Modeling Motivational States Through Interpreting Physical Activity Data for Adaptive Robot Companions

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Abstract. This research aims to develop an adaptive human-robot interaction system that works with users over long periods of time to achieve a common goal that is beneficial to the user. The particular scenario I focus on is that of a robot companion interacting with adolescents, helping them succeed at achieving daily physical activity goals. To develop such a system, I propose a method of modeling the user's motivational state and employing this model in order to adapt motivational strategies best suited for each user. The proposed system uses both physical activity data obtained from wearable sensors (such as wristband devices) and information acquired by the robot from its interaction partners.

1 Problem and Motivation

The benefits of physical activity are well known, as research shows that daily physical activity has wide-ranging benefits, from improving cognitive and academic performance to helping with bone development and health [17]. My work seeks to sustain these benefits with robot home companions through personalized, data-driven coaching.

The U. S. Department of Health and Human Services comprehensive guidelines on physical activity for individuals ages 6 and older state that children and adolescents should aim to accumulate at least 60 minutes of moderate- or vigorous-intensity aerobic physical activity on most days of the week, preferably daily [1]. Current evidence shows that levels of physical activity among youth remain low, and that levels of physical activity decline dramatically during adolescence [2]. These data show the importance of developing methods to keep adolescents on track to achieving daily-recommended levels of physical activity. With this in mind, I seek to develop a human-robot interaction system that motivates adolescents to engage in physical activity on a daily basis.

2 Background and Related Work

There exists a great deal of work concerning health and well-being applications, such as commercial systems that use motivational strategies to help users stay

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engaged in physical activity, or that support goal-setting and reflection for the user [14], [9]. Other prior work explores tracking of long term goals along with factors that have an important role in goal-setting theory [5].

In the field of human-computer interaction (HCI), wearable sensors are being used in the development of persuasive technologies that motivate healthy behavior. Work in this area is wide, ranging from activity recognition systems that employ this information to keep users engaged in physical activity [7] to how such applications should be evaluated [11].

Social robots have also been used to promote and keep users engaged in physical activity within the field of human-robot interaction (HRI). Work in this area touches on investigating the role of praise and relational discourse [8], as well as on how to create a long-term interaction for help with weight loss [10].

The user model I am building employs an ontology-based approach. Ontologies are defined as explicit accounts of shared understanding in a given subject area, and bolster communication between users, experts, and technology systems [18]. Since ontologies are extremely useful in providing a formalism that specifies and clarifies concepts in a domain and the relationships among them, their value for health applications has been recognized by different lines of research. Such research includes the investigation of computational models of dialogue trying to simulate a human health counselor [6] and that of computerized behavioral protocols that help individuals improve their behaviors [13].

Although the work presented above is wide-ranging, the current paper aims to link all the components important in maintaining physical activity motivation into one system by leveraging human-robot interaction techniques together with the benefits of wearable sensors.

3 Research Questions and Intended Main Contributions

The key research questions I am investigating within this context are as follows. *How can I develop an ontology-based user model of people's motivational states by employing long-term human-robot interaction to gather information needed for the model? How can I then use this interpretation of the user's motivational state in order to create an adaptive robot companion that chooses appropriate motivational strategies to help the user stay on track to achieving daily physical activity goals?* The contributions expected from answering these two research questions consist of the following.

The first contribution represents the ontology-based user model, validated via expert interviews. The model makes use of long-term human-robot interaction by acquiring data from the user about his or her motivational state each interaction, and also acquires contextual information about external factors from online sources (e.g. weather). The second contribution represents an adaptive algorithm based on Q-Learning that uses both the output of the user model and the physical activity data collected from the wristband device. Its output consists of choosing the most appropriate motivational strategy the robot companion employs for a user each day.

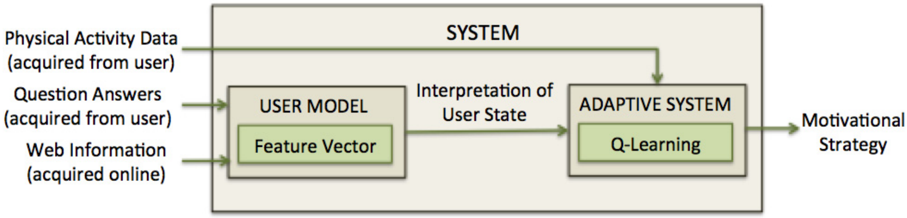

Fig. 1. System Diagram

Such a system would lie at the intersection of HRI, HCI, user modeling, and applied machine learning. Although there are a multitude of applications related to well-being and physical activity, there is no system to date that ties together continuous remote monitoring of user physical activity obtained from wearable sensors with an assistive robot for daily, long-term interactions.

4 Progress to Date and Plan of Further Research

4.1 Methodology and Design of the System

The robot platform chosen for this research is Keepon, a non-mobile platform with four degrees of freedom, designed to interact with children [12]. The adolescent wears a wristband device that keeps track of the number of steps taken throughout the day. He or she interacts with a robot once daily, both directly and via a phone application. The application presents an avatar for the robot with simple, 2D animations.

The system is depicted in Figure 1 above. When the adolescent interacts with the robot, the back-story of the robot unfolds in order to keep the user engaged in the long-term interaction. The robot asks the user a series of questions meant to obtain information about his or her motivational state, as well as acquires external information from online sources (e.g. weather information). This data is fed into the user model. The adaptive system then takes the user model output, together with the physical activity data from the wearable sensor, and outputs an appropriate motivational strategy for the user. This strategy is used to shape the new physical activity goal the adolescent needs to accomplish the next day.

4.2 User Model

The ontology my model relies upon needs to represent core concepts related to creating a profile of a user and keeping track of how this changes over time. Thus, I have initially performed extensive literature review in order to identify the key elements influencing the achievement of a goal. These are factors long studied in goal setting theory [15], social cognitive theory [4], and theory of planned behavior [3], and are introduced below. Since these key elements are part of the ontology-based model, the creation and validation of this model does not rely solely on literature review, but it is also heavily based on expert interviews.

As shown in Figure 1, the inputs to the user model are dichotomized into two categories. The first represents the user's answers to the robot's questions about how the participant felt while trying to accomplish a goal. These questions regard key elements influencing the achievement of a goal, namely *socio-structural factors* (composed of *facilitators* and *impediments*), *social pressure*, *self-efficacy*, and *attitude toward behavior*. They are phrased in an easy to understand manner, avoiding academic and arcane terms. The second input category represents external information acquired by the system online about factors that might have influenced the achievement of a goal, e.g. daily weather, school schedule changes. This information is fed into the socio-structural factors, into either the facilitators or impediments feature. All of these core factors make up the feature vector for a user, which contains numerical values based on the user's responses during the interaction with the robot.

The output of the user model is an interpretation of the user's state. It represents the state of the world (the state the user is in) at each time step (each day). The numerical value of each feature is mapped onto one of three discrete categories representing intensity levels, namely low, neutral, and high. This mapping is applied to reduce the state space size and produce a more intuitive interpretation of the user's state. For example, a value of 7 on a 1-to-7 scale for self-efficacy would be assigned to the "high" level. The interpretation thus consists of a feature vector with intensity levels for each feature.

To validate the user model and create an ontology that links the core elements modeling a user to motivational strategies employed by experts (e.g. health and physical activity counselors, physical education teachers, personal trainers), I utilize a formal interview process. This aims to validate and identify missing main concepts in the domain of physical exercise motivation and the relationships among them. The interview is structured in two parts, as follows.

The first part asks the expert to list (1) important factors for keeping students engaged in physical activity (*corresponding to the main concepts used in the ontology*), (2) techniques used by experts to identify the students' motivational state (*used to create a mapping from users' answers to the state space*), (3) information about students that helps the expert interpret the students' success or failure (*used to validate the user model's output*), and (4) strategies and techniques employed by the expert to keep students engaged in physical activity (*corresponding to motivational strategies*).

The second part presents the expert with the same categories, but with given answers (drawn from literature). The expert is asked to indicate how much he or she agrees with the specific answer, using a Likert scale. This part aims to check if experts indeed use concepts identified in literature as key factors, acquire new key factors used in practice, and acquire the basis for creating an ontology linking the user model to the motivational strategies used by experts.

4.3 Adaptive System

My adaptive human-robot interaction system chooses a motivational strategy based on the user model's interpretation of "why" and "how" the user was (un)successful at his or her previous goal, i.e. the interpretation of the user's state. This is possible since the motivational strategies identified from literature (such as cooperative and competitive strategies, making the user aware of the importance of engaging in physical activity, autonomy support, structure, and involvement) are associated with factors present in the user model, e.g. "Intrinsic motivation is associated with the desire to master a task and the satisfaction that comes with that, whereas extrinsic motivation refers to completing tasks solely as an ego boost, be it beating peers in a competition, or receiving praise from a parent, teacher or colleague" [16].

My system adapts to an individual user by following a Q-learning approach. In the current work, the actions the "agent" (in our case the robot) can take are the different motivational strategies mentioned above, $a \in \{m_1, m_2, m_3, ...\}$, which are to be finalized after concluding expert interviews. The states of the world are the interpretations of a user's state (the output of the user model). Thus, a state is a feature vector representing the interpretation of the user's state, and is defined as $intrp_t = [f_1\ f_2\ f_3\ f_4\ f_5]$, where the f_is represent the features discussed above that take values associated with intensity levels. The reward for a particular state is the difference between the number of steps taken by the user and the number of steps set as the goal, $r_t = \#steps_{taken} - \#steps_{goal}$.

At time step t, the algorithm observes the current state $intrp_t$, chooses an action a_t among the motivational strategies based on an ϵ-greedy policy, takes the action, observes the reward r_t as well as the new state $intrp_{t+1}$, and then updates the Q-value for the state using the observed reward and the maximum reward possible for the next state. The update is performed based on the following formula: $Q(intrp_t, a_t) = Q(intrp_t, a_t) + \alpha[r_t + \gamma \max_{a_{t+1}} Q(intrp_{t+1}, a_{t+1}) - Q(intrp_t, a_t)]$, where α and γ are both set between 0 and 1 and specify how quickly learning occurs and how much future rewards matter, respectively. The algorithm 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.

4.4 Future Work

Future work involves finishing the expert interview process in order to validate the ontology-based user model. The system itself is to be validated as part of two user studies. An initial month-long, in-home study is planned for data collection. Participants are assigned to either the robot or the wristband-only condition. The data from this study is to be employed to train the adaptive system used in a second similar study. This second study will employ the adaptive human-robot interaction system (adaptive robot condition) vs. a non-adaptive system that interacts with adolescents in the same manner, daily, but without adapting to the user (non-adaptive robot condition).

I am a third year Ph.D. student in the Social Robotics Lab, Computer Science Department, at Yale University. I have been working on better defining the currently proposed work, thinking through the details of the user model and the machine learning technique I am intending to apply as part of my adaptive system, and starting to conduct expert interviews in order to obtain data for creating an ontology-based user model. My background is in Computer Science, and I have been continuously involved in HRI research since my undergraduate years.

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