A ROS Architecture for Personalised HRI with a Bartender Social Robot*

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Abstract—BRILLO (Bartending Robot for Interactive Long-Lasting Operations) project has the overall goal of creating an autonomous robotic bartender that can interact with customers while accomplishing its bartending tasks. In such a scenario, people’s novelty effect connected to the use of an attractive technology is destined to wear off and, consequently, it negatively affects the success of the service robotics application. For this reason, providing personalised natural interaction while accessing its services is of paramount importance for increasing users’ engagement and, consequently, their loyalty. In this paper, we present the developed three-layers ROS architecture integrating a perception layer managing the processing of different social signals, a decision-making layer for handling multi-party interactions, and an execution layer controlling the behaviour of a complex robot composed of arms and a face. Finally, user modelling through a beliefs layer allows for personalized interaction.

I. INTRODUCTION

In recent years, service robots have been employed in a variety of contexts that involve direct interactions with multi-users in public environments. A particularly challenging one is the bartending domain that combines the complexity of efficiently manipulating objects and the need of keeping users engaged for a long-lasting interaction. This, particularly, reflects the approaches of modern businesses that aim to achieve customers’ satisfaction and retail by presenting an equally high quality product and service [1]. Several projects [2], [3] explored the robotic bartending domain by developing automatic serving robots that are able to serve multiple users. Long-lasting interactions, however, can be established when the service robot is capable of showing social intelligence through personalised interactions [4].

Current literature has identified several aspects that affect people’s perception of social intelligence in robots. For example, a robot with facial features can be perceived as more intelligent than one without any [5], a robot that is able to move naturally can enhance people’s acceptance of the robot and convey a sense of security [6], and a robot that is able to model human behaviours and express appropriate emotions can positively affect the interactions [7]. Among those, the possibility of providing personalised services can increase users’ interaction on a long-timescale and their involvement with the robot [8]. Socially intelligent bartender robots that are able to mix task execution, dialogue, and social interaction in response to customers’ states and intentions were more efficient than non-social ones [9]. A robotic system that integrates a “system of record” (e.g., analysing and storing past interactions, preferences to optimise sales with respect to the specific users) and a “system of engagement” (e.g., aiming at facilitating and enhancing the experience via a personalised and natural interaction) can play a crucial role in customers relationship management.

To achieve this goal, a complex human-robot interaction (HRI) and control architecture have to be designed that comprehend different software components allowing for efficient and simultaneous execution of multiple tasks and for providing essential capabilities, such as storing past events [10], constructing models of others’ actions, beliefs, desires, and intentions [11], modelling the domain knowledge, selecting actions and behaviours, and planning [12]. For example, in the JAMES project [9], a bartender robot was able to engage participants in conversation producing facial expressions and lip-synchronising speech. The iCub robot in Tanevska et al.’s study [13] adapted its gaze and body to convey comfort and discomfort according to the engagement of the participants. The CORTEX cognitive architecture [14] was used to allow a salesman robot to convince potential customers to follow the robot towards a selling boot. The robot was able to identify the customers, understand people’s willingness of following it, and answer some specific questions.

While cognitive architectures have been investigated for a long time, real social and service robot implementations in complex scenarios, such as the bartending service, have only recently been developed [15]. Moreover, there is an inconsistency between current robots’ ability to generate verbal and non-verbal expressive behaviours (such as spoken language, gestures, emotions), and their capability of understanding the situational context and engaging the users in natural dialogues according to the users’ states and intentions [16]. The BRILLO project aims to create a robotic platform that is able to accomplish both the expected management of a bar counter, such as drinks manipulation, and the socially intelligent interaction, context-awareness, and personalisation. The development of such interaction and personalization capabilities in real-world settings is still an open challenge for the HRI community due to the complexity of interaction pipelines and the lack of maturity of some of the underlying detection and processing algorithms [17].

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II. MULTI-MODAL AND MULTI-USERS SCENARIOS

A typical use case scenario of a BRILLO service point includes a human user, a bartender robot for preparing and serving drinks, and a totem kiosk to register, recognise the users and manage orders. Users’ first interactions are with the totem kiosk that welcomes them and allows them to register in case it is their first visit. If the users are returning customers, they are recognised via bio-metric face recognition. Then, the customers are able to order a drink from the menu displayed on the kiosk or they can decide to make their order sitting at the counter by directly interacting with the bartender robot. At the bar station, the bartender robot recognises the registered users, takes orders (in case they are not placed at the kiosk), and serves them. The bartender robot interacts with the users according to their profile which is built upon typical customers’ personas (such as workers on a lunch break, groups of friends or family members, and regular users) and needs, such as previous orders, knowledge about the user’s general interests, observing their engagement levels, processing their moods based on the sentiment analysis of their dialogues and facial expressions. The bartender robot is also able to manage multiple orders and users, by opportunistically scheduling and adapting its behaviours.

The richness of the one-to-one and one-to-many human-robot interactions in the above-mentioned scenarios requires the development of a complex and sophisticated HRI architecture that allows the robot to show a social comprehension of the context and other agents involved in the interaction, and, at the same time, generates matching verbal and non-verbal socially acceptable behaviours. The bartender robot, for example, needs to intelligently adapt its dialogues, pose and gestures, according to the user’s needs, in terms of situational context (drink orders, group dynamics, etc.).

A. BRILLO Bartender Robot

We adopted a minimalist anthropomorphic structure for the bartender robot (see Figure 1). The robot has two Kuka1 LBR iuwa 14 R820 robotic arms (each of 7 DoF and gripper), attached to a fixed-torso (only one arm has been integrated into the current version of the robot), and a Furhat Robotics head2 (called Furhat, 3 DoF). The bartender robot is equipped with a variety of external sensors to improve and support its capability to perceive and assess the environment, the users, and the activities of the other agents involved in the interaction. In particular, a 4x2MP IR 180° Multi-sensor Panoramic Network Bullet camera3 is mounted under the furhat head and two microphone arrays4 are placed on the right and on the left of the robot to perform source separation and noise reduction to isolate the customers’ voices.

Currently, this robot is able to prepare smoothies and cocktails. The choice to adopt an anthropomorphic structure for the robot comes from the evidence that people are social entities, and they are more comfortable while interacting with agents that can show social behaviours [18].

B. Interaction Patterns and Dialogue

The foreseen interaction pattern with the bartender robot is composed of the following phases: 1) greetings and wait; 2) recommendation; 3) orders and changes request; 4) order confirmation; 5) personalised casual interaction; 6) complimentary close. In the presence of a single user, the robot welcomes them (“greetings”) and, then, recommends drinks, while in the presence of multiple users, the robot welcomes them, and invites them to wait their turn to be served (“greetings and wait”). After the recommendation of the drinks phase, the customer can place their order and/or ask for order customisation (“orders and changes request”). If no other change is needed, the order can be confirmed to the robot (“order confirmation”). During the drink preparation phase, the robot can converse with the user to entertain them. The robot engages the customer in casual dialogues based on data collected in previous interactions. According to the social feedback received from past interactions or previous turns, appropriate topics of conversation are selected. The robot closes the interaction after it prepared the drink (“complimentary close”).

III. BRILLO ROS ARCHITECTURE

In a recent survey on cognitive architectures, Kotseruba and Tsotsos [19] identified seven core cognitive abilities - perception, attention mechanisms (used in multi-user interaction), action selection, memory, preference learning, reasoning, and metareasoning. We started from such core cognitive abilities (excluding metareasoning) to develop the functionalities of the BRILLO system to enable the robot to perceive the users, build dynamic and efficient interactions while adapting the robots’ behaviours to the users’ needs and preferences.

The global architecture adopted for the BRILLO project is shown in Figure 1. From a software engineering perspective, the developed modules operate asynchronously by means of ROS nodes and communication via topic subscriptions.

A. Percepts Layer

The Percepts layer manages the robots’ multi-modal perception capabilities which consist of the information obtained by the modules for processing the visual and speech inputs.

1) User, Facial and Engagement Recognition Nodes: Authentication mechanisms are widely used both in online and mobile systems. In particular, researchers have been conducting extensive efforts to create and improve authentication systems, such as biometric-based, that can be faster and easier to manage than password account management [20]. The biometric-based authentication systems may use data such as voice, iris, fingerprint, palm-print, and face. In a bartending scenario, multiple users access and complex

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1Kuka Robotics https://www.kuka.com
2Furhat Robotics https://furhatrobotics.com
3https://us.dahuasecurity.com/?product=4x2mp-ir-180-multi-sensor-panoramic-network-bullet
4PureAudio USB Array Microphone
interactions are expected, therefore the recognition of the user needs to be developed considering real-time constraints, such as disturbances caused by noisy and vast areas, the presence of many users, and the need for fast service to avoid crowds. The most used and appropriate technique for recognising users in similar scenarios is face recognition [20]. The identification, detection, and tracking of the users are carried out using two cameras (an RGB camera at the totem, and a panoramic camera at the bar station) that allow the agent to collect data in real-time. The processed visual information is used for the following reasons: 1) face biometric data to identify a registered customer; 2) customers' engagement via their body pose; 3) user tracking while at the counter; and 4) group recognition.

The data from the camera are processed by YOLO\(^5\) for object detection, while the face recognition is done through the OpenFace library\(^6\). The combination of these two techniques allows accurate results even with different lights, lower quality of the frames and not fully frontal faces. The user pose is estimated using a Skeleton-Based approach through the OpenPose library\(^7\). The system estimates whether a user belongs to a group of other people using a Multilayer Perceptron classifier trained on the dataset called Ego-Group [21] that is one of the few public datasets having a robot egocentric view of the surrounding space. Moreover, a Multilayer Perceptron model based on the user's pose and group information classifies, trained on the same dataset, the user's engagement with the robot. Screenshots from the used dataset with the results of the Engagement recognition module are shown in Figure 2. On 5-fold cross-validation, an average accuracy of 94.33% was achieved for engagement prediction and 97.12% for group identification.

2) Intent Recognition Node: A bartending stand is typically found in noisy areas where a lot of people chat and, possibly, where music is playing. For this reason, to enable speech-based interaction, it is necessary to design the stand to be equipped with adequate hardware to isolate the customers’ voices. This module makes use of the following different subprocesses: 1) automatic speech recognition (ASR) system to obtain the speech transcription, and 2) machine learning approaches for Natural Language Understanding (NLU).

The BRILLO bartender stand is equipped with two microphone arrays to perform source separation and noise reduction to isolate the customers’ voices. The audio stream is processed remotely using an instance of the Azure ASR service, which produces the utterances’ transcriptions.

Concerning the NLU module, the following seven intents are modelled using the Microsoft Azure Service LUIS\(^8\):

- **AnswerGreeting**: this answers to the greeting phase initialised by the robot; this phase can also include information concerning the user’s state.
- **OrderConfirm**: with this intent, the order is confirmed.
- **OrderReject**: with this intent, the order is conversely disconfirmed.
- **DeleteOrder**: the order is requested to be deleted.
- **Help**: with this intent, the user can ask for information about the possible actions the robot can perform.
- **Menu**: the user can request the available products.
- **Order**: the order is finalised or modified.
- **NewsConfirm**: the news proposed during the preparation phase is well received.

\(^5\)YOLO library https://pjreddie.com/darknet/yolo/  
\(^6\)OpenFace library https://github.com/TadasBaltrusaitis/OpenFace  
\(^7\)OpenPose library https://github.com/CMU-Perceptual-Computing-Lab/openpose  
\(^8\)https://www.luis.ai/
### TABLE I

**INTENT RECOGNITION PERFORMANCES**

| Intent        | Precision | Recall | F-score |
|---------------|-----------|--------|---------|
| AnswerGreeting| 1         | 1      | 1       |
| OrderConfirm  | 1         | 1      | 1       |
| OrderReject   | 1         | 1      | 1       |
| Help          | 0.5       | 1      | 0.67    |
| Menu          | 1         | 0.5    | 0.67    |
| Order         | 1         | 0.81   | 0.9     |
| NewsConfirm   | 0.71      | 0.83   | 0.77    |
| NewsReject    | 0.86      | 0.75   | 0.80    |
| Evaluation    | 1         | 1      | 1       |

- **NewsReject**: the news proposed during the preparation phase is not well received.
- **Evaluation**: the evaluation concerning a previous order is processed.

As far as orders are concerned, the user intents are modelled for the application domain, considering the type of product, possible modifications, and cancellations.

Intent performances were computed by dividing the example collected in the data set by subdividing them into a training set (80%) and a test set (20%). The results are shown in Table I. While for most intents, the F-score is high, for others (i.e., Menu, Help) the performance needs to be increased by adding further data. On average, the intent recognition module performed well with an F-score of 0.87.

### B. Users' Beliefs

According to Kotseruba and Tsotsos [19], different types of memory can be identified in a cognitive architecture. In our architecture, a short-term memory stores the information related to the current users and situation states (e.g., current customers’ engagement state, users’ interaction states).

A working memory keeps track of the global state of the systems in terms of the list of orders to be served, that are represented in terms of goals to be reached, the current active intentions to be executed, and their plans of execution that are composed by both service and interactive actions.

Long-term memory is used to store information about users’ static information (personal data), preferences, and previous interactions’ history. The users’ personal data are stored in a MySQL database, while the length of the interaction, topics found of interest for the conversation, and interaction preferences, such as the type of the ordering (at the totem or at the bar), and an average estimation of the engagement are stored with the drinks orders.

Finally, semantic memory is used to store semantic information (ontology-like structure) relying on the use of the Neo4j\(^9\) graph database platform. The relationships between orders, cocktails and drinks, ingredients, and flavors are connected in a semantic graph that also includes the flavorDB\(^10\) database. The users’ past interactions stored in the long-term memory are also associated with the semantic graphs.

\(^9\)https://neo4j.com/
\(^10\)https://cosylab.iiitd.edu.in/flavordb/

### C. Context Awareness and Decision Making Layer

This layer stores and processes the proper context-awareness information needed by the robot to produce socially acceptable and natural behaviour and to prepare the drinks. Moreover, such information is used to decide the user to be served/interacted with and the plan of actions.

1) **Turn-taking Node**: For each recognised user (/users topic), the BRILLO system instantiates a desire for interaction and drink order. To accomplish such a goal, we defined a set of possible interaction states for the user, starting from the initial greetings towards the serving and farewell state. Each active user is currently in one state and, in order to transition from one state to another one, the proper set of actions (both service and interactive) have to be planned. The Turn-taking module selects one active user at the time (considering the arrival order, the waiting time, the presence of a group) and instantiates an intention for transitioning from one state to the following.

However, based on the analysis of the users’ associated personas and engagement level, some users will be observed by the robot as more involved in a conversation than others. Similarly, at any moment during the interaction, some users might claim the robot's attention. Notwithstanding these situations, the robot tries to involve all users, albeit to a different extent, in order to increase engagement [22]. Such user and their current interaction state are shared on the /interactinguser topic. States and transitions as represented in Figure 3.

2) **Multi-modal Fusion Node**: The Multi-modal fusion module for the human assessment is deployed to keep the
user’s engagement in the interaction by recognising the user’s intentional state and emotional reactions in order to decide which appropriate interactive action should be executed.

Engagement and group detection information are here assessed also with emotion recognition from facial expressions that is carried out using the software called Affectiva\textsuperscript{11}. The classification of people’s emotions via Affectiva allows a classification of facial expressions according to seven main emotions (anger, contempt, disgust, fear, joy, sadness, and surprise). It also allows measuring the positive or negative valence for measuring the experience, with a frequency of a few hundred milliseconds and high accuracy.

The analysis of the voice, both simultaneous speech and high entropy, is implemented using the Python library called My-Voice-Analysis\textsuperscript{12}. It allows evaluating people’s mood (neutral, calm, or pacey), gender (female or male), speech rate, energy, frequency, average speech interval duration, and speaking duration. Moreover, in order to build a natural and fluid interaction, a social robot needs to be able to understand sentiments hidden in the content of the user’s speech \textsuperscript{23}. Therefore, the user’s voice is also further analysed to classify the emotions in the text. Currently, the sentiment analysis is carried out using the Azure Cognitive Services Text Analytics libraries\textsuperscript{13} which label the speech-to-text as positive, negative, or neutral.

The information collected here on the active user is used by the Interaction Manager to select the proper plan of interaction actions to keep the user engagement while transitioning to the following state.

3) Robots’ Actions Planner: In our system, we distinguished two types of actions:

- **Service actions**, that are at the bartending actions necessary to prepare and serve a drink. It may involve one or both arms of the robot;

- **Interactive actions**, that are the robot’s actions for interacting and entertaining the user while they are at the bar station. These actions may be verbal utterances, gestures (when one of the robot’s arms is not engaged in any service action), and facial expressions.

\textbf{a) Planner Node:} Orders (service actions) are processed by the robot as soon as the active user is in the serving state. ROS plan libraries for AI planning\textsuperscript{14} are used to schedule service actions according to the scheduled orders for each user. The Planner module creates, therefore, a sequence of basic actions for each arm and for each ordered drink to be executed by the robot. The trajectories necessary to achieve each basic action to serve a drink are pre-recorded and basic actions are expressed in terms of preconditions to be checked before the execution (e.g., the mixer is empty) and the time to execute each action.

\textbf{b) Interaction Manager Node:} The selection of the interactive actions relies on Influence Diagrams\textsuperscript{15}, which integrate the probabilistic estimates of engagement coming from the users’ interaction modes (i.e. speech, facial expressions, semantics, pose) with a utility estimation linked to the possible speech acts or gesture. Bayesian networks allow handling probabilistic input coming from the NLU module, among others, to take into account confidence measures when selecting the next action. The utility of each possible machine move (Action) is a function of the chosen Action and of the actual intent from the user, at decision time only an estimate of the actual intent is available. The data summarised in Table I inform the network of the probability of each intent to be correct and also assigns a utility value to the dialogue move consisting of a request for repetition (AskRepeat). Depending on the probability distribution over all intents, provided by the NLU module, the utility of each possible Action is computed. The Action with the highest utility is, then, executed.

Interaction customisation is applied in this phase when the user is known to the system. Pragmatic models of interaction are investigated and included in the architecture. For instance, clarification requests (CRs) expressing counter-expectations with respect to past ordering actions are adapted to engage the user in the dialogue and add further details to the user model. For order confirmation, CRs with a confirmation function are employed, i.e. when the CR initiator has some kind of hypothesis \textsuperscript{25}. Specifically, this is useful when low confidence scores occur due to background noise or multiple orders.

To support recommendations, previous interactions with the users are stored in the Neo4j database and used to build a profile. For past interactions involving drinks that were not previously selected, the robot asks for explicit feedback, in the form of a rating on a scale of 1 to 5. Using the graph structure represented in Neo4j and, in particular, the data coming from FlavorDB (see Figure 4), the system is able to compute drinks’ similarity in terms of shared ingredients. On this basis, different recommendation strategies can be selected according to different parameters: a) type of persona, a not mandatory piece of information asked at the totem kiosk during the registration phase; b) degree of knowledge of the user based on the number of interactions (known user: at least one previous interaction; unknown user: first interaction); c) evaluation of past consumed drinks (positive evaluation: $\geq 3$; negative evaluation: $\leq 2$); d) acceptance of the recommendation (if the recommendation is not accepted another strategy is selected) (see Table II).

For entertainment purposes, the robot is also able to present news extracted daily from different sources and categories. Explicit feedback is used in this case, too, to support user profiling and to select topics from the most appropriate categories. More specifically: first the robot suggests a topic of interaction, based on similarities among users and/or

\textsuperscript{11}Affectiva software \url{https://www.affectiva.com/}

\textsuperscript{12}My-Voice-Analysis library \url{https://github.com/Shahabks/my-voice-analysis}

\textsuperscript{13}Azure services \url{https://azure.microsoft.com/}

\textsuperscript{14}ROSPlan’s source code and documentation \url{https://github.com/KCL-Planning/ROSPlan}

\textsuperscript{15}In BRILLO, Influence diagrams are implemented using the AGRUM library\textsuperscript{[24]} \url{https://agrum.gitlab.io/}
| Persona | Recommendation Strategies |
|---------|--------------------------|
| worker  |                          |
| known user | a) client’s preferred drink  |
|          | b) users’ most ordered drink |
|          | c) ask what the client wants to order |
| new user | a) users’ most ordered drink |
|          | b) ask what the client wants to order |
| other   |                          |
| (specified or not) | last drink was positively evaluated |
| known user | a) similar drink from the same category (smoothie or cocktail) |
|          | b) similar drink from another category |
|          | c) users’ most ordered drink |
|          | d) ask what the client wants to order |
| new user | a) users’ most ordered drink |
|          | b) ask what the client wants to order |

Fig. 4. Graph showing the similarity between the last ordered DRINK node, *Green Power*, and another DRINK node (in green) belonging to the same category SMOOTHIE (in blue). The similarity is here computed on the highest number of FOOD_INGREDIENT nodes (in pink) in common.

 personas; once a topic is accepted, the corresponding news is selected from a serious or entertaining source; afterwards, the user is asked to give feedback concerning their interest about the news. If the feedback is positive, another news belonging to the same category is proposed, otherwise the category is changed. News items can be provided as long as available. Other social signals can also cause the robot to stop entertaining the current client, i.e. when the client is not engaged or interested, or when another registered client appears in the robot’s visual area.

### D. Execution Layer

The *Execution layer* manages the orders and the interactions of the robots with the users according to the knowledge and beliefs of the agents, and the situational context.

1) **Action Manager Node:** The Action Manager module acts as a scheduling mechanism to improve the efficiency in making the drinks by using one or two arms in parallel. It schedules the interactive actions, related to the robot’s gestures, and the service actions by orchestrating the robot’s arms movements. The next actions are chosen to balance the expected contribution of the action towards the goal of preparing a drink, and the robot’s actions needed to maintain the engagement and entertainment of the users to their social expectations. For example, the robot might engage the users in a casual conversation while preparing their drink for fostering a more endearing interaction if its arms are not busy in the drink preparation.

2) **Arms Node:** This module is a wrapper for favouring the communication between the BRILLO system and the two KUKA arms’ Programmable Logic Controller. The controller has been implemented using the KUKA SunriseOS system to securely manage the arms, the grippers and each movement in the stand.

3) **Furhat Interface Node:** To make the interaction more engaging, the robot is endowed with a module in charge of guiding the Turn-taking through gaze and speech pauses [26]. The system, in particular, manages the behaviours of this robot by considering the presence and the absence of the user’s attention. When a low user’s engagement is perceived, the robot produces facial expressions and vocal sounds to catch the user’s attention. During a dialogue, the robot adapts its facial expressions and vocal sounds whether it is listening to the user’s speaking, it understood or did not understand the speech, and to express an emotion in relation to the topic of conversation. The facial and vocal sounds are based on the Facial Action Coding System (FACS) for Ekman’s emotions\textsuperscript{16} and implemented using Python and Furhat Robotics’ APIs.

### IV. FUTURE WORKS / CONCLUSIONS

The use of robots for the automation of the supply of food and beverages is a commercially attractive and modern application of robotic technologies and it is used as a strategy to renew the image of the service and thus stimulate people’s curiosity. However, the maintenance, in the long term, of the degree of interest in a commercial proposal linked to leisure can be only effectively achieved by implementing strategies for personalising the experience according to previous interactions and adapting the robot’s behaviours.

In this work, we presented a ROS Architecture for a bartending robot aiming at providing an efficient service while keeping engaged the human customers in a dynamic

\textsuperscript{16}FACS shorturl.at/fvGP4
and personalised interaction. The system has been tested in a controlled environment evaluating the effectiveness of the single developed modules and of the whole architecture in terms of personalization of the experience and adaptation of behaviours, including content and frequency of dialogues, movements and poses to the customers’ moods and preferences. Software modules were designed for the management of dialogues and the perception of social signals, such as, for example, biometric-based algorithm for the recognition of social signals linked to the dynamics of interaction with the robot and Bayesian networks for the modelling of the interaction and the estimation of the probability of success of new proposals based on previous interactions.

As soon as the pandemic restriction will allow it, the system will be tested in an ecological environment to understand if BRILLO’s robots are able to meet also people’s expectations. We aim at demonstrating that receiving a service that is fast but also personalised can present an added value to the commercial proposal, taking it beyond the simple experience associated with the presence of a new technology and increasing customers’ loyalty.

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