Expert Systems and Home-based Telehealth: Exploring a role for MCRDR in enhancing diagnostics

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Abstract. Home-based telehealth services hold significant potential for integrating patient biological sensor data to support health management. At the same time, the deployment of telehealth into the home highlights the need for improved ways to collate, classify and dynamically interpret data safely and effectively. In relation to individual patients questions are posed as to how to most effectively communicate this data to them to support optimal health behaviour. For clinicians working at a distance, the huge amounts of data generated on all their home-based patients pose questions on how best to intelligently filter, analyse and interpret this data to make diagnoses and respond to changes in patient conditions. The paper reviews previous research work on expert systems in healthcare, in particular reviewing the capabilities of the expert system maintenance technology, Multiple Classification Ripple Down Rules, in healthcare. The paper also describes a home-based telehealth device, called MediStation that is being deployed in Korean homes to consider how MCRDR could enhance the decision-making for this device.

Keywords: eHealth, medical expert systems, MCRDR, telehealth

1 Introduction

Ubiquitous Healthcare [1] is one of the most active research fields. Typically uHealth applications fulfill two major functions. Firstly, “patient monitoring” through the use of biosensors and advanced sensor network technologies. Secondly, supporting the personalization of remote medical services, by providing patients with diagnosis and treatment directly rather than through physical consultation with a clinician. It is anticipated that these two functions will support patients to have more
control of decisions relating to their health whilst empowering clinicians by improving data on patients’ health status in real time [2].

At the same time, uHealth applications introduce a number of new challenges. Most obviously, the volume of data requiring collection, collation, analysis and interpretation will grow exponentially [3]. With medical knowledge having significantly specialized into subfields (e.g. lung function diagnosis [4]) and limited specialists available for consultation, there is much impracticality for having diagnoses performed remotely with an actual clinician present. For example, if a patient consults with only one specialist, there is possibility that the specialist may make a wrong diagnosis or treatment outside his/her major field. Therefore, diagnosing patients without automation puts a burden on healthcare practitioners. In order to solve this issue, many medical researchers are increasingly relying on support from Expert systems. These are systems that have large knowledge base provided by human experts to solve complicated problems by reasoning about knowledge [5]. An early technique that improved how knowledge maintenance in expert system occurs is Ripple Down Rule (RDR). It was developed for acquiring knowledge and handling the maintenance issue in expert systems [6]. However, RDR can be utilized for only a single classification domain. Kang [7] introduced an extension of the original RDR, Multiple Classification Ripple Down Rules (MCRDR) that has the basic form of RDR and provided multiple classifications. MCRDR has several characteristics, which may make it suitable to be applied for diagnostics in uHealth applications. These characteristics are: firstly, MCRDR provides not only justification for why the conclusion is correct, but also displaying a reasonable explanation how the system reach the certain conclusion. Secondly, MCRDR produces multiple conclusions (e.g. diagnosis or treatment). Thirdly, MCRDR enables the experts to acquire the knowledge by themselves without any knowledge engineer’s assistance. Finally, MCRDR updates its decision tree in an effective way. Unlike other expert system management techniques, when RDR detects the error, RDR does not request users to modify the whole part of knowledge base, but just adding new rules to solve the problem. Given MCRDR’s characteristics, this paper will explore the benefits of MCRDR integrated with uHealth.

2 Expert System and Health

This section briefly reviews research into expert systems and discusses their limitations in relation to home-based telehealth. This review develops a case for considering alternative techniques for knowledge acquisition and in the next section, one of these: MCRDR, which we have spent years developing for use in pathology laboratory settings [8], is introduced and envisaged in the uHealth field.

2.1 Expert system with healthcare service

As the medical knowledge has expanded so much over the past decades, it is impossible for health practitioner to be always available. To solve this issue, many researchers have focused on developing and deploying expert systems. Research into
Expert systems roughly began during the late 1950s. In 1959, Ledley and Lusted[9] suggested that using a computer for medical decisions making process, such as diagnosis and patient management was feasible. Since then, many machine learning approaches, including Probabilistic reasoning and Pattern recognition techniques, have been developed[10] and deployed for medical decision support services. A good overview of these developments can be found in review by Shortliffe et al. [10] of 800 research papers dealing with the computational clinical decision-making.

2.2 Expert system based on RDR and MCRDR

An expert system technique we have spent years developing and deploying into pathology settings has been Ripple Down Rules (RDR) with its successor being Multiple Classification Ripple Down Rules (MCRDR). As the primary aim of RDR is expert system development and maintenance, RDR has been applied for building and maintaining various types of expert systems. The particular area that RDR considered is handling the issues in the medical expert system field. This is because RDR was initially proposed to solve the maintenance problems in the medical expert system called “GARVANES1”[12]. Since then, according to the survey by Compton et al.[11], they focused on clinical diagnosis and pathology report management for assisting the clinicians and patients. MCRDR, the improved version of RDR, has found a niche use the in medical diagnostics field. Using MCRDR, Edwards et al.[8] developed PEIRS to interpret the chemical pathology reports automatically by applying RDR. This system enables pathologists to maintain and update the knowledge base easily as. Miranda-Mena et al.[13] implemented a breast cancer treatment system by integrating MCRDR and a breast cancer treatment knowledge base. For this system, MCRDR enables to acquire knowledge incrementally and constructs a rule-based knowledge base. When the error occurs in the knowledge base, domain experts can solve the problem by adding a new appropriate rule. The system does not ask experts to understand every rule in the knowledge base. From the experiments, users were content with the performance of system. Bindoff et al. [14] used MCRDR expert system to provide a decision support for pharmacists to practice medication reviews. The system extracts knowledge with an achieved 80% correct classification accuracy. As well as research, RDR (and MCRDR) has received a lot of attention for commercial medical applications. The company Pacific Knowledge Systems (PKS) is providing a knowledge system based on RDR and MCRDR. PKS is one of the most successful organizations in chemical pathology expert system development owing part of its success to their RDR-based system called LabWizard. LabWizard [11] has received a lot of attention around the world. Another example of successful commercial application of RDR (or MCRDR) is the Tesco online grocery ordering system. The system, called Sonetto, manages the detailed products information. The business users in Tesco have created and maintained a great number of rules.
3 Applying MCRDR for Diagnostics in uHealth

Recall that MCRDR is suited for use in medical pathology settings where data is constantly changing. With rapid advances in uHealth, with widespread deployment of technologies connected to the internet providing (near) real-time information on patient health, it is expected that expert systems will play an important role in reducing the diagnostic burden on medical practitioners by performing some of the classification work. Recall the previous section identified some limitations on previous work on expert systems, which seems to make those techniques less suited for use in uHealth. Consequently, in this section, we explore the core features of MCRDR and try to envisage how they would benefit classification in uHealth system. We do this by focusing on the major componentary of MCRDR and apply this to one proposed uHealth Monitoring device called the MediStation as an example of likely technology to be found in uHealth applications. MediStation is an uHealth device that integrates the telehealth, online patient-to-clinician video counseling services with a medical expert system.

Multiple Classification Ripple Down Rules (MCRDR) [7] is an incremental knowledge acquisition approach based on Ripple Down Rules (RDR). RDR uses rule-based approach for constructing the knowledge base; however, it is differentiated from traditional rule-based system. The unique function of RDR is the “handling exception rules”. When the error occurs in a certain rule or case, new rules are added to solve the error. For example, if the input context is very new, the system cannot solve the problem properly by the current expertise, a new rule will be added based on the conditions of a new conclusion and its corner stone case. RDR is effective here: it solves the issue in the knowledge base by adding a new rule. While traditional expert systems are required to apply knowledge engineering technique, RDR-based expert system need only the domain expert. RDR can acquire knowledge without any assistance from knowledge engineers or spending time for analyzing knowledge. Domain expert can add, modify and maintain their knowledge in the expert system. Therefore, RDR supports incremental modification for the exception cases, not the entire set reengineering. This feature of RDR would be suitable to MediStation or other uHealth devices. The devices in uHealth environments normally combine and share the data so this MCRDR-based remote expert system would be able to be managed by just adding new rules rather than reengineering the whole structure every time.

However, RDR has some limitations in decision-making. It is limited in a context having single classification as a conclusion. Owing to this issue, Kang [7] proposed MCRDR to preserve the benefit of original RDR strategy in dealing with multiple classifications. MCRDR has the basic features of RDR thereby providing the incremental knowledge acquisition that has competent V&V [15]. In order to determine the multiple classifications in RDR, it is necessary to increase the knowledge acquisition exponentially since a possible solution would be to separate sub-domains and build independent KBs for each sub-domain. However, the basic idea of MCRDR is that each context can have multiple classifications by following numerous rule paths appositionally. This feature of MCRDR, multiple classifications, would be useful to MediStation or other uHealth devices because the medical
diagnosis would most likely handle the possibilities that an input data from patient may have multiple independent conclusions.

Expert knowledge base in MCRDR would provide pooled knowledge based on effectiveness of particular clinicians over time. As particular decisions are proven to work most effectively with particular types of medical problems, the system would generate guidelines or rules around evidence-based practice and then create a feedback loop to re-invigorate the rule sets. In other words, large amount of patients’ data combines and clinicians shares the knowledge in uHealth environment. To maintain the knowledge base, MCRDR-based system does not require reengineering the whole structure of decision tree every single time. MCRDR maintains its existing rules and simply adds the new rule, only if there is any error.

Table 1. Problems in uHealth and Solutions from MCRDR features

<table>
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<tr>
<th>No</th>
<th>Problem: Issues in uHealth</th>
<th>Solution: MCRDR Features</th>
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<tbody>
<tr>
<td>1</td>
<td>Using uHealth care device, patients usually receive only the results (e.g. diagnoses or treatments) and hard to get the advice by experts directly.</td>
<td>MCRDR provides the reasonable explanation of “how” the expert system actually derives the conclusions, not only why the conclusion is correct</td>
</tr>
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<td>2</td>
<td>A patient may have multiple independent diseases.</td>
<td>MCRDR produces multiple independent classifications. It can handle the compound diseases by supplying multiple conclusions for a cases rather than providing the single conclusions.</td>
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<td>3</td>
<td>The domain expert (e.g. clinicians) should receive help from knowledge engineers to manage the expert system.</td>
<td>MCRDR enables domain experts to maintain the knowledge base by themselves without any knowledge engineering technologies. Therefore, it reduces the costly and time consuming.</td>
</tr>
<tr>
<td>4</td>
<td>In the uHealth environment, the devices combine patient’s data and share the knowledge base. Once the errors in any rules, expert should request a knowledge engineer to reengineer.</td>
<td>MCRDR does not require reengineering whole structure of decision tree every single time. It asks domain experts to add the new rule, only if there is any error (e.g. no or incorrect conclusion)</td>
</tr>
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A summary of uHealth challenges and MCRDR features appears in Table 1. The specified potential challenges may occur in the uHealth environment, and MCRDR features have abilities to solve those problems in effective ways. Therefore, if home-based teleHealth system, such as Medistation or other uHealth device, integrates with MCRDR-based expert system, it could provide the advanced uHealth device to both patients and clinicians more effectively.

4 Conclusion and Future Work

This exploratory paper has briefly reviewed research work on expert systems in healthcare and considered in detail the potential of the expert systems development techniques RDR, and MCRDR for supporting decision-making in home-based
telehealth. The paper has highlighted that MCRDR has real potential to advance home-based telehealth but that its effectiveness is also dependent on two sets of factors. Firstly, the need to improve the quality and granularity of data that can be generated by these devices including techniques for its presentation and communication to patients and clinicians. Secondly, the need to improve understanding of how decision support impacts on decision-making by both patients at home and clinicians from afar. The next step of this research will be investigating these two sets of factors as part of a broader study into home-based telehealth.

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