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Wearable Auto-Event-Recording of Medical Nursing

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Abstract: The constant hard work of providing nursing care, including handling emergencies, often causes medical accidents in hospitals. This paper proposes a wearable auto-event-recording system of medical nursing in order to capture the events that cannot be overlooked in analyzing such accidents. Our main concern is that the system be user-friendly for nurses. We have prototyped wearable sensors and conducted experiments. Experimental results show that, without disturbing nurses' work, our sensors can record data and reconstruct nursing histories, including the important events that are typically never recorded on written nursing logs.

Keywords: wearable, nursing, incident, accident

1 Introduction

One of the most urgent issues in hospitals is to construct an intelligent nursing environment to prevent medical accidents, since they damage the reputation of the hospital's reliability and thus its business success. Whenever an accident happens in a hospital, the analysis of the root cause depends on such sources as the doctors' and nurses' records. The Japanese Nursing Association states in its guidelines on writing the nursing record that it is not only an important tool for analyzing an accident's root cause but also legally admissible evidence if an accident results in a lawsuit. However, since they are based on the nurses' retracing their work each day, these records are often insufficient. One possible way to develop intelligent nursing environments is to utilize the technology of auto-event-recording with wearable sensors. Lately, several intelligent environments have been introduced, where nurses input bar-code data into a special PDA that is infection-proof (Hiratuka et al, 2002) and, as a result, very expensive. In such systems, every patient and piece of medical equipment is labeled by bar-codes. However, carrying and operating the PDA disturbs nursing duties such as lifting patients and carrying meals to patients. The PDA, therefore, is not user-friendly for nurses.

In order to provide a user-friendly device for nurses, nurses must be free from carrying the device during their nursing duties, and their nursing cares should not be impeded while inputting data by interacting with the device. Also, the device must not miss significant events that might be related to incident or accident cases, even if nurses fail to input the data of these events for some reason.

In order to meet these requirements, in this paper we focus on wearable sensors attached to a nurse rather than using a PDA. Our aim is to achieve comprehensive auto-event-recording. We describe our method as a way to capture the events that must not be overlooked in analyzing medical accidents by combining voice recording with wearable sensors.

2 Overview of Wearable Sensor System

Nurse's daily activities are normally recorded on a chart describing the transition of patient conditions, including the patient's vital signs and the nurse's care given to the patient during the day. Also, details focusing on specific problems of the patient are described on a flow sheet. The purpose of our sensor system is to identify job units automatically that appear in these records written by nurses. Our sensor system uses a pedometer and a tilt sensor to accomplish our purpose. The motion of the nurse indicates the specific pattern of each type of nursing care, so we assume that it is possible to identify job units of each nursing care by analyzing the features of the number of foot steps and the posture tilt of the nurse. We selected only these sensors because they do not impede the nurse's motion. In a real nursing environment, we cannot attach sensors to nurses as extensively as previous research efforts did (Naemura et al, 2001). We also adopt voice recording to obtain more detailed information on the nursing care such as patient's name, names of other medical staff and the room number related to the care. In order to add such tags to sensor data, we asked nurses to input voice data about the care currently performed. A non-touch switch is introduced for changing between recording time and privacy time. Their voice data is processed by the speech recognition system (Sumiyoshi et al, 2001), and the above information is extracted. Figure 1 shows a nurse wearing our sensors.

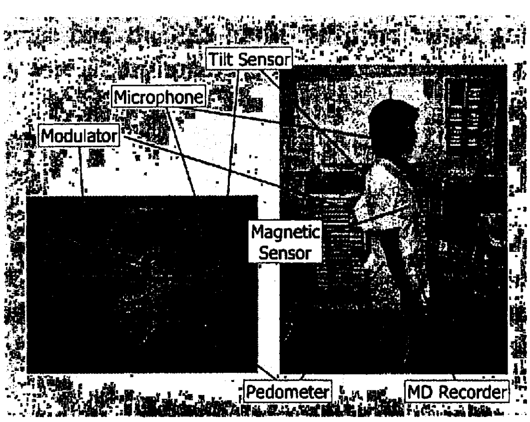

Figure 1: Overview of wearable sensor system

Our sensors system consists of a microphone, a magnetic sensor for the non-touch switch of the microphone, a pedometer for measuring the number of foot steps, a tilt sensor for measuring postures and a modulator for converting all sensor data to sounds by frequency modulation in order to record all observed data with Mini Disk (MD) or IC recorders.

3 Experiment / Discussion

We conducted our experiment at Tokyo Women's Medical University (TWMU) Hospital. The subjects were six nurses who belonged to the department of Neurosurgery, Neurological Institute. One of them worked in the Intensive Care Unit and the other five worked in the general ward. They performed their ordinary duties for a day (eight hours) while wearing our wearable sensors.

3.1 Foot Steps and Posture Tilt

We calculate the feature vector of the number of foot steps and posture tilt as follows.

(i) The number of foot steps in a frame
(ii) The average of posture tilt in a frame
(iii) The variance of posture tilt in a frame
(iv) The difference between adjacent frames of the average of posture tilt in a frame
(v) The difference between adjacent frames of the variance of posture tilt in a frame

The frame length is set to 40 seconds because the shortest job unit takes 40 seconds to finish. By analyzing the voice data of general ward nurses, five categories of job units were identified as follows.

(1) Communication jobs
(2) Taking care of the patient in bed
(3) Supporting the patient in moving from the bed to a wheelchair, etc.
(4) Monitoring the blood pressure of the patient
(5) Monitoring the temperature of the patient

Then, we performed multivariate analysis of variance (MANOVA) (Anderson, 1984) on the above feature vectors in order to statistically test whether the group means of categories were different from each other. From the results of MANOVA, among the five categories, (1) and (4) were not statistically different. However, the former is a job in the nurse centre, and the latter is a job in the patient room. Therefore, by incorporating the position data obtained from GPS or RFID, we will be able to separate these two categories. Figure 2

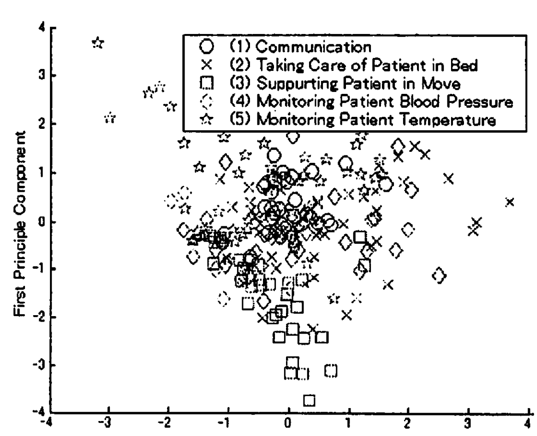

Figure 2: Result of principle component analysis of general ward nurses

shows the result of principle component analysis of general ward nurses' data. In the 1st principle component, the number of foot steps is dominant, while in the 2nd principle component, the variance in the posture tilt is dominant.

3.2 Reconstructing Nursing Histories from Sensor Data

For speech recognition, we established a dictionary containing possible words and syntax based on medical nursing guidelines in Japan, and the subjects were instructed to follow this dictionary. The dictionary consists of approximately 278 basic words for representing medical care, and the names of patients, medical staff and so on were also added. In order to improve speech recognition rate, we prepared a training tool that presented voice input examples to nurses for each nursing situation according to the dictionary. Nurses inputted their voice via a microphone to immediately check whether the system could recognize their voice inputs. Also, we provided a method for customizing the dictionary for each nurse.

Figure 3 shows an example of automatically reconstructed nursing history. The horizontal axis represents hours elapsed from the start of recording and the vertical axis represents types of medical care. We can also switch from the chart displaying mode by medical care to that by patient. In this example, there were 43 voice data entries of this nurse, and our system was able to recognize the job unit and patient from 36 entries (recognition rate is 83.7%). Also, we confirmed more than 80% recognition rate for other examples. We have not yet utilized the results of feature vector analysis in reconstructing nursing history. We are now studying a method to obtain more accurate nursing history by combining the results of speech recognition and feature vector analysis.

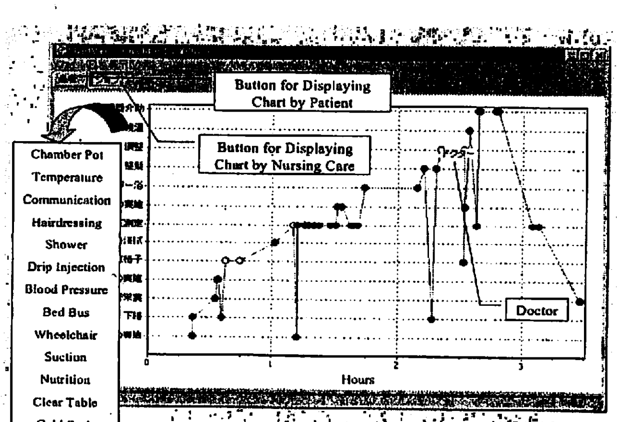

Figure 3: Example of reconstructed nursing history

3.3 Comparison with Actual Nursing Records

We compared the reconstructed nursing histories with actual nursing records with the cooperation of TWMU Hospital. We compared nursing histories that were reconstructed by our sensor system with actual nursing records of nurse A in general ward and nurse B in ICU. Nurse A is the primary nurse for six patients, and nurse B is the primary nurse for two patients.

We analyzed their actual nursing records to count how many jobs were recorded in these documents and then compared the numbers of these jobs with those of the reconstructed nursing histories. Figure 4 shows the results, where we categorized the jobs into three groups: Observation (Obs), Care (Care) and Communication and others (Comm).

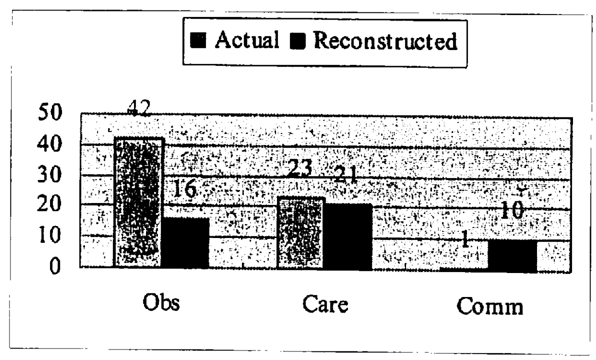

Figure 4: Comparison of numbers of jobs in actual nursing records with reconstructed nursing histories

The results show that our sensor system is insufficient for recording jobs of the observation type, since this kind of job is performed unconsciously during cares of the patient. For example, nurses observe the coma state of a patient by stimulating the patient's lip during mouth care, or they know a patient's pain through ordinary conversations with the patient, and so on. Even though nurses inputted their voice data about these kinds of jobs, we can only know the fact that the job was performed. There was no information on values of vital signs, conditions and complaints of the patient, and so on.

On the other hand, nurses recorded many voice data on their jobs for patients to whom they were not assigned as primary nurses. Nurse A took care of six patients and Nurse B took care of one patient other than those to whom they were assigned as primary nurses. These situations occur when nurses happen to encounter a patient who needs support for getting into a wheel chair from bed or for his taking dishes away from the bed, and so on. However, the actual nursing records do not note who did these unplanned acts of cares. Figure 5 presents the number of such jobs identified from the nurses' voice data. It shows that there were almost the same numbers of unrecorded Care jobs and Communication or other jobs as those recorded.

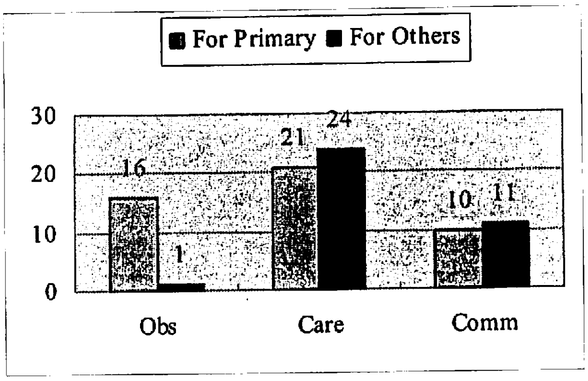

Figure 5: Comparison of numbers of jobs for patients primarily assigned with those for others recorded in reconstructed nursing histories

It is well known that one of the major causes of incident or accident cases of nurses is the interruption of their jobs by unscheduled tasks, but such interruptions are difficult to monitor and quantify from actual nursing records. In terms of recording unscheduled tasks for nurses, our sensor system can easily reveal this potential cause of accidents in their daily activities.

4 Conclusion

We introduced a wearable auto-event-recording system in order to capture the events that are important for analyzing medical accidents. Our system records the number of foot steps, posture tilt, and voice of a nurse by using wearable sensors and identifies the nurse's jobs with a recognizer. From the results of our experiment in an actual nursing environment, general ward nurses' job units could be classified into at least four categories by using a feature vector analysis of the foot steps and posture tilt data only. Furthermore, by utilizing speech recognition results only, nursing history, including important events such as interruption by unscheduled tasks, could be reconstructed with a more than 80% recognition rate. We are now studying a method for obtaining more accurate nursing history by combining the results of the speech recognition and the feature vector analysis and by incorporating these results with the position data of GPS or RFID. For future work, we are planning to design a ubiquitous sensor system (Sumi, et al, 2001) that cooperate with our wearable sensor system, where nursing care is monitored at everywhere in a hospital. Moreover, by using a medical knowledgebase, our system will be able to alert nurses pro-actively when it detects the possible occurrence of incident or accident case.

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