Intelligent Agents for Rehabilitation and Care of Disabled and Chronic Patients*

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Abstract

The number of people with disabilities is continuously increasing. Providing patients who have disabilities with the rehabilitation and care necessary to allow them good quality of life creates overwhelming demands for health and rehabilitation services. We suggest that advancements in intelligent agent technology provide new opportunities for improving the provided services. We will discuss the challenges of building an agent for the health care domain and present four capabilities that are required for an agent in the health care domain: planning, monitoring, intervention and encouragement. We will discuss the importance of personalizing all of them and the need to facilitate cooperation between the automated agent and the human care givers. We will review recent technology that can be used toward the development of agents that can have these capabilities and their promise in automating services such as physiotherapy, speech therapy and cognitive training.

Introduction

The number of people with disabilities is continuously increasing (Bickenbach 2011). This is the result of population growth, the aging of the population, the prolonging of life enabled by medical advancements, the survival of extremely premature babies, and the emergence of chronic diseases (Lakdawalla, Bhattacharya, and Goldman 2004; Seeman et al. 2010). Indeed, the most common causes of impairment and disability are chronic diseases such as diabetes, cardiovascular and cerebrovascular diseases, and cancer (Murray and Lopez 2013). Traditional causes such as trauma, injury and congenital defects are also major contributors to disability. Providing patients who have disabilities with the rehabilitation and care necessary to allow them good quality of life creates overwhelming demands for health and rehabilitation services.

Much research and industrial efforts have been invested in the development of computer systems to respond to these demands. In particular, serious games – games designed for a primary purpose other than pure entertainment – can be used in this effort (Rego, Moreira, and Reis 2010). For example, there are automated systems that are used to train cognitive functions and memory, and to diagnose and combat dementia (Imbeault, Bouchard, and Bouzouane 2011; Marin, Navarro, and Lawrence 2011); and there are games for physiotherapy and occupational therapy (Gamberini et al. 2008; Moreira et al. 2013; Lange et al. 2012). Furthermore, these training and diagnostic systems can be used over the internet in order to provide assistance to patients in their homes, which is of great benefit both to the patients and their home care providers. Others tried to build social robots (Tapus et al. 2007; Fasola and Mataric 2013; Pineau et al. 2003) that will assist in caring for the elderly and people with disabilities. However, currently, the success of using games and other software for care and rehabilitation is limited, with limited impact on the overwhelming demands for health and rehabilitation services. This is because serious games and most other software for care and rehabilitation lack involvement of the health care staff. Indeed, much better results are obtained when there is a human trainer in the loop with whom the patients form good relationships (Hall et al. 2010; Shirk and Karver 2003). However, adding humans to the loop makes the computer-based treatment much more expensive and decreases the effectiveness of computerized or remote treatment.

We suggest that advancements in intelligent agent technology provide new opportunities for augmenting existing environments to include support for patients in order to compensate for the lack of direct human intervention. While we strongly believe that human trainers and specialists should be involved in computerized rehabilitation and care in some capacity, we propose that intelligent agents can reduce the need for human involvement and facilitate the use and acceptance of computer systems in rehabilitation and care.

There are four required capabilities for an agent in the health care domain when interacting with a patient:

Planning: The intelligent agents should build a personalized dynamic training or care program for each patient.

Monitoring: The agent should monitor the patient's activities and identify problematic activities as well as successes. The activities can be part of the training program

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(e.g., lifting an arm in virtual physiotherapy training) or daily activities (e.g., putting on a sock). The monitoring report should be used by the planning, intervening and encouraging modules.

Intervention: When the patient has difficulties, the agent should consider intervening by pointing them out, demonstrating the correct action or, even better, by leading the patient to identify the correction.

Encouragement: The main task of the intelligent agent is to motivate the patient to practice and to participate in the therapy. Encouraging agents can also support patients throughout the rehabilitation process; automated coaching programs can help patients in meeting hard and painful rehabilitation goals and increase medical compliance. Motivating the patients can be accomplished via rewards, discussion and argumentation.

It will be even more beneficial if the agents will be able to work together as a team with human care providers and trainers on these tasks (Amir et al. 2013; Wickramasinghe et al. 2011; van Wissen et al. 2012). For example, the human trainer can form the basic training plan and the automated-agent can adapt it dynamically to the real time progress the user is making.

Recent progress that has been made in the development of automated agents which can interact proficiently with people, including negotiation agents (Rosenfeld et al. 2014b; Dsouza et al. 2013; Vahidov, Kersten, and Saade 2012; de Melo, Carnevale, and Gratch 2011; Gal et al. 2012; Oshrat, Lin, and Kraus 2009; Lin et al. 2008), advice and service provision agents (Azaria et al. 2012; Delecroix, Morge, and Routier 2013; Elmalech et al. 2015), automated mediators (Lin, Gev, and Kraus 2011), discussion agents (Fenster, Zuckerman, and Kraus 2012; Ren et al. 2014) and persuasion agents (Azaria, Aumann, and Kraus 2014), can be the basis for the development of agents capable of performing all four tasks. We will discuss a few ideas and difficulties in relation to such agents in this extended abstract.

Modeling Patients

Maximum and immediate system effectiveness for the provision of specialized care can be achieved only if intelligent agents for care and rehabilitation can be tailored to each patient as quickly as possible (Klinger et al. 2013). To match the best intelligent agent with individual people we need to predict their behavior and their response to different actions taken by the agent. This will allow the agent to choose its best actions in supporting the individual patient in all four tasks. In order to predict the individual patient's response to the agent's actions, the patient needs to be modeled. However, human behavior is diverse, and cannot be satisfactorily captured by a simple model. Humans tend to make mistakes, and they are affected by cognitive, social and cultural factors when making decisions (Bazerman and Neale 1992; Lax and Sebenius 1992; Ariely 2008; Elmalech and Sarne 2012; Chalamish, Sarne, and Lin 2012). Modeling people is a challenging problem (Elmalech, Sarne, and Agmon 2014; Mash, Lin, and Sarne 2014; Sarne and Grosz 2007).

Another possibility is to use collaborative filtering methods. They were shown to be useful for personalized training in e-learning (Segal et al. 2014). However, this requires data on a large number of patients as well as the need to face the problem of a cold start for each patient.

We propose to use machine-learning methods. However, it is generally not easy to build an accurate prediction model of a human patient since we would need to collect a large amount of data about the person, which can be costly and time consuming. In particular, by the time we would have enough data on a specific patient to provide personalized accurate treatment, she or he would drop out of the training or treatment. Therefore, rather than build a specific model for each person, we will build a general model from data collected by observing the behavior of many people. This, of course, adds even more noise to the data since people may act very differently from one another in the same setting.

One possibility is to cluster people according to type (Shrot et al. 2014; Gal et al. 2004; Sarne et al. 2011) or culture (Haim et al. 2012) and build models for each cluster. Once a new patient arrives, the agent can identify its type and use the relevant model. It may be possible to ask the health care provider to provide the new patient's type and the agent can adjust and refine the patient's model during its interaction with the patient.

Another approach is to integrate psychological and behavioral sciences with machine learning, which can help address the challenge of predicting patient behavior. For example, (Rosenfeld et al. 2012) showed that adding *Aspiration Adaptation Theory* (AAT) (Selten 1998) information as features to classical machine learning models improves predictions of how people will negotiate in complex domains. Another example involves using the hyperbolic discounting theory (Chabris, Laibson, and Schuldt 2006; Deaton and Paxson 1993) to model how people reason about the outcome of their actions over time (Azaria et al. 2012).

Combining Rule-Based Approaches with Machine Learning

Specialists are experts in all four of the tasks we would like the agent to perform. In particular, specialists are able to lead patients to perform the correct activities during treatment. For example, speech therapists know which clue to give a patient in order to encourage him to retrieve the correct word that is associated with a given stimulus. There are two main ways to use the experience of specialists. One is to extract rules from the experts and let the agent follow them. This approach has been successful in certain domains such as identifying early stages of cancer (Rosenfeld et al. 2014a) The other is to collect data on their behavior and use machine learning to predict what the human expert will do, and ask the agent to perform the same action. It is also possible that the agents will learn from numeric human online feedback (Knox, Stone, and Breazeal 2013). It is well known that extracting expert knowledge and creating rules are extremely difficult; this was one of the reasons for the failure of expert systems. Applying machine learning is also problematic since the data collected on expert activities is very noisy and collecting data is very difficult.

One possibility is to combine both methodologies. Shavlik and his colleagues (Kunapuli, Maclin, and Shavlik 2011), for example, developed methods of knowledge-based support vector machines (KBSVMs) that incorporate advice from domain experts, which can improve generalization significantly. "Cindy" is a virtual speech therapist; a development in which I am involved that uses the combined methods (http://www.gertnerinst.org.il/e/well_being_e/Tele_rehabilitation). Rules are extracted from human speech therapists. These rules are used to identify a relatively small set of possible actions for Cindy. Then, a machine learning-based module is used to choose the best actions.

Increasing Adherence to Treatment

Poor adherence to treatment of chronic diseases is a worldwide problem of striking magnitude (Sabaté 2003). Bickmore and his colleagues showed in a series of clinical studies that increasing adherence and compliance to treatment by patients is possible by creating an association between an automated agent and the patient (Bickmore, Gruber, and Picard 2005; Bickmore et al. 2010). We also found that an automated mediator that was associated with a simple avatar led people to reach agreements significantly more beneficial to both sides than an automated mediator that merely sends the same messages without an avatar (Lin, Gev, and Kraus 2011). However, in medical applications, the cost of the creation of the characters must be low while remaining realistic. The virtual characters should be able to communicate with real humans in a lifelike manner, understand their speech, express emotions and converse in different languages. The expression of emotions of such characters should be represented both by facial expressions as well as matching mannerisms (e.g., anger will result in an angry expression and agitated pacing, twiddling of fingers). While a lot of progress has been made toward this challenge, the creation of realistic characters is still relatively expensive and they can't understand the patients' free speech very well. Recently, we implemented a NegoChat agent that negotiates with people via chat (Rosenfeld et al. 2014b). Its main weaknesses was that often NegoChat misunderstood what the human negotiator's really meant in his or her text.

Persuasion agents (Vlachos and Schärfe 2014) may also contribute to increasing adherence. We recently showed that agents can assist in reducing drivers' energy consumption in electronic cars by advising them how to use the climate control system (Azaria et al. 2014; Rosenfeld et al. 2015). Using argumentation could be used as additional technology in order to convince patients compliance to treatment (Rosenfeld and Kraus 2015; Kraus, Sycara, and Evenchik 1998).

Evaluation

One of the main difficulties in the development of intelligent agents for rehabilitation and care of the disabled and of chronic patients is the time and effort it takes to evaluate the proposed techniques. I am involved in a project on personalized reinforcement for rehabilitation of patients in an inpatient rehabilitation center. Our goal is to develop and evaluate a personalized reinforcement treatment, based on the attitude of Strategic Behavioral Treatment. The objective of this treatment is to improve the patient's motivation for rehabilitation and for participation in a neurological rehabilitation inpatient program, ultimately improving the outcome of the rehabilitation. This proposed reinforcement plan is designed according to the patient's responses and the staff's reports. Positive reinforcement will be fitted to the patient's functional improvement. More than two years into the project, we are still collecting data for a baseline group. The main algorithmic development will begin only after another experiment with a naive agent that will send participants daily text messages on their cellular phones according to the fulfillment of their tasks. Those who fulfilled the tasks over the entire week will receive a monetary reward (vouchers) from the agent. This is an extreme case, but it will provide a good indication concerning the main problem; running experiments with patients is extremely time consuming and computer scientists should adjust their research expectations accordingly.

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