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

Sarit Kraus
Department of Computer Science
Bar-Ilan University, Ramat-Gan, Israel 92500
sarit@cs.biu.ac.il

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

*A preliminary version of this paper was presented at the AAMAS 2014 workshop "Towards Better and more Affordable Healthcare: Incentives, Game Theory, and Artificial Intelligence". This work is supported in part by the ERC Advanced Grant #267523.

(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.

References

Amir, O.; Grosz, B.; Law, E.; and Stern, R. 2013. Collaborative health care plan support. In *Proceedings of the Eleenth International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS-2013)*, 793–796.

Ariely, D. 2008. *Predictably Irrational*. Harper Collins.

Azaria, A.; Aumann, Y.; and Kraus, S. 2014. Automated agents for reward determination for human work in crowdsourcing applications. *Journal of Autonomous Agents and Multi-Agent Systems* 28:934–955.

Azaria, A.; Rabinovich, Z.; Kraus, S.; Goldman, C. V.; and Gal, Y. 2012. Strategic advice provision in repeated human-agent interactions. In *AAAI*.

Azaria, A.; Kraus, S.; Goldman, C. V.; and Tsimhoni, O. 2014. Advice provision for energy saving in automobile climate control systems. In *IAAI*.

Bazerman, M. H., and Neale, M. A. 1992. Negotiator rationality and negotiator cognition: The interactive roles of prescriptive and descriptive research. In Young, H. P., ed., *Negotiation Analysis*. The University of Michigan Press. 109–130.

Bickenbach, J. 2011. The world report on disability. *Disability & Society* 26(5):655–658.

Bickmore, T. W.; Pfeifer, L. M.; Byron, D.; Forsythe, S.; Henault, L. E.; Jack, B. W.; Silliman, R.; and Paasche-Orlow, M. K. 2010. Usability of conversational agents by patients with inadequate health literacy: Evidence from two clinical trials. *Journal of health communication* 15(S2):197–210.

Bickmore, T.; Gruber, A.; and Picard, R. 2005. Establishing the computer–patient working alliance in automated health behavior change interventions. *Patient education and counseling* 59(1):21–30.

Chabris, C.; Laibson, D.; and Schuldt, J. 2006. Intertemporal choice. *The New Palgrave Dictionary of Economics*.

Chalamish, M.; Sarne, D.; and Lin, R. 2012. The effectiveness of peer-designed agents in agent-based simulations. *Multiagent and Grid Systems* 8(4):349–372.

de Melo, C.; Carnevale, P.; and Gratch, J. 2011. The effect of expression of anger and happiness in computer agents on negotiations with humans. In *Proceedings of the Tenth International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS-2011)*.

Deaton, A., and Paxson, C. 1993. Intertemporal choice and inequality. Work. P. 4328, NBER.

Delecroix, F.; Morge, M.; and Routier, J.-C. 2013. A virtual selling agent which is persuasive and adaptive. In *Agreement Technologies*. Springer. 625–645.

Dsouza, S.; Gal, Y.; Pasquier, P.; Abdallah, S.; and Rahwan, I. 2013. Reasoning about goal revelation in human negotiation. *Intelligent Systems, IEEE* 28(2):74–80.

Elmalech, A., and Sarne, D. 2012. Evaluating the applicability of peer-designed agents in mechanisms evaluation. In *Proceedings of the 2012 IEEE/WIC/ACM International Conferences on Intelligent Agent Technology*, 374–381.

Elmalech, A.; Sarne, D.; Rosenfeld, A.; and Erez, E. S. 2015. When suboptimal rules. In *In proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence (AAAI 2015)*.

Elmalech, A.; Sarne, D.; and Agmon, N. 2014. Can agent development affect developer's strategy? In *Proceedings of the Twenty-Eighth AAAI Conference on Artificial Intelligence (AAAI 2014)*, 923–929.

Fasola, J., and Mataric, M. 2013. A socially assistive robot exercise coach for the elderly. *Journal of Human-Robot Interaction* 2(2):3–32.

Fenster, A.; Zuckerman, I.; and Kraus, S. 2012. Guiding user choice during discussion by silence, examples and justifications. In *ECAI*, 330–335.

Gal, Y.; Pfeffer, A.; Marzo, F.; and Grosz, B. J. 2004. Learning social preferences in games. In *AAAI*, 226–231.

Gal, Y.; Kraus, S.; Gelfand, M.; Khashan, H.; and Salmon, E. 2012. Negotiating with people across cultures using an adaptive agent. *ACM Transactions on Intelligent Systems and Technology* 3(1).

Gamberini, L.; Barresi, G.; Maier, A.; and Scarpetta, F. 2008. A game a day keeps the doctor away: A short review of computer games in mental healthcare. *Journal of CyberTherapy and Rehabilitation* 1(2):127–145.

Haim, G.; Gal, Y.; Gelfand, M.; and Kraus, S. 2012. A cultural sensitive agent for human-computer negotiation. In *Proceedings of the Eleventh International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS-2012)*, 451–458.

Hall, A.; Ferreira, P.; Maher, C.; Latimer, J.; and Ferreira, M. 2010. The influence of the therapist-patient relationship on treatment outcome in physical rehabilitation: a systematic review. *Physical therapy* 90(8):1099–1110.

Imbeault, F.; Bouchard, B.; and Bouzouane, A. 2011. Serious games in cognitive training for alzheimer's patients. In *Serious Games and Applications for Health (SeGAH), 2011 IEEE 1st International Conference on*, 1–8. IEEE.

Klinger, E.; Kadri, A.; andJ L Le Guiet, E. S.; Coignard, P.; Fuchs, P.; Leroy, L.; du Lac, N.; Servant, F.; and Joseph, P.-A. 2013. Agathe: A tool for personalized rehabilitation of cognitive functions based on simulated activities of daily living. *IRBM* 34(2):113–118.

Knox, W. B.; Stone, P.; and Breazeal, C. 2013. Training a robot via human feedback: A case study. In *Social Robotics*. Springer. 460–470.

Kraus, S.; Sycara, K.; and Evenchik, A. 1998. Reaching agreements through argumentation: a logical model and implementation. *Artificial Intelligence* 104(1):1–69.

Kunapuli, G.; Maclin, R.; and Shavlik, J. W. 2011. Advice refinement in knowledge-based svms. In *Advances in Neural Information Processing Systems*, 1728–1736.

Lakdawalla, D.; Bhattacharya, J.; and Goldman, D. 2004. Are the young becoming more disabled? *Health Affairs* 23(1):168–176.

Lange, B.; Koenig, S.; Chang, C.-Y.; McConnell, E.; Suma, E.; Bolas, M.; and Rizzo, A. 2012. Designing informed game-based rehabilitation tasks leveraging advances in virtual reality. *Disability and rehabilitation* 34(22):1863–1870.

Lax, D. A., and Sebenius, J. K. 1992. Thinking coalitionally: party arithmetic, process opportunism, and strategic sequencing. In Young, H. P., ed., *Negotiation Analysis*. The University of Michigan Press. 153–193.

Lin, R.; Kraus, S.; Wilkenfeld, J.; and Barry, J. 2008. Negotiating with bounded rational agents in environments with incomplete information using an automated agent. *Artificial Intelligence* 172:823–851.

Lin, R.; Gev, Y.; and Kraus, S. 2011. Bridging the gap: Face-to-face negotiations with an automated mediator. *IEEE Intelligent Systems* 26(6):40–47.

Marin, J.; Navarro, K.; and Lawrence, E. 2011. Serious games to improve the physical health of the elderly: A categorization scheme. In *CENTRIC 2011, The Fourth International Conference on Advances in Human-oriented and Personalized Mechanisms, Technologies, and Services*, 64–71.

Mash, M.; Lin, R.; and Sarne, D. 2014. Peer-design agents for reliably evaluating distribution of outcomes in environments involving people. In *Proceedings of the International conference on Autonomous Agents and Multi-Agent Systems (AAMAS 2014)*, 949–956.

Moreira, M.; de Amorim Lima, A.; Ferraz, K.; and Rodrigues, M. B. 2013. Use of virtual reality in gait recovery among post stroke patients-a systematic literature review. *Disability and Rehabilitation: Assistive Technology* 8(5):357–362.

Murray, C., and Lopez, A. 2013. Measuring the global burden of disease. *New England Journal of Medicine* 369(5):448–457.

Oshrat, Y.; Lin, R.; and Kraus, S. 2009. Facing the challenge of human-agent negotiations via effective general opponent modeling. In *Proceedings of the Eighth International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS-2009)*, 377–384.

Pineau, J.; Montemerlo, M.; Pollack, M.; Roy, N.; and Thrun, S. 2003. Towards robotic assistants in nursing homes: Challenges and results. *Robotics and Autonomous Systems* 42(3):271–281.

Rego, P.; Moreira, P.; and Reis, L. 2010. Serious games for rehabilitation: A survey and a classification towards a taxonomy. In *Information Systems and Technologies (CISTI), 2010 5th Iberian Conference on*, 1–6. IEEE.

Ren, J.; Bickmore, T.; Hempstead, M.; and Jack, B. 2014. Birth control, drug abuse, or domestic violence? what health risk topics are women willing to discuss with a virtual agent? In *Intelligent Virtual Agents*, 350–359. Springer.

Rosenfeld, A., and Kraus, S. 2015. Providing arguments in discussions based on the prediction of human argumentative behavior. In *AAAI*.

Rosenfeld, A.; Zuckerman, I.; Azaria, A.; and Kraus, S. 2012. Combining psychological models with machine learning to better predict people's decisions. *Synthese* 189(1):81–93.

Rosenfeld, A.; Sehgal, V.; Graham, D. G.; Banks, M. R.; Haidry, R. J.; and Lovat, L. B. 2014a. Using data mining to help detect dysplasia: Extended abstract. In *2014 IEEE International Conference on Software Science, Technology and Engineering, SWSTE 2014, Ramat Gan, Israel, June 11-12, 2014*, 65–66.

Rosenfeld, A.; Zuckerman, I.; Segal-Halevi, E.; Drein, O.; and Kraus, S. 2014b. Negochat: A chat-based negotiation agent. In *AAMAS*.

Rosenfeld, A.; Azaria, A.; Kraus, S.; Goldman, C. V.; and Tsimhoni, O. 2015. Adaptive advice in automobile climate control systems. In *Proc. of The AAAI Workshop on Artificial Intelligence for Transportation WAIT-15*.

Sabaté, E. 2003. *Adherence to long-term therapies: evidence for action*. World Health Organization.

Sarne, D., and Grosz, B. J. 2007. Sharing experiences to learn user characteristics in dynamic environments with sparse data. In *Proceedings of the Sixth International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS 2007)*, 202–209.

Sarne, D.; Elmalech, A.; Grosz, B. J.; and Geva, M. 2011. Less is more: restructuring decisions to improve agent search. In *Proceedings of the 10th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2011)*, 431–438.

Seeman, T.; Merkin, S.; Crimmins, E.; and Karlamangla, A. 2010. Disability trends among older americans: national health and nutrition examination surveys, 1988–1994 and 1999–2004. *American Journal of Public Health* 100(1):100.

Segal, A.; Katzir, Z.; Gal, Y.; Shani, G.; and Shapira, B. 2014. Edurank: A collaborative filtering approach to personalization in e-learning. In *Proc. of Seventh International Conference on Educational Data Mining (EDM 2014)*.

Selten, R. 1998. Aspiration adaptation theory. *Journal of Mathematical Psychology* 42(2):191–214.

Shirk, S., and Karver, M. 2003. Prediction of treatment outcome from relationship variables in child and adolescent therapy: a meta-analytic review. *Journal of consulting and clinical psychology* 71(3):452.

Shrot, T.; Rosenfeld, A.; Golbeck, J.; and Kraus, S. 2014. Crisp - an interruption management algorithm based on collaborative filtering. In *The ACM CHI Conference*.

Tapus, A.; Maja, M.; Scassellatti, B.; et al. 2007. The grand challenges in socially assistive robotics. *IEEE Robotics and Automation Magazine* 14(1).

Vahidov, R.; Kersten, G. E.; and Saade, R. 2012. Human–software agent negotiations: An experimental study. In *E-Life: Web-Enabled Convergence of Commerce, Work, and Social Life*. Springer. 356–367.

van Wissen, A.; Gal, Y.; Kamphorst, B.; and Dignum, M. 2012. Human–agent teamwork in dynamic environments. *Computers in Human Behavior* 28(1):23–33.

Vlachos, E., and Schärfe, H. 2014. Social robots as persuasive agents. In *Social Computing and Social Media*. Springer. 277–284.

Wickramasinghe, L. K.; Guttmann, C.; Georgeff, M.; Thomas, I.; and Schmidt, H. 2011. An adherence support framework for service delivery in customer life cycle management. In *Coordination, Organizations, Institutions, and Norms in Agent Systems VI*. Springer. 210–229.