4. Results

4.1. Linguistic Analysis Results

The best twenty characteristic words that appear in the incident report such as "Detail," "Reaction," and "Solution" with *tf* (term frequency) are shown in Table 1. The best twenty characteristic words that appear in the incident report with *tf-idf* (Eq.(1)) are shown in Table 2. Under the category of "Detail," the words "Patient," "Confirmation," "Medicine," and "Nurse," rank high in Table 1. Moreover, the fact that the word "Nurse" ranks high shows that there are many accidents related to nurses. Under the category of "Detail" in Table 2, the word "Medicine" ranks higher than the one in Table 1. Therefore, accidents related to medicines are important for analyzing the reports. Also, the characteristic words related to the medical process such as "before" and "after" are high rank in Table 2. In addition, the characteristic words related to patients' managements such as "Room Visit," "Toilet," and "Bed" are high rank in Table 2.

Figure 4, figure 5 and figure 6 show the networks of characteristic words created using the incident reports. Each node represents a characteristic word, and an edge represents the intensity of the co-occurrence between the words. In viewing the network for "Detail" (see Figure 4), most of the reports are about medicines, infusion and fallings. The accidents of medicines are happened in the morning because the peak of giving patients internal medicines is morning in this hospital. In viewing the network for "Reaction" (see Figure 5), the structure of the network is more complex. This is because that the action after an accident by medical staffs and the patient progresses are various depending on the situations. In viewing the network for "Solution" (see Figure 6) it is clear that the network is created around the characteristic word "Confirmation," and one can see that descriptions of solutions are about confirming the medicines, patients, or timings by nurses.

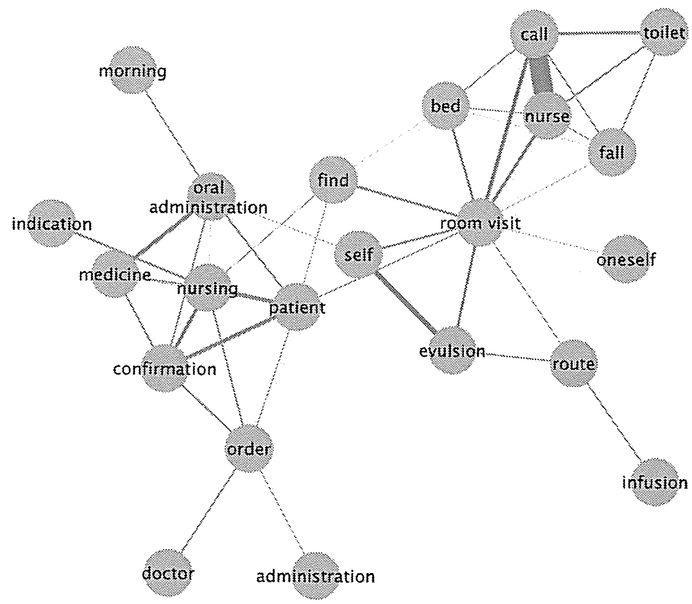

Figure 4. Co-occurrence Network of the Characteristic Words (Detail).

***Nodes mean the best 30 characteristic words based on tf-idf measures, and edges mean the existence of co-occurrences. Heavy lines between characteristic words mean strong connection between words.**

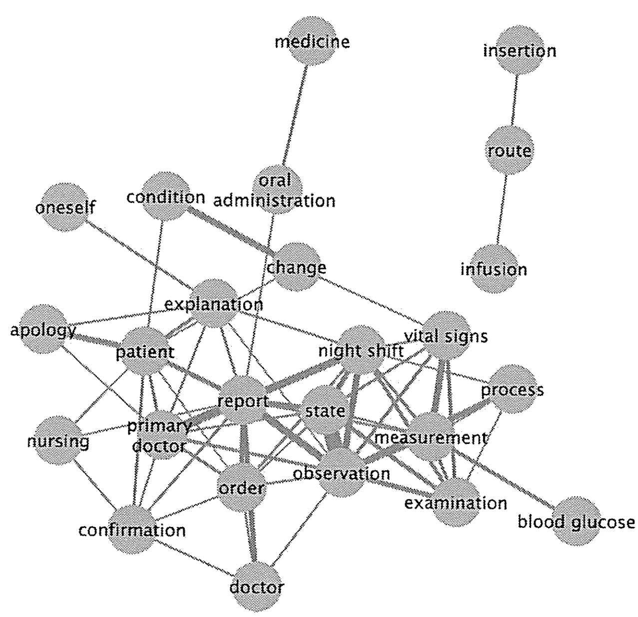

Figure 5. Co-occurrence Network of the Characteristic Words (Reaction)

****Nodes mean the best 30 characteristic words based on tf-idf measures, and edges mean the existence of co-occurrences. Heavy lines between characteristic words mean strong connection between words.**

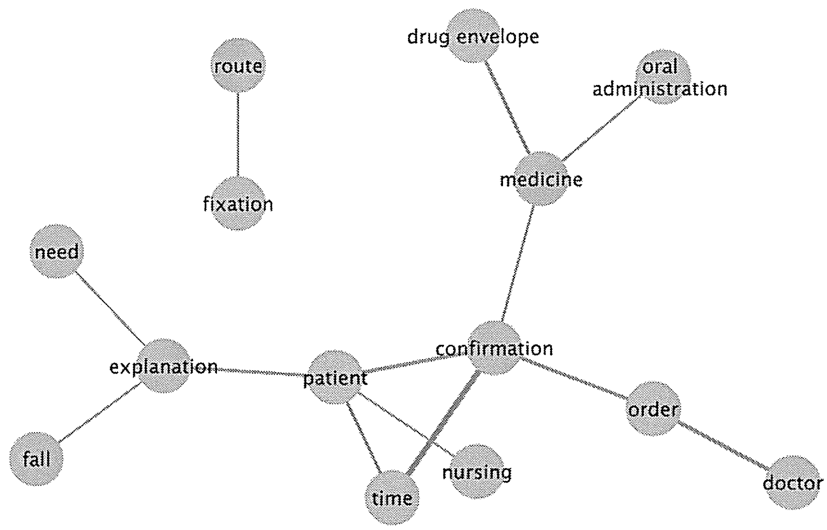

Figure 6. Co-occurrence Network of the Characteristic Words (Solution)

****Nodes mean the best 30 characteristic words based on tf-idf measures, and edges mean the existence of co-occurrences. Heavy lines between characteristic words mean strong connection between words.**

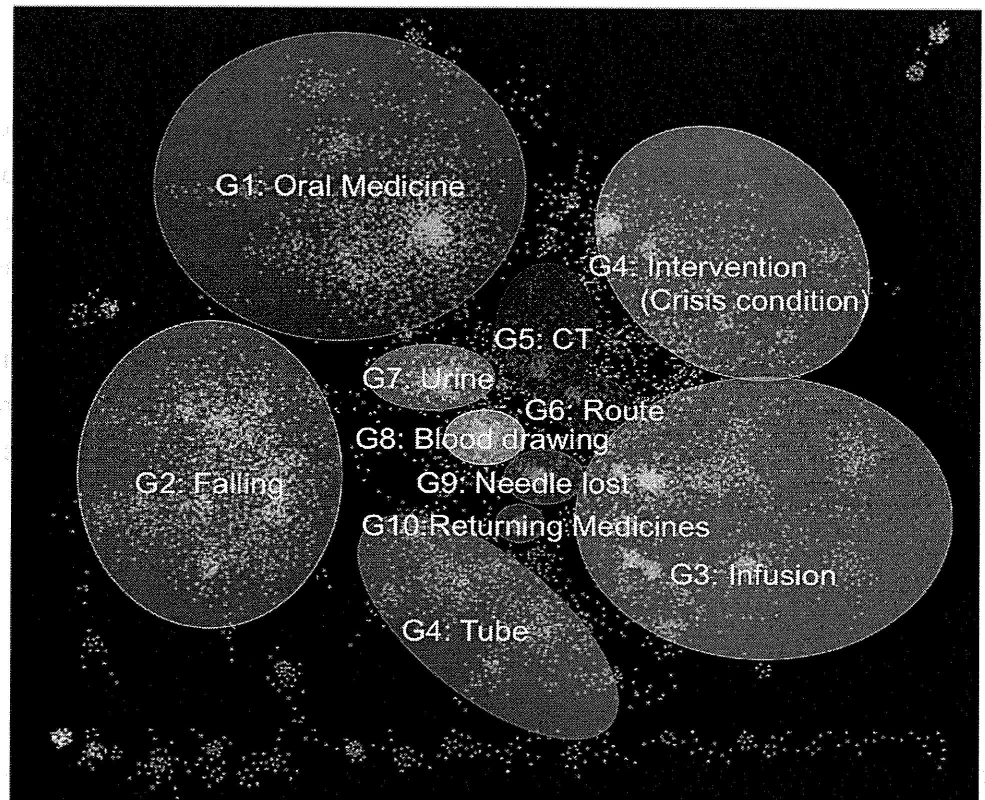

Figure 7. Clustering Results to the Network of incident reports (Detail)

***The name of the group means the rank of the number of nodes**

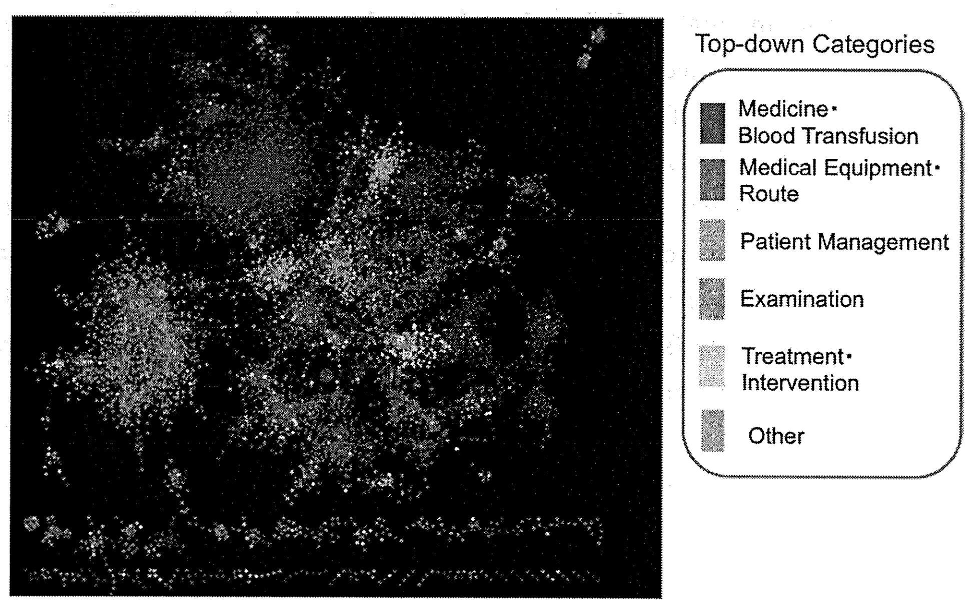

Figure 8. Comparison between Top-down Categories and Bottom-up Categories for Network of Documents (Detail)

*** The color of nodes mean the categories decided by the experts and the positions of nodes are plotted according to similarities between nodes.**

4.2. Categorizing Results based on Bottom-up Analysis

Figure 7 shows the best ten clusters and in "Details" categories. The reason of selecting the "Detail" section is that this category contains the most important information in order to divide the reports into some groups. The doctors in Osaka City University carried out labeling of each cluster based on the networks. The clusters from position 1 to 5 clearly appear the granted classes. In the cluster in position 1, the class of oral medicines is prioritized. In this group, administrations of medicines and preparations of medicines are included; in positions 2, the class of patient managements regarding patients' fallings is created clearly; however, in position from six to ten, the classes that clearly characterize clusters could not be seen.

5. Discussions

Figure 8 shows the comparisons between the top-down categories and bottom-up categories for network of documents in the section of details of situations. In this figure, the color of nodes mean the categories decided by the experts and the positions of nodes are plotted according to similarities between nodes.

The top-down category of "Medicine and Blood Transfusion (Blue)" has two main groups; one is about the oral medicine, the other is about the infusion. This means that top-down categories of "Medicine and Blood Transfusion (Blue)" should be divided into two new categories. In fact, some medical staff indicates that this category is too wide range as the categories of the incident reports in the interview.

The reports with "Patient Management (Orange)" category are mainly about the fallings, and most of them contain the second largest groups labeled as the Falling in figure 7. It is better for the medical staffs that the label of this category is "Falling" because some medical staffs labeled the accidents of fallings to "Others (Gray)." Actually, "G2: Falling" contains orange and gray nodes in figure 7.

The top-down categories of "Examination (Sky)" and "Medical Equipment and Route" are divided into some small groups. In the interview to the medical staff in Osaka City University Hospital, the idea of dividing the top-down category of "Examination (Sky)" and "Medical Equipment and Route (Red)" into the some small categories was appeared.

The top-down category of "Treatment and Intervention" can't be seen the large-sized groups. Most of the medical staffs don't use this top-down category because most of the accidents are divided into other suitable top-down categories. Therefore, this top-down category doesn't make any sense.

However, in position from six to ten, classes that clearly characterize clusters could not be seen. The possible future work is that the section for analyzing the bottom-up categories isn't only the detail section but also the combinations of the detail section and the reaction section.

6. Conclusion

In this paper, the characteristic words were extracted by analyzing incident reports, and the co-occurrence networks of the characteristic words were created. As a result, the language networks with the hub of the word "confirmation," thereby revealing that inadequate confirmations on the drug labels, instructions of a physician and patient were very significant causes of accidents. These results suggest the effectiveness of introducing the network analysis method. In addition, the class of patient managements regarding patients' fallings in top-down analysis is created clearly. On the other hand, some categorizes by top-down analysis don't reflect the category by the bottom-up analysis. These results suggest the effectiveness of introducing the network analysis method.

In the future work, we would like to focus on the medical repots for improving the notational rules for the names of drugs and dosages in incident reports. Also, we would like to analyze the differences of understanding of the incident reports between positions like doctors, nurses, pharmacists.

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PRELIMINARY LINGISTIC ANALYSIS OF LARGE NUMBER OF MEDICAL INCIDNET REPOTS FOR PATIENT SAFETY

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ABSTRACT

The analysis of medical incident reports is indispensable for the patient safety. Most of the incident reports include some free composition formats, therefore, the analysis of free descriptions gives new perceptions. We aimed to accumulate, to interpret information again by structured incident information, and to clarify the point that should be improved for the cause of the accident and safe medical treatment improvements in the present study. We employ the natural language processing to the analysis of medical incident reports in this paper. The network analysis can find various relationships that are not only direct relationships but also indirect relationships. First, some important characteristic words were extracted in three categories of the accident's background, details, and solutions using TF-IDF measure. By using the TF-IDF, we can get some important characteristic words for analyzing the reports. In addition, we show the co occurrence networks using these extracted words.

1. INTRODUCTION

"In the shadow of every serious accident, there exist 29 times more minor accidents and 300 times more near misses." This principle was published in 1929 by Herbert William Heinrich, an assistant manager in the technology and research division of an American insurance company [1]. This principle, which hits home the nature of the occurrence of accidents, is taken up in various fields, such as the study of failure, safety engineering, cognitive psychology as well as the study of reliability, and the incident analysis of minor accidents associated with this is recognized as being important in preventing accidents.

Also, the use of information pertaining to medical accidents is important when implementing medical safety measures. The medical safety mechanism of WHO aims to prevent accidents by reusing incident reports through the introduction of IT technology. Harvard University is engaged in the standardization for the collection of medical accident reports and accident information in the risk management consortium. In England, the National Health Service conducts the medical accident/incident report collection project. Even in Japan, the Ministry of Health, Labour and Welfare began the project to Collect Medical Near-Miss/Adverse Event Information in 2001[2]. Through this project, the Ministry conducts analyses based on the collected incident reports.

On the other hand, regarding patient safety, guidelines for the future deployment of incident analysis are set out in WHO's International Classification of Patient Safety (ICPS) [3]. ICPS states the necessity of first investigating the adequacy of classes of incident case studies such as those mentioned above, and second, methods of expressing incidents that adequately reflect these classes, i.e., it states the necessity of ontological construction. In this research, in line with WHO guidelines, we conducted an analysis regarding the adequacy of classes in case studies collected in the Project to Collect Medical Near-Miss/Adverse Event Information and the tendencies of description that aim at ontological construction.

In the Medical Near-Miss/Adverse Event Information including the abstract, background, and solution for a single case are described using a free composition format. In this paper, we analyze the large number of medical incident repots (more than 15,000 reports) provided by Osaka City University using the natural language processing and the network analysis. By using natural language processing, an understanding of the tendencies of description as well as guidelines for future ontological construction can be acquired.

The remainder of this paper is organized as follows. First, we describe the dataset of the medical incident reports provided by Osaka City University. Next, we describe the methodology based on the Natural Language Processing and the Network analysis for analyzing the large number of medical incident reports. Then, we present the results of analysis of incident reports. Finally, we present our overall conclusions.

2. MEDICAL INCIDENT REPORTS BY OSAKA CITY UNIVERSITY

2.1 Overview of Medical Incident Reports

With increasing social demand for the prevention of medical accidents, the Health, Labour and Welfare Ministry started the Project to Collect Medical Near-Miss/Adverse Event Information from 2001 in order to collect and analyze incident case studies and to provide information conducive to medical safety, such as measures for improvements. When the project was first started, a framework was in place in which the Pharmaceuticals and Medical Devices Agency collected incident case studies from participating medical institutions and then reported these case studies to the Health, Labour and Welfare Ministry, following which a Health, Labour and Welfare Ministry study group conducted aggregate calculations and analysis. The 1st–10th collection of incident case studies were conducted following this framework, and information based on these collected incident case studies was provided by the Health, Labour and Welfare Ministry. From 2004, the Japan Council for Quality Health Care took over the collection of incident case studies, collecting case studies from the 11th collection [4].

Osaka City University also collected 18,340 incident reports from 2007 to 2010. In the incident reports provided by Osaka City University, free composition formats are taken quite seriously compared with ones provided by other Hospitals. For instance, the average number of words in the incident reports by Osaka City University is 188 words, on the other hand, the one by the Project to Collect Medical Near-Miss/Adverse Event Information is 80 words[2]. In fact, doctors and nurses in Osaka City University have to input the reports for the free descriptions at first because of the Layout of data entry screen.

2.2 Data Sets

We used free composition format written in Japanese relating to medical agents from 2007 to 2011 by Osaka City University. The number of documents is 18,340. Each case study is in a free composition format, with the abstract, background, and solution being approximately 188 words long, respectively. In addition, the two classes of medicine and accident are granted to each case study. With regard to the class of treatment, there are six classes of general drug, preparation of drugs, drowsy of drugs, contraindicated drug, chemo treatment, and other drug; with regard to the class of operation, there are the nine classes of name of drug, amount of drug, regimen, amount and regimen, flow rate, drug sensitivity, diapedesis, forget to dose, and object person. With regard to the class of treatment, as all the classes of operation do not exist, there are 32 cross classes that cross calculate the class of treatment and the negligent class of operation.

When describing accidents in a free composition format, the reporter makes every effort to include every single circumstance. We can say that extracting important information from these circumstances means creating a foothold for a bottom-up type of ontological construction. Results obtained from this and links with classes granted top-down is in accordance with the future guidelines for incident analysis sought by ICPS.

3. METHODOLOGY OF NATURAL LANGUAGE PROCESSING AND NETWORKD ANALYSIS

3.1 Methodologies for analyzing the incident reports

In this paper, natural language processing was first conducted on the incident reports. Keywords that emerge characteristically were then extracted for each category of "background/causes," "details," and "solutions," using the tfidf method. After that, the semantic tendency of the incident report was investigated in order to create a network of words by calculating the co-occurrence information of the words using the Jaccard coefficient.

Also, we show the networks among each document which are determined by the similarities between documents based on the tfidf method. As natural language processing contains a lot of noise, there is a need to conduct preprocessing in order to obtain characteristic words that can be used in determining links.

3.2 Japanese language morphological analysis

In the first stage of preprocessing, we conducted morphological analysis in order to break down reports into words. Morphological analysis is a method used to delimit each word in the text where words are not delimited by spaces, such as in languages like Japanese [5]. In this research we used MeCab, one of the most common engines for conducting morphological analysis [6].

There is the possibility that words obtained using MeCab are too finely classified to conduct the analysis of links. Therefore, we connected words using the following methods and used them as new words.

We connected words using information on the parts of speech. The above-mentioned MeCab not only breaks down words but also grants major classes and minor classes relating to parts of speech. In cases where the minor class of parts of speech of certain words was a suffix and the word before it was a noun, these two words were treated as one word.

Next, we connected words based on the number of word occurrences [7]. Let us envisage a situation in which two words -hereafter called A and B- appeared consecutively. If we designate the number of word occurrences in instances where each word is considered separately as $n(A)$, $n(B)$, then the number of word occurrences in which

- (1)
- (2)
- (3)

they appear consecutively is expressed as $n\ (A \cap B)$. In cases where $n\ (A \cap B)/min\ (n\ (A),\ n\ (B))$ exceeded the threshold value (0.1 in this research) then we treated those two words as one word.

In the documents, nominalized verbs, general nouns, and proper nouns were targeted. Focusing solely on nouns is the method generally used in extracting characteristic words. Moreover, in the case of official documents in Japanese, as many of the verbs are nominalized, a lot of information can be obtained regarding action even if using only nouns.

3.3 TF-IDF Method

In this research, we calculated a value called *tf-idf* from the frequency of occurrence and conducted filtering based on this values. *Tf-idf* is one of the most widely used indices in extracting characteristic words for document classes and in cases where a certain word occurs several times in a small number of documents, it is defined so as to enlarge that value[8]. *Tf-idf* is calculated as follows:

$$tf - idf(t,d) = tf(t,d) \times idf(t)$$
$$tf(t,d) = n(t) / \sum_{k \in T} n(k)$$
$$idf(t) = \log |D| / \{d : d \in t\}$$

Here, t is a term, d is a document, $n(t)$ is the frequency of occurrence of term t, $|D|$ is the total number of documents, and is *{d:d\in t}* the number of documents in which word t occurs. T means the set of terms.

The *tfidf* of general words occurring in a large number of documents has a tendency to be of a low value, although words among even general words that have an abnormally high *tf* in some cases exceed the filter effect of *idf* and assume a high value.

3.4 Creation of Co-Occurrence Networks

The co-occurrence index is generally used as a method for finding links from the degree of similarities between words in documents. Here, the simplest co-occurrence index for finding links between the two word A and B is the number of co-occurrence $|A \cap B|$ for two words. Here, $|A \cap B|$ is the number of characteristic words that exist in A and B. If considered with only $|A \cap B|$, there are problems such as including as many characteristic words as in long texts and links with other documents being displayed as high. Consequently, a number of co-occurrence indices that improve on these points have been proposed, with representative indices including the Jaccard coefficient [9].

$$Jaccard : |A \cap B| / |A \cup B| \quad \text{-(4)}$$

A link is established between the two words in the event that these indices exceed the threshold value.

4. PRELIMINARY ANALYSIS RESULTS

Table1: Top 10 Characteristic Word in Incident Reports (*TF*; Term Frequency)

(TF)	Background	Details	Solutions
1	Patient	Report	Check
2	Check	Patient	Time
3	Drug	Check	Patient
4	Nurse	Attending Doctor	Direction
5	Direction	Monitor	Drug
6	Internal use	Duty Doctor	Explanation
7	Infusion	Doctor	Nurse
8	Pill	Direction	Thoroughness
9	Room	Nursing	Drug maker
10	Administration	Explain	Doctor

Table2: Top 10 Characteristic Word in Incident Reports (*TF-IDF*)

tf-idf	Background	Details	Solutions
1	Drug	Patient	Check
2	Patient	Report	Time
3	Check	Attending Doctor	Patient
4	Internal medicine	Check	Direction
5	Direction	Doctor	Drug
6	Nurse	Monitor	Explanation
7	Administration	Apologizing	Nurse
8	Infusion	Nursing	Thoroughness
9	Root	Duty Doctor	Before
10	Channel	Direction	After

The top ten characteristic words that appear in the incident report such as "background/causes," "details," and "solutions" with *tf* (term frequency) are shown in Table 1. The top ten characteristic words that appear in the incident report with *tf-idf* (Eq.(1)) are shown in Table 2. Under the category of "Background," the words "Patient" "Check," "Drug," "Nurse," and "Direction" rank high in Table 1. Moreover, the fact that the word "nurse" ranks high shows that there are many accidents related to nurses. Under the category of "Background," the words "Drug" "Internal medicine," "Infusion," and "Channel" rank high in Table 2. Therefore, accidents related to medicines are important for analyzing the reports. Also, the words "Check," "Direction," and "Explanation" rank high under the category of solutions. In addition, the words related to the medical process such as "before" and "after" are high rank.

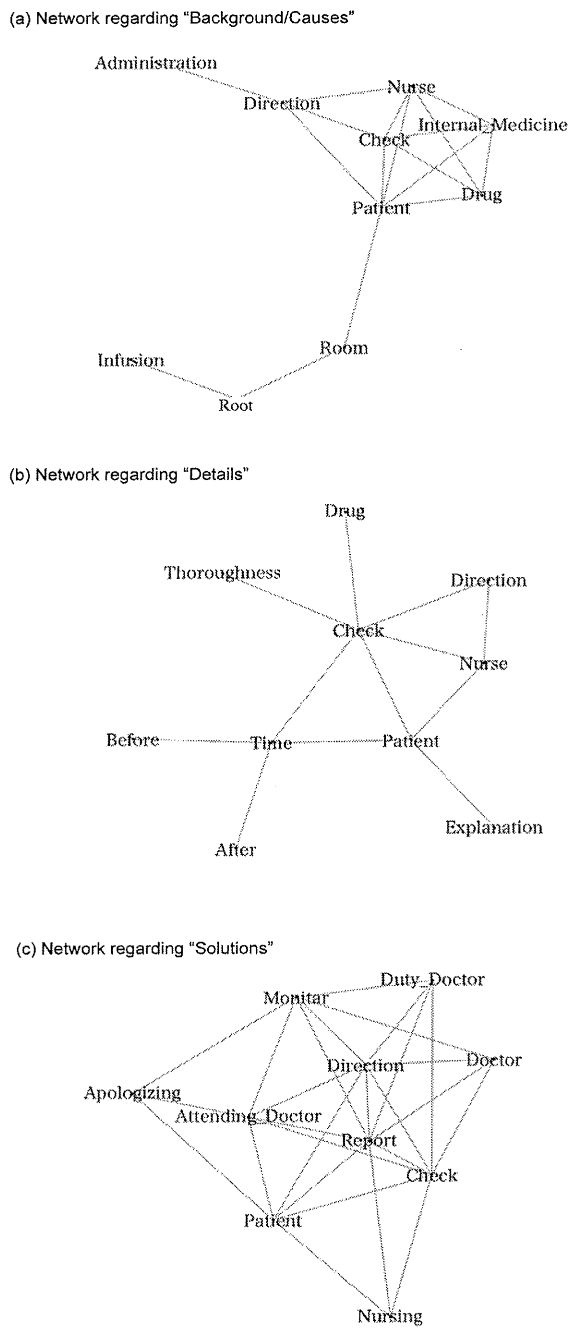

Figure 1: Co-occurrence Network of the Words in Incident Reports

One word such as "lack," "confirmation," or "drugs" alone cannot express the tendency of the accident. In this research, co-occurrence networks of words were created by connecting the words that co-occurred with each other at a high frequency. The degree of co-occurrence is calculated using the Jaccard coefficient [3] shown in Section 3.4.

Figure 1 shows the networks of characteristic words created using the accident reports related to incorrect drugs. Each node represents a word, and an edge represents the intensity of the co-occurrence between the words. First of all, in viewing the network for "background/causes" (see Figure 1 (a)) it is clear that the network is created around the word "Check," and one can see that the cause of many accidents is the fact that the "Check" on "drugs," "Patient," by "Nurse". Connecting the words that co-occur frequently allows us to understand what tends to become inadequate. In the network of "accident details" (see Figure 1 (b)) many different words appear at once, indicating the presence of diverse accident details. Viewing the network for "solutions" (see Figure 1 (c)), as with the network for "background/causes," it is created around the word "confirmation."

5. CONCLUSION

In this paper, the characteristic words were extracted by analyzing incident reports, and the co-occurrence networks of the characteristic words were created. As a result, the language networks with the hub of the word "check," thereby revealing that inadequate confirmations on the drug labels, instructions of a physician and patient were very significant causes of accidents. These results suggest the effectiveness of introducing the network analysis method. In the future work, we would like to focus on the medical repots for improving the notational rules for the names of drugs and dosages in incident reports. Also, we would like to analyze the differences of understanding of the incident reports between positions like doctors, nurses, pharmacists.

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An Approach to Scalable Multi-issue Negotiation: Decomposing the Contract Space

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Most real-world negotiation involves multiple interdependent issues, which makes an agent's utility functions nonlinear. Traditional negotiation mechanisms, which were designed for linear utilities, do not fare well in nonlinear contexts. One of the main challenges in developing effective nonlinear negotiation protocols is scalability; they can't find a high-quality solution when there are many issues, due to computational intractability. One reasonable approach to reducing computational cost, while maintaining good quality outcomes, is to decompose the utility space into several largely independent sub-spaces. In this paper, we propose a method for decomposing a utility space based on every agent's utility space. In addition, the mediator finds the contracts in each group based on the votes from all agents, and combines the contract in each issue-group. This method allows good outcomes with greater scalability than the method without issue-grouping. We demonstrate that our protocol, based on issue-groups, has a higher optimality rate than previous efforts, and discuss the impact on the optimality of the negotiation outcomes.

Key words: Multi-Issue Negotiation, Interdependent Issues, Bargaining and negotiation

1. INTRODUCTION

Negotiation is an important aspect of daily life and represents an important topic in the field of multi-agent system research. There has been extensive work in the area of automated negotiation; that is, where automated agents negotiate with other agents in such contexts as e-commerce(Kraus (2001)), large-scale argumentation (Malone and Klein (2007)), collaborative design, and so on. Even though many contributions have been made in this area (Faratin et al. (2002)), most have dealt exclusively with simple negotiations involving one or more independent issues. Many real-world negotiations, however, are complex and involve interdependent issues. When designers work together to design a car, for example, the utility of a given carburetor is highly dependent on which engine is chosen. The key impact of such issue dependencies is that they result in agent utility functions that are nonlinear, i.e. that have multiple optima. Most existing negotiation protocols, though well-suited for linear utility functions, work poorly when applied to nonlinear problems (Klein et al. (2003)).

Recently, some studies have focused on negotiation with nonlinear utility functions. The followings are the representative studies on multi-issue negotiations for complex utility spaces. A bidding-based protocol was proposed by Ito et al. (2007). Agents generate bids by finding high regions in their own utility functions, and the mediator finds the optimum combination of submitted bids from the agents. By Fujita et al. (2008), a representative-based protocol for reducing the computational cost was proposed. In this method, the scalability of agents was improved; however, the scalability of issues was not sufficient. Robu et al.

(2005); Robu and Poutre (2006) presented the utility graph for issue interdependencies of binary-valued issues. Utility graphs are inspired by graph theory and probabilistic influence networks to derive efficient heuristics for non-mediated bilateral negotiations about multiple issues. Hindriks et al. (2006) proposed an approach based on a weighted approximation technique to simplify the utility space. It shows that existing methods for the linear utility function can work well when the nonlinear utility function is possible to be converted to approximated linear utility function. Marsa-Maestre et al. (2009) proposed an auction-based protocol for nonlinear utility spaces generated using weighted constraints, and Marsá-Maestre et al. (2010); Marsa-Maestre et al. (2009) extended this work to address highly rugged utility spaces. However, an unsolved problem is the scalability of the protocols. Our protocol focuses on the large-scale (nearly 50 issues) and interdependent multi-issue negotiations.

We propose a new protocol in which a mediator tries to reorganize a highly complex utility space into several tractable utility subspaces, in order to reduce the computational cost. First, we have to define a measure for the degree of interdependency between issues, and generate a weighted non-directed interdependency graph. Note that while others have discussed issue interdependencies in utility theory (Tamura and Nakamura (1983)), the aim of these previous works weren't to generate the efficient issue-groups. Second, we propose an efficient and scalable protocol based on the issue-groups. Agents generate the idea of issue-groups based on their utility information, and the mediator combines the idea of issue-grouping from all agents. After that, the mediator finds the contracts in each group based on the votes from all agents, and combines the contract in each group.

Actually, it is possible to gather all of the agents' interdependency graphs in one central place and then find all optimal contracts using such well-known clustering techniques as the k-means or Girvan-Newman algorithm(Girvan and Newman (2002)) in deciding the efficient issue-groups. However, most of the clustering techniques have to decide on certain parameters in employing the clustering techniques. For instance, the number of edges to be progressively removed from the graph is fixed in advance in the Girvan-Newman algorithm. There is a trade-off between the optimality rate and the failure rate in selecting the number of issue groups. In real-life negotiation, it is hard to determine the optimal parameters for central clustering in advance without enough history data. For automated agents, it is possible to recognize their issue-group idea by themselves because each agent has enough utility information for deciding on the efficient issue-groups.

Finally, we demonstrate that our protocol, based on issue-groups, has a higher optimality rate than previous efforts, and discuss the impact on the optimality of the negotiation outcomes. In addition, we analyze the clustering parts of our proposed protocol. Especially, we analyze the effectiveness between the clustering parameter and the results of issue-grouping.

The remainder of this paper is organized as follows. First, we describe a model of nonlinear multi-issue negotiation and utility functions, a measure for assessing the degree of issue interdependency, and the structure of interdependency graph based on real-life negotiation. Second, we present a technique for finding issue sub-groups, and propose a protocol that uses this information to enable more scalable negotiations. Third, we present the experimental results. Finally, we describe related works and draw conclusions.

2. NEGOTIATION WITH NONLINEAR UTILITY FUNCTIONS

2.1. Preliminaries

We consider the situation where N agents $(a_1, \ldots, a_N)$ want to reach an agreement with a mediator who manages the negotiation from a man-in-the-middle position. There are M issues $(i_1, \ldots, i_M)$ to be negotiated. The number of issues represents the number of dimen-

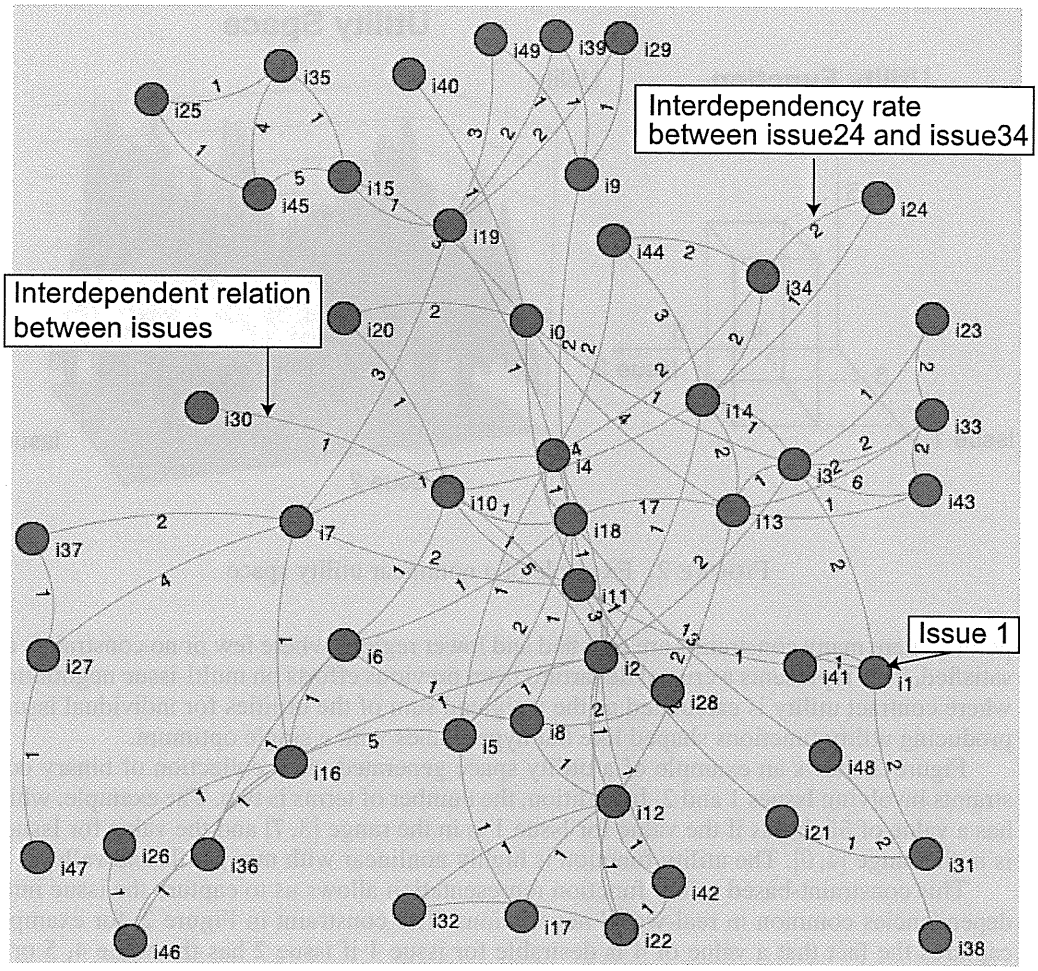

FIGURE 1. Interdependency Graph (50 issues)

sions in the utility space. The issues are shared: all agents are potentially interested in the values for all M issues. A contract is represented by a vector of values $\vec{s} = (s_1, ..., s_M)$. Each issue s_j has a value drawn from the domain of integers $[0, X]$, *i.e.*, $s_j \in \{0, 1, , \ldots, X\}(1 \leqslant j \leqslant M)$. [1].

An agent's utility function, in our formulation, is described in terms of constraints. There are l constraints, $c_k \in C$. Each constraint represents a region in the contract space with one or more dimensions and an associated utility value. In addition, c_k has value $w_a(c_k, \vec{s})$ if and only if it is satisfied by contract $\vec{s}$. Function $\delta_a(c_k, i_j)$ is a region of i_j in c_k, and $\delta_a(c_k, i_j)$ is $\emptyset$ if c_k doesn't have no relationship to i_j. Every agent has its own, typically unique, set of constraints.

An agent's utility for contract $\vec{s}$ is defined as the sum of the utility for all the constraints it satisfies, i.e., as $u_a(\vec{s}) = \sum_{c_k \in C, \vec{s} \in x(c_k)} w_a(c_k, \vec{s})$, where $x(c_k)$ is a set of possible contracts (solutions) of c_k. This expression produces a "bumpy" nonlinear utility function with high

[1] A discrete domain can come arbitrarily close to a 'real' domain by increasing its size. As a practical matter, many real-world issues that are theoretically 'real' numbers (delivery date, cost) are discretized during negotiations.

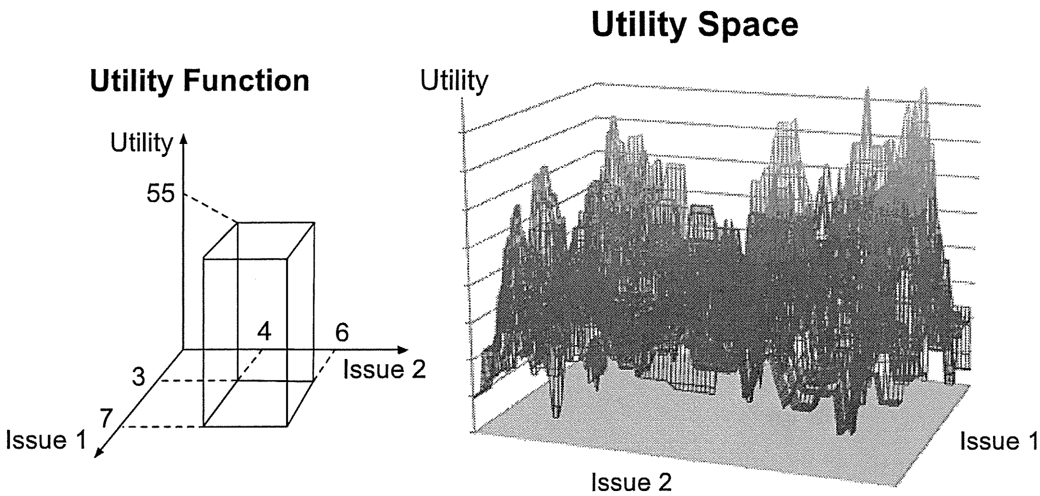

FIGURE 2. Example of a nonlinear utility space

points where many constraints are satisfied and lower regions where few or no constraints are satisfied. This represents a crucial departure from previous efforts on multi-issue negotiation, where contract utility is calculated as the weighted sum of the utilities for individual issues, producing utility functions shaped like flat hyperplanes with a single optimum.

Figure 2 shows an example of a utility space generated via a collection of binary constraints involving Issues 1 and 2. In addition, the number of terms is two. The example, which has a value of 55, holds if the value for Issue 1 is in the range $[3, 7]$ and the value for Issue 2 is in the range $[4, 6]$. The utility function is highly nonlinear with many hills and valleys.

This constraint-based utility function representation allows us to capture the issue interdependencies common in real-world negotiations. The constraint in Figure 2, for example, captures the fact that a value of 4 is desirable for issue 1 if issue 2 has the value 4, 5 or 6. Note, however, that this representation is also capable of capturing linear utility functions as a special case (they can be captured as a series of unary constraints). A negotiation protocol for complex contracts can, therefore, handle linear contract negotiations.

The objective function for our protocol can be described as follows:

$$\arg\max_{\vec{s}} \sum_{a \in N} u_a(\vec{s}). \tag{1}$$

$$\arg\max_{\vec{s}} u_a(\vec{s}),\ (a = 1, \ldots, N). \tag{2}$$

Our protocol, in other words, tries to find contracts that maximize social welfare, *i.e.*, the total utilities for all agents. Such contracts, by definition, will also be Pareto-optimal. At the same time, each agent tries to find contracts that maximize individual welfare.

Of course, it is theoretically possible to gather all of the individual agents' utility functions in one central place and then find all optimal contracts using such well-known nonlinear optimization techniques as simulated annealing or evolutionary algorithms. However, we do not employ such centralized methods for negotiation purposes because we assume, as is common in negotiation contexts, that agents prefer not to share their utility functions with each other in order to preserve a competitive edge.

This constraint-based utility function representation has been proposed in Ito et al. (2007). It allows us to capture the issue interdependencies common in real-world negotiations. It was

TABLE 1. Utility function for an agent: ID means the id number of every constraints. $[a, b]$ means that the agent has a value of the utility if the value for the Issue is in the range of a and b. $*$ means any value

ID	Issue1	Issue2	Issue3	Issue4	Utility
1	[2,4]	*	[4,6]	*	20
2	*	5	[3,7]	[1,6]	40
3	[3,8]	*	*	*	25
4	4	[2,7]	9	[4,5]	50

also assumed that many real-world utility functions are more complex than this, involving more than two issues as well as higher-order (e.g. trinary and quaternary) constraints. In recent work (e.g. Marsa-Maestre et al. (2009); Marsá-Maestre et al. (2010)), several types of constraints were proposed.

2.2. Interdependency among Issues

An issue interdependency for multi-issue negotiations is defined as follows. If there is a constraint between issue X (i_X) and issue Y (i_Y), then we assume i_X and i_Y are interdependent. If, for example, an agent has a binary constraint between issue 1 and issue 3, those issues are interdependent for that agent - see Table 1.

The strength of issue interdependency is measured by the *interdependency rate*. We define a measure for the interdependency between $issue\ i_j$ and $issue\ i_{jj}$ for agent a:

$$D_a(i_j, i_{jj}) = \sharp\{c_k | \delta_a(c_k, i_j) \neq \emptyset \ \wedge \ \delta_a(c_k, i_{jj}) \neq \emptyset\}.$$

This measures the number of constraints that inter-relate the two issues.

The agents capture issue interdependency information as an interdependency graph. An interdependency graph is represented as a weighted non-directed graph, in which a node represents an issue, an edge represents the interdependency between issues, and the weight of an edge represents the interdependency rate between the issues. An interdependency graph is thus formally defined as:

$$G(P, E, w) : P = \{1, 2, \ldots, |I|\}(finite\ set),$$

$$E \subset \{\{x, y\} | x, y \in P\}, w : E \rightarrow R.$$

Figure 1 shows an example of an interdependency graph. The interdependency graph can have the hyper-edges because the hyper-edges are a combination of the binary-edges. For example, a trinary constraint between i_1, i_2 and i_4 can be represented as the combination of the binary edges between i_1 *and* i_2, i_1 *and* i_4, i_2 *and* i_4.

Figure 3 shows what the interdependency graph consists of in an agent. The method of determining the interdependency between issues is as follows.

(Step 1) Small issue-groups are generated by connecting a part of the issues randomly.
(Step 2) The interface issues are decided randomly among issues in each issue-group. The interface issues are for connecting other small issue-groups. In small issue-groups, only the interface issues can connect to other issue-groups.
(Step 3) Each issue-group connects to other small issue-groups. Specifically, all combinations of each issue-group are searched for, and it is decided whether connection or disconnection according to the possibility of generating connections between the small issue-groups. We call the possibility the possibility of generating connections "the possibility of connecting to other issue-groups."

Note that in negotiations with multiple *independent* issues, we can find the optimal

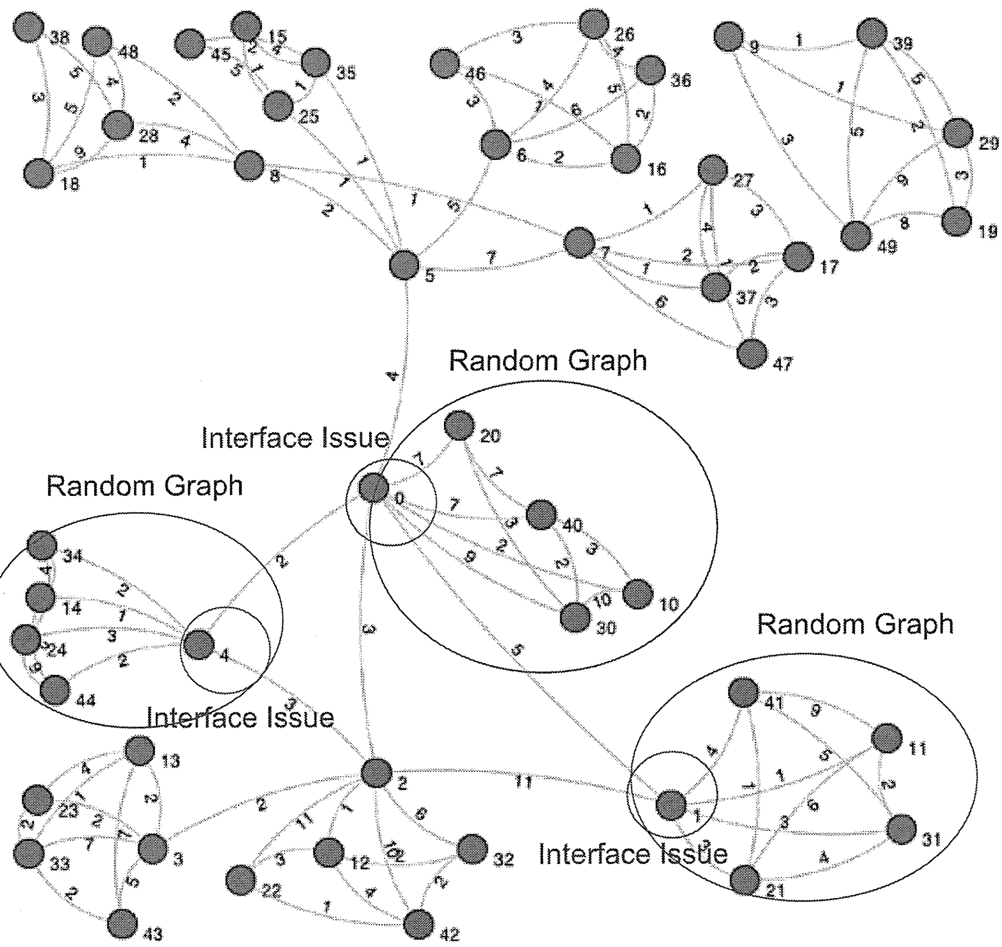

FIGURE 3. Method of determining interdependency graph

value for each issue in isolation to quickly find a globally optimal negotiation outcome. In negotiation with multiple *interdependent* issues, however, the mediator can't treat issues independently because the utility of a choice for one issue is potentially influenced by the choices made for other issues. Figure 4 shows the relationship between issue interdependency and negotiation optimality in an example with interdependent issues. In figure 4, we ran an exhaustive social welfare optimizer for each issue independently, as well as for all possible issue combinations. The number of agents is four, and the domain per issue is five. The linear utility function (independent cases) is generated by $u_a(x) = k * x + c$ (where x is the value for that issue, k and c are constants, and a is the agent). The nonlinear function is generated by some multi-dimensional constraints. If the mediator ignores the issue interdependencies (i.e. finds optima for each issue in isolation), optimality declines rapidly as the number of issues increases. This means that the mediator must account for issue interdependencies in order to find high-quality solutions. However, if the negotiation protocol tries to do so by exhaustively considering all issue-value combinations, it quickly encounters intractable computational costs. If we have, for example, only 10 issues with 10 possible values per issue, this produces a space of 10^{10} (10 billion) possible contracts, which

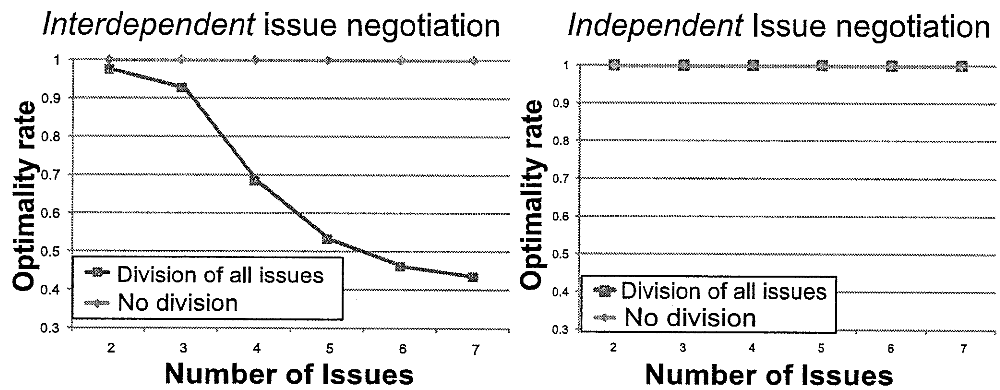

FIGURE 4. Relationship of interdependency and optimality rate with nonlinear utility function

TABLE 2. Votes and numeric values from agents

Votes	Numeric value
Accept	2
Weakly Accept	1
Weakly Reject	-1
Reject	-2

TABLE 3. Votes and utility in agents

(Utility of next situation) - (Utility of present situation)	Vote
$X_1 \sim$	Accept
$0 \sim X_1$-1	Weakly Accept
$X_2 \sim -1$	Weakly Reject
$\sim X_2$-1	Reject

(X_1, X_2 are arbitrary integer numbers.)

is too large to evaluate exhaustively. Negotiation with multiple interdependent issues thus introduces a difficult tradeoff between optimality and computational cost.

3. NEGOTIATION PROTOCOL BASED ON ISSUE INTERDEPENDENCY

3.1. Efficient Negotiation Protocol based on Issue-groups

Our proposed negotiation protocol works as follows. A mediator gathers ideas of issue-grouping from agents, identifies issue sub-groups by combining the ideas of issue-groups, and then uses that information to guide the search for a final agreement. In fact, we apply the concept of simulated annealing techniques(Klein et al. (2003)) in our negotiation protocol. By applying the concept of issue-grouping with the simulated annealing approach, we can propose a highly scalable and efficient protocol. We describe the details below.

[Step 1: Analyzing issue interdependency] Each agent analyzes issue interdependency in its own utility space by analyzing all constraints, and generates an interdependency graph. After that, each agent generates his/her own idea of issue-grouping using the Girvan-

Newman algorithm(Girvan and Newman (2002)), which is for computing clusters in weighted non-direct graphs based on edge betweenness. The edge betweenness shows the weighted shortest path in our protocol. Running time of this algorithm is $O(kmn)$, where k is the number of edges to remove, m is the total number of edges, and n is the total number of vertices.

[Step 2: Grouping issues] In this step, the mediator combines the ideas of issue-grouping submitted by each agent. The mediator employs the breadth-first search to generate the combined social issue-groups. If every issue-groups submitted by all agents have crossover parts, the mediator generates the union of sets of issue-groups from every agents (line 6~9 in Algorithm 1). For simple example, agent 1 submits the idea $A_1 = \{i_1, i_2\}, \{i_3, i_4, i_5\}, \{i_0, i_6\}$ and agent 2 submits the idea $A_2 = \{i_1, i_2, i_6\}, \{i_3, i_4\}, \{i_0\}, \{i_5\}$ when the number of issues is seven. $\{i_1, i_2\}$ means that i_1 and i_2 are in a same group, and A_1 is the idea of issue-groups submitted by *Agent 1*. The mediator combines A_1 with A_2, and decides the issue-groups: $A_1 \cup A_2 = \{i_0, i_1, i_2, i_6\}, \{i_3, i_4, i_5\}$. Algorithm1 shows the details of combining the idea of issue-grouping from each agent.

Algorithm 1 Combine_IssueGroups(G)

Ag: A set of agents, G: A set of issue-groups of each agent
($G = \{G_0, G_1, ..., G_n\}$, a set of issue-groups from agent i is $G_i = \{g_{i,0}, g_{i,1}, ..., g_{i,m_i}\}$)

1: $SG := G_0, i := 1$
2: **while** $i < |Ag|$ **do**
3: $\quad SG' := \emptyset$
4: $\quad$ **for** $s \in SG$ **do**
5: $\quad\quad$ **for** $g_{i,j} \in G_i$ **do**
6: $\quad\quad\quad s' := s \cap g_{i,j}$
7: $\quad\quad\quad$ **if** $s' \neq \phi$ **then**
8: $\quad\quad\quad\quad SG' := s \cup g_{i,j}$
9: $\quad\quad\quad$ **end if**
10: $\quad\quad\quad SG := SG', i := i + 1$
11: $\quad\quad$ **end for**
12: $\quad$ **end for**
13: **end while**

Theoretically possible to gather all the individual agents' interdependency graph into one central place and then find all optimal contracts using such well-known nonlinear optimization techniques like the k-means or Girvan-Newman algorithm, however, most of the clustering technique have to decide some parameters or the number of issue-groups previously. For instance, the number of edges to be progressively removed from the graph is fixed previously in Girvan-Newman algorithm. Also, there is a trade-off between the optimality rate and the failure rate in selecting the number of issue groups. In real life negotiation, it is hard to decide the optimal parameters previously without enough history data. In our approach, the mediator can recognize the efficient number of issue-groups because the agents in real life have some knowledge in their utility spaces. Therefore, the mediator can recognize the efficient number of issue-groups by combining the all agents' knowledge. In addition, the lack of knowledge of each agent is compensated based on a collective intelligence theory.

Algorithm 1 may not find the efficient grouping after merging because it sometimes generates giants issue-groups. However, we believe that all agents have a similar interdependent graph in real life, therefore, our algorithm can usually work well with avoiding one giant component.

In addition, Agents are at risk of making an agreement that is not optimal for themselves by dividing interdependent issues. In other words, there is the possibility of making a low utility agreement by ignoring the interdependency of some issues. However, agents can make a better agreement in this protocol because the mediator identifies the issue-groups based on the interdependency rates.

[Step 3: Finding the Solutions] We find the solutions based on simulated annealing techniques (Klein et al. (2003)) in order to find the optimal contract in each issue-group. The details of algorithm 2 are as follows. The mediator proposes a contract that is initially generated randomly (line 1 in Algorithm 2). Each agent then votes to accept, weakly accept, weakly reject or reject the next contract. When the mediator receives these votes, it maps them into numeric values and adds them together according to Table 2. If the sum of the numeric values from all agents is a positive value or zero, the mediator mutates the contract (by randomly flipping one of the issue values) and the process is repeated. If the sum of the numeric values from all agents is a negative value, a mutation of the most recent mutually acceptable contract is proposed instead (line 7$\sim$16 in Algorithm 2).
Each agent votes based on the utility space in each issue-group. In our protocol, the agents decide based on the difference between the utility of the present situation and the utility of the next situation in each issue-group. When the agents vote, it maps the differences into accept, weakly accept, weakly reject and reject according to Table 3.
This step is based on the simulated annealing technique(Russell and Norvig (2002)). Each simulated annealing is fixed at a virtual *temperature* T, such that it will accept contracts worse than the last one accepted with the probability $P(accept) = min(1, e - \Delta U/T)$, where ΔU is the utility change between the contracts (line 8$\sim$15 in Algorithm 2). In other words, the higher the virtual temperature, and the smaller the utility decrement, the greater the probability that the inferior contract will be accepted.

Algorithm 2 Simulated_Annealing()

$Value(N)$: the sum of the numeric values mapped from votes to N from all agents

1: S := initial solution (set randomly)
2: **for** $t = 1$ **to** ∞ **do**
3:     $T := schedule(t)$
4:     **if** $T = 0$ **then**
5:         **return** $current$
6:     **end if**
7:     $next$ **:= a randomly selected successor of** $current$
8:     **if** $next.Value \geqslant 0$ **then**
9:         $\Delta E := next.Value - current.Value$
10:         **if** $\Delta E > 0$ **then**
11:             $current := next$
12:         **else**
13:             $current$:=$next$ **only with probability** $e^{\Delta E/T}$
14:         **end if**
15:     **end if**
16: **end for**

3.2. Incentives for Truthful Voting

Any voting scheme introduces the potential for strategic non-truthful voting by the agents, and our method is no exception. For example, one of the agents always votes truth-