A Decision Support Architecture for Telecare Patient Management of Chronic and Complex Disease

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Abstract—A major challenge facing designers of telecare systems today is providing decision support to enhance the health carer’s review of remotely acquired monitoring data and to support clinical decision-making for the management of chronic and complex disease in this setting. We are implementing a decision support framework to analyze clinical information generated from subjects at their place of residence (home, residential care settings) and from other clinical environments. The telecare information generated from these environments is both substantial and multi-modal (physiological, questionnaire, medication data, etc.). Using the JBoss Application Server, a rules engine is used to analyze these data. The health carer will be alerted to any deterioration in the health status of a patient by way of a Web page that will stratify a clinical data summary into high, medium and low risk groups. In this way, outputs from the decision support system can be used to assist in the efficient review and risk stratification of multiple patient records, and ultimately influence changes in work flow by targeting scarce human resources to patients of most need.

I. INTRODUCTION

HOME telehealth services and tools have increased exponentially over recent years [1]. It has become accepted that telecare has significant potential for facilitating the improved management of patients with chronic and complex disease. This acceptance has extended to deployments in the home [2, 3] and in residential aged-care facilities, with the latter focusing on workflow implementation of clinical guidelines [4] as a means of improving patient outcomes and lowering health care costs [5].

The scientific and engineering literature is rich with reports on decision support systems (DSS) and knowledge management approaches applied to the health domain. However, there remains a surprising paucity of data on DSS designed specifically for supporting telehealth and telecare. A recent focus has been on agent-based systems for alert generation [6] and in constrained disease conditions where models of the underlying disease process are well-advanced –specifically for supporting diabetes management [7].

Thus, there remains a pressing need for decision support to be employed to stratify patients based on health risk. In an early home telecare monitoring trial [8] conducted by our research team, primary care physicians (PCPs) were allocated the task of screening clinical data on one or two of their patients suffering from chronic lung or heart disease over a six month period. They found it difficult to dedicate the little time required to perform this task within their busy work schedule. Many also had the concern of the possibility of ignoring data that indicated their patients’ health was at risk.

One of the conclusions drawn from the trial was the requirement for providing PCPs with summarized clinical reports together with alerting for data indicating ‘at-risk’ patients. This issue will become more critical as telecare systems become more widely adopted and there is a need to screen large volumes of electronically monitored patient data efficiently.

Our experience with monitoring remote telecare data is that often patients with exacerbations of chronic disease have subtle changes in measurement data way before they are at the point of them realizing they are unwell and reporting it [8]. Teasing out the subtleties in the data for the individual patient requires looking at patterns in the overall combined measurement data set. Increased confidence that a pattern is truly attributed to a disease exacerbation can be attained for an individual patient if (1) there is enough data to develop an understanding of what is normal and abnormal for the patient, (2) multiple changes in more than one measurement can be correlated for the same period, (3) the pattern changes cannot be explained by another reason (eg. changes to medications), and (4) it is useful knowing beforehand the particular pattern of changes occurring when a patient is becoming unwell.

This paper details a DSS architecture for home telecare that can cater for the above considerations. The tools and approaches in designing the system are described, along with some examples of early clinical data demonstrating system functionality.

II. DECISION SUPPORT SYSTEM ARCHITECTURE

A. Home Telecare System

The ‘Telemedcare’ home telecare system (HTS) with which the DSS interfaces, was initially developed in our laboratory [8, 9] but has since been commercialized by MedCare Systems (Sydney, Australia). The left hand picture in Fig. 1 illustrates the HTS and lists measurement,
questionnaire, medication and other data that can be routinely gathered by the system.

The main HTS unit comprises a complete monitoring and care management system used to record clinical parameters of health and can provide medications management, education, questionnaire delivery, and care planning facilities. The system is linked up via the Internet and has been designed to promote communication and health care delivery between health careers, pharmacists and the system users - all of whom, depending on their level of access, can view monitored clinical information and/or control the unit remotely (setting up medication schedules, measurement schedules, education links etc.) via a secure Web site.

B. Decision Support System

All DSS interactions with the HTS are managed and coordinated using an application server as the central management system. The JBoss Application Server framework provides an industry standard platform for facilitating the integration of a number of applications and managing the deployment of wide range of decision support services within an enterprise environment (http://jboss.org). Its highly flexible, open-sourced architecture makes it ideal for use as a customizable middleware platform for managing decision support services in an entirely scalable, secure, and efficient manner with full capabilities for auditing and monitoring, load balancing and fault detection. Services such as messaging and Web services that impact on telecare devices, reports, alerts etc. can be efficiently managed.

The application server environment supports the integration of a number of applications and analytical components that make up the DSS. Incoming patient information is analyzed initially by input sub-modules that have the specific task of extracting relevant information from clinical data depending on the type of information and the analysis required. Output sub-modules are able to define actions and tasks that result from the interaction of the inputs and decision support engine (Fig. 1).

JBoss Rules, a component of JBoss’ extensible suite of products, is used to process the widely varied data sets extracted from the different input sub-modules. JBoss Rules is a production rules engine (i.e. consisting of ‘If-Then’ rules) based on a variation of the Rete algorithm called ReteOO that is optimized for object orientated systems (http://labs.jboss.com/portal/jbosstrules). Previous work in our laboratory used ripple-down rules (RDR) approaches [10]. While this was useful in formulating initial rule-sets, we found the enterprise environment of JBoss more advantageous for our implementation.

Rules are a popular formalism for knowledge representation and have the advantage of making explicit the business rules from an application so that changes can be easily implemented and accessed at a common point.
Their modularity, transparency and relative ease of use make them an attractive option for representing knowledge about a clinical domain. Their disadvantage is in the overhead required to keep them consistent and accurate. In contrast RDR are most efficient in rules maintenance [11]. However maintenance can be managed using production rules as long as the clinical protocols that are implemented into rules are well-defined, taking into account conflict cases. It is also critical that the test combinations can be predicted and tested requiring input from both domain and knowledge engineer experts. Most rule-based systems including JBoss Rules, provide an environment for testing different rule conditions and their combinations.

Current development work is focused on implementing a framework for flexible management and localization of rules according to the organization and clinical scenarios. The use of an overarching business process engine is integral to this framework as rule engines are not really intended to handle process flows. The same process engine can also be used to handle decision support outputs as actions/tasks to accommodate institutional workflow patterns and influence changes within this environment. Scenarios including escalation of an alert response to various health care staff can be defined in this way and tailored to an institution with little effort.

The process flows and rules engine works effectively together and both formalisms have XML representations in JBoss. Critical sections of the domain knowledge can be transformed into a human readable or visual form and vice versa, acting as inputs and outputs to the decision support engine. These techniques are especially relevant to automated clinical guideline interpretation that can use published institutional protocols as input to the inference engine.

Development work is also focused on the sub-modules. It is envisioned that various component modules will be developed independently and gradually made available to the decision support engine for improved signal analysis and machine learning techniques to be employed. More atypical analysis modes can incorporate medications and clinical history in the decision process. Furthermore, development of the output sub-modules will make available to the decision support engine a wide complement of actions and tasks at its disposal.

As the DSS develops, it will draw information from a variety of health resources, such as hospital, PCP and pharmacy electronic health records (EHRs), and reference/terminology databases such as SNOMED (http://www.snomed.org). Likewise, the DSS will distribute information and trigger actions to similar groups. There is a large requirement for providing decision support interaction to all devices and services using common and consistent protocols and electronic interfaces. Web service technologies are extremely useful for specifying and publishing electronic interfaces that can be integrated automatically into applications irrespective of their programming language and OS platform.

Storage requirements and security are another important consideration. In addition to clinical data, the DSS will also need to accommodate storage and access of rules, guidelines, messages, EHRs and other supportive information, which may be in relational table form or stored as native XML depending on the suitability of the health information representation.
III. IMPLEMENTATION

The DSS will be specifically used to periodically explore and analyze all clinical data generated by the HTS, as it monitors patients living at home with clinical diagnoses of chronic obstructive pulmonary disease (COPD) and/or congestive heart failure (CHF).

When aggregating all measurement data even over a relatively short period, each patient can potentially generate hundreds to thousands of records. In reality, some of the measurement data can suffer noise partly due to human factors involved in taking the measurements. These render simple alert measures, such as alarm conditions that highlight out of range data points, as unreliable and the risk is that too many alerts would get ignored. For those parameters that have been extracted from waveform signals, factoring in the signal quality as an indicator of patient measurement technique can be used to prevent poorly taken measurements being included in the analysis.

Two input sub-modules are also specifically employed to improve robustness of the analysis, mitigate data complexity and identify noteworthy contexts to the rules engine. The first monitors for trends and differences in averages in the clinical measurement results that are statistically valid. An example of one such measurement for a lung function parameter is shown in the left panel of Fig. 2. Analysis of this type involves the use of the statistical package called ‘R’ (http://www.r-project.org) that is integrated into the DSS framework. A variation of this module also under trial is a trend fitting algorithm that searches for obvious shifts in parameters over adjustable time-scales (Fig. 2, right panel).

A second sub-module is able to test for measurement values that have exceeded thresholds that can be either preset or individualized statistically from a patient’s prior clinical results. In an attempt to improve the robustness of this technique, the threshold detection mechanism relies on specifying a minimum number of values that can occur within a set time frame at each particular threshold range before firing the alert. For each possible measurement, a number of threshold ranges can be specified in this way and the levels are stratified according to deviation from the normal range. This sub-module, which is in itself implemented in rules, can be used to manage several approaches to alert notification according to different institutional preferences.

Data that has been pre-analyzed by the input sub-modules is used by the rules engine to reason about the combination of trends, thresholds and average changes in the data in order to reach conclusions about the underlying health status. The framework facilitates the ability to incorporate the patient’s condition and medications in the interpretation and give recommendations that are localized to the institution in increasingly complex ways.

In our early implementation, the final output of the decision support system is an overall health status score that represents the rules engine’s interpretation of the health risk suggested by the clinical measurement data and questionnaire results. This score is used to stratify the patient records into high, medium and low priorities that will ultimately assist staff in determining their own reviewing priorities and resource allocation for intervention if required.

IV. CONCLUSION

DSS have been in use in medicine in various forms for several decades. However, there are only very limited scientific reports on DSS’s targeted specifically for the home telecare environment in which complex and chronic disease is prevalent. This paper details the system architecture and initial implementation of one such DSS. Our approach has been to develop these tools using as far as possible, open standards. This will provide interconnectivity between disparate health information systems.

Clinical trialing of various aspects of the DSS in collaboration with our commercial partner (MedCare Systems, Sydney, Australia) is currently underway at a number of sites in Australia with a focus on groups of home-dwelling COPD and CHF patients.

REFERENCES