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Information Driven Coordinated Air-Ground Proactive Sensing

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***Abstract*—**
This paper concerns the problem of actively searching for and localizing ground features by a coordinated team of air and ground robotic sensor platforms. The approach taken builds on well known Decentralized Data Fusion (DDF) methodology. In particular, it brings together established representations developed for identification and linearized estimation problems to jointly address feature detection and localization. This provides transparent and scalable integration of sensor information from air and ground platforms. As in previous studies, an Information-theoretic utility measure and local control strategy drive the robots to uncertainty reducing team configurations. Complementary characteristics in terms of coverage and accuracy are revealed through analysis of the observation uncertainty for air and ground on-board cameras. Implementation results for a detection and localization example indicate the ability of this approach to scalably and efficiently realize such collaborative potential.

I. INTRODUCTION

The use of robots in surveillance and exploration is gaining prominence. Typical applications include air and ground based mapping of predetermined areas for tasks such as surveillance, target detection, tracking, and search and rescue operations. The use of multiple collaborative robots is ideally suited for such tasks. A major thrust within this area is the optimal control and use of robotic resources so as to reliably achieve the goal at hand. This paper addresses this very problem of coordinated deployment of robotic sensor platforms.

Consider the task of reliably detecting and localizing an unknown number of features within a prescribed search area. In this setting, it is highly desired to fuse information from all available sources. It is also beneficial to proactively focus the attention of resources minimizing the uncertainty in detection and localization. Deploying teams of robots working towards this common objective offers several advantages. Large environments preclude the option for complete sensor coverage. Attempting to increase coverage leads to trade-offs between resolution or accuracy and computational constraints in terms of required storage and processing. A scalable and flexible solution is therefore desirable.

Efforts are directed toward commonly available and relatively low cost sensors and robotic vehicles. The primary sensor considered are consumer grade digital cameras. These may be fixed or carried on-board a sensor platform. Available sensor platforms include fixed wing unmanned air vehicles (UAVs) and unmanned ground vehicles (UGVs) derived from commercial model kits.

Intuition suggests aerial and ground vehicles exhibit complementary capabilities and characteristics as robotic sensor platforms. Fixed wing aircraft offer broad field of view and rapid coverage of search areas. However, minimum limits on operating airspeed and altitude, combined with attitude uncertainty, place a lower limit on their ability to resolve and localize ground features. Ground vehicles on the other hand offer high resolution sensing over relatively short ranges with the disadvantage of obscured views and slow coverage. This proposition will be tested through analysis of measurement uncertainty for the basic vision sensor and the combined characteristics once installed on air and ground platforms.

Simply bringing together a group of sensing resources does not necessarily ensure their potential is obtained. Careful decisions are required to establish system estimation and control architectures that achieve desired performance and scalability. This paper presents a decentralized architecture and solution methodology for seamlessly and transparently realizing the collaborative potential of air and ground robot teams.

This work builds on previous endeavors in decentralized data fusion (DDF) [2]. DDF provides a decentralized estimation framework equivalent to the linearized Kalman filter. Decentralized active sensor networks [1] extend this to include a control layer that refines the quality of the estimates obtained. The established architecture and methodology is used here. In particular, to jointly address the exploration and localization problems. The approach brings together decentralized methodologies for Gaussian state estimation as applied previously to aerial tracking of ground features [3], and spatial identification as applied to obstacle detection [4]. The fine details of the DDF architecture are not repeated here. A brief review of the detection, estimation, utility measures, control strategies and network node structure is presented in Section II.

Approaches to active sensing that implement alternative system architectures and techniques for estimation and control include [5], [6], [7]. The use of aerial and ground based sensor platforms is closely related to other efforts to exploit the truly complementary capabilities of air and ground robots. Examples of such initiatives include the DARPA PerceptOR program [8] and Fly Spy project [9]. The combined use of air and ground active sensing offers high resolution awareness from relatively low cost visual sensors. The approach presented enables this collaborative potential to be realized through seamless integration and refinement of information gathered by heterogeneous robot sensor systems.

This paper is organized as follows. Section II details the technical approach taken and the system architecture. Section III derives measurement uncertainty for features observed by vision sensors with uncertain state. The characteristics of the UAV and UGV platforms and comparative qualities of feature observations from on-board cameras are explored in Section IV. These elements are combined in Section V and applied to an illustrative example of collaborative ground feature detection and localization. Concluding remarks follow.

II. Information Driven Active Sensing

This section outlines architectural choices regarding modelling, utility and control that lead to an information driven framework for execution of multi-robot sensing missions. This constitutes a brief summary of the established *Active Sensor Network* (ASN) architecture [10]. Formulations of detection and estimation problems that lead to straight forward decentralized implementation are presented. The value of a sensing action is marked by its associated reduction in uncertainty. Mutual information [11] captures formally the utility of sensing actions in these terms. Dependence on the robot and sensor state and actions motivates consideration as an optimal control problem.

A general decentralized approach [2] to information fusion is developed from Bayes theorem in log-likelihood form.

$$l(x \mid z) = l(x) + l(z \mid x) - l(z) \tag{1}$$

Following this approach, detection and estimation problems are formulated in terms of summation and propagation of formal information measures. The feature detection and feature location estimation processes are now presented along with descriptions of the action utility, control strategy and architecture network node structure.

A. Feature Detection

Certainty Grids [4] provide a simple representation of spatially distributed random variables. The certainty grid is a discrete-state binary random field in which each element encodes the probability of the corresponding grid cell being in a particular state. For the feature detection problem, each cell C can take two values *detected* and *undetected*, written as $s(C_i) = \{Detected|Undetected\}$. The information measure $\hat{\mathbf{y}}_{d,i}(k \mid k)$ where subscript d denotes detection, stores the accumulated detection certainty for cell i at time k

$$\hat{\mathbf{y}}_{d,i}(k \mid k) = \log P(x) = \log P(s(C_i) = Detected). \tag{2}$$

Information associated with the likelihood of sensor measurements z

$$\mathbf{i}_{d,s}(k) = \log P(z(k) \mid x) \tag{3}$$

are calculated and fused to update the current detection estimate. The update rule is simply

$$\hat{\mathbf{y}}_{d,i}(k \mid k) = \hat{\mathbf{y}}_{d,i}(k \mid k-1) + \sum_s \mathbf{i}_{d,s}(k) + C \tag{4}$$

where C is a normalization constant.

B. Feature Location Estimation

Feature localization is posed as a linearized Gaussian estimation problem. As in [1], the information form of the Kalman filter is used. This filter maintains an information state vector $\hat{\mathbf{y}}_{f,i}(k \mid k)$ and matrix $\mathbf{Y}_{f,i}(k \mid k)$ distinguished by subscript f for each feature i, that relate to the feature estimate mean and covariance by

$$\hat{\mathbf{y}}_{f,i}(k \mid k) \triangleq \mathbf{P}^{-1}_{f,i}(k \mid k)\hat{\mathbf{x}}(k \mid k) \tag{5}$$

$$\mathbf{Y}_{f,i}(k \mid k) \triangleq \mathbf{P}^{-1}_{f,i}(k \mid k). \tag{6}$$

Each sensor measurement z contributes an information vector and matrix that captures the mean and covariance of the observation likelihood $P(z_s(k) \mid x) \sim \mathcal{N}(\mu_s, \Sigma_s)$

$$\mathbf{i}_{f,s}(k) \triangleq \mathbf{\Sigma}_s^{-1}(k)\mu_s(k), \quad \mathbf{I}_{f,s}(k) \triangleq \mathbf{\Sigma}_s^{-1}(k). \tag{7}$$

Fusion with accumulated prior information is simply

$$\hat{\mathbf{y}}_{f,i}(k \mid k) = \hat{\mathbf{y}}_{f,i}(k \mid k-1) + \sum_s \mathbf{i}_{f,s}(k)$$

$$\mathbf{Y}_{f,i}(k \mid k) = \mathbf{Y}_{f,i}(k \mid k-1) + \sum_s \mathbf{I}_{f,s}(k), \tag{8}$$

from which the state estimate can be recovered. Observation information equations for the camera sensor considered are developed in Section III.

C. Utility

Equations 3 through 8 detail how sensing processes influence estimate uncertainty. Entropy [11] provides a natural quantitative measure of information in terms of the compactness of the underlying probability distributions. Mutual information measures the information gain to be expected from a sensor *before* making an observation. Most importantly, this allows *a priori* prediction of the expected information outcome associated with a sequence of sensing actions.

Mutual information captures the utility of sensing actions given prior information and system configuration. Strong prior information reduces the value of taking measurements. The dependence of observation uncertainty on sensor and vehicle state and action will be explored in Section IV.

D. Control

The desire to reduce estimate uncertainty and its dependence on system state and action leads to an optimal control problem. Accumulation of information and the geometric variation of observation uncertainty leads to time-varying utility of the system configuration. The control strategy pursued is to allow the system to be driven by this field. Local controllers are implemented on each robotic sensor platform that direct the vehicle and sensors according to the mutual information gradient with respect to the system state. This is referred to as *information surfing* since the vehicles are driven by information gain contours.

E. Network Node

Estimation, utility and control elements are now brought together to develop a decentralized architecture for information driven active sensing. Straight forward Decentralization is made possible by the additive structure of the estimate update Equations 4 and 8. This characteristic allows all nodes in a network to be updated through propagation of inter-nodal information differences. A communications manager known as a *channel filter* implements this process at each inter-nodal connection. The resulting nodal architecture is depicted in Figure 1. A detailed description is presented in [10].

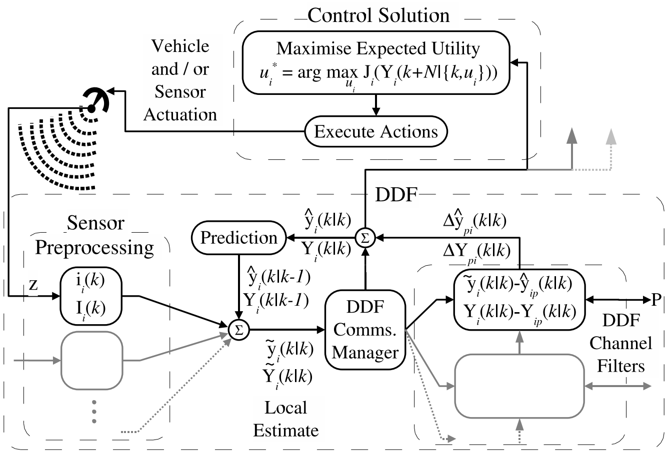

Fig. 1. Coordinated sensing node structure showing distinct sensor preprocessing, fusion, communication management and control functional elements.

III. Observation Uncertainty Analysis

In this section we derive the uncertainty in the location of a ground target observed by a perspective camera. The camera is assumed to be rigidly attached to some platform and is also assumed to be calibrated. By calibrated we mean that the intrinsic parameters such as focal length, aspect ratio, skew are known. We also assume that the relative orientation of the camera to the platform is known and remains constant. The relative orientation and pose of the platform to the ground can however change over time, but can be *measured* using sensors such as the *IMU* and *GPS*. The uncertainties we derive for target localization are parameterized in terms of orientation and position parameters of the platform and their respective uncertainties.

A. Relating image points to Ground Points

Referring to Fig.(2), the relative orientation of the camera to the reference frame of the platform its fixed on is given by the rotation matrix $\mathcal{R}_{cam}$ parameterized by the Euler angles α, β and γ. The relative orientation of the platform to the ground is given by another rotation matrix $\mathcal{R}_{pf}(\phi, \theta, \psi)$. These parameters are provided by an IMU. Also, the 3D position of the platform in terms of latitude (N), longitude(E) and altitude Z is provided by GPS.

We first derive the relationship between an homogeneous image point $\tilde{\mathbf{u}} = (\tilde{u}, \tilde{v}, 1)^T$ and the corresponding ground

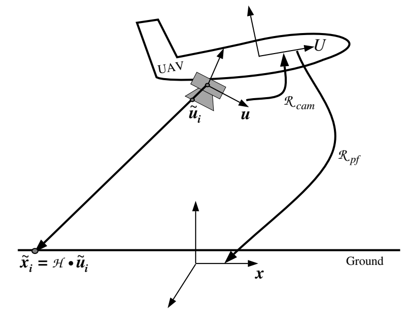

Fig. 2. A perspective camera is rigidly fitted on a robotic platform (an UAV). The camera is fully calibrated and its relative orientation to the UAV ($\mathcal{R}_{cam}$) is known a-priory. During flight, filtered *IMU* and *GPS* provides the orientation ($\mathcal{R}_{pf}$) and position of the UAV relative to the ground plane. Using these pose parameters, one can project a point in the image $\tilde{\mathbf{u}}_i$ onto the ground plane at homogeneous coordinates $\tilde{\mathbf{x}}_i$ Due to uncertainties in the measured pose parameters, the localization of the ground point is not reliable. We therefore analyze its uncertainty in terms of the pose parameters.

point $G = (X, Y)$ in terms of the orientation and position parameter set $\Theta = (\phi, \theta, \psi, Z, N, E)$. We assume that the camera is calibrated and its intrinsic matrix K is known. Given K and $\tilde{\mathbf{u}}$, the actual 3D point $\mathbf{u} = (u, v, w)^T$ on the image plane in the camera's coordinate frame is:

$$\mathbf{u} \quad = \quad K^{-1} * \tilde{\mathbf{u}}^T \ , \tag{9}$$

Given the fixed orientation $\mathcal{R}_{cam}(\alpha, \beta, \gamma)$ of the camera with respect to the platform, and the orientation $\mathcal{R}_{pf}(\phi, \theta, \psi)$ of the platform with respect to the ground, the 3D location of the image point is now given by:

$$\begin{aligned} \mathbf{U} &= \mathcal{R}(\phi, \theta, \psi) * \mathbf{u} \ , where & (10) \\ \mathcal{R}(\phi, \theta, \psi) &= \mathcal{R}_{pf} * \mathcal{R}_{cam}. & (11) \end{aligned}$$

Projecting this point onto the ground and accounting for the shift due to the position of the platform (provided by the GPS) gives us its ground coordinates $\mathbf{x} = (x, y)^T$:

$$\begin{aligned} x(\Theta) &= \frac{(Z * r_1 + N * r_3) \cdot \mathbf{U}}{r_3 \cdot \mathbf{U}} \\ y(\Theta) &= \frac{(Z * r_2 + E * r_3) \cdot \mathbf{U}}{r_3 \cdot \mathbf{U}} \ . \end{aligned} \tag{12}$$

where r_i denotes the i^{th} row of the rotation matrix $\mathcal{R}$. The ground point, in homogeneous coordinates $\tilde{\mathbf{x}} = (\tilde{x}, \tilde{y}, s)^T$ is:

$$\tilde{\mathbf{x}} \quad = \quad \mathcal{H}(\Theta) \cdot \mathbf{U} \ \text{,where:} \tag{13}$$

$$\mathcal{H}(\Theta) \quad = \quad \begin{pmatrix} Z * r_1 + N * r_3 \\ Z * r_2 + E * r_3 \\ r_3 \end{pmatrix} \ . \tag{14}$$

Note that, $\mathcal{H}$ is the parametric form of the homography that relates image points to their corresponding points on the ground plane.

B. Covariance of the Homography

In this section we use the parametric form of the homography derived above to derive it's covariance. In order to do so, we use a first order linear approximation of the homography about the mean of the parameters (also see [12]). This first order approximation is given by:

$$\tilde{\mathcal{H}}(\Theta) \quad = \quad \mathcal{H}(\bar{\Theta}) + \mathcal{H}'(\Theta) * (\Theta - \bar{\Theta}). \tag{15}$$

By definition the covariance of $\mathcal{H}$ is given by:

$$\Sigma_{\mathcal{H}} \quad = \quad \left(\mathcal{H}(\bar{\Theta}) - \mathcal{H}(\Theta)\right) * \left(\mathcal{H}(\bar{\Theta}) - \mathcal{H}(\Theta)\right)^T .$$

From Eq.(16), the first order approximation of the covariance is then:

$$\begin{aligned}
\Sigma_{\mathcal{H}} \quad &= \quad \left(\mathcal{H}(\bar{\Theta}) - \tilde{\mathcal{H}}(\Theta)\right) * \left(\mathcal{H}(\bar{\Theta}) - \tilde{\mathcal{H}}(\Theta)\right)^T \\
&= \quad \left(\mathcal{H}'(\Theta) * (\Theta - \bar{\Theta})\right) * \left(\mathcal{H}'(\Theta) * (\Theta - \bar{\Theta})\right)^T \\
&= \quad \mathcal{H}'(\Theta) * \Sigma_{\Theta} * \mathcal{H}'(\Theta)^T \ , \qquad (16)
\end{aligned}$$

where Σ_{Θ} is the 6×6 covariance matrix of the orientation and position parameters and $\mathcal{H}'$ is a 9×6 matrix of partial derivatives of $\mathcal{H}$ with respect to the parameters Θ.

C. Covariance of Ground Point Localization

We now determine the covariance in the localization of a point on the ground. In addition to uncertainties in the homography (see Eq.(16)), we also consider uncertainties in target detection in the image itself. The analysis presented here is similar to that presented in [13]

Let the uncertainty in detecting the ground target as an image point be $\Sigma_{\tilde{u}}^{2\times 2}$. If K is the intrinsic camera matrix. The covariance of the image point in 3D is:

$$\Sigma_{\mathbf{u}} = K^{-1} \begin{pmatrix} \Sigma_{\tilde{u}}^{2\times 2} & \mathbf{0} \\ \mathbf{0}^T & 0 \end{pmatrix} K^{-1^T}. \tag{17}$$

The covariance of a point $\tilde{\mathbf{x}}$ (in homogeneous coordinates) on the ground can be written as:

$$\Sigma_{\tilde{\mathbf{x}}}^{3\times 3} \quad = \quad \begin{pmatrix} \mathbf{B} & \vdots & \mathcal{H} \end{pmatrix} \begin{pmatrix} \Sigma_{\mathcal{H}} & \vdots & \mathbf{0} \\ \cdots & \cdots & \cdots \\ \mathbf{0} & \vdots & \Sigma_{\mathbf{u}} \end{pmatrix} \begin{pmatrix} \mathbf{B}^T \\ \cdots \\ \mathcal{H}^T \end{pmatrix},$$

$$\text{where: } \mathbf{B} \quad = \quad \begin{pmatrix} \tilde{\mathbf{x}}^T & \mathbf{0}^T & \mathbf{0}^T \\ \mathbf{0}^T & \tilde{\mathbf{x}}^T & \mathbf{0}^T \\ \mathbf{0}^T & \mathbf{0}^T & \tilde{\mathbf{x}}^T \end{pmatrix}.$$

Finally, the covariance of of the localization of the point on the ground as a 2×2 matrix is given by:

$$\begin{aligned}
\Sigma_{\mathbf{x}} \quad &= \quad \nabla f \Sigma_{\tilde{\mathbf{x}}}^{3\times 3} \nabla f^T, \\
\text{where: } \nabla f \quad &= \quad \frac{1}{s^2} \begin{pmatrix} s & 0 & -\tilde{x} \\ 0 & s & -\tilde{y} \end{pmatrix}. \qquad (18)
\end{aligned}$$

We now have an analytic form for the covariance in feature localization given the pose of the camera and uncertainties in its parameters. This is key to the success of the framework described in Section II.

IV. The Air and Ground Robot Platforms

In this section we first describe the hardware platforms used for the task of target detection and localization. Next, we analyze the effectiveness and reliability in target localization using these platforms under typical operating conditions.

We implemented the target detection and localization task using the framework described in Section II on the aerial and ground robot test-beds shown in Figure 3. The Ground vehicles are a commercial 4WD model truck modified and augmented with an on-board computer, stereo firewire camera, GPS and inertial sensors as described in [14]. The aerial vehicles are quarter scale Piper Cub model aircraft equipped with the Piccolo autopilot by Cloud Cap Technology (see [15] for further details). In addition to the sensors within the autopilot, the air vehicles carry a sensor pod containing a high resolution firewire camera, inertial sensors and a 10Hz GPS receiver. A spread-spectrum radio modem is used for Communications between air vehicles and the operator base station. The ground vehicles and base station communicate through an Ad-Hoc 802.11b network.

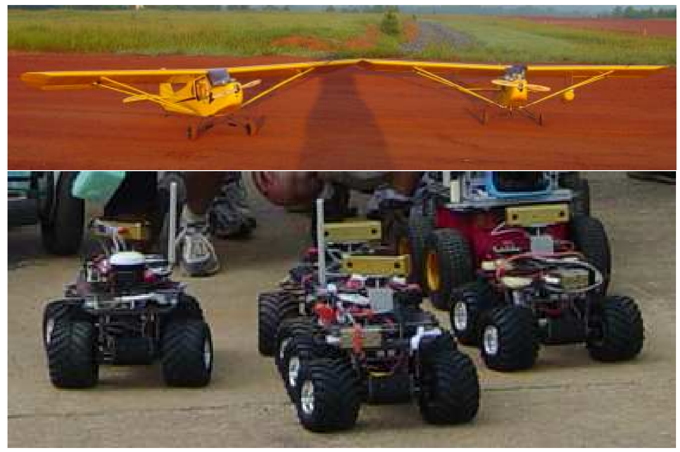

Fig. 3. Fixed wing UAVs (top) and ground robot platforms (bottom).

A. Visualizing Feature Observation Uncertainties

On-board cameras are the primary air and ground vehicle mission sensors enabling detection and localization of features in operational environments. We now use the covariance matrix derived in Eq.(18) to visualize the uncertainty ellipses associated with features on the ground plane. Figure 4 provides example images of a ground feature observed from air and ground based cameras.

We consider points across the image and illustrate how their corresponding uncertainties on the ground plane vary. We also compare the uncertainties in ground feature localization using an UAV and UGVs. This comparison reveals the pros and cons of either platform and highlights the advantage of combining sensor information from these different sources for reliable localization.

Figure 5 displays ground feature position confidence ellipses associated with different points in the air and ground imagery. These are obtained by evaluating Equation 18 with parameters

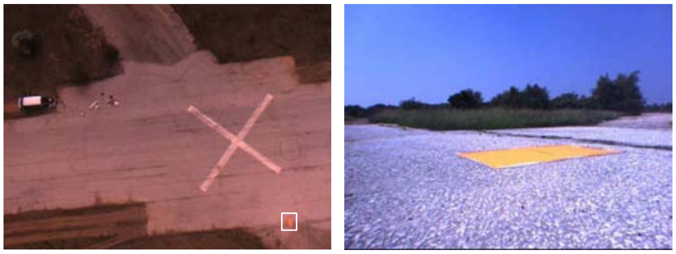

Fig. 4. A ground feature observed from the air *(left)* and ground platforms.

typical to the air and ground camera installations. Thus, we visualize how uncertainties in target localization vary across the field of view of the camera and from the different perspectives provided by the vehicles. The UAV cameras looks down from an altitude of $50(\mathrm{m})$, having a typical pitch angle of $\theta = 5\,\mathrm{deg}$. The UGV cameras nominally look horizontally and are positioned 0.32m above the ground plane. We assume the variance in roll and pitch to be $4\,\mathrm{deg}^2$, while that for heading to be $25deg^2$. The variance in GPS coordinates is $25(m^2)$.

This comparison confirms the complementary character of the air and ground vehicles as camera platforms. Airborne cameras offer relatively uncertain observations over a wide field of view. Ground vehicles offer high relative accuracy that degrades out to an effective range of approximately 5m. The ground vehicle field of view encompasses the aerial observation confidence region. This allows feature locations to be reliably handed off to ground vehicles. alleviating any requirement for ground vehicles to search for ground features.

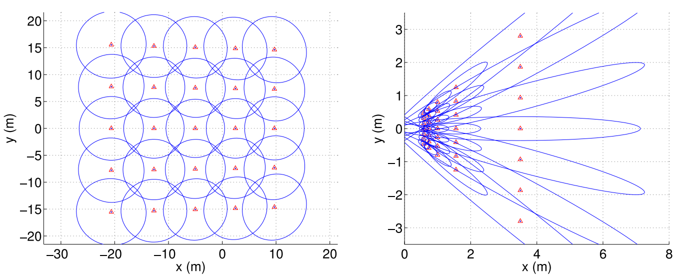

Fig. 5. Ground feature observation uncertainty for air *(left)* and ground *(right)* camera installations. The UAV camera looks down 5^o off vertical at 50m altitude. The UGV camera is mounted horizontally 0.32m above the ground plane. Comparative feature observation accuracy is illustrated by ground plane confidence ellipses associated with uniformly spaced pixels in the imagery.

V. Multi-Vehicle Air-Ground Feature Search and Localization

The approach to active sensing detailed in Section II is now implemented on the robotic sensor platforms described in Section IV and applied to a feature search and localization task in a two dimensional ground plane. This task consists of two components. Firstly, detection of an unknown number of ground features in a specified search area $\hat{\mathbf{y}}_{d,i}(k \mid k)$. Secondly, the refinement of the location estimates for each detected feature $\mathbf{Y}_{f,i}(k \mid k)$. These aspects are represented by the decentralized certainty grid Equation 4 and information filter Equation 8 estimation processes described in Section II. The utility of robot states and actions is the combined mutual information gain form on-board sensors towards the detection and localization processes. Local controllers drive the vehicles in the direction that maximizes the information gain. The process is terminated upon achieving desired detection and localization uncertainty thresholds. Each sensor platform executes and instance of the *Active Sensor Node* depicted in Figure 1. Observations are fused locally and subsequently propagated throughout the DDF network. This propagation informs and influences nodes modifying the knowledge on which subsequent control decisions are based.

A. Results

Results for an example solution with two UGVs and two UAVs are presented in Figures 6 and 7. The example contains four ground features distributed over a 60m by 40m search area. The problem is initialized with zero information as to the detection, number and location of features. Figures 6 details the UAV trajectories and evolution of the certainty grid throughout the detection process. Figure 7 details the confidence of feature location observations along with the UGV trajectories. The approach capitalizes on the UAV speed and field of view to successfully cover the search area and detect all features. As features are detected and propagated, the information seeking control scheme deploys UGVs to refine ground feature estimate uncertainty derived from UAV sensing alone. The feature location uncertainty is rapidly reduced while avoiding any requirement for UGVs to conduct a time consuming exhaustive search.

VI. Conclusion

This paper presented a consistent architecture and approach for enabling proactive collaboration among aerial and ground based sensor platforms. The architecture provides seamless and scalable integration of air and ground sensor platforms, allowing system elements to be transparently aware of and exploit collective knowledge and resources. Uncertainty analysis confirmed complementary nature of aerial and ground robot platforms in terms of sensing accuracy and coverage. Application of the information driven methodology to a ground feature search and localization problem realized performance benefits made possible by these characteristics.

VII. Acknowledgements

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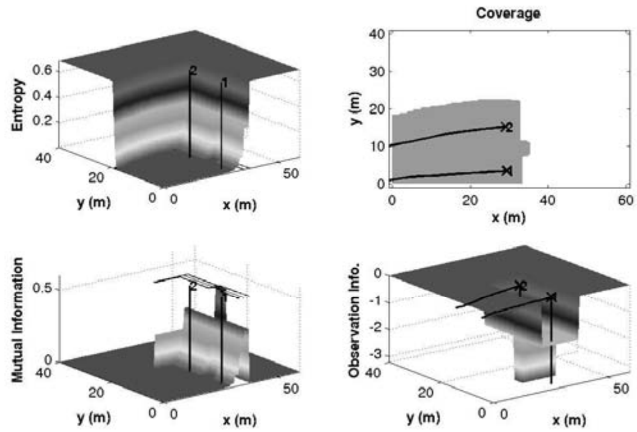
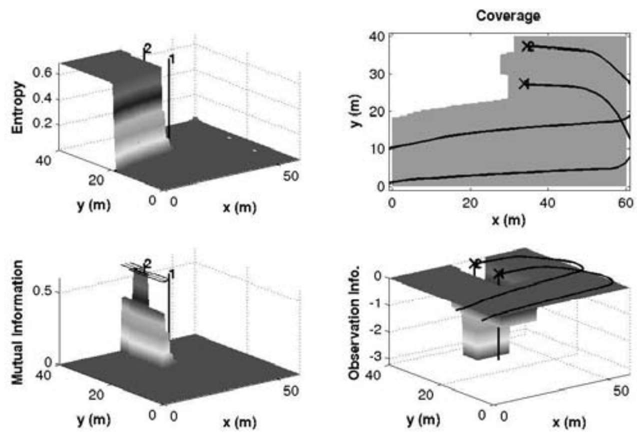


(a)



(b)

Fig. 6. Two snapshots in time of the UAV trajectories and information measures relating to the probability of of ground features remaining undetected over a specified search area. Each (a) and (b) indicates the detection probability entropy, extent of coverage, current mutual information gain and observation sensor information. The UAVs are directed by the mutual information gradient. Each UAV camera is considered to have an 80% detection probability over its projected field of view. The aerial detection is terminated when 99.9% detection confidence is reached. Coordinated trajectories arise due to coupling through accumulated information, without knowledge of the state of other UAVs. The information objective drives platforms apart and towards unexplored regions.

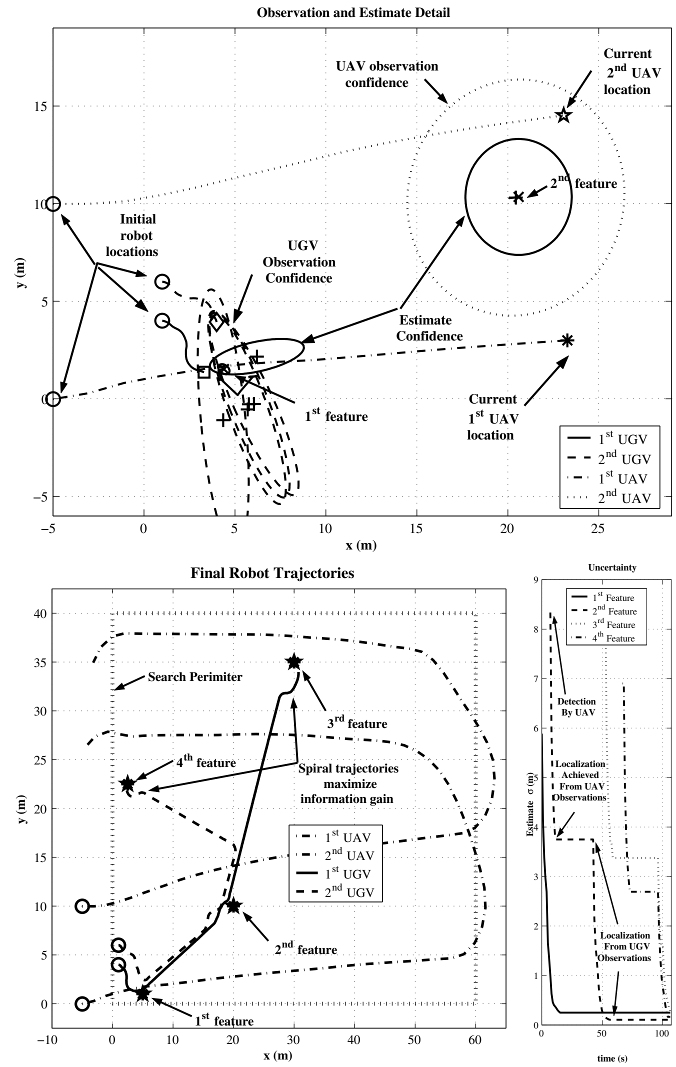


Fig. 7. Details of the feature localization process: *(top)* an early snapshot of the observation and estimation confidence, *(left)* the problem layout and final robot sensing trajectories, and *(right)* the feature uncertainty as standard deviation over time. The control scheme drives the UGVs toward the locations estimated from UAV observations. Constant feature uncertainty indicates the time between UAV detection and UGV refinement. UGV trajectories tend to spiral around the features and maintain orthogonal viewing angles. A result of the individual controllers seeking to take advantage of the spatial uncertainty variations in the predominantly bearing observations while accounting for accumulated measurement information. Control is local to each platform using local information without planning or negotiation. In this case, a symmetry in the information gain utility measure with respect to feature and robot geometry results in final UGV deployment to individual ground features.

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