

# A Context-Aware Adaptive Feedback Agent for Activity Monitoring and Coaching

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## Abstract

A focus in treatment of chronic diseases is optimizing levels of physical activity. At Roessingh Research and Development, a system was developed, consisting of a Smartphone and an activity sensor, that can measure a patient's daily activity behavior and provide motivational feedback messages. We are currently looking into ways of increasing the effectiveness of motivational messages that aim to stimulate sustainable behavioral change, by adapting its timing and content to individual patients in their current context of use.

## Introduction

One of the focus areas in the treatment of chronic diseases is to optimize levels of physical activity. We are investigating how to support this by objectively measuring a patient's daily activity patterns and providing regular feedback on the patient's performance via a Smartphone. The positive effects of regular feedback on behavior change are supported by numerous scientific studies. For example Kreuter et al. [1] showed the positive effect of regular feedback on four different kinds of health related behavioral change including increase of physical activity. Our own research has shown the positive effects of giving feedback to Chronic Low Back Pain patients throughout the day [2], while similar effects have been shown for patients with COPD and Chronic Fatigue Syndrome [3].

The system that was used in our activity monitoring and feedback research is depicted in Figure 1 below. On the left is the ProMove-3D physical activity sensor, developed by Inertia Technology; in the center is a screenshot of the Smartphone interface showing a graph of daily activity, and on the right is a screenshot showing a motivational advice (feedback) message: "Take a nice walk!".

These motivational text messages, which will be the focus of the rest of this article, are currently used in a relatively ad hoc manner. The Smartphone can be set to generate a motivational message every hour (or every  $x$  minutes), and at that time, the message to be presented to the user is picked randomly from a pre-defined list of



Figure 1. The Activity Monitoring and Feedback system from Roessingh Research and Development. Depicted is the ProMove-3D activity sensor, and two screenshots of the Smartphone interface showing a graph of daily activity and a motivational message.

around 25 messages. This message is then shown to the patient by displaying the text on the screen. As described in [4], we distinguish between three aspects of feedback: *timing*, *content*, and *representation* (when to give feedback, what to tell the user, and how to convey this to the user) which we are focusing on in our current research. The next section will shortly describe our work regarding feedback timing and content. The representation of feedback is an aspect left for future work.

## Method: Improving Feedback Timing and Content

Although the positive effect of giving regular feedback messages has already been shown, compliance to individual feedback messages is relatively low (59% on average over measurements from 86 different patients). Compliance here is defined as the immediate response to a given feedback message. If the patient is told to become more active (i.e. “*Please go for a walk.*”), and the patient does become more active in the 30 minute interval after the feedback message, as measured by the activity sensor, we define this as being compliant to the message, and vice versa. This immediate behavior change after feedback messages (compliance) can be computed in real time on the Smartphone. We use this direct feedback loop to the system to enable the system to learn to adapt to the patient in terms of when to give feedback and how to phrase the feedback message. The idea is that every individual patient has its own preferences in terms of this feedback timing and content, and we should be able to increase compliance to individual messages, by adapting these aspects to individuals. The way in which this real-time personalization is realized in the feedback system is explained for the feedback timing and the feedback content below.

In order to find an optimal timing for feedback messages, we have analyzed the messages generated in previous studies. We have a dataset of 2,374 feedback messages for which compliance is known. As mentioned earlier, only 59% of these messages were complied to, so the goal of this work was to find out why some messages were complied to and others were not. For this we have created a classifier that is able to predict compliance to feedback messages based on a set of features, consisting of context information (e.g. weather, time of day) and features related to the history of use of the system (e.g. how many messages were already received today). We were able to predict feedback compliance with **86% accuracy** on average over all patients. Compared to an average baseline score of 60%, this constituted a 64% increase in accuracy over baseline, proving the viability of the approach. The work in [5] describes the details of this work.

For the personalization of feedback content to individual patients, we took a slightly different approach. We exploit the same principles by using the direct measurement of behavior (compliance calculation) after a feedback message to adapt the system to individuals. But for the content generation system we chose not to take a classical machine learning approach. We designed an ontology of feedback messages in which motivational messages are organized by the type of activity they prescribe. For example, at the top of the Ontology, messages are divided into “Outside”, “Inside” and “Generic” categories (see Figure 2). These are three categories that relate to the content of the given advice: the “Outside” tree contains all advices that tell the patient to do something outside, the “Inside” tree contains everything that can be done inside, while the “Generic” tree contains advices, like “Be more active!”. We then developed an algorithm that can traverse the ontology, and at each level can select an appropriate path based on the user’s context and the user’s responses to previous messages. For example, choosing a message from the “Outside” section of the Ontology is only appropriate if the weather is nice. By looking at the patient’s context (weather at current location), the algorithm can decide to prune that part of the Ontology. Then, when a selection has to be made between Inside and Generic messages, the algorithm will favor the node to which the patient previously responded best. Similarly the Ontology can include other nodes that can be pruned based on contextual information. For example, a node “Bike”, containing advices that tell someone to go for a bike ride, can be pruned if the user has indicated that he or she does not own a bike. The Ontology based message selection algorithm and method is described in more detail in [6].

## Issues and Future Work

The feedback timing and content approaches are in an advanced state, both being implemented and currently undergoing trials on the Smartphone. A current pressing issue is the problem of *cold start*. Whenever a new

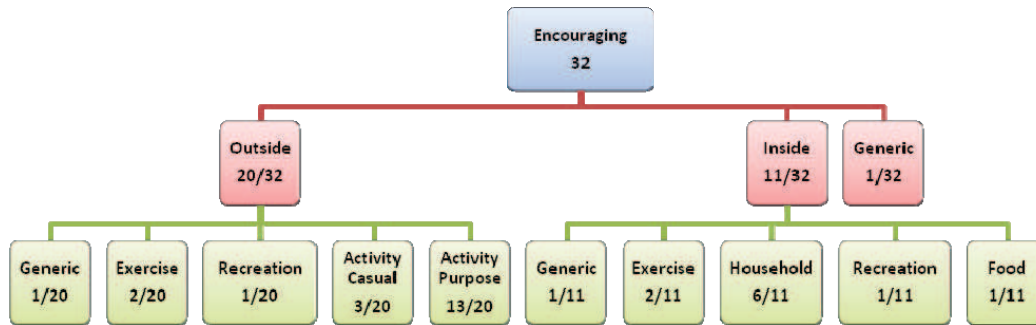


Figure 2. Message Ontology with high level categories for motivational feedback messages. The numbers in each node give information on the distribution of leave nodes (actual advice messages) under each node. E.g., in this example Ontology, there are 32 leave nodes: 20 under “Outside”, 11 under “Inside” and 1 under “Generic”. Of all the subcategories under “Outside”, there are 20 leave nodes, 3 of which are in the “Activity Casual” category, etc. These fractions are the prior probabilities of selection for each node, if no user data is available.

patient starts using the system, there is no data available to start the personalization algorithms. For the feedback timing module, we aimed to solve this problem by creating a cold start classifier. This classifier is trained on data from all of our previous patients and is used to find the right timing for the first 25 motivational messages (after which the system will train an individual classifier and switch to using this). This approach works, but the classification accuracy of this cold start classifier is only 67% (compared to 86% for the individual classifiers). On the one hand this shows that data from different patients is really different, which is a strong motivator for doing personalization in the first place. On the other hand, the cold start issue remains unsolved for our current application.

We are now looking into ways of improving our system’s cold start phase, specifically by looking into “behavior change personality clustering” of patients, or, clustering patients who respond similarly to motivational messages. This way we could compare a new patient with patients from earlier studies and hopefully increase our predictive power. This approach is well known in the field of recommender systems, and a similar approach in the field of eHealth was taken by Cortellese et al. [7], but to the best of our knowledge never implemented into a real-time system.

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