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MODEL-BASED APPROACH TO CHARACTERIZATION OF DIFFUSION PROCESSES VIA DISTRIBUTED CONTROL OF ACTUATED SENSOR NETWORKS

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Abstract: This paper presents a model-based distributed control framework for the problem of characterizing diffusion processes. Such systems arise in a wide variety of applications. We propose the use of multiple, robotic sensors that can be tasked to collect measurements of the process outputs from variable spatial locations. The notion is that a central controller uses the process model to compute a prediction of the process outputs. This prediction is then used to prescribe sampling locations, to which the sensors in a distributed sensor network are commanded. Samples obtained by the sensors are then used as constraints to correct the model-based prediction of the process outputs. The cycle of predicting, sampling, and prediction correction is repeated until the predictions converge. The idea of actuated actuator networks is also introduced. A control-theoretic formulation of the problem is presented that highlights a number of theoretical problems to be solved.

Keywords: Autonomous mobile robots, sensor networks, distributed control.

1. INTRODUCTION

Through the course of history many technologies have developed to the point of becoming ubiquitous. For example, the use of electric motors is today so pervasive that they are taken completely for granted by most people. Similarly, microprocessors and other digital hardware, such as FPGAs, are now found in every conceivable application – from washing machines to cell phones – to such an extent that it will soon be hard to imagine life without them.

Today, a new "technology" is developing that also has the promise of ubiquity. Due to a combination of advances in biology, electronics, nanotechnology, wireless communications, computing, networking, and robotics, it is now possible to:

1) Design *advanced sensors and sensor systems* that can be used to measure an increasingly wide range of variables of interest, from explosives and toxic, biological, and chemical agents, via the design and synthesis of functionalized receptors and materials; to the detection of objects and events, via advances in multi-spectral imaging systems, data fusion, and pattern recognition techniques; to sensors for physical measurements, such as force, pressure, acceleration, flow, vibration, temperature, humidity, and physical variables, such as mass, magnetic, optical, ultrasonic, chromatographic, and others.
2) Use *wireless communications*, or telemetry, to effectively communicate sensor data from a distance. Sensors can now be deployed in fixed locations or via mobile robots, without the constraint of wires, to operate in extreme environments, possibly autonomously, allowing humans to observe data while staying out of harm's way.
3) Build *networks of sensors*, using wireless communications and computer networking technology, which can provide the capability to obtain spatially-distributed measurements from low-power sensors that communicate and relay information between each other. Such sensor networks can be homogeneous, using a single type of sensor, or heterogeneous, employing multi-modal sensors, whose outputs are

combined and interpreted through data fusion algorithms.

4) Develop *reconfigurable, or adaptable, networks of distributed sensors* by providing mobility or actuation to the individual sensors in the network. For example, if each sensor was mounted on an autonomous robot, the network could perhaps self-organize, moving sensors to the appropriate locations needed to ensure adequate coverage.

Current research on these topics is leading to the promise of a new ubiquitous technology – distributed sensor networks – where "data about everything is available everywhere." However, with this promise comes a related challenge: how to interpret and use this data and for *what purpose*. Moreover, with a mobility platform, the networked sensors and actuators can be actively moved according to a high-level task or mission. There is a strong need for system level, mission-centered research for mobile actuator-sensor networks. In the remainder of this paper we propose such research, related to the interpretation and use of data in distributed sensor networks, with a focus on coordination strategies for networks of mobile sensors. We first discuss some issues related to such networks and then present a specific application scenario that is the basis for our main proposal: a model-based approach to sensor coordination. Next we formulate a general control-theoretic problem applicable to a large class of mobile sensor application scenarios. We continue by introducing one final consideration: the notion of a network of mobile actuators combined with a network of mobile sensors.

2. DISTRIBUTED SENSOR NETWORKS

Sensor networks are drawing increased attention from research communities, industry sectors and government agencies. As stated in (National Science Foundation, 2003), sensor networks will "*have significant impact on a broad range of applications relating to national security, health care, the environment, energy, food safety, and manufacturing. The convergence of the Internet, communications, and information technologies with techniques for miniaturization has placed sensor technology at the threshold of a period of major growth*." Recent surveys on sensor networks (Hairong, *et al*., 2001; Akyildiz, *et al*., 2002) also indicate the importance of sensor networks research. Many on-going efforts are focused on various specific issues in sensor networks such as the sensor structures (Abdelzaher, *et al.*, 2003; Yang and Sikdar, 2003), communication (Akyildiz, *et al*., 2002), data processing and sensor fusion methods (Hairong, *et al*., 2001; Kumar, *et al.*, 2002), sensor deployment and localization (Hairong, *et al*., 2001; Kumar, *et al.*, 2002; Wang, *et al.*, 2003), calibration (Whitehouse and Culler, 2002; Bychkovskiy, *et al.*, 2003), etc. However, from a dynamic systems and control point of view, the sensor networks should be part of a complete system with a specific mission defined. Recently, a habitat monitoring task was proposed as an "application driver" for wireless communications technology based sensor networks (Cerpa *et al*., 2001), although this is still an open-loop system simply for monitoring purposes. In (Sukhatme *et al.*, 2000) a future research effort was proposed to combine distributed sensing, robotic sampling, and offline analysis for *in situ* marine monitoring purposes, where the loop is closed using underwater robots that carry networked sensors and are deployed according to the sensed environment. This system is not real-time feedback-controlled due to the offline analysis. So far, there is no such real-time closed-loop distributed feedback control system involving networked actuators and sensors (Haenggi, 2002).

2.1 Application Scenarios.

<u>A Motivating Example</u>. To motivate our subsequent development, consider the sequence of illustrations given in Figs. 1-8. Fig. 1 depicts a situation where some type of biological or chemical contamination has occurred. As a result, there is a developing plume of dangerous or toxic material. Of course, the exact development of the plume will depend upon the prevailing weather conditions as well as the surrounding geography. There are sophisticated models that can be used to predict the development of the plume. Such models are based on partial differential equations that include diffusion and transport phenomena effects as well as forcing functions such as the prevailing weather conditions and boundary conditions and constraint equations defined by the surrounding geography. As shown in Fig. 2, such models can be used to build (an imperfect) prediction of the plume boundary. Next, assume that we have actuated sensors that can measure the concentration of the contaminant. These sensors are deployed in a swarm as a mobile sensor network. Their motion is coordinated so as distribute them around the predicted plume boundary as shown in Fig. 3. Existing work on swarm behavior often uses potential or attractor fields to coordinate swarm motion. The distinction in our approach is that the attractor field we use to coordinate the swarm motion is derived from a physics-driven model of the task.

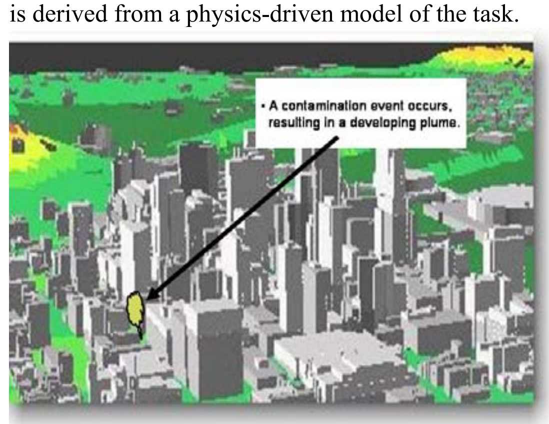

Fig. 1. Initiation of a diffusion process.

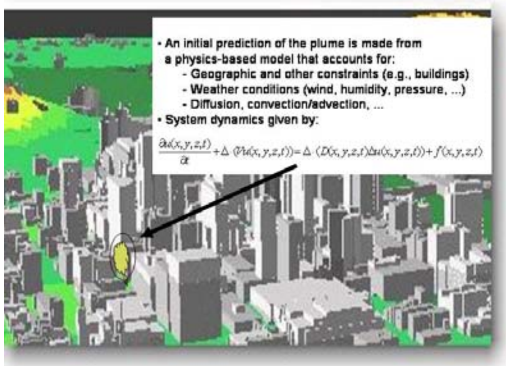

Fig. 2. Prediction of the diffusion process states.

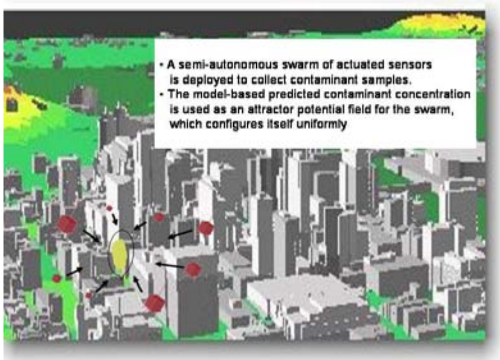

Fig. 3. A mobile sensor network collects samples.

Note that we assume the individual actuated sensors are an appropriate type of robot, in this example a flyer, and would have autonomous guidance and navigation (with waypoints defined by the predicted plume boundary). All the actuated sensors would be able, in this example, to communicate wirelessly with each other using some type of protocol to form an *ad hoc* network and with some presumed base station (where the actual plume prediction takes place). The continuation of the scenario is shown in Figs. 4-7. Fig. 4 shows that after arriving at the predicted boundary, the actuated sensors would take samples of the concentration. Again using the physics-based model and data about prevailing weather and geography, but now with the additional information of actual concentrations gathered from the swarm of actuated sensors, a new prediction of the plume boundary is computed (Fig. 5). After the new predicted plume boundary is computed, the swarm's attractor function is modified and the network of actuated sensors autonomously deploys to a uniform distribution around the new predicted boundary, where they collect new samples (Fig. 6), which are relayed to the base station, where a new prediction is made and then the process continues (Fig. 7). As more and more samples are collected, the predictions converge to the true plume location.

Other Application Scenarios. The motivating example depicted in Figs. 1-7 is just one of a number of applications that one may encounter. Here we suggest two others for which our ideas are directly applicable:

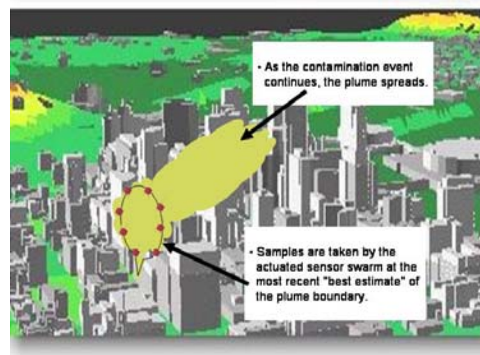

Fig. 4. While samples are collected by the actuated, mobile, robotic sensor net, the plume continues to spread.

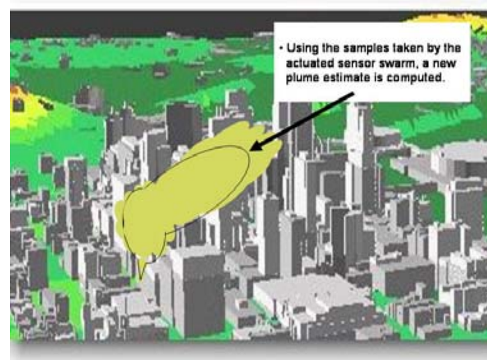

Fig. 5. New prediction of the diffusion process states.

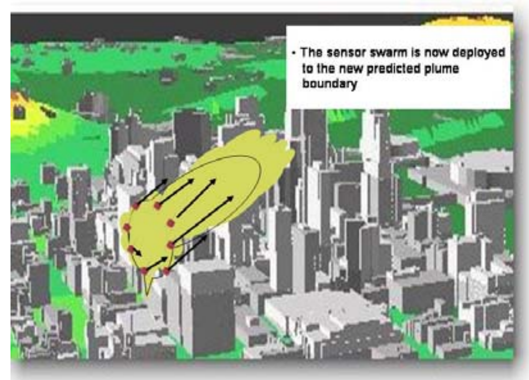

Fig. 6. Deploying the mobile sensor network to collect new samples of the process states.

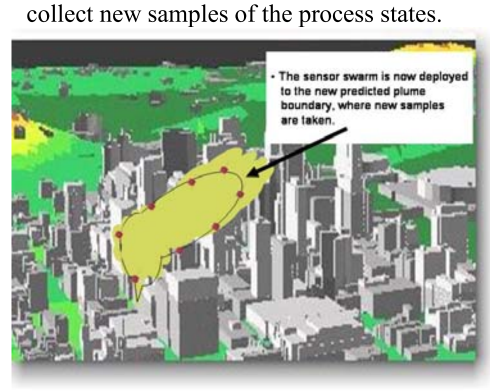

Fig. 7. The process repeats.

1. Safe ground boundary determination of the radiation field from multiple nuclear radiation sources. In this case, each networked sensor is mounted on a ground mobile robot. The mission is to determine the safe radiation boundary of the radiation field from possibly multiple nuclear radiation sources. Each robot is actuated according to spatial and temporal sensed information (radiation gradient, spatial position etc.) from more than one actuated or mobile sensors.

2. Nontoxic reservoir water surface boundary determination and zone control due to a toxic diffusion source. Similar to the radiation boundary problem, if the toxic diffusion source is a one-time pouring and the diffusion is in steady state. However, the boundary may be dynamically evolving if the toxic source keeps polluting the reservoir. The *actuated or mobile sensors* are autonomous boats or underwater robots mounted with toxic chemical concentration sensors. The boats are commanded according to the spatial-temporal sensed information from more than one sensor.

2.2 Issues Related to Distributed Sensor Networks.

Motivated by the application scenarios above, we see that the elements of a distributed, mobile, robotic sensor net should include:

1. A *sensor* relevant to the application at hand. For some classes of measurement problems, commercial off-the-shelf (COTS) sensors already exist, though work continues to make them smaller, more robust, and lower-power. In other applications, especially chemical-biological, sensor development is currently a subject of intense activity. For our purposes we suppose COTS sensors are available.

2. Some type of (typically wireless) *communication* capability. This could be radio frequency, microwave, or cellular communications, depending on the power and range requirements. At this time perfect COTS solutions do not exist, especially if the sensors might be deployed indoors and/or outdoors. However, a number of research teams and companies are actively pursuing development of wireless communication technologies, so again, for our purposes, we assume an appropriate communication capability is available.

3. Suitable *communication and data flow control protocols*. A set of sensors with communication hardware only become a network when they can communicate according to some standard. The issue is to ensure that available network resources are allocated to optimally control the data flow between nodes (i.e., sensors). Again, the development of such protocols has been an active area in recent year, particularly due to the emergence of computer networking solutions (e.g., the "mote" concept, the 802.11b standard, the FieldBus and CAN bus standards, *ad hoc* and infrastructure network protocols, etc.). For now we assume suitable protocols, but note that as one moves to consider integration of control efforts with distributed sensors, the existing protocols are inadequate and research may be required to achieve our ultimate vision of a network of mobile actuators combined with a network of mobile sensors.

4. Algorithms for *sensor placement and data interpretation and use*. Such algorithms are necessarily application-dependent. Generally, domain-specific expertise is adequate to address the issue of data interpretation. However, data interpretation is also related to a less well-developed topic: sensor placement to achieve a given task. For example, in the scenario of Figs. 1-7 one can ask: how are the mobile sensors optimally located? We submit that to date such questions have been handled in an *ad hoc* fashion. Below we establish a systematic way to address this issue for a class of problems (those with an underlying generating function, such as a diffusion process).). Note that for a network of actuated sensors the issue of sensor placement is in fact an issue of multi-agent coordination. Of course, such an issue is task-dependent. However, it is possible to define a general approach for coordination of multiple actuated sensors that are collected into a network in such a way that the approach can be applied to a variety of applications. In what follows we introduce such an approach.

3. DISTRIBUTED ACTUATED SENSOR NETS

A presumption of the question, "where are the best places to locate a set of sensors?" is that the sensors can indeed be placed. This can be done two ways: robotically or manually (i.e., "human-in-the-loop"). We are interested here in the idea of robotically-deployed sensors. To describe our ideas about a network of sensors that can be (robotically) moved from one location to another we introduce the following terminology:

Actuated sensor: An actuated sensor S^A is a sensor that can move in space, either through self-logic or in response to a command from a supervisor.

Actuated sensor network: An (actuated sensor) network NS^A is a networked collection of actuated sensors, which are working together to achieve some type of information collection and processing.

Two comments are in order about these definitions. First, we prefer to use the term "actuated" rather than "mobile," though in fact we will use them interchangeably. "Actuated" implies the ability to actively control the sensor's motion. Thus, a weather balloon is in fact a mobile sensor, but not, by our definition, an actuated sensor, whereas a radio-controlled blimp carrying sensors can be considered an actuated sensor. By definition, actuated sensors are also mobile sensors. Second, if an actuated sensor's motion is determined by self-logic, then we call it "autonomous." However, an actuated sensor also has a number of "autonomous" capabilities. Thus we will use the term "autonomous" loosely, letting the context define the meaning. Of course, to be precise, we should distinguish between "actuated" and "autonomous." An "autonomous (actuated sensor)" is different than an "actuated (autonomous sensor)," the former meaning a mobile sensor that makes its own decisions about its own motion and the latter referring to a mobile sensor that is commanded by a supervisor, but is autonomous in its data collection. However, from this point forward we assume all sensors are actuated (mobile) and also autonomous in data collection. Note that an autonomous, actuated sensor's self-logic could be based on local information or on shared information from other autonomous, actuated sensors. The design of information sharing structures is a key issue in the performance of a distributed sensor network.

4. CONTROL-THEORETIC PROBLEM FORMULATION

In this section we formulate the general problem of coordination of distributed networks of actuated sensors for real-time spatial diffusion characterization. There is quite a bit of existing related work on coordination strategies for swarm-type networks, most of it based on the notion of individual sensors following some type of a-priori energy function or gradient. Here we propose a new idea: that of a model-based coordination strategy. One argument for this approach is that: a) models are becoming increasingly well-developed in a variety of application arenas, and b) one should use all the information that is available when trying to solve a problem.

Sensor Net: We begin by assuming we are given a network of actuated sensors, NS^A, made up of a collection of individual sensors that are defined as follows:

$S_i^A(q_i)$: an actuated sensor with the following characteristics:

- located in space at $q_i(t) = (x_i, y_i, z_i)^T \in R^3$
- can communicate with all others and with a supervisor.
- can generate a measurement of interest to the application, defined by $s_i(q_i, t)$, which is assumed to be a function of both space and time.
- can move freely in three dimensions with dynamics given by $\dot{q}_i = f_i(q_i, u_i)$, where $u_i(t)$ is the motion control input for sensor $S_i^A(q)$.

System to be Characterized: Next, we assume that there exists a space-time distribution of interest that we wish to characterize with the distributed actuated sensor network. We denote the distribution as $V(q,t)$, which is assumed to be the solution a known PDE with a known initial condition $V(q_0, t_0)$. The plant dynamics are assumed to be of the following form (which takes into account diffusion and transport phenomena effects such as convention/advection), expressed in standard vector calculus:

$$\frac{\partial V(q,t)}{\partial t} + \Delta \cdot (FV(q,t)) = \Delta \cdot (D(q,t)\Delta V(q,t)) + g(q,t)$$
$$V(q_0, t_0) = V_0$$

where $FV(q,t)$ denotes the effect of external, possibly variable, "inputs" on the plant dynamics (e.g., wind, rain, dust, humidity, etc.), $D(q,t)$ is the diffusion function for the specific problem, $g(q,t)$ reflects the effects of constraints (e.g., gravity, buildings, terrain, etc.), and V_0, q_0, t_0 denote the initial conditions.

Sampling Action: It is assumed that the output of the sensor $S_i^A(q)$, defined above as s_i, is a measurement of the distribution of interest at wherever the sensor is located in space. Thus we can write:

$$s_i(q_i, t) = V(q_i, t)$$

Fig. 8 represents the relationship between the variables and system components defined so far.

Prediction: The next step in the problem formulation is to define the prediction. Of course, if we had perfect knowledge, the problem would be trivial. However, in fact we only have estimates of the initial conditions, of the external inputs, and of the constraints. Let is define these estimates as $\hat{F}\hat{V}(q,t)$, $\hat{g}(q,t)$, and $\hat{V}_0$, respectively (of course, there are other sources of uncertainty, such as parameters in the diffusion function $D(q,t)$, but for now we will assume these are known). Then we can compute the estimated diffusion $\hat{V}(q,t)$ as the solution of

$$\frac{\partial \hat{V}(q,t)}{\partial t} + \Delta \cdot (\hat{F}\hat{V}(q,t)) = \Delta \cdot (D(q,t)\Delta \hat{V}(q,t)) + \hat{g}(q,t)$$
$$\hat{V}(q_0, t_0) = \hat{V}_0$$
$$\hat{V}(q_i, t_{s_i}) = s_i(q_i, t_s) = V(q_i, t_{s_i}) \text{ for all } i \text{ and all } t_{s_i}$$

Notice the introduction of the actual sensor measurements at sample points and sample times (q_i, t_{s_i}) as constraints for the partial differential equation.

Control: The next piece we add in this section is the motion control of the actuated sensor. There are various ways to approach this piece. For instance, one could take control actions to be a function of the error

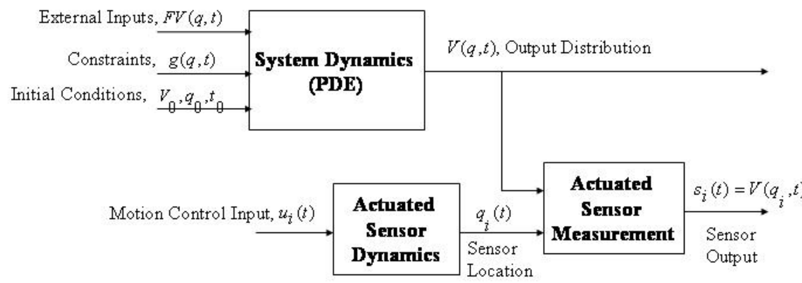

Fig. 8. Relationship between components and variables.

between the predicted samples and the actual samples. That is, given a set of samples, we make a prediction about the distribution. We then move to a new point in space and take new samples. The error between what we expect to measure and what we actually measure determines where we take our next samples. However, for the moment we consider a simpler approach. We simply move the sensors so they are uniformly distributed relative to the predicted distribution. Thus, we can write

$$q_i^{sp} = H(\hat{V}(q,t))$$

$$\dot{u}_i = h_i(q_i^{sp} - q_i)$$

where H denotes a type of feed-forward energy function that has the effect of computing a set of uniformly distributed locations around the distribution and h is the control law used to drive the actuated senor to its new setpoint q_i^{sp}.

Goal Statement: Finally, we need to define the goal of the control action. Ideally, one would like to achieve

$$\lim_{t \to \infty} \hat{V}(q,t) = V(q,t) \text{ for all } q$$

However, this is quite ambitious. Instead, it may be better to hope for making the prediction match at the sample points. Thus, we can define a cost function

$$J = \lim_{t \to \infty} \sum_i h_g((\hat{V}(q_i,t) - V(q_i,t)))$$

where $h_g(\cdot)$ is a positive function

So, given descriptions of the actuated sensor network and the sampling action, the system to characterize, the prediction strategy, and the motion control logic, we may now state the complete problem:

$$\min_{H,h} J = \lim_{t \to \infty} \sum_i (V(q_i,t) - \hat{V}(q_i,t))$$

subject to :

1a) $\dfrac{\partial V(q,t)}{\partial t} + \Delta \cdot (FV(q,t)) = \Delta \cdot (D(q,t)\Delta V(q,t)) + g(q,t)$

1b) $V(q_0, t_0) = V_0$

2a) $\dfrac{\partial \hat{V}(q,t)}{\partial t} + \Delta \cdot (\hat{F}\hat{V}(q,t)) = \Delta \cdot (D(q,t)\Delta \hat{V}(q,t)) + \hat{g}(q,t)$

2b) $\hat{V}(q_0, t_0) = \hat{V}_0$

2c) $\hat{V}(q_i, t_{s_i}) = s_i(q_i, t_{s_i}) = V(q_i, t_{s_i})$ for all i and all t_{s_i}

3a) $\dot{q}_i = f_i(q_i, u_i)$

3b) $s_i(q_i, t_{s_i}) = V(q_i, t_{s_i})$

4a) $q_i^{sp} = H(\hat{V}(q,t))$

4b) $\dot{u}_i = h_i(q_i^{sp} - q_i)$

We comment that the design freedom in the problem is found in the selection of the controller motion functions H and h_i. For the most part, the selection of h_i is a straightforward control system design activity that will be specific to the robotic strategy used to actuate the sensor. The selection of H is ultimately the major design effort in the problem.

Fig. 9 depicts the complete algorithm in a block diagram. Note that although this is essentially an open-loop system identification problem, there is in fact a feedback feature to the problem, due to the motion control coupling to the output of the predictor.

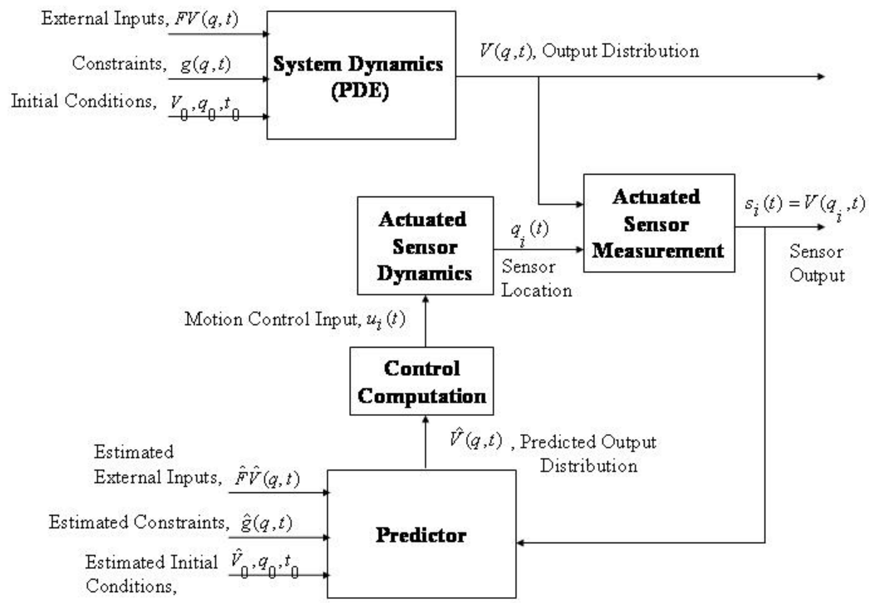

Fig. 9. Complete system block diagram.

5. DISTRIBUTED NETWORKS OF MOBILE (ACTUATED) ACTUATORS WITH ACTUATED SENSORS

Before concluding we propose one final concept. In addition to allowing mobile sensors, we would also like to consider mobile actuators as well. Fig. 10 illustrates the concept in the context of the motivating application described in Section 2.1. In this figure, we show mobile, or actuated, actuators being deployed to release a dispersal agent into the contaminant plume. Of course, such actuators might be co-located with the actuated sensors. But, in many applications dispersal or actuating agents will typically be much more expensive than sensing agents. Thus it is reasonable to consider them separately.

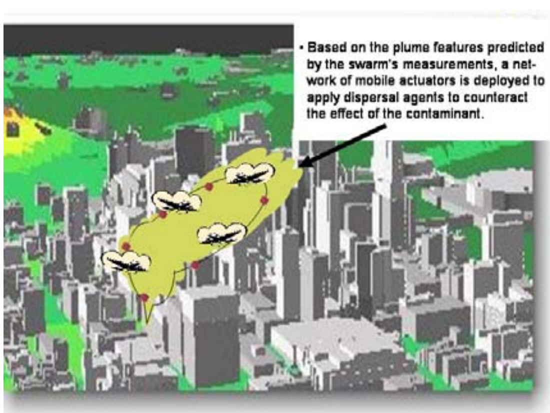

Fig. 10. Actuated actuator network.

The effect of such actuated actuators can be added to our problem by noting that the primary effect they introduce is that of modifying the diffusion function in the system dynamics. Then we proceed as follows:

Actuator Network: We begin by assuming we are given a network of autonomous, actuated actuators defined as follows:

$A_j^A(q_j)$: an actuated actuator with the following characteristics

- located in space at $q_j(t) = (x_j, y_j, z_j)^T \in R^3$
- can communicate with all others, with all sensors, and with a supervisor.
- can generate an effect of interest to the application, defined by $d_j^a(q_j, t)$, which is assumed to be a function of both space and time.
- can move freely in three dimensions with dynamics given by

$$\dot{q}_j = f_j^a(q_j, u_j^a)$$

where $u_j^a(t)$ is the motion control input for actuator $A_j^A(q_j)$.

For this set of actuators we define a motion controller given by

$$q_j^{sp} = H^a(V^d(q,t) - \hat{V}(q,t))$$

$$\dot{u}_j^a = h_j^a(q_j^{sp} - q_j)$$

We point out that in the case of an actuated actuator, the function H^a is primarily a comparator and $V^d(q,t)$, the desired distribution, can typically be taken as zero (i.e., we don't want any contaminant!).

Control Goal: Without going into the details, we propose the following cost function for the design of the functions H^a and h_j^a

$$J^c = \lim_{t \to \infty} \int (V^d(q,t) - \hat{V}(q,t))dq$$

This costs seeks to drive the predicted distribution to the final distribution everywhere in space.

Final Architecture and Problem Statement: The equations shown in Fig. 11 give the final form of the problem. Notice that we have actually stated two coupled problems. The sensor motion control problem is based on the output of the prediction. But the effect of the actuated actuators is shown in the diffusion function used in the prediction. We denote this as function

$$w(D(d,t), d_j^a(q_j,t))$$

because in general the effect of a dispersal agent may not necessarily be linear. At this time the effect of this coupling is not clear. One would hope to see the standard separation principle emerge, but that may not be possible. Deep research is needed to understand this problem. Fig. 12 shows the complete architecture in block diagram form.

6. CONCLUSION

In this white paper we have presented new ideas related to the interpretation and use of data in distributed sensor networks, with a particular focus on coordination strategies for networks of actuated sensors. We first introduced some of the research issues related to such networks. We then described our idea (of using a model-based approach to sensor coordination) in the context of a specific application scenario: the real-time mapping of contaminant plume development. Next we formulated the problem in a general control-theoretic framework, which we also extended to include the notion of a network of mobile actuators combined with a network of mobile sensors. Current work is aimed at considering a variety of theoretical problems associated with the complete problem statement of Fig. 11 as well as at developing an experimental testbed using mobile robots and a simple fluid-based diffusion process.

$$\min_{H,h} J^p = \lim_{t \to \infty} \sum_i (V(q_i,t) - \hat{V}(q_i,t))$$

$$\min_{H^a,h^a} J^c = \lim_{t \to \infty} \int (V^d(q,t) - \hat{V}(q,t))dq$$

subject to :

1a) $\frac{\partial V(q,t)}{\partial t} + \Delta \cdot (FV(q,t)) = \Delta \cdot (D(q,t)\Delta V(q,t)) + g(q,t)$

1b) $V(q_0,t_0) = V_0$

2a) $\frac{\partial \hat{V}(q,t)}{\partial t} + \Delta \cdot (\hat{F}\hat{V}(q,t)) = \Delta \cdot (w(D(q,t), d_j^j(q_j,t))\Delta \hat{V}(q,t)) + \hat{g}(q,t)$

2b) $\hat{V}(q_0,t_0) = \hat{V}_0$

2c) $\hat{V}(q_i,t_{s_i}) = s_i(q_i,t_{s_i}) = V(q_i,t_{s_i})$ for all i and all t_{s_i}

3a) $\dot{q}_i = f_i(q_i,u_i)$

3b) $s_i(q_i,t_{s_i}) = V(q_i,t_{s_i})$

4a) $q_i^{sp} = H(\hat{V}(q,t))$

4b) $\dot{u}_i = h_i(q_i^{sp} - q_i)$

5a) $\dot{q}_j = f_j^a(q_j,u_j^a)$

5b) $q_j^{sp} = H^a(V^d(q,t) - \hat{V}(q,t))$

5c) $\dot{u}_j^a = h_j^a(q_j^{sp} - q_j)$

Fig. 11. Complete problem statement.

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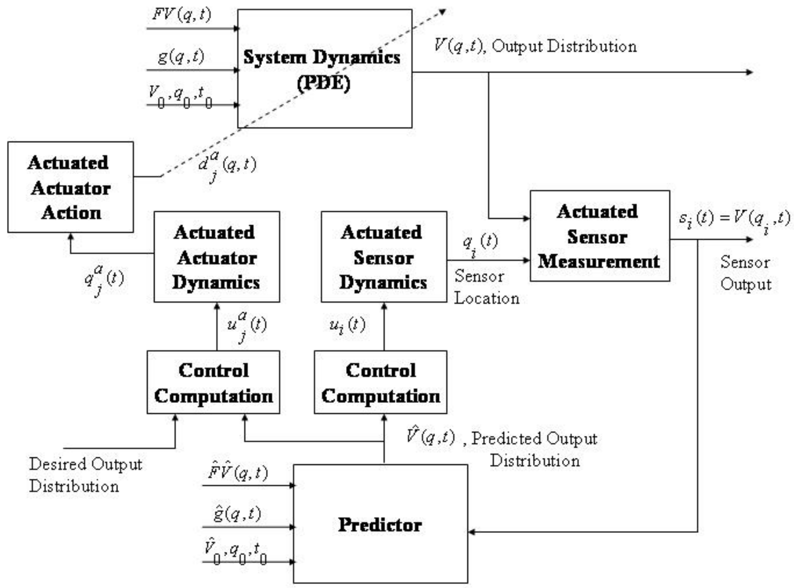

Fig. 11: Complete architecture of an actuated-actuator, actuated-sensor network,

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