Merging Context Perspectives: An Approach to Adaptive Agent Reasoning in Pervasive Computing Systems[1]

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Abstract

In open, heterogeneous, context-aware pervasive computing systems, suitable context models and reasoning approaches are necessary to enable collaboration and distributed reasoning among agents. This paper proposes, develops and demonstrates a novel approach to perform distributed reasoning by merging and partitioning context models that represent different perspectives over the object of reasoning. We show how merging different points of view contributes to an enhanced outcome in reasoning about context.

1. Introduction

In an environment typified by complexity, openness, heterogeneity and context uncertainty, approaches to model and reason about context in a distributed manner are essential. Agents operating in such environments need to independently reason about context without always relying on centralized reasoning services. Such a view generally differs from work on having agents utilize (and possibly becoming dependent on) centralized brokers or reasoning servers. While these and similar approaches make use of the agent paradigm, performing reasoning fundamentally relies on locally centralized reasoning services. These architectures can contradict the aim of open decentralized pervasive systems and incur restrictions limiting the cases for which such approaches are appropriate. For example, when the task of reasoning cannot be shared, when entities have different access to information, or many agents limit scalability.

Consider a collection of agents servicing different users or organizations. Each agent maintains a different context model describing relevant context and situations of interest as well as reasoning goals. While these agents might be capable of reasoning about similar or identical context, their underlying description of context and sensing capabilities are potentially different. In these circumstances what one entity knows about the environment, based on sensory information it uses or has access to, can be significantly different from another entity's knowledge. Further, consider the relative point of view of each agent over the object of reasoning. Not only accessible information might be different but also the model or representation of context, based on available knowledge, can be different. Finally, uncertain conditions governing sensory originated information require agents also to cope with imposed lack of information. With only partial views of the environment agents wish to consider other trusted agents' perspectives. This calls for an ability to merge context perspectives of other agents that possess different models about the environment. When information represented in their models is missing, agents also need to update their context model to reflect their current limited view.

This paper proposes an approach to enhance context-awareness by developing distributed reasoning in cooperative context-aware multi-agent systems. We develop and demonstrate an approach enabling agents to reason about context by considering additional information available from other agents at runtime. In Section 2, we briefly describe the Context Spaces model, providing the basis for developing the proposed approach. Section 3 develops approaches to merge context models and updating models due to lack of available information. Section 4 discusses application, implementation and evaluation of our approaches. We conclude in Section 5.

2. Context Spaces Modeling and Reasoning

Context Spaces uses geometrical metaphors to describe context and situations as first-class objects of

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the model. We represent context and situations as geometrical structures in multi-dimensional space. Dimensions of the space are defined by available information types, termed *context attributes* and denoted by a_i. The value of a sensor reading at time *t* is the context-attribute's value at time *t* and is denoted by a_i^t. Situations are represented by *situation spaces* and are defined over regions of acceptable values in selected dimensions, comprising collections of values that reflect real-life situations. An acceptable region of values is denoted by A_i^j and defined as a set of elements V that satisfies a predicate P, i.e. $A_i^j = \{V | P(V)\}$. The situation space is represented by a tuple of these regions and denoted by $S_j = (A_1^j, A_2^j, ..., A_n^j)$ (consisting of *n* acceptable regions for these attributes). Every region of acceptable values A_i^j in a situation space *j* is associated with a weight $w_i^j \in [0,1]$ ($\sum_{i=1}^{n} w_i^j = 1$), representing the importance of an attribute region A_i^j relative to other regions in the situation space. Every element within a region of acceptable values is also assigned a contribution level $c \in [0,1]$. The contribution level of an element in a region reflects how well that element is associated with the modeled situation. The actual values of sensory originated information are defined by the *context state*, e.g., the collection of current sensor readings.

Given the model, the occurrence of a situation is represented by a tuple of values (i.e., the context state comprising values obtained via sensors (and perhaps some reasoning)) being within a tuple of accepted regions (i.e. the situation space representing the situation). Therefore, the multi-dimensional position of the context state in reference to a chosen situation space provides an indication for the occurrence of the real-life situation. Once sufficient accumulation of supportive indications has been reached, the occurrence of a situation can be inferred. In [1] we have proposed and evaluated with cases using real sensors an elaborate algorithm that builds upon this idea. We refer the reader to [1] for a more detailed description. Mathematically, given a context state, the reasoning procedure computes a measure of confidence in a situation space by:

(1) $\mu(S) = \sum_{i=1}^{n} w_i \cdot \Pr(\hat{a}_i^t \in A_i) \cdot c_i$ where μ is the reasoning function applied over a situation space *S*, w_i is a weight value of importance assigned to a context-attribute a_i (in *S*), c_i denotes the contribution level of the specific value of a context-attribute a_i, and the term $\Pr(\hat{a}_i^t \in A_i)$ represents the confidence of having the correct value being sensed contained within its corresponding region of acceptable values.

3. Reasoning by Merging Perspectives

We now develop approaches to merge at runtime different context models into a richer representation of modeled situations. Our objective is to combine individual context models that reflect the beliefs and capabilities of different agents into a single one.

We distinguish between two kinds of merging operations governed by different assumptions: (i) the first assume a general case where models describing some situation are very different, making use of inherently different kinds of sensory information. In such conditions our goal is to combine these models into a single model and achieve the same reasoning result as the averaged result of performing reasoning separately with each original model. (ii) in the second approach we assume that certain similarities between models exists so that by merging them into a single representation we can achieve reasoning identical to a global model, which is defined over all existing information:

(i) We combine all information from the original situation spaces into a single situation space (similar to a union operation between tables). This guarantees that no information is lost during merge. Next, we transform the weights and contribution values of the original situation spaces into the new combined situation space, as follows.

Weight transformation. *Let q_i denote the sum of weights for a region of values of the same context attribute in each original situation space. A transformed weight in the new combined situation space for context attribute i is the relative weight between q_i and the sum of the total weights. This is computed by:* (1) $\hat{w}_i = q_i / (\sum_{j=1}^{n} q_j)$, *where $\hat{w}_i$ denote the new calculated weight and n is the total number of unique context attributes.*

Contribution transformation. *Let A, B,…,N denote corresponding regions of values of the same context attribute in n original situation spaces. Let*

$w_A, w_B, ..., w_N$ denote the original weight associated with each of these regions, respectively. Let e denote an element within some of the regions A, B,…,N. Let $c_A, c_B, ..., c_N$ denote the original contribution of element e in these regions, respectively.
For each element e compute a contribution level $\bar{c}$ by:
(2) $\bar{c} = (w_A c_A + w_B c_B + ... + w_N c_N)/(w_A + w_B + ... + w_N)$

The above combination assumes that models describing the same object are defined consistently over the same type of context attribute. To reconcile between different perspectives of agents we analyze the combined context attribute of the same type. If regions of acceptable values are defined differently they are treated as different types of contextual information. For example, if two agents require the projector to be turned on to indicate a presentation activity; this would be represented with a single context attribute in the combined space. If, on the other hand, one agents requires dimmed lights to indicate the presentation and another requires total darkness (resulting from less capable sensing), then we treat these as two different requirements, each associated with its own sensory originated information.

(ii) Assuming that there exist common attributes between original situation spaces, we can do better than in approach (i). Merging models using this assumption requires that some context attributes and their corresponding regions be shared between models, such that a model built with information from all sensors can be reverse-engineered. While such approach may not always be usable, its inverse, i.e., partitioning a model into partial sub-models is always feasible and can become quite useful in pervasive scenarios. With such capability, based on a complete representation of context, a partial model consisting of all attainable relevant information can be computed at runtime. An agent reasoning about context adjusts its model based on what sensory information is available, so that the updated model only describes information of available sensory data (with recomputed weights reflecting relative importance between available attributes. This provides the most suitable description of context given a limited subset of sensed/discovered information.

Definition. *Let there be a situation space $S = \{A_i, ..., A_k, ..., A_m\}$ and partial models representing the same situation: $S' = \{A_i, ..., A_k\}$ and $S'' = \{A_i, ..., A_m\}$ with at least one shared context attribute of a region. Let $W' = \{w'_i, ..., w'_k\}$ and $W'' = \{w''_i, ..., w''_m\}$ represent the sets of weights for corresponding context attributes in S' and S'' respectively.*

Merge *- a merged situation space S would consist of the union of all regions of acceptable values between S' and S''. A weight w_i of a shared context attribute A_i can be computed by: $w_i = \dfrac{w'_i w''_i}{w''_i + w'_i \sum_{w_j \notin W'} w''_j}$, remaining weights can be computed by: $w_m = \dfrac{w_i w'_i}{w'_m}$.*

Partition *– weights for a partial model of S, consisting of a subset of regions can be computed by the relative importance of weights in S applied between weights for regions in the partial model. A weight w'_i is then computed by: $w'_i = w_i / \sum_{w_j \in W'} w_j$.*

4. Application and Evaluation

From a theoretical perspective we turn to application and evaluation. The proposed ideas promote adaptive, context-aware behavior of computing entities in a pervasive system. Using our approach, such entities not only perform reasoning about context in a 'static' manner (i.e., based only on provided information) but can enhance the reasoning process by proactively seeking and considering information from other entities, including using different perspectives over the same situation.

For evaluation, we consider the case of agents reasoning about the context of a presentation in a smart room. We simulate a variety of sensors in a smart room such as multiple numbers of light, noise and motion sensors, the status of the projector, speakers and microphone, computed number of users in the room and whether a presentation is scheduled. Data is randomly generated, roughly corresponding to the presentation activity, with associated reading errors. Estimated confidences of sensor accuracies are computed and readings suggesting activities other than a presentation are always generated (e.g., a presentation is occurring but is not scheduled, or performed only verbally without lights turned off).

Different agents have access to different sensors in the room and hold different models about the presentation activity. Some models share common context attributes while others provide descriptions based on a unique set of sensory information. Agents actively merge and partition models to reach a more reliable reasoning outcome.

Figure 1 and 2 present outcomes of reasoning about the presentation activity by agents. Figure 1 depicts results of reasoning with individual models and Figure 2 depicts results of reasoning over the merged model, achieved by collaboration between agents. For comparison, we also average the result of reasoning by individual agents, and compute reasoning results performed over a global model, considering the complete set of sensors. Figure 1 illustrates the significantly different levels of support computed for the same situation, obtained by three different agents, each using a different sub-model with different subsets of information. The averaged result reflects the optimal reasoning outcome by sharing models, given simulated faults in communication and sensors, yielding only a partial set of sensory information available for reasoning an assumption that all models equally reflect the presentation and cannot be merged into a single model.

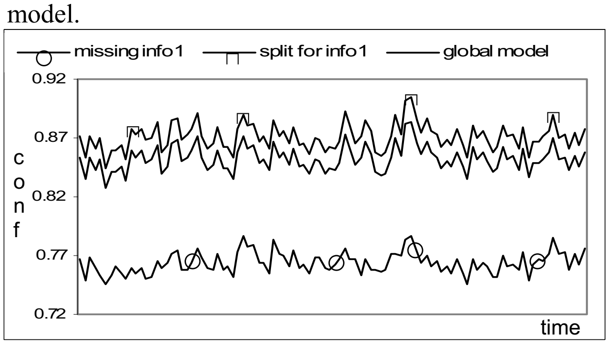

Fig. 1 – Reasoning with different models

Successful reasoning over the merged model is illustrated in Figure 2, where results obtained over the merged model are identical to averaging the results from each agent individually reasoning about the situation. Reasoning about a global model, yields different but significantly similar results to the merged model. This reflects the fact that all sub-models are more or less equally reflective of the situation.

Benefits of partitioning a model into partial representations of the situation are demonstrated in Figure 3. By using the partition operator, agents update the model describing a situation according to available sensory data. Here, we have simulated faults in communication and sensors, yielding only a partial set of sensory information available for reasoning.

Figure 3 compares reasoning with the original model with missing information and reasoning with the updated model (using partitioning). For comparison we also compute the optimal result, achieved by reasoning with the original model but with all information available (i.e. no faults). Results clearly show that outcomes of the split model are significantly closer to the optimal results. (We note that while this approach compensates the lack of available information in modeling, the confidence in the reasoning outcome is reduced since less information is used for inference.)

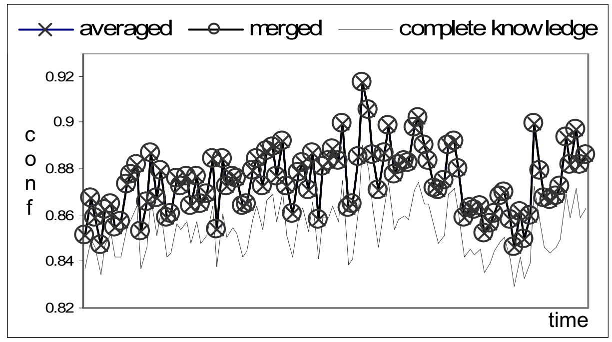

Fig. 2 – Comparing results of merging models

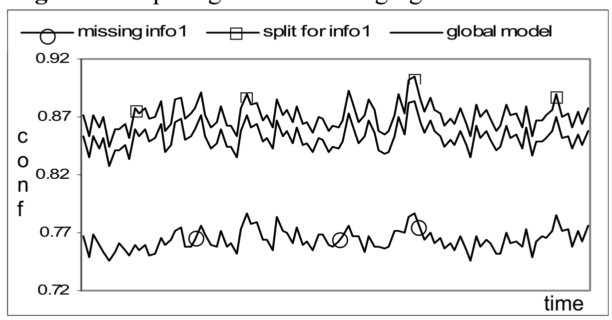

Fig. 3 –Splitting the model strengthens reasoning

6. Conclusion

We have presented an approach to push reasoning to the agents, providing means and motivation to perform collaboration and distributed reasoning. We have developed an approach to merge different perspectives of entities over situations (or objects) and partition models into partial representations to deal with lack of pertinent information.

The proposed operations are based on a novel approach to deal with context, describing context in multi-dimensional space and representing situations as geometrical structures in that space. These modeling and reasoning methods can be applied in a general way to different context scenarios and are further enhanced with operations over this representation.

7. References

[1] Padovitz A., Loke S. W., Zaslavsky A., Burg B. and Bartolini C., An approach to Data Fusion for Context Awareness, *5th International Conference on Modelling and Using Context*, Paris, France, July 2005.