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Robotic Aerial-Imaging and Ground-Sensing Network for Use in Rapid Emergency Response

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ABSTRACT
For emergency situations occurred to a large-scale structure or unfolded at a geospatial scale, and considering the ensuing demands of rapid damage assessment from first responders, we propose a novel sensing methodology, which is a robotic aerial-imaging and ground-sensing network (RAIGS-Net). The primary goal of realizing this methodology is to realize both multi-view imaging of visible damage and multi-mode sensing of intrinsic condition changes, which reasonably should serve better the first responders to make rational decisions regarding structural integrity assessment. Other technology novelties include the use of micro or small unmanned aerial vehicles (i.e. drones) for conducting and coordinating aerial imaging and ground sensing through robotic sensor deployment and path management. In this paper, we first briefly present the system architecture and realized prototype system. We then focus on the analytic aspects of the proposed system and describe two interwoven research problems that are crucial towards designing and developing the robotic prototype, including opportunistic networking towars energy efficiency and data provenance modeling towards trustful data analysis. In the end, we conclude this paper with summarizing the contribution of the paper and remarks on potential applications.

KEYWORDS: *Wireless Sensor Network, Opportunistic Networking, Aerial Imaging and Ground Sensing Network, Data Provenance*

1. INTRODUTION

Large-scale extreme hazards pose a great risk to the built environment. In recent years, the world has been shocked by numerous disasters and their immensely tragic consequences in terms of human and property losses. When structural and infrastructure losses due to disaster induced damage are considered, two classes of structural damage may be categorized. The first class of damage may be defined as change to the material and/or geometric properties of a structural system, including changes to the boundary conditions, local/global stiffness, and system connectivity, which adversely affect the structural performance of that system when further subject to loading (Farrar and Worden, 2007). Damage in this class usually is usually not directly measurable and even invisible, which demands an appropriate detection or identification methods that further demand a monitoring solution, i.e. a structural health monitoring (SHM) methodology (Sohn, Farrar, Hemez, & Czarnecki, 2002). The second class of structural damage occur at multiple scales usually featuring visible damage patterns, ranging from a scale of structural element (e.g. local cracks) to wide-spread damage or collapse in a city block. Damage in this class may be visually evaluated (through direct measurement) or directly sensed in images, such as cracks, buckling, partial or full collapse (Z. Chen, 2009).

The state-of-the-art sensing and computing technologies in today's SHM solutions include use of different variants of wireless sensing network (WSN), including smart sensors, decentralized sensing, and distributed computing (Gao, Spencer, & Ruiz-Sandoval, 2006; Lynch & Loh, 2006; Nagayama & Spencer Jr, 2007; Y. Wang, Lynch, & Law, 2007). Most WSN technologies focus on sensing of vibrational data due to external dynamic loading; therefore identification of damage or intrinsic system states is often treated as an inverse problem. Popular processing methods include system identification and machine learning (Farrar & Worden, 2012). One limitation may be recognized if vibration-based SHM methodology is used for damage identification is that that identified damage is typically characterized by indirect physical measures. For example, cracks cause reduction of system stiffness – the reduction may be identified using a SHM method; however, this stiffness reduction does not characterize directly the shape of cracks, such as areas and lengths. Therefore, the resulting damage measures are not comprehensible to naked eyes and hence do not provide decision-makers direct and visual reference for grading the damage levels (e.g. in terms of minor damage, moderate or severe damage) as used post-disaster damage assessing standards (e.g. the widely used ATC-20 (ATC, 1989)).

In contrast to SHM methodologies, remote sensing provides a direct means for identification of structural damage of the aforementioned second class, especially those at a large scale. The underlying basis is that images of structures or structural components provide pixels that can be viewed as spatially high-resolution 'sensors', which convey the appearance characteristics of structural integrity in a collaborative manner (i.e. as shown in resulting imagery). The scale of structural damage identified using imaging technologies vary significantly depending on imaging sensors. The damage may have a scale ranging from the visually significant level (e.g. damage of civil structures with a scale for 0.1 mm to a meter) to the geo-spatial scale (e.g. wide-spread urban damage with a geographical extent of more than a kilometre).

The use of remote sensing technologies, including space-/airborne sensors, is not new for mapping damage at a large scale, especially in the context of post-disaster response that demand rapid mapping of damage at a geospatial scale (LaCapra, Melack, Gastil, & Valeriano, 1996; Leone, Wright, & Corves, 1995; Lewis, Robichaud, Elliot, Frazier, & Wu, 2004; Richards & Jia, 2006; Showalter, 2001). Recent research endeavors include employing remotely sensed images captured by orbital satellites or other airborne platforms for rapid damage mapping. One of the major progresses for recent post-disaster responses is the use of very-high-resolution (VHR) satellite images that have a resolution at a sub-meter scale and are usually available days after the disaster. Therefore, remote sensing-based computational change and damage detection methods have been significantly developed in recent years, including the first author's previous work based on bitemporal remote sensing images (Z. Chen & Hutchinson, 2007; Z. Q. Chen & Hutchinson, 2008, 2010) and others' efforts based on oblique aerial images (Gerke & Kerle, 2011; Saito et al., 2010; Spence & Saito, 2011).

On the other hand, a disaster scene is far more complex than what are likely shown conventional remote sensing images. In Figure 1a, the damage scenes arising from the severely damaged community are complex in terms of the terrain complexity if it is captured by any orbital or airborne sensors. Figure 1b illustrates another complex imaging situation, wherein a bridge system was severely impacted by the accumulated debris under the bridge deck. In these two situations, any conventional remote imaging approach is not going to be feasible in order to capture the damage scene rapidly. In our previous work, we have proposed the solution that features *very-low-altitude imaging using small or micro-unmanned airborne vehicle* (UAV or drone) (ZhiQiang Chen). The UAV technology provides a more flexible and cost-effective approach to providing multi-view imagery of objects, potentially enabling 3D scene reconstruction.

(a) (b)

Figure 1. (a) A damage scene from the 2010 Haiti earthquake with complex terrain; (b) a damage scene showing debris impact on a bridge pier; and (c) a partially damaged building.

This UAV-based remote sensing approach has been conducted for several disaster scenes such as hurricanes and earthquakes as a rapid and alternative remote sensing approach (Murphy et al., 2008; Pratt, Murphy, Stover, & Griffin, 2009), including our recent work in assessing building and bridge damage during the aftermath of the 2014's South Napa Valley Earthquake (Figure 2). As shown in Figure 2, UAV-based multi-view imaging and associated 3D reconstruction, which provides a rapid approach to structural damage assessment especially for those hard-access structures (e.g. river-crossing bridge in Figure 2). However, like any imaging only approach, it does not reflect the intrinsic characteristics of the structures. In order to identify intrinsic parameters of a structure, which is of considerable importance for detailed static and dynamic structural integrity evaluation, the traditional SHM technique is to date the most effective approach.

(a) (b)

Figure 2. (a) Part of drone images of the Napa River SR37 Bridge with the area of interest covering the Piers 18, 19, and 20; and (b) reconstructed 3D fly-through of the bridge (see the completed fly-through at https://goo.gl/I1Ffv2).

SHM solutions, however, are mostly deployed for critical structures to date (e.g. the SR 37 bridge in Figure 2); and most civil structures and infrastructure objects are not equipped with SHM in practice. In the meantime, emergency situations (natural or technological disasters) usually allow little or no time to deploy sophisticate sensing network to monitor the abrupt changes that are intrinsic (mostly invisible) to engineering structures. Furthermore, the number of possibly damaged structures in the aftermath of a large-scale disaster is usually significantly large. These emergency situations motivate us proposing a novel damage assessment methodology that integrates UAV-based aerial imaging and ground-based structural health monitoring, termed *robotic aerial-imaging and ground-sensing network* (RAIGS-Net).

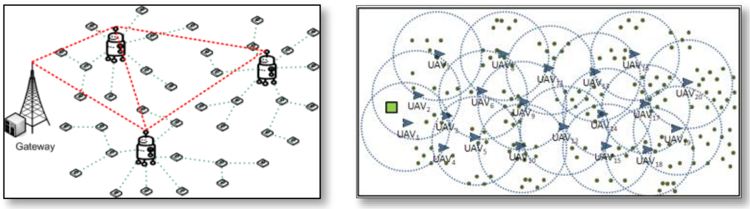
The primary goal of realizing this methodology is to realize both multi-view imaging of visible damage and multi-mode sensing of intrinsic condition changes, which reasonably should serve better first responders to make more rational decisions regarding structural integrity assessment. In the meantime, we describe the proposed system 'robotic' in order to reflect the key innovations, which include robotic sensor deployment and spatial management. In the following sections, we first briefly present the system architecture and realized prototype system. We then focus on the analytic aspects of the proposed system and describe research challenges that are crucial towards designing and developing a RAIGS-Net prototype, including opportunistic networking and data provenance modeling. In the end, we conclude this paper and remarks on potential applications.

2. SYSTEM DESIGN AND REALIZATION

2.1 Related Work

2.1.1. UAV Integration with Wireless Sensor Network

The aforementioned wireless sensor network (WSN) technology used in SHM solutions has relatively matured in recent years for practical applications. In addition, WSN has been applied in numerous agricultural and environmental sensing projects or used at different extreme conditions (i.e. volcano-environment monitoring) (Pompili & Akyildiz, 2009; N. Wang, Zhang, & Wang, 2006; Werner-Allen et al., 2006). To our best knowledge, there were only a few efforts that attempted to integrate UAVs with wireless sensor networks. In (Fodor & Vidács, 2007) (Figure 3a), UAVs are considered as mobile sinks for ground sensor data dissemination. This approach intends to optimize the route from a given sensor node on the ground to a few mobile sinks that move in the area. In (Pignaton de Freitas et al., 2010) (Figure 2b), it presents a different approach that keeps the sensor network continually connected. It uses multiple UAVs to establish a reliable relay network to guarantee the delivery of data produced by the wireless network nodes on the ground to the users. Given these few simulation-based and conceptual efforts, however, there is no physically realized UAV-based sensing network system that has undergone experimental or engineering evaluation. In the meantime, there is no such sensing network system that has been employed for civil structure or infrastructure monitoring.



(a) (b)

Figure 3. (a) Two-tiered wireless sensor network architecture (Fodor & Vidács, 2007). (b) Network of mobile sinks supporting connectivity for the wireless sensing network on the ground (Pignaton de Freitas et al., 2010).

2.1.1. Opportunistic Networking

The use of flying single or multiple UAVs either as a mobile sensor node or a sink triggers the effort of optimizing network communication between sensors and sinks. Opportunistic Network is the emerging technology that solve such optimization problem. In (Sadeghi, Kanodia, Sabharwal, & Knightly, 2002), it proposes protocols to better exploit durations of high-quality channels condition. Based on that, (Biswas & Morris, 2005) proposed routing protocols that increase the throughput of large unicast transfers in multi-hop wireless network. There are also research efforts on optimizing resource and performance in wireless sensor networks, such as (Small & Haas, 2005). It considers a different scenario where the paths from message sources and their destinations do not always exist. Then the authors analyzed protocols that alleviate the problem of chronically disconnected paths by having a node storing the packet, carrying it until meeting another relay node, and forwarding the packet to the other relay node. In a more recent effort, researchers also developed middleware that implemented the opportunistic network into mobile social networks, called CAMEO (Arnaboldi, Conti, & Delmastro, 2011).

2.1.3. Senor Network and Remote Sensing Data Provenance

Data provenance problem arises when complex spatial or temporal dynamics exist in a mobile sensor network or simply in case of complex data sets of various sources (e.g. remote sensing data from multiple sources), in both cases of which inherent uncertainties exist in the sensed data (Balazinska et al., 2007; Ledlie & Holland, 2005; Lim, Moon, & Bertino, 2010; Patni, Sahoo, Henson, & Sheth, 2010). In such sensing systems or sensing data scenarios, it becomes critically important to determine the origins, sensor types, data format, causes and sequences, incomplete data or failed sensors, interruption, and disturbance that are related to data acquisition. Therefore, data provenance is defined as archiving or modelling such 'metadata' information within a senor network such that the sensor data sets are self-describing. For both networked sensor data and remotely sensed images, a few research efforts have employed the Open Provenance Model (OPM) for characterizing the causal relations in data from heterogeneous sensors or the original metadata sets of remote sensing images (Feng, 2013; Liu, Futrelle, Myers, Rodriguez, & Kooper, 2010; Moreau et al., 2011), which result in machine-readable data provenance models readily for the subsequent trustful data processing or mining.

2.2 System Architecture and Prototype

The envisaged RAIGS-Net aims to realize rapid sensing for large-scale single infrastructure objects (e.g. long-span bridges or linear transmission structures) or for buildings at an urban scale, wherein a UAV is a mobile hub for aerial imaging and as a gateway for communicating with ground sensors deployed to single or multiple structures. Figure 4 illustrates the proposed RAIGS-Net architecture including the basic hardware/software units and network topology. In this system design, the UAV acts as the mobile sink and is responsible for receive and sending messages from/to the sensor nodes on the ground.

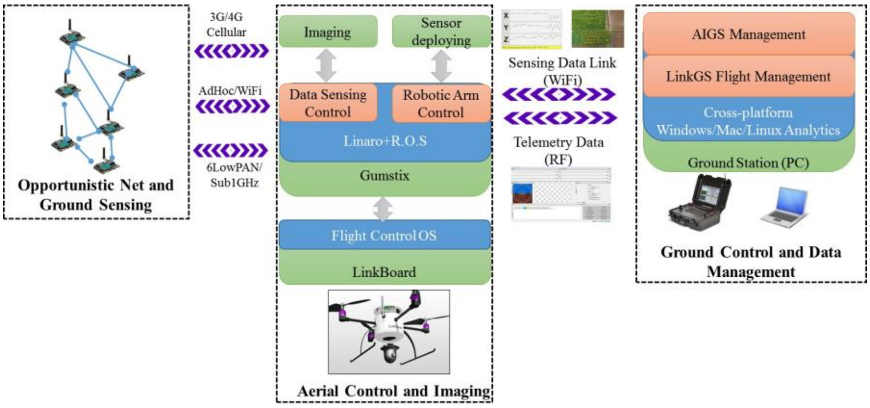


Figure 4. Proposed RAIGS-Net network units, communication, and topology.

3.1 System Prototype

One of the key robotic aspects in a RAIGS-Net is sensor deployment, which is crucial for realizing rapid sensing and assessment. A robotic arm has been designed and manufactured using 3D printing technology that features programmable servo and sensor operation (Figure 5a). For constructing ground sensor subnetwork, WaspMote from Libelium Inc. (http://www.libelium.com/) has been explored in our research, which provides an Internet of Thing solution for connecting any number of sensors using any wireless technology with the 6LoWPan mesh network capability. The WaspMote also comes with support from an opensource management and simulation environment developed by IBM Research, termed IBM Mote Runner, which connects sensor and actuator motes within wireless sensor networks based on the IETF 6LoWPAN protocol specification. This combination of hardware and software development environment is considered an ideal toolkit for the proposed RAIGS-Net development. Figure 5(b) presents a laboratory setup of a prototype system that consists of the UAV (a Linkquad quadcopter), a 6LoWPAN gateway within the drone, four inter-connected IPv6 sensors, and the network data communication and management station in a mobile computer.

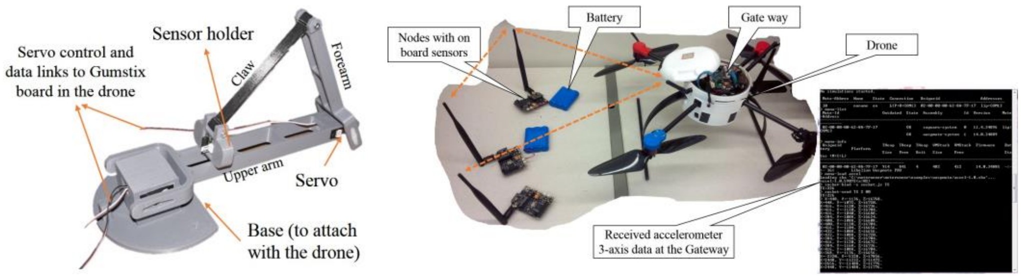


Figure 5. (a) Realized robotic arm with programmable servo-sensor subsystem; and (b) RAIGS-Net configuration in the laboratory and preliminary sensing interface.

4. ANALYTICAL RESEARCH PROBLEMS

Given the network design in Figure 4, besides being the imaging and computing hub, the UAV is designed as a flying robot that deploys sensors at strategic (yet sporadic) locations. The possible loss of sensors, sensor malfunctions, and out-of-range communication render the underlying networking opportunistic or disruptive, which in the meantime affects energy assumption and data quality. In the following, we address another crucial nature of being robotic path planning based on a thought experiment. To achieve this robotic nature, two analytical networking problems are formulated:

1) Opportunistic Networking toward energy efficiency;
2) Sensor Network Data Provenance Modeling towards trustful data analysis.

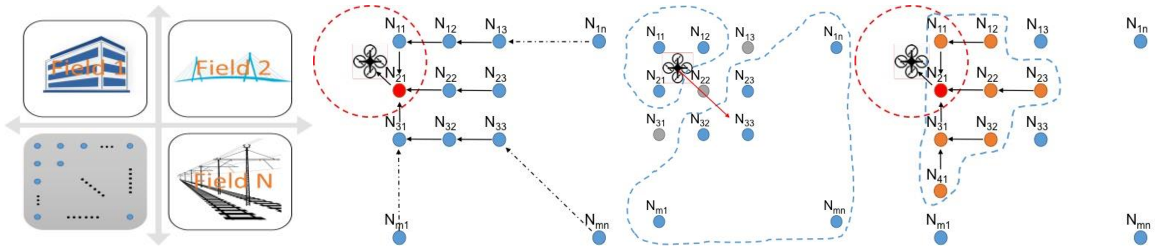


Figure 6. Conceptual field development and opportunistic networking.

In Figure 6a, four subnets are shown, which indicate four physically isolated sensor networks in the fields, except that the UAV can fly to each subnet to execute opportunistic sensing. Figure 6(b) indicates the idealized situation where sensor failure (or other malfunctions) and energy efficiency are not needed to consider. In Figure 6b, assuming each node N_{ij} can communicate with its neighboring nodes $N_{i\pm1,j\pm1}$ through wireless connection, when the UAV fly into this sub-network, some of the nodes are in communication range to the UAV, while some are not. The UAV will pick one of the nodes in the range as a relay node, and collect data from any other node in this subnet.

However, if multiple sensors are likely to fail (with a probability P_f of failure), it may cause the break of the relay chain thus create isolate areas (in this case N_{13}, N_{22}, N_{31}) (Figure 6c). The UAV will know which nodes are reachable (direct and through relay) and define this area as A1. Then the UAV will move automatically to one of the next possible working node (in this case, it could be N_{14}, N_{23}, N_{32}, N_{41}), and trying to get connection of the rest of the nodes, then define the nodes that are reachable (A2), until all the nodes are reached by the UAV. The resulting opportunistic network results in a linear optimization problem with the only constraints coming from the sensor failure.

One major limitation of this opportunistic network is energy efficiency. A simple and empirical solution may be to setup a maximum number of relay chain (in other words, how many times the data will be relayed before it reaches the UAV). For example, if the maximum relay number is 2 and the UAV sets N_{21} as the starting point, only 8 nodes are reachable this time, which (N_{21}, N_{11}, N_{12}, N_{22}, N_{23}, N_{31}, N_{32}, N_{41}) (Figure 6d). If both sensor failure and energy efficiency are integrated into the problem, a dynamic programming problem is incurred. This in turns gives rise to the first research problem, which is to compute an opportunistic and energy-efficient network through real-time optimization.

Due to the nature of opportunistic networking, the immediate challenge hence is data provenance-aware modeling towards trustful data processing and knowledge discovery. The data provenance characterizes the spatial-temporal characteristics of sensors and sensor data, and it becomes crucial if any data processing or fusion methods are to be used. Compared to classical modeling approach to data provenance modeling, the proposed AIGS-Net, however, imposes a new challenge due to two non-traditional constraints to the sensing system: (1) path-planed UAV flight or vision-driven UAV flights; and (2) complex spatial-temporal registration of multi-view imaging with ground sensing data.

3. CONCLUDING REMARKS AND FUTURE RESERACH

In this paper, we propose a novel sensing methodology and network system that features robotic aerial imaging and ground sensing, termed RAIGS-Net. The resulting sensing network emphasizes its nature of being robotic including robotic sensor deployment and path planning for the central and gateway unit of the network, a flying and mobile unmanned aerial vehicle. For the latter, two analytical problems are formulated, which include (1) opportunistic Networking toward energy efficiency and (2) sensor network data provenance modeling towards trustful data analysis. These two research problems are being investigated by the authors and will be reported in future publications.

The primary anticipated application of the proposed system is for civil infrastructure and structural health monitoring in the context of rapid emergency response, which can provide first responders both multi-view imaging of visible damage and multi-mode sensing of intrinsic condition changes. Nonetheless, we recognize that this concept of RAIGS-Net when realized as a networked and mobile sensing system has a great potential in a versatile applications including precision agriculture, environmental monitoring, and condition assessment in hazardous or challenging environments.

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