A Cloud Robotics Architecture to Foster Individual Child Partnership in Medical Facilities

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Abstract— **Robots and automation systems have become a valuable partner in several facets of human life: from learning and teaching, to daily working, including health monitoring and assistance. So far, these appealing robot-based applications are restricted to conduct repetitive, yet useful, tasks due to the reduced individual robots' capabilities in terms of processing and computation. This concern prevents current robots from facing more complex applications related to understanding human beings and perceiving their subtle feelings. Such hardware limitations have been already found in the computer science field. In this domain, they are currently being addressed using a new resource exploitation model coined as cloud computing, which is targeted at enabling massive storage and computation using smartly connected and inexpensive commodity hardware. The purpose of this paper is to propose a cloud-based robotics architecture to effectively develop complex tasks related to hospitalized children assistance. More specifically, this paper presents a multi-agent learning system that combines machine learning and cloud computing using low-cost robots to (1) collect and perceive children status, (2) build a human-readable set of rules related to the child-robot relationship, and (3) improve the children experience during their stay in the hospital. Conducted preliminary experiments proof the feasibility of this proposal and encourage practitioners to work towards this direction.**

I. INTRODUCTION

Latest advances in hardware architectures and software developments have raised robots to the foreground of human healthcare: from elderly mental therapy [1], to assisted surgery [2], including rehabilitation medicine [3] and medication monitoring [4]. Typically, these healthcare robots are devoted to conduct specific and repetitive tasks that have been previously scheduled and detailed by an expert according to every patient sickness. So far, this approach has been shown to work properly for a considerably large number of situations where the disease parameters and possible patient outcomes are strictly delimited [5]. However, there are some illnesses that still require a physical medic in order to provide patients with the most appropriate treatment and guidance. An appealing use case that portraits this concern is seen on how medics and nurses deal with the pain and anxiety that children generally feel when they have to be hospitalized. This process requires a deep and personalized interaction with every child in order to select the most convenient actions to reduce these symptoms.

In fact, the reduced processing power, storage capabilities, and number of sensors included in these robots prevent themselves to go beyond their historically static and predefined behavior [6], [7]. In opposition to what has been achieved in other domains [8], it is still not feasible to codify the knowledge of the expert (i.e., medic staff) inside a single robot on a reliable and cost-efficient way. Nonetheless, looking at the computer science field, an overwhelming amount of research has been conducted on distributed systems that take benefit from the Internet as a key resource to enable massive parallel computation and share vast amounts of data using commodity hardware—lately referred to as cloud computing [9], [10]. Such observation drove practitioners to officially coin the term cloud robotics in 2010 [11], which basically consists on applying the fundamentals of cloud computing (i.e., elastic resources, on-demand services, virtually infinite scalability) to robots.

The purpose of this paper is to present a prospective view of a new generation of healthcare robots—combining cloud robotics and artificial intelligence—that provide children patients with an effective and individualized assistance. More specifically, we aim to use a low-cost robot named Pleo—a human-social robot that successfully connects with children [12]—to (1) supply young patients with a kind partner to enhance their stay in medical facilities, (2) build a cloud multi-agent system able to perceive, collect, and share hospitalized children status, (3) design an intelligent layer to guide the behavior of every patient's robot, and (4) explore the most effective actions that the Pleo robot can carry to improve the patient experience by eliminating or minimizing pain and anxiety. The underlying idea behind this proposal is to monitor the interactions between the robot and its associated patient in order to share their local conclusions (e.g., when the robot flashes its lights the child relaxes) with other robots and obtain a dynamic pool of possible actions to be applied at every situation (e.g., flash robot lights when child is excited). Note that the intelligent system is in charge of selecting the best action at any time, since every patient may react differently to the same stimulus. The system will be tested under a project titled Pain and Anxiety Treatment based on social Robot Interaction with Children to

*This work was partially supported by Spanish Ministry of Economy and Competitiveness.

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Improve pAtient experience (PATRICIA). More specifically, the challenge of the project is to design pioneering techniques based on the use of social robots to improve the patient experience by eliminating or minimizing pain and anxiety.

The reminder of this paper is organized as follows. Section II details the anxiety and stress phenomena observed in children under cancer, and more specific, leukaemia treatment. Next, Section III summarizes the features, facilities, and limitations of the Pleo robot to reduce the aforementioned effects. Then, Section IV articulates the designed cloud robotics architecture to boost the Pleo capabilities and the distributed intelligent system deployed on top of it. Finally, Section V connects the Pleo with the children assistance and Section VI concludes the paper.

II. ANXIETY, STRESS & PAIN ASSOCIATED TO CHILDREN UNDER LEUKAEMIA TREATMENT

The overall outcome of the PATRICIA project is to reduce anxiety, stress and pain to long-term hospitalized children to ensure an optimal care mentally apart of the physically provided by the medical treatment. As a first tentative we have chosen children that suffer from leukemia because this disease entails painful procedures such as lumbar puncture or bone marrow aspiration. We propose the use of a robotic pet as a complementary therapy to the offered generic support. In the literature we can find examples of therapeutic alternatives aligned in the same direction as in [13], where toys and animated cartoons were used, [14] were music was played, and in [15] where the authors propose art therapy against the fact that during the treatment the child's balanced growth is under danger because of everything related to the illness cure.

Depression and anxiety [16] are correlated with cancer disease, and what all recommendations have in common is that try to engage in activities beyond the cancer experience helps to improve patient quality of life. In [17] is presented distraction as an action with a positive effect on children's distress that reduces the level of pain.

The reason to propose a pet robot for the approximation to reduce pain and stress is because being the owner of a pet is rewarding, which may let children feel better. There are studies like in [18], [19], and [20] as relevant references, where the therapy with pets is a success increasing the benefit from factors like warmth, mood, creativity, capacity for enjoyment, and empathy obtained from evaluation through vital signs, pain ratings, salivary cortisol levels, emotions, activity/rapport, perceived benefits, child/parental satisfaction, and impact on environment via self-report, interview, or observation and videotaping.

However there are a few aspects that makes an artificial pet robot a better solution than a real pet: (1) The risk of getting an infection, which is higher if you are under cancer disease treatment, and (2) the maintenance of a pet in a medical environment. In [21] is shown how a pet robot demonstrates a high social presence, thus it might be considered a good approximation to have a real animal.

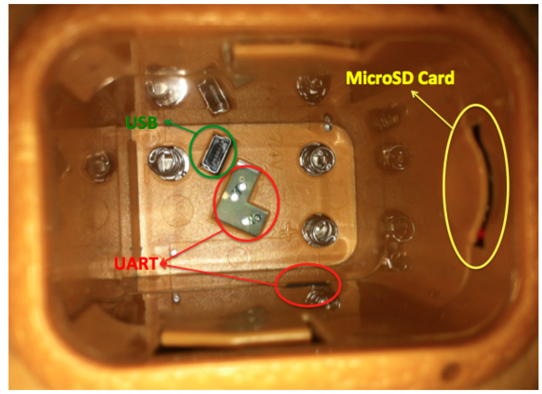

Fig. 1. Pleo input-output data connections

III. PLEO, THE ROBOT MATE

Pleo is a low-cost commercial entertainment pet-like robot imitation of a Camarasaurus dinosaur developed by Innvo Labs. Robot machines that are animal-like, in a small size, and friendly use to be accepted inmediatly by children, but also by adults. Pleo has a set of characteristics like expressiveness, baby-likeness, behaviors, and others that make the platform suitable for long-term interaction, mainly with children, as is shown in [21], [22], [23], and [24]. All these studies found the development of a social relationship and bond with the robot. More specifically, in [21] the authors proved that the score of Social Presence of the Pleo Robot is correlated with the score on Attitude, Emotional attachment and the attribution of social adjectives. In addition, children who interacted with the robot spent more time on affective and request for reciprocity activities against using the robot as an object. So it is clear that Pleo's characteristics provided by the equipped hardware like the different tactile sensors, speakers, microphones, a camera sensor, IR sensors, and a RFID sensor, as long as the software that compose the LIFE OS system inside the robot with the internal drives like hunger, sleep, and several mood modes: angry, happy, scared, etc., are good to have a similar social interaction experience compared to real pet animals.

However, the Robot has a strong limitation in terms of extracting internal data that can be useful to determine the causes of its behavior and how others are interacting with it. Furthermore, from the commercial version is impossible to bias the actions of the robot as we can do with trained pets. In Fig. 1 we can see what manufacturer provides to remotely interact with the PLEO: a micro SD card slot next to the battery and a serial interface that can be wired connected to a monitor device.

In order to add an on-line system to monitor and control the robot internal variables we propose to add wireless connectivity to the Pleo. We can do it in a non-invasive way, adding a bluetooth / WIFI gateway between the USB connector and remote computer. Or in a invasive way that consists on soldering two wires in an universal asynchronous receiver/transmitter (UART) placed in the body board. At the

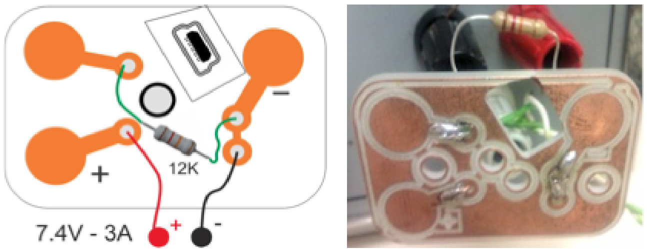

Fig. 2. Battery+Serial connector prototype

moment this paper is written we are using a wired connection with the USB terminal and an external power supply—as shown In Fig. 2—while we are designing a new battery with all the electronics embedded so we are not changing the embodiment of the robot.

IV. ADAPTING PLEO TO CHILDREN DEMANDS

Although the Pleo robot is a powerful and versatile tool to deal with children [12], its behavior has to be carefully addressed in order to effectively reduce their anxiety and stress when they are hospitalized. Indeed, every child may react differently to the same robot-driven-stimulus, which prevents practitioners from programming Pleo with a closed set of predefined actions. Therefore, we propose to use data mining techniques in order to (1) automatically analyze the behavior of every child, (2) compare it with past experiences, and (3) build the most appropriate response to the particular child status.

Data mining techniques are traditionally classified into two distinct disciplines, namely supervised and unsupervised learning paradigms. The former aims to make accurate predictions after assuming an underlying structure in data, which requires the presence of a teacher to train the system and obtain a reliable knowledge model. On the contrary, the latter aims to discover regular-occurring patterns beneath the data without making any a priori assumptions concerning their underlying structure.

Nevertheless, some modern problems in data mining have failed to fully fit into one of these paradigms [25]. In fact, constructing a predictive model from a pure supervised way in real-world domains is often unfeasible due to (1) the dearth of training examples and (2) the costs of labeling the required information to train the system [8]. In addition, the unsupervised paradigm does not take into account the particular characteristics of the problem domain, thus it cannot exploit the search guidance that uses the supervised approach. This issue make *pure* unsupervised learners prone to fail at recognizing the interesting patterns—i.e., those that are uncommon and valuable—from the uninteresting ones. This situation has driven practitioners to explore a new technique coined as semi-supervised learning, which consists on combining both approaches to overcome their individual limitations.

A. Semi-supervised Learning in Hospitalized Children

Certainly, neither supervised—too many examples to be labeled—nor unsupervised learning—some rare and specific examples might be relevant—approaches should work when discovering patterns of relations between Pleo and children. On the contrary, semi-supervised learning exploits the unsupervised strategy to obtain accurate predictive models from a reduced set of previously labeled (i.e., supervised) instances, which minimizes the costs associated to obtaining a reliable and fully mapped training set from real-world domains. In this regard, the algorithm first trains the system with a reduced set of labeled examples to obtain a preliminary *protomodel*, which will be used to label the vast amount of remaining data (this strategy is referred to as *self-training* [26]). Then, the final model obtained by the learner is used for future predictions.

So far, this strategy has been successfully applied in a variety of challenging domains such as artificial olfaction [27], gene classification [28], protein prediction [29], image retrieval and segmentation [30], handwritten word segmentation [31], and non-invasive diagnosis of Scoliosis [32], which supports its effectiveness.

An appealing framework for semi-supervised learning lies in the Michigan-style Learning Classifier System (LCS) approach [36]. This framework consists of an online cognitive-inspired system that combines a credit-apportionment algorithm with Genetic Algorithms (GAs) [34]. In what follows we introduce the intelligent architecture of the proposed algorithm in order to obtain high quality predictive models from the domain of long-term hospitalized children.

B. Intelligent System Architecture Based on Cloud Robotics

The reduced capabilities and features of Pleo prevent itself from behaving as a LCS. Also, selecting a more powerful robot may derive into an expensive approach, which is not suitable for this use case. Therefore, we propose to build a multi-agent system using the idea of cloud-robotics. Specifically, we propose to connect every robot to the Internet as shown in Fig. 3 and, thus, build a cloud of Pleos that continuously upload and share their collected data.

In order to obtain reliable models from the huge amounts of data provided by the cloud, it is mandatory to build a scalable approach. To settle this hurdle, we have divided the system into two distinct layers as shown in Fig. 3: (1) the low layer composed by a set of *Children Assistant Agents* (CAAs), each integrated in a different PLEO, which perceives information from the sensors of the robot, and (2) the *Information Management Agents* (IMAs), the upper layer that aggregates the information received by the CAAs thus building the knowledge model. From time to time—defined by the user—, distinct IMAs exchange rules in order to fulfill a global solution.

1) The Intelligent Layer: Each IMA incorporates an intelligent algorithm which trains in a self-supervised way in order to obtain the predictive models. More specifically, IMAs incorporate a Michigan-style LCS that is specifically suited for this tasks due to its online nature. The most

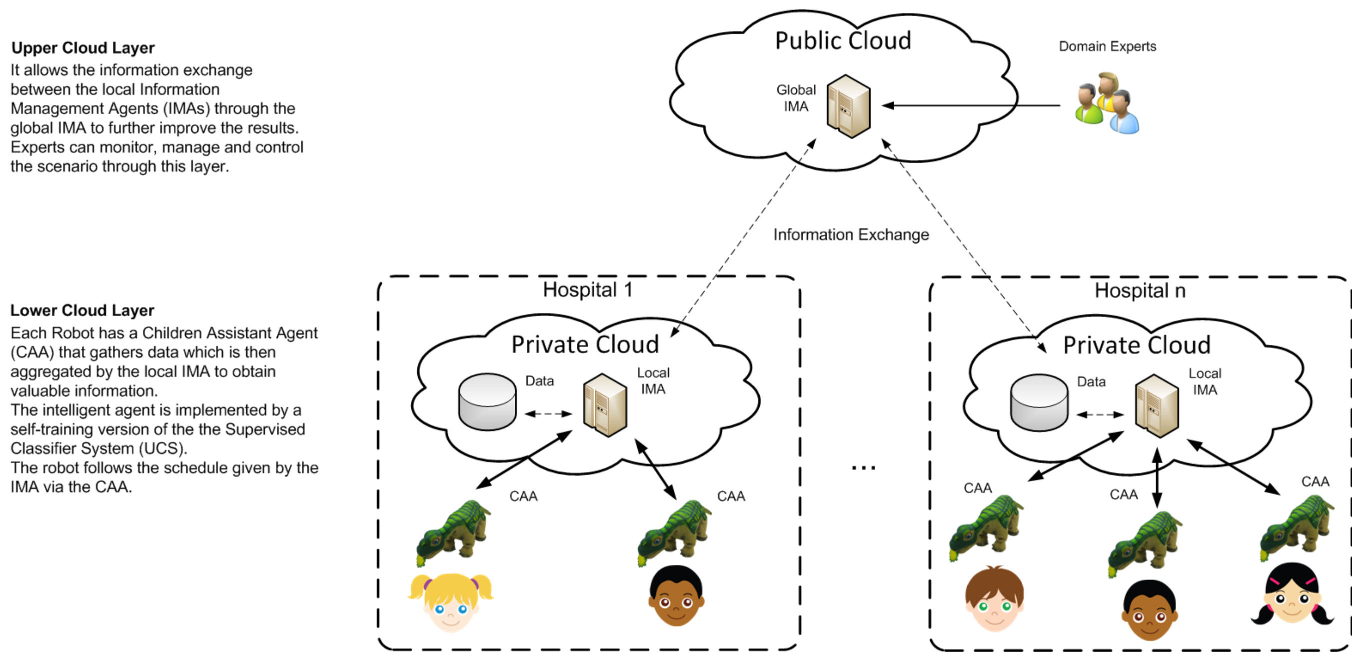

Fig. 3. Scheme of the proposed architecture

successful architecture for this class of task is found in the *supervised classifier system* (UCS) [35]. UCS is an accuracy-based Michigan-style LCS that takes advantage of knowing the class of the training instances, thus minimizing the explore phase by searching for the *best action map*, which consist of the set of maximally general and accurate classifiers that predict the correct class. UCS *evolves* a population $[P]$ of classifiers that, together, cover the input space, learning from streams of examples. The core of each classifier consists of a production rule and a set of parameters that estimate the quality of the rule. A rule takes the form **if** $x_1 \in [\ell_1, u_1] \wedge x_2 \in [\ell_2, u_2] \wedge \ldots \wedge x_k \in [\ell_k, u_k]$ **then** c_j, where the leftmost part contains k input variables that take values of the interval $[\ell_i, u_i]^k$, where ℓ_i and u_i are the lower and upper limits, respectively, of each interval and the rightmost part denotes the predicted class c_j. Each classifier has a set of parameters that evaluate the quality of the rule. These parameters are (1) the rule accuracy acc, (2) the fitness F of the rule, (3) the experience exp, (4) the numerosity num or number of copies of this particular classifier in $[P]$ and (5) cs, an estimate of the average size of the correct sets in which the classifier has participated. The learning organization is the following: UCS receives input instances from the environment in the form of streams, that is, that receives a training example of the form $e = (e_1, e_2, \ldots, e_k)$. If the system receives a supervised event, the correct label of the example c is also given. Otherwise, c is the estimated by the semi-supervised step. Then, the match set $[M]$ is created, containing all the classifiers in the population whose condition matches the example given by the environment. Afterwards, the correct set $[C]$ is generated out of all classifiers in $[M]$ that predict the class c. If $[C]$ is empty, the covering operator is activated generating a single classifier with a generalized condition matching the input instance e and predicting the class c. Following that, the parameters of all the classifiers in $[M]$ are evaluated: first, the experience of each one is incremented. Next, the accuracy, the niche size estimate and the fitness:

$$cl.acc \leftarrow \frac{\text{number of correct classifications}}{cl.exp}. \quad (1)$$

$$cl.cs \leftarrow cl.cs + \frac{\sum_{cl_j \in [C]} cl_j.num - cl.cs}{cl.exp}. \quad (2)$$

Finally, the fitness of the classifier is updated. In the first place, the relative accuracy $cl.k$ of each classifier is computed. For classifiers belonging to $[M]$ but not to $[C]$, $cl.k$ is set to zero; that is $\forall\, cl \notin [C] : cl.k \leftarrow 0$. For each classifier belonging to $[C]$, $cl.k$ is computed as $\alpha(cl.acc/acc_0)^{\nu}$ if $cl.acc < acc_0$ where acc_0 is the accuracy threshold and ν is an exponentiating function defined by the user, and 1 otherwise. Afterwards, the classifier fitness is updated:

$$cl.F \leftarrow cl.F + \beta \left(\frac{cl.k \cdot cl.num}{\sum_{cl_i \in [C]} cl_i.k \cdot cl_i.num} - cl.F \right). \quad (3)$$

Finally, if the average time since the last application of the GA of classifiers in $[C]$ is greater than the user-defined θ_{GA} threshold, the genetic rule discovery is triggered: a steady-state niche-based GA [33]. In our implementation, we used tournament selection and two-point crossover [36].

In the case of the deletion scheme, the offspring are introduced into $[P]$ via the subsumption mechanism: if there exists a sufficiently experienced and accurate classifier cl in $[P]$; that is, if $cl.exp > \theta_{sub}$ and $cl.acc > acc_0$—where θ_{sub} is a user-defined parameter—, whose condition is more general than the new offspring, the numerosity of this classifier is increased and the offspring discarded. Otherwise, the new offspring is introduced into $[P]$. At this step, until the population is full, classifiers in $[P]$ are deleted following:

$$cl.P_{del} \leftarrow \frac{cl.d}{\sum_{\forall cl_i \in [P]} cl_i.d}, \tag{4}$$

where $cl.d \leftarrow cl.num \cdot cl.cs \cdot F_{[P]}$ if $cl.exp > \theta_{del}$ and $cl.F < \delta F_{[P]}$, where $F_{[P]}$ is the average fitness of the population, θ_{del} is the classifier deletion threshold, and δ is and user-defined scaling factor, or $cl.d \leftarrow cl.cs \cdot cl.num$ otherwise.

During the test stage, UCS class inference is performed using the knowledge acquired during the previous training stage. A new unlabeled example, previously unknown by the system, is given to UCS and all the matching classifiers vote for the class they predict proportional to the fitness and accuracy and returning the most voted class.

The following section details which sensors of the Pleo robot are used by this intelligent system in order to learn from the children behavior and provide them with the best stimulus to reduce their anxiety and stress.

V. TEST SCENARIO

The PATRICIA project aims to design and develop specific human-social robot interaction with pet robots. This interaction is targeted to optimize the trade-off between minimizing the administration of medicines and maximizing the reduction of anxiety, stress, and pain. This section elaborates on how the proposed Pleo will be tested and utilized in the near future to conduct the experiments. The purpose of this experiments is twofold: (1) Assess up to what extent is possible to extract knowledge from a massive amount of patients—distributed among several geographically distant hospitals—through the Pleo robot, and (2) analyze the effects of the patient-robot interaction on reducing children stress.

The test scenario ranges from acute patients, even in emergency-room (e.g., orthopedic surgery), middle-term intervention (up to around 8 days) and long-term hospitalization and companionship at home in chronic diseases. Patients will be recruited from Hospital Sant Joan de Déu in Barcelona, as they are part of the coordinated project. First studies will be conducted with leukemia diagnosed children who have to stay in the hospital for at least a month and who, as mentioned in Section II, they are a suitable target for testing long-term interaction with a robot.

The purpose of this experiment is to take advantage of the functions provided by the Innvo labs company in order to deploy the aforementioned cloud robotics architecture. The operating system of the Pleo is structured in virtual machines. One of these virtual machines called SensorVM registers in real time a huge number of software variables able to perceive the intensity of the interaction between the pets and children. Some of these variables (e.g., SENSOR_HEAD, SENSOR_CHIN, SENSOR_BACK, SENSOR_LEFT_LEG) come from real electronic touch sensors installed on the the head, chin, shoulders, back and feet of the pet. Other variables (e.g., SENSOR_SOUND_DIR or SENSOR_SOUND_LOUD) come from 2 microphones that can be used to detect the direction of the sound or changes in sound volume. Additionally, there is another set of variables (e.g., SENSOR_LIGHT or SENSOR_LIGHT_CHANGE) that come from a camera-based vision system that can be used to detect light levels but also to take pictures in order to identify persons, objects, etc. Also, there are other variables (e.g., SENSOR_TILT) that come from a G-force sensor and identify how the pet is oriented once children hand it. Other variables are processed through in-built functions to give values (derived sensors) about the kind of interaction between the children and the pet (e.g., SENSOR_TOUCH_PETTED) to detect from a series of touch sensors how the child is petting its Pleo (e.g., caress the pet from back to head), or SENSOR_TOUCH_TAP, SENSOR_TOUCH_HOLD and SENSOR_PICKED_UP to detect how touch sensors are pressed or if the pet is lifted up from the surface. Finally, there are also many other variables coming from additional sensors that will probably not be monitored as they are not directly related with the interaction we are interested: foot switches, IR sensors, temperature sensors, timers, etc.

As each Pleo is different and reacts in a different manner, it is mandatory to take into account information about its personality and behavior. This information is registered in different hidden system variables. However, preliminary analyses show that the robot can be hacked to report further information about its age, gender, courage, temper, intelligence, health, feed, skill level, etc. Furthermore information about the actions the robot performs are also possible (i.e. joint movements or sounds). Note that some of this information is fixed and can not be modified but some data vary as children interact with the robot.

As a result, each Pleo robot generates an overwhelming amount of data that will be effectively addressed by the intelligent system deployed on top of the cloud infrastructure detailed in the previous section.

VI. CONCLUSIONS & DISCUSSION

The architecture proposed in this paper aims to establish an interesting paradigm to address the problem of human-robot interaction where the volume of information we have to monitor in real time is significantly high. The reasons to choose the commercial robot Pleo are in one side because is proved that this robot performs a good human-robot interaction close to the relation with a real pet, and in the other side because it is cost effective. In order to enable the Pleo Robot to behave as a cloud robotics tool we propose to modify the battery adding connectivity to the serial interface so it can be monitored while children are taking care and playing with it.

In order to provide a personalized answer to every child, we propose to utilize an intelligent system able to automatically find out the correlations between the child and its robot. To overcome the computing and storage limitations of every single robot, we have proposed a cloud-based architecture to (1) exchange the knowledge obtained by every Pleo, (2) isolate the perception layer from the model building layer, (3) tolerate that robots may elastically join and leave the system at will, and (4) handle the deployment of Pleo robots in hospital facilities on a scalable way.

We expect that results can foresee cause-effect reactions between the pets and children in cooperative environments between one child and his or her pet or even between several children and their pets. These results should help the therapists to determine possible relations between the anxiety of the patients and the interaction with their robots in comparison with classical video analyses. Moreover, this architecture will allow to learn from different patient's behavior and to share local conclusions with the community (even around the world). This way of operating provides a new scenario in medical facilities where the number of patients locally is often not enough to draw reliable conclusions.

ACKNOWLEDGMENT

Authors thank Spanish Ministry of Economy and Competitiveness for its support under grant TIN2012-38416-C03-01,02 and Generalitat de Catalunya for its support under grant 2012FI_B 01058 for Andreu Sancho-Asensio.

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