The Role of Social Signals in Telecommunication: Experimental Design

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Abstract. In this paper, we present the experimental design for the evaluation of the impact of social signal application on a user's decision making in the area of telecommunications. The aim of the design is to show that user's social signals are applicable feedbacks in conversational recommender systems. We use user satisfaction (with the system and content) evaluation criteria. During social interaction humans express social signals which provide quick feedbacks required by conversational recommender system. The experimental scenario is hands driven video-on-demand service with a conversational recommender system where the user selects among videos on screen. We limited our experimental scenario to the social signal of hesitation only. User is hesitating, when is faced with a variety of choices to make decisions (he is uncertain). The system adjusts the list of items to be recommended according to the extracted social signal {hesitation, no hesitation}.

Keywords: Human-Computer Interaction, Social Signals, Recommender System, Experimental Design

1 Introduction

The social signals (SS) have received much attention in recent years due to their additional natural information about human behavior which offers important benefits in human-computer interaction (HCI) [1]. Social signals similar to emotions are expressed with nonverbal behavioral cues (gestures, postures, etc.) and present human reactions to current social situations. From here on, the word system will be used as a synonym for video-on-demand system with recommender system. However, it is not clear how to utilize SS in telecommunication applications and that is the major reason why the most of the systems are socially ignorant. Based on our preliminary testing, social signal of hesitation is a frequently expressed signal when interacting with and selecting among multimedia items. It might provide additional information about how user selects one video on screen among others and not just information about which video is selected. Based on that, the system might recommend to user most suitable new videos. Recommendations of videos, provided by our system, are based on conversational recommender system.

We distinguished between two approaches in social and cognitive psychology perspectives of emotions: (i) emotion as individual experience and (ii) emotion as SS [2]. The theories of the first approach emphasize the relative significance of physiological changes, cognitive process, and the sensation and reaction where emotion emerges in an individual [2]. Instead of reflecting a person's inner feelings in emotion as SS approach, facial expressions are reflections of either real or imaginary interaction – no inner sensations need to play [2]. In our user to system interaction, emotion as SS, displays provide information about the user disposition and the situation as such.

The goals of this position paper are (i) to introduce an experimental design for the evaluation of the impact of SS in video-on-demand service, (ii) to show that social signals are applicable feedbacks in conversational recommender systems, and (iii) to list and discuss the identified potential flaws of the experiment in terms of a fair estimation of impact of SS (fair comparison of control and test group of users). However, the purpose of this paper is to describe experimental design without test results.

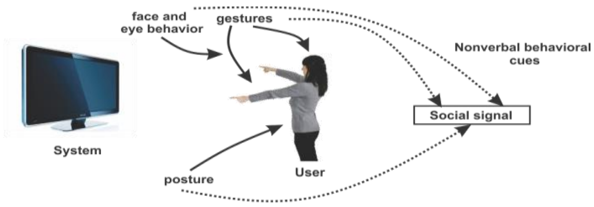

Fig. 1. Use of social signals in human-computer interaction

1.1 Motivation

The proposed methodology of our study is based on the use of social signals in human-computer interaction (Fig. 1). The system recognizes the user's social signals and uses them in interaction. Processing of social signals can be utilized in HCI in order to support a user's decision while passing through the user's interaction procedure. For humans, it is natural to produce social signals in several verbal and nonverbal ways. Consequently, the whole procedure is based on utilization of human social intelligence. We assume that social signals as additional information can improve the user experience and increase the efficiency level of a communication service, and that is why we should use these naturally produced signs by user.

1.2 The Role of Social Signals in Telecommunication

As was previously discussed, we will merge three domains in the context of our solution. We will present domains of human-computer interaction (HCI), social signal processing (SSP) and recommender systems (RS) below.

Human-Computer Interaction (HCI). Human-computer interaction (HCI) in its basic form involves the study, planning, and design of interactions between people (users) and computers [3]. We can divide HCI into two groups, simple and intelligent

HCI [4]. We are interested in intelligent interaction, where the computer understands the meaning of the message of the user, which is typically performed using speech and body gestures. Human – Centered Intelligent (HCI^2) [1] is one of the foremost challenges of computer science [4]. The domain of HCI^2 is bridging the gap between computer science and cognitive science. In the context of HCI^2, computers must have the ability to understand the meaning of the information expressed by a user and also the context of this information [4]. There are only few studies that use social signals in HCI. In [5], hesitant hand motion used by people is proposed as natural modality for a robot to communicate uncertainty in human-robot interaction.

Social Signal Processing (SSP). Social signal processing (SSP) [6] is the research domain that aims to understand social interactions through machine analysis of nonverbal behavior [7]. Social signals are initiated by the human body and present reactions to current social situations. They are expressed with nonverbal behavioral cues (gestures and postures, face and eye behavior, etc.). One of the most distinct social signals in this interaction is hesitation, which can be expressed with a facial expression, head movement, shoulder movement, etc. [8]. A review of the social signal processing research domain is given in [7], [9], and [10]. The goal of our research is the application of social signals that are inherent in our gestures, postures, facial expressions, and gaze behavior. There are not many applications that include social context. In [11] the spontaneous agreement and disagreement recognition approach is presented. The impact of mimicry on social interaction is shown in [12].

Social Signal of Hesitation. The social signal of hesitation belongs to a type of micro movement called microslip - nonverbal stutters during execution of low level action primitives [13]. Another psychological definition describes hesitation as elapsing time between the external or internal stimulation of an organism and his, her or its internal or external response [14]. Hesitation can be expressed through a facial expression, head movement, shoulder movement, prosody and special verbal markers like *eh* or *hm* [8].

Recommender System (RS). Recommender systems (RSs) are software tools and techniques that predict user preferences for the purpose of suggesting items to be of use to a user [15]. There are plenty of reasons for using the RS, but for our purposes the most important reason is increasing user satisfaction when using the system. In our case, conversational RS is used, where recommendations are generated based on natural language dialog between the user and system. However, in our video-on-demand service, RS is used for recommendations of various multimedia contents. Two functions of RS are implemented in a way to reflect the user's social signal of hesitation. If the user is hesitating, the function of get diverse multimedia items (videos) is used. If not, the function of get similar multimedia items is used. Further details are given in Subsection 4.4. RSs are directed towards users who do not have enough personal experience or priori knowledge about recommended items to make an autonomous decision [16]. Conversational RSs use natural language support, where the user and the system may query or provide information to the other partner [15]. The biggest challenges of this domain of RSs are how to design the effective dialogue strategy between user and system and what actions must be performed in the interaction between them [15].

This paper is organized as follows. Section 2 describes the problem statement of research domain with included hypothesis. Section 3 includes the description of the experiment with experimental scenario and description of application interfaces for recording. In Section 4 are described selected details of the test procedure and evaluation plan. Discussion about experiment is presented in Section 5. Finally, Section 6 presents our conclusions.

2 Problem Statement and Hypotheses

The problems addressed in this article are how to evaluate the impact of social signal on user's satisfaction in application in the area of telecommunications and to show that social signals are applicable feedbacks in conversational recommender systems. Based on study described in [5], we assumed that social signal of hesitation is distinct enough that can be extracted in human-computer interaction. It can be described with different types of cues used in [11] and [12]. The system presented here is used conversational RS on LDOS-CoMoDa, a contextual personalization dataset [17] and [18].

In the most basic form hesitation can be considered as a kind of uncertainty, when a user is faced with a variety of choices to make decisions. Nonverbal signs of the social signal of hesitation, which can be recognized from video, will be used for our purposes. Based on results of our prior test we extracted the most often applied signs of social signal of hesitation. The most often is SS expressed as facial expression and arm moving. We can describe the facial expressions with facial action coding system (FACS) [19]. We can use actions below; outer brow raiser (2), upper lip raiser (10), dimper (14), chin raiser (17), lip suck (28), blink (45), head tilt left (55), head tilt right (56), eyes up (63) and eyes down (64). Social signal of hesitation can be presented in various combinations (we use action unit number whose identify the action): 2+10, 2+17, 28, 45, 17+55+56, 14+55+56 and 14+63+64. Social signal is also presented with shoulder movements up and down, whole torso moving, arm moving up and down on side of the body (minor moving) and hand rotating. However, hesitation can also be measured by unusual delays in response time. The 'significant absence' of non-verbal communications is also considered in the context of our scenario.

Two hypotheses will be tested in the context of proposed experimental design. The statement "*Social signals improve the quality of experience (QoE)*" presents the first hypothesis. QoE, subjective measure of user experience with the system, in our case depends on various factors. We can merge them into the following equation

$$\mathrm{QoE}(u) = \psi_{SS}(\mathrm{SS}(u,\mathrm{system}))+\psi_{P}(\mathrm{personality}(u))+\psi_{M}(\mathrm{mood}(u))+ \psi_{C}(\mathrm{content})+ \psi_{O}(\mathrm{other}) \quad (1)$$

where the factors ψ present the different impacts on user's QoE. Factors were selected according to preliminary case study. Theoretical background is based on statistical theory on explained and unexplained variance [20]. Factor ψ_{SS} presents the impact of social signals expressed by user during his interaction with the system, ψ_P presents the impact of user's personality, ψ_M presents the impact of user's current mood (Subsection 4.1), ψ_C presents the impact of current contents on screen (Subsection 4.4), and ψo that presents the impact of the unknown factors in our design. The contribution of each factor in equation (1) will be estimated from user's answer on questions in two (pre and post) questionnaires that we will use. We identify the user's personality through pre-questionnaire (control of ψ_P). Questions in a questionnaire based on description of personality with five dimensions of personality (Big Five personality traits) [20]. These five factors are; openness, conscientiousness, extraversion, agreeableness, and neuroticism. Results of personality test will be analyzed in a standard way using statistical testing.

"*The use of social signal reduces the content selection time*" presents the second hypothesis. If social signals of the user are taken into account, the time of selection of video that user wants to watch is shorter. This is the possible assumption for a user who uses video-on-demand service. However, to test this hypothesis we must ensure the same conditions for test and control group of users.

3 Experimental Design

Experimental design must allow the control of all factors in equation (1) in order to reliably estimate the contribution of ψ_{SS} to QoE. As was previously mentioned, we will extract social signals and recognize gestures in user to system interaction, when the user selects among various video contents (video-on-demand service) in order to estimate the impact of social signals in the following specific scenario. The user selects video contents with hand gestures, while the social signals can be extracted from facial expression, head movements, shoulder movement, etc. The human operator substitutes the automatic gesture recognition and social signal extraction in real time. User is not aware of human operator. The aim of this experimental design is the design of a fair experiment in terms of fair comparison between test and control group. The test group will be represented by a group of users whose social cues during the interaction with the system will be taken into account. The control group will be represented by a comparable group (in size and other selected parameters) of users whose social cues during the interaction with the system will not be taken into account. In proposed work we apply independent-measures experimental design from the aspect of feasibility of an experiment and variables control. In this section we describe the experimental scenario and technical realization of experiment.

3.1 Experimental User Scenario

Experimental user scenario can be divided in three steps, where the first one includes activities before the interaction, the second presents the interaction between user and system, and the third includes the activities after the interaction is done. All descriptions of scenario below refer to the test group of users.

Figure 2 presents the experimental environment that consists of three rooms. In room 1 there is only a monitor where the user watches emotionally neutral induction video and fills in the questionnaire before and after interaction with the system. In the room 2 there is a system that is used in a process of interaction between user and system. In room 3 there is a human operator and a monitor. Human operator watches the interaction between user and system through a camera. He makes notes of recognized actions and social signals through a human operator interface and provides video recommendations based on recommender system.

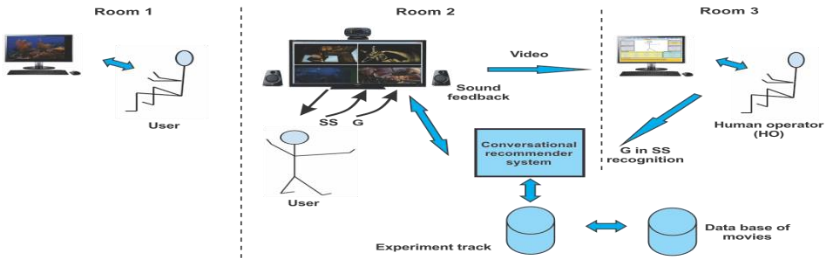

Fig. 2. Experimental environment

The first step takes place in room 1. The whole scenario is explained to the user. Then he goes to the monitor and watches the emotionally neutral video. After that, the user fills in a pre-questionnaire. At the second step the user enters room 2 and with special gesture indicates that he wishes to use the video-on-demand service. The system switches on and the interaction with the system starts. The recommender system provides four video contents – movie trailers (see Fig. 3b). These four videos are then in parallel projected on the screen. The user with a gesture (G) indicates which of four movies he is mostly interested in. The system recognizes how confident he is about his/her decision based on the social signal of hesitation (SS). If the user is not hesitating, then the system provides three additional similar items, otherwise the system provides four new diverse items and projects items on the screen together with sound feedback. User is repeating video selection process until he finds the video he wants to watch. When the user with a gesture indicates that the final decision has been made (selects the video he wants to watch), the system extends the selected video to the whole screen and turn on the sound. Then the user watches the selected movie for about 20 seconds. After this, step two is completed. The third step also takes place in room 1, where the user fills in a post-questionnaire.

The scenario for the control group of users is almost the same in all three steps. As we previously mentioned, in the control group the user's social signals are not taken into account by the system. Based on that, in the second step the system provides next three similar items. For this group, we can assume that all user decisions are made without hesitation. The decision of the system in that case is based only on gestures for video selection without social signals.

3.2 Technical Realization of the Experiment

Unfortunately, gesture recognition algorithms do not always guarantee correct results and, consequently errors in gesture recognition could provide a new uncontrolled parameter of already very complex design of our experiment. That is the main reason why human operator takes the role of automatic gesture and social signal recognition algorithms. Human operator decisions are made in real time. Technical realization of the experiment includes human operator interface and video-on-demand interface (showing videos in parallel). The human operator interface (Fig. 3a) consists of various buttons through which the human operator reports his decisions about recognized gestures and social signals. In the middle of the interface is a panel where live video from a camera recording the user takes place. User interface (Fig. 3b) represents the applied version of the video-on-demand service. It consists of four panels where videos are playing. Each decision made by the human operator is playing to user through the user interface with sound feedback.

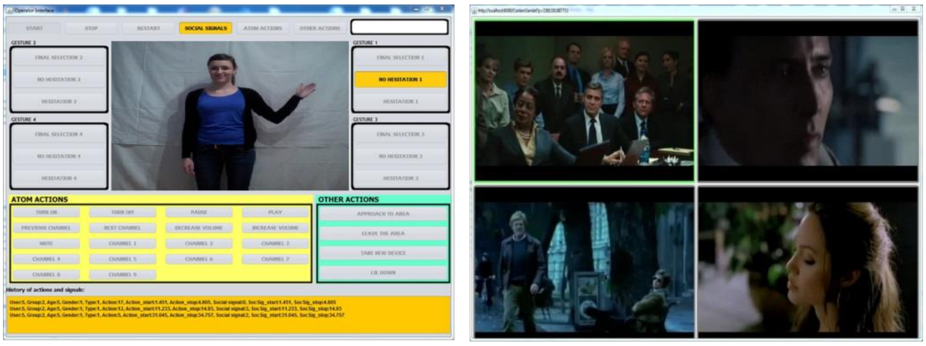

Fig. 3. a) Human operator Interface and **b)** Video-on-demand user interface

3.3 Test User Selection

As test users will be select people who reflect the generic population of moviegoers. They will be asked if they want to participate. The required number of users in test and control group will be estimated based on a-priori statistical power analysis.

4 Selected Elements of the Experiment

In the previous section, we described only the basic procedure of the experimental scenario without the details of scenario. However, we have made some assumptions on which the described scenario is based. We will discuss these assumptions and decisions below.

4.1 Role of Emotionally Neutral Video

Users that will use our system will certainly not all be in the same initial mood. This can be very critical for the control of our experiment. Therefore, we induced the neutral emotions to users by watching a short video clip. Users watched an emotionally neutral video at the beginning of the experiment before interaction with the system starts. The result of the use of this video is the approximately the same initial emotional state of all users. Video is documentary clip from a National Geographic and was already used in [22] and [23]. Clip is portraying a fish at the Great Barrier Reef.

4.2 Role of the Human Operator

The human operator is used to provide ground truth action recognition, social signal extraction and system feedback to the user in real time. He is not additionally trained to recognize the gestures, because we use simple movements. On the other hand, social signals are not simple to extract, so we need a trained person who will able to recognize the social signal from various perspectives. However, the consistency of recognitions made by the human operator will be tested with additional human operators estimating their inter-agreement using standard statistical procedures.

4.3 System Sound Feedback

The feedback from the system to the user is necessary. We assume that the user's emotional response is much less distinctive, if he does not know how his/her social signals and gestures are interpreted than if he knows. This can lead to an unpleasant user experience and consequently to useless test results. Based on that, we decided on text-to-speech synthesis system for the Slovenian language [24] with predefined sentences. The system plays a sound feedback when human operator recognizes user's gestures or social signals. The texts for the test group of users are: *"I am offering you four diverse items."*, *"I am offering you three similar items."*, and *"I see you have chosen the item you like."* The texts for control group are: *"I am offering you three similar items."* and *"I see you have chosen the item you like."*

4.4 Video Selection Functions

The whole test scenario includes TV remote, mobile phone and video-on-demand system selection. We limit our experiment only to the video-on-demand sub-scenario. Video-on-demand simulates an event in the video rental store or at home. The user wishes to get a video but he is not sure which one. The support person provides him with four videos and he expresses an opinion. If he is not satisfied at all, it provides him with four completely new items. If he picks one out, that one stays on and three similar ones are added. This is repeated until a final selection is made. Therefore we need three video selection functions provided by conversational RS:

`[hA,hB,hC,hD] = getInitialItems(),` (2)

```
[hS,hA,hB,hC] = getSimilarItems(hS,h1,h2,h3),         (3)
[hA,hB,hC,hD] = getDiverseItems (hDi,h1,h2,h3).       (4)
```

Function (2) provides four videos for the first screen. It should diversely cover the whole matrix factorization space. Function (3) provides four videos that are similar to hS (selected video); one of them is hS. It narrows the search. Function (4) provides four videos that are not similar to h1, h2, h3 and h4. It expands the search. The function should diversely cover all factorized space of videos except those covered by h1, h2, h3 and h4. Distance metric that measures similarity among movies is based on matrix factorization space.

A conversational recommender system with no previous knowledge about the user is used. Functions `getInitialItems()`, `getSimilarItems()`, and `getDiverseItems()` based on matrix factorization feature space [25] of the LDOS-CoMoDa research dataset [17], [18]. We do not use all videos from the LDOS-CoMoDa dataset. Our subset contains over 300 videos (trailers of movies).

4.5 Role of Gestures and Social Signals

We use gestures to control the system and social signals to find out if the user is hesitating when selecting the content. Based on latter, the system expands or narrows the search. Therefore, there is only one social signal transmitted of two classes {hesitation, no hesitation} about the content the user sees. The absence of hesitation means that user is confident in his decision. In our case this is the same as the user is not hesitating. Social signal is used only to decide on diverse or similar new items.

The user uses gestures to pick up the best video or say I do not like them. With a gesture, the user also makes his first decision (select video-on-demand service) and final decision (select video he wants to watch).

4.6 Data Tracked During the Experiment

All the tracked data are stored in two files. The first includes the information about activities and social signals of the user recognized/extracted by human operator. We track the time when the activity/social signal starts and when it stops. In the second file, the feedback of the recommender system is stored. The whole interaction between user and system is also recorded. The inter-rater agreement of human operators will be tested based on these videos.

4.7 Inter-rater Agreement of Human Operators

The social signal of hesitation can be expressed in several different ways (with facial expression, head movement, shoulder movement, etc.). All forms of this kind of social signal are difficult to determine in advance so it is necessary to check the consistency of recognitions made by a human operator. We will use additional human operators who will estimate gestures and social signals based on a recorded video of user interaction. The result of test of inter-rater agreement will be presented with a coefficient of internal consistency (Cronbach's alpha).

4.8 Evaluation of the Impact of Social Signals

Evaluation of the impact of SS is based on comparison between the test and control group of users. These two groups of users will be tested in order to allow realistic estimation of effect size of the impact of social signals. Determination of the intensity of impact of social signals on user decisions in a user interaction with a system is the basic aim of this comparison.

In the test group of users, induced social signals during interaction with a communication device are taken into account. In control group of users, social signals are not taken into account. Our main task is therefore the determination of the size of the impact of social signals on a user's decisions during a communication scenario based on comparison between the test and control group of users. Comparison will be based on two questionnaires, one before interaction (pre-questionnaire) and one after interaction (post-questionnaire). For both of them, we will measure psychometric characteristics such as reliability and variability. If there is an impact of social signals on the user's decisions, the comparison between both groups of users must show the difference in contentment with the selected content, in contentment with the system, and in the user's interaction time with a system.

Pre-questionnaire consists of 17 questions and based on the 7-point Likert scale proposed in [26] and [27]. Post-questionnaire consists of 24 questions and like-wise based on a 7-point Likert scale.

5 Discussion

The expected result of the experiment is increase of statistically significant user satisfaction with a video-on-demand service when social signals are taken into account. Satisfaction may be reflected directly through faster selection of video or indirectly through results of the post-questionnaire. However, there are more factors that have an impact on user decisions, not only the social signals. We have included those factors that are expected to influence on QoE.

6 Conclusions

The proposed experimental design will be used for determination of the impact of social signals on user satisfaction with selected content and not on user's decisions or user's satisfaction with the system. The user selects among four videos projected on a screen. With simple gestures, he chooses only one. Together with gestures, the user also expresses social signals. Our work is focused on the social signal of hesitation. If the user is hesitating, the recommender system in the background offers him four diverse items according to the selected one. If not, the recommender system offers him three similar items. Most of evaluation is based on questionnaires. User fills in questionnaire before and after interaction. Tracked data about expressed social signals and gestures are also used for evaluation.

One of the advantages of the proposed design is the use of social signals in interaction. Consequently, this can increase user satisfaction with a video-on-demand system. Videos that are suggested to users are not selected randomly but recommended based on a recommender system that uses data from the LDOS-CoMoDa dataset. The next advantage is the use of an emotionally neutral video at the start of experiment. Based on that, we can get a more similar initial mood of the users.

The experiment is extremely sensitive to unknown or uncontrolled factors of a user's decision making process and that could be one of the drawbacks of the proposed design. The impact of the social signals will be measured based on a statistical analysis. A recommender system with no previous knowledge about the user is used. This is a realistic assumption for new system users with no applicable history of movie selections. The advantage of such a system is that the system is not provide additional uncontrolled parameters.

Our future plan is to implement described experimental design on a sufficiently large set of users. One of the future tasks could also be the testing of new groups of users where videos will be suggested randomly between functions that recommend similar and diverse items. This group will be compared with the control group of users where the similar items are always suggested. Based on the comparison, we can get the information regarding whether our assumption that the control group of users always gets the similar items is correct.

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