JAPAN

Visualizing and analyzing processes of medical acts with ICT

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ABSTRACT

We can show the methods to capture data on processes of medical activity and data visualization and analysis on the data. This visualization and analysis of the data contribute to empower patients by disclosure of care processes as well as improve hospital operation through quality improvement and cost control. It will benefit both health care workers and patients. Point-of-Act System is one of ICT tool that was designed to capture every process of all medical acts was employed to capture data of medical process. Data on injection process captured by POAS was analyzed by visualization methods such as bar and line graphs and aggregated by some indicators such as time and wards. To improve injection operation, time of mixing and injection of drugs was considered by calculating time difference.

The analyses showed orders of injection by physicians have been increasing recently. In spite of hard efforts to improve hospital operation by health care workers, process data showed hospital operation was still improvable. Variation of activity by time was wide and there are injections mixed or injected early that would be a cause of medical accidents. This is first study to describe processes of injection by real data from hospital IT system.

Concern on performance measurement has been increasing. As discussion of process and outcome indicators, both indicators have useful meanings for patients. This study will help to understand the benefits of process data and show possibility of process indicators as objective indicators for quality of care.

COMFIRMATION AS A KEY FOR PATIENT SAFETY: A NETWORK ANALYSIS OF INCIDENT REPORTS

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ABSTRACT

According to the results of the statistical analysis on incident reports released by the Japanese Ministry of Health, Labour and Welfare, drug-related medical accidents account for more than half of all medical accidents. With respect to the causes of medical accidents, those caused by human carelessness, such as "incorrect drugs" or "incorrect drug dosages," account for more than 40% of all medical accidents. Therefore, establishing a method to prevent the occurrence of accidents due to human carelessness is a highly contributing factor in achieving safe, worry-free medical care. Accordingly, the purpose of this research is to construct a knowledge base that is useful for examining accident prevention measures by specifying a drug group closely related to the accident as well as the causes of the accident through the structuring of bibliographical information.

Natural language processing and network analysis are used as research methods. The network analysis method facilitates analysis on various relationships that are not only direct relationships but also indirect relationships, which are at least two steps away from the former. The incident reports in Japan are used as the subjects of this research. First, the frequently appearing characteristic words were extracted according to the three categories of the accident's background, details, and solutions described in the report, and then networks using these extracted words were created. Next, using the pharmaceutical dictionary and our own rules for dissolving the "discrepancy in descriptions," drug information was extracted from the accident report, and a drug network was created. From the above analyses it has become clear that inadequate information on drug labels, physician's instructions, and patient misunderstanding are the more important factors in medical accidents. Moreover, drugs and the combinations of drugs that frequently cause accidents have been revealed. The POAS (Point of Act System) is known as a cutting-edge medical information system that prevents confirmation errors made by humans. Finally, using the above results, the degree of effectiveness of POAS in the prevention of drug-related accidents was calculated. Of all the drugs that were returned through POAS, the ones that had actually caused medical accidents accounted for 31.6%. In addition, with regard to the ten most frequently returned drugs through POAS, the Pearson's Correlation between the number of drugs returned and the number of accident cases was high at 0.508, thus confirming the effectiveness of POAS implementation.

From this point forward, in order to achieve an even more effective analysis, the following factors are important in incident reports: (i) unification of descriptions pertaining to drug(s) and prevention of discrepancy in descriptions; and (ii) encouraging more descriptions pertaining to the confirmation details.

1. INTRODUCTION

There has been an increase in the awareness that 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. Through this project, the Ministry conducts analyses based on the collected incident reports and releases their results.

According to the research conducted by the Japan Council for Quality Health Care, it was revealed that of approximately 1,067 incident reports, majority of them were drug-related incidents (see Table 1). With regard to the details of such accidents, "incorrect drugs" and "incorrect drug dosages" accounted for 40% of all the accidents. For the causes of these medical errors, descriptions such as "I did not confirm with the physician" and "I did not firmly confirm the name of the drugs written on the prescription" are seen in the reports, suggesting that human carelessness is the cause of many errors.

However, all the analyses conducted till date are relatively simple. It can be assumed that by conducting an analysis while paying attention to the semantic information of the language contained in the report, knowledge that is effective in accident prevention can be extracted. Accordingly, the purpose of this research is to construct a knowledge base that is useful for the examination of accident prevention measures, by specifying a drug group closely related to the accident and the causes of the accident through the structuring of bibliographical information. Regarding the subjects of research, the focus was on cases related to drugs having high incidence rates.

Table 1 Categories and the Number of Incident Reports

Category	# Cases	Category	# Cases
Extravasation	15	Combination	24
Incorrect speed	76	Incorrect method	50
Incorrect patient	71	Incorrect drug	219
Forgot to give or take drug	30	Drug hypersensitivity	31
Incorrect drug	219	Incorrect dosage	223
Dosage and usage	29	Others	299

2. METHODOLOGY & DATA

2.1. Methodology

In this research, 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 morphological analysis, the tfidf method, and the Ngram method. Subsequently, 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.

The tendency of the drug-related accident was then specified by creating a drug network which specified the drug names and the combination of the drugs described in the incident reports using the pharmaceutical dictionary. The co-occurrence information between the drugs required for specifying the combination was calculated using the Jaccard coefficient. Moreover, the drug categories that tend to cause accidents or those whose concomitant use tends to cause accidents were clarified by organizing the drugs into their corresponding drug categories.

Lastly, the effectiveness of introducing the Point of Act System (POAS), the cutting-edge medical information system, for the prevention of drug-related accidents was calculated through the investigation of the correlations between drugs with high rates of return and those with large numbers of return cases under POAS.

2.2. Data sets

Of all incident reports provided by the Project to Collect Medical Near-Miss/Adverse Event Information, drug-related data that had been published during the period between 2005 and 2010 were used in this research. In order to achieve an accurate analysis, of all the cases provided, only 1,067 documents that included the abstract, background, and solutions were used. The free composition style was taken for each case, with the abstract, background, and solutions being approximately 300 characters long. Moreover, each case was classified into one of two groups—"drugs" and "accidents." As shown in Table 1, there are twelve categories.

For POAS data, the Act data from October of each year during the five-year period from 2002 to 2006 was used. Of all the 473,337 cases in the Act data, the number of drugs returned and the rate of return recorded as type 2 and type 3 Acts were used.

As pharmaceutical dictionary, the glossaries for drugs for medical professionals and the general public provided by the Japan Pharmaceutical Information Center (JAPIC) were used.

3. RESULT

3.1 Keyword Extraction

When working on a document, the frequently used method in natural language processing is that each word from the document (Part of Speech) is extracted first and the importance of the frequency of the word in the document is then calculated. The significance of these words determined through this method is used for the classification or ranking of the document.

First, the sentences written in natural language were divided into morpheme lines, and the part of the speech of each word was identified. Mecab [1] was used as a morphological analysis engine. In the morphological analysis, a word that has an independent meaning, such as "prescribe," "form," "double," and "check," are handled as independent morphemes. It is therefore necessary to connect several morphemes based on the frequency of the continuous occurrence of the word in order to obtain compound words such as "prescription," "double check," and "brought drug." In other words, compound words in which word B emerges immediately after word A is determined as AB (2 grams). If AB emerges more than at a certain frequency in the copus (more than five times in this research), it is handled as a candidate for a characteristic word. Eventually, compound words that connect up to six individual words (6 grams) are handled. Next, the significance of the word is calculated using the tfidf formula [2] as shown below.

$$tfidf_i = tf_i \times \log(\frac{N}{df_i}) \quad (1)$$

Here, tf_i represents the occurrence of i and df represents the number of documents in which i appears (i.e., the number of cases) and N represents the number of all cases.

The top ten keywords that appear in the incident report such as "background/causes," "details," and "solutions" are shown in Table 2. Under the category of "accident background," the words "lack," "confirmation," "inadequacy," "drugs," and "instruction" rank high. Moreover, the fact that the word "nurse" ranks high suggests that there are many accidents related to nurses. Also, the words "confirmation," "drugs," and "double check" rank high under the category of solutions. Tables 3 and 4 show the keywords obtained from the reports of the accidents caused by incorrect drugs and drug dosages. With regard to incorrect drugs, the words "similar," "standard," "dispensation," and "inspection" rank high. With regard to incorrect drug dosages, the words "instruction," "unit," and "standard" rank high.

Table 2 Keywords in Case Reports

Top	Background/Causes	Details	Solutions
1	Lack	Patient	Confirmation
2	Confirmation	Administration	Drugs
3	Inadequate	Prescription	Thorough
4	Drugs	Instruction	Occasion
5	Instruction	Infusion	Instruction
6	Prescription	Nurse	Caution
7	Not present	Dispensation	Double check
8	Patient	Ward	Brought drug
9	Description	Physician	Ensure
10	Nurse	Injection	Prescription

Table 3 Keywords in Case Reports (Incorrect Drugs)

Top	Background/Causes	Details	Solutions
1	Similarity	Dispensation	Drugs
2	Drugs	Prescription	Confirmation
3	Standard	Patient	Thorough
4	Prescription	Ward	Dispensation
5	Confirmation	Nurse	Label
6	Inadequate	Injection	Caution
7	Lack	Error	Medicine
8	Medicine	Instruction	Standard
9	Dispensation	Administration	Inspection
10	Inspection	Drugs	Occasion

Table 4 Keywords in Case Reports (Incorrect Drug Dosages)

Top	Background/Causes	Details	Solutions
1	Instruction	Prescription	Thorough
2	Unit	Administration	Confirmation
3	Prescription	Instruction	Instruction
4	Lack	Unit	Prescription
5	Confirmation	Appreciation	Prescription
6	Check	Oral administration	Drugs
7	Not present	Dispensation	Brought drug
8	Standard	Nurse	Double check
9	Brought drug	Ward	Input
10	Dispensation	Physician	Caution

3.1 Network of Characteristic Words

One word such as "lack," "confirmation," or "drugs" alone cannot express the tendency of the accident. In this research, the co-occurrence networks of the 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]. Here, if the co-occurrence frequency is expressed as $|A \cap B|$ when word A and word B appear in the same accident case and the number of cases in which either word A or B appears is expressed as $|A \cup B|$ the ratio of the Jaccard coefficient can be obtained. This ratio is used as an index to indicate the tendency of co-occurrence of the words A and B.

$$\text{Jaccard coefficient} = \frac{|A \cap B|}{|A \cup B|} \quad (2)$$

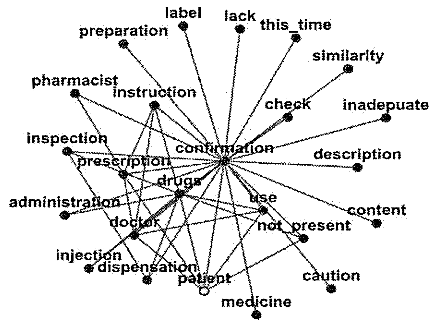
Figure 1 depicts the networks of words created using the accident reports related to incorrect drugs. Each node represents a word, and an edge represents the intensity of the co-occurrence between the words. The stronger the relationship between the words, the shorter the length of the edge. First of all, in viewing the network for "background/causes" (see Figure 1 (a)) it is clear that the network is created around the word "confirmation," and one can see that the cause of many accidents is the fact that the "confirmation" on "drugs," "label," "prescription," and "physician's" "instruction" "lack" or is "inadequate." 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." Furthermore, when using the MCODE [4] method on the network for "solutions," a clique shown in Figure 1(d) can be depicted. A clique is a group of nodes that are mutually connected in the form of direct coupling, i.e., a group containing the edges created with the combinations of all nodes. For instance, one can see that in clique 1 "confirmation" of "prescription" is mostly required as a solution for the accidents related to "similarity" and "drugs," and that in clique 3 the solutions of "thorough" "check" for the "patient" is mostly required. Both cliques indicate that it is important to reduce human carelessness.

3.3 Drug Networks

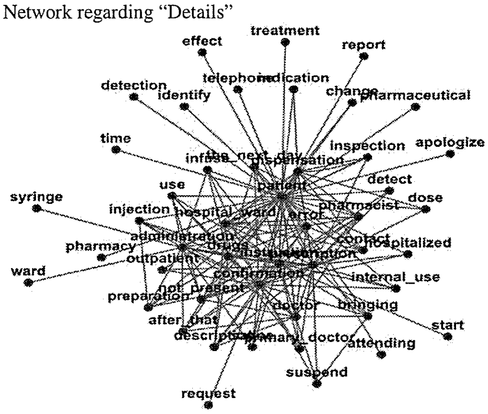
The accident tendency that depends on drugs—more specifically the drugs that most frequently cause accidents or the combinations of drugs that most frequently cause accidents—was investigated. Drug glossaries for medical professionals and the general public provided by JAPIC were used to specify the drugs appearing in the reports.

Figure 1 Networks of the Words in Incident Reports

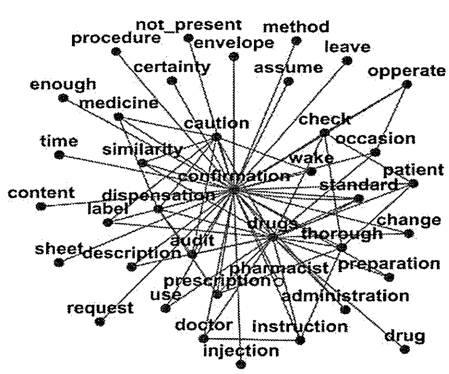
(a) Network regarding "Background/Causes"



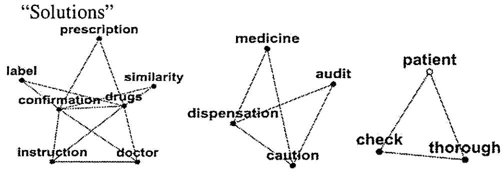
(b) Network regarding "Details"



(c) Network regarding "Solutions"



(d) Clique of the Words Extracted from the Network regarding "Solutions"



However, in the reports there were many descriptions using the drugs' superclass names. For example, for "10 mg of Dormicum injection" it is described as "after the placement of Dormicum, Proternol and Dormicum were administered." Therefore, matching was conducted after converting the drug names to superclass names using our own rules for drug name conversions (see Table 5).

Table 5 Rules for Drug Name Conversions

Rule	Drug Name => Superclass Name
Excluding dosage, specifications, unit	* Aspora Capsule **5**, Aspora Capsule **10** => Aspora Capsule -- * Atarax Tablet **10 mg,** Atarax Tablet **25 mg,** => Atarax
Excluding formulation	* Artane **Powder 1%**, Artane **Tablet (2 mg)** => Artane -- * Akineton **Tablet 1 mg**, Akineton **Injection 5 mg,** Akineton **Granule 1%** => Akineton
Excluding supplementary explanations provided in the parentheses such as 「」,[ ] and ( )	*Aspirin **(Kenei)** Aspirin **(Bayer),** Aspirin **(Hishiyama)** => Aspirin -- * **[Deleted Product]**Elental P=> Elental P -- * Anaesthesine **(Hishiyama)** **[Interim Measures]**=> Anaesthesine

Figure 2 depicts the drug networks, in which each node represents a drug and in each node the name of the drug is described. The size of the node represents the number of accident reports containing the name of the drug. The edge represents the presence of the co-occurrence relationship. The intensity of the co-occurrence relationship when two drugs appear in the same accident is represented by the length of the edge. The co-occurrence intensity can be calculated using the following formulae: Jaccard(x,y) = $|x \cap y| / |x| + |y|$. In other words, this is the rate of accidents caused by drugs x and y simultaneously among all the accidents described in the reports. The bigger the node, the more frequent the drugs will cause accidents. Also, the more the edges, the more frequent the drugs will cause accidents when used with other drugs. For example, drugs such as "saline (95 cases)," "sodium chloride (28 cases)," and "glucose (21 cases)" frequently appear in accidents, thus suggesting that those drugs frequently cause accidents when used with other drugs.

Next, the names of the drugs were organized according to the categories specified by JAPIC to obtain the drug category networks (see Figure 3). Each node represents a drug category, and the size of each node reflects the total number of accident reports in which the drugs belonging to the concerned category appear. The edge indicates the intensity of the co-occurrence among the categories. The ratio of the co-occurrence of drugs belonging to the same category was calculated using the Jaccard coefficient. For example, one can see that the categories of "blood substitute (164 cases)," "adrenal hormone drugs (58 cases)," "drugs for psychoneurosis (53 cases)," and "antipyretic analgesics (51 cases)" frequently cause accidents by themselves or when used with other drugs.

One can also see that the concomitant use of drugs belonging to the category of "antacid" and drugs belonging to the category of "laxative, enema" frequently causes accidents.

Figure 2 Network of Drugs

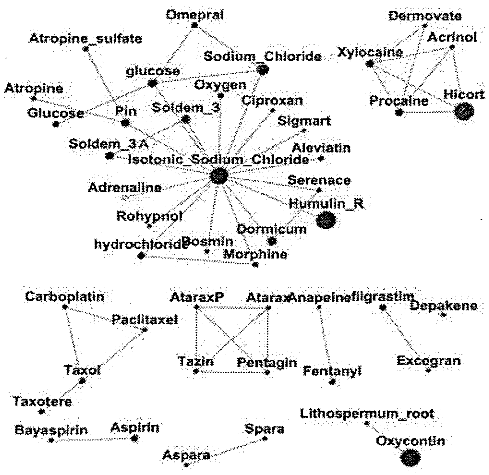
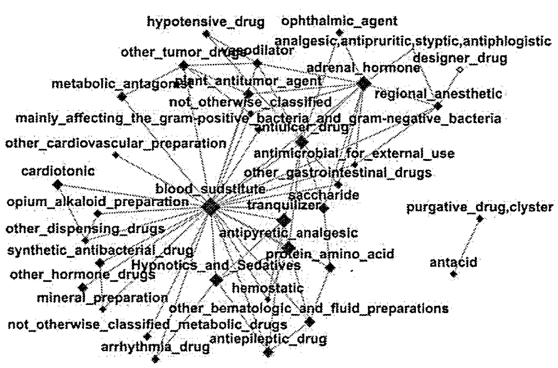


Figure 3 Network of Drug Categories



4. PROPOSAL FOR PREVENTION OF MEDICIAL ACCIDENTS THROUGH POAS

4.1. Point of Act System (POAS)

POAS is a system for managing the point (Point) of a medical action (Act). In this system, the main focus is placed upon the "6Ws and 1H" information (when, where, who, whom, why, what, and how), and such information is collectively managed. Accurately recording the implementation information of a medical action at the point where the action occurs, through the use of bar codes and PDA (Personal Digital Assistant), facilitates the progress management of the process.

In the conventional ordering system, information was managed for each order. However, in POAS an order is deemed as a type of act, and the subject of the management is the POA. In POAS, all "act" processes, from the instructions of the physician for the injection, drug dispensation by the pharmacist, to the nurse's co-injection and (final) implementation of the injection are recorded. An act in which all the processes have been completely performed is classified under type 1. An act that was discontinued before the co-injection of the drug and an act that was discontinued after the co-injection of the drug are classified under types 2 and 3, respectively. Akiyama et al. have proposed a measure to reduce wasted drugs in types 2 and 3 due to product returns by adjusting the time of the drug bring co-injected based on this information [5]. There are many causes of act types 2 and 3, in which drugs are returned due to the discontinuation of orders, such as changes in the condition of the patients and the replacement of drugs. In any case, if no alarm call is given and the process is not discontinued then, this raises the possibility of an accident. In POAS, if a nurse attempts to use a drug that is different from the one ordered by the physician, an alarm call will be given to her/him requesting that he/she reconfirm the drug, thereby preventing accidents caused by human carelessness. In Japan, four hospitals (International Medical Center of Japan, Morioka Red Cross Hospital, Kyoto Red Cross Hospital, and Japanese Red Cross Kochi Hospital) have already introduced POAS, and have reduced the number of incidents to zero [5]. Furthermore, because all act information, i.e., total population can be collected in POAS, it is possible to calculate the percentages of the drugs that are returned (i.e., the rate of return) for each drug appearing in the prescription given by a physician. Using the aforementioned analysis results, the correlations between drugs that are frequently returned or those with high rates of return under POAS, and the drugs that tend to appear in real accidents, can be calculated.

4.2 Correlation between POAS and Incident Reports

The overlap between the drugs for which alarm calls were frequently given and those that actually caused accidents was obtained. As shown in Figure 4, of all the drugs that actually caused accidents, 193 evoked alarm calls more than once (types 2 and 3), 242 appeared in actual accidents more than once, and 61 overlapped. Statistically, 31.6% (i.e., 61/193 ×100%) of the returned drugs under POAS caused an accident, so it can be said that by introducing POAS, such accidents have been prevented. In addition, it is obvious that when a drug accident or a drug dosage error has occurred under POAS, 25.2% of all accidents can be prevented by giving an alarm call prior to the procedure. These drugs include those that have high rates of return and those that tend to cause accidents as well as those that cause accidents with other drugs. Regarding these 61 drugs, i.e., the overlap between the POAS and incidents, the Pearson's Correlation between the number of returned drugs under POAS and the number of incidents is 0.329. In particular, regarding the ten drugs most frequently returned, the Pearson's Correlation between the number of returned drugs and the number of incidents is 0.508. The names of these top ten drugs are listed in Table 6, and one can see that many of them are medically important drugs.

When considering only the number of cases, one cannot say that drugs with high rates of return always cause accidents. Figure 5 shows the distribution of the number of incidents for each range of rate of return and the number of returns. It is obvious that the number of returns (115) and that of incidents (62) are the greatest in the drugs whose rates of return range from 0.1 to 0.2. Consequently, in this range of rate of return, 53.9% of the drugs returned may cause accidents, and it can be assumed that these accidents can be prevented by giving alarm calls for those drugs through POAS prior to the procedure.

Figure4 Diagram of Drug Overlap

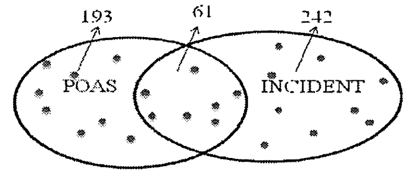
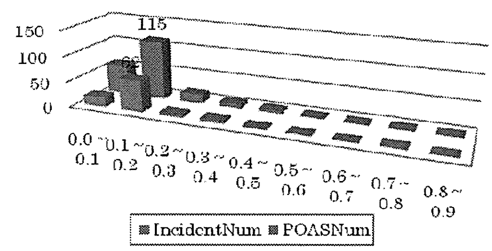


Table 6 Top Ten Drugs with High Rates of Return Under POAS

Drug Name	Return Rate	# Returns	# Cases
Droleptan	0.75	3	2
Metilon	0.75	12	2
Perdipine	0.51	15	2
Prograf	0.48	63	3
Dobutrex	0.38	6	2
Sandimmun	0.31	38	4
Navelbine	0.30	7	3
Vasolan	0.28	35	5
Lepetan	0.25	30	4
Anapeine	0.223	25	5

Figure 5. Number of Incidents for Each Range of Rates of Return and the Number of returns of POAS



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 well as an analysis focusing on drugs was conducted. 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. Moreover, it has become clear which drugs and combinations of drugs frequently appear in incident reports. These results suggest the effectiveness of introducing the network analysis method.

POAS (Point of Act System) is a medical information system that can prevent confirmation errors due to human carelessness and is currently being implemented at four hospitals. Thus, using the above analysis results, the degree of effectiveness of this system in terms preventing accidents related to drugs was calculated. Of all the drugs that were returned through POAS, the ones that had actually caused medical accidents accounted for 31.6%. In addition, regarding the ten most frequently returned drugs through POAS, the Pearson's Correlation between the number of drugs returned and the number of accident cases was high at 0.508, thus confirming the effectiveness of implementing POAS. Moreover, it has been shown that accidents can be more effectively analyzed by focusing on the drugs and the combinations of the drugs that have been deemed important through this research.

We want to propose the collection of more descriptions of the word "confirmation," which has been recognized as extremely important for accident prevention in incident reports because doing so will enable a more effective analysis. In addition, it was necessary to use the glossaries

analysis. In addition, it was necessary to use the glossaries
provided by JAPIC as well as our rules for the conversion of names of drugs. For facilitating a more accurate analysis, we want to propose an improvement of notational rules for the names of drugs and dosages in incident reports

6. REFFERENCES

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Linguistic Analysis of Medical Incident Reports for Patient Safety

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ABSTRACT

Attention is being drawn to the use of incident reports as a means of increasing patient safety. Research teams are being formed across the world by WHO and in Japan by the Health, Labour and Welfare Ministry. In this instance, what is being emphasized as a major direction for future incident analysis is the assimilation of the existing top-down type class grants and bottom-down ontological construction. In this research, targeting incident case studies collected in Japan, we evaluated the degree of similarities between incident documents obtained bottom-up and the links between existing classes granted top-down. In doing so, we made it possible to evaluate overall similarities regarding incident documents through the method of network analysis. In addition, it became clear that the use of the Cos coefficient or the Jaccard coefficient is appropriate in creating networks.

As a result of this analysis, existing classes correspond comparatively well with the characteristics of reports regarding the abstract and solution; on the other hand, regarding the background, it demonstrated that existing classes are inadequate in representing the characteristics of documents and that there is a need to improve classes.

By using the methods employed in this research, suggestions that are not possible through conventional methods can be made regarding the investigation of how classes should be.

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, ergonomics, 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.

In order to eradicate medical malpractice, medical institutions break down barriers between departments, collect and analyze incidents, and work out countermeasures. With this background, the Health, Labour and Welfare Ministry in Japan started the Project to Collect Medical Near-Miss/Adverse Event Information from 2001[2]. This project collects, analyzes, and publishes incident reports. The guidelines for analysis are to calculate the total of each class, including related medical departments, occurrence factors, and time periods, and to root out the causes of accidents.

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 data provided in the Project to Collect Medical Near-Miss/Adverse Event Information, the abstract, background, and solution for a single case study are described using a free composition format. In addition, in each case study the class of treatment and the class of operation are granted. There is a need to investigate whether classes granted here are in accord with the characteristics of each document item. In order to achieve the above, this research used the techniques of natural language processing and 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. Moreover, by networking the reports obtained from this, discoveries of overall links that could not be found from comparing only two reports are expected.

2. MEDICAL INCIDENT REPORTS

Here, we will explain approaches and issues relating to medical incidents and characteristics of the data used in this research.

2.1 Overview of Incident Reports Sought by ICPS

ICPS's general description sets out past activities and future guidelines relating to incident reports[4]. Until now, the main work of ICPS has been the granting and maintenance of classes to accidents by specialists. By granting this kind of top-down "agreed upon class," it becomes possible to convey a summary of incidents and accidents to even those who are not medical specialists. On the other hand, top-down type of classes created from present conditions are not detailed enough to provide satisfactory explanations of the characteristics of individual incident case studies. In addition, as class is granted in advance, opportunities to find valid unknown classes for patient safety are lost. Consequently, ICPS has stated that it will introduce ontological thought as part of future guidelines. Ontology in medicine refers to conducting from the bottom up and based on actual data the construction of methods necessary for describing individual case studies without misinterpretation as well as the discovery of classes of case studies that use these methods. ICPS indicates that the granting of top-down type categories by specialists as well as the granting of information that uses bottom-up type of ontology are necessary.

2.2 Collection of Incident Information in Japan

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 1^{st}–10^{th} 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 11^{th} collection. The results of aggregate calculations and analysis are published on the website of this organization.

2.3. Data Sets

From among incident data provided by the Project to Collect Medical Near-Miss/Adverse Event Information, in this research, we used data relating to medical agents from 2005 to 2010 that was published on the Internet. In order to conduct a detailed analysis, from the case studies provided, we used only 1,067 documents that included the information of the abstract, background, and solution. Each case study is in a free composition format, with the abstract, background, and solution being approximately 300 characters 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. NATURAL LANGUAGE PROCESSING

In this research, we extract characteristic words using natural language processing as a first step in extracting important information that characterizes each document with the aim of ontological construction. The links between each document are determined from similarities between characteristic words obtained here. 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. Preprocessing mainly comprises three stages of "breaking down into words in reports," "connecting words that have been broken down too much," and "filtering the obtained words." Details of these are set out below.

3.1 Breaking Down into Words

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].

3.2 Connecting Phrases

There is the possibility that words obtained using MeCab are too finely classified to conduct the analysis of links. Therefore, in this research we connected words using the two methods set out below and used them as new words.

First, 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 they appear consecutively is expressed as n (A∩B). In cases where n (A∩B)/min (n (A), n (B)) exceeded the threshold value (0.8 in this research) then we treated those two words as one word.

3.3 Filtering Words

Words obtained through the above two processing methods still contain a lot of noise, which can be expected to exert a bad influence on the calculation of links in documents. Thus, it is necessary to select words to be used in calculating links. The following sets out details on filtering.

First, we conducted filtering using the class of parts of speech. As stated above, major and minor classes are granted to words. Nouns were the targets of research on this occasion as major classes of parts of speech. Nominalized verbs, general nouns, and proper nouns were also targeted as minor classes of parts of speech. 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.

Next, we conducted filtering based on the frequency of occurrence. In this research, we calculated a value called tfidf from the frequency of occurrence and conducted filtering based on this values. tfidf 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]. tfidf is calculated using the following formulas.

$$\mathrm{tfidf} = \mathrm{tf} \cdot \mathrm{idf} \tag{1}$$

$$\mathrm{tf}_i = \frac{n_i}{\sum_k n_k} \tag{2}$$

$$\mathrm{idf}_i = \log \frac{|D|}{|\{d : d \ni t_i\}|} \tag{3}$$

Here, ni is the frequency of occurrence of word i, |D| is the total number of documents, and $|\{d: d \ni t_i\}|$ is the number of documents in which word i occurs.

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. In this research, we set the maximum value of tf to 50 and eliminited the noise from words with an abnormally high frequency of occurrence. On the other hand, words that make a small number of appearances also have an extremely small value for idf and, as a result, the tfidf has a tendency to increase. Therefore, this time we treated all tf under 10 as 0.

4. NETWORK ANALYSIS

Network analysis is an extremely effective method of looking at the links between documents[9]. By conducting network analysis, the discovery of hidden links between two nodes can be expected. In cases where links between only two documents are considered, even if there are no links, there are instances where overall links can be discovered by creating networks.

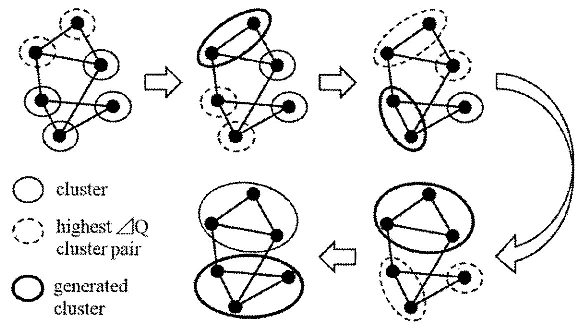

Fig.1 Newman Clustering

4.1 The Creation of 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 documents A and B is the number of co-occurrence |A∩B| for two documents. Here, |A∩B| is the number of characteristic words that exist in A and B. If considered with only |A∩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, the Simpson coefficient, and the Cos coefficient[10]. Each formula is shown in (4), (5), and (6) and is generally Simpson coefficient > Cos coefficient > Jaccard coefficient.

$$\text{Jaccard coeffcient:} \frac{|A \cap B|}{|A \cup B|} \tag{4}$$

$$\text{Cos coeffcinet:} \frac{|A \cap B|}{\sqrt{|A||B|}} \tag{5}$$

$$\text{Simpson coeffcinet:} \frac{|A \cap B|}{\min(|A|,|B|)} \tag{6}$$

A link is established between the two documents in the event that these indices exceed the threshold value. The network created changes acutely depending on which of the above indices are selected and how the threshold value is established. As the aim of this research is to investigate the extent to which top-down type of classes are reflected in links in document content that is sought bottom-up, when forming networks, we selected the index and determined the threshold values so as to reflect most the given classes.

4.3 Network Clustering

In this research, other than given classes, we conducted clustering using the Newman method in order to carry out labeling of each document based on networks. The Newman method is a widely used method for clustering networks[11]. It can be applied even if the number of clusters is unknown; in recent years, it is also being widely applied in large-scale network analysis, such as SNS and blog, due to it being scalable in regard to increases in node numbers. As shown in formula (7), clustering was conducted by maximizing modularity Q, an index for evaluating the modularity of defined networks.

$$Q = \sum_i (e_{ii} - a_i^2) \quad (7)$$

Here, element e_{ij} of line e represents the fraction of the total number of edges of the number of edges that connect cluster i with cluster j, and a_i represents the sum of row i of line e. Maximizing Q corresponds with maximizing the disparity between the number of edges that exist within clusters and the number of edges that link clusters together.

5. RESULTS

5.1 Extraction of Characteristic Words

We conducted the extraction of characteristic words using the methods outlined in section 3. Table. 1 and 2 show the number of occurrences by category for the 10 words in which tfidf is at the top. We see from these tables that all characteristic words extracted here occur selectively in each class. In addition, when focusing on the combination of class and occurring word, we see that words that aptly reflect the characteristics of the class are being extracted, such as "injected part" occurring largely in the diapedesis class and "allergia" occurring largely in the drug sensitivity class. On the other hand, as the index in this research uses tfidf as an index of the degree of characteristics, general words do not appear at the top, even if the frequency of occurrence is high. For example, although "patient" had the highest number of occurrences, as this word appears in most case studies, tfidf as an index of class capability of documents takes on a low value and does not appear at the top.

5.2 Network Analysis

In this research, we aim at uncovering links between classes granted top-down and clusters discovered bottom-up. Thus, we created a network so that documents belonging to identical classes relating to the identical treatment and operation are grouped together the most. To achieve this, we used the index of Class Closeness (CC) defined in formula (8).

$$CC = \sum_i (D_{ii} - \overline{D_i}) \quad (8)$$

Here, D_{ij} of line D calculates the distance from all of the nodes within category i to all of the nodes within category j and takes the averages of these. Also, $\overline{D_i}$ is the average of the i row of D. The classes here refer to 32 cross classes that cross calculate the class of treatment and the class of operation. CC taking a high value indicates that the nodes of identical classes come close to cases seen across the entire network. If the threshold value of the co-occurrence index is high, there is a tendency for CC to become high as only links with strong links remain. On the other hand, if the threshold value is made too high, a large proportion of the links are lost, the maximum number of connections (LC) of nodes within the network decreases, and the analysis of overall links becomes impossible. Thus, in this research, in order that the product of the maximum number of connections of CC and nodes (CCLC) are at the maximum, we conducted the selection of co-occurrence indices and the determination of threshold values. Table 3 shows the maximum value of CCLC for each co-occurrence index and the values of indices in these instances. By doing so, we discovered that a network that reflects given classes could be obtained by using the Cos coefficient for networking the content and the Jaccard coefficient for networking the background and solutions. Although the Cos coefficient and Jaccard coefficient

Table.1 characteristic word and class of operation

characteristic word	diapedesis	flow rate	object person	forget to dose	composition
insulin	0	0	4	0	0
furosemide	0	1	0	0	0
injected part	14	0	9	0	1
allergia	0	0	5	0	0
setup	0	51	0	0	0
flow rate	1	38	2	0	0
coinjection	0	3	7	0	3
anticancer	3	3	7	0	0
periphery	1	2	10	0	2
set	0	5	1	13	1

characteristic word	regimen	name of drug	amount of drug	drug sensitivity	amount and regimen
insulin	0	22	16	0	0
furosemide	4	13	17	0	0
injected part	0	0	1	0	0
allergia	0	1	0	19	0
setup	0	0	4	0	0
flow rate	2	0	9	0	0
coinjection	4	22	9	1	0
anticancer	0	2	5	0	7
periphery	4	4	2	3	0
set	1	9	16	0	6

Table.2 characteristic word and class of treatment

characteristic word	chemo treatment	contraindi-cated drug	dowry of drugs	preparation of drugs
insulin	0	0	3	2
furosemide	0	2	10	1
injected part	14	1	0	0
allergia	0	23	0	0
setup	14	0	0	0
flow rate	8	0	0	0
coinjection	5	7	0	0
anticancer	26	0	2	0
periphery	5	5	0	0
set	0	1	29	3

Table.3 class closeness and co-occurance index

abstract

Index	Value	CC	LC	CCLC
jaccard	0.290	3.162	510	1612.4
cos	0.459	2.908	594	1727.9
simpson	1.000	0.430	750	322.5

back ground

Index	Value	CC	LC	CCLC
jaccard	0.334	1.441	580	835.8
cos	0.580	3.348	241	806.8
simpson	0.860	0.192	970	186.5

solution

Index	Value	CC	LC	CCLC
jaccard	0.338	1.441	550	1444.7
cos	0.544	2.955	428	1264.9
simpson	0.700	0.279	1023	285.3

Table.4 cluster and characteristic class

cluster index	characteristic class	share of the class	ratio of the class in the cluster	number of the node
1	dowry of drugs	84.80%	60.50%	147
2	preparation of drugs	58.80%	51.30%	111
3	flow rate	55.30%	70.30%	37
4	diapedesis	55%	30%	27
5	-	-	-	25

demonstrate almost identical CCLC in the abstract, background, and solution, it is markedly low regarding the Simpson coefficient. This is because documents that include large numbers of characteristic words are connected with many documents and are close to documents that belong to other classes in the network.

6. DISCUSSION

The characteristic words displayed in Table 1 and 2 were all selected based on actual data. Networks obtained from similarities with these characteristic words remove the effects of similarities shared in common with all documents and are formed from the overall combination of an independent degree of similarity between two documents. This kind of network is first realized by extracting characteristic words bottom-up. In cases where keywords that should be checked top-down are decided, there are instances when, after having conducted class, there is no guarantee that that keyword is not valid and a network of documents linked only by the characteristic similarities such as those described above cannot be obtained.

Figure 2 shows the abstract network from among the networks created based on the characteristic words obtained bottom-up. In addition, Table 4 shows the abstract network

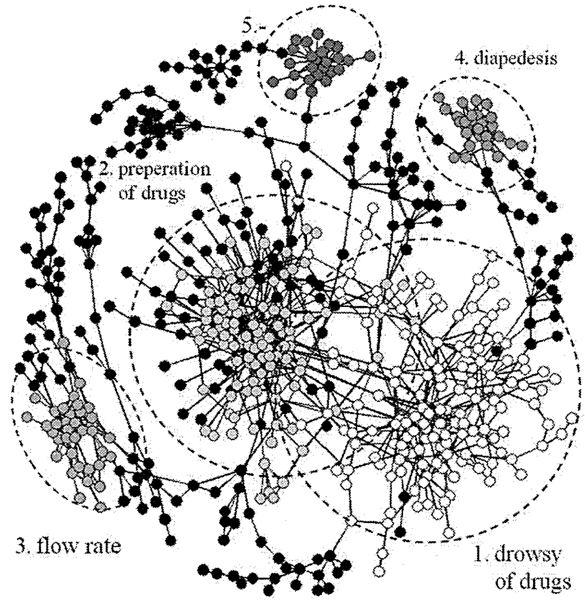

Fig.2 network of an abstract in Near-Miss/Adverse Event

resulting from having conducted clustering using the Newman method. Table 4 shows the top five clusters of the number of nodes and the main classes within these. The clusters from position 1 to 4 clearly reflect the granted classes. In the cluster in position 2, the class of treatment is prioritized and collects together documents classified as drowsy of drugs and preparation of drugs; in positions 3 and 4, the class of operation is prioritized and clusters reflecting flow rate and diapedesis are created; however, in position 5, classes that clearly characterize clusters could not be seen.

Moreover, regarding the solution network, links between clusters and classes such as those described above were extracted. On the other hand, clusters that clearly reflected the given class could not be seen among the clusters of the background network. The fact that networks created through background do not reflect overall given classes is in accord with the results of analysis in which the value of CC corresponding to the co-occurrence index used in creating networks in Table 3 is around 3 in abstract and solution, while in background it is less than 1.5.

So, is the class of background not related in some way to networks created bottom-up? In order to investigate this, we conducted an investigation into how many identical classes exist within the k step from certain nodes. The results of this investigation are shown in Fig. 3. We can see that in no matter which network, the ratio of nodes with identical classes decreases to the extent of the number of steps increasing. Here, attention should be drawn to the point that the proportion of identical classes existing within a single step is almost the same in each of the categories of abstract, background, and solution. This indicates that the same classification also takes place in case studies with an extremely high degree of similarity in background. On the other hand, when looking at the overall network, given

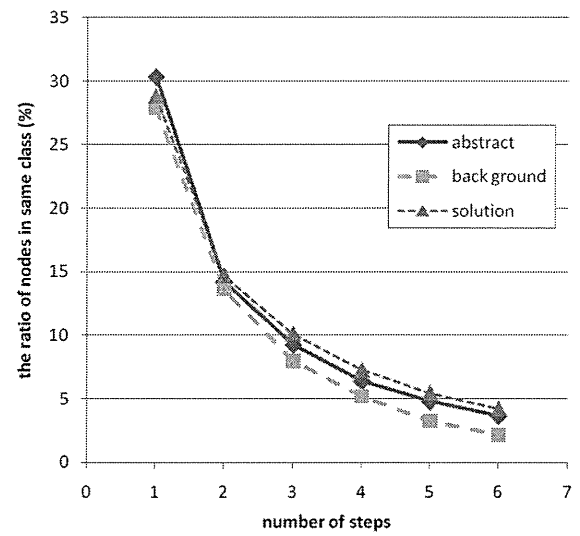

Fig.3 the ratio of nodes in same class

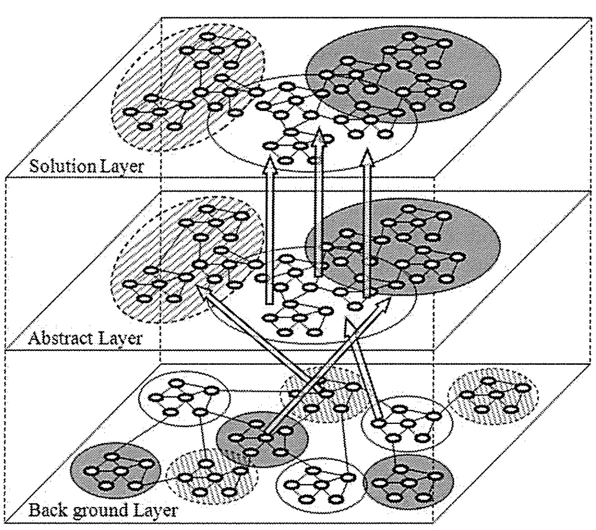

Fig.4 structure of network in each layer

classes relating to the background are scattered compared with abstract and solution. This concept is outlined in Fig. 4.

With regard to the abstract and solution, links determined from ontology reflect comparatively given categories; however, regarding the background, when looked from the perspective of ontology, there is the possibility that it is completely different from the classes of abstract and solution, even those matters in proximity to step numbers, i.e., it is difficult to predict accidents that occur from information on background. Therefore, it shows that the content of descriptions of background is inadequate from the perspective of preventing reoccurrences. On the other hand, regardless of differences between abstract, background, and solution, the reporter is likely to have taken care to use descriptions that express accurately the maximum limits and the reality of the situation. Class methods that give appropriate suggestions to on-site reporters are required. We can say that there is a strong desire for an ontological construction relating to descriptions of background.

Considering the similarities between only two documents without using network analysis is equivalent to looking at the similarities of the nodes within step one in Fig. 3. In this case, in order to obtain almost identical values between abstract, background, and solution, differences relating to the power of expression of descriptions in the three divisions are not seen. The discovery that descriptions of background are inadequate was made possible for the first time by considering the overall similarities through the networking of case studies.

7. CONCLUSION

In this research, we evaluated the degree of similarities between incident documents obtained bottom-up and the links between existing classes granted top-down. In doing so, we made it possible to evaluate overall similarities regarding incident documents by using the method of network analysis. Moreover, it became clear that the use of the Cos coefficient or the Jaccard coefficient is appropriate for determining similarities in creating networks.

With regard to the background, the results of the analysis demonstrated that, compared with abstract and solution, existing classes are inadequate for representing the characteristics of documents and that there is a need to improve classes.

By using the methods employed in this research, suggestions otherwise unobtainable through conventional methods can be made regarding the investigation of how classes should be.

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Analysis of data captured by barcode medication administration system using a PDA; aiming at reducing medication errors at point of care in Japanese Red Cross Kochi Hospital.

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Abstract

Preventing medication errors by using a barcode administration system has become prevalent in patient safety. Analyses of data captured by bar code systems provide opportunities to understand the actual situation at the point of care. Our study aims at understanding issues of medication safety as well as investigating measures taken to prevent medication accidents, by analyzing data captured by a bar code system and a personal digital assistant (PDA),. The barcode administration system named Point-of-Act-System implemented in Japanese Red Cross Kochi Hospital was designed to capture every activity at the bedside. Complete activity data captured by the system, which included injections, treatment and other nursing activity, as well as injection warning data, were used for our analyses. We describe the data and analyze them statistically to find potentially times of risk and to ascertain the relation between busyness and error. The injection warning rate as a whole was 6.1% on average. The results showed there was a negative correlation between the number of injections given and the injection warning rate (-0.48, $p<0.05$). The warning rate was low during the hours when a large number of injections were administered. The data also showed that a variation in activities being performed has a negative effect on medication safety. A bar code administration system is quite an effective way not only to prevent medication error at point of care, but also to improve patient safety through analyses of data captured by such a system.

***Keywords:* Point of Care System, Medication Errors, Administration and Organization, Handheld Computer, Patient Safety**

1. Introduction

It is widely believed that patient safety is an important issue for health care systems. Many organizations and hospitals have been accumulating information on patient safety and medication errors to improve patient safety based on the data collected. These data is accumulated to provide information on threats to patient safety. Such data are quite useful in understanding the threats and actual situations related to medication errors in hospitals. However, most of this evidence is basically information on medical accidents and incidents, compiled from voluntary reports submitted by medical workers. This information is not detailed enough to enable the discovery of underlying general principles, because accidents and errors are part of the reality in a hospital setting. A complete picture of the situation in hospitals, including details of medical accidents and incidents, is essential to identifying general causes and frequencies of medical errors. However, it is extremely costly to obtain by observational research sufficient data to enable an understanding of all the activities conducted in a hospital, and furthermore, the accuracy of data collected by observation is sometimes defective. Information technologies such as electronic medical records and barcode administration systems at the point of care have the potential to provide new opportunities for us to understand the overall picture of medical activities by digital capturing data on daily medications and patient care in hospital settings. By using information systems for all patients in all wards, data captured by the systems become useful resources to understanding various phenomena in medical situations and investigating research questions. In terms of medication accidents, the point of care is a potentially risky area in medical activities [1-3]. Therefore, data captured at the point of care is quite effective in understanding medication accidents. One potential candidate system for this is a barcode administration system for safe injections and medication. Barcode medication administration systems prevent medication errors by authenticating the "5 Rights" of medication: right patient, right drug, right dose, right time, right route. Performed at the bedside, the system offers an excellent opportunity to gather data on medications [4-7]. In addition to their contribution to the authentication of the 5 Rights, data captured by barcode administration systems have the potential to provide sources of research to improve patient safety in terms of actual injections and medication data.

Our study aims to use and analyze complete data on medical activities captured at the point of care by the system to understand all the activities and issues related to medical safety, and to investigate preventive measures for medical accidents to manage healthcare situations. We focused on injections, which a major cause of medical accidents, and investigated the relation between mistakes and the context of medical activities including how busy staffs were, and shift work.

2. Materials and Methods

2.1 Settings and items to be addressed

Japanese Red Cross Kochi Hospital has 482 registered beds and approximately 290,000 out-patients and 9,355 in-patients per year. The hospital implemented a hospital information system called "Point of Act System," or POAS, in 2004. POAS is a real time bar-code capturing health information system designed to prevent medication errors by capturing the barcodes of patients, workers and drugs, and then authenticating the 5 Rights of each medical action [10-12]. Figure 1 shows a Personal Digital Assistant (PDA) for barcode capturing, nursing work management, and risk management for injections and intravenous drips (IV). When nurses scan the barcodes of drugs or IV bags for patients, the system checks the correctness of the injections and IVs against real-time accurate information in a computerized order entry system and electronic health record within 2 seconds.

At the same time, POAS captures complete data on each medical action including 6W1H information (When, Where What, Why, for What, to Whom and How) conducted in the hospital. The units of data recorded by the system are: Who—the implementer (the person who initiated the order, or the person who carried it out), to Whom—the patient, How—medical activities and changes in them, What—materials used (pharmaceuticals, medical materials and others), How much—amount of materials used and number of applications, for What—name of patient receiving medical services, When—date the order was placed, implemented and discontinued and the activities that were implemented, and Where—place of implementation (department, hospital, ward, etc.). The principal characteristics of data captured by this system are (1) complete data at a specific place including every action recorded in real time and accurately and (2) process data-based process management that enables POAS to ensure the correct process of medication and assures it captures complete data. The collection of complete data including 6W1H information is an innovative source in understanding actual situations directly without estimation or bias, and enables the investigation of solutions to prevent errors.

2.2 Data

Data captured at the sites of the injection process were used for our analyses of medication administration. In this study, data on injections means both injections and IVs. 6W1H information was captured at each point of the injection process: Order to give injection, Drug selection, Drug audit, Drug mixing, and Injection. Although the first objective of a bar code administration system is to ensure patient safety by verifying the 5 Rights of medication, another objective is to record the activities of nurses to support nurses' request of drugs and devices consumed, and enforce medication for patients.

At the point of care, nurses uses PDAs to scan the barcodes of ampoules or vials containing the medication to be injected or scan the barcodes of activities to enter information on their actions such as treatment, care, observations, counseling and emergency. This information is primary used for the documentation of nursing activities. However, this information can also be used not only for hospital management—by understanding the workloads of nurses and the actual costs of administering medications—but also for patient safety by understanding the prevailing situations when mistakes are made. In addition to these data entered by nurses, we also used warning data demonstrating mistakes that can be made in scanning the barcodes on drug vials. Warning data do not directly mean data on medication errors, because the system prevents error by alerting staff before a mistake is made. However, warning data are useful sources of information in analyzing the causes of medication errors, because a warning means a potential medication error without a barcode administration system. Therefore, high warning rates at specific times, places, situations and workers mean risky times, places, situations and workers in terms of patient safety. Basic types of warning are basically: a wrong or expired vial scanned by a nurse for a patient; wrong patient; and mixing error meaning incorrect mixing of drugs. Data collected from January 2005 to June 2008 were used for the analyses. The total numbers of activities represented by the data are 14,824,046 individual acts, and the number of injections and IVs administered were 604,847. The data covered almost 100% of the injections and 99% of the activities by nurses in the hospital according to internal research.

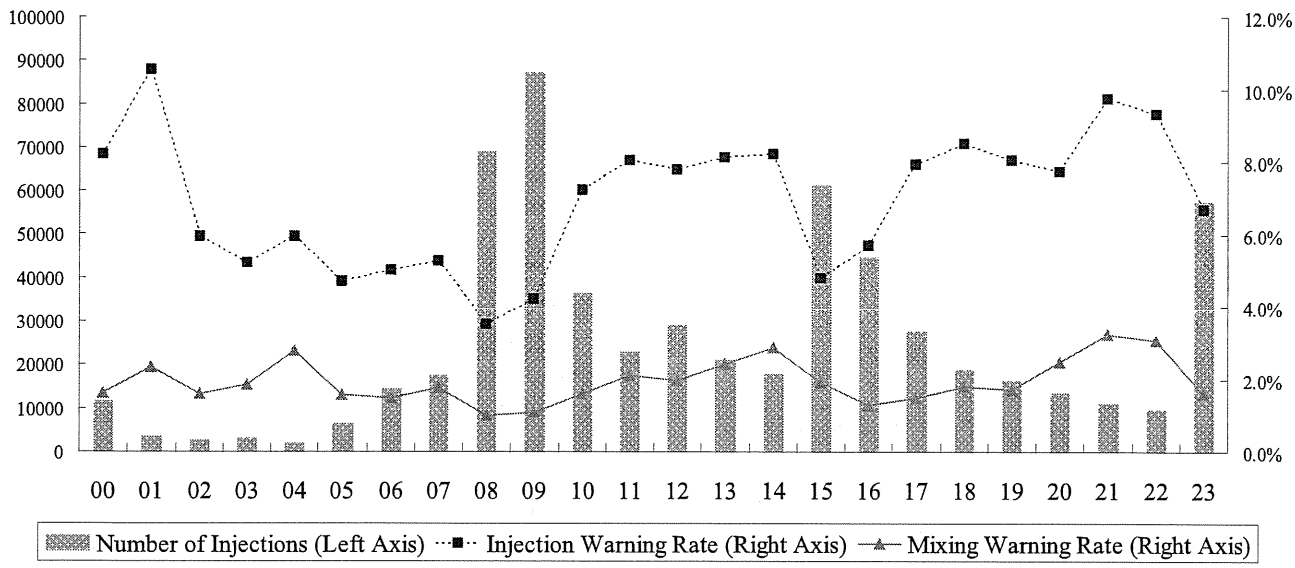

Fig. 1 Number of injections per hour and warning rate

2.3 Data Analysis

We accumulated data for each hour (for 24 hours a day) to identify times of high risk so as to understand the big picture of medical activities and medical errors in hospital wards. Warning rates were computed for each hour. These rates were treated as indicators to show risky times and situations.

We described these data, and analyzed them statistically to investigate correlations between situations and warning rates. Total number of injections per hour, total number of activities, total number of injections per PDA by hour, and total number of activities per PDA by hour were used as indicators for a nurse's workload at the time. The fraction out of total activities spent giving injections was used as an indicator for variation in hours. We calculated the proportion of the number of injections among total activities at that time. We employed Pearson Correlation Analysis to investigate relations and the significant level was 5%.

3. Results

Total number of activities was 14,824,046 including 69,276 injections (0.4%), 535,571 IV starts (3.6%), 483,770 IV finishes (3.3%), 1,979,804 care giving (13.3%), 10,437,250 observations (70.4%), 14,713 counseling (0.1%), 824,743 treatments (5.6%) and 478,919 emergencies (3.2%). The number for observations is extremely high. The total number of injections including IVs was 604,847, and the total warnings for injections were 37,046 (6.1%). The injection warning rate during early periods of implementation was around 9%, but has decreased to around 6 %.

Figure 1 shows the trend in warning rate and activities by the hour. The bar graph shows the number of injections by hour. There is a variability in the number of injections by hour, with three peeks for injections administrated: 9:00, 15:00 and 23:00. Most injections were administrated around these three peaks. The two line graphs show injection warning rates and mixing warning rates by the hour. Minimum and maximum of injection warning rates were 4.2% and 10.5%, while the minimum and maximum mixing warning rates were 1.0% and 3.2%. These figures vary quite a bit over the hours. This graph shows the warning rate was lower when nurses where administrating a large number of injections. For example, the warning rates between 8:00 and 10:00 are lowest, although the numbers of injections are highest. The warning rates between 15:00 and 17:00 are also lower compared with the warning rates around the time.

In this hospital, the nurses work three shifts: Day shift (8:00-16:40), Evening shift (16:00-0:40), and Night shift (0:00-8:40). The warning rates per shift were 5.5% Day shift, 7.3% Evening shift, and 6.0% Night shift. Some researchers have reported that warning rates during nighttime are higher than during daytime [5]. However, there is no clear evidence to support the statement in our analyses. The trends in injection warnings and mixing warnings have basically the same tendency, although the tendency can be recognized more clearly in the injection warning rates. Especially during Day shifts, this tendency was demonstrated quite clearly.

We ran some statistical analyses to investigate the relation between warning rate and other variables. According to the results of a correlation analysis between variables, there was a negative correlation between the number of injections and injection warning rates. Figure 2 is a scatter plot of the number of injections per nurse and injection warning rate. The correlation coefficients between the number of injections and injection warning rates was -0.48 ($p<0.05$), and that between the number of injections per PDA and injection warning rates was -0.34 ($p<0.05$). Both results were statistically significant at the 95% level. This results show there is a tendency that more injections means safer injections at specific times as described above.

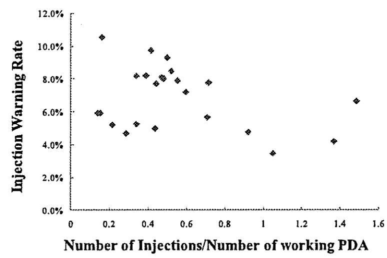

Fig. 2 Scatter plot showing number of injections per nurse and warning rate

Variation in activities had a negative effect on the injection warning rate according to other correlation analyses. Figure 3 is scatter plot showing the relation between the injection fraction of total activities computed by the number of injections divided by the total number of activities and injection warning rates. The correlation coefficient between the treatment fraction of total activities and injection warning rates was 0.35 ($p<0.05$) and statistically significant. This indicator implied a high fraction of treatment, meaning nurses should administrate injections along with other treatments for patients and discourage nurses from concentrating on injections.

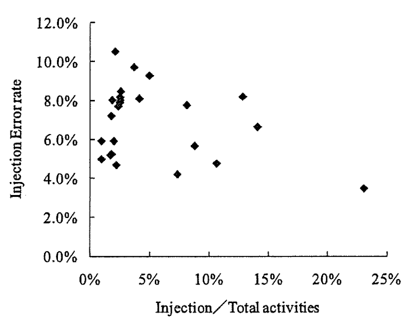

Fig. 3 Scatter plot showing number of injections and warning rate

4. Discussion

There are some differences between our study and previously published literature. In past literature on patient safety, many studies had said workloads and busyness are the principal cause of medication errors, based on observatory studies of nursing practice [13-14]. These studies implied that it was acceptable that healthcare workers were so busy that they had to rush tasks, which caused a lack of due care and attention to be given to the administration of medications, and sometimes resulted in the certification processes being skipped. However, this study shows an opposite tendency in the medication errors rate. This study implies that people made mistakes not because they were doing too many things, but because they were doing too many different kinds of things. During a high frequency time for injections, nurses can concentrate on administrating injections to patients. Literature on human factor engineering indicate the same kinds of conclusions to ensure quality of activities [15-16]. It basically says that doing too many kinds of things is not a good way to ensure quality and reduce costs of activities, and that specialization is essential to redesigning workflow to improve management.

There is also another difference in our results compared with previously published literature. Injection warning rates in this study were relatively high compared to other studies on administration errors in injections [1-3, 13-14]. Many researchers have assumed injection error rates by observation of daily work, and their results gave a figure of around 4% for injection error rates as opposed to the 6.1% found in our study. Of course, there is a possibility that the difference in the injection warning rate came from environmental or other factors. However, the accuracy of data used in the analyses and detection of mixing errors could be regarded as the cause of the difference in results. Data captured by observational study has a bias in that people administrate more carefully when being observed. Therefore, the data captured by observational studies might be better than in reality. Other reason for the difference stem from the fact that other studies could not detect incorrect mixing of drugs. To identify incorrect mixing, drugs need to be managed not by a drug name ID but by a serialized ID [11]. A serialized ID on each product makes it possible to distinguish mixed and unmixed vials by recording the mixing for each drug and injection.

Clarification by time is an aspect of related factors for medication processes. Multivariate analyses with risk adjustment are needed to investigate more precisely reasons for medication errors. It is possible to accumulate data by place and people to identify a risky situation more precisely and in more depth, instead of clarifying by time. Figure 4 shows an example of another type of analysis, a scatter plot for the number of injections and injection warning rates per ward. The numbers of injections administered are totally different, but the injection warning rates are similar.

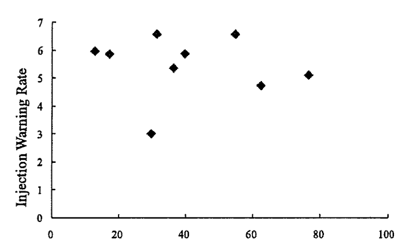

Fig. 4 Scatter plot showing number of injections and warning rate per ward

We can identify one outlier whose warning rate is lower than for the other wards. To investigate the reason for this result, we need more in-depth analyses based on multiple variables and qualitative analyses.

One limitation to our research is in treating injections and other activities as the same workload activities, though actually there are quantitative and qualitative differences between these activities. It is necessary to assign weighs to each activity based on a time study or some methodology so as to capture more deeply and accurately the workloads of nurse for subsequent analysis. Another issue to be developed in this kind of analysis is privacy protection. In this analysis, data accumulated by hour and ward was utilized. The results did not contain personal data such as health care workers performance or data on patients. All patients and healthcare workers have unique identification numbers in this hospital. Therefore it is possible to analyze data using the identification numbers—including patient identification and worker identification. To utilize digital data from electronic health records and other hospital information systems, discussions on the utilization of data and privacy protection is essential for the development of methodologies for data utilization and protection, as well as for frameworks supporting and sometimes restricting the use of data.

5. Conclusion

This study showed general trends in medication mistakes in practice using data captured by the hospital information system "Point-of-Act System" in real time and accurately. The results suggested that a high variation in activities performed might have negative effects on patient safety, and that busyness could not be regarded as the main causes of errors. Our study also implied the possible effects of bar code administration systems. According to the results, the injection warning rate was about 6%, and these warnings prevented nurses from committing errors and accidents. The lack of accidents with respect to injections in the hospital provides the system's ability. In conclusion, the bar code administration system might be quite an effective way not only to prevent medication errors at point of care, but also to improve patient safety through the analyses of data captured by them, if a system were designed correctly. Further research is needed to make progress in digital data usage and the utilization of healthcare IT.

Acknowledgments

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情報の構造化による医療事故・ヒヤリハット情報の利活用

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Efficient Reuse of the Incident Reports by Structurizing Information to Increase Patient Safety

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The use of incident report is indispensable to do the medical treatment safety measures to be based on the evidence. The incident information reports are the data of the importance also the risk on the medical treatment safety is verified. We have 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. The study is a combined of the research on the regulatory science to use the profit in shape that the personal privacy is not violated as for the research and accident information on the profit use of accident information for a safe, safe medical treatment. We in the former structured accident information by using information engineering techniques of the natural language processing and the network analysis etc. and analyzed it the radical of the cooperation of its doctor, nurse, and pharmacist.

We discussed the technical mortgage plan and the legal framework because of the violation of neither the medic nor the patient's privacy by such profit use, and tried the regulatory science that promoted the profit use of information for the latter. The result is expected to become a model case with the second use for accident information use and information because it discusses it in consideration of the examination concerning not only the technology and the method for analyzing for these second use but also regulatory science.

Keywords: Patient Safety, Incident Report, Privacy, Regulatory Science, Risk Management

1. 目的

本研究の目的は、医療事故情報、ヒヤリハット情報などのデータを構造化することによって、利活用の進展に繋げ、医療安全の向上に寄与することである。現在、財団法人医療機能評価機構を中心に、医療事故やヒヤリハットの情報を収集する事業が進展している。これらのデータは、当初、標準化されておらず、またフリーテキストデータを含んでいるため、利活用の用途は制限されていた。

そこで、本研究では、オントロジーなどの技術を用いて、事故・ヒヤリハット情報を構造化し、解析を試みる。構造化の手法により、諸概念の関係性やユースケース毎の分類に基づいて情報を集積、再解釈することで、事故の原因や医療安全の向上のために改善すべき点を明らかにする。また、これらの利活用が効果的に実現されるための基盤構築として、利活用の際の技術的課題や法的課題の検証にも取り組んだ。さらに、米国や世界保健機関(WHO)での取り組みや日本の事例を検討し、国際的な連携や応用可能性を検証する。

2. 方法

2.1 事故情報の構造化手法の検討

2.1.1 概要

研究資料・研究フィールドとしては、日本医療機能評価機構が実施する医療事故情報等収集事業によって収集された医療事故情報、ヒヤリハット事例データを使用した。このデータは、2010年度より一般公開が決定されており、公開に関しては、病院・患者団体からの同意を得ている。公開データは、匿名化されたものを本研究で用いた。事故・ヒヤリハット情報の利用に関しては、後信博士(日本医療機能評価機構)の協力のもと事業を進めた。

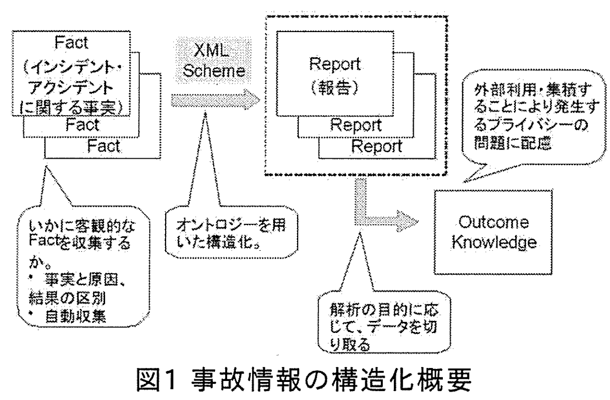

図1 事故情報の構造化概要

このデータにオントロジーなどの情報工学的な手法

を用いて、自然言語による事故情報に構造を与え、視覚化を行った。また、他分野で行われているオントロジーを参考に、事故情報のオントロジーに関するモデル構築を試みた。また、WHOの患者安全部と連携を図り、解析結果の国際的公表・標準化への検討を進めた。

2.1.2 本研究で用いたデータセット

具体的には、Project to Collect Medical Near-Miss/Adverse Event Informationにおいて提供されるヒヤリハットのデータのうち、Web公開されている2005年から2010年までの薬剤に関するデータを用いた。詳細な分析を行うために、提供されている事例のうち文書が概要・背景・改善策の3項目を全て含む1067件のみを用いた。一件の事例は概要・背景・改善策それぞれ300文字前後の自由作文の形を取っている。また各事例には薬品の分類・災害の分類の二つの分類が与えられている。treatmentの分類としてはgeneral drug、preparation of drugs、drowsy of drugs、contraindicated drug、chemo treatment、other drugの6件があり、operationの分類としてはname of drug、amount of drug、regimen、amount and regimen、flow rate、drug sensitivity、diapedesis、forget to dose、object personの9件がある。treatmentの分類に対し全てのoperationの分類が存在するわけではないため、treatmentの分類とoperationの過失の分類をクロス集計したクロス分類は32通りとなる。

自由作文で事故の記述を行う場合、報告者は状況が最大限含まれるように努力する。その中から重要な情報を抽出することはボトムアップ型のオントロジー構築の足掛かりを作ることと言える。そこで得られた結果とトップダウンで与えられた分類の関連性を求めることはICPSが求める今後のヒヤリハット分析の指針と合致している。

2.1.3 自然言語処理による特徴語抽出

本研究ではオントロジー構築を目的とした各文書を特徴づける重要な情報の抽出の第一歩として、自然言語処理を用いて特徴語の抽出を行う。各文書の関連性は、ここで得られる特徴語の類似性から決定する。自然言語は多くのノイズを含むため、関連性の決定に利用可能な特徴語を得るために前処理を行う必要がある。前処理は主に"文書の単語への分解"、"分解されすぎた単語の連結"、"得られた単語のフィルタリング"の3段階からなる。以下にその詳細を示す。

前処理の第一段階では、文書を単語に分解するために形態素解析を行った。形態素解析は、日本語のように単語がスペースによって区切られていない文章を単語毎に区切る際に用いる手法である。本研究では形態素解析を行う上で最も一般的なエンジンの一つであるMeCabを用いた。MeCabを用いて得られた単語は関連性の分析を行うには細かく分類されすぎている可能性がある。そこで、以下に示す二つの方法を用いて単語を連結し、新たな単語として用いた。

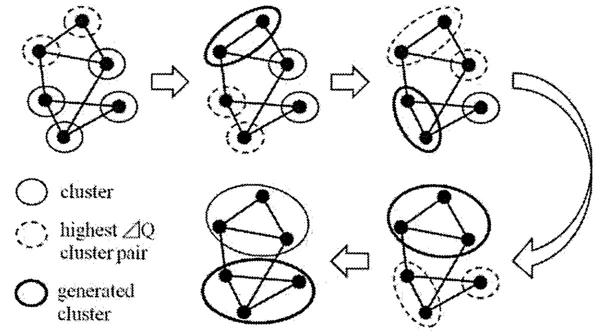

図2 単語の連結

初めに単語の品詞の情報を用いて単語の連結を行った。上で述べたMeCabは単語の分解だけでなく、品詞に関する大分類、小分類も与えられている。ある単語の品詞の小分類が接尾辞であり、その前の単語が名詞である場合には二つの単語は一つの単語として扱った。
続いて単語の出現回数に基づいて単語を連結した。ある二つの単語AとBが連続で出てきた場合を想定する。各単語を単独に考えた場合の出現回数をn(A)、n(B)とし、連続で出てくる回数をn(A∩B)と表す。n(A∩B)/min(n(A),n(B))が閾値(本研究では0.8)を超える場合、その二つの単語を一つの単語として扱った。

上記の二つの処理を経て得られた単語は依然として多くのノイズを含み、文書の関連性の計算に悪い影響を与えることが予想される。そこで関連性の計算に用いる単語を選出する必要がある。以下にフィルタリングの詳細を述べる。

まずは品詞の分類を用いたフィルタリングを行った。上に述べたように単語には大分類と小分類が与えられている。今回の研究では品詞の大分類として名詞のみを対象とした。また小分類としては動詞の名詞化、一般名詞、固有名詞のみを対象とした。名詞のみに注目することは特徴語抽出において一般的に行われる手法である。また日本語の公式文書の場合、多くの動詞は名詞化されるため、名詞のみを用いても動作に関する多くの情報を得ることが出来ると考えられる。

続いて出現頻度に基づいたフィルタリングを行った。本研究では出現頻度からtfidfと呼ばれる値を計算しそれに基づきフィルタリングを行った。tfidfは文書分類のための特徴語抽出において最も一般的に用いられる指標の一つであり、ある単語が小数のドキュメントに多数出現する場合にその値を大きくするよう定義されている。tfidf は以下の式より計算される。

tfidf=tf idf (1)
tf_i=n_i/(Σ_k n_k) (2)
idf_i=log |D|/|{d:d∋t_i }| (3)

ここでniは単語iの出現頻度、|D|は総文書数、|{d:d∋t_i }|は単語iが出現する文書数となる。

多数の文書に出現する一般語のtfidfは低い値になる傾向があるが、一般語の中でも異常にtfが高い単