SIMS: Self-adaptive Intelligent Monitoring System for Supporting Home-based Heart Failure Patients

[1]Hua Wang, [1]Ji Zhang, [1]Jeffrey Soar, [1]Xiaohui Tao and [2]Wei Huang

[1] University of Southern Queensland, Australia 4350
{Hua.Wang, Ji.Zhang, Jeffery.Soar, xtao}@usq.edu.au
[2] Hubei University of Technology, Wuhan 430068, China
tonny_hw@hotmail.com

Abstract. This paper presents our research work to develop an advanced Self-adaptive Intelligent Monitoring System (SIMS) to help patients, families and clinicians manage chronic conditions associated with heart failure more effectively at home. SIMS takes advantages of a number of advanced technologies from software intelligence, data/knowledge retrieval, data mining and database. SIMS is able to provide a number of advanced functions. It can effectively prioritize patients, provide automatic recommendation for checking frequency and risk assessment, and carry out correlation analysis in order to pinpoint relationships between external factors and the development of patient's heart condition overtime. All these functions can significantly reduce patients' burden for checking, build up their self-confidence of health and enhance their general quality of life.

Keywords: Self-adaptive technology, home-based healthcare, risk analysis, recommender system, correlation analysis

1 Introduction

Healthcare spending is growing at unsustainable rates in most OECD countries; cost pressures and challenges of access and affordability are commonly reported [1]. Whilst treatments and outcomes for chronic diseases have improved they require extensive, long-term application and chronic diseases are increasing as causes of mortality [2]. With Baby-boomers now entering their late-60s it is critical to incorporate smart technology-enabled solutions to facilitate the delivery of cost-effective home care and address many of the challenges of managing chronic diseases.

There is interest in available Telehealth and smart home technologies but adoption remains low despite its expected value in timely and cost-effective management [3]. One of the reasons for this recalcitrance may be the lack of studies that have progressed beyond pilot scale; there is also criticism of the quality of the available evidence [4]. The better known large studies are the UK's Whole System Demonstrator projects [5] and the USA Veterans' Administration's implementation [6]. These found significant reductions in hospital admissions and re-admissions, and other benefits. This paper draws upon work of the CIs and others internationally to integrate SIMS intelligent software with home Telehealth technology; it will integrate with smart home technologies and the PCeHR (Personally Controlled Electronic Health Record).

The case of HF (Heart failure) is selected for this project because of their massive impact, the expectation of benefits indicated by our pilot project and also because of their diversity as chronic diseases. Over 2.5% of Australians aged 55-64 years have heart failure increasing to 8.2% for those aged 75 years or over [7]. Australians with heart failure in 2004-05 numbered 263,000. It is a major cause of hospital admissions with readmission rates of 30% and 60% at 30-day and 12 months respectively following discharge. It is associated with high levels of health-service utilisation across all settings of care as the disease progresses. Management of risk factors such as smoking, lack of exercise, obesity, excessive alcohol use and poor diet can greatly reduce the impact of heart disease. There is also evidence that cardiac rehabilitation can help decrease the risk factors [7].

A key in the effective treatment of chronic diseases, such as heart failure, is regular monitoring and management [9]. Home-based healthcare support can assist patients to proactively manage their conditions through self-monitoring and early intervention; it can help prioritise home visits and decrease visits that are for only routine check-ups. Existing chronic illness outreach services such as those at the project hospitals lack a strong technology support for effectively prioritising patients. Monitoring systems can highlight the occurrence of abnormal readings for further investigation. When there is a large volume of abnormal readings, which is common with seriously ill patients, then it can be difficult to triage patients to identify those in most urgent need. SIMS will assist with triage and also help identify patients who are stable and their visits could be reduced.

2 Limitations of the Current HF Services

The development of SIMS aims to address the following three key limitations associated with the current HF services:

- **A lack of automatic patient prioritisation and risk assessment**

The current HF service lacks automatic patient prioritisation and risk assessment mechanisms. Patient prioritisation and medical risk assessment aim to prioritise patients on the basis of their health status and treatments in order to optimise the deployment of resources to the patients who are in most need. Sorwar and Hassan [12] proposed a similar integrated tele-monitoring framework exploiting agent technology; that work was theoretical only. Lucien et al. [13] also proposed a sensor based tele-monitoring system, while Yuan and Herbert [14] proposed a real-time web-based remote monitoring system for healthcare. These models did not take account of temporal dimension in the medical data, which is important to depict the change in and accurately describe the patient's medical status. Focusing on the temporal dimension in medical data analysis, Cui et al. [15] introduced a Semantic-Web based framework called CNTRO (Clinical Narrative Temporal Relation Ontology), which contains three major components: time normalizer, SWRL (Semantic Web Rule Language) based reasoner, and OWL-DL (Web Ontology Language) based reasoned but does not provide decision-support. SIMS will adaptively learn a temporal patient profile based on patient self-reported data, patient monitoring data and compliance monitoring to provide an innovative decision support system and help deliver personalised healthcare to patients.

- **A lack of automatic prediction and recommendation**

The current HF services do not provide automatic prediction and recommendation in order to support high-level decision making. Tawfik et al. [10] proposed a semantic search approach to study semantic meanings including and beyond health records and try to reduce cognitive load in health care. Building a recommender system is a preferable approach as it can provide high-quality decision support to health carers, not only a search tool to facilitate data location. Our work will provide targeted monitoring based on patient self-reported data, patient monitoring data, and compliance monitoring and offer important recommendations as to the testing frequency that patients need to follow and necessary medication need to be provided to patients. Our work will build on that of Neuvirth et al. [11] who conducted a study on recommendation based on two criteria: the need for emergency care services and the probability of the treatment producing a sub-optimal result, by exploiting data mining techniques. SIMS will assist clinicians in assessing risk of clinical deterioration through multiple domains.

- **A lack of intelligent discovery of correlation patterns for external factors**

Current chronic illness outreach services do not provide analysis functions which can offer data–based evidence and insight regarding the correlations between patient's conditions and various relevant lifestyle factors. These external influencing factors include nutrition, obesity, alcohol use, physical exercise, quality of sleep, and others.

3 System Architecture and Innovative Features of SIMS

The system architecture of SIMS is presented in Figure 1. There are three major components of the whole monitoring and analysis system, that is, heart failure patients, SIMS itself, and doctors and nurses. The patients take their readings of heart-related measurements such as heart rate, blood pressure and weight, etc in a particular frequency (such as every day or every two days) according to the instruction given by their doctors and/or nurses at their home. The test results are taken by various portable measuring devices and transmitted to SIMS via wireless/3G communication. SIMS then carries out complex monitoring and analysis of the data it receives and produces the results and relevant recommendations which can be reviewed by doctors and/or nurses through a wide variety of media such as mobile devices, desktops or laptops. If necessary the doctors and/or nurses will contact the patients for follow-up discussions and, should emergency occurs, the emergency division such as hospitals will be informed in the first instance.

More specifically, SIMS contains three core functional modules which deliver the following innovative features:

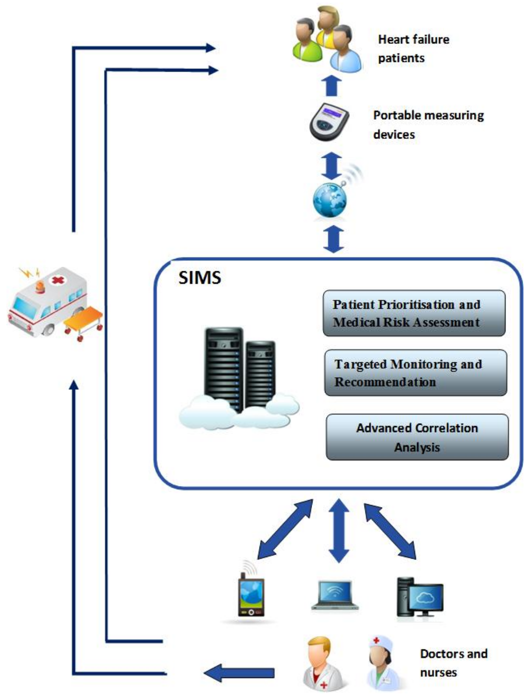

Figure 1. System architecture of SIMS

- **Innovation 1: Automatic Patient Prioritisation and Medical Risk Assessment**

SIMS will evaluate the urgency of the heart failure patients by ranking them based on their readings and also on the trends that that have been displayed, which a strong indicator is showing whether their condition is improving or deteriorating over time. Medical risk assessment aims to prioritise patients on the basis of their medical status and treatments in order to optimise the deployment of medical resources to the patients who are in most need of healthcare. Evaluation of massive data in various types remains the greatest challenge for assessing risk. Generally speaking, the raw data reflecting patients' medical status and treatments can be categorised into two types:

a) *Quantitative clinical data* is collected by medical instruments when monitoring patients. The data is continuous, discrete, structured and quantitative. Such datasets are complex, massive, sometimes inconsistent, sparse, and/or noisy (i.e., containing irrelevant data). These are challenges for risk assessment, such as extracting features for reducing dimensionality, cleaning data to improve data quality, and transforming data into an analytic model;
b) *Qualitative clinical data* is collected from prescriptions, carers' reports, and patients' questionnaires. It could be in Boolean type (e.g., the answer to "Do you feel better today?"), nominal (e.g., medicines in prescriptions), ordinal (e.g., the answer to "Rate the level (1-5) of pain you feel when …"), or textual (e.g., the answer to "Describe the symptoms of …" in the patient report). Such qualitative data, especially textual

data, is difficult to model for data analytic, due to the characteristics of high dimensionality, heterogeneity, unstructured, and ambiguity.

- **Innovation 2: Targeted Monitoring and Recommendation for Heart Failure Patients**

SIMS will manage the heterogeneous data collected from patients, including the time series data, binary answers (yes/no) to predefined questions and free text. Specific healthcare services, such as clinic/home monitoring can then be delivered to patients targeting on their personalised medical status, treatments, and demand. Highly individualized prediction and recommendation are carried out. For example, a patient with severe symptoms may need to take three measures per day using multiple methods; whereas another in recovery phase (or stable phase) may only require a single method of measurement every 3 days. Decisions for when, how, and what medical monitoring methods a patient requires will be supported by the SIMS intelligent system providing recommendations for personalised, targeted monitoring. Specifically, the following several components are developed for deliver the functions of targeted monitoring and recommendation:

a) A generic user model to formally describe HF patients' behaviour including symptoms, monitoring methods, treatments, demands, and feelings, etc. Though user modelling has been studied for decades, there is much to learn in user modelling for HF;
b) An adaptive learning algorithm to temporally profile individual HF patients, based on the generic patients' user model. The temporal patient profile will reveal the changes in the patients' medical status, and help uncover the relationships within different tuples in the profile. The adaptive algorithm will learn patient profile exploiting expert knowledge in the domain ontology. It will help access patients' individual medical status and personalised demands;
c) An intelligent recommender system to provide decision support for targeted medical monitoring, such as when the patient should take next test. The intelligent recommendations are made based on the patient's individual medical status and personalised demands specified in the temporal patient profile, as well the inference rules defined in the axiom repository with heart failure domain ontology. The intelligent system is an innovative applicable contribution to transform expert knowledge to practice in personalised health care.

- **Innovation 3: Advanced Correlation Analysis of External Factors**

SIMS will conduct advanced correlation analysis between conditions of patients and the external influencing factors to uncover interesting and critical correlation patterns existing between the patient's conditions and external lifestyle factors. Existing associate rule mining techniques are not able to effectively discover correlation patterns. The reason is that those correlation patterns are unique in the sense that they are typically time-shift patterns as there may be some time delay before symptoms are observed. Our new algorithm will take into account the unique feature of time delay to effectively discover the time-shift correlation patterns.

A novel time-shift association rule mining algorithm will be developed and incorporated into SIMS to effectively discover unique patterns. One of the most crucial technical challenges for time-shift association rule mining is that different external lifestyle factors will feature varying possible time delay durations. By utilising an advanced correlation analysis module, SIMS will be capable of providing data-based evidence which is individualised for each patient. The input information required for the correlation analysis can be easily collected through clinician-developed on-line questions to patients which will take only a few minutes to complete. Input of this information every day is desirable but not required as the module can conduct the correlation study in a coarser time granularity such as per week instead of each day. This feature can significantly enable both clinicians and patients to better understand not only which external lifestyle factors that may have affected their chronic condition but also how they exert influence. Customised articles and newsletters can be automatically subscribed to different patients based on the discovered contributing factors to assist patient self-care.

5 Methods

The development of SIMS is at the confluence of several fields including computer science, behavioural sciences, health and design and involves the study, planning, and design of the interaction between people (users) and computers in healthcare. From the perspective of computer science and information technology, SIMS takes advantages of a number of advanced technologies from software intelligence, data/knowledge retrieval, data mining, and database. Next, we discuss in more details the technical tasks that we need to accomplish in SIMS.

- **Pre-processing patients' data for feature extraction**

Patients' data are generated continuously in a dynamic operating environment, with huge time series data and free text data. It is impossible to store such data streams completely in a data warehouse. Such vast-sized raw data make the follow-up analysis and prediction extremely difficult. To find interesting or unusual trends variation, it is essential to perform efficient feature extraction, which enables the efficient solutions for several subtasks with different data set including real-time warning, online indexing, querying and efficient storage.

- **Designing a time-series based model for patient prioritisation and risk assessment**

The measurement readings of patients (e.g., weight, heart rate, blood pressure) are collected at most once every day, which are by nature time series data considering the time dimension involved. A key feature of the time series data is the trend that the data exhibits, which is fully considered in the process of patient prioritisation and risk assessment in our system. Specifically, we considered two criteria for each of the health measurements under study based on the time series data for ranking purpose. The first criterion is the deviation of the observed value of reading from the normal range and the second one is the recent reading tendency that is observed during a time window. Both of these criteria can be quantitatively calculated.

Since there are two different criteria associated with each measurement, we thus utilise the technique of multi-objective ranking which guarantees that the patients with abnormal reading and worsening situation are assigned with higher priority scores in the ranking results. The multi-objective ranking is based on a notion called *dominance* that has been used in the area of multi-objective optimisation. A patient p_1 is said to dominate another patient p_2, denoted as $p_1 > p_2$, if both of the two criteria of p_1 are worse than those of patient p_2. For each patient, we can calculate the number of other patients in the whole patient population that are dominated by this patient based on the definition of dominance. In this way, the ranking score from the time series data can be generated with the patients with worse heart conditions being assigned with a higher dominance score.

We can further classify patients based on these two criteria into the following four broad categories in order to provide more informative interpretation of the time series data (with Category 1 having the highest urgency while Category 4 having the lowest one):

Category 1: abnormal reading and worsening situation

Category 2: abnormal reading and stable/improving situation

Category 3: normal reading but worsening situation

Category 4: normal reading and stable situation

- **Designing text mining algorithms for free text data**

The patients will be provided with opportunities to provide free text input in the user interface where they or their family carer can input through the Telehealth device or other input devices; free text can range from several sentences to a few paragraphs to report their symptoms. This provides the patients with a much higher level of freedom to describe their symptoms and express their concerns that may not be covered and captured by the yes/or questions. Natural language processing techniques are utilised to parse those free text and extract key words which are represented as features. Domain-specific ontology, the carrier of domain knowledge containing the semantic meaning and weights of different keywords and terminology, is used to quantify the severity of symptoms described by patients. The domain ontology can be generated with the help of domain experts.

6 Conclusion

The adoption of smart home and telehealth technologies for chronic disease support has been disappointing despite evidence of the benefits. In this paper, we present our latest research work in developing an advanced intelligent monitoring and analysis system, called SIMS, for supporting heart failure patients. SIMS will improve the adoption and effectiveness through providing a system that will continually learn about patient patterns and trends. SIMS will assist patients in self-care and also better help carers and clinicians monitor the progress of the patient's conditions and the effectiveness of interventions.

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References

1. Hagist C and Kotlikoff L. Who's Going Broke? Comparing Growth in Healthcare Costs in Ten OECD Countries. NBER Working Paper No. 11833, December 2005, National Bureau of Economic Research
2. AIHW 2010 “Cardiovascular disease mortality: trends at different ages” Australian Institute of Health and Welfare, Canberra
3. Nick Goodwin, (2010) "The State of Telehealth and Telecare in the UK: Prospects for Integrated Care", Journal of Integrated Care, Vol. 18 Iss: 6, pp.3 - 10
4. Williams, T., Maya, C., Mair, F., Mort, M. and Gask L. (2003) Normative models of health technology assessment and the social production of evidence about Telehealth care. Health Policy, Volume 64, Issue 1, Pages 39-5
5. Steventon A, Bardsley M, Billings J, Dixon J, Doll H, Hirani S, Cartwright M, Rixon L, Knapp M, Henderson C, Rogers A, Fitzpatrick R, Hendy J and Newman S. Effect of Telehealth on use of secondary care and mortality: findings from the Whole System Demonstrator cluster randomised trial. BMJ2012;344, 21 June 2012)Prentice, L. 2010 RBWH Heart failure service guidelines, Queensland Health, Brisbane
6. Darkins A, Ryan P, Kobb R, Foster L, Edmonson E, Wakefield B, Lancaster A (2008). ‘Care Coordination/Home Telehealth: the systematic implementation of health informatics, home Telehealth, and disease management to support the care of veteran patients with chronic conditions’. Telemedicine and e-Health, vol 14, no 10, pp 1118–26.AIHW 2011. “Cardiovascular disease: Australian facts 2011”. Cardiovascular disease series. Cat. no. CVD 53. Australian Institute of Health and Welfare Canberra
7. AIHW 2012 Heart Failure. http://www.aihw.gov.au/heart-failure accessed 17/11/12 AIHW
8. AIHW (Australian Institute of Health and Welfare & Australasian Association of Cancer Registries) 2010. Cancer in Australia: an overview, 2010. Cancer series no. 60. Cat. no. CAN 56. Canberra: AIHW
9. Gemmill M. 2008 Chronic Disease Management in Europe. LSE andEuropean Commission
10. Tawfik A, Kochendorfer K, Saparova D, Al Ghenaimi S and Moore J. Using Semantic Search to Reduce Cognitive Load in an Electronic Health Record. 2011 IEEE 13th International Conference on e-health Networking, Applications and Services
11. Neuvirth, H.; Ozery-Flato, M.; Hu, J.; Laserson, J.; Kohn, M. S.; Ebadollahi, S. & Rosen-Zvi, M. Toward personalized care management of patients at risk: the diabetes case study. Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining, ACM, 2011, 395-403
12. Sorwar G and Hassan R. Smart-TV Based Integrated e-Health Monitoring System with Agent Technology. 2012 26th International Conference on Advanced Information Networking and Applications Workshops, pages 406-411, 2012.
13. Lucian N., Mihai C. and Anamaria H. 2011. System for Remote Patient Monitoring and Data Collection with Applicability on E-health Applications. The 76th international symposium on advanced topics in electrical engineering, Bucharest 12-14 May 2011.
14. Yuan B and Herbert J 2011. Web-based Real-time Remote Monitoring for Pervasive Healthcare. IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOM Workshops), Seattle.
15. Cui Tao, Harold R. Solbrig, Deepak K. Sharma, Wei-Qi Wei,Guergana K. Savova, and Christopher G. Chute. Time-Oriented Question Answering from Clinical Narratives Using Semantic-Web Techniques. ISWC '10, Springer, pages 241-256, 2010.
16. Vredenburg, K., Isensee, S. and Righi, C. 2002. User Centered Design An Integrated Approach. Prentice Hall, Upper Saddle River