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Towards Intelligent Dynamic Deployment of Mobile Sensors in Complex Resource-Bounded Environments

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Technical report

TOWARDS INTELLIGENT DYNAMIC DEPLOYMENT OF MOBILE SENSORS IN COMPLEX RESOURCE-BOUNDED ENVIRONMENTS

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Abstract

Decision-making in the face of uncertainty requires an understanding of the probabilistic mechanisms that govern the complex behavior of these systems. This issue applies to many domains: financial investments, disease control, military planning and homeland security. In each of these areas, there is a practical need for efficient resource-bounded reasoning capabilities to support optimal decision-making. Specifically, given a highly complex system, with numerous random variables and their dynamic interactions, how do we monitor such a system and detect crucial events that might impact our decision making process? More importantly, how do we perform this reasoning efficiently—to an acceptable degree of accuracy in real time—when there are only limited computational power and sensory capabilities? These questions encapsulate non-trivial key issues faced by many high-profile Laboratory missions: the problem of efficient inference and dynamic sensor deployment for risk/uncertainty reduction. By leveraging solid ideas such as system decomposition into loosely coupled subsystems and smart resource allocation among these subsystems, we can parallelize inference and data acquisition for faster and improved computational performance. In this report, we propose technical approaches for developing algorithmic tools to enable future scientific and engineering endeavors to better achieve the optimal use of limited resources for maximal return of information on a complex system. The result of the proposed research effort will be an efficient reasoning framework that would enable mobile sensors to work collaboratively as teams of adaptive and responsive agents, whose joint goal is to gather useful information that would assist in the inference process.

1.0 Motivation

This research is revolutionary in that instead of *just* trying to make inference more efficient, we seek to "close the loop" on inference by making the observation process **interactive** with the inference process. This is a transition from static sensors to dynamic sensors, that can "follow the action" of the complex system, in that these sensors can dynamically station themselves at locations where target events may be anticipated. In our reasoning framework, the inference results will be used as feedback to guide the sensors to the next set of observations that would yield the most information about the uncertain attributes of the complex system. In having the observation process **react** to the needs of the inference process, we have the advantage of maximizing the utility of our sensing capabilities to selectively focus attention on the part of the system that requires the most computation or that can benefit from the greatest reduction in risk/uncertainty. This would clearly aid the inference process, which improves our general understanding of the complex system. The proposed research will have significant impact on the design of autonomous multi-agent systems, offering an efficient inferential framework and coordination between multiple agents (e.g., mobile sensors or robots) to enable them to work collaboratively in crucial applications, such as military reconnaissance, emergency search-and-rescue, hazardous environment monitoring and security protection.

2.0 Problem Definition

The proposed research addresses the quintessential problem of optimizing strategies for reasoning and information collection within the context of bounded resources—an issue that has serious ramifications across many scientific endeavors. Given fixed computational power and memory storage for only a limited amount of data, how does one decide which set of data to acquire and process, which would best benefit the scientific discovery process? The intuitive answer is to use our understanding of the complex system to hypothesize causal relationships between parts of the system, and to postulate which set of measurements would yield the most information gain about the overall system from just measuring a small but perhaps crucial part of the system. However, we cannot always expect this approach to work. As our scientific endeavors become more ambitious, we are interested in more complex and high-dimensional systems that are difficult to dissect and understand. To further exacerbate the problem, many systems are autonomous and dynamic in nature, in that the complex system may reconfigure itself or exhibit different interactions between its components as the system evolves in time. As a result, it becomes even more difficult to develop an a priori judgment of the system's structure and hidden mechanisms when deciding which set of measurements to take, because the set of relevant measurements may evolve over time as the system changes.

As daunting a challenge as this may be, while systems have become more complex, technology has somewhat kept up its pace with the development of faster computing machines and more sophisticated sensory devices. In particular, the field of mobile sensor networks [1] is a recent technological advancement that has enabled the deployment of small, inexpensive, low-power, distributed devices that have sensing, computation, communication and locomotion capabilities. This advancement opens up possibilities in our information collection process. Before the advent of mobile sensors, we were trying to understand a complex dynamic system with a limited number of static sensors that once positioned, might be cumbersome or costly to move to a different location. But with the emergence of mobile sensors, this obstacle is lifted. Mobile sensors are small and inexpensive, so we can afford to deploy more of these devices. More importantly, these sensors can move from one location to another. As the system changes, the groups of mobile sensors can reconfigure themselves in concert with the system so that the sensors can adapt their locations and even coordinate their data acquisition efforts to obtain the most informative set of measurements at all times.

In this way, mobile sensors can be used to tailor our measurement process so that our sensors can be **reactive** to perceived changes in the system. In addition, measurements can be coupled with our reasoning process, so that if we have a high degree of uncertainty about a particular part of the system, we can temporarily dispatch more mobile sensors to that given location. Consider the deployment of mobile sensors for the search of radiological dispersal devices (RDDs) hidden within an urban environment. With limited time until a RDD's detonation and/or the end of the sensors' battery life, the sensors need to work quickly to discover and neutralize the RDD. Initially, the sensors may be spatially distributed far away from one another, to increase the coverage of space being explored. As information from each sensor contributes to a hypothesis of where the RDD might be, the sensors may swarm collectively to that same location to gather more information for inference and validate the hypothesis. We will be using this example throughout this paper, because this will serve as a likely scenario that we hope can be used to validate our research efforts.

3.0 Current Work

Currently, the body of research in mobile sensor networks encompasses:

- Constrained coverage [2]: the search for deployment configurations that can maximize the collective sensor coverage while keeping each sensor within the proximity of some fixed number of neighboring sensors.
- Localization [3]: the estimation of the spatial coordinates of the sensors.
- Self-deployment [4]: automatic sensor positioning based on greedy heuristics, whereby mobile sensors are deployed one at a time, using information from previously deployed sensors to determine its optimal deployment position.

So far, the research on mobile sensor networks has focused primarily on the practical aspects of distributed deployment and localization in a static environment. Although this body of research lays the fundamental foundation for our preliminary understanding of mobile sensor networks, the current emphasis on uniform sensor coverage is rather shortsighted. In realistic situations, sensors should probably be **non-uniformly** deployed in locations where they can extract the most *useful* information, instead of simply spanning areas of uninteresting space. To enable mobile sensors to adapt to system events and to collect information from hotspots or anomalous regions whenever possible, non-uniform sensor coverage will be a key element in our sensor deployment strategies.

In addition, the current body of research neglects the rich exploratory area of teamwork possibilities, which underlie the basis for collaborative and adaptive sensors that would tremendously increase the efficacy of data acquisition for any general scientific discovery process. Instead of having each mobile sensor act as an individual entity and using its neighboring sensors only for localization, we should exploit the collaborative capabilities that **teams** of mobile sensors can offer. In working as a team, mobile sensors can share resources (e.g., computing power), compensate for individual limitations (e.g., specialized sensory capabilities) and achieve larger-scale measurement objectives more effectively. Thus, teams of collaborative mobile sensors can expand our horizons on strategic information collection, because such an infrastructure can **adapt** to our inference needs and **react** to system events.

4.0 Technical Plan

In our technical plan, the high-level objective is to optimize strategies for reasoning and information collection under the constraint of bounded resources. To satisfy this objective, the plan is to deploy teams of mobile sensors with adaptive and collaborative capabilities. However, intelligent sensor deployment is not a trivial task, as it entails much more than simply acquiring a multitude of mobile sensors. The crucial yet difficult part is the know-how that will make the sensors adaptive and collaborative. What we need is the “glue” that will bind the mobile sensors as teams and drive them to behave reactively and adaptively. This glue takes on the form of an underlying reasoning framework that can ideally:

- support efficient inference based on asynchronous measurements coming from mobile sensors at different times and spatial locations
- detect when inference can be improved by additional measurements

- recommend when and where these additional measurements should be taken and which mobile sensors should be responsible for acquiring these measurements

The focus of the proposed effort is the development of such a reasoning framework that can work concurrently with the mobile sensors, to achieve optimal information collection.

Since the mobile sensors are to be deployed in teams, it is sensible to decompose our inference in a manner that is consistent with the system structure and leverages the decomposition of the system into subsystems. In this way, each team of sensors is responsible for data acquisition over the domain of a particular subsystem and there is a natural correspondence between the way information is gathered and the way we reason about the system. Along this line of thinking, our success impinges on our abilities to meet the following challenges:

1. Given a complex system as described above, how do we decompose this system into weakly coupled subsystems, so that we can treat these subsystems as nearly independent and enable parallelization of inference with minimal loss of reasoning accuracy?
2. Since the random variables may have different dynamics and/or depend on different sets of factors at each point in time, how and when do we update this decomposition scheme?
3. Given that we have identified a near-optimal decomposition of the system into weakly coupled subsystems, how should we allocate computational resources to the reasoning of each subsystem?

To clarify our definition of systems, subsystems and variables, we return to our previous example, in which RDDs are hidden within an urban environment. Given that the RDDs are planted by terrorists, it would enhance our search if we can apply our intelligence about the terrorists to reconstruct their involvement with the RDDs. If we model the terrorist organization as a complex system, then its covert cells are the subsystems and any quantities that are relevant to its operations (e.g., risk averseness, capabilities and available resources) are variables in the system. Understanding this system can help generate hypotheses about the locations and destructive potentials of the RDDs. Specifically, we can use the decomposition of covert cells to define subproblems for our inference. By examining the activities of each cell and dispatching sensors to areas accessed by the cell's members, we can improve our chances of finding the RDDs than if we had spread our resources thin to consider the joint activities of the entire terrorist organization.

We will now explain in detail these challenges and how we plan to overcome them. First, we will choose an appropriate graphical model that can readily capture the causal relationships between variables. A standard representation for modeling temporal stochastic systems is a dynamic Bayesian network (DBN) [5]. A DBN is a graphical model with two sets of nodes, one that represent the random variables at one time step and another set representing those at the next time step. Connecting the nodes are directed arcs that indicate the flow of causality between the variables. The causality is characterized by a conditional probability distribution that makes explicit how each variable contributes to the probabilistic transition of another variable. We have found in the literature and in our own research experience that DBNs are quite effective in the modeling of temporal stochastic processes [6].

Using DBNs as the basis for representation, we will address the decomposition question (embodied in questions 1 and 2) by applying information-theoretic analysis [7] on the variables in the DBN. In particular, as the system evolves, we will routinely compute the mutual information between sets of variables to verify the fitness of our decomposition. The mutual information of two random variables measures how much the knowledge of one variable's value can reduce our uncertainty about the other variable. In fact, if we can ensure that variables within the same subsystem have high mutual information and variables across different subsystems have low mutual information, we can be confident that our decomposition scheme is indeed partitioning our system into loosely coupled subsystems, thus minimizing the approximation error induced by the decomposition. However, dynamic systems bring an additional challenge: An optimal decomposition for one time point can become ineffectual for the next. As time evolves, the system as a whole may reconfigure itself into a completely new set of subsystems. In our RDD example, we acknowledged that terrorist activities are correlated with the locations of the hidden RDDs, so it is in our interest to understand the terrorist organization. Applying decomposition, we can interpret the terrorist organization as being composed of loosely coupled covert cells (analogous to our subsystems), whose operations are nearly independent from one another. As one cell disintegrates or as cells combine forces to execute a coordinated attack, the structure of the terrorist organization is changed. Our reasoning framework will need to detect these structural events and redefine our subsystems to mirror the new composition of the covert cells. This in turn will help us update our hypotheses about the future targets for RDDs.

To maintain an optimal decomposition at *all* times, we need to adapt our DBN representation and update our decomposition scheme. We are currently involved in the active research of adaptive

DBNs [8] as part of the Predictive Knowledge Systems (PKS) Strategic Initiative and we plan to leverage this knowledge for the proposed effort. To the best of our knowledge, there has been no published work on the dynamic decomposition of static or adaptive DBNs. Thus, any theoretic or algorithmic development on this front will be completely original and constitute a significant contribution to the machine learning field.

The last question of optimal resource allocation requires a basic understanding of how we plan to proceed with the reasoning or inference. Inference involves the tracking of the state of a dynamic system and is also known as monitoring or filtering. The general idea is to maintain a probability distribution over the system state at each point in time, based on the observations obtained up to that point. This distribution is commonly referred to as the *posterior distribution*. As previously described, system decomposition into loosely coupled subsystems enables us to break down the inference task so that reasoning is performed over each subsystem, instead of the entire system, in a parallel and efficient manner. Due to the inherently parallel design of sampling algorithms, we plan to use sequential Monte Carlo (SMC) sampling [9] (also known as particle filtering) to compute the posterior distribution of each subsystem. In particular, we will be leveraging the method of factored sampling [10, 11, 12, 13], a specialized form of SMC developed by Ng et al., in the reasoning of these subsystems.

For each subsystem, SMC maintains a random set of *particles*, or realizations of the subsystem state, that as a whole can be interpreted as a histogram that can be used to approximate the true (unknown) posterior distribution. At each time step, SMC propagates these particles forward in time by applying the forward dynamics of the system to each of these particles. The resultant particles now represent realizations of the subsystem state at a new point in time. As the mobile sensors gather information about the subsystem, these observations are then used to weight the likelihood of these new particles. In essence, the observations gauge how probable each of the new realizations is, based on how well the realization agrees with the observations. These new particles are then sampled according to their likelihood weights. This is done to focus computation on the promising zones of probable state space. The particles with high weights correspond to probable scenarios and are likely to propagate into the next time step.

The computational resource involved in the SMC procedure is measured in the unit of a particle. The more particles used in the SMC procedure, the more accurate the estimate is of the true posterior distribution. In fact, in the limit of infinite particles, the SMC estimate of the posterior distribution converges *almost surely* to the true posterior distribution. As a result, the number of particles used and the resulting inference accuracy are linearly related. But the cost of each particle can differ across subsystems. A subsystem with more variables and more complex dynamics will naturally have a higher cost attributed to its particles. Hence, if all subsystems are equally important to the inference process, it may be advisable to balance out computational resources by using fewer particles on a large subsystem and more particles on a smaller subsystem, where the cost for each particle is cheaper.

However, in a dynamic system, subsystems will almost always not be considered equal. Some subsystems will have more priority, either because they represent more important parts of the physical system or they have fallen into critical states that deserve more attention. As a result, to address the last question, our plan is to "time-share" the computational resources across different subsystems, so that particles are allocated to subsystems that would benefit most from the added attention (i.e., most reduction in uncertainty) and thus, particles are not wasted on subsystems that are not in critical state or whose state did not change significantly from the last time step. The difficulty in this task lies in automating this process and having this process react intelligently to unexpected situations, which includes fast detection of when and which subsystems are in critical states and a quick means to anticipate the information gain that additional inference power may bring. Again, to the best of our knowledge, the research topic of resource allocation across different subsystems within the context of SMC is quite novel.

But resource allocation does not stop at the computational level. Optimizing information collection is crucial. Specifically, how do we deploy our mobile sensors? If the sensors have different measurement capabilities and energy consumption rates, how do we best allocate the sensors into separate teams and what type of measurements are to be taken of the subsystem? Fortunately, since the efficacy of inference is intimately tied to the quality of the data, we will gain some insights on sensor deployment from dealing with the issues that we have to face in the design of the reasoning framework. In particular, we envision that there will be analogs between the way inference is optimized and the way the sensors are to be deployed:

- It makes sense for the mobile sensors to be grouped based on the way the system is decomposed. If a given system is decomposed into three subsystems, then the mobile sensors should be split into three groups, one in charge of each subsystem. Each group then works collaboratively, independent of the other groups, to gather information that would benefit the inference process of each subsystem. As the system changes and a new decomposition is proposed for improved performance, the sensors can reconfigure themselves according to the grouping scheme as outlined in the updated decomposition.

- The same heuristics for resource allocation of computation power should apply directly to sensor deployment. The intuitive idea is to divert resources to the subsystem that would allow inference to derive the most information gain about the overall system. To achieve this, we can divert more computational resources (particles) to enable inference to be more accurate for that subsystem. A complementary approach is to further aid inference by providing additional observations, at higher resolution, that would more accurately characterize the behavior of that same subsystem. This can be accomplished by diverting more sensory resources (i.e., more mobile sensors or those with more advanced data-acquiring capabilities) to the location of interest, so that through increased observations, a better understanding of the subsystem can be achieved.

We plan on implementing our sensor deployment strategies based on these ideas.

To validate the effectiveness of our reasoning framework and to evaluate its strategies for dynamic sensor deployment, we will build a simulation platform in addition to our reasoning algorithms. As part of this simulation platform, the mobile sensors will be simulated as virtual objects with different sensory capabilities and physical/energy limitations. The virtual environment within this simulation platform will be designed to mimic an actual testbed for mobile sensors. As a first step, we will orient our simulation efforts towards the task of detecting radiological materials. We plan to consult with nuclear nonproliferation experts to identify the physical specifications of the sensors and the intelligence capabilities specific to these scenarios. Currently, we have identified two real, official-use-only data sets from a previous study of mobile detection systems for urban defense [14]. These data sets were obtained from gamma radiation detection sensors installed in moving vehicles, which has a direct analog to the mobile sensors that we are studying in this effort. We plan to utilize these data sets to augment our synthetic data and to calibrate our simulation platform in our algorithm testing. Using the nonproliferation scenarios constructed from expert knowledge and real data, we will derive results that characterize the performance of our reasoning and deployment capabilities.

5.0 Summary

We plan on maintaining a versatile design of our reasoning framework so that it can be easily tailored for use in the analyses of a wide variety of complex systems. Any complex system with the following properties should be able to benefit from the developed reasoning framework:

- High complexity: The system variables are high dimensional and the variables are coupled with one another to form intricate subsystems.
- Stochastic dynamics: The evolution of the system is non-deterministic and is subject to uncertainty.
- Changing interactions between variables: Dependencies between variables can change and manifest in different clustering of interacting variables. This is analogous to a physical system being able to reconfigure its components to form different subsystems.
- Bounded resources: The resource (e.g., battery life) available to each sensor in the system environment is well defined and any extra resource beyond this limit comes at an exorbitant cost. This point is especially relevant if the environment is hazardous to the sensors, in which the key resource becomes the amount of time the sensors can sustain within the environment.

These assumptions encapsulate a rich variety of complex dynamic systems. Many real-world systems, such as crime/terrorist networks, disease epidemics and natural science phenomena of seismology, biology, ecology and physics, are characterized by these properties. We are confident that the findings of this study will have widespread impact on resource-bounded reasoning and sensor deployment for many practical applications.

In summary, our grand vision for this effort is to develop algorithms and deliver a toolkit that enables programs to apply this methodology to actual mobile sensors and assess their field performance. For example, if a biochemical agent is released into a building through the ventilation system, our hope is that one can simply deploy a box full of mobile sensors and these mobile sensors will form into groups that would best allow them to work collaboratively to gather information about the source or the spread of the toxin, using the algorithms developed under this proposal. At the end of this effort, we are confident that these algorithms will enhance the effectiveness of important real-world applications, some of which may include:

- Wide area detection and cleanup of radiological dispersal devices
- Contaminant sampling and emergency response in nuclear fallouts

- Detection of chemical, biological and radiological releases in underground transportation systems
- Monitoring of water, air and food for intentional contamination
- Development of multi-use sensors for vehicle deployment

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