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Networked UAVs as aerial sensor network for disaster management applications

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Advances in control engineering and material science made it possible to develop small-scale unmanned aerial vehicles (UAVs) equipped with cameras and sensors. These UAVs enable us to obtain a bird's eye view of the environment. Having access to an aerial view over large areas is helpful in disaster situations, where often only incomplete and inconsistent information is available to the rescue team. In such situations, airborne cameras and sensors are valuable sources of information helping us to build an ''overview'' of the environment and to assess the current situation.

This paper reports on our ongoing research on deploying small-scale, battery-powered and wirelessly connected UAVs carrying cameras for disaster management applications. In this ''aerial sensor network'' several UAVs fly in formations and cooperate to achieve a certain mission. The ultimate goal is to have an aerial imaging system in which UAVs build a flight formation, fly over a disaster area such as wood fire or a large traffic accident, and deliver high-quality sensor data such as images or videos. These images and videos are communicated to the ground, fused, analyzed in real-time, and finally delivered to the user.

In this paper we introduce our aerial sensor network and its application in disaster situations. We discuss challenges of such aerial sensor networks and focus on the optimal placement of sensors. We formulate the coverage problem as integer linear program (ILP) and present first evaluation results.

Keywords: aerial sensor networks; embedded computer vision; object tracking; sensor placement

Vernetzte unbemannte Fluggeräte als „fliegende Sensornetzwerke" für Anwendungen in Katastrophenfällen.

Die technologischen Fortschritte der letzten Jahre ermöglichten die Entwicklung von kleinen unbemannten Fluggeräten, welche mit Kameras und anderen Sensoren ausgestattet sind. Diese erlauben die einfache Aufnahme von Bildern aus der Vogelperspektive, die vor allem in Katastrophenfällen sehr hilfreich sind. Den Einsatzkräften stehen in solchen Situationen oft nur unvollständige und inkonsistente Informationen zur Verfügung. Luftbilder helfen dabei, einen raschen Überblick über die Situation zu gewinnen und diese zu beurteilen.

In diesem Artikel beschreiben die Autoren ein aktuelles Forschungsprojekt, das sich mit dem Einsatz von batteriebetriebenen, drahtlos vernetzten Quadrokoptern im Kontext des Katastrophenmanagements beschäftigt. In diesem „fliegenden Sensornetzwerk'' kooperieren mehrere Quadrokopter, um eine vorgegebene Mission zu erfüllen. Das Ziel ist es, ein System zur Analyse von Luftbildern zu entwickeln, in dem mehrere Quadrokopter im Flug eine Formation bilden, das Einsatzgebiet überfliegen und dabei Bilder bzw. Videos aufnehmen. Das Bildmaterial wird im Flug an die Bodenstation übertragen und dort analysiert bzw. für den Benutzer aufbereitet.

Die Autoren diskutieren in diesem Beitrag die Herausforderungen für den Einsatz von fliegenden Sensornetzwerken. Hauptaugenmerk dabei ist die starke Ressourcenbeschränkung (z. B. Energie, Rechenleistung und Gewicht) sowie die autonome Koordination der Quadrokopter. Abschließend werden erste Ergebnisse in der Auswertung von Luftbildern eines einzelnen Quadrokopters sowie der Erkennung und Verfolgung von Objekten in Luftbildern präsentiert.

Schlüsselwörter: luftfahrzeuggebundene Sensornetzwerke; eingebettete Bildverarbeitung; Objektverfolgung; Sensorpositionierung

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1. Introduction

Wireless sensor networks (WSNs) provide an interesting field of research in different domains, ranging from hardware architecture over communication and network architecture, resource awareness to deployment and coordination. The applications of sensor networks are also manifold. In environmental monitoring sensor networks are used to observe various atmospheric parameters or to track the movement of animals. Other applications of WSNs include health care and smart environments.

Sensor nodes of the first generation had only very simple sensing capabilities, providing scalar sensors for parameters such as temperature, humidity, movement, lightning conditions, pressure, and noise level (*Akyildiz et al., 2002*). These sensor nodes basically collect the sensed data over some period of time, transmit the collected (and potentially filtered) data to a base-station or raise an alert in case of certain events. Sensor nodes of the second generation are equipped with more capable sensors such as CMOS cameras and microphones forming wireless multimedia sensor networks (WMSNs) (*Akyildiz, Melodia, Chowdhury, 2007*). Analyzing and aggregating this kind of sensor data requires increased computational power, storage and communication bandwidth (*Rinner et al., 2008*).

In this paper we present a step towards aerial sensor networks. We combine the sensing and communication capabilities of wireless

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sensor networks with small-scale unmanned aerial vehicles (UAVs). While traditional sensor nodes usually sense their environment passively – either deployed statically or attached to some mobile objects – the tight integration of sensing and controlling UAVs allows for actively placing the sensors at locations of great interest. This introduces a whole set of new applications and also raises new research challenges. Related to this is also the research domain of ''sensor/actuator networks'' (*Akyildiz, Kasimoglu, 2004*).

UAVs are valuable sources of information in many application domains such as environmental monitoring, surveillance and law enforcement, and disaster management (*Quaritsch et al., 2008*). Obviously, these application domains have different requirements and constraints regarding available resources, timing, etc. But one important task for which UAVs are used is to provide a bird's eye view and thus allow to assess the current situation. In our project we focus on the application domain of disaster management situations because this is in our opinion the most challenging one due to the stringent timing constraints.

Usually, in disaster situations the first responders cannot rely on a fixed infrastructure and the available information (maps, etc.) may no longer be valid. The overall goal of our *collaborative microdrones* (*cDrones*) project, hence, is to provide the first responders a quick and accurate overview of the affected area, typically spanning hundreds of thousands of square meters, and augment the overview image with additional information such as detected objects or the trajectory of moving objects. Covering such a large area with a single image from a UAV flying at low altitude (up to 100 m) is not possible. Moreover, a set of images is taken and stitched together for a large overview image. Due to the limitations of a single UAV and stringent time constraints we use multiple UAVs which form an airborne wireless sensor network. The UAVs coordinate themselves during flight requiring as little control by a human operator as possible.

In this paper we focus on the first step in generating an overview image, namely where to place the sensors in order to cover the whole area at a given resolution while minimizing the resource consumption, i.e., energy, flight time and communication bandwidth.

The remainder of this paper is organized as follows: Section 2 gives a short overview on related work. Section 3 elaborates challenges and research questions of aerial sensor networks. Section 4 presents a high-level system overview, shortly introduces our project, and sketches the intended use-case. Section 5 describes our approach for sensor placement in order to optimize coverage. Section 6 presents experimental results and finally Section 7 concludes the paper.

2. Related work

2.1 UAVs in disaster management situations

UAVs have already been deployed after several disasters in the recent past such as Hurricane Katrina and Hurricane Wilma, or the earthquake in L'Aquilla, Italy. After Hurricane Katrina UAVs equipped with three different sensors (pan-tilt thermal and visual sensor, and a fixed visual sensor for pilot view) were controlled by three operators (a pilot, a flight director, and a mission specialist) to inspect collapsed buildings (*Pratt et al., 2009*). Images from a micro aerial vehicle and an unmanned sea surface vehicle were used for inspection of bridges and seawalls for structural damages after Hurricane Wilma (*Murphy et al., 2008*).

After the earthquake in L'Aquilla, UAVs equipped with cameras were used for building inspection and situation assessment. (*Nardi, 2009*) concludes that micro-UAVs are potentially useful and provide a new source of information to first responders. However, he identifies a number of open research questions in order to make this technology applicable in disaster management situations.

(*Murphy, Pratt, Burke, 2008*) address the difficulties and risks of manual operation of wireless airborne sensor networks in unknown urban environments, besides describing the roles in a rescue team in detail. Approaches to decrease the number of roles required for operating multiple UAVs are introduced and options for equipping the UAVs with the ability to accomplish certain tasks autonomously are discussed.

2.2 Sensor placement

Sensor placement is an important and active research area in WSNs, considering the limited sensing and communication range while taking into account the very limited resources, most prominently energy (*Younis, Akkaya, 2008*). Basically, two different strategies for sensor placement can be distinguished: (1) deterministic placement, and (2) random placement, depending on the type of sensor, application and environment.

In deterministic sensor placement, the position of each sensor is carefully planned in order to meet certain performance and optimization goals. This is typically done if the position of the sensor significantly affects its operation, e.g., sensor nodes with a camera attached.

On the other hand, sensor nodes are often placed randomly in areas with no or only little control. This is particularly true for harsh and unknown environments where nodes are simply dropped from an aircraft. The density of sensor nodes in an area ensures a connected sensor network and can be used to estimate the coverage. Different distribution functions, e.g., simple diffusion or uniform distribution, are used to model such sensor networks (e.g., *Ishizuka, Aida, 2004*).

Typical optimization objectives for WSNs are area coverage, network connectivity and longevity as well as data fidelity. Each sensor has a limited sensing range. In order to completely cover a certain area the sensors have to be placed accordingly. As discussed in (*Younis, Akkaya, 2008*) and (*Poduri et al., 2006*), optimal sensor placement raises several research challenges, even in the case of deterministic placement. Complexity is introduced by the request to employ a minimal number of nodes and the uncertainty in sensing capabilities.

The communication range is usually much larger than the sensing range. However, in order to ensure a connected sensor network even in case of node failure different approaches are proposed (*Bredin et al., 2005*). Due to the limited communication range, multi-hop communication is exploited to relay sensed data from the sensor node to a base-station. Hence, nodes close to a base-station have a higher communication load and thus consume more energy.

3. Challenges of aerial sensor network

The system we describe in this paper is somewhat different to traditional WSNs and MWSNs. However, the fundamental idea is the same: deploy sensors with different sensing capabilities in an unknown environment and provide ''useful'' information. Hence, most of the challenges in wireless sensor networks apply for our project as well while facing additional challenges introduced by the aerial sensing platform.

3.1 Resource awareness

Resource awareness is probably the most important aspect in WSNs. Computing power, communication bandwidth, and memory consumption, among others, are very limited. Nodes are usually battery powered and should operate as long as possible. While sensing, simple data analysis, and storing the data is typically power-efficient, more complex data analysis (e.g., image analysis in MWSNs) and wireless communication consume significantly more power. Thus, research focuses on efficient use of energy and finding trade-offs between storing data locally, processing data and communicating data.

In aerial sensor networks the emphasis is shifted a bit and additional degrees of freedom in spending resources arise. Power consumption is dominated by the UAV's propulsion. The engines of our small-scale UAV, for example, consume more than 120 W (four engines each with 35 W on average). Sensing, processing, and communication, in contrast, consumes less than 10 W on our platform and thus can be almost neglected.

The largest potential for increasing operation time, thus, is to plan the flight routes of the UAVs in an energy-efficient way. Ascending, for example, consumes much more power than flying at constant altitude. Environmental conditions, most importantly wind, have to be considered as well. Obviously, this requires a highly accurate energy model of the UAV as well as information on the environmental conditions. Estimates on the wind speed and direction can be obtained from the UAVs inertial sensors and engine feedback during flight.

3.2 Sensor mobility and sensor placement

Due to the small size and limited payload, a single UAV will only carry a single image sensor. However, different sensors may be used on different UAVs, e.g., one UAV is equipped with a high-resolution color camera while another UAV carries a low-resolution infrared camera. Mobility of sensors allows to take images of the same scene with both sensors. Either both UAVs fly individually and visit the same point at different times and take images, or the UAVs cooperate and fly in a formation over the area (e.g., one UAV next to the other).

In our project, the basic goal is to provide overview images of certain regions with certain resolution. The regions to cover are typically in the order of hundreds of thousands of square meters. So multiple images have to be taken to cover the whole area. Hence, the system has to compute the optimal positions for taking pictures. Optimization criteria are minimizing the number of pictures and energy consumption while maximizing the coverage.

3.3 Communication

Aerial sensor networks have different requirements on the communication links than conventional WSNs.

First of all, UAVs have to exchange flight data on a regular basis in order to coordinate themselves. This flight data includes the current position, speed, direction, etc. For individual UAVs this data can be exchanged every few seconds. But if two or more UAVs fly in a formation, the UAVs need to know each other's position more accurately. Thus, the position update interval is in the range of several milliseconds. Hence, communication links with low latency and a communication range of several hundred meters are required.

Second, the UAVs send their sensor data, i.e., images, to the base station during flight. The sensor data are significantly larger than the flight data and thus require considerably more bandwidth. However, low latency is not of primary concern in this case.

3.4 Sensor coordination and self-organization

The high mobility of the aerial sensors requires different approaches of sensor coordination in terms of flight routes, sensing points, UAV formations, data analysis and data fusion. The spectrum ranges from completely pre-planned mission execution over pre-planning with plan adaptation to completely de-centralized and self-organized execution.

Depending on the given application domain, e.g., environmental monitoring or disaster management, one or the other approach may be preferred. In static environments pre-planned missions may be applicable, but if the environment changes over time adaptive approaches are necessary. Another issue is whether sensor coordination is controlled centrally from the base station or the UAVs have enough autonomy to coordinate themselves and adapt the mission accordingly. The second approach is, of course, more challenging but may lead to a more robust and scalable system.

4. System overview

In the cDrones project we focus on the deployment of multiple small-scale UAVs for disaster management. In particular we use commercially available quadrocopters, also called microdrones, since these are agile, easy to fly, and very stable in the air. Each UAV is equipped with several sensors such as gyroscopes, accelerometers, a barometer, and a GPS receiver. The development of a system comprising multiple cooperating UAVs imposes substantial technological and scientific challenges. In this section we give an overview of the intended use-case.

4.1 Use-case

In case of a disaster such as an earthquake or flooding it is important to have an accurate and up-to-date overview of the situation. For first responders some areas are of great interest while others are of minor interest (*Murphy et al., 2008*). Hence, the operator specifies the scenario by the observation areas as well as forbidden areas where the UAVs are not allowed to fly[1] on a digital map (e.g., Google Maps, cf. Fig. 1). Each observation area has certain quality parameters assigned (e.g., spatial and temporal resolution).

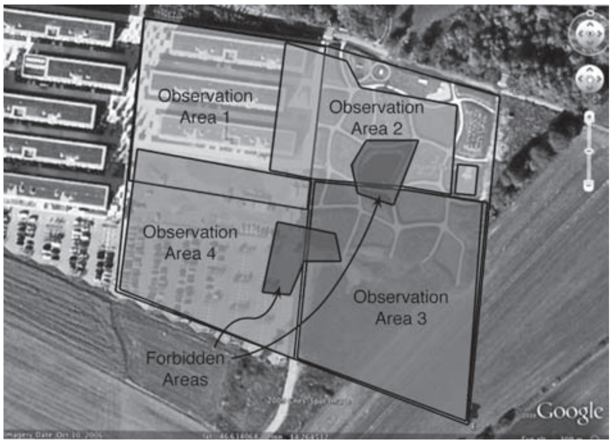

Fig. 1. Example of a scenario definition given by the user

During mission execution the overview image is presented to the user and incrementally refined and updated as the mission advances. Interesting objects such as persons or cars within the observation areas are highlighted. Hence, the user can adapt the observation areas according to the current situation.

4.2 Autonomous UAV operation

The goal of our project is that the whole system operates as autonomous as possible. Given the user's scenario definition the three main steps performed by the system for generating an overview

[1] This is necessary because our UAVs currently do not have the capabilities to detect obstacles or dangerous regions during flight.

image are: (1) planning the mission, (2) executing the mission, and (3) analyzing the image data.

The user's scenario definition serves as the input for the planner. Together with the available resources, i.e., UAVs and sensors, and its capabilities, the first step is to compute the positions where to take pictures in order to cover the whole area while providing the required image quality. The picture points are optimized to minimize the number of pictures and at the same time cover the forbidden areas as good as possible without entering them.

The next step is to compute routes for the UAVs so that each picture point is visited while minimizing the energy consumption of each UAV and distributing the workload equally. The plan is then sent to the UAVs which fly individually or in formations sensing the environment. Mission execution can be done either in real-world or in a simulation environment. Simulation is used to study algorithms for coordination of UAVs, UAVs flying in formations, and the impact of wireless communication (i.e., delays, communication errors, connection losses, bandwidth limitations, etc.) before testing them in real.

During flight the UAVs take images at the planned picture points. The images are pre-processed on-board the UAV and then sent to the ground station. Pre-processing includes annotating the images with meta-information such as time-stamp, position and attitude of the UAV or aligning consecutive images to one larger image. On the ground station image data from different UAVs is fused, giving a detailed map of the area which is then presented to the user.

4.3 UAV platform

The UAV platform we currently use is a MD4-200 produced by Microdrones GmbH, Germany. The drone's diameter is approximately 1 m and it weights less than 1 kg, including the camera. The maximum payload is 200 g and the flight time of the drone is up to 20 min which limits the operation radius to approx. 500 m. With the included auto-pilot it is possible to pre-plan the flight route on the PC by specifying the GPS waypoint coordinates and load the waypoints onto the drone. In addtion to the auto-pilot we equipped the drone with a BeagleBoard[2], comprising a TI OMAP processor with 128 MB RAM and 256 MB flash memory, running embedded Linux. Communication to the ground station for sending the acquired pictures and the telemetry data is achieved via standard 802.11 g WLAN. The drone is equipped with a Pentax A40 compact camera which has a 12 M Pixel sensor.

Our software framework, however, is not limited to work only with the above described drone but is able to employ drones from other vendors as well, even in a heterogeneous setting.

5. Sensor placement for optimal coverage

In this section we present our approach for generating high-quality overview images. The optimization criteria we consider are (1) the quality of the resulting image, and (2) the resource consumption. By quality of the overview image we primarily focus on the coverage of the resulting overview image. The resources we consider are energy (and thus flight time) and communication bandwidth. Both are directly influenced by the number of pictures required to adequately cover an area.

Basically, the problem of generating an overview image of a defined area is similar to covering the area with a sensor network. However, the given application domain and the use of airborne sensors introduce additional constraints. As presented in Sect. 4, a scenario contains one or more observation areas, which should be covered by an overview image, and optional forbidden areas within the observation areas. Although the UAVs are not allowed to fly over a forbidden area, the parts intersecting the observation areas should be covered as much as possible. In addition, adjacent images must have some overlap. The overlap is necessary to stitch the individual images to a single overview image.

The observation areas and forbidden areas are drawn by the user on a digital map in world coordinates (latitude, longitude, or ECEF). In a first step we transform all world coordinates into relative coordinates with an arbitrarily chosen origin (inside the observation areas) and the *x*- and *y*-axis pointing east and north, respectively. The whole computation of optimal sensor placement and optimizing the route is done in relative coordinates. Approximating the range of application as plane is sufficiently accurate in our case.

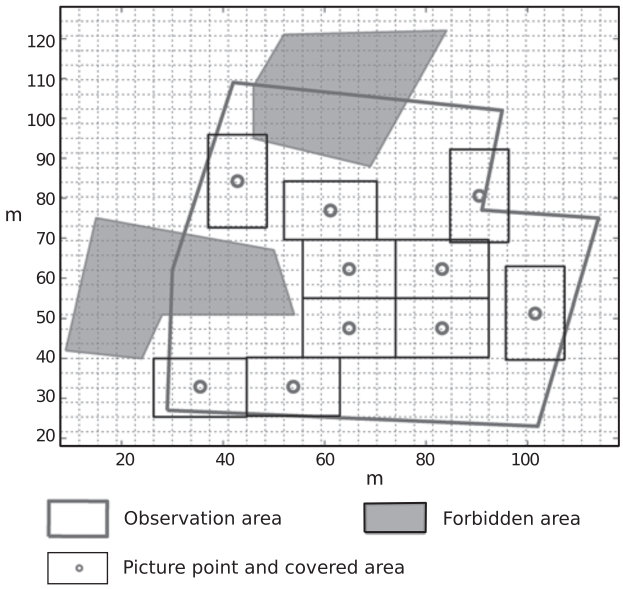

Fig. 2. Observation area (outer polygon) and forbidden areas (shaded polygons) partitioned into rectangular cells together with some picture-points and the covered area

For optimizing the sensing points in order to cover an observation area we formulate it as ILP (integer linear programming) problem. The observation area is partitioned into rectangular cells of sufficiently small areas (e.g., 2×2 m, 4×4 m, etc., cf. Fig. 2). The matrix $\boldsymbol{G}$ represents the area which has to be covered by an image, i.e., $g_{i,j} = 1$ if the cell is inside the observation area and 0 otherwise. Similarly, the matrix $\boldsymbol{X}$ represents the cells at which a picture has to be taken (the actual point is at the center of a cell). Taking a picture in cell $x_{i,j}$ also covers adjacent cells, depending on the camera's orientation, focal length, and the UAV's altitude. Hence, the matrix $\boldsymbol{A}$ represents the cells that are covered when taking a picture in cell $x_{i,j}$ (we assume that the camera has a vertical view and thus the covered area is rectangular). Finally, the matrix $\boldsymbol{C}$ is used to define the costs of taking a picture in a certain cell.

Using this model, we formulate the ILP as follows:

$$\begin{aligned} &\min c^T x \\ &s.t.\ \boldsymbol{A}x \geq g \\ &\quad x_{ij} \in \{0, 1\} \end{aligned}$$

with the vectorized data $c = \text{vec}(\boldsymbol{C})$, $g = \text{vec}(\boldsymbol{G})$, and $x = \text{vec}(\boldsymbol{X})$.

The requirement that two adjacent pictures need to have a certain overlap is modeled by using an accordingly smaller image size for the computation. Ideally, the optimization algorithm computes the picture points such that the areas covered by two adjacent picture

[2] http://beagleboard.org/.

points do not overlap but exactly fit next to each other. Since the real picture is larger than the image size used for the computation, the pictures will have the required overlap.

An optimal solution can be found, for example, by using CPLEX (*CPLEX User Manual, 2010*), GLPK (*GNU Linear Programming Kit, 2010*) or another ILP solver. The result is a set of points where to take a picture together with the size and orientation of the pictures. In order to reduce complexity it is possible to economize variables and constraints. Constraints which are always satisfied can be eliminated or variables which have no influence on the solution because they are too far away from the observation area can be ignored.

6. Experimental results

In this section we compare the method to optimize the coverage of an observation area (cf. Sect. 5) with a naive approach as described in the next paragraph. Our main evaluation criterion is the coverage of (1) the observation area, and (2) the forbidden areas. Other evaluation criteria are the number of pictures required to cover the observation area, the length of the route to visit all picture points and take the pictures (which directly corresponds to the energy consumption), and the time it takes to compute a solution.

A naive approach to cover the observation area is to partition the whole area into smaller rectangles. The size of these rectangles is exactly the size of the area covered by a single image. Similar to the optimized approach, we reduce the image size by a certain amount so that adjacent images overlap. The centers of all these rectangles give the points at which a picture has to be taken. Since the UAVs are not allowed to fly over forbidden areas, we remove all those points that lie inside a forbidden area.

Hence, this approach supports only one (fixed) image size and image orientation. Moreover, the partitioning is rather coarse. So if the center of a partition lies inside the forbidden area the whole partition is left uncovered.

6.1 Evaluation scenario

For the evaluation of our proposed method for sensor placement and comparison with the naive approach we defined a single observation area and three forbidden areas that intersect the observation area, as depicted in Fig. 3. The shaded polygons illustrate the forbidden areas which the UAVs are not allowed to fly over. The dashed lines around the forbidden areas show the safety-margins we add around each forbidden area to ensure that the UAVs do not collide with obstacles in the forbidden areas, even under position uncertainties due to inaccurate GPS information. The whole observation area spans approximately 16,500 m^2 and the forbidden areas together span about 3800 m^2.

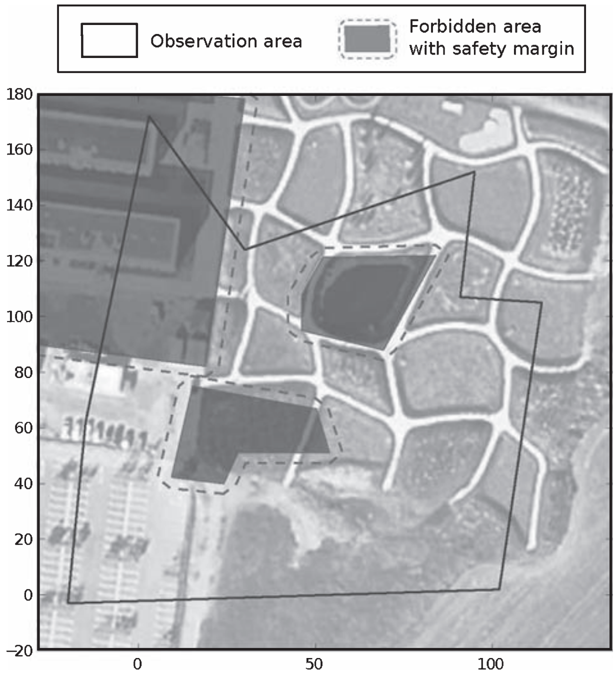

Fig. 3. Scenario definition with one observation area and two forbidden areas

6.2 Evaluation

Foremost, we are interested to cover the observation area as good as possible. Figure 4a and b show the scenario definition together with the points where to take pictures and the area covered by a picture (dashed rectangles) for the naive approach and the optimized solution, respectively. The (reduced) size of an image is set to 29×22 m. This corresponds to a UAV flying at 40 m and a camera with a 35 mm equivalent focal length of 37 mm.

For the optimized approach we partitioned the observation area in 4×4 m squares and allowed two different image orientations, namely ''landscape'' and ''portrait''. The naive approach, in contrast, supports only one image orientation.

Figure 4 also shows the route for a single UAV to visit all picture points and take a picture. Computation of the optimal route is

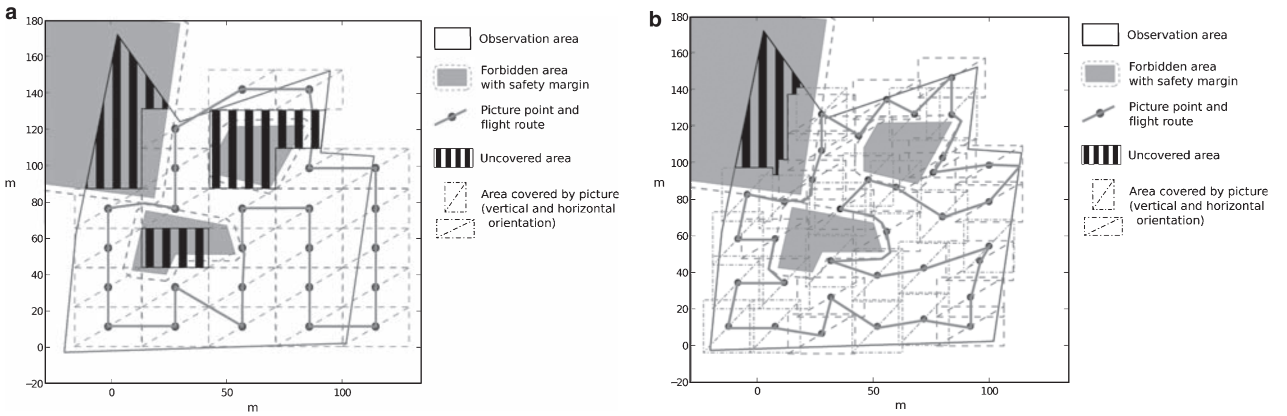

Fig. 4. Comparison of the coverage when using a naive approach and the optimized solution. (a) Area covered using the naive approach, (b) area covered using ILP optimization

Table 1. Quantitative comparison of the naive approach and the optimized solution

	Naive approach	Optimized solution
Number of pictures	25	38
Uncovered forbidden area	2118 m^2	875 m^2
Route length	550 m	820 m
Picture point computation	1 ms	6.47 s
Route optimization	3.12 s	2.95 s
Total computation time	3.12 s	9.42 s

known to be NP-complete. Hence, we use a genetic algorithm to compute a near-optimal route.

As summarized in Table 1 the coverage optimized placement requires 38 pictures to cover the whole area and it takes about 6.5 s to compute the picture points. Computing a route to visit all picture points requires about 3 s. The naive approach, on the other hand, only needs 25 pictures to cover the area. The computation of a solution is much faster than for the optimized approach. But when taking into account the time required to execute the mission in real, i.e., fly the route and take pictures, which is in the order of several minutes, the additional computational effort can be neglected.

However, while the optimized approach covers the observation area completely, the naive approach is not able to fully cover the observation area (cf. Fig. 4a, approx. 5% of the observation area are not covered). Comparing the coverage of the forbidden areas, the optimized approach outperforms the naive approach. The latter one does not cover more than 2000 m^2 (i.e., a coverage of less than 45%) of the forbidden areas while the optimized approach is not able to cover about 800 m^2 (i.e., a coverage of approx. 80%). Obviously, the route is somewhat longer in the optimized approach because more pictures have to be taken.

Summing up, the naive approach computes a fast solution but the resulting coverage is not satisfying since parts of the observation area are uncovered and the forbidden areas are hardly covered. The optimized approach, on the other hand, requires more computation time for computing a solution which achieves optimal coverage. However, there is room for further improvements. Some pictures, for example, only slightly increase the coverage (especially of forbidden areas) but consume valuable energy resources. One approach could be to add additional cost-functions to trade increased coverage for shorter flight time.

6.3 Image analysis

We used a single UAV to fly according to the computed route and take pictures for later investigation. Figure 5 shows an overview image which is the result of stitching a subset of pictures together. Note that the area in the upper part is not covered which is the consequence of inaccurate positioning (i.e., GPS deviation, inaccurate barometric altitude), wind gusts, and inaccurate on-board controller. Since we have little influence on the positioning of the UAV (it is a closed system), we have to consider much larger overlap between adjacent images.

Aerial images pose several challenges that need to be addressed effectively. Firstly, any aerial platform used for imaging has its own motion due to self-induced mechanical vibrations and external conditions like wind flow. Hence, the camera position and orientation may change significantly. The COCOA framework (*Ali, Shah, 2006*) addresses, among others, the issue of ego motion compensation in images and videos taken from UAVs. Hence, we use COCOA as foundation for image stitching. In cases where the view is purely orthogonal, the relationship between one image frame to the subsequent frame is affine and the transformation parameters (2×3 matrix) are computed using direct registration technique proposed by Bergen et al. in (*Bergen et al., 1992*). However, when the view changes from orthogonal to oblique, a more refined projective estimation (Homography) is applied. This is a two step process in which initially features on a source image frame are computed using any of the algorithms suggested in (*Shi, Tomasi, 1994; Bay, Tuytelaars, Van Gool, 2006*), or (*Lowe, 1999*). The image coordinates of the feature descriptors, so computed are then input to a fast optical flow computation algorithm, in order to find corresponding coordinates in the subsequent frame. An iterative procedure is then applied on these pairs of points to compute the Homography parameters (3×3 matrix). The transformation parameters (affine or Homography) are required to finally generate an overview image as shown in Fig. 5.

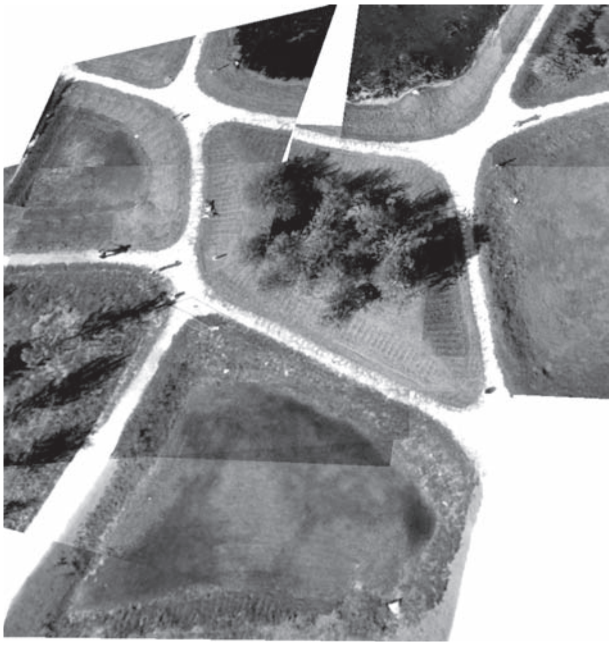

Fig. 5. Generated overview image

7. Conclusion

In this paper we have introduced our system comprising multiple UAVs for the application in disaster management. The UAVs are equipped with different sensors and thus can provide information important for first responders. Through wireless communication channels the UAVs can exchange status information and transmit the pre-processed sensor data to the ground station. Thus, such an aerial sensor network is very similar to traditional WSNs but introduces new challenges such as more stringent resource limitations, most prominently energy, active placement of sensor nodes, and coordination and collaboration of the highly mobile sensor nodes.

We have presented the high-level system architecture and sketched the intended use-case. Moreover, we have elaborated on the challenges of aerial sensor networks in the context of wireless sensor networks. The main focus was on how to place the sensing points in order to cover an observation area with forbidden areas as good as possible. We described our approach and also presented experimental results.

Future work includes to enhance the optimization algorithm such that we can trade coverage for sense-points. Some pictures, for example, only slightly increase the coverage but consume valuable energy resources. Another topic for future research addresses the exploitation of meta data of the individual images, such as GPS position and UAV orientation, for the generation of the overall image.

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