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Reduced Context Consistency Diagrams for Resolving Inconsistent Data

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Abstract

The ability of pervasive context-aware systems to perform efficiently relies on their ability to gather full and unambiguous information about the environment. But raw data collected from sensors is often noisy, imprecise and corrupted, which leads to inconsistencies and conflicts in gathered data. Also environment is only partially observable, thus allowing ambiguities in the knowledge about its state. In the paper we present reduced context consistency diagrams (RCCD), data structures that allow to store the information about the environment even with the presence of inconsistencies, conflicts, and ambiguities. We provide a mechanism for reasoning about the current situation using these diagrams, and show how to obtain information about the most probable situation at each moment of time. The case study shows the 50% reduction in incorrect sensor readings. The evaluation shows RCCD to be applicable to real-time context inference problems.

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1. Introduction

Pervasive context-aware systems become increasingly more complex and penetrate our daily life in forms of smart environments [13], context-aware applications on mobile devices, context aware autonomous systems, etc. The ability of such systems to perform efficiently fully relies on the ability to obtain the most detailed, specific, and correct information about the environment.

However, before high-level applications may use the information to make the appropriate decisions and adjust their behavior, several steps are required to obtain the information in a proper form. First of all, raw sensor readings should be gathered by a system's middleware from surrounding sensors. Then they should be pre-processed, converted to a logical form, and combined together to obtain an image of the current environment. Afterwards the information should be converted to a form, understandable by a high-level application.

Unfortunately, several challenges arise during this process. The sensors are often noisy, imprecise, and their readings are easily corrupted, which may lead to inconsistencies and conflicts in gathered data. Also, the full information about the environment is practically impossible to obtain. Some portions of the environment can not be physically read by given technology, and there is always something happening that sensors miss to detect, e.g. the study by Jeffery et al. [12] showed that in dynamic environments the percentage of correctly read RFID tags may drop down to 60-70%. Another issue of sensor readings gathering is that information becomes obsolete rapidly. The data that was correct at the time of reading may be already obsolete when it reaches the system middleware and gets processed. The asynchronous nature of sensor readings leads to alterations in the order of readings arrival to the middleware. Finally, the automated processing of sensor readings to an interpretation of the environment may introduce errors by itself. The classical examples of such errors are image recognition mistakes.

In the presence of a conflict among sensor readings, the conventional research [5, 20] suggests to discard

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one of the readings that is deemed as incorrect one based on some heuristic strategy. Different heuristics are proposed, among which the removal based on relative frequency [5], drop-latest, drop-oldest, drop-all, or drop-random [20] strategies.

Such a removal is usually done as soon as a conflicting sensor reading is received, to keep the full interpretation of an environment without conflicts. The removal of sensor readings in an ambiguous situation may, however, cause even more problems, in case the correct sensor reading is removed instead of an incorrect one. The more cautious approach that removes all conflicting sensor readings, may drastically reduce the available amount of information, which is used by high-level applications to make decisions.

In [6] we introduced originally context consistency diagrams (CCD), which are capable of storing all gathered information, and define several possible context interpretations in a presence of a conflict or an ambiguity, either because of incomplete knowledge about the environment, or because of erroneous sensor readings. If all the information is kept, further sensor readings help to refine the knowledge and make more informed decisions about the correctness of certain sensor readings. In this paper we extend a notion of CCD and introduce a reduced context consistency diagram (RCCD) for dealing with inconsistent and incomplete data, which severely reduces the resulting diagram size comparing to the original full CCD. The CCD and RCCD are capable of storing all the information without discarding anything, even if the data has conflicts. RCCD, while having a less extensive querying capabilities than CCD, requires much less computational and storage power. Pervasive systems can implement either CCD or RCCD mechanism to deal with ambiguous or conflicting context data.

The rest of the paper is organized as follows. Section 2 overviews a proposed architecture of a context-aware system with implemented CCD or RCCD functionality. In Section 3 we formally define *environment* and an information about it in a form of different *contexts*. Section 4 introduces CCD. RCCDs are introduced in Section 5, and their respective maintenance is described in Section 6. Section 7 shows querying capabilities of RCCD, and describes a way to obtain useful information about the state of environment out of them. In Section 8 we present some complexity considerations over CCD and RCCD, and in Section 9 we perform a case study and evaluate performance of RCCD. Section 10 discusses the related work. Finally, in Section 11 we provide our concluding remarks.

2. System overview

In this section we describe a system that collects raw sensor readings and interprets them to create an image of the environment. A high-level overview of the proposed system architecture is shown in Figure 1.

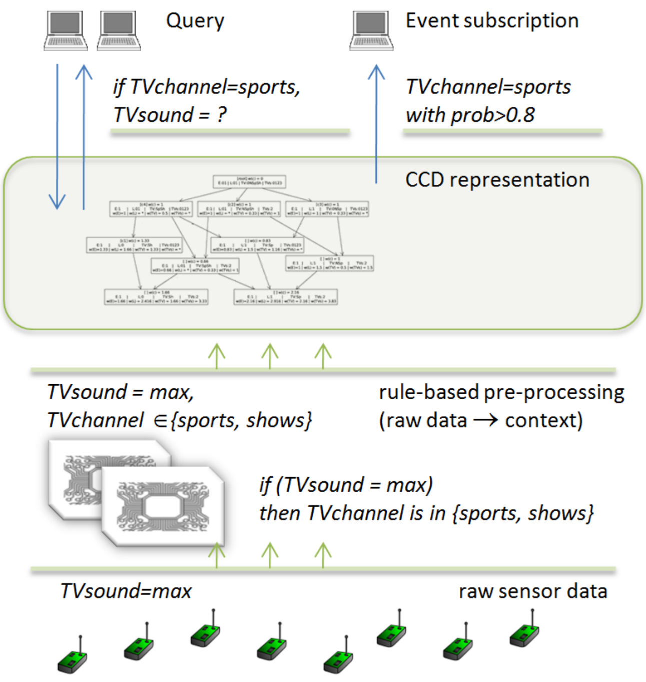


Figure 1. Context reasoning using CCD.

At the bottom level the sensors read the state of certain entities and pass it to the system's middleware. Readings can be of different nature, with the most common being a stream of '$variable = value$' pairs, for example $TVchannel = sports$. Also ranges of values can be given, if a sensor is imprecise. After the system obtains this raw sensor data, a rule-based pre-processing is performed. The rules define the interdependence of variable among each other, and the limitations that one variable value puts on other variables. The pre-processing transforms a raw data into a context information. For example, as shown in Figure 1, a rule ($TVsound = max \implies TVchannel \in \{sports, shows\}$) is applied to a sensed value ($TVsound = max$). The resulting pre-processed context ($TVsound = max, TVchannel \in \{sports, shows\}$) is then passed to a context subsystem, which is shown in the figure as "CCD representation" layer. This layer will be described in details in further sections. The CCD (or RCCD) structure is responsible for efficient storage of acquired context information, resolving inconsistencies, answering to queries, or triggering events to the subscribed top-level applications. CCD allows efficient representation of acquired context information together with all possible context inconsistencies and interpretations. CCD is considered *inconsistent*, if there is no single interpretation that is confirmed by all sensed (and then pre-processed) data. Ideally, conflicts caused by a failed sensor or by data expiration should not stop the system from providing the best possible interpretation for the acquired context information. Several techniques exist to resolve an ambiguous conflict in favor of one interpretation. But if the resolution is incorrect, further interpretations of a situation will also be wrong, even if further information may show that another solution was preferable.

To deal with this, CCD keeps several interpretations, each with its own probability of being true. We associate a likelihood of being true to each acquired chunk of data. Whenever chunks "support" each other (there is an interpretation of a situation that is consistent with all of them), their mutual truth likelihood is higher comparing to the conflicting ones. Additionally, each arrived and pre-processed information shares a certain degree of truth likelihood, thus compensating the effect of a faulty sensor over the inferred information received from that particular sensor. The most probable interpretation is then the one that is "supported" by the majority of consistent contexts. Even if a particular context does not support the most "popular" interpretation, it is still stored in a CCD. It might happen that with the acquisition of new data, the context is considered more likely, if the new data supports it. With such a structure the context interpretation is never final, as new data may change the interpretation by contributing to an interpretation previously considered wrong.

High-level applications can use CCD layer for obtaining different information about the environment. One of such possible usages is querying. Among the queries that CCD supports are "What is the most probable situation at this moment of time?", "What are the probable values of a certain variable?" (For example, in Figure 1: "What are probable values of TV channel?"), "Assuming certain additional information, what are the probable values of a certain variable?" (For example, "Assuming TV channel is 'sports', what is the probability distribution of TV sound values?"), etc.

Another possible usage of CCD layer is *event subscription*, which commonly appears in a form "Notify as soon as a certain situation happens with a certain probability." (For example, "Notify in case TV channel is 'sports' with probability more than 0.8.")

3. Environment and context

A server that collects raw data (pre-processing layer in Figure 1) obtains information from the underlying layer in a form $v_i = d_{ij}$, i.e., a variable v_i has a value d_{ij}. It is possible that the sensors return a set of values, i.e., $v_i \in \{d_{ij_1}, d_{ij_2}\}$. For example, a location variable may be sensed by a sensor (e.g. RFID) that is known to be imprecise.

Definition 1 (Environment). An *environment* $\langle V, D\rangle$ is defined by a set of context variables $V = \{v_1, v_2, ..., v_n\}$. Each variable v_i varies over a domain $D_i = \{d_{i1}, d_{i2}, ..., d_{im_i}\}$ with size m_i.

Many variables either cannot be directly observed, or can only be partially sensed. If the heating mechanism is broken, we can sense that the heater is turned on, but we cannot observe if it actually started to heat the room, unless we have a reliable temperature sensor. Fortunately, many variables influence each other. For example, it is impossible to have a light turned on, if there is no electricity in the house; a location of a person and of the tool that she works with must be the same, etc. If these correlations are taken into account, even a few observed variables may give an overall, yet possibly incomplete, knowledge about the environment.

Definition 2 (Context, Interpretation). For a given environment $\langle V, D\rangle$, a *context* c is a valuation of all variables in V with a non-empty subset D^c of D. If all variables v_i are assigned one and only one specific value in D_i, a context is called an *interpretation*.

Non-emptiness ensures that a context is always possible in practice, i.e. each variable has at least one possible value.

We represent a context by enumerating its possible context variables values: $D_0^c, \ldots, D_n^c$, or, alternatively, as $v_0 \in \{d_{0l}, \ldots, d_{0k}\}$. We write $c.v_i$ to refer to i-th variable of context c.

Our knowledge about an environment is described by a set of contexts $c_0, \ldots, c_n$. If for any two interpretations x, y s.t. $\forall c_i : x \in c_i \wedge y \in c_i$, it follows that $x = y$, then we have *complete* and *unambiguous* knowledge about the given environment.

More than one interpretation represents an ambiguity or incomplete knowledge of the environment. Intuitively, each new sensor reading adds some more knowledge about the environment, thus it reduces the number of possible interpretations. Faulty contexts can be detected when an impossible situation is created, i.e. when there is no interpretation x, s.t. $\forall c_i : x \in c_i$.

For example, in Table 1a a portion of a smart home is modelled by 4 variables. In Table 1b, few preprocessing rules are defined that represent the interrelation between the context variables. Note though, that it is not important how these rules are defined, as far as they result in a context information shown in Table 1c. The first two rules represent basic physical laws: there must be electricity in the house for the light and TV to be turned on, and the TV volume must be higher than null if the TV is turned on; and the third rule is set specifically by a smart house's resident: if the channel is set to TV 'shows,' the room's light should be turned off. Using these rules, from a reading that the light is on, we infer that the electricity is on, and if the TV is on as well, the channel is definitely not 'shows.'

Table 1. Example of environment and context creation.

(**a**) Variables.

Variable	Domain
Electricity	off, on
Light	off, on
TV	off, news, sports, shows
TV sound	0, 1, 2, 3

(**b**) Dependency rules.

$\neg(E = off \wedge (L = on \vee \neg(TV = off)))$	Light and TV can be turned on only if electricity is on.
$\neg(TV = off \wedge TVs \in \{1, 2, 3\})$	Non-silent TV sound means TV is turned on.
$TV = shows \Rightarrow L = off$	If TV channel is ‘shows’, light should be turned off.

(**c**) Sensor readings and contexts.

ID	Sensor reading	Context
c_1	$TV = Sh$	$E:1 \mid L:0 \mid TV:Sh \mid TVs:0123$
c_2	$TVs = 2$	$E:1 \mid L:01 \mid TV:NSpSh \mid TVs:2$
c_3	$L = 1$	$E:1 \mid L:1 \mid TV:0NSp \mid TVs:0123$
c_4	$TV \in \{Sp, Sh\}$	$E:1 \mid L:01 \mid TV:SpSh \mid TVs:0123$

A set of contexts $C = \{c_k\}$ is *consistent* if there exist at least one interpretation $x : x.v_i = d_{ij_i}, \forall i \in 1..n$ such that $d_{ij_i} \in c_k.v_i$, $\forall c_k \in C$, $\forall i \in 1..n$. A set of contexts is *inconsistent* otherwise.

Additionally, we define two relations over contexts:

Inclusion: $c_1 \subset c_2$ iff $\forall i \in 1..n :\ c_1.v_i \subset c_2.v_i$ Inclusion can be viewed as a relation of a more precise and less precise contexts. If $c_1 \subset c_2$ then context c_1 is more precise, than c_2, in other words, each variable of c_1 contains less values that are possible.

Intersection: $c_u = \bigcap_{j=1}^{k} c_j = c_1 \cap c_2 ... \cap c_k$ iff $\forall i \in 1..n :$ $c_u.v_i = c_1.v_i \cap c_2.v_i ... \cap c_k.v_i$ An intersection of inconsistent contexts always equals to $\varnothing$. An intersection of consistent contexts is a context, that is at least as precise, that any of the originals: $\forall j \in 1..k\ \ c_u \subseteq c_j$.

4. Context consistency diagram

To compactly represent all possible interpretations for a given set of contexts, we use relations defined in the previous section, thus forming a diagram with arrows representing inclusion relation. Any two contexts c_i, c_j are connected in the diagram, if $c_i \subset c_j$, and there is no such c_k, so that $c_i \subset c_k \subset c_j$.

The idea of putting contexts into the diagram structure is essentially an introduction of a compact representation of all possible interpretations of the environment. The “full domain” context is always at the top, meaning “no information is received; any situation is possible.” Starting from the top and going down, contexts become more and more restrictive, with the most restrictive (as well as the most knowledgeable) contexts at the bottom. Formally, CCD is defined as follows:

Definition 3 (Context consistency diagram (CCD)). Given an environment $\langle V, D\rangle$ and a set of contexts $C_0 = \{c_k\}$, $k \in 1..N$, a *context consistency diagram (CCD)* is a tuple $G = \langle C, E, r\rangle$, where:

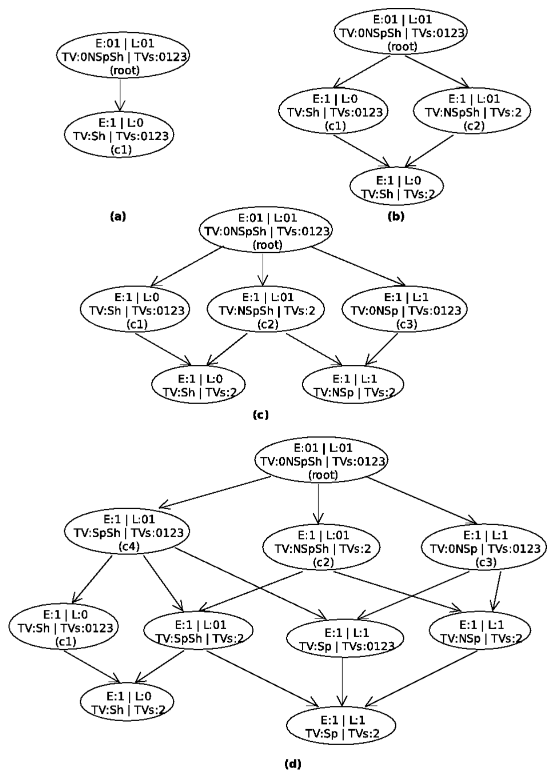


Figure 2. Example of context consistency diagrams.

- $r = D$, is a special context, the *root;*
- $C = C_0 \cup C_u \cup r$ where C_u is the full set of intersections of a power set of C_0;
- $E \subseteq C \times C$, such that $(c_2, c_1) \in E$ iff $\exists c_1, c_2 \in C :$ $c_1 \subset c_2$ and $\nexists c_m \in C : c_1 \subset c_m \subset c_2$.

Contexts from a set C are vertices of the diagram and E is a set of directed edges. In a relationship $(c_1, c_2) \in E$, c_1 is called a **parent**, and c_2 is called a **child**. c_p is called a **predecessor** of c_c, and, respectively, c_c is called a **descendant** of c_p if either of the following holds:

1. $(c_p, c_c) \in E$
2. $\exists \{c_i\} \in C, i \in 1..k \; s.t. \; (c_p, c_1) \in E \wedge (c_k, c_c) \in E \wedge (c_i, c_{i+1}) \in E, \forall i \in 1..k-1$

We write $\psi(c)$ to denote the full set of descendants of c and $\Psi(c)$ to denote the full set of predecessors of c.

For a set $C_0 = \{c_1, c_2, c_3\}$, the corresponding set of intersections of its power set is equal to $C_u = \{c_1 \cap c_2, c_1 \cap c_3, c_2 \cap c_3, c_1 \cap c_2 \cap c_3\}$.

For a set of contexts listed in Table 1c the corresponding CCD is shown on Figure 2.

In [6] we describe in details the characteristics of the CCD, its properties, and algorithms for maintaining the CCD in real time.

5. Reduced context consistency diagram

While CCD provides a full picture of the information together with existing inconsistencies, it is a verbose structure that shows all the possibilities of environment knowledge explicitly, thus at the expence of computational and storage power.

For this we devised the way to reduce a classic CCD, while still keeping the knowledge about existing inconsistencies intact. The reduced context consistency diagram (RCCD) uses the fact that some of those nodes that are not received from sensor readings, but are created as intermediate ones, are combined together to create a more knowledgeable common descendant. If this is the case, those intermediate nodes can be truncated from the diagram, while still keeping the information about the most probable situation.

For example, in the case, described in Figure 3a a full CCD is shown for the following three contexts:

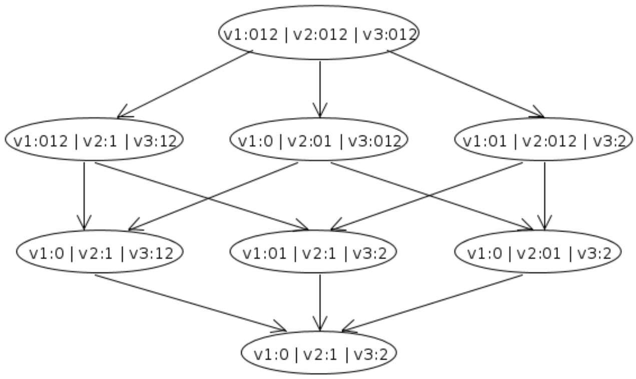
$$c_1 = (v_1 \in (0,1,2);\; v_2 = 1;\; v_3 \in (1,2))$$

$$c_2 = (v_1 = 0;\; v_2 \in (0,1);\; v_3 \in (0,1,2))$$

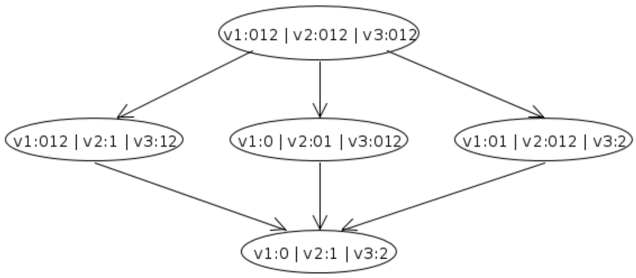
$$c_3 = (v_1 \in (0,1);\; v_2 \in (0,1,2);\; v_3 = 2)$$

However, the three generated nodes of the second tier can be reduced, as they all are combined in the more knowledgeable context $(v_1 = 0; \quad v_2 = 1; \quad v_3 = 2)$. The corresponding reduced CCD is shown in Figure 3b.

Notice that the RCCD may reduce only nodes that were not originally obtained from sensor readings (in other words, those nodes that do not belong to C_0 group and do not have associated initial weight $w_0(c)$). In the same example, the full CCD will be exactly the same as reduced CCD (both as shown in Figure 3a) in case we also receive three more sensor readings that account for



(**a**) Full CCD of three contexts



(**b**) Reduced CCD of the same contexts

Figure 3. Example of a full CCD (a) and a corresponding reduced CCD (b)

the following contexts:

$$c_4 = (v_1 = 0;\; v_2 = 1;\; v_3 \in (1,2))$$

$$c_5 = (v_1 \in (0,1);\; v_2 = 1;\; v_3 = 2)$$

$$c_6 = (v_1 = 0;\; v_2 \in (0,1);\; v_3 = 2)$$

The formal definition of RCCD goes as follows:

Definition 4 (Reduced context consistency diagram (RCCD)). Given an environment $\langle V, D \rangle$ and a set of contexts $C_0 = \{c_k\},\; k \in 1..N$, a *reduced context consistency diagram (RCCD)* is a tuple $G_r = \langle C, E, r \rangle$, where:

- $r = D$, is a special context, the *root*;
- $C = C_0 \cup C_r \cup r$ where C_r is defined as $C_r = \bigcup c_p \in C_u \backslash (C_0 \cup r) \; s.t. \; \nexists c_c \in C_u \cup C_0 : \; (c_c \subset c_p))$
- $E \subseteq C \times C$, such that $(c_2, c_1) \in E$ iff $\exists c_1, c_2 \in C : c_1 \subset c_2$ and $\nexists c_m \in C : c_1 \subset c_m \subset c_2$.

The only difference with the Definition 3 of CCD is the definition of a context set C, which, however, drastically changes the resulting diagram.

To describe properties of the RCCD we split the contexts of the CCD into the two categories: solid and non-solid. A set of **solid** contexts C_s consists of the root and all contexts out of the original context set C_0. **Non-solid** contexts C_{ns} are all the contexts out of a full set of intersection of a power set C_u that are not included into a solid set (thus that are not among original contexts).

$$C_s = C_0 \cup r \tag{1}$$

$$C_{ns} = C \backslash C_s \tag{2}$$

As in CCD, vertices of the RCCD include all the solid contexts. However, unlike in CCD, where all non-solid contexts are also kept, in RCCD they are kept in the diagram only in case they are the most knowledgeable contexts.

This leads us to the first property of the RCCD:

Property 1. All non-solid nodes of RCCD do not have children.

Proof. If a node $c \in C$ has a child, then by the definition of a context set C, this node may not be the part of C_r, because $\forall c \in C_r : \nexists c_c \in C_u \cup C_0 : (c_c \subset c))$. From facts that $C = C_0 \cup C_r \cup r$, and $c \in C$, but $c \notin C_r$, follows that $c \in C_0 \cup r$, and by definition of a solid node from equation 1, c must be solid. Thus if a node of RCCD has a child, it is always a solid node. Thus non-solid nodes do not have children. □

The second property of RCCD is:

Property 2. If all nodes with children of a full CCD are part of the original context set C_0, then a corresponding reduced CCD is equal to the full CCD.

Proof. Solid nodes $C_0 \cup r$ are always part of both CCD and RCCD context sets, thus only non-solid nodes differ. We are given that all nodes of CCD with children are in C_0 set, thus for the remaining nodes the following holds:

$$\forall c \in C_u \backslash (C_0 \cup r) : \nexists c_c \in C_u \cup C_0 : \ (c_c \subset c))$$

which is exactly the definition of corresponding C_r from RCCD. So

$$\forall c \in C_u \backslash (C_0 \cup r) : c \in C_r$$

or

$$C_u \backslash (C_0 \cup r) = C_r$$

Thus,

$$C^{full} = C_u \cup C_0 \cup r = (C_u \backslash (C_0 \cup r)) \cup C_0 \cup r =$$

$$= C_r \cup C_0 \cup r = C^{reduced}$$

The fact that $C^{full} = C^{reduced}$ also means that $E^{full} = E^{reduced}$ by definition of edges construction. So CCD and RCCD under the given conditions are equal. □

All the original properties of CCD also hold for RCCD. Those are:

Property 3. For a given set of contexts there is one and only one non-isomorphic representation of its RCCD.

Property 4. The order of contexts addition does not change the resulting RCCD.

Property 5. Adding and then removing a context does not change the resulting RCCD.

The proof of these three properties for RCCD is exactly the same as for CCD and is presented in [6].

6. RCCD maintenance

In this section we present algorithms to add and remove a context to the RCCD.

Algorithm 1 Adding context to RCCD

function AddContext($context, parent, weight$)
if $\exists ch \in parent.children$ *s.t.* $ch = context$ **then**
  $W_0(ch) \leftarrow W_0(ch) + weight$
  exit
else if $\exists child \in parent.children.nonsolid$ s.t. $context \subset child$ **then**
  $\forall child$:Move parents from $child$ to $context$
else if $\exists child \in parent.children.solid$ s.t. $context \subset child$ **then**
  $\forall child$:AddContext($context, child, weight$)
else
  CheckChildren($context, parent$)
  Add link from $parent$ to $context$
end if

function CheckChildren($context, node$):**boolean**
$result \leftarrow false$
for all $child \in node.children$ **do**
  if $child \subset context$ **then**
    if $node$ is a parent of $context$ **then**
      Remove link from $node$ to $child$
    end if
    Add $child$ to $context$ as descendant
    $result \leftarrow true$
  else if $isConsistent(context, child)$ **then**
    $x \leftarrow context \cap child$
    if $\neg isSolid(child)$ **then**
      Move parents from $child$ to x
      Add link from $context$ to x
      $result \leftarrow true$
    else if $\neg CheckChildren(context, child)$ **then**
      Add link from $context$ to x
      Add link from $child$ to x
    end if
  end if
end for
return $result$

The addition of a new context to the RCCD is shown in Algorithm 1. The algorithm is split on two parts:

AddContext recursively searches predecessors of the *context* to find its parents, i.e. contexts, to which the new context should be added as a child. As soon as those parents are found, the second part, *CheckChildren*, recursively checks if a *context* is consistent with its brothers, and a child should be generated.

The first part, *AddContext*, checks if a *parent* is a parent of a *context*. It starts by checking if there is a child of a *parent*, equal to the *context*. If this is the case, a corresponding weight is added to the initial weight of a child, and algorithm finishes its work.

Otherwise it checks, if there are any non-solid children of a *parent* that are more general, than a *context*. In this case all the parents of such children are moved and become parents of a *context*. Note that this effectively deletes those children from the diagram, because they do not have parents anymore and non-solid nodes never have their own children.

If no suitable children are found yet, the algorithm checks, if there are solid children of a parent that are more general than a *context*. In case they are found, the algorithm repeats recursively for them.

Otherwise we found a parent of a *context*. Second part of the algorithm, *CheckChildren*, is then called, and a *parent* adds a *context* as a child.

CheckChildren function receives two nodes as input, a *context*, which is a newly added to the diagram node, and another *node*, for which we suspect that its children may be consistent with a *context*. We process all the children of the *node* in the following manner:

If a *child* is included into a *context*, we add it as a descendant to a *context*, and remove it as a child from *node*, in case a *context* is already a child of a *node*.

Otherwise we check for consistency of a *context* and a *child*. If they are consistent, and a *child* is non-solid, we remove it from the diagram, and put an intersection of a *child* and *context* in its place. We also add a link from a *context* to the new node.

If a child is solid, however, we check, if there is already (or should be created) a common descendant between a *child* and a *context* by calling *CheckChildren* recursively on those nodes. If it returns negative result, we add a new node (their intersection) to the diagram, by adding it as a child to a *context* and a *child*.

Algorithm 2 describes the removal of an outdated context from RCCD.

First of all, the context can only be removed in case the context becomes non-solid after reducing the initial weight by the amount, corresponding to the outdated sensor reading. I.e. in case there are no more other sensor readings that support this context.

If a *context* has children, we first remove a link from context parents to it, and than add links from context parents to its children, connecting them directly.

After this, on lines 14-20 we check non-solid children of a *context*, or a context itself in the absence of children, for the maximum generality. That means that each such *node* should stay on the diagram only if it still has more than one parent, and if the intersection of all its current parents is exactly equal to a *node*. It may be the case that after the removal of a parent, a non-solid *node* is now less general, than it should be. In this case we create a new node x, which is the intersection of all its current parents, and move all the parents of a *node* to x, effectively removing a *node* from the diagram.

Algorithm 2 Removing context from RCCD

1: **function** RemoveContext($context, weight$)
2: $W_0(context) = W_0(context) - weight$
3: **if** $W_0(context) = 0$ **then**
4:   **if** *context* has children **then**
5:     **for all** $parent \in context.parents$ **do**
6:       Remove link from *parent* to *context*
7:       Add all *context.children* to *parent* as descendants
8:     **end for**
9:     $nodes \leftarrow context.children.nonsolid$
10:     Remove links from *context* to all its *children*
11:   **else**
12:     $nodes \leftarrow context$
13:   **end if**
14:   **for all** $node \leftarrow nodes$ **do**
15:     $x \leftarrow \bigcap node.parents$
16:     **if** $x \neq node$ & $\nexists brth \in node.brothers$ s.t. $brth \subset x$ **then**
17:       Add link from all *node.parents* to x
18:       Remove links from all *node.parents* to *node*
19:     **end if**
20:   **end for**
21: **end if**

7. RCCD reasoning

In [6] we describe a way to calculate probabilities of all the interpretations possible using CCD. The method is applicable and very useful in situations, where sensor readings are highly erroneous, so system must account for interpretations that are second- or third- most probable. The RCCD can not be used for these kinds of queries, because second-, third-, etc. most probable interpretations are often reduced in favor of the single, the most probable one. However, RCCD is capable of answering to the question “What is the most probable situation at this moment of time?”. To prove this, we use the fact that the most probable situation is always the one among the most knowledgeable situations, i.e. those that do not have children. Indeed, let’s assume that a context that contains a most probable situation has a child. A child is always more knowledgeable than a parent, in other words it contains a subset of interpretations that a parent contains. As a child has its own weight, only those interpretations of a parent that are also contained in a child gain this additional weight. Which by itself means that they become more probable, than the others. So, we proved that the interpretations, contained in a child, will always be more probable, than interpretations of a parent, which are not contained in any of its children. Which means that the most probable interpretation of a situation is always the one among nodes with no children.

RCCD by the definition 4 never reduces nodes that do not have children, so they are always present on a diagram. Moreover, all the initial weights from original contexts are also transferred to these nodes, and all the consistency among original nodes is kept, as the way of inheriting nodes in RCCD is the same, as in CCD. Due to these facts the most probable interpretation has the biggest weight among all interpretations. The probability calculation, presented in [6] still can be used in RCCD for finding the most probable interpretation.

As well as CCD, RCCD never discards any information from sensors, and if the most probable interpretation changes with the arrival of a new context, the RCCD immediately catches this change.

7.1. Unfolding of RCCD to CCD

The previous subsection shows that for systems that are mostly concerned with a question "What is the most probable situation at this moment of time?" the RCCD is a more preferable choice of a diagram, than CCD. However, even for such systems sometimes there are cases when additional information about other possible situations or conditional probabilities are important to know. Fortunately, the choice of RCCD over CCD does not permanently hinders the ability to obtain the answers to these queries. We present an Algorithm 3 that allows to unfold a RCCD to obtain a full CCD.

The function $UnfoldNode$ will be called for every node of the diagram. At the beginning of the algorithm the $queue$ contains all the most knowledgeable nodes (described by $RCCD.lastnodes$), i.e. nodes that do not have children. In other words, the algorithm unfolds nodes from the bottom to the top. The last node to be unfolded is always the $root$.

$UnfoldNode$ is called either for all, or for a subset of node parents. When a node is polled from a $queue$, the function is always called for all node parents, but later it can be recursively called for a subset of them. The function checks if there is only one parent among the input $parents$. If it is the case, it checks, if all the children of a parent are already marked, and if it is the case, it adds a $parent$ to the $queue$. If there are more than one parent in $parents$ subset, the function tries to remove a single parent from this subset one by one, and checks, if the remaining parents can create a more general consistent child x, than a $node$. If it is the case,

Algorithm 3 Unfold RCCD to CCD

```
function UnfoldRCCD
queue ← RCCD.lastnodes
while queue is not empty do
    node ← queue.poll()
    UnfoldNode(node, node.parents)
end while

function UnfoldNode(node,parents)
Mark node
if parents.size = 1 then
    if parents(0).children are marked then
        queue.add(parents(0))
    else
        for all par ∈ parents do
            x ← ⋂(parents\par)
            if x ≠ node then
                for all parent ∈ parents\par do
                    Remove link from parent to node
                    for all child ∈ parent.children do
                        if child ⊂ x then
                            Remove link from parent to child
                            Add link from x to child
                        else if isConsistent(x, child) then
                            y ← x ∩ child
                            Add y as descendant to child
                            Add link from x to y
                        end if
                    end for
                    Add link from parent to x
                end for
                Add link from x to node
                queue.add(x)
            else
                UnfoldNode(node,parents\par))
            end if
        end for
    end if
end if
```

the link from all such parents to the $node$ is removed, and x is added as a child to them instead. Also each parent checks, if it has other children that either should now be the children of x (in this case the link from $parent$ to $child$ is removed, and a link from x to $child$ is added instead), or that have a consistent child y with x (y is than added as descendant to both $child$ and x in this case). After this is done, the link from x to $node$ is added, and a new node x is put to the queue.

8. CCD vs RCCD complexity

Explicit description of different interpretations in a CCD can potentially grow in space exponentially with the number of distinct contexts in the original set.

However, there are several considerations that help to keep the size of a CCD reasonable.

The biggest growth of a CCD results from faulty contexts. While correct contexts tend to have the same descendants, faulty contexts will generate many new CCD nodes. With a growth of a CCD, one may discard contexts that support the most unlikely interpretations, as most probably they represent faulty or imprecise sensors.

Each environment in a CCD should only contain interdependent variables (i.e. associated by dependency rules, as in Table 1b). We split independent variables on non-intersecting subgroups and produce a smaller CCD for each subgroup.

RCCD, on the other hand, produces a much smaller diagram. First of all, notice that RCCD does not generate new nodes, unless they are the most knowledgeable. In case all the contexts are correct, the maximum number of nodes in RCCD will be $N_c + 2$, where N_c is the number of distinct nodes in the original context set, and the number 2 corresponds to the *root* and a possibly generated single child. The child is single, because if all contexts are correct, they are all consistent with each other, thus they all have the same the most knowledgeable descendant.

Each erroneous context potentially adds N_v new children (alternative “most knowledgeable” nodes), one per each variable, where N_v is the number of variables. Thus with the presence of erroneous contexts the maximum number of nodes in RCCD is equal to $N_c + N_v * N_{err} + 2$, where N_{err} - number of erroneous contexts. Notice that normally we assume a situation, where $N_{err} \ll N_c$, thus we expect small sizes of RCCD in practice. If this is not the case, with bigger numbers of errors the RCCD size will grow as well.

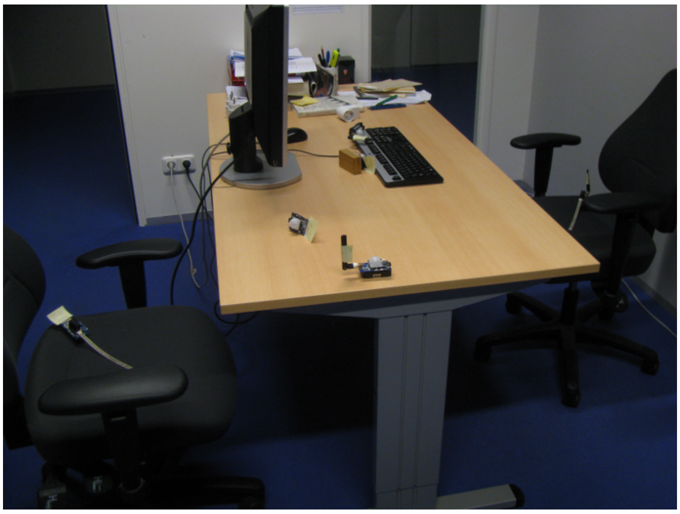
9. Evaluation

Our evaluation section is split on two parts. First, in Section 9.1 we show a sample run of the system and discuss it in details. Second, in Section 9.2 we make a general overview of system’s performance based on several experiments, and study the dependence of system’s performance on different system parameters.

9.1. Case study

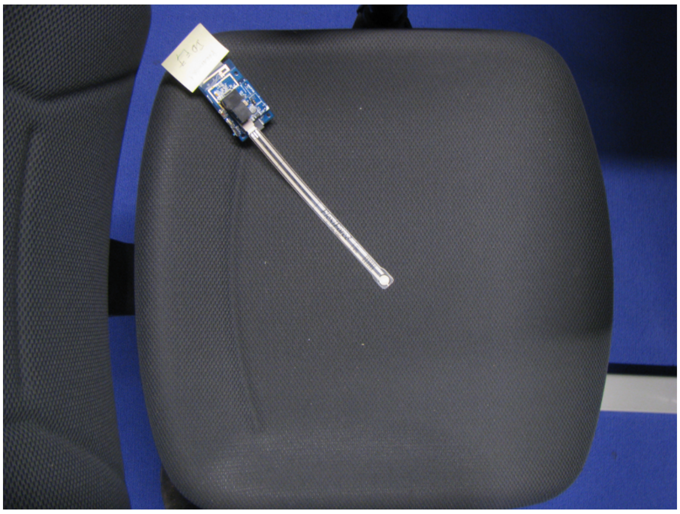
To evaluate the system in real conditions we performed an experiment with several sensors. The setup of the experiment can be seen in Figure 4.

We used six sensors altogether: 2 acoustic sensors, 2 PIR motion sensors, and 2 pressure sensors. The sensors are produced by Advantic Systems [1]. They are IEEE 802.15.4 compliant wireless sensors that use open-source “TelosB” platform [17]. All sensors are equipped with ultra low-power 16bit microcontroller



(**a**) General view on the experimental place.

(**b**) Acoustic and PIR motion sensors.



(**c**) Pressure sensor.

Figure 4. System’s experimental setup

MSP430. The pressure sensor uses the Tekscan® A201-100 FlexiForce® sensor, which provides force and load measurements for both static and dynamic forces (up to 100lb or 400N). The Passive InfraRed (PIR) motion sensor uses the Perkin Elmer Optoelectronics® LHI878 sensor to detect motion in the given direction. The SE1000 acoustic sensor has a mini-microphone (20-16000 Hz, SNR 58 dB) that is designed to detect the presence of sound. All sensors were configured to measure intensity of corresponding signals and thresholds were applied to readouts of each sensor in order to return a higher-level boolean value (presence or absence of sound/motion/pressure) once every second. The data was then sent to the RCCD structure, which in turn returned the current most probable situation.

Figure 4a shows the general placement of the sensors. The setup shows the office of a single person and the idea of using such sensors is to be able to recognize a current activity of a person. Among those activities we assume work with or without PC, meeting with another person, or absence from the working desk. While each of sensors occasionally produces faulty readings, their mutual dependencies that we described in terms of rules, help RCCD to recognize the correct situation.

First we describe, what each sensor is aimed to recognize, then we describe their mutual interdependecies, and afterwards we will show the results of the experimental run of such a system.

Sensors description. **Pressure sensor 1** (PR_1) is located on a chair of the main person in front of the PC, and is triggered if someone is sitting on this chair.

Pressure sensor 2 (PR_2) is located on a "guest" chair, and is triggered if someone is sitting on it.

Acoustic sensor 1 (AC_1) is placed near the keyboard and is aimed to detect the sound of keys pressing, in order to recognize the typing activity.

Acoustic sensor 2 (AC_2) is a general acoustic sensor that is aimed to recognize a sound in a room. It is placed in between the two chairs, because the sound usually means the conversation between the two people.

We want to note that keyboard typing, while triggering sound recognition on AC_1, is not loud enough to trigger sound recognition on AC_2, thus AC_2 remains silent in this case. However, when two people are speaking with each other, both acoustic sensors detect sound. So we can only definitely recognize the keyboard typing when AC_2 is silent, while AC_1 is detecting sound.

PIR motion sensor 1 (M_1) is directed exactly at the front of the PC (looking directly at the first chair), and is aimed to detect any motion in this direction. The sensor gives us additional source of information, and can help to recognize the innacuracies of other relevant sensors.

PIR motion sensor 2 (M_2) is looking directly at the guest chair, and is aimed to detect any motion on or around this chair. This sensor as well gives us additional source of information, and can help to recognize the innacuracies of other relevant sensors.

Interdependencies rules. As already noted, sensors in our case study have common dependencies. For example, when AC_2 is detecting sound, AC_1 is also detecting sound (but not the other way around). When a person is sitting in a chair, both pressure PR_1 and motion M_1 sensors will detect activity. These and other dependies we capture by creating the following rules:

"Pressure implies motion." Both motion sensors are directed exactly on the chairs, and located very closely to it. When someone is sitting on a chair, in most cases the motion sensors detect small motions of a person in it. We help our system to detect the faulty readings of no motion by adding these two rules:

$$PR_1 \implies M_1 \tag{3}$$

$$PR_2 \implies M_2 \tag{4}$$

"Who is typing, if no one is there?" If we detect no motion, and no pressure from the chair in front of the PC, and there is no general sound in the room, the keyboard acoustic sensor should also remain silent. Thus the third rule:

$$\neg PR_1 \land \neg M_1 \land \neg AC_2 \implies \neg AC_1 \tag{5}$$

Note that given the rule 3, we can cancel out the variable PR_1 from this formula. However, we prefer to keep it in this format both for ostensive purposes and for each rule to remain completely independent from other rules.

"I heard something. Did you hear it?" The first acoustic sensor is placed very close to keyboard in order to detect soft noise of keyboard typing, which second sensor is unable to detect. The second sensor, however, placed just in the middle of the meeting area, in order to detect all loud noises in the room, the most common noise being human speech. The first sensor is able to detect all those loud noises also, which means it should always be triggered when the second acoustic sensor detects something:

$$AC_2 \implies AC_1 \tag{6}$$

"Room is busy." If we detect sound on keyboard acoustic sensor, and a motion in general area, but not on the chair in front of the PC, it means the sound comes from somewhere else in the room, so the second acoustic sensor should also be able to detect it.

$$AC_1 \land M_2 \land \neg M_1 \implies AC_2 \tag{7}$$

System's run. We did an experimental run of the system with the abovementioned setup, to see how RCCD is able to detect the correct situation. The system was collecting data for thirty minutes, during which the situation was the following:

Table 2. Experiment results

Sensor	Number of errors			Error rate,%			% of errors fixed		
	Latest	Averaged	RCCD	Latest	Averaged	RCCD	Latest	Averaged	RCCD
M1	631	563	77	35.06	31.28	4.28	0.0	10.78	87.80
PR1	270	259	274	15.00	14.39	15.22	0.0	4.07	-1.48
AC1	398	336	314	22.11	18.67	17.44	0.0	15.58	21.11
M2	132	116	11	7.33	6.44	0.61	0.0	12.12	91.67
PR2	18	8	9	1.00	0.44	0.50	0.0	55.56	50.00
AC2	160	126	123	8.89	7.00	6.83	0.0	21.25	23.13
Total	1609	1408	808	14.90	13.04	7.48	0.0	12.49	49.78

1. For the first 10 minutes the person was working with the computer. Thus the expected correct values of sensors would be:

   $M_1 = true$; $PR_1 = true$; $AC_1 = true$;
   $M_2 = false$; $PR_2 = false$; $AC_2 = false$

2. Then the short meeting with another person was held for 5 minutes. The expected values are:

   $M_1 = true$; $PR_1 = true$; $AC_1 = true$;
   $M_2 = true$; $PR_2 = true$; $AC_2 = true$

3. After this the person was reading papers silently for 10 minutes. Corresponding expected sensor values:

   $M_1 = true$; $PR_1 = true$; $AC_1 = false$;
   $M_2 = false$; $PR_2 = false$; $AC_2 = false$

4. Last 5 minutes the room was empty:

   $M_1 = false$; $PR_1 = false$; $AC_1 = false$;
   $M_2 = false$; $PR_2 = false$; $AC_2 = false$

Results. Now we present the results that we obtained from the run. The experiment was running for 30 minutes, with sensors sending their readings each second. The lifetime of sensor readings is set to 5 seconds, so for each sensor we have 5 latest readings that are still to be considered. This is done in order to smooth the readings, as many sensors occasionally return incorrect readings (e.g. for a motion sensor it is common to return sequences such as “1; 2868; 2852; 1; 1; 2861; 2853”, where high values indicate movement, and 1 indicates no movement).

We compared the results of three possible sensors interpretations: first interpretation always takes the latest sensor reading and considers it correct; second one takes all readings with valid lifetime and chooses the most common (average) value; third one uses RCCD in order to find the expected correct sensor readings.

The results can be seen in Table 2. All sensors were returning faulty readings from time to time, with M1 sensor being the least reliable (35% of erroneous readings), and PR2 sensor being the most reliable with only 1% of readings being erroneous. While averaging the value of sensors over their lifetime helped to reduce a number of erroneous sensors reading by 12.49%, the usage of RCCD to get the most probable situation reduced the number of errors for 49.78%, going from 1609 total erroroneous readings, to just 808.

Table 3. Times seen each number of correct sensors

Correct sensors	Latest	Averaged	RCCD
0	0	0	0
1	2	1	0
2	11	1	1
3	89	54	44
4	303	262	151
5	682	713	370
6	713	769	1234

The more important metric, however, is not just the total number or erroneous readings, but the total number of times, when the situation was detected correctly. The correctly recognized situation is the one where we know the correct values of all sensors. In our case we update our knowledge about the environment each second, and the situation is detected correctly, if we are able to detect the correct state of all six sensors during this second. Table 3 shows the total number of times when certain amount of sensors was detected correctly. As can be seen, at no point were all six sensors giving the wrong data, but there were at least two moments, when only one out of six sensors was providing the correct data (both of which RCCD was able to detect and fix), etc. The number of times, when the situation was detected fully correctly by latest sensor readings, was 713 (thus sensors were fully correct 39.61% of the total time). Averaging sensor reading didn’t help much, with 769 number of times (thus providing fully correct readings 42.72% of the total time). RCCD, however, was able to detect the fully correct situation 1234 number of times, which accounts for 68.56% of the total time, and is a considerably higher and better value.

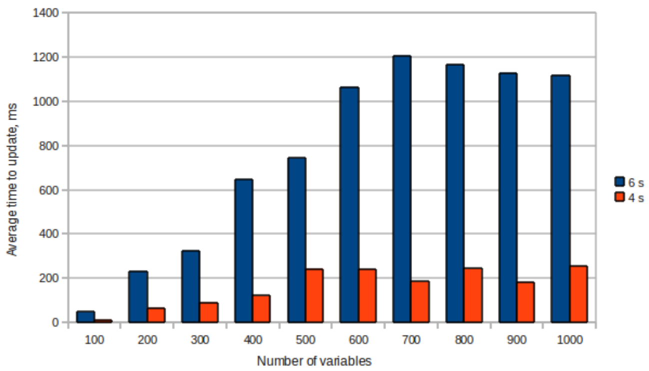


Figure 5. Dependence of update time on number of sensors.

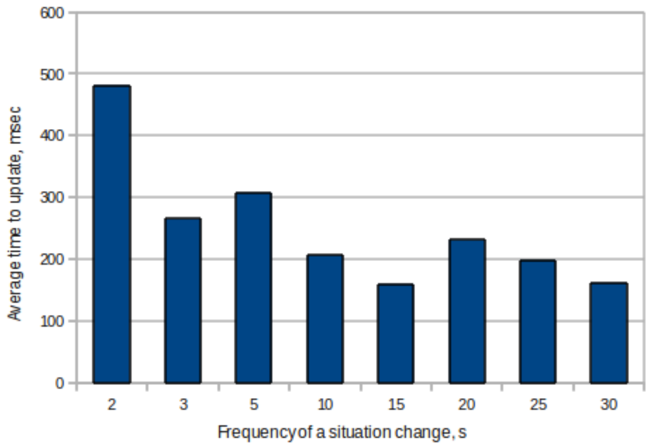


Figure 6. Dependence of update time on frequency of a situation change.

9.2. Performance

In this chapter we describe, how the system's performance depends on parameters of a system. The experiments are performed on a Intel Core2Duo P7370 2GHz PC with 3 GB RAM running OS Ubuntu 10.04. The software is written in Java JDK 1.6. The simulated test environment consists of a test generation part that generates situation and contexts, and a middleware part that collects contexts and maintains a diagram.

The most important among all the parameters is the size of an environment, which is described by a number of sensors, or variables. We performed several experiments with the same parameters, while varying the number of sensors. The context arrival rate is set to 0.01 seconds; context lifetime is set to 4 seconds in the first experiment, and 6 seconds in the second. The test generation part creates a situation. Contexts are generated based on it with a 5% error rate and are sent to the middleware part. The results can be seen in Figure 5. As can be seen in this figure, the average time needed to update a RCCD with each new context increases linearly with the increasing of sensors number, until it reaches some point (in this case 700 variables), after which the time remains on a same level. This can be explained by a fact that while environments are relatively small, the increase in the environment size leads to an increase in RCCD number of nodes. However, for a certain context arrival rate and a certain context lifetime there is a certain maximum number of contexts that are usually present on a diagram simultaneously. When new contexts arrive, old contexts are removed, so the number stays on the same level. If the environment is big enough, this maximum level is reached, and beyond this the RCCD will not grow, even if environment has bigger size. Increasing the context arrival rate, or context lifetime, on the other hand, may increase this threshold. To prove it we did the same experiments, but used the context lifetime 4 seconds instead of 6 seconds, so there was generally a smaller number of contexts on a diagram. As you can see in the Figure 5, the threshold was reached with smaller environment, around 500 variables, for the smaller context lifetime with the same arrival rate.

The last but not the least important parameter is the dynamicity of environment, in other words the rate at which the situation changes. We performed several experiment with the same parameters, while changing only the frequency of situation alteration. The results can be seen in Figure 6. Note that the average time of update for 2, 3 and 5 seconds is higher, while for all others, from 10 to 30 seconds, it stays approximately on the same level. The reason for this is that in all those experiments lifetime of a context was set to 6 seconds, and in the first three experiments the situation changed faster, thus leaving a lot of obsolete contexts in a diagram and increasing its complexity. The proper solution for such cases is to decrease contexts lifetime.

10. Related work

Correct context determination is a crucial component of a pervasive system and has been extensively studied in the literature. In particular, various authors address the issue of inconsistent sensor readings and precise context determination.

Xu and Cheung et al. [18, 19, 21] study the detection of context contradictions based on predefined constraints. They propose to convert each constraint into a tree with constraint operators as vertices and contexts as edges. Then they introduce a partial constraint checking (PCC) algorithm that is capable of re-checking only parts of the constraint tree that may be affected by a new context. The work is extended by Huang et al. [10], who propose to check branches probabilistically. This enables fast processing of large trees and adds scalability to partial constraint

	CCD	RCCD
Computation efforts	Is rather computationally heavy, though ways exist to always keep the CCD within the given size, while losing some information.	Computationally light, can be maintained and updated much faster, than CCD, and is capable of handling more data without losing information.
Information handling	Keeps all the arrived information in itself, and handles inconsistencies in the existing information. Further information updates can change the most probable situation.	
Quering and reasoning	Can be used to find the most probable situation. Also can rank other situation by their probability, and answers to the different kinds of queries, such as "What are the situations that are at least 20% probable?", "What is the second-, third-, etc. most probable situation?", "What is the probability distribution of values of the certain variable?", etc.	Has a simple and fast way to find the most probable situation. Answers to this question much faster, than CCD.
Inter-dependence		If needed, RCCD can be unfolded into a full CCD at any moment of time.

Table 4. CCD vs RCCD comparison

checking, but reduces the percentage of correctly found inconsistencies. The papers aim at fast detection of contradictions, while in the present approach we concentrate on the problem of different context interpretations after inconsistencies are found. Their findings can also be combined with our approach, as inconsistencies found through their method may be interpreted using CCD.

Bu et al. [4, 5] perform context reasoning by modelling the context ontology and then finding inconsistencies using ontological reasoning. The context is modelled as RDF-triples using OWL-lite language. They also present a context lifecycle, where new context starts at "beginning" phase, can be "updated" during its lifetime, stagnate at "inert" phase and finish its life as "disappearing". In the presence of a conflict they propose to discard one of conflicting contexts based on their relative frequencies. Xu et al. [20] propose similar resolution strategies, among which are drop-latest, drop-all, drop-random, and drop-bad. The latter heuristic counts the number of conflicts for each context and drops the one with the biggest number. While those techniques can be used to successfully resolve the straightforward inconsistencies, our approach is helpful when proposed heuristics cannot confidently resolve the conflict, which may lead to retaining the incorrect interpretation.

Henricksen and Indulska [9] classify context properties and outline initial ideas on handling several inconsistencies. They introduce classification, but do not provide precise algorithms for dealing with possible context inconsistencies. Lu et al. [15] provide a mechanism for detecting failures in context-aware applications and means to test such applications. Huang et al. [11] study the detection of inconsistencies that emerge due to asynchronous arrival of concurrent events. The proposed algorithm detects the original order of such events based on *happen-before* relation. On the other hand, we do not consider inconsistencies caused by the order in which context information is arriving.

Kong et al. [14] propose to extend the OWL ontology with fuzzy membership to tolerate inconsistencies. Their proposal involves manual assignment of membership values and does not propose a way to retrieve useful information from it.

A similar fuzzy approach to ours is discussed in [16]. The authors try to minimize the impact of early incorrect decisions made during software design. They show that wrong classification of an entity to one of the mutually exclusive classes if done early, may lead to further incorrect or suboptimal design of the software system. They propose to improve the process by deferring decisions about entity's classification as long as possible, instead of assigning fuzzy membership values to each of possible classes. However, the solution is not applicable to context reasoning, as it is based on human decisions about entity's properties membership values that have to be updated with each information change. This is acceptable for the prolonged and slow software development process, but impossible in highly dynamic automated context-aware systems.

The search for frequent itemset problem was first formulated by Agrawal et al. [3], and many algorithms to solve it use structures similar to CCD and RCCD. Given a large number of transactions that contain subset of items from a certain set, the frequent itemset task is to find subsets of items that appear together in at least a certain percentage of transactions. The Apriori algorithm [2] uses the fact that an itemset is frequent only if all of its sub-itemsets are frequent, thus finging a bigger itemsets by combining smaller itemsets. FP-growth [8] enhances this algorithm by removing the need to generate all candidates. Alternative Eclat algorithm [22] uses lattice decomposition to decompose original powerset of items into smaller sets to process them independently. Many other proposed algorithms include tweaks in order to make existing algorithms faster and more scalable. The survey of such algorithms by Han et al. [7] describes all the latest advancements in frequent itemset mining. To the opposite of the frequent itemset problem, where all transactions are always correct, context consistency diagrams aims to find the inconsistencies, and fully or partially incorrect context readings. The RCCD allows to represent an environment with many variables, where each variable has its own set or range of values. Also, contrary to the frequent itemsets, where a set of transactions is given in advance, the RCCD structure aims at efficient representation of gradual changes in context over time, thus at fast addition and removal of contexts.

11. Conclusion

We introduced reduced context consistency diagrams (RCCD), novel data structures for reasoning about situations with incomplete knowledge of the environment and context conflicts that cannot be unambiguously resolved. RCCD is able to find the most probable situation at each moment of time, and can be unfolded into CCD to obtain the full quering functionality of the latter diagram. Our experiments show that diagrams can be efficiently maintained and computed in real-time and provide a considerable improvement in situation interpretation by correcting erroneous sensor readings.

In table 4 we collect all the previously given information to present a concise comparison between the two structures. That should help to decide, which of the structures is better suited for given projects.

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