Features of Terms in Actual Nursing Activities

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Abstract

In this paper, we analyze nurses' dialogue and conversation data sets after manual transcriptions and show their features. Recently, medical risk management has been recognized as very important for both hospitals and their patients. To carry out medical risk management, it is important to model nursing activities as well as to collect many accident and incident examples. Therefore, we are now researching strategies of modeling nursing activities in order to understand them (E-nightingale Project). To model nursing activities, it is necessary to collect data of nurses' activities in actual situations and to accurately understand these activities and situations. We developed a method to determine any type of nursing activity from voice data. However we found that our method could not determine several activities because it misunderstood special nursing terms. To improve the accuracy of this method, we focus on analyzing nurses' dialogue and conversation data and on collecting special nursing terms. We have already collected 800 hours of nurses' dialogue and conversation data sets in hospitals to find the tendencies and features of how nurses use special terms such as abbreviations and jargon as well as new terms. Consequently, in this paper we categorize nursing terms according to their usage and effectiveness. In addition, based on the results, we show a rough strategy for building nursing dictionaries.

1. Introduction

Based on allegations of malpractice in medical care (nursing), hospitals have been sued and sometimes forced to pay huge amounts of money. Therefore, some hospitals insure themselves against medical malpractice to avoid the risk of bankruptcy. Taking out insurance might protect hospitals from bankruptcy, but it cannot save the lives of patients. Accordingly, it must be considered merely a passive measure of preventing malpractice in medical care. Recently, medical risk management has been recognized as very important for both hospitals and their patients. To carry out medical risk management, it is important to model nursing activities as well as to collect many accident and incident examples. That is, by modeling various types of nursing activities, we can find critical points for both known and unknown accidents or incidents. Abstract models of accidents or incidents can more flexibly and effectively work to avoid unpredictable accidents and incidents than a simple collection of accident and incident examples. Therefore, we are now researching strategies of modeling nursing activities in order to understand them — the *E-nightingale Project* (Kuwahara N. et al., 2004).

To model nursing activities, it is necessary to collect data on nurses' activities in actual situations.

As a first step, dialogues and conversations were collected by using a wearable device developed in the *E-nightingale Project*. Nurses wore it so that their dialogues and conversations could be recorded at any time in their actual working situations. Thus we could collect data sets for a whole day's dialogues and conversations without any restrictions on the nurses' performance. Then we developed a method to determine the types of nursing activities carried out from voice data (Ozaku et al., 2006). However, we found that our method could not determine several activities because it misunderstood special nursing terms.

To improve the accuracy of the method, we also collected data on nursing behaviors such as number of footsteps and body angle. Naya et al. attempted to analyze the data to derive a statical model of nursing workflow (Naya et al., 2005). For example, when nurses forgot to record their voice while concentrating on patients' care, we expected the behaviors data to help our understanding of nursing activities. However, since the behavior data may simply provide statistical guesses, it is difficult to accurately determine activities by using only the behaviors data.

It would be ideal to automatically extract nursing activities by using speech recognition techniques. However, it is necessary to prepare a sufficient dictionary set to achieve good speech recognition. Such a dictionary set also needs to improve the accuracy of the method for determining activities. We prepared a dictionary built from terms found in computerized patient record systems as well as manuals of nursing activities provided by hospitals and nursing academies. However, by only using such dictionaries, it was not possible to improve both the accuracy of speech recognition and the ability to determine activites. This was because terms that nurses actually use are not identical to those in computerized patient record systems or manuals of nursing activities. By briefly checking dialogues and conversations by nurses we found that a lot of abbreviations and jargon were used. Accordingly, it is necessary to analyze nurses' dialogues and conversations to find the features and tendencies of how they actually use specialized terms such as abbreviations and jargon as well as new terms.

In this paper, we analyze data sets of nurses' dialogue and conversation after manual transcription and show their features. In addition, we roughly show a strategy for building a nursing dictionary.

Section 2 overviews the *E-nightingale Project* and explains our role in the project. Section 3 illustrates strategies for collecting nurses' conversations and dialogues. Section 4 analyzes the collected data to show features of nurses' terms and to present the possibilities of building a nursing dictionary.

2. E-nightingale Project

The Japanese Ministry of Health, Labor and Welfare has reported that nursing teams are most frequently involved in medical accidents in hospitals (Healthcare Safety Precaution Network Project). To prevent actions leading to medical malpractice, the Japanese Nursing Association states in its guidelines that nurses are encouraged to make nursing reports and to analyze reasons for accidents and incidents. However, it is difficult for nurses to make detailed reports during their working hours. As a result, they usually make them after their works. Since it takes much times to make acceptable reports, this task itself becomes extra works that might cause other accidents or incidents. Accordingly, we launched the "*E-nightingale Project*" to develop a nursing service support system. The aim of the project is to establish the fundamental technologies of a system for knowledge-sharing based on understanding everyday activities within the context of their surrounding situations. These technologies should improve everyday activities not only in manufacturing but also in such fields as medical services, elderly care, emergency services, firefighting, and policing, all of which require expertise. Among these fields, this project focuses on medical services because of their importance and the urgent need for such technology. The project has chosen nurses in medical institutions as intended users because they most often experience medical accidents and incidents. The intention of this project is to develop the following three systems:

- A nursing duty record and analysis system;
- A just-in-time nursing advice system; and
- An accident/incident video documentation system.

In the project, Kuwahara et al. proposed an integrated nursing-activities monitoring system that couples ubiquitous apparatus including wearable devices (Fig. 1) with fixed apparatus (Kuwahara N. et al., 2004). This system was designed to monitor the workflows of nurses' activities and thus report their entire workflows in real time on their behalf. Therefore, it can collect multimedia data in the actual work environment. In addition, it was decided that the data should be analyzed in real time, since the monitored data could be used to determine the root cause of a nursing error as it occurs and thus give proper warning to nurses. This is one of the final goals of the system.

In the project, our role is to develop strategies for accurately understanding nursing activities and statuses in detail from voice data recorded by the developed wearable computers and text data such as manuals, workflows, and computerized patient records. In addition, we develop strategies to find nursing activities that may lead to medical malpractices, which can then be used to develop a system for preventing and reducing medical accidents.

Figure 1: Wearable devices.

In the next section, we describe experiments conducted in actual hospitals and analyze the collected data by using the devices.

3. Collection of nurses' dialogues and conversations

3.1. Wearable recording device

In this section, we describe our voice collection method. In the *E-nightingale Project*, we developed a device to record all of the nurses' voice data during their working hours by using wearable computers. That is, we developed a wearable voice recording system (Fig. 2). We intend to introduce speech recognition techniques to our system in the future, so the system needs to be able to record high-quality voice data onto a small device. Currently, this system can record all voice data from a day's work in the wav format (16 kHz, 16-bit sampling).

Nurses wear the device as shown in Fig. 1 to record their dialogues and conversations while doing actual work. The system shown in Fig. 2 is kept in the nurse's chest pocket. Thus we could collect data sets for whole day's dialogues and conversations without any restrictions on nursing duties. After several experiments, we have collected 800 hours of nurses' dialogues and conversations in hospitals.

3.2. Nursing dialogue corpora and nursing task corpora

To computationally analyze nurses' activities, it would be ideal to automatically extract nursing activities from collected voice data by using speech recognition techniques. To do this, it is necessary to prepare sufficient dictionary sets in order to achieve good speech recognition. We first prepared a dictionary built from terms in computerized patient record systems or manuals of nursing activities. However, it was not possible to improve the speech recognition accuracy by using only such dictionaries. This is because the terms that nurses use are not identical to those in computerized patient record systems or manuals of nursing activities. After briefly checking the data, we found that a lot

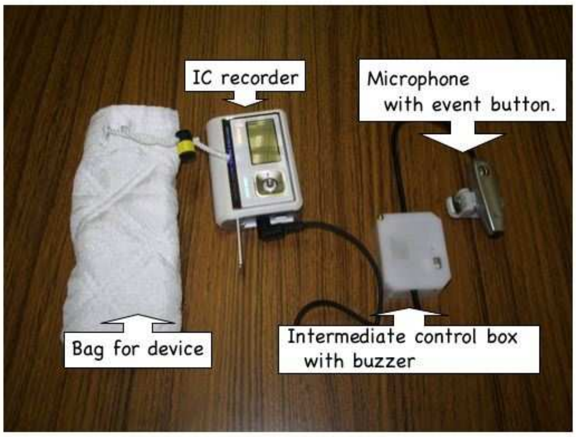

Figure 2: Voice recorder

of technical terms and jargon were frequently used. It is understood that nurses frequently use technical terms, abbreviations and jargon in order to hide certain information from patients or their families and to achieve effective communication. The use of abbreviations is easy to understand: We often use abbreviations for effective or fashionable conversation. In addition, since nurses deal with many new medicines and carry out many new medical treatments, it is quite natural that many words are recognized as unknown terms when using a standard dictionary. Consequently, in preparing dictionaries for accurate speech recognition during nurses' work, it is necessary to collect such new terms as well.
Therefore, we need to manually analyze voice data in preparation for automatic voice data analysis. After certain manual analyses, we can generate a model for automatic voice data analysis. Accordingly, we transcribed the collected voice data to build spoken nursing corpora for use in understanding nurses' tasks and analyzing nursing terms including technical terms in daily nursing assignments (Ozaku et al., 2005).
The process of creating the corpora is as follows;

1. Data of the sounds, including buzzer and short sentences, are extracted by the signal processing,
2. Transcriptions of all extracted data are made manually.
3. Task names from a job category list are attached as tags to each transcription of the short sentences to make the Nursing Task Corpora.
4. Time periods of conferences or clinical meetings are highlighted by time stamps in the Nursing Task Corpora.
5. For the Nursing Dialogue Corpora, voice data in conferences or clinical meetings, highlighted in the Nursing Task Corpora, are transcribed in detail, and words that are not included in the IPA dictionary (IPADIC) are tagged as "unknown" words.

The transcription was made by four staff members, including an experienced specialist in transcription, an ex-nurse who used to work in hospitals for more than three years, a pharmacist, and a part-time employee. We could obtain corpora including such conversation and dialogue data as shown Table 1, 2 [1] .

Nurse-ID	Utterances
A	Patient A-san will be discharged tomorrow. Please do not forget the Ento sheet.
B	Yeah, .. the Ento sheet.
C	The drip infusion is still being given, isn't it?
A	Yes. It's still dripping now.
B	Ah, until when?
A	Until tomorrow. Until 6 o'clock.

Table 1: Example of the Nursing Dialogue Corpora

In the previous paper (Ozaku et al., 2006), we manually analyzed types of nurses' tasks while referring to the generated corpora. In (Ozaku et al., 2006), we divided corpora into two types, nursing dialogue corpora (Table 1) and nursing task corpora (Table 2). We mainly analyzed the nursing task corpora to attach annotations to nursing practices. As a trial, we analyzed 1467 dialogues in the task corpora, These were categorized into 35 job categories established by the Japanese Nursing Association (Kango Gyoumu Kubun Hyou) and the Japan Academy of Nursing Science (Classification of Nursing Practice). These categories include, for example, 1-1-2D0401 (Hygiene/Haircare/Washing-hair), 13-58 (Doctor assistance/Rounds). In fact, currently we must manually categorize dialogues and conversations in order to attach annotations to nursing practices with the assistance of ex-nurses or nurses. We plan to attach such annotations to large numbers of dialogues and conversations, a task which will take a long time to complete. However, if we do complete it, as well as performing certain machine learning procedures, we think we will be able to obtain a model that can automatically attach annotation to nursing practices on the nursing corpora.
In this paper, we focus on the nursing dialogue corpora to determine features of terms in nurses' dialogues and conversations. Details are given in the next section.

4. Features of nurses' dialogues and conversations

4.1. Analysis of nurses' dialogues and conversations

In the previous sections, we pointed out that nurses tend to use a lot of abbreviations and jargon in their conversations. In addition, since they deal with many new medicines and carry out many new medical treatments, they also use many new terms. Accordingly, it is necessary to analyze nurses' dialogues and conversations to find tendencies or features in their usage of specialized terms, such as technical words, abbreviations, and jargon as well as new terms. We fully analyzed the voice data sets after manual transcription to find their features. We analyzed 1-hour transcribed data sets (14388 dialogues) by using a morphological analysis tool,

[1]The dialogues and conversations are originally spoken in Japanese. They are manually translated into English here.

Time	Utterances	Job Category
11:01:00	I'm going to join a short meeting.	18-106 conference
11:20:48	The short meeting is finished.	18-106 conference
11:28:11	I'm going to prepare a set of drip infusions for Patient B-san.	13-63-6A0502 intravenous infusion
11:32:01	I've finished preparing the drip for Patient B-san.	13-63-6A0502 intravenous infusion

Table 2: Example of the Nursing Task Corpora

Chasen (Chasen), with standard dictionaries. As expected, many misclassifications and unknown words were detected. For instance, "cardex (カーデックス[2])," which should be a single word, is divided as follows:

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カー (car) noun
デック (deck) noun
ス (do su) verb
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"Chuzai (中材[3])," which should also be a single word is divided as follows:

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中 (China) noun (country)
材 (Material) noun (suffix)
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In addition, Rinkode (リンコデ[4]) is recognized as an unknown word. Since Chasen's standard dictionaries do not include those words, it cannot correctly recognize them. In the worst case, it divides a single word into multiple words. In this case, since the word is divided into known words, facially no surface error can be observed. For language analysis, this case is worse than the unknown-word detection case. We assume that the same or similar situations might occur in the minds of novice nurses. Therefore, we focus on specialized terms that seem to be easy to misunderstand of difficult to correctly understand for beginning nurses. In our actual analysis of the corpora provided by Chasen implemented with standard dictionaries, we focused on unknown words since abbreviations, jargon, and new words are mostly extracted as unknown words. In addition, we extracted words that are not recognized as unknown words but whose meanings are not consistent with a particular context.

Based on the above assumption, we analyzed the 1 hour of transcribed data by using Chasen with standard dictionaries. Specialized terms that are easy to misunderstand are used 951 times in 14833 dialogues. Among them, 196 terms are used twice or more. Among them, three words that are especially frequently used are hair-bath (ヘアバス: 53 times), PEA (cataract operation: 24 times), and rinkode (リンコデ: 23 times). If we analyzed the corpora by using Chasen with standard dictionaries, they would be recognized as follows;

- Hair-bath (ヘアバス: hea-basu)

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ヘア hair (noun)
バス bus (noun)
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or[5]

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ヘヤ room (noun)
バス bath (noun)
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- PEA (cataract operation)

  P (alphabet) + E (alphabet) + A (alphabet)

- (リンコデ: rinkode)

  リンコデ (unknown)

4.2. Categorization of nurses' specialized terms

Thus even frequently used terms cannot be correctly recognized if we use standard dictionaries for Chasen. Accordingly, we need to check the categorization of such specialized terms. For instance, we can categorize them as follows:

- Technical terms
  - ハルン (harun): Harn (urine in German)
  - エルケー (LK): lung cancer
- Jargon
  - 定期外出 (Teikigaishutu): regular outgoing
  - 青ヒビ (Aohibi): ヒビテン (Hibitaine (Chlorhexidine hydrochloride))
- Technical terms (abbreviations)
  - エント (ento): Entlassen (discharge in German)
  - リンコデ (rinkode): codeine phosphate
  - アン (an): アンプル (ampoule)
  - 筋注 (kintyu): 筋肉注射 (intramuscular)
  - 朝絶 (asazetsu): not eating at breakfast
  - 即入 (sokunyu): 緊急入院, 即時入院 (emergency admission)
  - ムンテラ (muntera): MunThera (abbreviation of Mund Therapy; explanation of condition in German)
- Jargon (abbreviation)

[2] Nursing activities recording system

[3] Sterilization processing section in hospital

[4] Abbreviation of the name of a medicine. リン酸コデイン (codeine phosphate)

[5] "Hea" is sometimes pronounced as "heya."

– テル連 (teruren): 電話連絡 (telephone connection)
– 夕 R6(yuu-aaru-roku): 夕方にノボリンRを6単位 (take 6 units of Novolin R in the evening (after dinner))
– 糖内 (tounai): 糖尿病内科 (internal medicine for diabetes)

In order to make guidelines for building an additional dictionary, we roughly checked the nursing corpora. In an actual in 1-hour sample of data, we found 82 technical terms. Since Chasen with a standard dictionary cannot correctly analyze nursing corpora, and it is better to computationally analyze the corpora, we analyzed the data by using Chasen with a technical dictionary. The technical dictionary was built by referring to nursing term sets such as JNPSM (Japan Nursing Practice Standard Master) (JNPSM), which contains names of nursing activities, prepared by the Medical Information Center Development Center (MEDIS-DC). However, we could correctly recognize only 22 terms (around 25%). In addition, 114 jargons and abbreviations were found in the 1-hour data set, but we could correctly recognize only 12 terms (less than 10%) by Chasen with the technical dictionary. Clearly, the technical dictionary is not sufficient for analyzing actual nursing dialogues and conversations. Thus it is necessary to build a specialized term dictionary for technical terms, abbreviations and jargon from other term resources such as nurses' actual dialogues.

4.3. Toward specialized dictionary building

In building a dictionary, we usually prepare the necessary vocabularies from certain sources. In fact, we can build a specialized term dictionary by analyzing the generated nursing corpora. Since language is a living entity, such specialized terms should be constantly created and updated. As a result, even if we could collect all of the terms currently used, they would someday become old fashioned and we would have to collect new ones again. Therefore, a more effective way is to model the features or generation process of the specialized terms such as abbreviations and jargon. It is necessary to apply certain machine-learning techniques to generate general features or generation processes, but intuitive or simple ones can be observed through a brief review of nurses' dialogues and conversations. In the following, we briefly discuss the features of specialized terms in nurses' actual jobs.

We can observe many abbreviations in nurses' conversations, for instance, 筋注, 即入, and エント. One explicit rule for abbreviations is to use the first one or two syllables (or morae) of meaningful words. For instance, 筋肉注射 (Kinniku-Tyusha) becomes 筋注 (Kin-Tyu), 即時入院 (Sokuji-Nyu-in) becomes 即入 (Soku-Nyu), and エントラッセン (Entlassen) becomes エント (Ent(o)). The above type of abbreviation rule is usually followed; however, we found an exception where 腹部膨満 (Fukubu-Bouman) becomes 腹満 (Fuku-man).

As for jargon, it mainly originates from German words. Since doctors and nurses in hospitals mainly use German for technical matters, it might be a natural phenomenon to select a German word to generate a jargon. These phenomena are also mainly observed in conversation between nurses. On the contrary, nurses do not use this type of jargon when they talk with patients or patients' families. Instead they try to use another word that expresses a less serious situation. For instance, when they have to mention "stomach cancer," they usually use the term "stomach ulcer" instead.

Since we have not yet finished analyzing the data sets, it is still difficult to find general tendencies or patterns of specialized nursing terms. However, as discussed above, we could find several patterns through a brief overview of the gathered data. After we have analyzed the dialogue and conversation data in detail, we should be able to find general rules for abbreviation, jargon generation patterns and dealing with unknown words. These rules will help to improve the speech recognition of comments uttered by nurses during their actual jobs.

We could extract around 50 words as technical terms, and around 150 words as abbreviations and jargons from 1-hour data sets. We currently have 40-hours of transcribed data sets and are still transcribing the remaining data sets. We think that by processing the 1-hour data sets, considering the fact that some words appear more than twice, we will be able to obtain around 200 words and thus build a small dictionary of abbreviations, jargon, and technical terms. Of course, since we have another 800 hours of data sets, if we repeat the same procedure on the remaining data sets, we can significantly increase the contents of the dictionary in the future.

5. Conclusions

In this paper, we described voice data collection experiments in the *E-nightingale Project* and discussed features of nursing terms in real situations as well as the possibilities of building a nursing dictionary. As a first step, we manually transcribed the collected dialogues and conversations, because the voice data includes many specialized terms that are not included in the standard dictionaries and authorized term sets for nursing activities. We found certain features of nursing terms as specialized terms. These terms are roughly categorized into abbreviations, jargon, and new words. These types of terms are frequently observed in nurses' dialogues and conversations. Then, we showed the possibilities of developing a dictionary containing specialized nursing terms. After building the dictionary, we can apply speech recognition tools to it to achieve automatic transcription of voice data. Then we will be able to improve the efficiency of understanding nursing assignments.

Dialogue and conversation data by various nurses are included in the same data sets. Currently, we are analyzing the data without giving any consideration to the differences between individuals, but if we analyzed the data sets by considering such individual differences, we could build a situational dictionary. For instance, we would be able to build a dictionary that could distinguish terms according to department, nurses' experience, nurses' working situations, etc. In addition, we are now collecting dialogue and conversation data in more than one hospital. We can analyze the data to find both common and different features between different hospitals. Furthermore, if we compared the voice data sets and the incident accident reports at the same time, we could better determine the causes of the incidents. We would then be able to develop a system to prevent nurses from making errors leading to medical malpractices.

In the *E-nightingale Project*, we also proposed computational models for nursing risk management (Abe, Kogure, and Hagita, 2004a; Abe, Kogure, and Hagita, 2004b; Abe et al., 2006). In addition, we proposed a dynamic risk prediction procedure that observes nurses' conversations to determine critical points in nursing accidents or incidents (Abe et al., 2005). These points would be indicated by words that have a certain feature. We believe that the results from this research can be applied to building a knowledge base for effective risk management of nursing tasks.

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6. References

Abe A., Kogure K., and Hagita N. (2004). *Determination of A Chance in Nursing Risk Management*, Proc. of ECAI2004 Workshop on Chance Discovery, pp. 222–231.

Abe A., Kogure K., and Hagita N. (2004). *Nursing Risk Prediction as Chance Discovery*, Proc. of KES2004, Vol. II, pp. 815–822.

Abe A., Naya F., Ozaku H. I., Sagara K., Kuwahara N., and Kogure K. (2005). *Risk Management by Focusing on Critical Words in Nurses' Conversations*, Proc. of KES2005, Vol I, pp. 1167–1173.

Abe A., Ozaku H.I., Kuwahara N., and Kogure K. (2006). *Scenario Violation in Nursing Activities — Nursing Risk Management from the viewpoint of Chance Discovery*, Soft Computing Journal, Springer (to appear)

Chasen homepage. `http://chasen.aist-nara.ac.jp/`

Japan Academy of Nursing Association *Classification of Nursing Practice* (看護行為用語分類), ISBM 4-8180-1142-8,2005. (in Japanese)

Healthcare Safety Precaution Network Project (2001). `http://www.mhlw.go.jp/topics/2001/0110/to1030-1.html#2-1`. (in Japanese)

IPADIC version 2.7.0 (IPA 品詞体系辞書) `http://chasen.aist-nara.ac.jp/stable/ipadic/ipadic-2.7.0.tar.gz`

Japan Nursing Association *Kango Gyoumu Kijunsyu* (看護業務基準集), Japan Nursing Association, pp.336–337, ISBM 4-8180-1089-8,2004. (in Japanese)

Kuwahara N. et al. (2004). *Ubiquitous and Wearable Sensing for Monitoring Nurses' Activities*, Proc. of the 8th World Multi-conference on Systemics, Cybernetics and Informatics (SCI2004), Vol. VII, pp. 281–285.

Medical Information System Development Center eds. *Japan Nursing Practice Standard Master* `http://www.medis.or.jp/4_hyojyun/kango/kango.html` (in Japanese)

Naya F., Kuwahara N., Ozaku I.H., Ohmura R., Noma H., and Kogure *Nursing Workflow Analysis Toward Automatic Classification of Nursing Work*, JCMI25, 3-D-2-5. (in Japanese)

Ozaku H., Sagara k., Naya F., Kuwahara N., Abe A., and Kogure K. (2005). *Building Dialogue Corpora for Nursing Activity Analysis*, Proc. of the 6th International Workshop on Linguistically Interpreted Corpora, pp. 41–48.

Ozaku H, Abe A., Sagara K., Kuwahara N., and Kogure K. (2006). *A Task Analysis of Nursing Activities Using Spoken Corpora*, Advances in Natural Language Processing, Research in Computing Science (RCS06), Vol.18, pp. 125–136.