Artificial Intelligence for Human-Robot Interaction
Papers from the AAAI 2015 Fall Symposium

Modeling Motivational States in Adaptive Robot Companions

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Abstract

Motivation impacts people's lives in a powerful way and is at the heart of a plethora of day-to-day activities and achievement settings, from success at the workplace to learning and acquiring knowledge to trying to quit bad habits. The current work aims to develop an adaptive robot companion that models a user's daily motivational state and chooses appropriate motivational strategies to keep the user on track for achieving a daily goal. The two main components we are focusing on in this context are creating an ontology-based user model of the person's motivational states and using an appropriate strategy selection algorithm that chooses the best motivational strategies for the user each day based on the user model's output. Specifically, we are focusing on the important application domain of physical activity and aim to help early adolescents achieve daily-recommended levels of physical activity. Our human-robot interaction system uses information acquired from the user to feed the user model and physical activity data from a wristband device to inform the strategy selection algorithm.

Introduction

Achievement motivation, a field that has been extensively studied, has a strong impact on a variety of application domains that touch on self-regulated learning, coping, disengagement, social comparison, and much more (Elliot and Dweck 2013). Sustaining motivation over long periods of time is thus of paramount importance in a multitude of contexts and tasks faced by people on a daily basis. Our work aims to develop an automatic method of estimating a person's motivational state while trying to achieve a goal and use this estimation to adapt to the user in order to help him or her accomplish the respective goal.

Due to its extreme importance for people's health, the application domain we chose for this scenario is physical activity (Trudeau and Shephard 2008), (Boreham and Riddoch 2001). This is an example of a task during which, even when people are already highly motivated to succeed, their motivation drops over time, so constant monitoring and support is needed. Our target population consists of adolescents aged 13 to 15, since research shows this is when physical activity drops dramatically (HHS 2013). Thus, our work uses a Socially Assistive Robotics (Feil-Seifer and Mataric 2005) approach to sustain the benefits of physical activity and help adolescents achieve daily-recommended levels (HHS 2008).

Background and Related Work

Work on applications that support people engaging in physical activity is wide and stems from various fields of research.

In the persuasive systems field, there exist a multitude of wellness applications that aim to help people achieve healthier lifestyles. Examples include applications providing an interface for goal setting and self reflection (Consolvo et al. 2008), (Lin et al. 2006), work on long term goals (Barua et al. 2014), as well as online commercial systems (Lifetick 2014), (HealthMonth 2014). Wearable sensors have also become an integral part, being used for activity recognition systems aiming to engage users in physical activity (Consolvo et al. 2008) or work on the role of contextual information in daily physical activity (Li, Dey, and Forlizzi 2012).

In the field of user modeling, there has been considerable work using machine learning to infer users' goals and plans. Such work includes contextual requirements modeling (Ali, Dalpiaz, and Giorgini 2010), different approaches for plan inference (Carberry 2001), Bayesian user modeling (Horvitz et al. 1998), and computational frameworks for improving learning (Conati and Vanlehn 2000).

Human-robot interaction research in this area is less present and includes investigating the role of praise and relational discourse in human-robot interaction systems (Fasola and Matarić 2013), the perceived competence of a robot in a fitness instructor vs. social co-participant role (Sussenbach et al. 2012), and maintaining users engaged in the weight loss process for as long as possible (Kidd 2008).

Regarding the use of ontologies in this domain, research focuses on computational models of dialogue for simulating a human health counselor (Bickmore, Schulman, and Sidner 2011), and on building computerized behavioral protocols aimed at behavior improvement (Lenert et al. 2005).

The wide range of work concerning wellness and physical activity applications recognizes the importance of investigating this problem. To date, however, there is no system that tries to tackle the complex task of developing a companion that adapts to the user long-term, in an autonomous way, in order to help him or her achieve long-term behavioral goals.

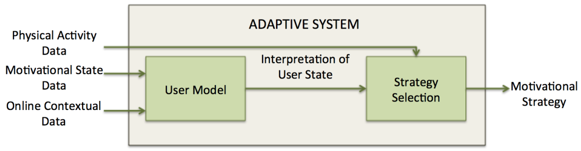

Figure 1: System Diagram

System Design

Our system is designed with our two main research questions in mind. First, how can we *develop an ontology-based user model for estimating a user's daily motivational state by employing long-term human-robot interaction*? Second, how can we then *use a strategy selection algorithm that takes in this estimation and chooses an appropriate daily motivational strategy for the user*?

Figure 1 above reflects these two components and represents the logic followed by the system at each time step (a time step is one day). The interaction takes place once at the end of each day, when the robot asks the user a series of questions meant to gauge his or her motivational state while trying to achieve the goal for the day and then sets a new goal for the next day. Each goal consists of a particular number of steps the user should aim to take throughout the course of a day, and is monitored by the wristband device. The interaction between the user and the robot is facilitated by the use of a smartphone application that displays an avatar of the physical robot, and allows the user to respond to the robot.

Interaction Design

The user interacts with the robot over the course of a month, duration which has shown to be effective in achieving behavior change (Locke and Latham 2002). The interaction takes place once at the end of each day in order for the system to obtain information about the effectiveness of the motivational strategy. Throughout the day, the user can access the application on their smartphone at any point, and a screen with information relevant for that particular strategy will be displayed. This way, the robot can build a rapport with the user by interacting with him or her both in its physical form (once daily), and through displaying the avatar on the phone application the rest of the time.

The robot keeps the user engaged by unfolding its backstory throughout the duration of the study. The story is that the robot is a robot-alien, named EphyT, that was traveling through space until its space ship broke down on Earth. The only way EphyT can return back home is by fixing its space ship, and in order to do so it needs a human friend who can collect energy points. Energy points get transferred onto EphyT through the fitness tracker the adolescent wears on his or her wrist throughout the day. Thus, the closer the user gets to accomplishing the physical activity goal given by the system daily, the more energy points EphyT gains.

The interaction with the physical robot lasts for approximately 5 - 10 minutes, time in which the robot first asks a set of questions meant to gauge the user's motivational state for the day, and then proceeds with the interaction corresponding to the motivational strategy in use for that day. When the user is not interacting with the physical robot, he or she can still access the application on their phone. The application will display information about the user's progress throughout the day, encapsulated in the motivational strategy in use.

Ontology-based User Model

The user modeling approach we are taking in order to estimate users' daily motivational states is based on the creation and refinement of an ontology (Uschold and Gruninger 1996) for our current context.

The user model takes as inputs two different types of information. The first type consists of users' answers to questions posed by the robot during the daily interaction. The questions are meant to obtain information with respect to the user's motivational state throughout the day while trying to achieve his or her physical activity goal, and are displayed all at once on the smartphone application screen. The second type consists of contextual data the system acquires online. This is information that might have played a role in the success or failure of a user at a particular daily goal, e.g. weather for the day or school schedule changes.

The inputs are fed into the user model, which uses an ontology-based approach to estimate the user's motivational state for the day. The ontology's main concepts have been defined through literature review in the fields of self determination theory (Deci and Ryan 2008), goal setting theory (Locke and Latham 2002), and social cognitive theory (Bandura 1991), as well as through an on-going process of expert interviews for validation. The main concepts identified are the user's *attitude toward the physical activity goal*, *self-efficacy*, *social pressure*, and *socio-structural factors* composed of *facilitators* and *impediments*. The relationships between these concepts, as well as other relationships with concepts related to the user's personality are to be added after running a first study meant for data collection. The study is a month-long in-home experiment during which the system chooses motivational strategies at random in order to allow us to correlate findings about which strategies work well in which situations and for what types of users.

The output of the model is an estimation of the user's daily motivational state. It consists of a feature vector whose values are based on the result of the ontology inferences. Since the relationships between the ontology's main concepts are to be refined after data collection, this can allow us to reduce the number of features needed for representing the motivational state estimation.

Strategy Selection Method

The strategy selection method we are using for our first pass is based on a Q-learning approach (Watkins and Dayan 1992) and aims to select the most appropriate motivational strategy for each user daily. The algorithm can choose between four motivational strategies that have been selected based on the same process of literature review (Staiano, Abraham, and Calvert 2013), (Lin et al. 2006), (Taylor and Ntoumanis 2007), and expert interviews, and are also to be validated through the first in-home study.

The current module takes as input the motivational state estimation obtained from the user model. This represents the state of the world, $intrp_t = [f_1\ f_2 ... \ f_n]$, at time step t. The algorithm chooses based on an ϵ-greedy policy between the four different motivational strategies to use daily, representing the actions the system can take at each time step: $a \in \{m_1, m_2, m_3, m_4\}$. The reward signal at step t is defined as the difference between the number of steps taken by the user throughout the day and the number of steps set by the system as the user's daily physical activity goal: $r_t = \#steps_{taken} - \#steps_{goal}$. The update is based on the standard Q-value update formula. The strategy selection method will thus work toward finding an optimal policy, in order to maximize the expected return, i.e. positive reward or small values for negative rewards.

Although the user model provides us with an output vector that contains a low number of features (approximately three), a single month-long study would not provide sufficient data for the algorithm to compute an initial policy. We are getting around this issue by running our initial month-long study, during which we set our system to choose motivational strategies at random. This way, we can explore the state space and obtain an initial policy for use in the adaptive phase of the second month-long study.

Motivational Strategies

The four motivational strategies the system can choose among are *cooperation*, *competition*, *self reflection*, and *lessons on physical education*.

In literature, cooperation strategies include setting out a physical activity goal in a way that fosters cooperation between the user and other agents, such as the user's friends, family members or virtual characters the user interacts with. In (Staiano, Abraham, and Calvert 2013) cooperative exercise game players lost significantly more weight than players in the control condition, who gained weight over time. In our cooperation scenario, the user is asked to help the robot gain energy points in order for it to be able to fix its space ship and return home. Thus, the adolescent is engaged in a cooperative task, trying to help the robot through achieving his or her daily activity goals.

Competition can and has been shown to be effective within exercise game interventions, e. g. for most participants in (Lin et al. 2006), competitiveness presented a more stimulating challenge than cooperation. Some of the participants, however, felt like competitiveness was incompatible with the spirit of the game, creating the need to develop an adaptive system. In our work, the user competes against virtual characters with the same back-story as our robot, each with human friends helping them gain energy points. The competition strategy implements a mini-game consisting of the user racing against the human friends of the other robot-aliens, represented as virtual characters in the application.

Of high importance in achieving daily physical activity goals are also strategies that emphasize self reflection and conveying information about the benefits of physical education (King et al. 1990), (Taylor and Ntoumanis 2007). These strategies focus on making the user understand and think about his or her goals, as well as about the importance of physical activity. The self reflection strategy uses questions and feedback meant to cause the user to think about his or her progress with respect to the goal for the day (Zimmerman 2002), while the lessons on physical education strategy relays information about the importance of physical activity (King et al. 1990) and implements a mini-quiz about the information contained in the lessons.

Progress and Future Work

We have already run an in-school pilot study to test the back-story and the interaction mode with our target population. From an initial analysis of the data, we can identify subjects are enthusiastic about the interaction and about the different motivational strategies to be employed throughout the in-home studies. We are currently working on implementing our system to deploy in homes for our first study meant for data collection. After having analyzed the data obtained from this first study, we plan to refine our user model and strategy selection algorithm and run a second in-home study to investigate the effectiveness of such an adaptive system.

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