques have been proposed in [11, 12, 13]. The effectiveness of the proposed control has been illustrated through extensive simulations.

Compared with the model-based control, approximation-based control yields better tracking performance in the presence of model uncertainties.

4.2. Cooperative Control of Multi-Vehicles Systems

Fig.5: UAV Formation

While autonomous vehicles that perform solo missions can yield significant benefits, greater efficiency and operational capability can be realized from teams of autonomous vehicles operating in a coordinated fashion. Potential applications for multi-vehicle systems include space-based interferometers, surveillance and reconnaissance, hazardous material handling, and distributed reconfigurable sensor networks [14, 15]. Compared with the single vehicle, it will be more effectiveness and robustness while using multi-vehicles to search a very large area. To enable these applications, a variety of cooperative control capabilities need to be developed. One fundamental problem in multi-helicopter cooperation is formation control, in which the UAVs keep a desired formation configuration and at the same time complete the assigned tasks as in Fig. 5. A large focus of multiple UAVs research community has been on coordination in flight formation and this ability has been demonstrated in [16, 17, 18].

Various approaches have been proposed for formation control, including behavioral, virtual structure, and leader-following [19]. Most of the works use a formation representation that is structured after graphs with nodes and edges. It is noted that the nodes and edges scheme is very useful in applications which require strict adherence of each robot to specific points in the graph. However, as highlighted by Ge and Fua [20, 21], there are also many applications (e.g. during pursuit, encirclement and convoy movement) in which flexibility (and the 'appearance' of the formation's shape) is more important than rigidity. For schemes based on nodes and edges, algorithms for fault management and scaling involve changes in the graphical definition of the formation (addition and/or removal of nodes and edges). However, for complex formations, it becomes difficult to track how the definition changes in response to the many different cases of agent failures or additions dynamically. There is therefore the need for formation schemes to be amenable to dynamic scaling. An efficient formation representation scheme, the Q-structure, was introduced in [20, 21], which present the concept of queues, instead of nodes, to define and support a large variety of formations. In [22], the concept of target region was proposed, where decentralized control was developed to drive a swarm of mobile agents into a moving target region while avoiding collisions among themselves. Both Q-structure and target region scheme are independent of reshuffling of agents thus facilitating scalability and flexibility.

4.3. Adaptive Task Allocation for Multiple Agents

In the operation, the UAVs group and UGVs group working together to perform the reconnaissance in unison. Then we invariably encounter the question: "which robot should execute which task?" This question must be answered, even for relatively simple multi-robot systems, and the importance of task allocation grows with the complexity, in size and capability, of the system under study. Even in the simplest case of homogeneous robots with fixed, identical roles, intelligent allocation of tasks is required for good system performance, if only to minimize physical interference.

Considering the different ability and usage of each robot, a cooperative backoff adaption scheme (COBOS) system was proposed for multirobot task allocation amongst team heterogeneous robots in [23]. The COBOS operates in regions with limited communication ranges, and is robust against robot malfunctions and uncertain task specifications, with each task potentially requiring multiple robots. The adaptive feature of COBOS further increase the flexibility of robot teams, allowing robots to adjust their actions based on past experience. The properties of COBOS, such as operation domain, communication requirements, computational complexity, and solution quality and the compare the scheme with other mechanisms are also studied in [23], which results show that the COBOS can be used for the real-time task-allocation usage in our reconnaissance tasks in over large area.

5. Supporting systems

In this section, we will give some brief descriptions of our three subsystems.

5.1 Unmanned Aerial Vehicles (UAVs)

The UAVs used in our system is outfitted with a sensor payload containing inertial measurement unit (IMU), differential global positioning system (DGPS), and a digital compass for localization and navigation; stereo vision cameras for collecting image information. There are typically three PC-104 processors onboard performing: (i) localization, navigation and flight control; (ii) sensor processing; and (iii) dynamic path planning and decision making. Geo-referenced images are gathered using the above sensors that will be used to create a map of the operating region.

5.2 Unmanned Ground Vehicles (UGVs)

We use PackBot 510 from iRobot as the base of our UGV with a six degree-of-freedom arm or manipulation as in Fig. 6. The UGV system consists of several sensors which communicate with the data acquisition CPUs, which transmit the data through the ethernet switch with the computer inside the PackBot. The processing units onboard used on the UGV are PC104, which manage to collect data, calculate and send commands to the corresponding actuators. The UGVs use the above sensors and the map provided by the UAVs to traverse the region, locate and isolate danger region.

5.3 Ground Station (GS)

The base station provides a communication link between the UAVs and UGVs. The GS facility contains a weather station, DGPs base station, and GS terminals for each UAV. Each GS is used to send commands and monitors mission and health status of the UAV. All ground-to-air communications are sent via a radio modem. Each GA receivers and displays the UAV path and vital information such as airspeed, engine revolutions per minute, and battery voltates, as well as other telemetry data. Remote control signals (the UAVs are piloted remotely for takeoff and landing), DGPS corrections, and mission commands are sent from the ground through the same channel. The Linux operating system was used in the ground station, and a number of graphical user interfaces (GUI) have been developed for viewing real time images arriving at the ground station from different vehicles. It also provides the operator with system operation information and statistics.

Fig.6: UGV

5.4. Path Planning and Decision Making

This is the highest level of autonomous control responsible for determining where the UAVs and UGVs should move next as shown in Fig. 7. Actions are determined by maximizing an information-based utility function. Shortest paths are planned online and sent to the guidance module. When the UAV team and UGV team are cooperating, they share utilities with each other such that planned actions are globally optimal. Both purely-sensor-based and map-aided approaches, combined with different strategies, are considered in order to accomplish global convergence to the goal, the primary aim of a path planning task. In [7], a hierarchical framework for incremental path finding and optimized dynamic motion planning in unknown environments. A deliberative path planning approach robustly searches a map containing unknown information for an optimal path, and a local motion planning method produces optimized motions from a one-dimensional velocity space such that the robot can trace sub-goals at a relatively high speed and effectively avoid collision with obstacles when needed [8]. In [9, 10], a new potential field method has been proposed for mobile robot motion planning in a dynamic environment where both the target and obstacles are moving. The new potential functions take into account not only the relative positions of the robot with respect to the target and obstacles, but also the relative velocities of the robot with respect to the target and obstacles. Paths generated dynamically through the path planning module are uploaded to the UAVs and UGVs. The decision making module decides to choose among the paths generated. Fig. 8 is one example of our information recognition and reconstruction result, which facilitates the scene understanding.

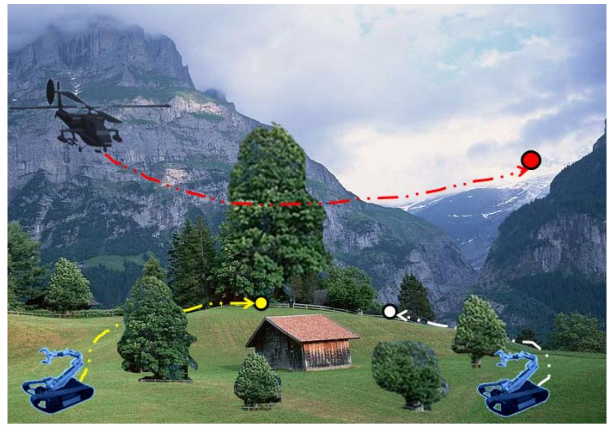

Fig. 7: Path Planning of UAV and UGV

Fig. 8 Information recognition and reconstruction

6. Conclusion

Intelligent information acquisition and scene understanding at large scale requires cooperation between teams of mobile agents of different modalities, linked through a common objective. This paper has presented the research involving UAV/UGV collaboration at a large scale, which extended the sensing capabilities of the UGV system by incorporating the environmental perception abilities of UAVs. By seamlessly fusing the technologies of autonomous systems, communication, pattern recognition, and scene reconstruction together, those problems with higher complexity at a larger scale can be handled more effectively.

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