What Should Be Abducible for Abductive Nursing Risk Management?

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Abstract. In this paper, we analyze the hypothesis features of dynamic nursing risk management. In general, for risk management, static risk management is adopted. However, we cannot manage novel or rare accidents or incidents with general and static models. It is more important to conduct dynamic risk management where non-general or unfamiliar situations can be dealt with. We, therefore, propose an abductive model that achieves dynamic risk management where new hypothesis sets can be generated. To apply such a model to nursing risk management, we must consider types of newly generated hypotheses because sometimes newly generated hypotheses might cause accidents or incidents. We point out the preferable hypotheses features for nursing risk management.

1 Introduction

Despite recent high-quality nursing education and advanced medical treatments, the number of medical accidents due to nursing activities has not decreased. Instead, expectations about the safety and quality of nursing care have increased, and the range of nursing responsibilities has expanded. Therefore, to lower medical accidents, it is important to reduce nursing accidents and incidents to benefit both hospitals and patients. Medical risk management is one realistic solution to solve the problem, and many hospitals have introduced it. Currently medical risk management is based on a statistical model, which can be generated by inductive methodologies such as data mining. Around 80% of all accidents and incidents can be prevented by applying such inductive nursing risk management. However, if we only use inductive risk management, we cannot deal with novel or rare cases because all accidents or incidents cannot be known. Inductive (static) risk management cannot deal with novel or rare situations. We, therefore, think it would better to make risk models that dynamically perform risk management, which can be achieved by abduction. Risk management includes a concept — risk prediction. For computational prediction, abduction is the best selection. For dynamic risk management, we need to model nursing activities or human behaviour for errors. Based on Vincent's model, we previously proposed abduction-based nursing risk management [Abe et al. 2004] and extended the model to a scenario violation scheme [Abe et al. 2006]. Both models are quite flexible for conducting risk management, but currently they suffer certain

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limitations when dealing with new error models. For instance, we can adopt CMS [Reiter and de Kleer 1987] or AAR [Abe 2000] for abduction, but for nursing risk management, abduced hypotheses cannot always adopted as chances.

In this paper, we analyze both the features of hypotheses and suitable hypotheses for nursing risk management. Section 2 offers an overview of abductive nursing risk management. Section 3 discusses the features of abducible hypotheses in nursing risk management.

2 Abductive Nursing Risk Management

In previous papers, we pointed out the importance of dealing with possibly hidden (ignored or unconscious) events, factors, environmental elements, personal relationships, or matters likely to cause an unrecognized but serious accident in the future. Such factors can be regarded as chances. In [Abe 2003], we proposed an abductive framework for Chance Discovery [Ohsawa 2002] that can be achieved by abduction. In this section, we model risk management based on abduction. First, we briefly outline a pure abduction-based risk management model and then illustrate a scenario violation model for risk management.

2.1 Abduction Model

In [Abe et al. 2004], we formalized nursing risk management with an abductive framework. In cases where we know all possible hypotheses and their ideal observations[1], we can detect malpractice beforehand because if someone selects a wrong hypothesis set or fails to generate a necessary hypothesis set, an ideal observation cannot be explained. When an ideal observation cannot be explained, an accident or incident occurs. By this mechanism, we can logically determine exactly where accidents or incidents might occur in advance. A simple logical framework for completing an activity is shown below (using the framework of Theorist [Poole et al. 1987]):

If

$$F \cup h_1 \not\models ideal\_observation, \tag{1}$$

then find h_2 satisfying (2) and (3).

$$F \cup h_2 \models ideal\_observation \tag{2}$$

$$F \cup h_2 \not\models \Box. \tag{3}$$

$$h_1, h_2 \in H, \tag{4}$$

where F is a set of facts that are always consistent and h_1 and h_2 are hypotheses that are not always consistent with the set of facts and other hypothesis sets.

[1] If we use a workflow sheet for nurses or an electronic medical recording system, we can determine ideal observations.

Hypotheses are generated (selected) from hypothesis base H. $\Box$ is an empty set. Therefore, the last formula means that F and h_2 are consistent.

If we complete formula (2), the activity is successfully completed. On the other hand, if we cannot generate enough hypothesis sets to complete formula (2), certain problems will disturb the completion of the activity. Thus, beforehand we can determine the possibility of risk by abduction. That is, when we cannot explain an *ideal_observation* with a current hypothesis set, a particular error might occur. If objective (*ideal_observation*) cannot be explained, it cannot be completed. This situation is caused by particular accidents or incidents. This very simple logical that does not consider any effects of the generation order of hypotheses.

2.2 Scenario Violation Model

In a pure abduction model, we cannot deal with time information. For time information, Brusoni proposed a theoretical approach for temporal abduction [Brusoni et al. 1997], that shows abduction with absolute time information. However, we do not need to prepare strict models for temporal projection; instead we need to have a simple strategy to express a series of events.

For that, we introduced scenario in abduction and proposed a scenario violation model [Abe et al. 2006]. As shown in [Ohsawa et al. 2003], scenario is a *time series* of events under a coherent context. Accordingly, by introducing scenario, we can deal with time information in abduction. Thus, we introduced the effects of the generation order of hypotheses on the abduction model. In a scenario violation model, scenario violation means the possibility of error. This is a formalization of nursing risk management considering a series of events (time).

A simple logical model for checking a scenario violation is illustrated below. When all candidate scenarios are in a scenario base (SB), risk determination inference can be achieved as follows:

$$s_i \in SB \tag{5}$$

$$s_i = \sum_{j(in \quad chronological \ order)} e_{ij}, \tag{6}$$

where s_i is a scenario and e_{ij} is an event.

As shown above, to avoid accidents or incidents (by completing an activity), it is necessary to reach a final goal. When reached, we observe a particular result. Accordingly, we can set an observation as a result from the final goal. Therefore, our aim is to explain observations with sets of scenarios. Thus when no accident or incident occurs, the following formulae are completed:

$$F \cup \sum_{i(in \ chronological \ order)} O_i \models O \tag{7}$$

$$F \cup s_i \models O_i, \tag{8}$$

where F is background knowledge and O_i and O are observations (results of nursing activities). O_i can be regarded as a sub-observation of O. Of course, in some cases, we do not need to consider sub-observations.

Formulae (7) and (8) show abduction (hypothetical reasoning) that determines whether a scenario is completed. The most important difference from the hypothetical reasoning model is that formula (7) requires the verification of the chronological order of scenarios (hypotheses).

When

$$F \cup s_j \not\models O'_j, \tag{9}$$

$$F \cup s_j \models O_j, \tag{10}$$

$$O_j \neq O'_j, \tag{11}$$

and

$$F \cup \sum_{i(in\ chronological\ order)} O_i \not\models O, \tag{12}$$

particular scenarios appear to be violated, indicating the possibility of an error. The possibility of accidents or incidents occurring can logically be determined (explained) by abduction before they occur.

In this formalization, a scenario can be regarded as a structured and ordered hypothesis. In addition, each event can also be regarded as an ordered hypothesis.

3 Features of Abducible Hypotheses

We proposed abducive nursing risk management to achieve dynamic risk management. However, the current formalization is still based on hypothetical reasoning where hypotheses are generated (selected) from a hypothesis base. In this section, we discuss the features of hypotheses to be generated in actual dynamic risk management.

3.1 Abduction Model

In abduction models, part or all necessary hypotheses are previously prepared as an hypothesis base. We can extend hypothetical reasoning by introducing a mechanism of CMS [Reiter and de Kleer 1987] where missing hypotheses can logically be generated (created). For instance, consider the following case (h_1 is another necessary hypothesis set):

$$F \cup h_2 \models injection(Diamox), \tag{13}$$

$$h_2 = Diamox \vee h_1. \tag{14}$$

Even if the hypothesis base does not include *Diamox* as an hypothesis, if we have the following *fact*, we can apply CMS to generate *Diamox* as a missing hypothesis:

$$injection(X) \coloneq content(X) \wedge distilled\_water \wedge give\_injection. \tag{15}$$

In fact, CMS can logically generate missing hypotheses, but its limitation is that it can only generate clauses, that is, a minimal conjunction of known or to be known terms or their negations. For instance, in the above example, *Diamox* is not a known hypothesis, but it can be known from observation. Then *Diamox* can be abduced. We presume that a fact base must be complete. We believe that after a complete model of nursing activities is obtained from data in the E-nightingale project [Kuwahara et al. 2004], if we consult with electronic medical recording systems, we can presume the completeness of the fact base.

However, it would be better to generate completely unknown knowledge during abduction, which is "real abduction."

3.2 Abductive Analogical Reasoning

For "real abduction," in [Abe 2000], we proposed Abductive Analogical Reasoning (AAR) that logically and analogically generates missing hypotheses. Its generation mechanism is similar to CMS's. Structures of generated knowledge sets are analogous to the known knowledge sets. In the framework of AAR, not completely unknown but rather unknown hypotheses can be generated. The inference mechanism is briefly illustrated as follows (for notations, see [Abe 2000]):

When

$$\Sigma \not\models O, \qquad (O \text{ cannot only be explained by } \Sigma.) \tag{16}$$

Σ (background knowledge) lacks a certain set of clauses to explain O. Consequently, AAR returns a set of minimal clauses S such that

$$\Sigma \models S \vee O, \tag{17}$$

$$\neg S \notin \Sigma. \tag{18}$$

The result is the same as CMS's. This is not always a guaranteed hypothesis set. To guarantee the hypothesis set, we introduced analogical mapping from known knowledge sets.

$$S \mapsto S', \qquad (S' \text{ is analogically transformed from } S.) \tag{19}$$

$$\neg S' \in \Sigma, \tag{20}$$

$$S' \mapsto S'', \tag{21}$$

$$\Sigma \models S'' \vee O, \tag{22}$$

$$\neg S'' \notin \Sigma. \tag{23}$$

O is then explained by $\neg S''$ as an hypotheses set. Thus we can generate a new hypothesis set that is logically abduced whose structure is similar to authorized (well-known) knowledge sets.

3.3 Features of Abducible Hypotheses in Nursing Risk Management

We introduced AAR to Chance Discovery [Abe 2003] where we defined two types of chances. The first suggests unseen or unknown events as chance, and the second suggests known events as chance by generating new rules. In both types of chances, abduction and analogical mapping play a significant role. The role of abduction is the discovery and suggestion of chance, and the role of analogical mapping is the adjustment and confirmation of chance. AAR works well in usual situations, but in the case of nursing risk management, such alternatives cannot always be applied. Actually, we cannot adopt optional medicine as an hypothesis. Sometimes, nurses mistakenly give a similarly named medicine that causes an accident or incident. Even if the effectiveness of the medicine is similar, it might cause a problem. Thus, for a medicine, we should abduce the same medicine or one that has identical effectiveness to remove nursing accidents or incidents. For other factors, the situation is identical. Thus we cannot always apply the first framework to determine nursing accidents or incidents. Instead, we can adopt the second framework.

In the second type of chance discovery, we refer to the structure of a knowledge set that can be regarded as a scenario for generating an hypothesis set. In [Abe et al. 2006], we introduced the concept of a scenario to express flow and time in nursing activities. For a scenario violation model, the main aim is to determine the violation of a scenario, for which we need to prepare all possible scenarios. We proposed to utilize nursing practice manuals provided by hospitals and nursing academies to build a nursing scenario base. Even if we automatically generate a nursing scenario base by referring to those materials, it is still difficult to compile a perfect one. As pointed out in [Abe et al. 2006], in nursing scenarios, not all but just part of the scenario order is important. For similar activities, the important part of a scenario is almost identical. For instance, a necessary medicine must be dissolved before an injection. Thus for similar activities, there should be common unchangeable scenarios. We can refer to such scenarios to determine scenario violations even if we do not know the complete scenario of the activity.

3.4 Ontology for Nursing Risk Management

For analogical mapping, we need to prepare dictionaries that show similarities between multiple scenarios. A thesaurus can be applied to such problems. Of course it can be partially applied to nursing risk management based on scenario violation. However, a thesaurus usually gives linguistic similarities. We need similarities for actual activities. That is, we need to prepare a dictionary that can provide similarities for actual nursing activities. For that, we are currently building an ontology that deals with nursing activities [Abe et al. 2005]. We are also trying to build a set of nursing corpora [Ozaku et al. 2005] and to extract nursing workflow patterns (scenario) by analyzing transcribed nursing dialogues [Ozaku et al. 2006a, Ozaku et al. 2006b]. We manually add the tags of nursing tasks to the transcribed nursing dialogues (Table 1 (Private information is modified.)). The types of tags are determined by referring to authorized job categories provided as Classification of Nursing Practices [CNP 2005] and Nursing Practice Classification Table [NPCT 2004]. They include such labels as "conference (18-106)" and "intravenous infusion (13-63-6A0502)." After adding such tags, we can build an ontology that can be applied to AAR-based nursing risk management.

Table 1. Labeled dialogues from nurses

Time	dialogue	Job Category
11:01:00	I'm going to a short conference (meeting or handover).	18-106 conference
11:20:48	The short conference is finished.	18-106 conference
11:28:11	I'm going to prepare a drip infusion for Abe-san.	13-63-6A0502 intravenous infusion
11:32:01	I have finished preparing the drip for Abe-san.	13-63-6A0502 intravenous infusion

4 Conclusions

For dynamic risk management, we need to deal with an incomplete knowledge base that lacks knowledge. To supplement the missing knowledge, we can apply abduction, and we proposed abduction-based nursing risk management. In this paper, we analyzed the features of hypotheses for nursing risk management. The results are as follows:

- Hypotheses that suggest unseen or unknown events as chance
  An exact hypothesis set is necessary to conduct nursing risk management.
- Hypotheses that suggest known events as chance by generating new rules
  Similarly structured scenarios can be referred to for conducting nursing risk management.

As shown in this paper, for nursing activities, we cannot always freely adopt alternatives as new hypotheses. Even if analogically correct, an accident or incident might occur. Thus we should abduce the same element or one that has the same effectiveness for removing nursing accidents or incidents by preparing a specialized knowledge base that can be applied to such problems as shown above. We need to prepare proper categorization of nursing tasks for knowledge. Thus we need to prepare an ontology that deals with the categorization of nursing tasks, which are now building by collecting nursing activities from hospitals.

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