

A Neuro-Fuzzy-Bayesian Approach for the Adaptive Control of Robot Proxemics Behavior

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Abstract—A robotic system that is designed to coexist with humans has to adapt its behavioral and social interaction parameters not only with respect to the task it is supposed to accomplish, but also with respect to the human being it is interacting with by profiling her habits, preferences, and personality. This is particularly relevant in the domain of assistive robotics where the behavioral adaptability has been shown to enhance the users’ acceptability of a robot. In this work, we propose a neuro-fuzzy-bayesian system able to adapt the robot proxemics behavior with respect to the human users’ personality and the action she is currently performing. The user’s personality is evaluated according to the Big-Five factors model and the activity recognition is obtained by classifying data from a wearable device through the use of a Bayesian Network classifier. As shown by a statistical study, the proposed framework is capable of computing the most appropriate robot proxemics behavior in order to improve human feeling in interacting with artificial agents, such as robots.

I. INTRODUCTION

For acceptance of robots to occur, there are three basic requirements: a motivation for using the robot, sufficient ease of use, and comfort with the robot physically, cognitively and emotionally [1]. Current research shows that the majority of people are still skeptical or even against the application of robots in real contexts, and, in particular, for child, elderly and disabled care [2]. In this direction, research suggests that a robot’s ability to adapt its behavior with respect to a user profile (e.g. to the user’s preferences on the social aspects modeling the interaction) can improve acceptability [3]. The possibility of modeling such interaction preferences in order to modulate the robot behavior has been shown to have a great impact on the robot acceptance by the user as well as to provide a feeling of safety [4]. Conversely, an interactive robotic device whose behavior is unrelated to the specific needs of a person, her abilities and preferences can cause discomfort [5].

The majority of robotic applications are based on user static models and contexts of interaction [6]. This makes such systems incapable of adapting independently and proactively to changes in the users needs and preferences. More generally, such assistive technology products do not take into account the cognitive and personality characteristics (including specific deficit of an individual, emotional and behavioral problems,

the attitude towards technology and the physical and social environment), which could affect the acceptance, use and effectiveness. A valid robotic system providing a high degree of user acceptance must be based on knowledge of the potential users, as well as contextual information on the user current behavior, that provide essential parts of effective planning and customization of the assistance process. However, the typical uncertainty and vagueness that characterise a human profile make the design of adaptive robotics frameworks very hard to be successfully achieved and, consequently, there is a strong emergence for computational techniques useful for dealing with this gap in an appropriate way. Neuro-Fuzzy frameworks could represent a suitable approach for enabling robots to be tolerant with human ambiguity and make human-robot interaction (HRI) as a more natural and adaptive to humans’ needs and preferences.

In a previous work [7], we showed, with an user study, that the perception of comfortable interacting distances by the user is affected by users’ personality factors, as well as the current users’ activity. In this paper, our goal is to design a robotic control system able to adapt the robot proxemics behavior, and, in particular, the distance a robot has to keep in order to interact with a user, with respect to her current data on the activity and the personality. In spite of its apparent simplicity, robot proxemics behavior is one the most challenging and fascinating issue in the field of cognitive robotics. Indeed, as robots are accessing the everyday physical world of people, it is very important that they abide by society’s unspoken social rules such as respecting people’s personal spaces [8] so as not to affect the feelings of fear and confidence that people can have towards the robots. In this paper, a Neuro-Fuzzy system will be integrate into a human-robot interaction framework to prove the efficiency of this methodologies in modeling a robot proxemics behavior that is adaptive with respect to human activities and personalities. The proposed system is characterized by a two-layer architecture, where a first level, based on a Bayesian Network, will be used to perform the human activity recognition process and a second Neuro-Fuzzy layer will be used to correlate the classified current activity with the user’s personality and testing condition to infer the most comfortable stopping distance for the particular user.

As shown by a statistical study, the proposed framework for human-robot interaction is capable of computing the most appropriate stop distance in order to guarantee a comfortable interaction.

II. RELATED WORKS

The correlation of acceptable social distances with the user personality has been addressed before in the literature. For example, [9] studied the impact of personality on human-robot mutual distancing, while [7], [10] examined the effects of the subject's personality and her position, namely sitting or standing, on the preferred stopping distance and on the robot approaching direction. Here, the goal of this paper was to rely on this data (and, in particular, on [7]) to model a robot proxemics control mechanism able to show an adaptive behavior.

Studies on proxemics and on the recognition of user's pose and movements in the environment may help in developing adaptive behaviors for robots, in particular in the context of service robotics. For example, in [11], starting from the analysis of data on service staff members collected in a shopping mall, the authors propose a robot that can adapt its approaching behavior depending on a visitor's intention. The goal is to not disturb visitors until it is clear that they intend to interact with the robot. Hence, the robot modulates its behavior by orienting toward visitors and waiting, when their intentions are not certain, and by moving towards them, when their intentions are perceived as willing to interact. Another example is [12], where the authors used proxemics data, in terms of general preferences and robot predictions on the user state for deciding to move to a better position to maximize the potential for its performance in the interaction. In particular, the robot detects the inter-agent pose that could be used to predict how loudly the user will likely speak and so the performance of the speech recognition process. In the presented work, preferences of proxemics are combined with the current activity of the user to model the robot behavior.

Finally, in literature, adaptivity with respect to personality has been approached mainly from the point of view of the robot intrinsic personality, and the way it can affect the robot behavior or the user's perception. For example, in [13] the authors presented the results of different experiments where each of the children has various game session with a robot that chooses its personality: extrovert or introvert. In these experiments, an extrovert robot challenges players and moves faster, while introvert robot moves slower, encourages and comforts with many positive comments the player. On the contrary, in [3], the authors presented a behavior adaptation system, characterized by a hands-off therapist robot, which adjusts its therapy style behavior basing on users' introversion-extroversion personality traits. The system was tested in a rehabilitation domain and resulted in user improvements of the exercise task performance.

Different from state-of-the-art systems, in this paper, we introduce a novel robotics framework based on the integration of methodologies such as neural networks, fuzzy logic and

bayesian classifiers, able to directly deal with intrinsic uncertainties characterising human personalities and daily activities. Thanks to this synergic vision, robots will be able to better approach human beings without affecting their feelings of fear and confidence.

III. ROBOT PROXEMICS BEHAVIOR: PROBLEM DESCRIPTION

The customization of the interaction is one of the fundamental issues to tackle in order to achieve effective HRI applications [14]. In particular, the proxemics, e.g., the study of spatial distances used in the interaction by human and/or robot agents, is one of the main topics since people react and behave differently depending on how their space is occupied. Examples of behaviors requiring the proper modulation and adaptation of proxemics parameters are the approaching behaviors, but also the following or avoidance ones.

Previous studies have established that the proxemics behavior of the robot has a strong impact on the level of the users' acceptability and it strongly depends on subjective and demographic characteristics. Among the fundamental aspects to characterize a user, there is the personality. Personality is a key determinant in human social interactions, since there is a direct relationship between personality and behavior [15]. Personality factors, in particular, affect the way in which public spaces are shared and the perception of socially acceptable movements. Thus a robot should be able to perform the same actions, but in a different way depending on the personality of the person, whom it interacts with.

Moreover, while the user personality can be considered as characterized by stable attributes in time, the effectiveness of the robotic interaction should also consider context depended characteristics of the users that have to be evaluated and recognized from time to time, and that may have potentially an impact on whether the user is willing to interact and, consequently, on proxemics decisions. In particular, the effective recognition of the user activity constitutes an enabling technology in order to develop effective HRI applications, since users may not want to interact while being occupied in particular activities, and their own movements may have an impact on perceived conformable distances [7].

While, our long term goal is to dynamically adapt a robot user's monitoring behavior with respect to a more complete user's profile, here, we are interested in providing an adaptive control mechanism with respect to both the user personality (that can be evaluated by using questionnaires) and the activity she is currently performing (that are evaluated with an online recognition mechanism). In particular, the proposed architectures aims to decide the comfortable monitoring distances starting from data collected in a previous work [7], where we evaluated the preferred stopping distance with respect to both the activity and the personality. Data for the activity recognition process will be extracted from wearable devices (e.g., wristbands, wristwatches, armbands), that represent an non-intrusive way to monitor the user and that can provide a

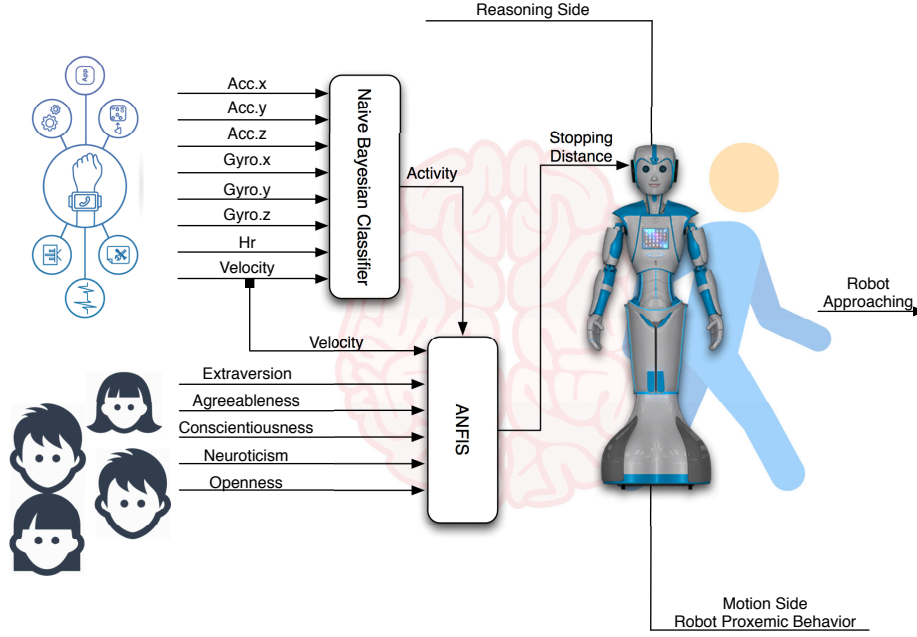


Fig. 1. The architecture for a robotic control system aimed at deciding the robot comfortable stopping distance for the users

fast sampling of human motion including acceleration, angular rate, and magnetic field [16].

The next section is aimed at introducing a proposal for a Neuro-Fuzzy-Bayesian framework for identifying suitable robot proxemics behavior that adapts to the inherent imprecision that characterize human personality and daily activities.

IV. A NEURO-FUZZY-BAYESIAN SYSTEM FOR ROBOT PROXIMIC BEHAVIORS

Our proposal for a robotic control system able to adapt the human-robot comfortable stopping distance with respect to the activity the user is performing and her personality is based on a hierarchical architecture which combines the Adaptive Neuro Fuzzy Inference Engine (ANFIS) [17] with a Naive Bayes (NB) classifier. Precisely, the hierarchical architecture of our proposal is characterized by two layers: 1) the bottom level uses a NB classifier to recognise the activity the user is performing; 2) the top level uses ANFIS to infer the most comfortable stopping distance for the particular user starting from her personality and the activity recognised by the bottom level. Figure 1 shows the architecture of our robotic control system. Hereafter, more details about the two layers are given.

A. Bottom layer: activity recognition

The bottom layer of our robotic control system is devoted to identify the activity the user is performing. In order to achieve this aim, it exploits a usual classifier, i.e., Naive Bayes (NB) classifier. NB classifiers are a family of simple probabilistic classifiers based on applying Bayes' theorem with strong (naive) independence assumptions between the features. However, they have good performance also if the independence assumptions are wrong. In this work, we use a

NB characterized by a kernel density method. The choice of this method is tied to unknown nature of the data. Indeed, the absence of prior knowledge about data leads to believe that the considered features will not conform to a certain parametric distribution, and, as a consequence, using a non-parametric probability distribution could fit data more accurately.

The features used by the exploited NB classifier to identify the user activity are eight (Acc.x, Acc.y, Acc.z, Gyro.x, Gyro.y, Gyro.z, Hr, Velocity). The first seven inputs are captured through three sensors whose a smart watch worn by the user is equipped. In particular, Acc.x, Acc.y and Acc.z represent, respectively, the three coordinates X, Y and Z of the acceleration measure in g units provided by an accelerometer. Gyro.x, Gyro.y and Gyro.z represent, respectively, the three coordinates X, Y and Z of the angular velocity provided by a gyroscope. Hr represents the heart rate of the user provided by a heart rate monitor. Finally, Velocity represents the velocity assumed by the robot while approaching the user in order to interact.

B. Top layer: stopping distance computation

The top layer of our robotic control system is devoted to produce the stopping distance to be used by a robot during the interaction with a user. In order to achieve this aim, it exploits ANFIS to build a Takagi-Sugeno-Kang (TSK) fuzzy inference system able to control the stopping distance in an opportune way.

ANFIS is an adaptive network and, as such, it works to achieve a desired input-output by updating parameter sets according to given training data and a gradient-based update procedure [17]. In particular, this updating feature is used in

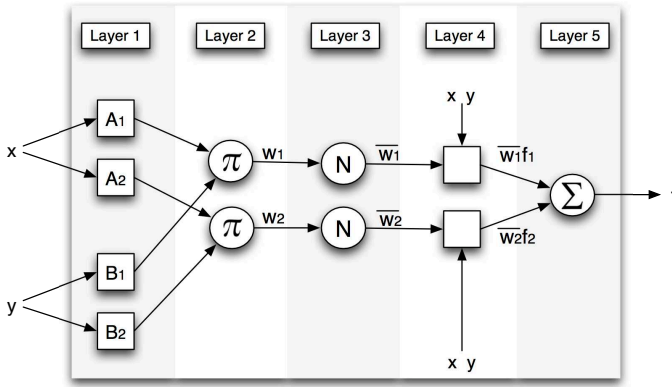


Fig. 2. The Adaptive Neuro Fuzzy Inference System [17]

ANFIS to learn and adapt the parameters of a given TSK system.

As example, Figure 2 shows an adaptive network that models a first-order TSK fuzzy inference systems composed by two rules:

- 1) If x is A_1 and y is B_1 Then $f_1 = p_1 \cdot x + q_1 \cdot y + r_1$
- 2) If x is A_2 and y is B_2 Then $f_2 = p_2 \cdot x + q_2 \cdot y + r_2$

ANFIS works by updating an initial TSK during a set of epochs. In this work, we execute ANFIS for 5 epochs with an initial TSK whose input variables are characterized by gbell membership functions.

The inputs used by ANFIS are seven (Velocity, Activity, Extraversion, Agreeableness, Conscientiousness, Neuroticism and Openness). The first input is related to the robot, whereas, the other ones are related to the user. In particular, Activity represents the activity performed by the user and identified through the bottom level system. Instead, Extraversion, Agreeableness, Conscientiousness, Neuroticism and Openness represent aspects of the personality of the user obtained through a questionnaire filled by the user.

During the design, the input variables are considered be characterized by three gbell membership functions, except for the variable Activity that has been considered with four membership functions since the user can perform four kinds of activities (lying, sitting, standing and walking).

V. EXPERIMENTS

This section is devoted to show the benefits of the proposed hierarchical approach to HRI. In order to achieve this aim, in a previous work [7], an experimental session has been performed in order to collect training and test data. All details related to this experimental session are reported in Section V-A. Once collected data, the proposed approach has been evaluated through a set of metrics described in Section V-B. The results of the proposed approach in terms of the considered evaluation metrics are reported in Section V-C.

A. Experimental session configuration

a) *Participants*: The subject sample set consists in 50 adult volunteers that were not paid for the participation. In

detail, 37 men and 13 women with an average age of 27 ± 9 . Most of the participants were master students, for the majority of the cases in Computer Science. They were all Italian, and 38% of the participant, in the average, declared not to have confidence with robotics applications (e.g., by answering YES/NO to a specific question). The sessions lasted on average 15 minutes.

b) *The Robot*: The robot used for the experimentation was a Pioneer 3DX with a 16 sonars range. The robot was opportunely modified in order to have a kinect at the height of 1.3m and a tablet at the height of 1.1m. The robot is shown in Figure 3 (right). The robot behavior was controlled in a Wizard of Oz mode.

c) *Data collection*: For the activity recognition phase, the Microsoft Band 2 was used. The users wearing this smart watch were monitored through an app installed on a smartphone. The sensors of the smart-watch send the measured data to the proposed control system for the activity recognition, while a supervisor manually annotated with a label each activity (lying, sitting, standing and walking). The sensors used for the activity recognition are: Accelerometer, Gyroscope, Heart rate. The accelerometer provides the acceleration measures in g units in three coordinates X, Y, Z at 62 Hz. Gyroscope provides angular velocity measured in three coordinates X, Y, Z at 62 Hz. Heart rate provides the number of beats per minute at 1 HZ.

Personality was classified with respect to the BFI (Big Five Inventory), as in [18], in terms of Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness. We used the BFI questionnaire reported in [19], where users were asked to define a certain number of characteristics that may or may not be applied to themselves, by associating a rate from 1 (Disagree Strongly) to 5 (Agree Strongly) to each question. The scoring analysis of the results will provide the personality evaluation calculated through specific formulas that relate these answers with personality traits, and it will generate the membership with a certain percentage to one of the 5 possible traits.

d) *Procedure*: The design of this study is a within-subjects, counterbalanced, repeated measures experiment. That means that each participant is subjected to more than one experiment under different conditions (activity to perform) and that these settings are randomly presented to her.

Following the work of [9], we designed the experimental procedure as follows:

- 1) *Co-habitation and Personality*: the user enters to a room (an empty lab) and sits on a sofa while answering the personality and demographic questionnaire on a laptop. While the subject is filling in the questionnaires, the robot wanders randomly around the test area.
- 2) *Test*: The user is asked to perform one of the following activities: lying, sitting, standing and walking. The order of the activity is randomly established for each user. During each activity the robot, starting from a predefined position, approaches the person with an approaching angle of 90 degrees. The users are asked to stop the robot

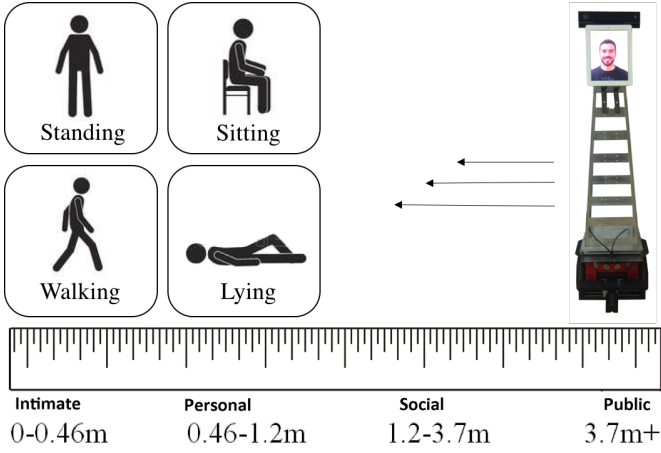


Fig. 3. Data collection: the considered activities and the used robot (right). Proxemics distances scale is set according to [20].

(by saying the word “STOP”) when the robot comes as close as they felt is comfortable. Whenever the user stops the robot, the distance from the user is stored and the robot stops.

An operator supervised each test. Each experiment was also repeated three times, with different robot velocities, as consistency check.

B. Evaluation procedures

Once collected data, we perform a ten-fold cross-validation procedure in order to evaluate the performance of the proposed approach. This procedure consists in dividing data in 10 folds. Of these 10 folds, in each round, a single fold is used as test data and the remaining ones are used as training data. The exploitation of this technique allows to assess how the performance results of our proposal will generalize to new data sets.

As for performance metrics, since we are dealing with a regression problem, we consider the well-known Root-Mean-Square Error $RMSE$. This metric is a frequently used measure of the differences between values predicted by a model and the values actually observed. The formal definition is as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{n}} \quad (1)$$

where y is the vector of the observed values, $\hat{y}$ is the vector of the predicted values and n is the length of the vector y .

In order to compute an evaluation independent from the unit/scale of the output variable, we consider together $RMSE$ other two evaluation metrics: Normalized Root-Mean-Square Error $NRMSE$ and the Coefficient of Variation of the $RMSE$ CV_{RMSE} . Formally,

$$NRMSE = \frac{RMSE}{y_{max} - y_{min}} \quad (2)$$

where y_{max} and y_{min} are respectively the maximum and the minimum of the vector of the observed values.

$$CV(RMSE) = \frac{RMSE}{\mu(y)} \quad (3)$$

where $\mu(y)$ is the mean of the observed values.

In order to give a statistical significance of the performance of the proposed approach, we use a statistical test to verify if an equivalence between the observed and predicted values exists. A typical equivalence test is Schuirmann’s two one-sided test (TOST) [21], but it cannot be used in our context, because our data do not follow a normal distribution. Unfortunately, there is not a well-known equivalence test for non-parametric context¹, but TOST test can be replaced² by Wilcoxon’s signed rank test [22]. This test is used to compare two related samples and to assess whether their population mean ranks differ. Therefore, in Wilcoxon’s test, the null hypothesis states no difference between samples, i.e $H_0 : \Theta_D = 0$, indicating that in the underlying populations represented by the two samples, the median of the difference scores is equal to zero [23]. On the contrary, the alternative hypothesis is $H_1 : \Theta_D \neq 0$. Once computed the Wilcoxon’s statistic by ranking differences between the two samples, a p -value can be performed by means of the normal approximation for the statistic. If the p -value is lesser than the used level of significance α , the null hypothesis is rejected in favor of the alternative one. Since we use the Wilcoxon’s test to assess equivalence between the observed values and those predicted by our model, the null hypothesis is expected not be rejected.

In the next section, the performance of the proposed approach in terms of the considered evaluation metrics and the results of the Wilcoxon’s test are reported.

C. Results

Table I shows the performance of the proposed approach in terms of $RMSE$, $NRMSE$ and CV_{RMSE} and the computed p -value for each round of the cross-validation procedure. By analyzing the Table I, $RMSE$, $NRMSE$ and CV_{RMSE} averaged on the ten considered folds are 0.3188, 0.0873, 0.3425, respectively. By taking into account the $RMSE$ value, it is possible to state that the proposed control system allows the robot to stop itself to a distance by a user that deviates, on average, from the distance desired by that user by about 0.32 m. This amount of error is less than the 10% of the size of the range containing the users’ desired distances collected during the experimental session (see Section V-A), as described by the $NRMSE$ value. The proposed robotic control system is characterized by an enough stable behavior since, in average, it produces an error that approximately deviates by 35% from $RMSE$ value (as described by CV_{RMSE} value).

As for the statistical analysis of the behavior of the proposed robotic control system, by considering a typical significance value for α ($\alpha = 0.05$), it is possible to state that in each round of the cross-validation procedure the Wilcoxon’s null hypothesis is not rejected (all p -values are greater than α). Hence, it is possible to put in evidence that the stopping distance values

¹https://help.xlstat.com/customer/en/portal/articles/2062457-which-statistical-test-should-you-use-?b_id=9283

²https://ncss-wpengine.netdna-ssl.com/wp-content/themes/ncss/pdf/Procedures/PASS/Equivalence_Tests_for_Paired_Means-Simulation.pdf

predicted by the proposed system are not significant different from the observed values at 95% confidence level.

TABLE I
PERFORMANCE OF THE PROPOSED FUZZY-BASED HIERARCHICAL
APPROACH TO CONTROL HRI

Test data	RMSE	NRMSE	CV _{RMSE}	p-value
fold 1	0.34239	0.093699	0.366711	0.888233
fold 2	0.28117	0.076946	0.30353	0.525081
fold 3	0.315564	0.086358	0.336541	0.57697
fold 4	0.316919	0.086729	0.341382	0.227968
fold 5	0.359135	0.098282	0.38369	0.760833
fold 6	0.316966	0.086742	0.345193	0.873294
fold 7	0.324449	0.088789	0.35108	0.432143
fold 8	0.298769	0.081762	0.319779	0.249871
fold 9	0.341981	0.093587	0.365056	0.770238
fold 10	0.291083	0.079658	0.312358	0.695476
average	0.3188	0.0873	0.3425	0.6000107

VI. CONCLUSION

Robot proxemics behavior is one of the most challenging problems in the area of cognitive robotics. In this paper, the problem has been tackled by means of an innovative synergic approach where fuzzy logic, neural networks, and Bayesian classifiers are used to adapt the robot proxemics behavior (stopping distances) with respect to the human personality and activities. Thanks to this framework, humans will not suffer from negative feelings of fear and distrust in the interaction with robots, making this enhanced kind of communication as safe and natural. Starting from the data collected in a previous work, here the proposed approach was tested in order to evaluate the ability of the system to reproduce the desired robot proxemics behavior. Statistical tests proved the reliability of the proposed model. In the future, more complete experiments involving a real human trial will be performed to actually measure the level of involvement of users in this kind of interaction with artificial agents. Moreover, different classifiers will be integrated withing the framework in order to improve activity classification results and to enrich the user profiling mechanism with more data.

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