としても以下に示すリスクは残存する。

1. コンピュータウイルス等の悪意のあるソフトウエアの侵入:
   Zero Day Attack は前述の対策では防止できない。Zero Day Attack とは開発された悪意のあるソフトウエアが、OS のアップデートやワクチンソフトの定義ファイルが対応する前に感染することであり、事前に阻止することは原則として不可能である。一部のワクチンソフトはソフトウエアの振る舞いをチェックしているが、確実に検出できるとは言えない。現在、多くの悪意のあるソフトウエアが東アジアで作られていることを考えると、ネットワーク的に近い我が国で Zero Day Attack による被害の出る可能性はある。
2. 利用者を含む内部の不正な振る舞いによるリスク:
   一定の規模以上の医療機関等では利用者も多く、また常に常勤の職員とは限らない。さらに施設内には多くの外来者が存在し、そのすべてに運用規程の徹底や教育が可能とは限らない。医療機関等では建物内の構成が変更されることが多く、情報コンセントの管理さえ用意ではない。また無線ＬＡＮの使用もあり、ネットワーク自体へのアクセスを管理することは不可能ではないにしても、容易ではない。内部からの不正な振る舞いを事前に完全に防ぐことは相当困難と言わざるを得ない。ただし、このリスクは外部ネットワークへの接続とは一次的には無関係であり、むしろ外部ネットワークに接続していた場合、被害を外部に拡散させる可能性があるということになる。

５－５．　残余リスクへの対策

上記の残余リスクへの事前に防止する対策はきわめて難しく、事故が起こった場合の対策を十分に行うしかない。その医療機関等のBCPに含めておくべきであろう。その場合にもっとも重要なことは事故の早期発見であり、効果的なモニタリングを行う必要がある。

Ｄ．考察

比較的ＩＴリテラシが高く、人員にもゆとりがある大学病院での調査でも診療情報システムから必要な外部ネットワーク上のリソースに自由にアクセスできる環境は１病院でのみ実現されており、他は限定的であった。もっとも現在構築中の１病院はOpt in方式ではあるが、将来はかなり自由にアクセスできる環境になることが期待された。その一方で、現状行われている方法が必要十分な解であることは、いずれの病院のネットワーク管理者も確信を持ち得ていない状況といえる。本研究で示す現実的解によって、少なくとも一定規模以上の病院など、専属ではないにせよ、医療情報技師など一定の専門知識を持つ管理要員の配置が可能な医療機関では安全にインターネット上の資源にアクセス可能となるような、指針の必要性が明確になったと言える。ただ大部分の小規模医療機関はITリテラシーの点からも人員の点からも実際には利用不可能であり、管理要員が配置できなくても、安全な接続を可能とするためには管理を一括して行うゲートウエイセンタが有効な解決方法となりうる。本年度はゲートウエイセンタの構成要素である、ファイアウォールとSPAMフィルタの評価を行い一定の成果はあるものの、引き続き検討が必要であることがわかった。ま

たインターネットのセキュリティ上の脅威の調査では、これまでの我が国での事例の内、４割は内部の従業者による犯罪であり、４割はファイル交換ソフトの誤用あるいはファイル交換ソフトへのウイルス感染によるもの、のこりは少数であるが、SQLインジェクションと、WEBサーバの設定ミスであった。従業者による犯罪は技術的に防止することは難しいが、その他はいずれも技術的に、あるいは技術的対策と運用規則で対応可能であり、対策を具体的に示す必要が明確になった。

診療情報システムをInternetに接続するニーズは確実に存在する。その中には今後の診療の継続や、診療情報システムを真に役立つものにするために避けられないニーズもあり、現時点はともかく、近い将来には何らかの接続は避けられない。本研究では管理されない接続を対象にはしなかったが、現在は携帯電話網を通じたインターネット接続や公衆無線ＬＡＮも普及しており、妥当なニーズに対して適切な管理下に接続を行わない場合、管理されない接続が行われる可能性もある。管理されない接続は極めて危険なことを考えれば、適切に管理された接続は必須と考えて良い。

Internetに接続した場合、リスクは確かに存在する。その多くは適切に管理することで、対応可能であるが、Zero Day Attackのように事前の予防としては対応不可能な残余リスクも存在する。ただし、残余リスクとしてあげたZero Day Attackと内部からの不正行為は、Internetに接続しない場合にもリスクとして存在するもので、Internetに接続することで改めて生じるリスクではない。つまり、Internetに接続していなくても何らかの情報システムを用いる以上は対応をしなければならない。

そのようなリスクを除けば適切に管理された接続であれば、対応可能である。問題は適切な管理のためのコストである。運用規定の制定や教育はともかく、適切なファイアウォールの設定や、不正アタック、不正使用の監視はネットワーク管理に関する一定の知識が必要で、また経済的にもコストが生じる。大学病院のような大規模医療機関では対応可能な場合もあるが、小規模医療機関では困難であることが推測される。一般には組織内の人員で対応できない場合は、外部事業者に管理を委託するが、常時監視であり、委託費用もそれなりの価格になるであろう。これを解決にするには、高度のネットワーク知識を持たない場合でも十分な管理ができるような、マニュアルや指針を整備するか、委託先を大規模化したコストを下げることが考えられる。ASP・SaaSによる診療情報システムの場合はサービス提供者と医療機関等の間のネットワーク管理はサービス提供者が行うことが普通であろうし、さらに外部との接続もサービス提供者の管理下に行われれば、医療機関等としてのコストはサービス利用料の含まれることになる。ただASP・SaaSを利用する場合でも、ハイブリッド型のシステムである場合が考えられる。つまり一部の診療情報システム機能は医療機関等内に存在し、一部をASP・SaaSで利用する場合である。この場合、外部接続の管理の責任主体は複雑になる。外部への接続はASP・SaaSのサービス提供者に委託することも考えられるが、その場合、サービス提供者は自らの管理するシステム以外からの通信も管理することになり、一体的なサービス対価にはならない可能性がある。また双方で外部接続を行う可能性もあるが、この場合は責任の所在が複雑になり、事故があった場合の対応等

を契約で明確にしなければならない。この場合で単独で医療機関等が外部接続する場合より運用コストが増加する可能性もある。

本研究のとりまとめの議論の中で、望ましいと考えたことは外部接続に関するゲートウエイセンタを設置することである。ゲートウエイセンタはファイアウォール機能を含む適切な外部接続管理を集中して行い、利用する医療機関等はこのセンタにVPN接続する。医療機関等は自らの診療情報システムの異常の監視は行う必要があるが、それはネットワークに接続しない場合でも同様であり、追加の労力なく、必要な外部アクセスが可能になる。またこのゲートウエイセンタがDMZとして機能し、共同利用型のサーバを設置すれば外部への情報発信も行うことができる。

Internet接続は近い将来には必須であり、適切な対応を行わない場合、管理されない接続によって危機的状況が起こりえない状況と言える。行政からの情報発信もInternetを利用していることを考えれば、行政的・制度的な手当も必要と考えら得る。研究班では２点の提言を行いたい。

１点目はゲートウエイセンタの誘導である。行政が直接ゲートウエイセンタを設置する必要性はないが、一定の信頼が必要であり、関与はすべきものと考えられる。可能性としては現在レセプトオンラインの受け口となっている支払基金や国保連合中央会もこのような機能を持つ主体としては有望と思われるが、レセプトオンラインより、トラフィックは飛躍的に増大する可能性があり、もう少し分散することが必要と思われる。管轄の公益法人を活用するか、一定の基準と定期的な監視を行う仕組を整備することで、民間事業者の参入を誘導する等の対策をとることが望ましいと考えられる。

２点目は「医療情報システムの安全管理に関するガイドライン」の改訂である。現在のガイドラインではInternet接続に関する項目は系統的でなく、理解しにくいという問題はあるが、さらに、2010年の外部保存用件の緩和により、今後普及することが予想されるASP・SaaSの活用に関する指針や、Zero Day Attackや内部からの不正行為のための障害に対する対応には記載が見られない。本来BCP (Business Continuing Plan)として考慮すべきことであるが、現状のBCPは6.10章で主に災害や、システム異常について完結に書かれているのみで、外部接続や、外部接続を行わない場合でも起こりうる障害に十分対応できているとは言い難い。さらに本研究とは無関係であるが、東日本大震災のような大規模災害やそれにともなう電力事情の悪化にも対応できているとは言い難い。改訂が必要である。これらの改訂が適切になされれば、８章は原則として不要と考えられる。

Ｅ．結論

比較的ＩＴリテラシが高く、人員にもゆとりがある大学病院での調査でも診療情報システムから必要な外部ネットワーク上のリソースに自由にアクセスできる環境は１病院でのみ実現されており、他は限定的であった。その一方で、現状行われている方法が必要十分な解であることは、いずれの病院のネットワーク管理者も確信を持ち得ていない状況といえた。ゲートウエイセンタの構成要素である、ファイアウォールとSPAMフィルタの評価を行い一定の成果はあるものの、引き続き検討が必要であることがわかった。またインターネットのセキュリティ上の脅

威の調査では、これまでの我が国での事例の内、４割は内部の従業者による犯罪であり、４割はファイル交換ソフトの誤用あるいはファイル交換ソフトへのウイルス感染によるもの、のこりは少数であるが、SQLインジェクションと、WEBサーバの設定ミスであった。従業者による犯罪は技術的に防止することは難しいが、その他はいずれも技術的に、あるいは技術的対策と運用規則で対応可能であり、本研究でさらに対策を具体的にする必要が明確になった。

また、ニーズ分析、リスク分析をおこなった上で、対策と残余リスクを整理し、提言をまとめた。提言では人員に余力のない医療機関等が安心して診療情報システムをInternetに接続するためには、ASP・SaaSによる診療情報システムを用いるか、ゲートウエイセンタの利用が強く求められるために、その誘導策をとることと、「医療情報システムの安全管理に関するガイドライン」の改訂が必要であることを示した。

F. 研究発表

1.　論文発表

なし

2.　学会発表

なし

G. 知的財産権の出願・登録状況
（予定を含む。）

1. 特許取得

なし

2. 実用新案登録

なし

3. その他

なし

Ⅲ. 研究成果の刊行に関する一覧表

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Capturing Nursing Interactions from Mobile Sensor Data and In-Room Sensors

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Abstract. In this paper, we show two approaches for capturing nursing interactions in a hospital: 1) finding nursing intervals from mobile sensors with accelerometers and audio on nurses, and 2) recognizing nurses' entrance to a patient's room from in-room sensors of bed, loudness, and illuminance sensors. For 1), we firstly detect the nurses' entrance to the patient's room by walking detection from accelerometers and noise level on mobile sensors, and detect the interval of interaction between nurses and the patient. For 2), we recognize the nurse's entrance to the patient's room with in-room sensors, using separate algorithms between day and night. We developed the algorithms using the sensor data collected in a cardiovascular center in a real hospital for one year. It could be a important baseline technique to find valuable intervals from long and big data of sensors.

Keywords: Activity Recognition, Annotation, Speech Interval Estimation, Nursing Activity.

1 Introduction

In this research, we aim at capturing nursing interactions with patients from mobile accelerometers attached to each nurse. Capturing nursing is important, since 1) it helps understanding what/when/how interactions should be performed for better health results of the patients, and 2) it can be utilized to improve the skills of nurses. If we have evidences of interactions and the health result, we can analyze the correlations between them, and find the key factors for better interaction.

However, very few data sets for such purpose have been published and shared among the research community so far, either because of the immaturity of sensing/network/storage technology, or because of the privacy risk.

In our one-year trial in a cardiovascular center in a hospital, we have collected 7,400 hours of mobile sensor data in total from nurses after one-year trial in a hospital[1]. We asked nurses to bring smart devices (iPod touches), which records

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sounds and accelerations, into their breast pockets with a roughly fixed direction. They also attached small 2 accelerometer devices on their right wrists and the back waists. Moreover, each of them attached a semi-passive RFID tag in the breast pocket to recognize entrees and exists from the patientsf rooms.

We also asked to 70 hospitalized patients who have been applied PCI (Percutaneous Coronary Intervention) or CABG (Coronary Artery Bypass Graft), and have consented to the experiment, to provide vital sensor data such as monitoring cardiogram, bed sensor to measure heart rate and breath, accelerometer, environmental sensors, and also medical information which were recorded in the electronic clinical pathways and indirectly in patients' sensor data.

In this paper, we show two approaches for capturing nursing interactions: 1) finding nursing intervals from mobile sensors with accelerometers and audio on nurses, and 2) recognizing nurses' entrance to a patient's room from in-room sensors of bed, loudness, and illuminance sensors. For 1), we firstly detect the nurses' entrance to the patient's room by walking detection from accelerometers and noise level on mobile sensors, and detect the interval of interaction between nurses and the patient. For 2), we recognize the nurse's entrance to the patient's room with in-room sensors, using separate algorithms between day and night.

Although this is the first step to analyze and mine the nursing interactions leading to clinical pathways, it could be an alternative to install costly RFID readers to all rooms, and could be an important baseline technique to find valuable intervals from long and big data of sensors.

2 Background

In our one-year trial in a cardiovascular center in a hospital, we have collected large-scale mobile sensor data from nurses and patients, along with the medical records of the patients[1](See Fig.1). We asked nurses to bring mobile devices (iPod touches), which records audio and accelerations, into their breast pockets with a roughly fixed direction. They also attached small 2 accelerometer devices on their right wrists and the back waists. Moreover, each of them attached a semi-passive RFID tag in the breast pocket to recognize entrees and exists from the patients' rooms. To realize them, RFID readers are installed on the entrance of each of the patients' rooms. As a result, we have collected total 7,400 hours of real nursing activities and 4,600 hours of RFID data.

We also asked 70 hospitalized patients who have been applied PCI (Percutaneous Coronary Intervention) or CABG (Coronary Artery Bypass Graft), and have consented to the experiment, to provide vital sensor data such as monitoring cardiogram, bed sensor to measure heart-rate/breath/body-movement, accelerometer, in-room sensors, and also medical information which were recorded in the electronic clinical pathways and indirectly in patients' sensor data.

We used a bed sensor system in which a thin, air-sealed cushion is placed under the bed mattress of the patient[3]. The system measures heartbeat, respiration and body movement of the patient non-invasively by detecting the changes of air pressure of the cushion caused by their vital signs. Finally, we have collected total 2,500 hours of bed sensors.

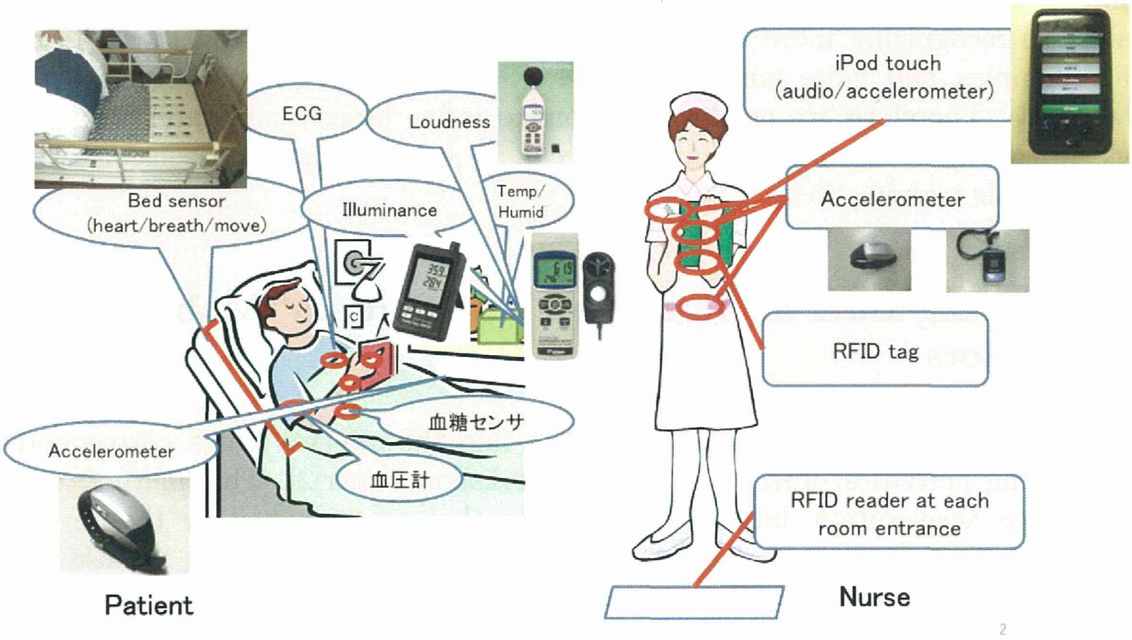

Fig. 1. Illustration of sensor installation

We also installed three in-room data loggers at the patients' room, and recorded four types of data: temperature/humidity, illuminance and loudness. Temperature and humidity are recorded every 5 seconds and the others are recorded every second. As a result, we have collected 5,600 hours of in-room sensors' data.

In the experiment, we have a requirement to know the nursing activity interval to know what kind of care are done to each patient. We can focus on the intervals when the nurses are in the patients' rooms, so the RFID system is thought to be useful. However, RFID system is not always available, since the readers and antennas should be placed many places, such as every entrance of the patients' rooms. Therefore, it is welcomed if we can know when nurses stayed in patient rooms without using RFID, but with mobile sensors or other in-room sensors.

3 Related Work

In the literature, some work utilizes accelerometer and audio data to recognize human context. Lukowicz et al.[5] recognizes activities in a wood shop using body-worn multiple microphones and accelerometers. Lester et al.[6] shows the performance of activity recognition for 8 activity classes using accelerometers, audio, and barometric pressure sensor in a single device. Choudhury et al.[7] developed to implement them on a mobile embedded system. In the device, audio is down-sampled as not to be able for humans to harm privacy of the owner.

One of the differences of our work from above is that these work assume simple activity classes to recognize such as, "walk", "stair up", but our research aims at recognizing more complex and more number of nursing interactions. For complex and more number of interactions, the recognition accuracy will be worse. Therefore, we need more effort to refine larger-scale dataset as well as sophisticated machine learning that can be used in higher dimensions with larger-scale training data.

4 Nursing Interval Detection from Nurses' Mobile Sensors

In this section, we describe the method to find the interval which corresponds to nursing activities, introduced in the workshop paper[2]. This method uses three-axis acceleration data and audio data that are collected by the devices attached to the breast pockets. Upon the collected activity data, we use two characteristics in order to efficiently locate the intervals where nurses performed medical activities.

One is the characteristic that a nurse certainly speaks to a patient when s/he performs medical practice to a patient. Nurses always talk to the patients what to do for medical practice. Therefore, if we can find an interval where nurses are talking, we can guess that the interval of medical activities is being performed.

The other is that a nurse walks for a specific while when s/he moves into a patient 's room. If we can detect the walking of nurses to move into the patient's room from 3-axis accelerometer, we can segment the time to either of being inside or outside the room. In addition, we can estimate if s/he is in the patient's room by examining the noise level from the audio data after a walking period.

In order to utilize the above characteristics, we adopt mobile sensors which record three-axis acceleration and audio data. With the data collected by the devices, we apply walking detection method for the accelerometer, speech interval estimation for audio data, and location estimation for the environmental noise level of the audio data. We can find the duration of walk from three-axis acceleration data by walking detection, location estimation from the environmental noise level of the audio data after walking periods, and the durations where a nurse talks from audio data by speech interval estimation.

Walking Detection. In order to detect the walk of nurses, we recognize the walk of nurses using the technology of activity recognition. We calculate the feature vectors to train an activity recognition model from the three-axis acceleration data. Feature vectors are calculated with the time window of 2 seconds being shifted by 0.5 seconds. A feature vector consists of the variance and the entropy of the intensity: the square root of the sum of squares of the three-axis values of acceleration data. The recognition model is trained by Support Vector Machine (SVM) with linear kernel. To smooth continuous walking, the duration of less than 15 seconds between detected walks are also assumed as walk.

Location Estimation. We can estimate if s/he is in the patient's room by the environmental noise level from the audio data. If the audio is recorded in 16-quantization bit rate, the amplitude bandwidth is from -32768 to +32767. From our experience, environmental noises of our target were found to be from -1500 to 1500. Therefore, at first, we remove the intervals of amplitudes outer than -1500 from 1500, which contains human voices and metal sounds. After that, we estimate the location by the median amplitude value of 30 seconds after the end of walking period.

Speech Interval Estimation. To find the nurses' speech interval, we estimate the speech interval by seeking fundamental frequency of the audio data. The fundamental frequency is one of the speech features used in speech recognition, and it represents the height of the voice. Calculation of the fundamental frequency is performed by the cepstrum method[4]. Although the cepstrum technique is weak for noises, there are advantages that the fundamental frequency can be correctly acquirable in any languages.

In this study, using the Cepstrum method, fundamental frequency is calculated with the time window of 0.04 seconds being shifted by 0.02 seconds. By obtaining the time window with high peak quefrency, we can obtain the spoken interval.

4.1 Experiments

We have conducted the experiments using real nursing data to evaluate the proposed method. The used data is activity data of one day of a nurse.

Walking Detection In order to evaluate the walking detection, each of the training and test data with annotation for 300 seconds were prepared from a day of a nurse. Two kinds of annotations, "walk" and "others", are attached to the data. The data contained 100 seconds of "walk", and 200 seconds of "others". Recognition model was created by the modelusing the training data, and was evaluated by the test data. Tab. 1 shows the recognition result before smoothing. From the table, the whole recognition rate is 93.6%.

Table 1. Confusion matrix of the number of time windows for walking detection

→ Ground truth	Walk	Others
Walk	52	18
Others	19	492

4.2 Location Estimation

We picked up 43 data points from 4 audio data, and investigated the environmental noise level, which is put together in Fig. 2. In Fig. 2, the left box is the distribution of the median environmental noises in the patient's room, and the right is in other places. Since the inter-quartile ranges (IQRs) do not overlap each other, we can estimate that we can differentiate the location at more than 75%. If we take priority on the recall rate, we can achieve at least 87.5%.

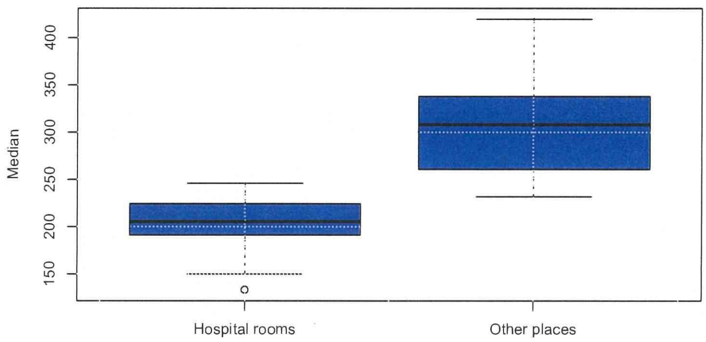

Fig. 2. Distribution of median environmental noise levels of 43 data points of 30 seconds after a walking period. The left is in the patient's room and the right is in other places.

Speech Interval Estimation. We evaluated the speech interval estimationusing audio data of 300 seconds. The audio data was prepared from a day of a nurse.

Table 2. Confusion matrix of the durations for speech interval detection.

→ Ground truth	Nurse	Patient	Noise	Silence
Speech	27.62[s]	7.65[s]	0.14[s]	0.76[s]
None-speech	0.83[s]	2.6[s]	13.72[s]	246.68[s]
Total	28.45[s]	10.25[s]	13.86[s]	247.44[s]

The confusion matrix which counts of the results are shown in Tab. 2. For comparison, the ground truths are classified as the nurses' speeches, patients' speeches, noises, and the silent intervals, whereas the proposed method only estimates speech or non-speech. The silent intervals of the ground truths were determined by whether the amplitude is greater than a specific threshold value, which resulted in that negligible small voices were included in the silence class. From the table, the method recognizes the speech intervals with the accuracy of 98.6%. However, the recognized speech includes patients' speeches. If we evaluate the rate of recognizing nurses' speeches only, it becomes 96.9%, which is still a higher recognition rate.

Integration. We integrated the three method described above, and applied to 300 seconds which are obtained from a day of a nurse.

Fig. 3 shows the results of the speech interval estimation and walking detection. The above figure of the figure is the result of walking detection, in which three walking periods are detected. After applying location estimation method to the three intervals of 30 seconds after walking, only the first one of after 65.5 second was estimated to be in a patient's room. Then, applying speech interval estimation to that interval, the total time of speech interval were found to be 24 seconds.

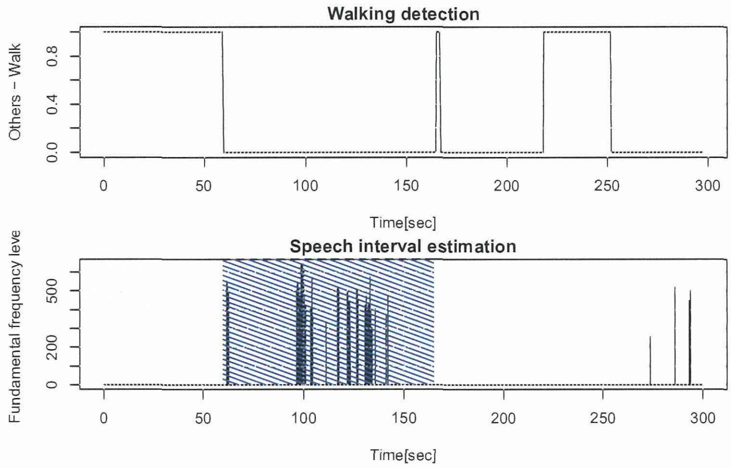

Fig. 3. Result of integrated process. The upper is the result of walking detection, and the lower is the speech interval estimation. After applying 3 parts of 30 seconds after walking period detected by the upper part, the first 30 seconds were detected as in the patient's room, which could be applied by the speech interval estimation of the lower part.

5 Nursing Interval Detection from In-Room Sensors

In this section, we try to analyze the in-room sensor data, and detect the intervals when a nurse enters the room only from these in-room sensors. In the previous study[1], we found that the candidate sensors which have correlations with nursing intervals are 1) bed sensors, 2) loudness sensors, and 3) illuminometer. Therefore, we focus on these sensors in this section.

In this section, we target on recognizing nurse's entrance to a patient's room and intervals where the nurses are absent from the room. This is the first step of the nursing interval detection from in-door sensors, and if it is accurate, we can step further to add recognition of nurse exits, and apply for any time using time window method.

5.1 Method

Dataset. To prepare the dataset for target classes for nurses' entrance and absence, we picked up 100 durations from each sensor data, in which

- (*ENTER*) 50 of them include the RFID event of a nurse's entrance, and
- (*ABSENT*) the rest 50 are between the events of nurse's exit and entrance, which could be estimated that there are no nurses in the room.

Moreover, since we found that the sensor data behave differently between day and night, each of the 50 durations are divided into:

- (*day*) 25 durations of between 8:00 and 18:00 of a day, and
- (*night*) 25 durations of between 18:00 of a day and 8:00 of the next day.

Features. For each duration of each sensor in the dataset, we extract the feature vectors. The idea for recognizing ENTER and ABSENT is that the sensor values will change in the former case, but not in the latter case. Therefore, we take the difference between statistic values of several while after and before a target time, considering a margin. For a duration, a feature vector (v_1, v_2) consists of:

$$v_1 = ||E(t+10, t+40) - E(t-40, t-10)||$$

$$v_2 = ||V(t+10, t+40) - V(t-40, t-10)||$$

where $||x||$ is the absolute value of x, $E(a, b)$ is the mean of the sensor values of a duration $[a, b]$, and $V(a, b)$ is the variance of them. Moreover, we set different t for ENTER and ABSENT: the time (sec) of the RFID event of a nurse's entrance for ENTER, and the the center time (sec) of the duration for ABSENT.

This means that we take the difference of statistic values of 30 seconds after and before the target time, including a margin of ± 20 seconds.

Recognition. To recognize the entrances of nurses, we train the feature vectors with SVM with radial kernel. We applied 5-fold cross validation to evaluate the accuracy, in which the feature vectors of the dataset are randomly divided in to 5 groups, and each of them is treated as a test data, while the others are as training data.

As we mentioned, we found that the feature values are different between day and night from the preliminary study. Therefore, we compared the 3 cases of using all feature vectors together, those of daytime only, and those of nighttime only.

Moreover, we tried several combinations of sensors from bed sensors, illuminance sensors, and loudness sensors, for the sake of finding better combination of input variables for recognition.

5.2 Result

Fig. 4 is the accuracy of recognition for nurses' entrances and absence, for several combinations of day/night and those of sensors which have conducted best accuracies among our trials. In Fig. 4, (a) is with all dataset, (b) is only with daytime, and (c) is only with nighttime. Each of them shows both of with all sensors (bed, loudness, and illuminance) and without illuminance sensors.

From Fig. 4, we can see that (a) which use all the dataset, is almost worse than the corresponding ones which use only daytime or nighttime dataset, except for (c) right. From this, we can conclude that the features behaves differently between daytime and nighttime, and we should firstly distinguish the recognition algorithms of day and night.

Moreover, from Fig. 4, we can see that, for the daytime, (b) is the same if we omit illuminance sensors, and illuminance sensors improves the accuracy for the nighttime. This means that the illuminance sensors do not necessarily play effective role for recognition at daytime, but do at nighttime. Therefore, we can

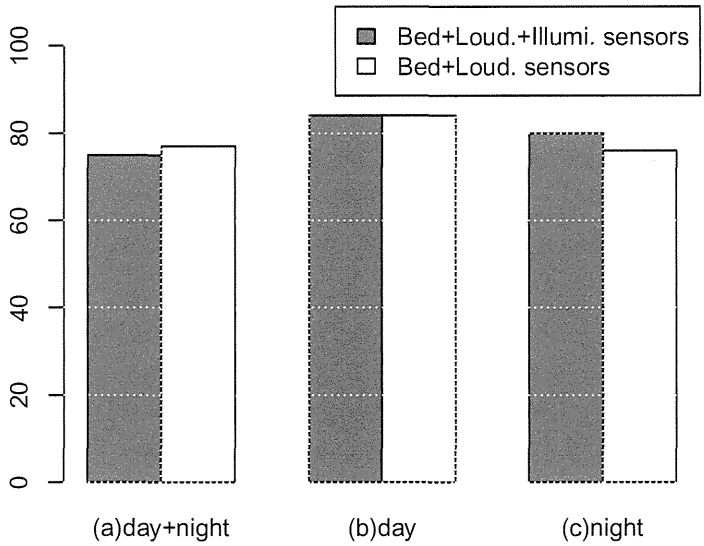

Fig. 4. Accuracies of entrance recognition

conclude that the best and smaller combinations of sensors is bed sensors and loudness sensors at daytime, and is plus illuminance sensors at nighttime.

Based on the consideration above, we show the confusion matrix of the recognition for the best cases, which are (b) right and (c) left, in Tab. 3, respectively.

From Tab. 3(a), the recall rate of entrance recognition at daytime is 72.0%, and the precision rate is precision 94.7%. Those at night time is 87.5% and 77.9% from Tab 3(b), respectively.

Table 3. Confusion matrix for entrance recognition

(a) Daytime without illuminance sensors
Accuracy: 84.0%

Ground truth→	ENTER	ABSENT
ENTER	18	1
ABSENT	7	24

(b) Nighttime with all sensors
Accuracy: 80.0%

Ground truth→	ENTER	ABSENT
ENTER	21	6
ABSENT	4	19

6 Conclusion

In this paper, we described two approaches for capturing nursing interactions: 1) finding nursing intervals from mobile sensors with accelerometers and audio on nurses, and 2) recognizing nurses' entrance to a patient's room from in-room sensors of bed, loudness, and illuminance sensors. For 1), we firstly detect the nurses' entrance to the patient's room by walking detection from accelerometers and noise level on mobile sensors, and detect the interval of interaction between nurses and the patient by Cepstrum method. For 2), we recognize the nurse's entrance to the patient's room with in-room sensors, using separate algorithms between day and night.

Although this is the first step to analyze and mine the nursing interactions leading to clinical pathways, it could be an alternative to install costly RFID readers to all rooms, and could be an important baseline technique to find valuable intervals from long and big data of sensors. The future step should be applying the proposed methods to the longer period, and evaluate the accuracy combining the approaches.

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Portable Health Clinic: A Pervasive Way to Serve the Unreached Community for Preventive Healthcare

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Abstract. One billion people (15% of the world population) are unreached in terms of accessing to quality healthcare service. Insufficient healthcare facilities and unavailability of medical experts in rural areas are the two major reasons that kept the people unreached to healthcare services. Recent penetration of mobile phone and the unmet demand to basic healthcare services, remote health consultancy over mobile phone became popular in developing countries. In this paper, we introduce two such representative initiatives from Bangladesh and discuss the technical challenges they face to serve a remote patient. To solve these issues, we have prototyped a portable health clinic box with necessary diagnostic tools, we call it a "portable clinic" and a software tool, "GramHealth" for archiving and searching patients' past health records. We carried out experiments in three remote villages and in two commercial organizations in Bangladesh by collaborating with local organization to observe the local adoption of the technology. We also monitored the usability of the portable clinic and verified the functionality of "GramHealth". We display the qualitative analysis of the results obtained from the experiment. GramHealth DB has a unique combination of structured, semi-structured and un-structured data which can be considered as BigData. We have partly analyzed the data manually to find common set of rules to build a better clinical decision support. The model of analyzing the GramHealth BigData is also presented.

Keywords: Portable Clinic, Personal Health Records (PHR), Remote Health Consultancy, BigData, CDSS (Clinical Decision Support System).

1 Introduction

There are 1 billion people are unreached in terms of accessing to quality healthcare service [1]. About four thousand children die of diarrhea in a day, one pregnant mother dies in every 90 seconds. This scenario can be dramatically changed if we can simply convey few simple medical tips to the target unreached community. Most of the unreached people are from rural areas in developing countries [2]. Healthcare

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