Fusion Considerations in Monitoring and Handling Agitation Behaviour for Persons with Dementia

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Abstract – This paper presents the fusion considerations for a smart hospital application. In particular, we present the subtle design and implementation of a fusion architecture for monitoring and handling agitation behaviour for persons with dementia. In addition, we exploit Semantic Web standards to provide a reusable fusion middleware support for providing services that facilitate care-giving and clinical assessment of dementia patients in a context enlightened fashion.

Keywords: Fusion considerations, monitoring and handling, agitation, persons with dementia, fusion architecture

1 Introduction

There is an increasing interest worldwide in applying the latest developments in pervasive computing, context aware systems and sensor networks [1,2] for healthcare. One specific area of focus is to develop smart hospital applications such as context aware hospital bed and pill container [3], activities tracking system [4], etc. Although there are some works describing prototyping of smart hospital applications, there is still limited work taking into account the detailed fusion considerations using multimodal sensors for monitoring and handling patients in a pervasive clinical manner, and the applications tend to take the piecemeal approach. This paper will seek to bridge the gap by describing the subtle design and implementation of a smart healthcare application from the fusion perspective. As a first step, we target applications on persons with dementia, and behaviors that are of clinical interest to the doctors. One common behavior of persons with dementia is agitation. One of the challenges faced by doctors and caregivers is the detailed and continuous monitoring of such agitation behavior. Due to the nature of the observations that must be taken, time-pressed doctors and over-stressed caregivers are not the ideal people to make detailed records of behavioral patterns of these individuals. Our fusion works involve collaboration with a local hospital to semi-automatically monitor elderly patients with dementia in a hospital ward for the purpose of detecting the onset of agitated behavior and facilitate clinical assessment and informal care-giving in a context enlightened fashion.

Our work is based on the Scale to Observe Agitation in Persons with Dementia of the Alzheimer Type (SOAPD) [5]. Developed by Ladislav Volicer, Ann Hurley and Lois Camden, leading authorities in the world on palliative care for patients with dementia, this tool seeks to objectively classify the degree of agitation experienced by a demented person. In order to perform SOAPD measurements, observation of patients must be made from several angles and along several dimensions such as vocalizations, whole body movements, partial body movements, repetitive movements and so on. Human observers often tend to miss out on one or more types of behavioral patterns while focusing on a particular pattern of interest. With the use of modern sensor and networking technology, and with algorithmic techniques based on sensed context information and fused information from various combinations of sensing modalities, we hope to successfully detect the onset of agitated behavior. Furthermore, we hope to support flexible and standardized schemes for automated intervention triggering and activity planning management so as to handle dementia patients in a context enlightened fashion.

In this paper, we present the fusion considerations for multimodal sensors in a distributed manner to monitor and handle dementia patients. The rest of the paper is organized as follows: Section 2 discusses the fusion design considerations for dementia patient monitoring application. Section 3 describes a fusion middleware for monitoring and handling dementia patients. Section 4 presents some of the preliminary results we collected. Section 5 concludes with a discussion on future work.

2 Fusion Design

In this section, we will describe our fusion design considerations for adaptive monitoring and handling of persons with dementia based on feedback from doctors, caregivers and our prototyping experience. Our initial work focuses on four of the behavioral features of SOAPD, namely the Total Body Movement, Up Down Movement, Repetitive Movement and Outward Movement. The multimodal sensors adopted for understanding the agitated behaviours are ultrasound sensors, optical fiber grating pressure sensors, acoustic sensors such as microphones or microphone arrays, infrared sensors, RFID and video cameras. In addition we are also investigating the possibility of using microphones for studying the human vocalization related SOAPD...
indicators, such as High Pitched or Loud Words, Repetitive Vocalization and Negative Words.

2.1 Design Considerations

We deal with fusion at sensor, ward and hospital level based on the requirements of the doctors and caregivers. We will not exhaustively list all the considerations but selectively elaborate on the important ones that are relevant from a clinical perspective. For sensor level consideration, we focus on dealing with quality, uncertainty and data association issues. For ward level consideration, we focus more on situation awareness and summarized report issues. For hospital level consideration, we focus more on exploiting knowledge base of user’s intention such as the doctors and caregivers for intervention and planning.

2.1.1 Sensor Level

In dementia patients monitoring applications, data acquired from sensors are used for many different potential clinical purposes, e.g., detecting patients' agitation for possible intervention, monitoring the effectiveness of medicine-taking, studying the possible factors related to agitation, etc. From a clinical perspective, two basic considerations during the sensor data fusion are, a) to correctly associate sensor readings with monitored events and, b) to minimize data uncertainty. One effective solution is the proper deployment of sensors in a manner that increases the possibility for a sensor’s reading to be confirmed by the readings of other sensor positioned nearby. However, the sensor redundancy introduced by this approach increases the system cost and resource utilization in terms of processing, energy and bandwidth. The data quality requirements posed by queries should be used as a basis to determine the level of sensor redundancy. In this section, the considerations on sensor level fusion in a clinical context are further elaborated along two dimensions, namely Inter-sensor fusion and Inter-modality fusion.

**Inter-sensors Fusion:** Multiple sensors of the same modality can be deployed to increase the total geographic sensing coverage and also to reduce the uncertainty of the data from a single sensor. In our hospital ward sensor deployment, multiple ceiling mounted ultrasonic sensors are used to provide better coverage for localization information, which is used mainly to monitor certain types of agitation and to detect the presence of doctors and caregivers. Within the cone-shape sensing area, the variation of the distance reading from an ultrasonic sensor may be interpreted as either as noise or the presence of a person anywhere within a circle area with the radius of \(h \cdot \tan(a)\), where \(h\) is the height of the ceiling and \(a\) is the angle between center beam and sensing boundary of the ultrasonic sensor. However, when a neighboring ultrasonic sensor exhibits similar reading variations, the possibility for there being noise may be ignored and the presence of a person may be further localized into the intersection of the two respective circles. Placing sensors too close to each other may create the problem of interference. The effects of interference are taken into account as a trade-off against the data precision requirements of applications which consume the sensor data.

**Inter-modality Fusion:** Sensors of different modalities may be deployed to reduce their mutual data uncertainty in a similar way as that used for two or more sensors of the same modality. For example, a passive infrared sensor (PIR) can report the presence of a person within its circle-shape sensing area. Therefore, a PIR may enhance the localization information from an ultrasonic sensor in the same way as the ultrasonic modality itself. In some situations, different sensor modalities exhibit mutual supplementing functions to increase the detection rates of certain events. In Up Down Movement (UDM) agitation detection (one of the types of agitation being measured), ultrasound and pressure sensors can supplement each other in capturing the following observed behavior patterns of patients:

1. While agitated, patients may only trigger ultrasonic sensors but not pressure sensors by avoiding constantly touching the surface where the pressure sensors are deployed.
2. While agitated, patients may only trigger pressure sensors but not ultrasonic sensors by moving body with high intensity but low amplitude.
3. While not agitated, patients may still trigger pressure sensors but not ultrasonic sensors by adjusting body position normally but frequently.

A significantly higher agitation recognition rate is achieved with both ultrasonic and pressure sensor modalities deployed, comparing to the detections from single modality as shown in the experimental section.

It is noted that one good strategy discovered during multimodality sensor deployment is to maximize the possibility to confirm sensor readings by those sensor sources that are primarily used to provide other unique information. For example, while identifying entities, e.g., visitors, medicines, etc., with their RFID tags, a RFID reader could also enhance the localization information from other modalities such as PIR or ultrasonic sensors by reporting the presence of an entity within its valid cone-shape sensing area.

2.1.2 Ward Level

At the ward level, the doctors and caregivers would like to have a daily or monthly customized summarized behavior report on all agitation behaviors of the patient. Due to the unpredictable behavior patterns of patients and uncontrollable sensor reading errors, an inference engine, such as a Bayesian network, is necessary for any reliable report on agitation behavior detection given features extracted from sensor level. During the ward level fusion, the most vital step is to select appropriate sensor modalities to fuse. It is shown in the experimental section that sensor modalities that give no significant evidence to
Starting from an initial Bayesian network, for each node, point and have found a locally optimal network that has a not change in an entire iteration, we have reached a fixed deletion action for each node in the net. If the score does iteration of the algorithm involves performing this edge metric to decrease, the resulting network is retained or such action causes the score calculated by the scoring we try to delete an existing edge to its nearest neighbor. If all the events to be monito red. Then the customized assumption that every sensor deployed is contributing to Bayesian network initially constructed with the training data, and use this to tune and optimize the training data sets. In our approach, we collect a set of customize a Bayesian network by learning from the relationship between an agitated behavior and the detection results from different sensor modalities is not obvious. For example, the sensor modalities, e.g., ultrasonic or pressure sensors, triggered by UDM are not constant; and symptoms of the same agitated behavior can also be varied from patient to patient, e.g., some patients tend to make sounds during UDM while the others not. Therefore, it is more appropriate to construct and customize a Bayesian network by learning from the training data sets. In our approach, we collect a set of training data, and use this to tune and optimize the Bayesian network initially constructed with the assumption that every sensor deployed is contributing to all the events to be monitored. Then the customized Bayesian networks are used in the actual monitoring to fuse the readings from multiple modalities of sensors.

During the training data set collection, in addition to the data on agitation detection reported by each modality of sensors, a series of time-stamped manual observations are also required for the training set. Whenever agitation behaviors of patients are observed, some simple input mechanisms, e.g., through pressing anywhere on the keyboard, is used by a human observer to notify the system the current timestamp. The training data is further processed based on the additional clinical criteria to obtain a combined agitation record from both manual observations and sensor detections. For example, for the short duration agitation detection, the time domain is uniformly divided into 16-second slices and a binary value is assigned to each time slice for both manual observation and detection of sensors from each modality, with '1' for agitation presence and '0' for no agitation observed. Such processed binary values will be used to compute the Conditional Probability Table (CPT) for constructing a Bayesian network. The score of the current network $B$ is computed using the scoring metric defined as [6]:

$$L'(E, B) = - \sum_{i=1}^{m} \log p(v_i) + \frac{|B| \log m}{2}$$ (1)

where:
- $E$: the data consists of $m$ samples.
- $p(v_i)$: the joint probability that the variable has the values specified by $v_i$.
- $|B|$: the number of parameters in $B$
- $v_i$: an n-dimensional vector of values of the $n$ variables

Starting from an initial Bayesian network, for each node, we try to delete an existing edge to its nearest neighbor. If such action causes the score calculated by the scoring metric to decrease, the resulting network is retained or otherwise we undo the change and continue. Each iteration of the algorithm involves performing this edge deletion action for each node in the net. If the score does not change in an entire iteration, we have reached a fixed point and have found a locally optimal network that has a lower score than all the alternatives. The process terminates with a network customized to a particular patient. It is noted that the manual observations required for training data set can be an ongoing process from doctors and caregivers, and the Bayesian network may therefore be continually improved and optimized whenever more training data are available.

### 2.1.3 Hospital Level

At the hospital level, a key challenge is to fuse all related information from the sensors and other information sources with knowledge of user’s intent such as the doctors or caregivers to come out with a knowledge management system or electronic patient system that interfaces with the multitude of other systems that actuate specific interventions, e.g. music therapy systems or that provide important context information e.g. a care-giver’s digital calendar and mobile phone, and a doctor’s decision-making aid, to support automated intervention triggering and activity planning/drug therapy management facilitation. It should have the capability to allow the doctors and caregivers to search the system for desired information and then establish a connection to the desired service.

In more advanced requirements, we will likely look to facilitating effective drug therapy though side-effect monitoring. This is because most drugs used to treat dementia have many serious side-effects, and hence determination of the best dosage (i.e. treat symptoms with least side-effects) is important. At present, dosage titration is based largely on incomplete information provided by familial caregivers through reviews. With automated monitoring and a good model relating to drugs and their side-effects, the system can be extended to monitor for behavioral changes in relation to the side effect.

We exploits Semantic Web standards [7,8] to provide a reusable fusion middleware support for flexible event representation, query and reasoning, and standardized schemes for automated intervention triggering and activity planning to handle agitation detected in persons with dementia. To augment ambient intelligence for the application and services, we will explore the use of DL Implementation Group (DIG) [9] compliant classifiers, specifically RACER reasoner [10] to make inferences over our ontology base. Context reasoning will largely be employed to detect mid-to-long term patterns of disturbed behaviors (e.g. time of occurrence) and cognitive decline as well as short-term analysis relating to new drug administration. As such, it may involve the fusion of information in the form of ontology from two different sources. To illustrate, assuming that the system can discern automatically when a patient is emotionally disturbed, the doctors and caregivers may proceed to make provisions for timely therapeutic interventions. As an example, they may want the system to perform automated intervention that provides a combination of relaxing music and colored images which may decrease agitated behaviour of a patient, or plainly need the system
to send an SMS message to them. Mechanisms for intervention in many existing systems are usually hard-coded. In our system, using ontology and web services approach, we can fuse the information of multiple ontologies from different sources as shown in Figure 1, 2 and 3 to provide flexible intervention by interfacing with the multitude of other systems that actuate specific interventions.

![Figure 1: Intervention Ontology](image1)

![Figure 2: Actuate SendSMS Intervention from System A](image2)

![Figure 3: Actuate Music Intervention from System B](image3)

3 Fusion Middleware Architecture

Here, we describe our reusable fusion middleware architecture as shown in Figure 4 which aims to help application developers to design a patient data collection system and facilitates fusion of information from distributed sensor sources or other information sources to build healthcare applications more efficiently and effectively.

![Figure 4: Reusable Fusion Middleware Architecture](image4)
modality, moment of patient in a vertical axis using ultrasound sensor and movement of patient from one region to another using pressure sensors.

**Tier-2 Fusion Node (Sensor/Ward Level Fusion):** It is here whereby low level information and features extracted from the sensors are fused together to form high level context that are more meaningful and relevant to human. It consists of a repository, query engine, inference engine, Bayes engine and UPnP control point. Sesame [13] provides the context storage, with Sesame RDF Query Language (SeRQL) as the context query language. The query engine provides the abstract interface for applications to extract desired contexts. The inference engine consists of a variety of techniques ranging from rule based systems to neural networks and fuzzy logic, to aid in the decision making process by injecting rules or logic encoded into the inferencing stage. The UPnP control point coordinates the discovery of behavioral context of the bedridden patients and disseminates this information to the ontology knowledge base using SOAP messages. A Bayes engine is integrated to perform information fusion between multiple modality sensors.

**Tier-3 Fusion Node (Hospital/Ward Level Fusion):** It is the node which provides customization for fusing higher level contexts into one that is relevant to an application or services. It consists of web service daemons and an application server using tomcat that is integrated to a knowledge base consisting of the user’s intent. Auxiliary sources in the form of ontology for providing the context of the patient and related personnel in term of profiles, schedules, social networks, etc. can be integrated into the node. The situation awareness module helps to discover important relationships previously not known to exist, and perform fusion and correlate a variety of higher level information or data types into knowledge that form the basis for triggering intervention. Specifically, it performs fusion of information in different ontologies from multiple sources.

### 4 Experiments and Results

We are putting together an observational system in a hospital ward composed of multiple sensors of different modalities in order to collect data from dementia patients as shown in Figure 5 and 6. It is hoped that through the deployment of these sensors coupled with our fusion architecture and technique, we can automate the detection of the onset of agitation in dementia patients and trigger intervention. While the preliminary deployment phase for data collection is ongoing, we perform a number of experiments to evaluate whether our fusion considerations can meet the requirements of doctors and caregivers.

For sensor and ward level fusion considerations, we focus on the results for Up Down Movement agitation behavior on both the bed and chair. Figure 7 and 8 shows the Bayesian networks to deal with uncertainty and improve recognition rate for UDM in chair and bed respectively.
Using the initial sets of data collected, we found that with careful consideration of the supplemental sensing capability of each modality during sensor deployment, much higher patient agitation detection rate can be achieved with multi-modalities fusion as shown in Table 1 and 2.

Table 1: Experimental Results on UDM Agitation in Chair Recognition Rate Improvement with Multi-Modalities Sensor Fusion through Bayesian Inference shown in Fig. 7.

<table>
<thead>
<tr>
<th>Sensor Modality</th>
<th>UDM Agitation in Chair Recognition Rate</th>
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<tbody>
<tr>
<td>Ultrasonic sensor alone</td>
<td>59%</td>
</tr>
<tr>
<td>FBG pressure sensor alone</td>
<td>75%</td>
</tr>
<tr>
<td>Both Sensor Modalities</td>
<td>94%</td>
</tr>
<tr>
<td>with Bayesian Inference</td>
<td></td>
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</tbody>
</table>

Table 2: Experiment Results on UDM Agitation in Bed Recognition Rate Improvement with Multi-Modalities Sensor Fusion through Bayesina Inference shown in Fig 8.

<table>
<thead>
<tr>
<th>Sensor Modality</th>
<th>UDM Agitation in Bed Recognition Rate</th>
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</thead>
<tbody>
<tr>
<td>Ultrasonic sensor alone</td>
<td>83%</td>
</tr>
<tr>
<td>FBG pressure sensor alone</td>
<td>83%</td>
</tr>
<tr>
<td>Accelerometer sensor alone</td>
<td>84%</td>
</tr>
<tr>
<td>Acoustic sensor alone</td>
<td>80%</td>
</tr>
<tr>
<td>All Sensor Modalities</td>
<td>88%</td>
</tr>
<tr>
<td>with Bayesian Inference</td>
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We also found that the acoustic modality acts as good supplemental evidence to other modalities for agitation detection as the patient monitored in the experiment shown in Table 2 tends to shout when he exhibits UDM agitation behaviour in bed. However, for the patient who does not shout for the experiment shown in Table 3, the data captured by acoustic sensors give no significant evidence to agitation. In fact, the selection of acoustic modality during fusion greatly hinder the recognition rate. Higher agitation recognition rate can be achieved with a customized Bayesian network learned from the training data from that particular patient by removing acoustic modality from the network shown in Figure 8.

Table 3: Experimental Results on UDM Agitation in Bed Recognition Rate Reducing with inappropriate Sensor Modality selected through Bayesian Inference shown in Figure 8.

<table>
<thead>
<tr>
<th>Sensor Modality</th>
<th>UDM Agitation in Bed Recognition Rate</th>
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<tbody>
<tr>
<td>Ultrasonic sensor alone</td>
<td>85%</td>
</tr>
<tr>
<td>FBG pressure sensor alone</td>
<td>81%</td>
</tr>
<tr>
<td>Accelerometer sensor alone</td>
<td>82%</td>
</tr>
<tr>
<td>Acoustic sensor alone</td>
<td>40%</td>
</tr>
<tr>
<td>All Sensor Modalities</td>
<td>52%</td>
</tr>
<tr>
<td>with Bayesian Inference</td>
<td></td>
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</table>

With the above results coupled with our ontology and web service based fusion middleware architecture, a sample of web-based real time summarized report on instant of agitation behaviour of a dementia patient for a single SOAPD session as shown in Figure 9 is generated.

Figure 9: Observation Results for a SOAPD Session

Preliminary results for intervention are also quite encouraging and indicate that the response can be easily less than few seconds subjected to network delay which is sufficient for most real time intervention. We are now further validating our results in the hospital deployment in the preliminary deployment phase scheduled to end in middle of year 2006. It is hope that the joint effort with a local hospital should see us achieving our long term objective to deploy the system in a real life setting.

5 Conclusions

The monitoring and handling of persons with dementia in hospital and nursing home or even one’s home is going to be increasingly important in the coming years due to aging population. It is important for the patients and caregivers that automated and non-obtrusive means of monitoring and handling procedure be developed. Our research on fusion considerations is a first step in this direction. It is expected that with our fusion technique and fusion middleware, we will increase the success rates of detection and enable the technology to be deployed pervasively in hospitals, nursing homes and patients’ homes.
References