Towards an Empathic Social Robot for Ambient Assisted Living

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Abstract. In the context of Ambient Assisted Living, assistance and care are delegated to the intelligence embedded in the environment that, in our opinion, should provide not only a task-oriented support but also an interface able to establish a social empathic relation with the user. This can be achieved, for instance, using a social assistive robot as interface towards the environment services. In the context of the NICA (Natural Interaction with a Caring Agent) project we developed the behavioral architecture of a social robot able to assist the user in the interaction with a smart home environment. In this paper we describe how this robot has been endowed with the capability of recognizing the user affective state from the combination of facial expressions and spoken utterances and to reason on in order to simulate an empathic behavior.

1 Introduction

One of the new trends in the context of Ambient Assisted Living (*AAL*) concerns the integration of new technologies with a social environment to support people in their daily activities increasing their quality of life [1,2]. In this view, an assistive home environment should provide not only a task-oriented support but also an interface able to establish a social empathic relation with the user. This is what we call a "caring home". Achieving this objective, in our opinion, requires developing:

- *Methods and models for defining and developing Ambient Intelligence (AmI) systems for Assisted Living* that are able to define environments that manage devices and services autonomously and proactively with respect to the needs of the users populating the environment.
- *Methods and models for analysis of the user behavior* with particular emphasis on affective aspects in order to achieve personalization, adaptation and proactivity that are typical of an AAL system.
- *Natural Interaction of the user* with the information and services offered by the system. Such an interface has two fundamental and interconnected objectives: being a means to interact with the environment and being, for the user, a friendly caring agent. For this reason it is important to understand not only the meaning of the communication but also the conveyed emotions and the user's attitude during the interaction. This requires the emotional analysis of the user's verbal and non-

verbal communicative acts (i.e. linguistic and prosodic aspects of the user's vocal input, facial expressions, postures and gestures).

In the context of the NICA (Natural Interaction with a Caring Agent) project we developed the behavioral architecture of a social robot able to assist the user in the interaction with a smart home environment [3]. In this paper we propose the use of a social empathic robot acting as a virtual caregiver. In particular we discuss how it has been endowed with the capability of recognizing the user's affective state from the combination of facial expressions and spoken utterances and of reasoning on it in order to simulate an empathic behavior.

The choice of a social assistive robot as an interaction metaphor is driven by the following considerations. If properly designed, social and conversational agents and robots may improve the naturalness and effectiveness of the interaction between users and systems [4]. They have the potential to involve users in human-like conversations using verbal and non-verbal signals for providing feedback, showing empathy and emotions in their behavior [5,6]. Indeed, several studies report successful results on how expressive conversational agents and robots can be employed as an interaction metaphor in the assisted-living domain and in other ones [7,8] where it is important to settle long-term relations with the user [9].

Empathy can be defined as "an affective response more appropriate to someone else's situation than to one's own" [10]. Then the expression of empathy aims at demonstrating that the other's feelings are understood or shared. Moreover, according to [11], empathy facilitates the creation of social relations. Empathic agents are perceived as more caring and trustworthy than neutral agents [12] and they can induce empathy in users [13]. In particular, the simulation of empathy in socially assistive robotics is supported by the findings of many psychologists showing that empathy plays a key role for therapeutic improvement and that empathy mediates pro-social behavior (e.g., [14,10]).

Taking these findings into account, we decided to endow a social assistive robot with the capability of recognizing the user affective state and attitude, reasoning on it and, consequently, deciding whether to trigger an empathic behavior toward the user. Moreover, in order to improve the long-term relation between the user and the robot, it keeps in its social memory information about which are the antecedents of emotions for the user, that is what triggers the emotions (events, situations, thoughts, etc.) in order to improve its empathic capability. These behaviors have being modeled according to the analysis of a corpus collected by human caregivers.

The paper is structured as follows: after providing an overview of the related work in Section 2, in Section 3 we show how the empathic behavior is simulated in the robot; in Section 4 a brief illustration of a case study is described; finally we conclude the paper with discussion and directions for future work.

2 Related Work

The main aim of Ambient Assisted Living (AAL) is to improve the life quality of elderly people who need special care and assistance by providing cognitive and physical support and access to the environment services [15]. Many of these projects besides developing technological platforms to monitor the health state and comfort of the user, provide natural and pleasant interfaces for interacting with the smart environment services. Several studies report successful results on how expressive conversational agents and robots can be employed as interaction metaphor in the assisted living domain. For instance, projects *ROBOCARE* [16], *Nursebot* [17], *Care-o-bot* [18], *CompaniAble* [19] and KSERA [20] aim at creating assistive intelligent environments in which robots offer support to the elderly at home, possibly having also a companion role. van Ruiten et al. [21] conducted a controlled study using *I-Cat* [22] in which they confirmed the results that, as shown in [23], elderly users like to interact with a social robot and to establish a relation with it. The reason of the success of socially intelligent agents and robots is due to the fact that interaction between human and machine has a fundamental social component [24]. Thus endowing social agents with user models that involve the consideration of both cognitive and affective components of the user state of mind is a key issue for enabling the adaptation of the agents behavior to both physical and emotional user's needs, as in the case of the simulation of the empathic behavior.

As far as simulating empathic behavior in social agents is concerned, there are several studies that aim at evaluating the impact of empathy on the interaction and in particular on settling a social relation between the agent and the user [29].

Paiva [25] defines empathic agents as "agents that respond emotionally to situations that are more congruent with the user's or another agent's situation, or as agents, that by their design, lead users to emotionally respond to the situation that is more congruent with the agent's situation than the user's one ". In this view, Klein et al. [26] describe an experimental study aimed at evaluating interfaces that implement strategies for affectively supporting users experience with negative moods and emotions by showing empathy and by actively supporting them. Results show how the affect-support was effective in relieving the user negative affective states when interacting with the computer. Along this perspective we find the work by Prendinger et al. [27] that developed an embodied agent in the scenario of job interviews that is able to recognize physiological data of users in real-time, to interpret this information as affective states, and to respond to affect by employing an animated agent. Sabourin et al. [28] present a study about designing pedagogical empathic virtual agents in a narrative-centered learning environment. They adopt a cognitive model, structured as a Bayesian network, which includes personal attributes of users (i.e. personality and goals of students), environment variables (i.e. dynamic attribute capturing a snapshot of the student's situation and activity) and physiological data about the user behavior (i.e. biofeedback parameters such as heart rate or galvanic skin response).

Recently several projects on AAL are endowing assistant robots with social capabilities. In [30] the possible role of empathy in socially assistive robotics is discussed. Leite et al. [29] propose a multimodal framework for modeling some of the user's affective states in order to personalize the learning environment by adapting a robot's empathic responses to the particular preferences of the child who is interacting with the robot.

Looking in more details to human-robot interaction, several EU-projects have addressed the modeling, definition, and implementation of social and cognitive skills in Social Assistive Robots (SARs) [44,45,20]. In particular, in order to enhance human robot interaction, emotional behavior recognition and generation have also been developed for social robots. In literature, two different approaches can be found to address this issue: social robots as agents able to generate emotions in human - robot interaction and robots able to recognize emotions of the human partners and to consequently adjust their behaviors. We reported here some examples of both approaches by considering only a mobile humanoid robot, the NAO by Aldebaran [37].

In their work, Cohen et al. [38] proposed two robots, the NAO and the i-Cat, able to express recognizable emotions and compared the recognition rates of the emotions in the two cases. For both robots, recognition rates for the expressions were relatively high but they focused their attention on NAO robot considering its body and colored eyes to express recognizable emotions. Tielman [39] proposes a model for adaptive emotion expression for the NAO. The robot communicates these emotions through its voice, eye colors, posture and gestures. An experiment with 18 children and two NAOs was carried on to test the effect of adaptive emotions on robot-child interaction. In the experiments, the children played a quiz with both an affective robot using the model for adaptive emotion expression and a non-affective robot. The experiment results confirmed that children responded more expressively to a robot that adaptively expressed itself than to a robot that did not.

Others studies present robots able to recognize and generate emotions. In the work of Zhang et al. [42], Facial Action Coding System has been incorporated in order to describe physical cues and facial behavior useful for the detection of six basic emotions plus neutral from real-time and posed facial expressions. The system was implemented on NAO humanoid. In Lim et al. [40] a developmental robot able to understand and express emotions in voice, gesture and gait using a model trained with voice data was presented. The recognized emotions were happiness, sadness, fear and neutral. In experiments, authors assumed an adult-infant simple interaction based on 4 Japanese words for ‘hello’, ‘look’, ‘no’, ‘bye bye’.

Another important field of application are robotic tutors developed with the ability to perceive emotions experienced by learners, and to incorporate these into pedagogical strategies. In a recent study, researchers addressed the problem of creating empathic robot tutors to support school students studying geography topics on a multi-touch table. The NAO robot tutor was equipped with a game-specific AI player that allowed it to play any of the different roles in the game. The next steps will be to use the AI to generate appropriate commentary feedback from the robot in a way that it can seem empathic to the users while still portraying its tutor role [41].

Most of the previous works with empathy in robotics focused on the perception and impact of empathy on participant attitude towards the robot.

3 Simulating Empathic Behavior

The concept of empathy is related to the understanding of what is happening to the other person. Therefore, according to [46], a model for simulating empathy in a robot should be able to i) recognize the affective cues and the affective state of the user and ii) interpret the motivations that triggered that emotion, iii) answer by expressing its emotions (as a consequence of the recognized state) by using different modalities (voice, facial expressions, and body movements and gestures) since the combination of verbal and non-verbal communication provide social cues that make robots appear more intuitive and natural. Our first attempts towards simulating empathy with a socially assistive robot are based on the understanding of the emotions of others (i.e., human users). We have developed a simple vision-based facial expression detection system capable of identifying a basic set of facial expressions including smiling, frowning, sadness, anger, etc. The list of facial expressions our system is capable of detecting is a subset of the Ekman's six basic emotions on human facial expression: joy, sadness, fear, anger, disgust and surprise [51]. The recognition of facial expressions is combined with the analysis of speech-based communication. In particular the speech prosody is analyzed in order to recognize its valence and arousal.

3.1 Collecting a behavioral information from human caregivers

To define and implement feasible behaviors of the robot, we integrated data collected from human caregivers with the guidelines that they follow in assistance of elderly people. In particular two human caregivers recorded their experience during the assistance of two elder women, both affected by a chronic disease, for a period of one month. These women lived alone and had a son/daughter which could intervene only in case of need and for solving relevant medical and logistic problems. Data have been collected using a paper-diary on which the caregiver had to annotate two kinds of entries: (i) the schedule of the daily tasks and (ii) the relevant events of the day, using a schema like the one reported in Table 1.

Table 1 - Some entries from the caregivers' paper-diary

Time	Event	Signs	Reason	Action	Communicative action	Recognized affect	Effect
10.00	...	...	medical visit	I remind Maria about the appoint-ment with the doctor at 11.00.	Remind *Maria, I would like to remind you that today you have an appoint-ment with the doctor at 11.00 a.m..*	...	...
10.30	...	...	medical visit	I ask and help Maria to dress up.	Ask_for *Today is a wonderful day. You can put on your beautiful dress that you like so much!*	...	Maria is dressed
10.40	...	...	medical visit	I send a reminder to Maria's daughter about the medical visit.	...	...	The daughter answered that she is coming.

10.45	Maria is worried	Sit down, Moaning "Oh my… Oh my", Sad face	medical visit	I go toward Maria and try to console her.	Console *I'm sorry to see you so sad! You will see that everything will be all right*.	sadness	Maria is less sad

In particular, each row of the table represents a relevant event with the attributes for describing it and the action performed by the caregiver when this event occurred. For example, let's consider the 4th row: at 10.45 (*time*) Maria is worried (*event*). The caregiver inferred Maria's state since she was moaning, saying "Oh my, oh my" (*signs*) because she had to go to the doctor (*reason*). The caregiver recognized Maria's sadness (*recognized affective state*). Hence, she went toward Maria (*action*) trying to encourage her by saying "Come on, don't worry! You will not have any problem for sure." (*communicative action*). After this action she noticed that Maria was less sad (*effect*).

From the collected data, we extracted the knowledge needed to build the reasoning strategies of the agent, so as to make its behavior believable. Overall, we collected a corpus of about 900 entries, which we used for: i) understanding which are the events and context conditions relevant to goal and action triggering; ii) understanding when considering affective and social factors is important during the interaction in real-life scenarios; iii) defining situation-oriented action plans and dialogue strategies; iv) collecting example dialogues between elderly people and human caregivers useful for testing the robot behavior.

3.2 An overview of NICA Architecture

As described in [5], the approach that we adopted in designing the architecture of NICA consists in interfacing the agent's Body (for example Nao, Aibo, a conversational agent,…) with a Mind that, using several knowledge bases, reasons on which goal to pursue. NICA's Mind has been modeled as a **BDI** (Belief, Desire, Intentions) agent, whose behavior is driven by persistent goals [38].

Briefly, the agent has a mission stated in the list of its persistent goals that have to be pursued during the agent lifecycle. At each stage of its life cycle, the agent evaluates whether there have been changes in the environment or in the user's state that may threaten its persistent goals and cause a change in the planned behavior by triggering new goals and/or by modifying the scheduled actions.

At the present stage of development the agent considers a set of persistent goals related to the user's wellbeing, the execution of necessary actions of the user's daily routine, and so on. These goals correspond to the ones that human caregivers indicated as the most important ones in their daily assistance.

The agent implements a life cycle based on the following steps:

1. *Perception*: allows collecting data from sensors present in the environment and to handle the user input (speech, gestures, facial expressions or actions in the environment).
2. *Interpretation*: evaluates changes in the world and user state that are relevant to the agent's reasoning and transforms them into a set of agent's beliefs. In

particular it interprets the user's input.

3. *Goal Activation*: goals are triggered based on the current beliefs.
4. *Planning and Execution*: once a goal has been triggered it is achieved through the execution of a plan appropriate to the situation.

Although the agent can purse different persistent goals, since this paper focuses on how it reasons on the user affective state and how to trigger empathic behaviors in our examples we will consider the following goal as the most relevant one:

(BEL A NOT(Is(U, Negative(affective_state)) - "The Agent A has to belief that the user U is not in a negative affective state".

This means that NICA has to believe that the user is not in a negative affective state. As illustrated in Figure 1, in order to check whether this goal has been threatened the agent has to:

i) interpret the user's communicative actions expressed through speech and facial expressions;

ii) in case of expression of an emotion, recognize it and react emotionally to it;

iii) trigger a goal accordingly;

iii) achieve this goal through a communicative plan ("what to say") that can then be rendered as a combination of voice and animations of the agent's body ("how to say") [35];

iv) keep in its social memory information about which are the antecedents of emotions for the user, that is what triggers the emotions (events, situations, thoughts, etc.).

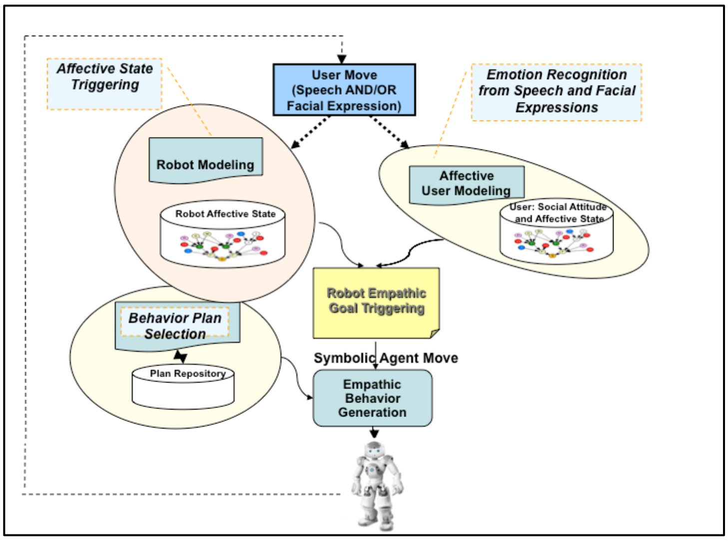

Fig. 1. A schema illustrating the triggering of the empathic behavior in the robot.

The social memory is used to remember relations about events and the user's affective state. The importance of this piece of knowledge in the agent's mind is related to the need of establishing empathy with the elder person by remembering relevant data and this requirement was outlined several times by the human caregivers during the data collection phase.

As far as reasoning is concerned, in order to deal with the uncertainty typical of this domain (e.g. dealing with exceptional situations or with the smooth evolution of the user's affective state over time), we employ probabilistic models to reason on the user and to decide which behavior to adopt, that is the most appropriate set of actions to perform for satisfying the inferred user's goal.

At the present stage of the project, we simulate the interaction between the agent and the user by embodying NICA's Mind in the Nao robot. We adopted the approach proposed by Johnson et al. [43] to simulate emotion through Nao eyes by combining specific LED color patterns (Fig. 2).

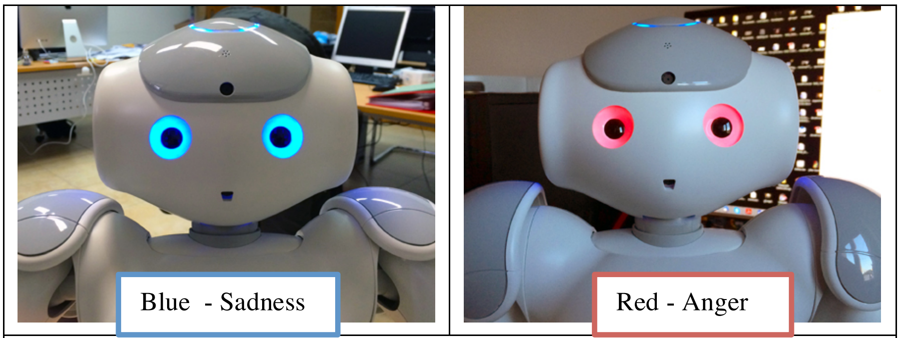

Fig. 2. A simulation of two emotion expressions with Nao.

3.3 Recognizing the User Affective State

In the current prototype of the system, we use a simple vision-based facial expression detection system capable of identifying a basic set of facial expressions in order to recognize the emotions of the human users. The list of facial expressions our system is able to detect is a subset of the Ekman's six basic emotions on human facial expression. The facial expression recognition system we adopted is fully automatic and, considering four-class expressions classification, the recognition rates we achieved were 82%, 76% and 95% using respectively Multi-SVM, k-Nearest Neighbors and Random Forest.

As far as spoken interaction is concerned, we employ VOCE (VOice Classifier for Emotions) a module that classifies the valence and arousal in the voice prosody. Our classifier follows an approach similar to [33,34]. In particular, the valence dimension is classified from positive to negative along a 4-point scale (from 1=very negative to 4=positive). Arousal is classified in a 3-point scale from high to low.

As far as the valence classification is concerned, the accuracy of the C4.5 algorithm is 83.12%, very close to the one of the K-NN that is 82.45%. As far as the arousal is concerned, C4.5 has an accuracy of 79.8% while the one of K-NN is 83.63 (validated using a *10 Fold Cross Validation* technique).

3.4 Reasoning on the User's Affective State

In our model of empathy for a virtual caring robot we start from the *recognition of the user's affective state for monitoring the belief* associated to this emotional state. In this way, during its lifecycle, the agent evaluates whether it is appropriate to trigger an affective communicative goal aimed at triggering the empathic behavior.

The robot's beliefs about the user's affective state are monitored with a dynamic model based on Belief Network (DBN) [32]. In fact, when modeling affective phenomena we must take into account the fact that affective state smoothly evolve during the interaction, from one step to the subsequent one and the state at every time of the interaction depends on the state it assumes in the previous turn. For this reason, the DBN formalism is particularly suitable for representing situations that gradually evolve from a dialog step to the next one. Moreover, Belief Networks are a well-known formalism to simulate probabilistic reasoning and deal with uncertainty in the relationships among the variables involved in inference process. The DBN model is shown in Figure 3. The model is employed to infer which is the most probable emotional state the user is experiencing at every step of the interaction by monitoring speech and facial expressions and it is also used to monitor the overall evolution of the user's affective state (i.e. the belief of the agent about the positive or negative affective state of the user). In the model this is expressed by a temporal link between the *Bel(AffectiveState)Prev* and the *Bel(AffectiveState)* variables. At present we consider only a subset of the affective states that can be relevant for the generating an empathic response: sadness, happyness and anger.

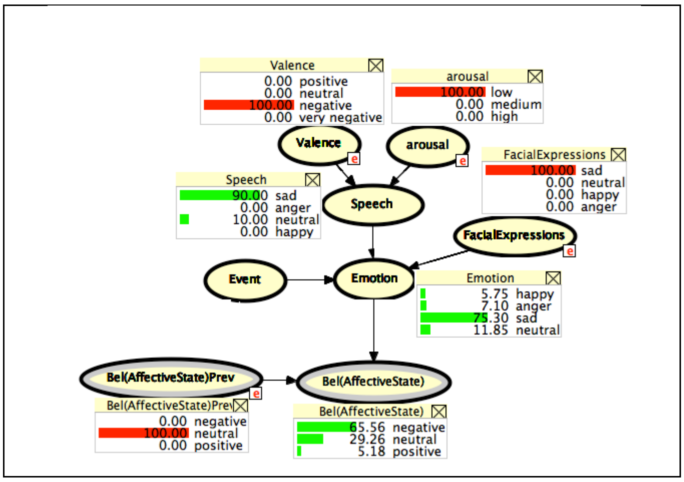

Fig. 3. The DBN model of the agent's beliefs about the user affective state.

In particular, every time a new user move is entered, its acoustic features are analyzed and the resulting evidence are introduced and propagated in the network to recognize the user's emotion and the overall polarity of her affective state. The same happens for the facial expression recognition module. The new probabilities of individual emotions are read and contribute to formulate the behavior of the agent; the probability of the dynamic variable (Bel(AffectiveState)) representing the valence of user's affective state is employed by the agent to check the consistency between its persistent goal of maintaining the user in a positive or neutral affective state and the actual emotional state the user is in at the time ***t***, thus causing the activation of the empathic goal.

3.5 Emotion Activation in the Robot's Mind

In order to activate an affective state in the robot for triggering affective goals we revised the emotion modeling method that we employed in another project [47]. The model is based on event-driven emotions according to Ortony, Clore and Collin's (*OCC*) theory [48]. In this theory, *positive* emotions (happy-for, hope, joy, etc.) are activated by *desirable* events while *negative* emotions (sorry-for, fear, distress, etc.) arise after *undesirable* events. In addition we considered also Oatley and Johnson-Laird's theory in which positive and negative emotions are activated (respectively) by the belief that some goal will be achieved or will be threatened [49]. In the context in which we employ the robot, we consider emotions in the *Well-being* category (joy, distress) and those concerning the *FortuneOfOthers* category (happy-for, sorryfor). Then, the cognitive model of emotions that is built on these two theories should represent the system of beliefs and goals behind emotion activation and endows the robot with the ability to *guess the reason why she feels a particular emotion and to justify it*.

The model of emotion activation is also represented with a DBN since we need to reason about the consequences of the observed event on the monitored goals in successive time slices. We calculate the intensity of emotions as a function of the *uncertainty* of the robot's beliefs that its goals will be achieved (or threatened) and of the *utility* assigned to achieving these goals. According to the utility theory, the two variables are combined to measure *the variation in the intensity of an emotion* as a product of the change in the probability to achieve a given goal, times the utility that achieving this goal takes to the robot.

Let us consider, for instance, the triggering of *Sorry-for* in the robot's model that is represented in Figure 4. This is a negative affective state and the goal that is involved, in this case, is *preserving others from bad*. In this figure R denotes the robot and U the user. The robot's belief about the probability that this goal will be threatened (Bel R (Thr-GoodOf U)) is influenced by his belief that some undesirable event E occurred to the user (Bel R (Occ E U)). According to Elliott and Siegle [50], the main variables influencing this probability are the desirability of the event (Bel R not(Desirable E)) and the probability that the robot attaches to the occurrence of this event (Bel R (Occ E U)). The user moves are interpreted as *observable* consequences of occurred events, that activate emotions through a model of the impact of this event on the robot's beliefs and goals. The user may say that a not desirable event occurred to him and may feel sadness or distress (Feel U(emotion)) that denotes that the event is undesirable. The probability of this node to be true depends on the emotion node in the network in Figure 3. This influences R's belief that U would not desire the event E to occur (Bel R Goal U ¬(Occ E U)) and (since R is in a *empathy* relationship with U, R adopts U's goals), its own desire that E does not occur (Goal R ¬(Occ E)). This way, they concur to increase the probability that the robot's goal of *preserving others from bad* will be threatened. Variation in the probability of this goal activates the emotion of *sorry-for* in R.

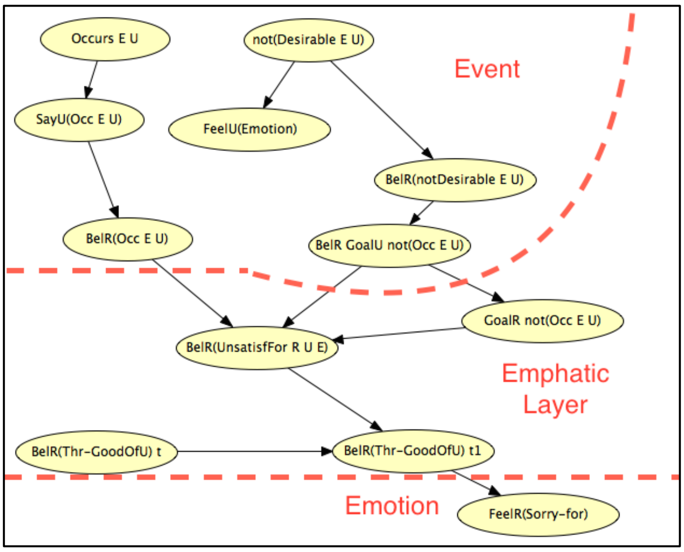

Fig. 4. A portion of the DBN representing the robot's mental state for the triggering of Sorry-For

The intensity of this emotion is the product of this variation times the *weight* the robot gives to the mentioned goal. The strength of the link between the goal-achievement (or threatening) nodes at two contiguous time instants defines the way the emotion, associated with that goal, decays, in absence of any event affecting it. By varying appropriately this strength, we simulate a more or less fast decay of emotion intensity. Different decays are attached to different emotion categories (positive vs. negative, FortuneOfOthers vs. Wellbeing and so on) and different temperaments are simulated, in which the *persistence* of emotions varies.

3.6 Triggering Empathic Behavior in the Robot

In order to decide how to behave as a consequence of the triggering of an emotion in the agent state of mind the agent triggers an affective goal. The list of empathic goals is inspired by the indications that human caregivers gave us during the data gathering phase at the beginning of the project, by the literature of empathy and pro-social behavior [29] and by the results of another study on the influence of empathic behaviors on people's perceptions of a social robot [21].

Currently, the empathic goals are the following:

- *console* by making the user feel loved and cuddled;
- *encourage* by providing comments or motivations like for example " don't be sad, I know you can make it!"
- *congratulate* by providing positive feedback on the user's behavior;
- *joke* by doing some humor in order to improve the user's attitude;

- *calm down* by providing comments and suggestion to make the user feel more relaxed.

For instance in case the *sorry-for* emotion is felt by the robot, the *console* goal should be triggered. Once a goal has been selected as the most appropriate to the emotion felt by the agent, the behavior planner module computes the agent behavior using plans represented as context-adapted recipes. Each plan is described by a set of *preconditions*, the conditions that have to be true to select the plan, the *effect* that the plan achieves and the *body*, the conditional actions that constitute the plan. After the execution of each action in the plan, the correspondent effect is used to update beliefs in the agent's mental state.

A sample of a portion of plan used to achieve the Console goal is the following:

```
<Plan name="Console">
<SelectCond> <Cond var="affective_goal" value="console"/></SelectCond>
<Body>
        <Act name="Move" to="U"/>
        <Cond var="Feel(U,Sad)">
        <Act name="Express" to="U" var="Sorry-for(R,U))"/>
        </Cond>
        <Cond var="Know_Reason" value="0" >
        <Act name="Ask" to="U" var="Why(U,Feel(U,Sadness))"/>
        </Cond>
        <Cond var="Know_Reason" value="1">
        <Act name="Inform" to="U" var="Understand(R,U)"/>
        </Cond>
        <Act name="Express" to="U" var="Console(R,U)"/>
        … … …
</Body>
</Plan>
```

The tag <Cond> allows selecting actions on the basis of the current situation.

For instance, the action <Act name="Express" to="U" var=" Sorry-for(R,U)/> is used to express the sorry attitude of the robot R and will be performed only if the user feel sad. In the same way, the action "Ask" about "Why the user is sad" will be performed only if the agent does not know why the user is in the current state. Moreover, if the action is complex, then it can be specified in a subplan describing elementary agent actions. Each communicative act in the plan is then rendered using simple template-based surface generation technique [35]. These templates are selected on the basis of the type of communicative act and its content and are expressed in metalanguage [36] that is then interpreted and executed by the agent's body. Plans and surface generation templates have been created and optimized combining actions on the basis of pragmatic rules that were derived from the corpus dataset.

4 A Case Study

In this section we show an example of an empathic behavior of the agent in a typical interaction scenario that we envisaged as a suitable one for testing our agent framework.

It's morning and Nicola, a 73 y.o. man, is at home alone. He doesn't feel very well since he has a cold and fever. Nicola is sitting on the bench in his living room that is equipped with sensors and effectors. According to the situation the smart environment selects a workflow and starts to execute scheduled tasks accordingly. The caring robot has to check Nicola's health state and recommend him to take some medicine. After a while Nicola starts whispering and says with a sad facial expression: "Oh My …oh poor me…". This is perceived by the robot that interprets it and activates the most appropriate behavior.

The voice classifier recognizes a *negative* valence with a low arousal from the prosody of the spoken utterance and the facial expression classifier recognizes the *sadness* emotion. These evidences are propagated in the DBN and the belief about the affective state of the user is in a negative affective state with the higher probability (65.56), as shown in Figure 3. Then, since the goal of keeping the user in a state of well-being is threatened, the DBNs modeling the robot's affective mind are executed to trigger the robot's affective goal (sorry-for in this case). As described in the previous section, the goal to pursue in this situation is the "console" one. Then, the correspondent plan is selected (see previous section) and the execution of its actions begins. The plan includes the following actions since the agent does not know why the user is sad and it will ask the user about it:

```
MoveTo(NAO,NICOLA)
Express(NAO,Sorry-
for(NAO,NICOLA))
Ask(NAO,NICOLA,Why(Feel(NICOLA,Sa
dness)))
Express(NAO,Console(NAO,NICOLA))
```

Fig. 5 A simulation of the scenario with an elderly person.

When a new belief about the event that occurred to the user related to a particular affective state is acquired by the robot during the interaction, it is stored in the agent Social Memory. In this way the robot will remember which event causes a particular affective state in the user, for instance the event "has_disease" is associated to the affective state "sadness". This information can be used by the agent in the dialogue with the user for preventing this state or for improve the relation between the user and the robot.

5 Discussion and Future Work

This paper presented issues concerning the importance of taking into account affective factors when modeling the user in social interaction with a caring agent. In our opinion, besides assisting the elderly user in performing tasks, the agent has to establish a social long-term relationship with the user so as to enforce trust and confidence.

The underlying idea of our work, in fact, is that endowing the robot with a social empathic behavior is fundamental when the devices of a smart home are integrated pervasively in everyday life environments. In this paper we illustrated how this capability has been designed and implemented in a caring assistant for elderly people.

Evaluating the efficacy of the empathic behavior of the social robot in a real-context at the moment is not feasible due to the lack of enough smart homes equipped with social robots. Therefore, we performed a quantitative evaluation of the decisions and plans executed by the agent compared to the behaviors of the human caregivers that we annotated in a previous phase of the project. To this aim we randomly split our corpus into 70/30 training/test partitions. For each item of the test set, we formalized the corresponding scenario in order to set the evidences in the simulation test. Then, we observed the robot's behavior in terms of selected communicative acts: the behavior of the robot was classified as 'correct' if it matched the choice of the human caregiver, as 'incorrect' vice versa. Results of the evaluation are encouraging and indicate that the system performance is quite good since the choices of the agent match the human actions in the dataset in the 79% of cases. We are aware that it is important to conduct an evaluation study with real elderly users. This kind of experiment should aim at assessing the impact of the use of a social robot vs. seamless interaction with the environment services in smart environments. Another important issue to be addressed in our future work concerns the interpretation of gestures and postures of the user.

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