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From Sensory Data to Situation Awareness – Enhanced Context Spaces Theory Approach

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Abstract—**High-level context awareness can be significantly improved by the recognition of real-life situations. The theory of context spaces is a context awareness approach that uses spatial metaphors to provide integrated mechanisms for both low-level and high-level context awareness and situation awareness. Taking context spaces theory situation awareness as a baseline, we propose and analyze the enhanced situation awareness techniques, which allow us to reason about broad class of real-life situations. We also improve reasoning about the relationships between situations, and discuss how it relates to newly proposed situation awareness approaches. Practical evaluation of the results is also discussed.**

Keywords-context awareness, situation awareness, context spaces theory, pervasive computing

I. INTRODUCTION

Context awareness is a key feature of pervasive, ubiquitous and ambient computing. For example, ambient intelligence systems (like smart homes or smart offices), social networks and micromarketing applications extensively utilize context awareness methods. High-level context awareness can be enhanced by situation awareness – the recognition of real-life situations.

Consider an example scenario. John works in the office at the construction site, and his workplace environment is at constant risk of problems: surrounding works can produce excessive noise, air might get dusty and polluted, power outages can lead to illuminance problems. In order to provision environmental conditions for his work, pervasive system needs to be aware of situations like "Light_Level_Insufficient", "Noise_Level_Too_High" or "Workplace_Environment_OK". If there are any problems, system should take corrective actions: for example, switch to backup power supplies, engage additional ventilation, close doors and windows to reduce noise. So, situation awareness is important enhancement of context awareness and backbone functionality for further decision making.

The situation from context awareness perspective can be defined as «*external semantic interpretation* of sensor data»[17]. The situation model is a method to represent a situation in a manner plausible for automated inference. The situation can be modeled as a cluster in a space of context features [12], as an entity in the ontology [7, 9, 16], as a conjunction of context properties [1], among other non-exhaustive definitions. The important features of a situation model include acceptable reasoning complexity, clarity and readability by the expert, and the flexibility to represent the wide class of real-life situations.

Context spaces theory (CST) [13, 14] is a context awareness approach that uses spatial metaphors to reason about context and situations. Using context spaces theory as a baseline, this paper proposes qualitative extension and novel situation awareness techniques that achieve flexibility, concise and clear situation representation and tractable reasoning complexity.

The paper is structured as follows. Section 2 describes the related work. Section 3 addresses the basics of context spaces theory, describes situation reasoning approach and derives the complexity evaluation for it. Section 4 provides the sample motivating scenario. Section 5 proposes and analyzes the enhanced situation awareness approaches. Section 6 contains the practical evaluation of new situation awareness methods. Section 7 provides summary, further work directions and concludes the paper.

II. RELATED WORK

Detecting real-life situations received considerable attention in context awareness research community.

The solutions presented in this paper are based on context spaces theory. The theory of context spaces was proposed by Padovitz et. al. [13, 14]. In context spaces approach the context information was viewed as a vector in multidimensional space of context attributes, and situations were viewed roughly as subspaces in that space. The paper by Delir et. al. [8] proposes fuzzy set based extension to situation definitions for context spaces theory. Comparing to the original context spaces approach, we propose more powerful situation awareness techniques that address broader class of real-life situations and significantly enhance reasoning about the relationships between situations.

Anagnostopoulos et. al. [1] proposed the situation awareness technique that inferred the situation as the conjunction of Boolean context features. This approach resembles the CST method of confidence level calculation (see section 3). However, the situation awareness methods of CST work with confidence levels, and that provides more flexibility when working with real-life situations. Moreover, CST is capable of handling unequal importance of different

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context features and, using the results of this paper, can avoid the independent contribution assumption.

The papers [2, 10, 11, 15] perform situation and activity inference using naïve Bayesian approach. Despite the seeming similarity, CST situation awareness and the Bayesian approach employ different semantics. The Bayesian approach assumes that situation either occurs or not, and estimates the probability of occurrence. Context spaces theory uses semantics of uncertainty (in particular, fuzzy logic [8] and Dempster-Schafer [13] approaches) and degree of occurrence.

Mayrhofer [12] viewed context as a vector in a multidimensional space of context features. Situations were represented as the clusters in that space. That approach enabled automated situation detection with clustering algorithms, so the method proposed in the article [12] is effective if initially the situations of interest are unknown. In addition, that solution works well if context prediction is involved. Comparing to the paper [12], our concept of situation enables more clear and more concise situation definition, as well as simpler situation reasoning. Moreover, our approach features situation algebra, which allows us to reason about relationships between situations. Context spaces approach can also integrate context prediction and acting on predicted context [3, 4] (but context prediction is out of the scope of this paper).

Papers [7, 9, 16] suggested ontology-based situation reasoning. Ontologies provide powerful solutions to represent the relationships between different situations. However, context ontologies usually do not address the level of raw sensory data, and therefore ontology-driven situation awareness requires additional complementary low-level reasoning. Comparing to ontology-based situation awareness our approach addresses all levels of context and features an integrated set of reasoning methods for both high-level context and low-level context.

III. THEORY OF CONTEXT SPACES

The context spaces theory (CST) is an integrated approach for context awareness and situation awareness. CST uses spatial metaphors to achieve clear and insightful context representation. The foundations of context spaces theory are provided in the article by Padovitz et. al. [14]. In this section we define a set of related terms that will be used throughout the paper.

A domain of values of interest is referred to as *context attribute*. Context attributes can be either measured by sensors directly, or derived from sensory data. For example, air temperature, light level, noise level, air humidity, etc. can be the context attributes for a smart office.

Context attribute can be viewed as an axis. The exact value on the axis (e.g. particular air temperature at certain time or particular light level at certain time) is referred to as *context attribute value*.

An entire set of relevant context attributes constitute a multidimensional space. This space is referred to as *application space* or *context space*.

A set of all relevant context attribute values at a certain time is referred to as a *context state*. So, a context state represents a point in the context space. Context state point is usually imprecise due to sensor uncertainty.

Situation space is designed to represent real life situation. Reasoning about the situation in original context spaces theory worked in a following manner [14]. The input data for the reasoning process is the context state. The reasoning result is a confidence level – a value within the range [0;1] , that numerically represents the confidence that the situation is occurring. Confidence level can be calculated according to formula (1).

$$\mathrm{conf}_S(X) = \sum_{i=1}^{N} w_i * \mathrm{contr}_{S,i}(x_i) \quad \textbf{(1)}$$

In formula (1) $\mathrm{conf}_S(X)$ is a confidence level for situation S at context state X, a particular context attribute within X is referred to as x_i, the importance weight of i-th context attribute is referred to as w_i (all the weights sum up to 1), the number of relevant context attributes is N, the contribution value of certain context attribute into total confidence value of the situation is referred to as $\mathrm{contr}_{S,i}(x_i)$.

Contribution function is usually a step function over certain context attribute. It can be expressed by formula (2).

$$\mathrm{contr}_{S,i}X = \begin{cases} a_1, x \in (b_1, b_2] \\ a_2, x \in (b_2, b_3] \\ \dots \\ a_{K_i}, x \in \left(b_{K_i}, b_{K_i+1}\right] \\ a_{i,default}, otherwise \end{cases} \quad \textbf{(2)}$$

In formula (2) the values a_j are the contribution values, corresponding to certain interval. If the i-th context attribute value does not correspond to any interval, $a_{i,default}$ contribution is assigned. Contribution values are within the range [0;1]. The boundaries of the intervals $(b_j, b_{j+1}]$ can be either included or excluded, as long as the intervals do not overlap with each other. The total number of intervals for all context attributes from now and on will be referred to as $P=\sum_{i=1}^{N} K_i$.

So, according to formula (1), the original CST situation implies that the total situation confidence level comprises independent contributions of various context attribute values. Independent contributions of different context attributes can be a benefit from the perspective of reasoning complexity and memory consumption. However, the independence of contributions can result in significant lack of flexibility, especially for representing the relationships between the situations. We are going to address this problem in more details in sections 4 and 5.

As a part of this work, we analyzed the complexity of original CST situation reasoning. The results are depicted in table 1. If there exist at least one interval per context attribute, it means that $P \geq N$. In practice often P>>N, and therefore the expectation is to have O(P) reasoning time – linear dependency between reasoning time and number of intervals. Practical evaluation of that claim is provided in section 6.

TABLE 1. ORIGINAL CST SITUATION REASONING COMPLEXITY

Operation	Order	Explanation
+	O(N)	Sum in formula (1) has N summands.
*	None	Sum in formula (1) has N summands. Every summand has 1 multiplication operation. However, if the weights are multiplied by corresponding contribution levels in advance, there is no need for multiplication at all.
comparison	O(P)	Consider formula (2). In the worst case K_i comparisons will be required to find the contribution level. For N context attributes the number of comparisons is $\sum_{i=1}^{N} K_i = P$.
memory	O(P)	For every context attribute situation needs to store K_i contribution values and K_i+1 interval borders and inclusion levels per every axis. That gives $O(\sum_{i=1}^{N} K_i) = O(P)$ memory consumption. The situation also needs to store N weights, but if they are applied in advance, no additional memory is needed.

In order to reason about situation relationships, original CST provides the following situation algebra operations.

1. AND: Confidence in the fact that all situations occur simultaneously.
2. OR: Confidence in the fact that at least one of the situations occurs.
3. NOT: Confidence in the fact that situation is not occurring.

Expressions (3) present the definitions of the operations.

$$\begin{aligned} &\text{AND: } confA \,\&\, B(X) = \min(confA(X), confB(X)) \\ &\text{OR: } confA \mid B(X) = \max(confA(X), confB(X)) \\ &\text{NOT: } conf!A(X) = 1 - confA(X) \end{aligned} \quad \textbf{(3)}$$

More complex situation algebra expressions can be calculated recursively, using the set of operations (3) as a basis.

IV. CST SITUATION AWARENESS CHALLENGES – MOTIVATING SCENARIO

CST situation representation provides a set of tools, useful for many practical situation awareness cases. However, when the situation relationships are involved, the capability of original CST situation definition might be insufficient.

Consider a sample scenario – a smart office that monitors the workplace environment. Smart office has a light sensor and a sound sensor deployed. Each of those sensors has a directly corresponding context attribute: respectively *LightLevel* (measured in lx) and *NoiseLevel* (measured in dB).

Consider two CST situations: *LightLevelOK* and *NoiseLevelOK*. They define respectively whether the workplace has sufficient illuminance and whether the noise level at the workplace is acceptable. Expressions (4) and (5) represent situations *LightLevelOK* and *NoiseLevelOK*.

$$LightLevelOK = \begin{cases} 0, LightLevel < 350 \\ 0.5, LightLevel \in [350,500) \\ 1, otherwise \end{cases} \quad \textbf{(4)}$$

$$NoiseLevelOK = \begin{cases} 1, NoiseLevel \leq 40 \\ 0.7, NoiseLevel \in (40,50] \\ 0.3, NoiseLevel \in (50,60] \\ 0, otherwise \end{cases} \quad \textbf{(5)}$$

A compound situation *ConditionsAcceptable* determines whether the workplace has acceptable environmental conditions for the office worker. The proposed example is simplified, so in this scenario *ConditionsAcceptable* comprises only illuminance level and noise level. We define *ConditionsAcceptable* as *LightLevelOK & NoiseLevelOK*, where AND operation is performed according to the rules of CST situation algebra, presented in formulas (3).

The construction of *ConditionsAcceptable* situation is depicted on figure 1.

In order to derive *ConditionsAcceptable*, situation algebra was applied to expressions (4) in a straightforward manner. The resulting situation *ConditionsAcceptable* is depicted in figure 2. In a formal way *ConditionsAcceptable* situation can be defined according to formula (6).

$$ConditionsAcceptable = \begin{cases} 1, (LightLevel \geq 500) \wedge (NoiseLevel \leq 40) \\ 0.7, (LightLevel \geq 500) \wedge (NoiseLevel \in [40,50)) \\ 0.5, (LightLevel \in [350,500)) \wedge (NoiseLevel \leq 50) \\ 0.3, (LightLevel \geq 350) \wedge (NoiseLevel \in [50,60)) \\ 0, (LightLevel < 350) \vee (NoiseLevel > 60) \end{cases} \quad \textbf{(6)}$$

So, *ConditionsAcceptable* can be viewed as real life situation from common sense point of view. Moreover, situation *ConditionsAcceptable* is a result of a simple situation algebra expression over original CST situations. But the distribution of confidence levels, provided in formula (6), is unrepresentable in terms of the original CST situation definition.

For the reasons of memory efficiency and reasoning complexity in original CST situations every context attribute contributes independently to the total confidence level. However, sometimes this assumption is too restrictive, especially if situation algebra is involved. For example, in this scenario *LightLevel* has zero contribution

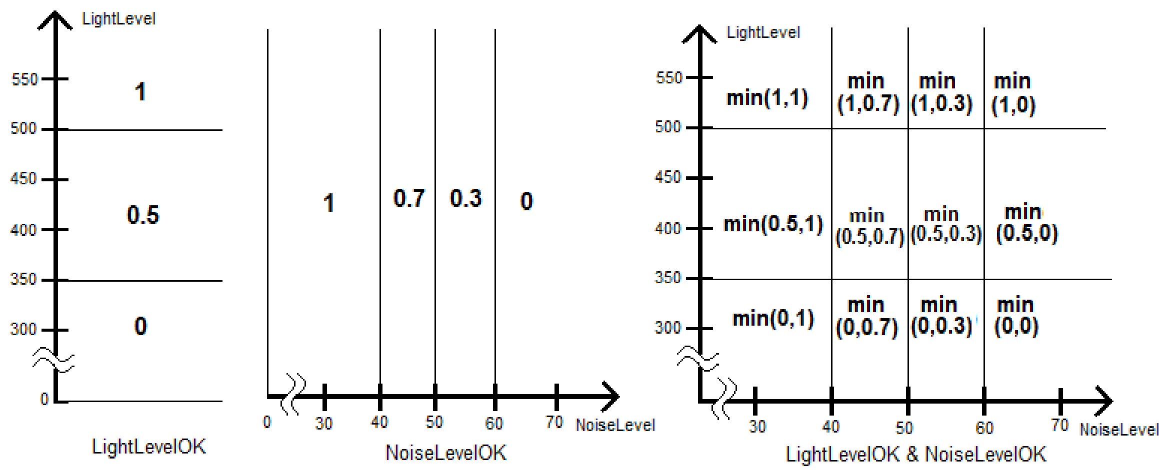

Figure 1. Constructing ConditionsAcceptable situation

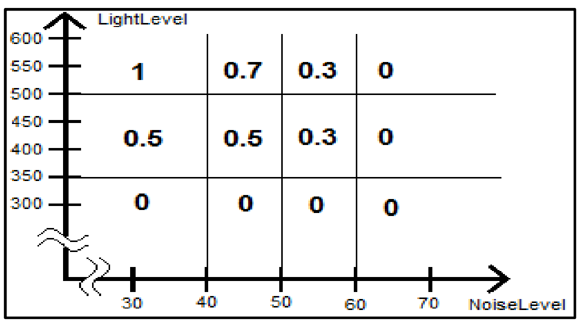

Figure 2. ConditionsAcceptable situation

to *ConditionsAcceptable* if noise level is high and non-zero contribution otherwise.

We are going to refer to that sample scenario throughout the paper.

V. ENHANCED SITUATION REPRESENTATION

In order to make situation reasoning faster and cover the broader range of possible situations, we propose additional types of situation representation.

Dense orthotope-based situation space. Consider the situation *ConditionsAcceptable* from the example scenario presented in section 4. The distribution of confidence levels for *ConditionsAcceptable* is depicted in figure 2. The structure presented in figure 2 can be straightforwardly formalized into formula (7).

$$\mathrm{ConditionsAcceptable} = \begin{cases} 0, (\mathrm{LightLevel} < 350) \land (\mathrm{NoiseLevel} \le 40) \\ 0, (\mathrm{LightLevel} < 350) \land (\mathrm{NoiseLevel} \in [40,50)) \\ 0, (\mathrm{LightLevel} < 350) \land (\mathrm{NoiseLevel} \in [50,60)) \\ 0, (\mathrm{LightLevel} < 350) \land (\mathrm{NoiseLevel} > 60) \\ 0.5, (\mathrm{LightLevel} \in [350,500)) \land (\mathrm{NoiseLevel} \le 40) \\ 0.5, (\mathrm{LightLevel} \in [350,500)) \land (\mathrm{NoiseLevel} \in [40,50)) \\ 0.3, (\mathrm{LightLevel} \in [350,500)) \land (\mathrm{NoiseLevel} \in [50,60)) \\ 0, (\mathrm{LightLevel} \in [350,500)) \land (\mathrm{NoiseLevel} > 60) \\ 1, (\mathrm{LightLevel} \ge 500) \land (\mathrm{NoiseLevel} \le 40) \\ 0.7, (\mathrm{LightLevel} \ge 500) \land (\mathrm{NoiseLevel} \in [40,50)) \\ 0.3, (\mathrm{LightLevel} \ge 500) \land (\mathrm{NoiseLevel} \in [50,60)) \\ 0, (\mathrm{LightLevel} \ge 500) \land (\mathrm{NoiseLevel} > 60) \end{cases} \quad (7)$$

Original CST situation space uses separate contribution levels for every interval of every context attribute. In order to achieve more flexibility, a separate confidence level can be defined for every combination of context attribute intervals. Every row of formula (7) is a Cartesian product of intervals, and thus defines an orthotope [5]. Orthotopes are the basis of situation awareness improvements proposed in this paper.

By definition an orthotope is a Cartesian product of intervals [5]. So, for example, one dimensional orthotope is a line segment, two dimensional orthotope is a rectangle, three dimensional orthotope is rectangular parallelepiped. The example orthotope is provided on figure 3.

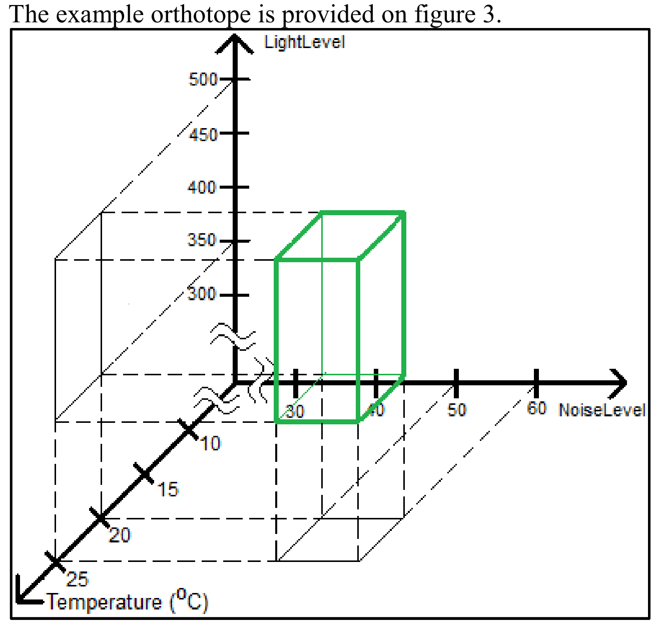

Figure 3. An orthotope corresponding to intervals [20;25] on temperature axis, [50;60] on NoiseLevel axis and [350;500] on LightLevel axis.

In formula (7) the orthotopes densely cover (tesselate) the entire application space, so that any context state belongs to some orthotope. Therefore, this kind of situation representation is referred to as *dense orthotope-based situation space*.

Formal definition of generic dense orthotope-based situation space can be represented as follows. Consider that there are N context attributes involved in the situation. For the situation *ConditionsAcceptable* from the sample scenario, N=2 (*LightLevel* and *NoiseLevel*). Without the loss of generality, we can consider that the relevant context attributes correspond to positions *1...N* in the context state vector. Let *LightLevel* and *NoiseLevel* be the values number 1 and 2 in the vector respectively. The number of intervals, defined over *i-th* context attribute, is referred to as r_i. In the sample scenario, $r_1 = 3$ and $r_2 = 4$. The boundaries of i-th interval for j-th context attribute are referred to as $low_{j,i}$ and $high_{j,i}$. Every boundary of every interval can be either included or excluded, as long as every possible context state is included in one and only one orthotope. We define the total number of orthotopes as $L = \prod_{i=1}^{N} r_i$. For *ConditionsAcceptable* situation L=12. The total number of involved intervals is referred to as $R=\sum_{i=1}^{L} r_i$. For *ConditionsAcceptable* situation R=7.

Dense orthotope-based situation space is defined according to formula (8).

conf(X) =

$$\begin{cases} a_1, (x_1 \in [low_{1,1}, high_{1,1}]) \wedge \ldots \wedge (x_N \in [low_{N,1}, high_{N,1}]) \\ a_2, (x_1 \in [low_{1,1}, high_{1,1}]) \wedge \ldots \wedge (x_N \in [low_{N,2}, high_{N,2}]) \\ \ldots \\ a_L, (x_1 \in [low_{1,r_1}, high_{1,r_1}]) \wedge \ldots \wedge (x_N \in [low_{N,r_N}, high_{N,r_N}]) \end{cases} \quad \textbf{(8)}$$

For every involved context attribute the set of intervals should cover the entire set of possible context attribute values. Also for every involved context attribute the intervals should not overlap with each other.

Table 2 presents reasoning complexity analysis for dense orthotope-based situation spaces. Table 2 shows that reasoning complexity is O(R). This claim is practically tested in section 6. Also table 2 shows that the major drawback of this situation representation is high memory consumption. In practice reasoning about orthotope-based situation space is done using decision trees. Pruning the decision tree is a way to improve both memory consumption and reasoning time. The exact potential benefit of decision tree pruning is a subject of future work.

In order to improve memory consumption while retaining the flexibility, we developed another kind of situation representation.

Sparse orthotope-based situation space. Consider the situation *ConditionsAcceptable,* defined in the sample scenario in section 4. Formula (7) was derived by straightforward formalization of figure 2. But it is clearly visible that formula (7) is redundant, and formula (6) represents *ConditionsAcceptable* situation in a much more concise manner. Formula (6) can be derived from formula (7) by merging the neighboring orthotopes, if those orthotopes have the same associated confidence level. Situation algebra operators, presented in formulas (3), make it likely that the adjacent orthotopes will share the confidence level.

Formula (6) can be even further simplified, and the situation *ConditionsAcceptable* can be defined according to formula (9) or figure 4.

ConditionsAcceptable=

$$= \begin{cases} 1, LightLevel \geq 500 \wedge NoiseLevel \leq 40 \\ 0.7, LightLevel \geq 500 \wedge NoiseLevel \in [40,50) \\ 0.5, LightLevel \in [350,500) \wedge NoiseLevel \leq 50 \\ 0.3, LightLevel \geq 350 \wedge NoiseLevel \in [50,60) \\ 0, otherwise \end{cases} \quad \textbf{(9)}$$

In formula (9) the entire situation space is defined as a set of orthotopes in the context space, and each orthotopes is assigned a confidence level. But in contrast with dense orthotope-based situation space, the orthotopes are sparsely scattered throughout the context space, and the default confidence level is associated with the context state that do not belong to any orthotope. This kind of situation representation is referred to as *sparse orthotope-based situation space*.

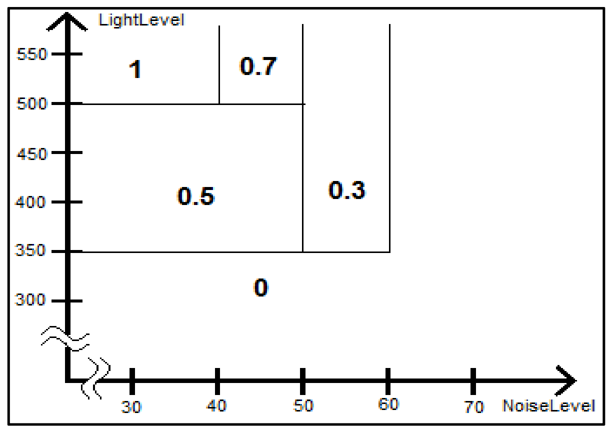

Figure 4. ConditionsAcceptable situation – simplified

Generic sparse orthotope-based situation space can be formally defined as follows. Consider that situation space is defined over N context attributes. Without the loss of generality, we can consider that the relevant context attributes correspond to positions *1...N* in the context state vector. For the situation *ConditionsAcceptable*, similarly to dense orthotope-based situation representation, N=2 (*LightLevel* and *NoiseLevel*). Let *LightLevel* and *NoiseLevel* be the values number 1 and 2 in the context state vector respectively. The number of orthotopes is referred to as Q. For the situation *ConditionsAcceptable* Q=4. Every orthotope is defined over N context attributes and contains one interval for each context attribute. Let the boundaries of i-th orthotope for j-th context attribute be $low_{j,i}$ and $high_{j,i}$. Every boundary of every orthotope can be either included or excluded, as long as orthotopes do not overlap.

Sparse orthotope-based situation space can be defined according to formula (10).

conf(X) =

$$\begin{cases} a_1, (x_1 \in [low_{1,1}, high_{1,1}]) \wedge \ldots \wedge (x_N \in [low_{1,N}, high_{1,N}]) \\ a_2, (x_1 \in [low_{2,1}, high_{2,1}]) \wedge \ldots \wedge (x_N \in [low_{2,N}, high_{2,N}]) \\ \ldots \\ a_Q, (x_1 \in [low_{Q,1}, high_{Q,1}]) \wedge \ldots \wedge (x_N \in [low_{Q,N}, high_{Q,N}]) \\ a_{default}, otherwise \end{cases} \quad \textbf{(10)}$$

TABLE 2. REASONING OVER DENSE ORTHOTOPE-BASED SITUATION SPACES

Operation	Order	Explanation
comparison	O(R)	In the worst case the proper interval will be encountered the last for every axis. In that case r_i interval inclusion tests will be performed for every context attribute, and it will result in $\sum_{i=1}^{L} r_i$ =R total comparisons.
memory	O(L+R)	Confidence level for every cell needs to be stored, as well as all the boundaries.

TABLE 3. REASONING OVER SPARSE ORTHOTOPE-BASED SITUATION SPACES

Operation	Order	Explanation
comparison	O(Q*N)	At most N interval inclusion checks are required for each of Q orthotopes.
memory	O(Q*N)	Situation space stores Q contribution levels and Q*N interval boundaries. The total order is O(Q*N).

We performed complexity analysis for reasoning over sparse orthotope-based situation spaces. The results are given in table 3 and some necessary explanations are provided below.

Comparing to dense orthotope-based situation space, sparse orthotope-based situation space often represents situations in more clear and concise manner, and yet provides the same level of flexibility. Transitioning from dense to sparse orthotope-based situation space might improve memory consumption and reasoning time, but it depends on how many neighboring orthotopes share the same confidence level.

Situations of different types can be combined in the same application space and, moreover, different kinds of situation spaces can be combined in situation algebra expressions without altering the original concepts of CST situation algebra. Mixed situation spaces that have the features of original CST situation spaces on high level and dense orthotope-based or sparse orthotope-based situation spaces on low level are the subject of future work (see section 7).

Practical evaluation of different situation representation techniques is presented in section 6.

VI. REASONING COMPLEXITY EVALUATION

The theoretical evaluation of situation inference complexity is presented in section 3 and section 5 (particularly, in table 1, table 2 and table 3). In this section we will address the practical aspects of situation reasoning.

Original situation space. Figure 5 shows testing results of ECSTRA reasoning for original context spaces theory situation space. Every point of the plot is the testing results for randomly generated situation. Abscissa contains the number of intervals for the situation (value *P*), and ordinate contains the average reasoning time in milliseconds. We generated 60000 random situations. For every situation the total number of intervals was chosen from [1;60] range uniformly. The distribution of intervals between context attributes was generated uniformly. The reasoning was performed at 1000 random context states for every situation. The result of every experiment is the average reasoning time.

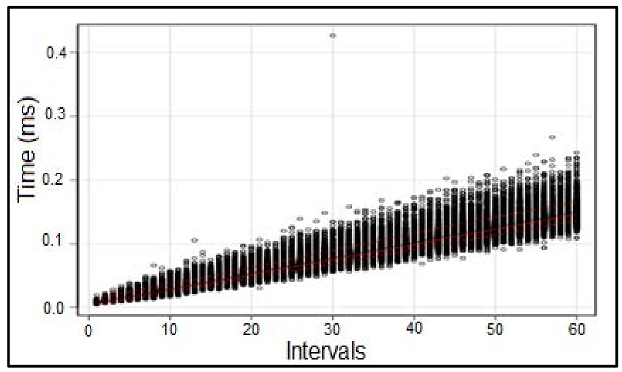

Figure 5. Situation Reasoning Time – Original CST Definition

The plot on figure 5 has visible heteroscedasticity, and it can obscure the results and mislead the analysis. The reason for heteroscedasticity is following: for any situation with *P* involved intervals, if *P=N* (one interval per axis) there are *P* inevitable interval inclusion checks. It is the worst case for a situation. In the best case there are *P/2* interval inclusion checks in average: if *N*=1 the number of comparisons varies from 1 to *P* with average at *P*/2. So the expected lower border and upper border are linear, with the upper border around twice higher than the lower border. And that is visible on figure 5.

In order to have reliable estimations in presence of heteroscedasticity, we used the weighted regression technique. We used the method suggested, for example, in [4]. In addition we took the advantage of discrete explanatory variable, which allowed us to have variance estimations for every relevant point on abscissa. Regression analysis was performed using R [18] statistical software. The testing have shown that R^2 coefficient of weighted regression is equal to 96.18%, which shows good fit and practically proves the claims about linear algorithm complexity.

Dense orthotope-based situation space. The experiment settings for dense orthotope-based situation reasoning evaluation were similar to those for original CST situation reasoning evaluation. We generated 60000 random situations, where every situation contained up to 40 intervals.

The testing results are presented on figure 6. The abscissa contains *R* – the number of involved intervals, while the ordinate contains average reasoning time in milliseconds.

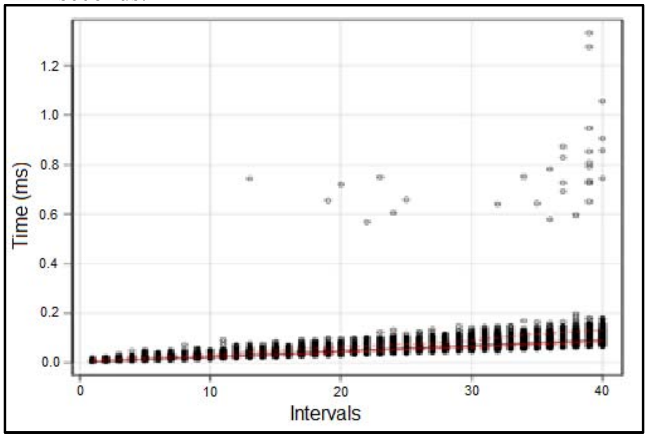

Figure 6. Situation Reasoning Time - Dense Orthotope-based Situation Space

In order to prove linear trend, we performed regression analysis over testing results. To overcome heteroscedasticity weighted regression technique was used. R^2 coefficient is 0.87, and it shows good fit and practically proves linear dependency between reasoning time and total number of intervals.

Sparse orthotope-based situation space. Figure 7 contains evaluation results for reasoning over sparse orthotope-based situations. The experiment settings were similar to the experiments for evaluating original CST situation space and dense orthotope-based situation space. Test engine generated 60000 random situations with up to 60 intervals.

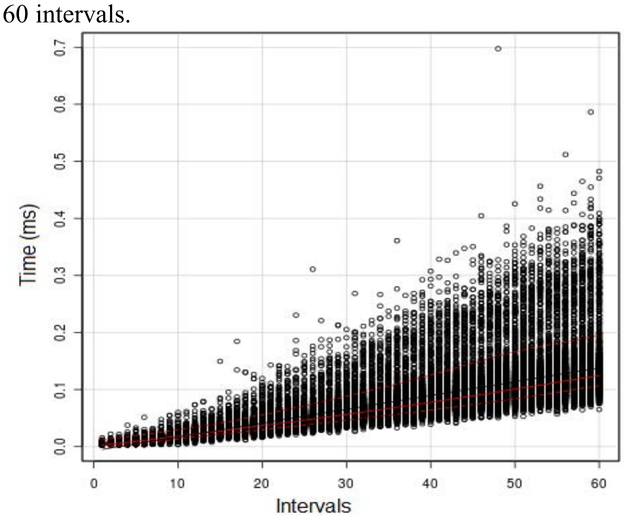

Figure 7. Situation Reasoning Time - Sparse Orthotope-Based Situation Space

Figure 7 shows clearly visible heteroscedasticity. The reasons for heteroscedasticity are quite similar comparing to other experiments, but the features of situation representation introduce more variability in reasoning time. In order to analyze the data in presence of heteroscedasticity, we employed weighted regression technique. R^2 coefficient is 0.82, and it practically proves the linear trend.

To summarize, for all three mentioned situation representations, theoretical claims about reasoning complexity were proven practically. In addition, for all situation definitions the testing results showed heteroscedasticity: with growing explanatory variable, the variability of reasoning time grows as well. It makes reasoning time less predictable when the number of involved intervals increases.

VII. SUMMARY AND FUTURE WORK

In this paper we addressed the problem of situation awareness and made significant improvement to the situation awareness technique based on context spaces approach. Taking context spaces theory as a baseline, we developed enhanced situation awareness techniques that can address the broad class of real-life situations and reason about situation relationships in more efficient manner. The increasing flexibility of situation representation enables more versatile situation awareness, better generalization of context information and more intelligent decision making.

We consider the following directions of further work in situation awareness area:

- **Mixed situation representation.** Situation space can be defined by combining the elements of original, sparse orthotope-based and dense orthotope-based situation spaces. However, in order to construct mixed situation space, we need to identify which context attributes have mutually dependent contributions.
- **Automated situation space definition.** Situations in CST are currently defined manually. This process can be cumbersome and prone to errors. Existing knowledge bases (e.g. ontologies of the subject area) might already have the necessary information to generate the situations, and extracting the situations from knowledge bases can eliminate the need for manual work.
- **Run-time situation inference.** Situations of interest can as well be unclear during the system startup. Identifying the areas of context space that are likely to be the situations of interest is a subject of future work. For example, it can be achieved by clustering context states history.
- **Situation awareness in absence of information.** Due to the sensor uncertainty and unreliability, the sensory data can become erroneous or missing. The goal of situation aware system is to retain as much situation awareness capability as possible in these circumstances.
- **Context prediction and proactive adaptation.** Some papers addressed the problem of context prediction and acting on predicted context in context spaces theory [3, 4], but still there is a large room for improvements in the field. In particular, situation awareness advancements can enhance situation prediction area.

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