PAPER

A Flexible and Accurate Reasoning Method for Danger-Aware Services Based on Context Similarity from Feature Point of View

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SUMMARY Context awareness is viewed as one of the most important goals in the pervasive computing paradigm. As one kind of context awareness, danger awareness describes and detects dangerous situations around a user, and provides services such as warning to protect the user from dangers. One important problem arising in danger-aware systems is that the description/definition of dangerous situations becomes more and more complex, since many factors have to be considered in such description, which brings a big burden to the developers/users and thereby reduces the reliability of the system. It is necessary to develop a flexible reasoning method, which can ease the description/definition of dangerous situations by reasoning dangers using limited specified/predefined contexts/rules, and increase system reliability by detecting unspecified dangerous situations. Some reasoning mechanisms based on context similarity were proposed to address the above problems. However, the current mechanisms are not so accurate in some cases, since the similarity is computed from only basic knowledge, e.g. nature property, such as material, size etc, and category information, i.e. they may cause false positive and false negative problems. To solve the above problems, in this paper we propose a new flexible and accurate method from feature point of view. Firstly, a new ontology explicitly integrating basic knowledge and danger feature is designed for computing similarity in danger-aware systems. Then a new method is proposed to compute object similarity from both basic knowledge and danger feature point of views when calculating context similarity. The method is implemented in an indoor ubiquitous test bed and evaluated through experiments. The experiment result shows that the accuracy of system can be effectively increased based on the comparison between system decision and estimation of human observers, comparing with the existing methods. And the burden of defining dangerous situations can be decreased by evaluating trade-off between the system's accuracy and burden of defining dangerous situations.

key words: *pervasive computing, context awareness, danger awareness, reasoning method, context similarity*

1. Introduction

Pervasive computing is emerging as one of the future computing paradigms in the event of contemporary advances in the fields of wireless, sensor networks, distributed systems, and mobile computing etc.

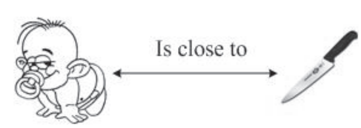
One of the most important research topics in pervasive computing is the context awareness, which provides a user with personalized services adapted to the user's context, such as current location and time, features and favorites of the user, and available facilities or information around the user, etc.

Danger awareness is a special kind of context awareness, describing and detecting dangerous situations around users, and providing services such as warning message or shutting down the dangerous device to protect users from damage by the dangers.

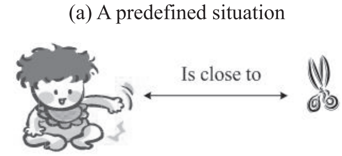
In order to detect the dangerous situations correctly, it is necessary to describe/define those situations clearly in advance and identify dangers in a timely manner.

A danger situation is dependent on various information, e.g. features and position of the user, physical environment, object information, and the relation between the user and the object. The definition of dangerous situation becomes more and more complex, in order to specify various situations personalized to every different user clearly. If a dangerous situation is not described/defined clearly in advance, the system may not detect it correctly, which reduces the reliability of the systems greatly. And the description/definition of every dangerous situation becomes a hard work for developers/users, since a lot of similar situations will be defined repeatedly.

Figure 1 shows an example of a pair of similar situations. For simplified description, the example just employs three parameters in describing a context/situation, i.e. user, object, and distance between them. Here, a situation "a one-year-old child is creeping to a knife" is predefined as dangerous situation. Then if the system detects a situation "a three-year-old child is close to a pair of scissors", even though the detected situation is not exactly same as the predefined situation, and the system should immediately provide services, since the detected situation is very similar to the predefined situation. Therefore, a flexible reasoning method based on



(a) A predefined situation



(b) A detected situation

Fig. 1 An example to show a pair of similar situations.

Manuscript received October 22, 2010.
Manuscript revised March 26, 2011.

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DOI: 10.1587/transinf.E94.D.1755

similarity of situations is urgently demanded to ease the development of danger-aware systems.

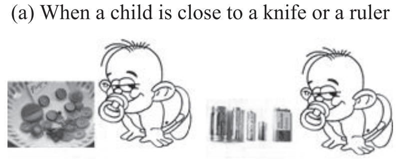
To solve the above problems, some ontology-based methods [22], [23], [25] have been proposed by computing similarity based on basic knowledge in ontology. These methods sometimes help with specification and detection of dangers, but they are not always effective and accurate, since the similarity is computed from only basic knowledge, e.g. nature feature, e.g. material, size etc, and category information, by only using taxonomy similarity. It is very important, since it can be the basis to compute similarity for each element in contexts. However without consideration of feature similarity, the methods will be not so accurate in some cases, i.e. they may cause false positive and false negative problems. For example, even though some objects are similar based on basic knowledge, they are different from the danger point of view. On the contrary, even though some objects are not similar from the point view of basic knowledge, they are similar from the danger point of view.

For example, a child is close to a knife or an iron ruler as shown in Fig. 2 (a). Even though the knife and the iron ruler are similar based on basic knowledge, since both of them are metal tools and similar in the shape, they are not similar since the knife has a danger feature that may easily cause harm to the child (the rule has no such feature). Another example is shown in Fig. 2 (b), i.e. a child is close to a button or a battery. The button and battery belong to different categories in object ontology, i.e. they are not similar based on basic knowledge. However, they are viewed as similar for danger-aware systems, since both of them have the danger feature such that they may be swallowed by the child.

In order to solve the above problems, in this paper we propose a new flexible and accurate method from feature point of view, besides the basic knowledge point of view. Firstly, a new ontology integrating basic knowledge and danger feature is designed for computing similarity in danger-aware systems. Secondly a new method is proposed to compute object similarity from both basic knowledge and danger feature point of views.

It is possible to integrate danger properties and basic knowledge of objects in ontology. However, the ontology will become too complex and very hard to be designed, since an object may contain multiple nature and danger properties.

(a) When a child is close to a knife or a ruler



(b) When a child is close to buttons or batteries

Fig. 2 An example to show danger features of objects.

To compute context similarity, in this paper, we have employed and improved the methods of computing concept similarity in ontology, i.e. taxonomy similarity and feature similarity. Taxonomy similarity is used to represent the similarity between two concepts in ontology based on basic knowledge, e.g. nature feature and category information. And feature similarity is used to represent the similarity based on features of concepts in ontology (based on the numbers of the same features and different features two concepts have in ontology).

The method is implemented in an indoor ubiquitous test bed and evaluated through the experiments supported with some human observers. The experiment result shows that the accuracy of the system can be effectively increased based on the comparison between system decision and estimation of human observers, comparing with the existing methods. And the burden of defining dangerous situations can be decreased by evaluating trade-off between accuracy of the system and burden of defining dangerous situations.

In the rest of the paper, Sect. 2 presents related works and Sect. 3 presents the method in detail. In Sect. 4, the evaluation method and result are shown in detail. Finally the paper is concluded in Sect. 5.

2. Related Works

Danger/risk detection and prevention systems play a very important role in our daily life and have been developed for many years, e.g. warning system for gas leakage [1]. However, this kind of system cannot detect more complex dangerous situation based on user properties, object properties and etc. Recently, with the progress of pervasive computing, the detection of a detailed and complex dangerous situation in our daily life becomes realizable. For example, a dangerous situation may happen when a special person is close to a specified dangerous object at some place and time, in some kinds of environment, which is called danger-aware systems, e.g. some danger-aware systems for children in [2], [3]. An infant behavior simulator was proposed in [4], [5], which can simulate behaviors of infant based on environment model and development behavior model to protect children. The advantages of the work include classification of elements related to infant behavior and creating model to represent these elements and simulate infant behavior. However, in these systems, there is no effective and flexible mechanism to represent and reason dangerous situations.

To represent and reason a context, various kinds of context model have been proposed [6], e.g. key-value model [7], markup scheme model [8], graphical model [9], object oriented model [10], logic based model [11] and ontology based model [12]–[21]. Ontology based context model has been shown to be the most effective one with variety of reasons, e.g. easy for apprehending, sharing, and reasoning [6]. The ontology based context model has been used in many context-aware systems, e.g. CoBrA [12], [13], Gaia [14], [15], GLOSS [16], [17], ASC [18], [19], CONON in SOCAM [20], and GAS [21].

A GLObal Smart Space (GLOSS) [16], [17] is architecture to support interaction among people, artifacts and places. In GLOSS, some ontology was designed to describe a small set of concepts for a universe of discourse. The GAS ontology [21] aims to provide a common language for communication and collaboration among smart objects. However, the shortcoming of these models is that relationships in ontology have not been used in reasoning contexts. For example, if a person is in a room, and that room is in the university, then we can know the person is in the university based on relationship of *part-of*.

The other context models provide more flexible reasoning mechanism by inferring contexts based on ontology, i.e. CoBrA [12], [13], Gaia [14], [15], ASC [18], [19], and CONON in SOCAM [20]. The Context Broker Architecture (CoBrA) is a broker-centric, agent-based architecture to support context-aware computing systems. In CoBrA [13], a rule-driven logic inference engine was designed based on user-predefined rules, ontology knowledge and contextual knowledge. Gaia is an infrastructure for smart spaces, which employs and extends the common concept/function in operating system to context-aware systems. In Gaia [15], a reasoning engine based on descriptive logic was built, which is supported by the rules predefined by developers. The CONtext Ontology (CONON) [20] is a hierarchical approach to design a context model. Two types of contextual reasoning are supported, based on ontology reasoning with description logic and user-predefined rules in first-order logic. Aspect-Scale-Context (ASC) [18], [19] is a model for describing contexts and their relationships using ontologies as fundamental, considering entities like person, place or a general object. All of these reasoning mechanisms need support from the predefined contexts/rules by developers or users. However, there is no reasoning mechanism to detect similar situations and thus ease the definition of various contexts/situations. Therefore, the developers/users have to define all the possible contexts/rules in advance, even though many of them are similar. When an unspecified situation happens, the situation may not be detected properly.

Some prior works have been performed for computing similarity. Yang et al. proposed a concept of similarity based context aware system in [22]. However, the method to compute concept similarity only accounts for features of the concepts, and without consideration of the taxonomy similarity. Anagnostopoulos et al. proposed a method to compute context similarity in [23] based on ground similarity [24]. However these methods did not consider object information when computing context similarity. Object similarity is very important in a danger aware system, since many accidents occur when the user is close to a dangerous object. A similarity measure method was proposed based on the normalization of Tversky's model and set-theory functions of intersection and difference in [24]. Based on the method, similarity of concepts in two ontologies can be computed based on the number of common and difference features. However the method considers two features are common feature just when the two features are exactly the same, but cannot deal with similar features (e.g. similar danger properties).

To provide context-aware services, the basic works are collecting useful information from sensors and then describing the information in a higher level, i.e. context level. Therefore, we have proposed a composition based method to integrate pieces of useful information automatically compose contexts for providing context-aware services in [25]. In the method, firstly, pieces of useful information compose together to represent contexts. Secondly, context similarity is computed between a predefined context and a detected context based on taxonomy similarity. Finally, services are provided based on the context similarity. However the method is not so precise without consideration of feature similarity i.e. it may cause false positive and false negative problems as discussed in Sect. 1.

3. The Reasoning Method for Danger-Aware Services

3.1 Basic Idea

Figure 3 shows an outline of the basic idea. Suppose that there is a detected context and some predefined contexts. The detected context describes the current situation of the user by detecting information with sensors. The predefined contexts are defined by users/developers in advance, to describe the dangerous situations in which services should be provided.

There are three steps to provide services based on context similarity as shown in Fig. 3. Firstly, the system computes the context similarity between the detected context and the predefined contexts, based on basic knowledge and danger features. Then the system assigns danger degree to the detected context based on context similarity. Finally the system provides services based on the danger degree of the detected context.

3.2 A New Ontology to Consider both Taxonomy and Feature Explicitly

As discussed in Sect. 1, a new ontology to explicitly con-

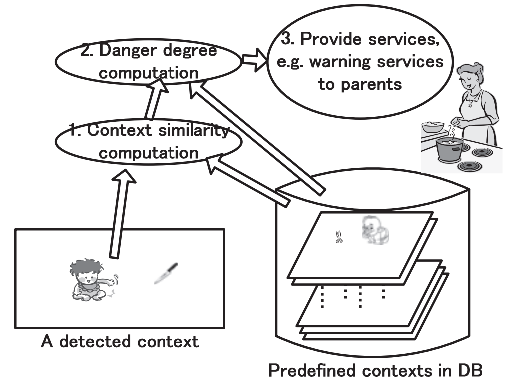


Fig. 3 An outline of the basic idea.

sider both basic knowledge and danger feature is very important for danger-aware systems. To achieve the goal, we design the object ontology as shown in Fig. 4. Firstly, basic knowledge and danger feature information are considered explicitly in object ontology, i.e. the part 1 and the part 2 as shown in Fig. 4. The part 1 is to classify objects by basic knowledge (Fig. 4 (a)), i.e. categorized based on common knowledge and nature feature. The part 2 is to classify the danger features (Fig. 4 (b)). Meanwhile, for each concept in the part 1, it includes various danger features, which are instances of the part 2.

In the paper, we call the similarity based on basic knowledge as *basic similarity*, which is computed based on the part 1. And we call the similarity from danger feature point of view as *danger feature similarity*, which is calculated based on the part 2. Finally, the similarity is represented by integrating *basic similarity* and *danger feature similarity*.

For example, as shown in Fig. 4 (c), there are predefined objects *scissors* and *iron nail*. The danger features of the *scissors* are *sticker* and *with blade*. The danger features of the *iron nail* are *sticker* and *wrong swallow*. These danger features are instance of the part 2 in ontology. *Basic similarity* is computed based on the part 1 of the ontology and *danger feature similarity* is computed part 2 of the ontology. Finally, the *object similarity* is computed by integrating *basic similarity* and *danger feature similarity*.

3.3 The Proposed Method

3.3.1 Definition

Definition 1: Single-User Context
In this paper, same with [25] the information to be used to adapt a single user, including the user's information, related surrounding objects, relation between the user and objects,

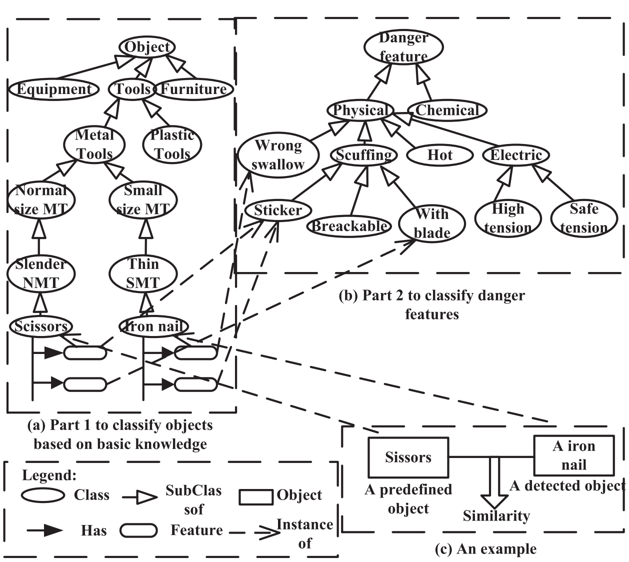


Fig. 4 A new ontology integrating basic knowledge and danger features.

and environment factors, is called *single-user context*, which is a 4-tuple and can be described as follows.

$suc = < u, O, REL, e >,$ where

- u represents the user.
- $O = \{o_1, o_2, \ldots, o_k, \ldots, o_m\}$ is a finite set including all the related objects with u.
- $REL \subseteq \{REL(u, o_1), REL(u, o_2), \ldots, REL(u, o_k), \ldots REL(u, o_m)\}$ is a finite set including the relations between u with each object in O.
- e is the surrounding environment of u.

We use $REL(i_1, i_2) = < rel^p(i_1, i_2), rel^s(i_1, i_2) >$ to denote a relation pair of two individual i_1 *and* i_2. $rel^p(i_1, i_2)$ is used to represent the position relation between two individual*s* and $rel^s(i_1, i_2)$ is used to represent the social relation between two individual*s*. For example, position relation can be *inSameRoom*, *inAdjoiningRoom*, *isCloseTo*, and so on. Social relation can be *isFatherOf*.

Definition 2: Multi-User Context
In this paper, same with [25] a *multi-user context* contains more than one user, all the related surrounding objects and environment factors. For the simplicity of discussion, we mainly focus on the situation including two users. It can be extended to the situations including more than two users.

We use *muc* to denote a multi-user context, which is a 3-tuple and can be described formally as follows,

$muc = < U, REL(suc_1, suc_2), S\_UC >$ where,

$U = \{u_1, u_2\}$ is a set of users.
$REL(suc_1, suc_2) = < rel^p(u_1, u_2), rel^s(u_1, u_2) >$ is a 2-tuple which represents the relations of two *single-user contexts*/two users.
$S\_UC = \{suc_1, suc_2\}$ is a set of *single-user contexts*.

3.3.2 Context Similarity in the Previous Research

The *single-user* context similarity proposed in [25] is computed based on the following formula (1),

$$Sim(suc, pre\text{-}suc) = w_{11}Sim(u,\ pre\text{-}u) + w_{12}Sim_{O\_REL} + w_{13}Sim(e, pre\text{-}e) \quad (1)$$

where *suc* and *pre-suc* are used to represent a detected *single-user context* and a predefined *single-user context*, respectively.

$Sim(u, pre\text{-}u)$, Sim_{O_REL}, and $Sim(e, pre\text{-}e)$ are used to represent user similarity, object and relation similarity, and environment similarity respectively, between a detected *suc* and a predefined *pre-suc*.

The context similarity between two *multi-user contexts*, i.e. $Sim(muc, pre\text{-}muc)$ is computed based on the formula (2)

$$Sim(muc, pre\text{-}muc) =$$
$$w_{21} \times Sim(suc_1, pre\text{-}suc_1) +$$

$$w_{22} \times Sim(suc_2, pre\text{-}suc_2) + \\ w_{23} \times Sim(REL(suc_1, suc_2), REL(pre\text{-}suc_1, pre\text{-}suc_2)) \quad (2)$$

where w_{21}, w_{22}, and w_{23} are weights, and the sum of these weights is 1.

$Sim(suc_1, pre\text{-}suc_1)$ and $Sim(suc_2, pre\text{-}suc_2)$ are single-user context similarities, which can be computed based on the formula (1).

$Sim(REL(suc_1, suc_2), REL(pre\text{-}suc_1, pre\text{-}suc_2))$ is the similarity of two set of relations.

However, the above method proposed in [25] is not so accurate in some cases, since it considers only basic knowledge by taxonomy similarity but it cannot account for feature similarity when computing similarity as discussed in Sect. 1 and 2.

Therefore, in this paper we propose a new method to compute similarity by integrating basic knowledge and danger features. In this paper, we also use formula (1) and (2) to compute context similarity, since we consider same factors to represent contexts as in [25]. However, we have proposed a new method to compute object similarity in formula (1) and (2).

3.3.3 Single-User Context Similarity

We still use formula (1) to compute single-user context similarity. However, we have proposed a new method to compute object similarity by integrating basic knowledge and danger features as follows.

In formula (1), Sim_{O_REL} is a value which means the similarity of objects and relations between the two contexts.

$$Sim_{O\_REL} = \sum_{i=1}^{m}(w_{3i}Sim_i) = \sum_{i=1}^{m} w_{3i}\,(w_4 Sim(o_i, pre\text{-}o_i) + \\ (1 - w_4)Sim(REL(u, o_i), REL(pre\text{-}u, pre\text{-}o_i))) \quad (3)$$

where w_4, and w_{3i} are weights, and $\sum_{i=1}^{m} w_{3i} = 1$.

$Sim(o, pre\text{-}o)$ represents the *object similarity* between two objects, which can be computed based on the formula (4),

$$Sim(o, pre\text{-}o) = w_5 \times B\_sim(o, pre\text{-}o) + \\ (1 - w_5)DF\_sim(o, pre\text{-}o) \quad (4)$$

$B\_sim(o, pre\text{-}o)$ and $DF\_sim(o, pre\text{-}o)$ represents *basic similarity* and *danger feature similarity*, respectively. w_5 in the formula (4) is a weight to adjust the balance of the formula.

In this paper, *basic similarity* is computed based on the taxonomy similarity of object ontology in part 1, as shown in following formula (5),

$$B\_sim(o, pre\text{-}o) = T\_sim(o, pre\text{-}o) \quad (5)$$

where $T\_sim(o, pre\text{-}o)$ represents taxonomy similarity of the two objects.

Danger feature similarity $DF\_sim(o, pre\text{-}o)$ will be presented in Sect. 3.3.5 in detail.

$Sim(REL(u, o_i), REL(pre\text{-}u, pre\text{-}o_i))$ is the similarity of two set of relations, which can be computed by formula (6). w_6 is a weight to adjust the balance of the formula.

$$Sim(REL(u, o_i), REL(pre\text{-}u, pre\text{-}o_i)) = \\ w_6 T\_Sim(rel^p(u, o_i), rel^p(pre\text{-}u, pre\text{-}o_i)) + \\ (1 - w_6)T\_Sim(rel^s(u, o_i), rel^s(pre\text{-}u, pre\text{-}o_i)) \quad (6)$$

3.3.4 Taxonomy Similarity

The method presented in [26], [27] is used to compute the taxonomy similarity of two concepts in an ontology, i.e., formula (7).

$$T\_Sim(x, y) = 1 - \partial(x, y) \quad (7)$$

where $\partial(x, y)$ denotes the weighted distance of two concepts x and y in ontology, which can be computed by formula (8),

$$\partial(x, y) = [w(p(x, y)) - w(x)] + [w(p(x, y)) - w(y)] \quad (8)$$

$p(x, y)$ represents the closest common parent of x and y, and $w(x)$ is a weight value of concept x, which can be calculated by using formula (9).

$$w(n) = \frac{1}{k^{l(n)+1}} \quad (9)$$

where $l(n)$ is an integer, representing the length of the path from root to concept n, and k is a predefined parameter which is larger than 1 to indicate the decrease rate (currently it is set to 2) [26].

Example 1:
We use the example 1 to show how to compute taxonomy similarity of *Scissors* and *Iron-nail* based on the part 1 of ontology in Fig. 4.

Firstly, l(*Scissors*) in formula (9) is equal to 5, since the length from root to concept *"Scissors"* is 5, as shown in Fig. 5. Similarly, l(*Iron-nail*) is also equal to 5.

Secondly w(*Scissors*) and w(*Iron-nail*) can be computed based on formula (9). They equal to 0.015625 by setting $k = 2$.

In the formula (8), $p(x, y)$ represents the closest common parent of x and y.

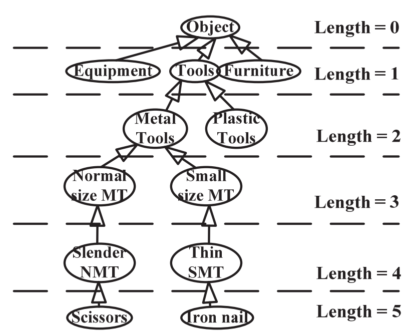


Fig. 5 Part 1 of object ontology.

Here $p(Scissors, Iron\text{-}nail)$ should be *Metal-Tools* in the Fig. 5. $w(Metal\text{-}Tools)$ is equal to 0.125, which is computed based on formula (9), similarly with $w(Scissors)$ and $w(Iron\text{-}nail)$.

Then the weighted distance of two concepts *Scissors* and *Iron-nail* can be computed based on formula (8) as follows,

$$\partial(Scissors, Iron\text{-}nail) = [w(Metal\text{-}Tools) - w(Scissors)] + [w(Metal\text{-}Tools) - w(Iron\ nail)] = [0.125 - 0.015625] + [0.125 - 0.015625] = 0.21875.$$

Finally, taxonomy similarity of *Scissors* and *Iron-nail* based on part 1 of object ontology is computed based on formula (7) as follows,

$$T\_Sim(Scissors, Iron\text{-}nail) = 1 - \partial(Scissors, Iron\text{-}nail) \approx 0.781.$$

3.3.5 Danger Feature Similarity

Besides taxonomy similarity, feature similarity is also very important to compute the object similarity, since the features of an object contain valuable information about the object. The following formula (10) is a method to compute feature similarity proposed in [24]. The method considers not only the common features of two concepts, but also the differences between the two concepts. In other words, the more common features they have and the less non-common features they include, the more similar they are.

$$S(a,b) = \frac{|A \cap B|}{|A \cap B| + \varsigma(a,b)\,|A \backslash B| + (1 - \varsigma(a,b))\,|B \backslash A|} \quad (0 \le \varsigma \le 1) \tag{10}$$

Where a and b are concepts in ontology; A and B corresponds to feature sets of a and b; || is the cardinality of a set; A ∩ B means intersection of A and B; A\B and B\A means difference of sets; and $\varsigma(a,b)$ is a function that defines the relative importance of the non-common features, which can account for asymmetric measure in similarity. The detail description can be found in [24].

However, when using the above method to reason dangerous situations, it is not so flexible and accurate, since the above method consider only two features as common features if they are exactly the same, but it cannot deal with similar features. For example, *normal sticker* and *serious sticker* are similar danger features, but in the above method they will be treated as totally different features. Therefore, we extend the above method as shown in formula (11) to compute danger feature similarity in the paper.

$$DF\_Sim(o, pre\text{-}o) = \frac{sd(DP_o \tilde{\cap} DP_{pre\text{-}o})}{sd(DP_o \tilde{\cap} DP_{pre\text{-}o}) + \varsigma \times \left|DP_o \tilde{\backslash} DP_{pre\text{-}o}\right| + \eta \times \left|DP_{pre\text{-}o} \tilde{\backslash} DP_o\right|} \tag{11}$$

In the formula (11), $DF\_sim(o, pre\text{-}o)$ denotes the *danger feature similarity* between a detected object o and a predefined object *pre-o*.

And $DP_o \tilde{\cap} DP_{pre\text{-}o}$ is a special kind of intersection of sets, which contains all the pairs of similar features. A pair is denoted as $p_i(dp_u, dp_v)$, consisting of two similar features, i.e. dp_u and dp_v, where dp_u belongs to DP_o and dp_v belongs to $DP_{pre\text{-}o}$. dp_u and dp_v are the instances of danger feature ontology.

For simplified description, we assume for each object, there is no similar danger features predefined. For example, if there is a danger feature *serious sticker* predefined for a nipper, it is not necessary to define the danger feature *normal sticker* for the nipper, since two danger features are too similar. Therefore, in $DP_o \tilde{\cap} DP_{pre\text{-}o}$, there will be no pair including duplicated danger feature with other pairs.

We call two features are similar if and only if the taxonomy similarity of the two features in the danger feature ontology is larger than a threshold, i.e.

$$dp_u \text{ and } dp_v \text{ is similar, iff } T\_Sim(dp_u, dp_v) > Threshold. \tag{12}$$

In formula (11), $sd(DP_o \tilde{\cap} DP_{pre\text{-}o})$ is to represent the similar degree of two sets, computed based on similarity of all the pairs of similar features.

$$sd(DP_o \tilde{\cap} DP_{pre\text{-}o}) = \sum_{i=1}^{m} (T\_Sim(p_i)) \tag{13}$$

where $m = \left|DP_o \tilde{\cap} DP_{pre\text{-}o}\right|$ and $T\_Sim(p_i)$ represents taxonomy similarity of the pair $p_i(dp_u, dp_v)$, i.e.

$$T\_Sim(p_i) = T\_Sim(dp_u, dp_v) \tag{14}$$

Furthermore, in the formula (11), $DP_o \tilde{\backslash} DP_{pre\text{-}o}$ and $DP_{pre\text{-}o} \tilde{\backslash} DP_o$ are special kinds of difference between the sets, which represent non-similar features computed by excluding the similar features.

Finally, ς and η are weights to adjust the balance between the similar features and non-similar features in the detected object and predefined. For danger-aware systems, $\varsigma + \eta$ should be set less than 1 to decrease the impact from non-similar features, since for dangerous objects they are similar as long as they have same/similar danger features, the different danger features should play a very limited role in computing danger feature similarity.

Example 2:
Here we use the example 2 to explain how to compute object similarity in detail.

Suppose there are predefined objects *Scissors* and detected object *Iron-nail*. The scissors have the danger feature of *sticker* and *with blade*, and the iron nail includes *sticker* and *wrong swallow*.

Firstly, the taxonomy similarity between the *Scissors* and *Iron-nail* can be computed similar with Example 1, i.e.

$$T\_Sim(scissors, iron\ nail) \approx 0.781.$$

Then let's see the danger feature similarity which is based on danger feature ontology. Similarly, we can get taxonomy similarity of danger features based on part 2 of object ontology shown in Fig. 4 as follows,

$$T\_Sim(sticker,\ sticker) = 1$$
$$T\_Sim(with\ blade,\ wrong\ swallow) \approx 0.688.$$

Suppose 0.688 is less than the threshold in the formula (11).

Then we can get

$$DF\_Sim(iron\ nail,\ scissor) = \frac{1}{1 + \varsigma \times 1 + \eta \times 0} = 0.87,$$

if we suppose $\varsigma = \eta = 0.15$.

Finally, the $Sim(o, pre\text{-}o)$ can be computed based on formula (4) as follows, if we suppose $w = 0.5$,

$$Sim(o, pre\text{-}o) = 0.5 \times 0.781 + 0.5 \times 0.87 = 0.825.$$

3.3.6 Multi-User Context Similarity

We still use formula (2) to compute multi-user context similarity, where $Sim(suc_1, pre\text{-}suc_1)$ and $Sim(suc_2, pre\text{-}suc_2)$ represent single-user context similarity between a detected *single-user context* and a predefined *single-user context*, computed based on the method proposed in Sect. 3.3.3.

$Sim(REL(suc_1, suc_2), REL(pre\text{-}suc_1, pre\text{-}suc_2))$ is the similarity of two sets of relations, which is computed as follows,

$$\begin{aligned} &Sim(REL(u_1, u_2), REL(pre\text{-}u_1, pre\text{-}u_2)) = \\ &\quad w_7 T\_Sim(rel^p(u_1, u_2), rel^p(pre\text{-}u_1, pre\text{-}u_2)) + \\ &\quad (1-w_7) T\_Sim(rel^s(u_1, u_2), rel^s(pre\text{-}u_1, pre\text{-}u_2)) \end{aligned} \tag{15}$$

where $REL(u_1, u_2)$ and $REL(pre\text{-}u_1, pre\text{-}u_2)$ represent sets of relation two users in suc_1, suc_2 and $pre\text{-}suc_1$, $pre\text{-}suc_2$, respectively. w_7 is weight for balancing the position relation and social relation.

3.3.7 Danger Degree Assignment

We use δ to denote the danger degree, which shows how much a situation is dangerous. $\delta(c)$ and $\delta(pre\text{-}c)$ are used to represent the danger degree of a detected context and a predefined context, respectively.

Then we assign the danger degree of the predefined context to the detected context if the context similarity is larger than a threshold as shown in formula (16). It can be used for both single-user context and multi-user context.

$$\delta(c) = \begin{cases} \delta(pre\text{-}c) & Sim(c, pre\text{-}c) \geq Threshold \\ 0 & Sim(c, pre\text{-}c) < Threshold \end{cases} \tag{16}$$

4. Evaluation

Experiment Environment

The method is implemented in an indoor text bed, i.e. U-tiles sensor network [28], [29]. Figure 6 (1) shows the structure of U-tiles sensor network. The U-tiles, consisting of tiles, antenna switch, RFID reader and micro computer, is implemented in a real floor. The antenna switch is controlled by the micro computer.

Each tile is embedded with pressure sensors and an RFID antenna. The RFID reader is selectively connected with the antenna of each tile, through the antenna switch controlled by micro computer program. When an object or a person with an RFID tag is on the tile, RFID reader can recognize which tile the person/object is on. Meanwhile, the relative position between the person and the object can also be detected. Furthermore, there is a DB storing the information of persons/objects, by using which, the system gets the information of the person/object by querying the information based on the detected RFID tag.

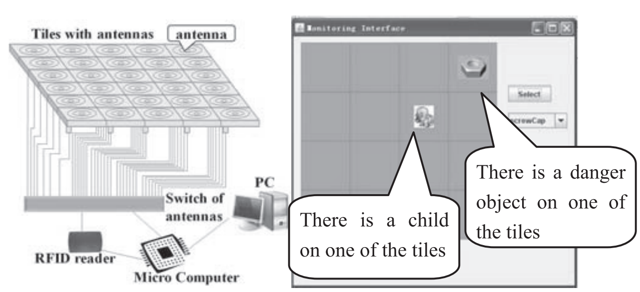
Figure 6 (b) shows the monitoring interface. Based on the information from u-tiles, the interface shows the current situation in the room and the danger degree of the current situation.

Experiment Objectives

We have evaluated the proposed method in the following two aspects, (1) accuracy of the proposed method comparing with related researches and (2) accuracy of the system employing reasoning mechanism based on context similarity.

Evaluation on Accuracy of Object Similarity Comparing with the Related Researches

To evaluate the accuracy of the object similarity in this paper, we have employed the object ontology as shown in Fig. 7. The part 1 of the object ontology (Fig. 7 (a)) classifies the normal tools used in daily life in detail on material, size, shape, and so on. Figure 7 (b) shows part 2 of the object ontology. The danger features of the instances of part 1 in ontology are shown in Table 1. The ontologies also can be employed by the existing ones, since a big advantage of using ontology is easily for sharing knowledge. In formula (3) w_4 is set as 0.5, and for simplicity of discussion w_{3i} is set as



(a) Structure of U-tiles (b) Monitoring interface

Fig. 6 Implementation of the system.

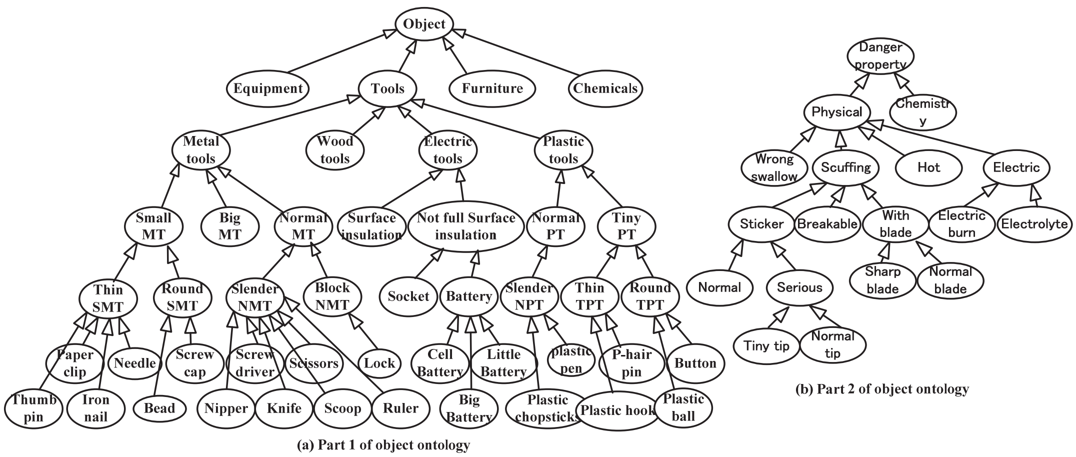


Fig. 7 Object ontology.

Table 1 Dangerous features of the objects.

Object Name	Dangerous Features
button bead screw cap	{wrong swallow}
thumb-pin needle iron nail	{wrong swallow; serious sticker with tiny tip }
plastic hairpin plastic hook	{wrong swallow; normal sticker }
cell battery little battery	{wrong swallow, electrolyte}
paper clip	{wrong swallow; serious sticker with normal tip }
screw driver nipper	{ serious sticker with normal tip }
p-chopsticks plastic pen	{ normal sticker }
big battery ruler scoop lock	{null}
scissors	{ sharp blade; serious sticker with normal tip }
knife	{sharp blade; serious sticker with tiny tip}

1/m, where m is the number of objects in predefined context. w_5 in formula (4) is set as 0.3.

We have evaluated the accuracy of the proposed method to compute object similarity by comparing with two existing researches,

(1) the previous research based on only basic knowledge by using taxonomy similarity [25].
(2) the existing method to compute feature similarity in [24], which has been used to compute context similarity in [22], [23]. Here, we employ the method to compute danger feature similarity instead of the proposed method, i.e. formula (11).

In the experiment, for each object in object ontology, the system computes the object similarities with all the other objects, based on the proposed method and the above exiting methods, respectively. For simplified discussion in the paper we select the experiment results of two typical objects in the object ontology to evaluate the method, i.e. a thumb-pin (*wrong swallow* and *serious sticker with tiny tip*) and a knife (*sharp blade* and *serious sticker with tiny tip*), as shown in Fig. 8 and Fig. 9 respectively.

In the figures,

(1) PreviousM represents the previous method in [25] which only accounts for basic knowledge by using taxonomy similarity.
(2) ExsitingSetM represents the existing set based method in the exiting research in [24].
(3) ProposedM represents the proposed method integrating basic knowledge and danger features in the paper.

Here, x-axis shows different objects and y-axis represents the corresponding object similarity with the object thumb-pin in Fig. 8 and the object knife in Fig. 9 respectively.

From Fig. 8 and Fig. 9, we can see that, comparing with the previous research, the similarities based on the proposed method, (1) can be raised when they have similar danger features even though belong to different categories, (2) be decreased clearly when they are not similar from the point view of danger even though belong to very close categories.

In Fig. 8, comparing with the previous research, the ones based on the proposed method between a thumb-pin and button/plastic-hairpin/plastic-hook/plastic-chopsticks are raised clearly even though they belong to different categories with the thumb-pin, since they have similar danger features, *wrong swallow* or *serious sticker with tiny tip*. Meanwhile the object similarities between the thumb-pin and the ruler/scoop/lock are decreased clearly; even though they belong to close categories to the thumb-pin, since from the point view of danger, they are not similar.

In Fig. 9, comparing with the previous research, the similarities based on the proposed method between a knife and plastic-chopsticks/plastic-pen have been increased since they have similar danger features, i.e. *sticker*. For ruler/scoop, the object similarities are decreased clearly, even though belonging to very close categories (high similarity based on basic knowledge), since they are not similar from the point view of danger (without similar danger features).

Furthermore, from Fig. 8 and Fig. 9 we can see that, comparing with the existing method in [24], the proposed method not only accounts for feature similarity, but also can deal with similar danger features.

In Fig. 8, the object similarities with nipper/screw-driver/plastic-chopsticks/plastic-pen in ExsitingSetM are computed very low even though they have similar danger features, i.e. sticker. However, in ProposedM, the object similarities with those objects are raised by accounting from similar danger features. Also from Fig. 9 we can see that, the object similarities in ProposedM with plastic-hairpin/screw-driver/plastic-chopsticks/plastic-pen/nipper/scissors are higher than the ones in ExsitingSetM since they have similar danger features with knife.

Evaluation on Accuracy of the System Employing Reasoning Mechanism Based on Context Similarity

We have evaluated the accuracy of the system with support of five subjects, who have experience/knowledge to take care of a child. Firstly, some dangerous objects were put on the U-tiles. Secondly an almost two-year-old child was asked to play on the U-tiles, and the subjects were asked to be human observers to evaluate the danger degree in the current situation. Finally, the accuracy of the system was evaluated based on the system decision and human evaluation. We set the weights in the formula (1) and formula (2) as follows, i.e., $w_{11} = 0.2$, $w_{12} = 0.6$, $w_{13} = 0.2$, $w_{21} = 0.4$, $w_{22} = 0.4$, and $w_{23} = 0.2$.

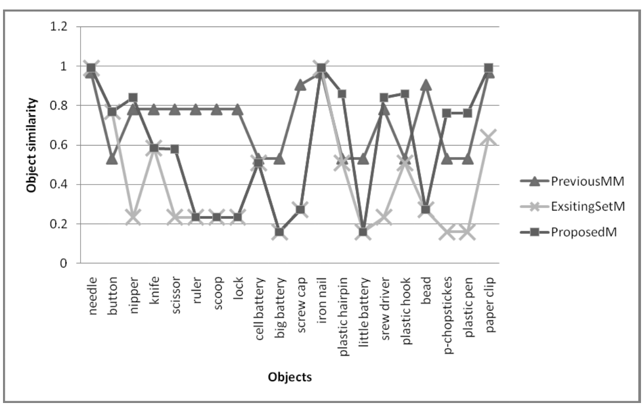


Fig. 8 Similarities between a thumb-pin and other objects.

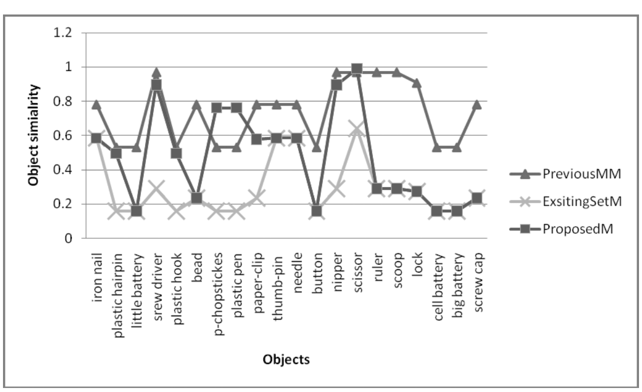


Fig. 9 Similarities between a knife and other objects.

In the experiment firstly, the whole extent of danger degree is divided into various ranges and different ranges represent different levels and types of danger as shown in the Table 2.

The formula (16) is extended into Table 3 to assign the danger degree in detail based on context similarity.

The room for experiment is almost 50 square meters. The sensing area in the room for experiment is about 4 square meters, since the size of our u-tile system is around 4 square meters. The limitation can be removed by addicting more tiles with sensors.

As shown in the Fig. 10 (a), we put a TV and a desk close to the sensing area and some daily necessities on the desk. Currently, our u-tiles sensor network is just implemented on the floor. However, similarly it can be implemented on the surface of desks, tables or bookshelf to detect the objects around users.

Then the whole u-tiles sensor network is divided into various areas as shown in Fig. 10 (b), where length of an edge of each piece of the tile is almost 50 cm. And distance ontology is employed to compute the context similarity as shown in Fig. 11 (a). Figure 11 (b) shows person ontology used in the system.

In the experiment, two scenarios have been designed to evaluate the proposed method. The scenario 1 accounts

Table 2 Danger level definition.

Danger level	Level 4	Level 3	Level 2	Level 1
Danger degree	[0, 0.7)	[0.7, 0.8)	[0.8, 0.9)	[0.9, 1]
Danger type	Not danger	A little danger	Danger	Very danger

Table 3 Assignment of danger degree based on context similarity.

Context similarity	[0, 0.9)	[0.9, 0.925)	[0.925, 0.95)	[0.95, 0.975)	[0.975, 1]
Danger degree ($\delta(suc)$)	$\frac{6}{10}\left(\begin{matrix}\delta(pre\\-suc)\end{matrix}\right)$	$\frac{7}{10}\left(\begin{matrix}\delta(pre\\-suc)\end{matrix}\right)$	$\frac{8}{10}\left(\begin{matrix}\delta(pre\\-suc)\end{matrix}\right)$	$\frac{9}{10}\left(\begin{matrix}\delta(pre\\-suc)\end{matrix}\right)$	$\frac{10}{10}\left(\begin{matrix}\delta(pre\\-suc)\end{matrix}\right)$

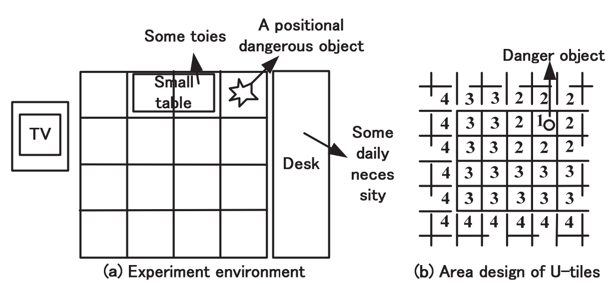


Fig. 10 Experiment environment and area design.

for evaluation of single-user context and the scenario 2 is for evaluation of multi-user context as shown in the Fig. 12. In the scenario 2, we divided the whole sensor network into two parts to simulate two rooms as shown in Fig. 12 (b).

Scenario 1:
In the scenario 1, three dangerous situations are predefined as shown in Table 4.

Table 5 shows some experiment result in scenario 1, where *PreviousM*, *ExsitingSetM*, *ProposedM* and *DL_human* represent the danger degree based on the previous research, the existing set based method, the proposed method and human observers evaluation, respectively.

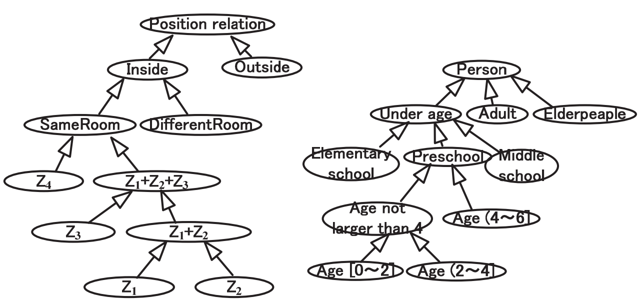
Scenario 2:
The predefined contexts in the scenario 2 are

"a two-year-old child is close to a knife within 0.5 m and his mother is watching TV in a different room".

"a two-year-old child is close to a plastic hairpin within 0.5 m and his mother is watching TV in a different room". The danger degrees are set as 0.9.

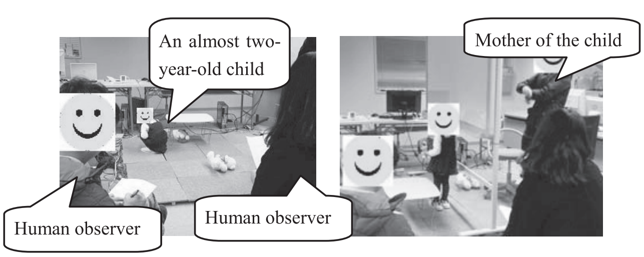
Table 6 shows the experiment result for scenario 2.

From Table 5 and Table 6, we can see that the proposed method works well in the two scenarios, and is more accurate than the previous method and existing set based method.



(a) Distance ontology (b) Person ontology

Fig. 11 Distance and person ontology.



(a) One room situation (b) Two room situation

Fig. 12 Snapshot of experiment.

Table 4 The predefined situations.

No.	Situation	Danger degree
1	A two-year-old child is close to a knife	0.9
2	A two-year-old child is close to a button	0.9
3	A two-year-old child is close to a plastic hairpin	0.9

In Table 5 and Table 6, we show some experiment result in two scenarios, by changing objects, position relation between the mother and child, distance between the child and object and age of the child. From the experiment result we can see that, based on the previous research, the system cannot detect some situations correctly, e.g. situations for the needle, even though it has similar danger feature with predefined object. And the system has some false alarm in some situations, e.g. situations for ruler by employing previous method. Meanwhile the system based on the exiting set based method cannot detect some situations, e.g. for object needle and scissors, even though they have similar danger features with predefined objects.

Also from the experiment result we can see that, the system based on the proposed method works well in these

Table 5 Experiment result for scenario 1.

The detected contexts				PreviousM	ExsitingSetM	ProposedM	DL_human
No.	Person	Object and relation	Area				
1	The two-year-old child	Close to a needle	1	4	4	1	1
2			2	4	4	1	1
3			3	4	4	2	2
4			4	4	4	3	3
5	The four -year-old child		1	4	4	1	2
6			2	4	4	2	2
7			3	4	4	2	3
8			4	4	4	3	3
9	The two-year-old child	Close to scissors	1	1	4	1	1
10			2	1	4	1	2
11			3	2	4	1	3
12			4	3	4	2	3
13	The four -year-old child		1	1	4	1	2
14			2	2	4	1	3
15			3	2	4	2	3
16			4	3	4	3	4
17	The two-year-old child	Close to a ruler	1	1	4	4	2
18			2	1	4	4	3
19			3	2	4	4	3
20			4	3	4	4	4
21	The four-year-old child		1	1	4	4	3
22			2	2	4	4	4
23			3	2	4	4	4
24			4	3	4	4	4
25	The four-year-old child	Close to a screw cap	1	4	1	1	1
26			2	4	1	1	2
27			3	4	2	2	2
28			4	4	3	3	3
29	The two-year-old child		1	4	1	1	2
30			2	4	2	2	3
31			3	4	2	2	3
32			4	4	3	3	4

Table 6 Experiment result for scenario 2.

No.	The detected contexts	PreviousM	ExsitingSetM	ProposedM	DL_human
1	A two-year-old boy is close to/in the area 1 of scissors. His mother is watching TV in the different room	1	2	1	1
2	A two-year-old boy is close to/in the area 1 of scissors. His mother is watching TV in the same room	2	4	2	2
3	A two-year-old boy is close to/in the area 1 of scissors. His mother is watching TV and close to the child(same room)	2	4	2	3
4	A two-year-old boy is close to/in the area 1 of a needle. His mother is watching TV in the different room	4	1	1	1
5	A two-year-old boy is close to/in the area 1 of a needle. His mother is watching TV in the same room	4	3	2	1
6	A two-year-old boy is close to/in the area 1 of a needle. His mother is watching TV in the same room and close	4	3	2	2
7	A two-year-old boy is close to/in the area 1 of a ruler. His mother is watching TV in the different room	1	4	4	2
8	A two-year-old boy is close to/in the area 1 of a ruler. His mother is watching TV in the same room	2	4	4	4
9	A two-year-old boy is close to/in the area 1 of a ruler. His mother is watching TV and close to the child(same room)	2	4	4	4

situations, by considering both of basic knowledge and danger feature, and dealing with similar danger features. Furthermore, the system works well with changing of other factors in contexts, i.e. position between mother and child, distance between child and object and age of the child. And the reasoning ability is enhanced by predefining limited situations and detecting more similar situations.

However, there are also some cases that the danger degrees computed based on the proposed method are less/larger than the human observer evaluation. But most of them are detected more danger than the user evaluation. We think it is acceptable for the normal danger-aware systems. We have performed a short interview after the experiment. In the interview, some subjects reported that even though the ruler and scoop are not so danger/similar to the knife, i.e. danger features are different, the children also may hurt themselves when very close to these objects. Also some subjects reported that, for some objects, e.g. iron nail, the child may step on these objects and hurt himself when he is running. In the future, we will further consider other appropriate danger features to enhance accuracy of the system.

Analysis of Trade-Off between Burden of Defining Dangerous Situations and Accuracy of System

Generally speaking, if the developers/users can design all the possible dangerous situations, the detection and reasoning will be easy, and the accuracy of the system will be very high. Meanwhile, it will give a big burden to them. By employing reasoning mechanism based on context similarity, we want to ease the burden of defining all the possible dangerous situations and increase accuracy of the system. In the paper, we have performed experiment to evaluate the trade-off between burden of defining dangerous situations and accuracy of the system, by employing the above three context similarity based methods and the reasoning method without consideration of context similarity.

In the scenario 1, five human observers totally estimated 168 dangerous situations, with changing of 21 objects in Table 1, 4 kinds of distance between child and objects, and considering two different age children. In the experiment, we predefine dangerous situations based on the estimation result from human observers, and gradually add the number of predefined dangerous situations.

The first 21 predefined dangerous situations are for a two-year-old child close to 21 different kinds of objects within zone 1(almost 0.5 m), by increasing the number of objects gradually. The predefined situations from 22 to 84 are for a two-year-old child close to the 21 dangerous objects in other three kinds of distance, i.e. zone 2 to zone 4. Finally, the predefined situations from 85 to 168 are for a four-year-old child close to 21 different objects in four kinds of distance.

In Fig. 13, x-axis shows numbers of predefined dangerous situations and y-axis represents the accuracy of system. For example, 2 in the x-axis represents there are two predefined dangerous situations in the system. Here, Accuracy is computed by comparing the danger degree computed by system and estimation result from human observers. Here, we consider the case that the danger degree computed by the system is one level higher than the human observers is correctly detection.

From Fig. 13 we can see that, the context similarity based methods can clearly increase accuracy of the system and ease the burden of definitions, compared with non-similarity method. For example, when there are 21 predefined situations, to detect all the possible dangerous situations, i.e. 168 situations, the accuracy of system is almost 0.935 by employing context similarity compared with almost 0.139 based on non-similarity method.

Furthermore, comparing with other method to compute context similarity, i.e. PreviousM and ExsitingSetM, the proposed method in the paper can increase accuracy of the system and ease burden of definitions when there are new

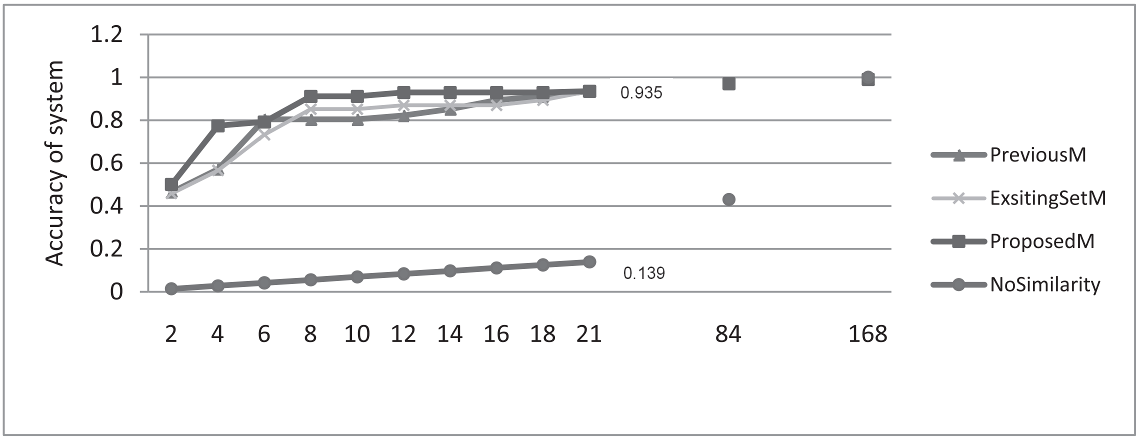


Fig. 13 Trade-off between accuracy and burden of defining dangerous situations.

objects to be predefined. For example, in the first 21 predefined situations, the proposed method has a higher accuracy than PreviousM and ExsitingSetM. Meanwhile, to achieve higher accuracy, the proposed method need less predefined objects compared with PreviousM and ExsitingSetM. For example, the proposed method needs predefine 8 situations to achieve 0.9 accuracy, comparing with almost 18 predefined situations based on the other methods. The proposed method can be expected more effective when there are more objects should be predefined, e.g. in our daily life.

5. Conclusion

To reduce the burden of defining all possible dangerous situations normally imposed on developers/users and increase reliability and accuracy of danger-aware systems, in the paper, a new method was proposed to assign a danger degree to the detected context by computing context similarity from feature point of views. The method was implemented in a ubiquitous test bed and evaluated through experiments. The experiment result shows that the accuracy of the system can be effectively increased and the burden of defining dangerous situations can be decreased.

By using the method, (1) the system can detect unspecified situations by comparing similarity to the predefined situations, and (2) ease the developers/users from the complex and abundant definitions.

The method can be used in various danger-aware systems, e.g. the kinder-garden care systems, hospital accident avoidance systems to compute similarity of the medicines etc. The method also can be extended to the other systems when the user, object, and distance information should be considered in detail, e.g. ubiquitous learning systems for ecology, where the system can provide the corresponding services based on the similar predefined contexts.

In the future, we will enhance the method to increase the accuracy and apply the method to other systems. Meanwhile, we will enhance the system to let it be employed in our daily life. Furthermore, we are planning to perform research on combining RF-ID and image processing techniques to detect children behavior and dangerous action.

Acknowledgments

The authors would like to say thanks to all subjects who attended to the experiment and gave various useful comments and suggestions.

References

[1] http://www.ogpeindia.com/fixed-portable-gas-leak-detection-system.html

[2] K. Takata, J. Ma, and B.O. Apduhan, “A dangerous location aware system for assisting kids safety care,” Proc. 20th International Conference on Advanced Information Networking and Applications, pp.657–662, Vienna, April 2006.

[3] G. Biffi Gentili, F. Dori, and E. Iadanza, “Dual-frequency active RFID solution for tracking patients in a children’s hospital. Design method, test procedure, risk analysis, and technical solution,” Proc. IEEE, vol.98, no.9, pp.1656–1662, Sept. 2010.

[4] K. Kitamura, Y. Nishida, N. Matsumoto, Y. Motomura, T. Yamanaka, and H. Mizoguchi, “Development of infant behavior simulator: Modeling grasping achievement behavior based on developmental behavior model and environmental interest induction model,” J. Robotics and Mechatronics, vol.17, no.6, pp.705–715, 2005.

[5] A. Simo, K. Kitamura, and Y. Nishida, “Behavior based children accidents’ simulation and visualization: Planning the emergent situations,” Proc. Fourth IASTED International Conference on Computational Intelligence (CI 2005), pp.164–169, July 2005.

[6] T. Strang and C. Linnhoff-Popien, “A context modeling survey,” 1st International Workshop on Advanced Context Modelling, Reasoning and Management, pp.34–41, 2004.

[7] B.N. Schilit, N.L. Adams, and R. Want, “Context-aware computing applications,” IEEE Workshop on Mobile Computing Systems and Applications, Santa Cruz, CA, US, 1994.

[8] A. Held, S. Buchholz, and A. Schill, “Modeling of context information for pervasive computing applications,” Proc. SCI2002/ISAS 2002, 2002.

[9] J. Bauer, Identification and Modeling of Contexts for Different Information Scenarios in Air Traffic, Diplomarbeit, March 2003.

[10] A. Schmidt, M. Belgl, and H.W. Gellersen, “There is more to context than location,” Comput. Graph., vol.23, no.6, pp.893–901, 1999.

[11] V. Akman and M. Surav, “The use of situation theory in context modeling,” Computational Intelligence, vol.13, no.3, pp.427–438, 1997.

[12] L. Kagal, V. Korolev, H. Chen, A. Joshi, and T. Finin, "Centaurus: A framework for intelligent services in a mobile environment," Proc. 21st International Conference on Distributed Computing Systems (ICDCSW'01), IEEE Computer Society, pp.195–201, Washington, DC, 2001.

[13] H. Chen, T. Finin, and A. Joshi, "An ontology for context-aware pervasive computing environments," Special Issue on Ontologies for Distributed Systems, Knowledge Engineering Review, vol.18, no.3, pp.197–207, May 2004.

[14] M. Roman, C.K. Hess, R. Cerqueira, A. Ranganathan, R.H. Campbell, and K. Nahrstedt, "Gaia: A middleware infrastructure to enable active spaces," IEEE Pervasive Computing, vol.1, no.4, pp.74–83, Oct.–Dec. 2002.

[15] R.E. McGrath, A. Ranganathan, R.H. Campbell, and M.D. Mickunas, "Use of ontologies in a pervasive computing environment," Technical Report UIUCDCS-R-2003-2332 UILU-ENG-2003-1719, Department of Computer Science, University of Illinois, Urbana-Champaign, Urbana, Illinois, 2000.

[16] A. Dearle, G.N.C. Kirby, R. Morrison, A. McCarthy, K. Mullen, Y. Yang, R.C.H. Connor, P. Welen, and A. Wilson, "Architectural support for global smart spaces," Proc. 4th International Conference on Mobile Data Management (MDM'03), pp.153–164, Springer-Verlag, London, UK, 2003.

[17] J. Coutaz, A. Dearle, S. Dupuy-Chessa, G.N.C. Kirby, C. Lachenal, R. Morrison, G. Rey, and E. Zirrintsis, "Working document on gloss ontology," Technical Report D9.2, Global Smart Spaces Project IST-2000-26070, 2003.

[18] T. Strang, C. Linnhoff-Popien, and K. Frank, "CoOL: A context ontology language to enable contextual interoperability," Proc. 4th IFIP WG 6.1 International Conference on Distributed Applications and Interoperable Systems (DAIS2003), LNCS 2893, pp.236–247, Paris/France, November, Springer Verlag, 2003.

[19] T. Strang, C. Linnhoff-Popien, and K. Frank, "Applications of a context ontology language," Proc. International Conference on Software, Telecommunications and Computer Networks (SoftCom'03), pp.14–18, Split/Croatia, Venice/Italy, Ancona/Italy, Dubrovnik/Croatia, 2003.

[20] T. Gu, X.H. Wang, H.K. Pung, and D.Q. Zhang, "An ontology-based context model environments," Proc. Communication Networks and Distributed Systems Simulation Conference (CNDS'04), Society for Computer Simulation, pp.270–275, 2004.

[21] E. Christopoulou and A. Kameas, "Gas ontology: An ontology for collaboration among ubiquitous computing devices," International Journal of Human-Computer Studies, vol.62, no.5, pp.664–685, 2005.

[22] J. Yang, Y. Bai, F. Wang, and Y. Qiu, "To select the services in context aware systems using concept similarity mechanism," Proc. IEEE International Symposium on Electronic Commerce and Security, pp.143–147, 2008.

[23] C. Anagnostopoulos and S. Hadjiefthymiades, "Enhancing situation-aware systems through imprecise reasoning," IEEE Trans. Mobile Comput., vol.7, no.10, pp.1153–1168, 2008.

[24] M.A. Rodriguez and M.J. Egenhofer, "Determining semantic similarity among entity classes from different ontologies," IEEE Trans. Knowl. Data Eng., vol.15, no.2, pp.442–456, 2003.

[25] J. Wang, Z. Cheng, L. Jing, K. Ota, and M. Kansen, "A two-stage composition method for danger-aware services based on context similarity," IEICE Trans. Inf. & Syst., vol.E93-D, no.6, pp.1521–1539, June 2010.

[26] Y. Ganjisaffar, H. Abolhassani, M. Neshati, and M. Jamali, "A similarity measure for OWL-S annotated web services," Proc. 2006 IEEE/WIC/ACM International Conference on Web Intelligence.

[27] J. Zhong, H. Zhu, J. Li, and Y. Yu, "Conceptual graph matching for semantic search," Proc. 2002 International Conference on Computational Science(ICCS2002), Amsterdam, April 2002.

[28] T. Ichizawa, M. Tosa, M. Kansen, A. Yishiyama, and Z. Cheng, "The attribute and position based ubiquitous development environment using antennas with an automatically switch," IPSJ SIG Technical Reports, vol.2006, no.14, 2006.

[29] J. Wang, M. Kansen, Z. Cheng, T. Ichizawa, and T. Ikeda, "Designing an indoor situation-aware ubiquitous platform using rule-based reasoning method," Proc. 2008 International Computer Symposium, Taiwan, Nov. 2008.

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