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 never to be overlooked for analyzing such accidents. Our main concern is user-friendliness of the system for nurses. We've prototyped wearable sensors, and conducted experiments. Experimental results show that, without disturbing nurses' jobs, our sensors can record data, and reconstruct their nursing histories including the important events never recorded on their 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 reliability of the hospital and 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. Based on the nurses’ retracing their work each day, their records are often insufficient for such an analysis. 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 are proof against a disinfectant and, as a result, very expensive. In such systems, every patient and piece of medical equipment is labeled by bar-codes. However, bringing 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 this paper, we focus on wearable sensors attached to a nurse rather than using a PDA to allow auto-event-recording without impeding nursing care. We describe such a method as a way of capturing the events never to be overlooked for preventing medical accidents.

2 Overview of Wearable Sensor System

We adopt voice recording for identifying job units in nursing care in place of the PDA. Nurses speak the name of the patient they are taking care of and what type of medical care is 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. Nurse’s motions are assumed to indicate the specific pattern of each type of medical care, but in real nursing environments, we cannot attach sensors to nurses as extensively as former research efforts did (Naemura et al, 2001). Therefore, in the first version of our implementation, sensors record only number of foot steps and the posture tilt in addition to voice. By utilizing features of these data and voice data, more accurate nursing histories will be reconstructed. Figure 1 shows a nurse wearing our sensors.
Our sensors consist of a microphone, a magnetic sensor for the non-touch switch of the microphone, a pedometer for measuring the number of footsteps, a tilt sensor for measuring postures, and a modulator for converting every sensor data to sounds by frequency modulation in order to record all observed data in MD or IC recorders. Afterwards, the sounds are processed by using FFT, and then voice, footsteps, and posture data are extracted.

3 Experimental Results

We conducted our experiment at TWMU Hospital. The subjects were six nurses who belonged to the department of Neurosurgery, Neurological Institute, and one of them worked in Intensive Care Unit and others worked in 4F ward. They performed their ordinary duties for a day with our wearable sensors. For the 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 cares, and names of patients, medical staffs and so on.

3.1 Reconstructing Nursing Histories from Voice Data

We conducted preliminary experiment (Kuwahara, 2002), and found that they didn't input voice data according to the dictionary so that speech recognition did not work well. Then, we prepared the training tool that presented voice input examples to nurses for each nursing situation according to the dictionary. Nurses inputted their voice via the microphone, and they could immediately check whether the system can recognize their voice inputs or not. Also, we provided a method for customizing the dictionary for each nurse.

Figure 2 shows one of the examples of automatically reconstructed nursing history. The horizontal axis represents hours elapsed from the start of recording and the vertical axis represents types of the medical care. Patients are identified by the colors of each plotted point. In this example, there were 43 voice data of this nurse, and our system was able to recognize the job unit and the patient from 36 examples (recognition rate is 83.7%). Also, we confirmed more than 80% recognition rate of other examples.

3.2 Comparison with Actual Nursing Records

We compared reconstructed nursing histories with actual nursing records with cooperation of TWMU Hospital. Usually, nurses write a lot of kinds of records. For examples,

(1) Patient data sheet describing his/her condition when he/she is hospitalized
(2) Patient problem lists
(3) Care Plans for each problem of the patient
(4) Chart describing the transition of the patient conditions including vital signs in a day
(5) Flow sheet describing detail conditions focusing on specific problems of the patient
(6) Summary and Assessment of nurse’s cares to the patient, so called SOAP

Among above documents, the history of nurse’s cares to the patient is described on (4) Charts and (5) Flow Sheet, so that our sensor system is considered to make it possible to records these documents.
automatically. Then, we compared nursing histories that were reconstructed by our sensor system, with actual nursing records of nurse A in 4F 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 analyze actual nursing records of them in order to count how many items were recorded in these documents, and show the result in Table 1. In Table 1, we categorize items in three groups. One is Observation category, the second is Care category and the last is Communication and others category.

<table>
<thead>
<tr>
<th>Nurse</th>
<th>Observation</th>
<th>Care</th>
<th>Communication or Others</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>26</td>
<td>8</td>
<td>0</td>
</tr>
<tr>
<td>B</td>
<td>16</td>
<td>15</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>42</td>
<td>23</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 1: Numbers of jobs in actual nursing record

Table 2 shows the analysis result of items in nursing histories reconstructed by our sensor system from their voice inputs.

<table>
<thead>
<tr>
<th>Nurse</th>
<th>Observation</th>
<th>Care</th>
<th>Communication or Others</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>10</td>
<td>6</td>
<td>3</td>
</tr>
<tr>
<td>B</td>
<td>6</td>
<td>15</td>
<td>7</td>
</tr>
<tr>
<td>Total</td>
<td>16</td>
<td>21</td>
<td>10</td>
</tr>
</tbody>
</table>

Table 2: Numbers of jobs identified from voice inputs

Comparing Table 1 with Table 2, our sensor system is insufficient to record jobs of the observation type, because this kind of job is performed unconsciously during their cares to the patient. For example, nurses observe the coma of the patient by stimulating patient’s lip during a mouth care, or they know patient’s pain through ordinary conversations with patients, and so on. Even though nurses inputted their voice about this kind of jobs, we can only know the fact that the job is done. There was no information of values of vital signs, conditions and complaint of the patient, and so on.

On the other hand, nurses recorded many voice data on their jobs for patients to whom nurses were not assigned as a primary. Nurse A took care of six patients, and Nurse B took care of one patient other than their primary. These situations occur when nurses happen to encounter the patient who needs to support for his riding the wheel chair from his bed, or for his taking dishes on his bed, and so on. However, on the actual nursing records, it is not noted who did these cares. Table 3 presents the number of such type of jobs identified from their voice data. It shows that there were almost the same amounts of unrecorded cares as those on actual nursing records, and there are much more communication or other jobs than those on them.

<table>
<thead>
<tr>
<th>Nurse</th>
<th>Observation</th>
<th>Care</th>
<th>Communication or Others</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1</td>
<td>12</td>
<td>10</td>
</tr>
<tr>
<td>B</td>
<td>0</td>
<td>12</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>1</td>
<td>24</td>
<td>11</td>
</tr>
</tbody>
</table>

Table 3: Number of jobs that are not recorded on actual nursing records (identified from voice inputs)

It is well known that one of the major causes of incident, accident cases of nurses is the interrupt of their jobs, but it is hardly to know from actual nursing records whether the interrupt happens or not, or how many interrupts occurs. However, as mentioned before, our system can easily reveal this type of danger in nurses’ daily activities.

3.3 Foot Steps and Posture

In our preliminary experiment, it was possible to categorize job units that were identified from voice data into three types. In this experiment, we show that job units are categorized into those three groups and several new ones. Feature vector is defined as same as that of our preliminary experiment.

(1) The number of foot steps in a frame
(2) The average of posture tilt in a frame
(3) The variance of posture tilt in a frame
(4) The difference between adjacent frames of (2)
(5) The difference between adjacent frames of (3)

The frame length is set to 40 seconds because the shortest job unit takes 40 seconds to finish. Then, we calculated the feature vector of each job unit and performed multivariate analysis of variance (MANOVA) (Anderson, 1984).

3.4 Analysis of Feature Vectors

In the voice data of 4F ward nurses, two types of jobs were newly identified in addition to the result
of preliminary experiment. We performed MANOVA to nurses’ foot step and posture tilt data in order to statistically test whether the group mean of categories as follows was different from each other.

1. Communication jobs
2. Taking care of the patient in the 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

From the result of MANOVA, among above five categories, (1) and (4) are not statistically different. However, the former is the job in the nurse centre, and the later is the job in the patient room, so that, by incorporating with the position data obtained from GPS or RF, we will be able to separate these categories. We also analyzed ICU nurse data. In her data, we identified (6) recording type of jobs in addition to (1) and (2), and these three types of jobs were statistically different from each other. Figure 3 shows the result of principle component analysis of 4F ward nurses’ data.

![Figure 3: The result of the principle component analysis of 4F ward nurses](image)

In 1st principle component, the number of foot steps is dominant, and in 2nd principle component, the variance of the posture tilt is dominant.

4 Conclusion

We introduced a wearable auto-event-recording system in order to capture the important events for analyzing medical accidents. Our system records the number of foot steps, the posture tilt and the voice of a nurse by using the wearable sensors, and identifies the nurse’s jobs by the recognizer. The first, our experiment shows that nurses can input voice data for identifying their jobs, and from these data, nursing history that includes important events such as interrupt of their jobs can be reconstructed. Next, we identified six types of jobs from nurses’ voice data, and their job units can be classified into at least five categories by using feature vectors of the foot step and posture tilt data. By incorporating with the position data of GPS or RF, another one type of jobs will be separated from others. We are now studying to apply more sensors that do not impede their move for classifying their jobs into more precise categories. Also, we are preparing for the long-term field-testing at TWMU Hospital for improving the reliability of our system.

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