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Big Data Analytics as a Service for Affective Humanoid Service Robots

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Abstract
This paper identifies and analyses the advanced capability requirements for humanoid service robots to serve in highly complicated and intelligence demanding applications, such as children education and home care, in future smart home environments. In particular, a Distributed Collaboration and Continuous Learning (DCCL) mechanism is identified as the key capability of a humanoid service robot to succeed in these applications. Based on the latest Big Data Analytics tools with distributed machine learning technologies integrated as services, a novel DCCL middleware platform is developed to facilitate the realisation of the DCCL mechanism. A user preference based children toy recommendation application is introduced as a use case study of the DCCL mechanism and platform.

Keywords: Affective Computing, Big Data Analytics, Continuous Learning, Distributed Collaboration, Humanoid, Service Robots

1 Introduction

As the rapid developments in the physical performance (i.e., hardware) and intelligent capability (i.e., software) of humanoid service robot technologies in recent years, the real-world applications of human service robots as companions in entertainment, education, and healthcare domains have been widely proposed and explored. As part of the autonomous nature, these humanoid service robots conventionally solely depend on the local built-in software to realise their intelligent capability and localised decision-makings.

However, as humanoid service robots are being widely deployed and distributed as daily life companions into highly complicated and intelligence demanding application domains, such as children education, ageing society in a smart home/school/campus environments, a gap emerges between the decision-making capability requirements of these applications and a humanoid service robot's localised intelligence capacity.

Facing these new application domains, an independent humanoid service robot is expected to fill the gap by accessing external/remote intelligence resources and services at runtime and even to

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collaborate with other humanoid service robots via an external open platforms. Although, in recent years, many Cloud computing technologies based systems or platforms have been designed and implemented to improve robot computation and collaboration abilities [1][2][3][4][5], the explorations on leveraging Big Data Analytics tools and distributed machine learning technologies and empowering both the intelligence and affection aspects of humanoid service robots were rarely reported.

In this paper, we tackle the highly complicated and intelligence demanding applications by using a Big Data Analytics as a Service approach, with which a novel Distributed Collaboration and Continuous Learning (DCCL) middleware platform is developed to support collaborative humanoid service robots in these domains. The main contributions of the paper are:

1. It identifies Distributed Collaboration and Continuous Learning (DCCL) mechanism as the key capability of a humanoid service robot companion to accomplish ever increasingly intelligence demanding applications such as children education and ageing society.
2. It proposes and develops a Big Data Analytics tools and distributed machine learning technologies based flexible and open DCCL middleware platform to support the capability.
3. It proposes and introduces use cases of the DCCL platform with preliminary experimental results to validate the platform.

The rest of the paper is organised as follows. Section II introduces related work on the Cloud services based collaborations of robots. Section III introduces the general model of affective interaction between humans and humanoid service robots and the main challenges in highly intelligent demanding scenarios; a Distributed Collaboration and Continuous Learning (DCCL) model is proposed to tackle the challenges. Section IV describes why and how Big Data Analytics could be used to realise the DCCL model and a Big Data Analytics as a Service approach is developed to construct a DCCL middleware platform. Finally, Section V concludes the paper and plans future works.

2 Related Work

In recent years, a development trend has merged in empowering an individual robot with more advanced social intercalation capabilities and connecting individual robots with Cloud services to facilitate computation intensive applications.

The DAvinCi [1] project develops a Cloud computing software framework for robotic ecosystem. The framework provides the scalability and parallelism advantages of Cloud computing for service robots in large environments. The framework is implemented on a Hadoop Cluster [6] with ROS (Robotic Operating system) [7] as the messaging framework. The RoboEarth project [2] develops a Cloud service based platform for sharing knowledge between robots and offloading computations into the Clouds. On this platform, robots are able to collaborate to exchange information and achieve a common task. The Cloud Robotics project [3] proposes a Cloud-based thin-client model for object recognition engine for service robots access to distributed computing resources and datasets and are able to share training and labelling data for robot learning. Two recent papers [4] and [5] conducted and reported comprehensive surveys on the topic of integration of robots with Cloud services.

Although these works exhibit a common theme of offloading intensive computation into the Cloud and sharing knowledge among robots, the support of fusing a coherent representation of world/context for facilitating advanced decision-making capabilities are largely missing. Moreover, the role of Big Data Analytics as a Service in the establishing of the representation and leveraging the representation for realising a DCCL mechanism is the main concern and contribution of the paper.

3 Affective Humanoid Service Robots

3.1 The General Model of Affective Human and Robots Interaction

The participation of a humanoid service robot in affective interactions with a human character is a standard two phases' process of recognition and reaction. Firstly, the robot recognises the human character's emotion state/general mood during a conversion by receiving and processing emotion related stimuli (e.g., facial expressions, speeches and gestures) and then it responses to the character accordingly by performing an appropriate affective expression of synthesized speeches and gestures.

The recognition phase is modelled as a combination of individual classifications and overall information fusion. Individual supervised machine learning modules are used to train the robot to classify the emotion states of human encoded in facial expressions, speeches and gestures respectively. A high level of information fusion module is used to merge these individual classification results to decide an overall much more accurate and realistic emotion state. Since the temporal features (coordination and correlation) of individual classification results, e.g., the timing correlation of gesture changes and facial expression changes, is capable of affecting the overall judgment, the information fusion module should be flexible and robust to accommodate the temporal and dynamic characteristics of individual classification results when merging them.

The reaction phase is modelled as a decision-making and high-level motor control process. After recognising the facial emotion states of a human character, during the second phase of an affective interaction between a humanoid and the human character, the humanoid will facilitate the interaction by talking to the character with a synthesized emotional gestures (e.g., mimicking body languages). A single or a set of appropriate gestures will be decided at runtime by consulting a simple body language rule based matching model of emotions and gestures. The model consists of a set of conditional statements, which direct the selections of appropriate gestures for representing certain emotions. These rules also consider certain timing features of the interaction process by preferring lightweight gestures for smooth movements. An example of this reaction phase is the selection of an emotional gesture of crossing arms in front of the chest, which can be used as part of the reactions to the 'contempt' emotion state exhibited by the human character. A gesture is synthesized by invoking the body motion functionalities that support the basic individual movements of arms, legs and head of the robot.

3.2 The Challenges of Humanoid Service Robot as a Daily-life Companion

The participation of a humanoid service robot in affective interactions with a human character is a standard two phases' process of recognition and reaction. Firstly, the robot recognises the human character's emotion state/general mood during a conversion by receiving and processing emotion related stimuli (e.g., facial expressions, speeches and gestures) and then it responses to the character accordingly by performing an appropriate affective expression of synthesized speeches and gestures.

With these fast developments of and higher expectations to robotics in the past decade, a trend of exploring and enabling humanoid service robots as a daily-life companion (e.g., assistive robots and service robots) is emerging [8][9][10][11][12][13][14]. While humanoid service robots have been matching on their way to actively participating in real-world human activities and serve the purpose of improving the quality of human life, as a daily-life companion, they are expected to accompany and serve human in a longer time period and under higher intelligence demands rather than to complete simple one-off mechanical and intelligent tasks.

Due to the companion nature of the humanoid service robot in these application scenarios, some common capability requirements can be identified:

1. Recommendation: Provide personalised assistances and services.

2. Decision Support: Support decision-making assistance and even delegation.
3. Emotional Intelligence: Understand affections and even exhibit certain degree of empathy.

Although these requirements can be partly met by the existing basic information processing capabilities of a humanoid service robot, such as vision, speech and mobility, those advanced intelligent capabilities enable a humanoid to fulfill these requirements. These advanced capabilities are essential for a humanoid service robot. Hence, in order to support a consistent real world representation and collaborations within it for a team of robots, the different version of the world observed and represented by an individual robot will be collected and fused into a single consistent version of world representation. In a more generalised sense, a world can be an abstract context or scenario, which might not necessarily depend on the existence of physical objects. For example, the emotion state or mood of a human can be considered as a kind of context in which multiple collaborative service robots may be interested. By fusing the observation of each robot from different perspective over the time, a true state of the context can be established and shared by all the robots for collaboration.

3.3 The Role of Distributed Collaboration and Continuous Learning Capability

As a gap emerges between the capability requirements of these applications and a humanoid service robot's localised intelligence capacity, an independent humanoid service robot is expected to fill the gap by accessing external/remote intelligence resources and services at runtime and even to collaborate with other humanoid service robots via an external open platform. Hence, a Distributed Collaboration and Continuous Learning (DCCL) mechanism will be a key capability for a group of coordinated humanoid service robots. On one hand, the Service Robots participating in the collaboration may be distributed on different locations but need to share a common presentation of the world or context within which the collaborative services are provided to the human users; on the other hand, these robots need to learn from each other by contributing individual knowledge and sharing experience. All the robots will update the common model governing the collaboration continuously and learn continuously by referring to the model.

4 Big Data Analytics for Distributed Collaboration and Continuous Learning

4.1 A Big Data Analytics as a Service Approach

Big Data Analytics is a methodology of seeking insights from a huge amount of disparate data collected, processed and analysed on a massive scale. Volume, velocity, and variety (3Vs) are the key characteristics of Big Data and the analysis on the Big Data utilises scalable data processing platforms such as Cloud computing with customised Data Mining or Machine Learning techniques. For the case of DCCL of service robots in smart home/school/campus applications, due to the distributed nature of service and heterogeneous data sources, the Big Data Analytics, equipped with distributed and scalable data processing and intelligent analysis ability, is a flexible and efficient method to support incremental data collection, storage and knowledge model. In our work, corresponding to the DCCL model, a DCCL middleware platform is designed and implemented to provide the foundations for service collaboration and continuous learning among these robots.

The platform aims to support distributed collaboration and continuous learning mechanism to facilitate effective the affective interactions between a humanoid service robot and its human user. On one hand, the distributed collaboration ability enables robots to coordinate and share their services and new acknowledge among a group of distributed robots; on the other hand continuous learning ability enables an independent robot to learn from its peer by acquiring the acknowledge shared among them. The basic vision, speech and mobility capabilities of a humanoid robot can be enhanced by interacting with certain advanced capabilities such as recommendation, decision support and emotional intelligence via a remote intelligence interface; these advanced capabilities are based on Big Data Analytics facilities of classification, recommendation and clustering hosted in the Cloud; and the advanced capabilities and Big Data Analytics facilities together are exposed as a DCCL service to the service robots.

4.2 DCCL Platform Architecture

A scalable and flexible messaging system is used to build the DCCL middleware platform on which a team of robots are integrated with the Big Data Analytics facilities hosted in the Cloud. Figure 1 illustrates the architectural view of the DCCL middleware platform. Within the DCCL platform, the messaging system connects key data generation and processing algorithms, which are executed on the service robot side and the Cloud based Big Data Analytics Service side respectively. On the Humanoid Service Robot side: A facial emotion recognition algorithm uses unsupervised automatic facial point detection integrated with regression-based intensity estimation for facial action units (AU) and emotion clustering to recognize seven basic emotions as well as neutral expressions. The detailed descriptions of facial emotion recognition was published in [16][17]. A world/context representation update algorithm that associates human emotion state with the interaction scenario. Human character is a pre-defined type of object in the world presentation. An individual human character is an object of the people type and defined by a set of attributes such as ID, Name, and facial emotion state. On the Cloud based Big Data Analytics Service side: A data fusion algorithm combines data sent by the multiple robots engaged in the interaction scenario to construct a fused context representation. The opinions of each robot are fused to establish a consensus on the emotion state of the human character by using the consensus operator defined in the binary subjective logic [18]. A user preference based recommendation algorithm to generate a highly intelligent and appreciate decision-making based on the query to fused context representation.

4.3 DCCL Platform Prototype Implementation

The DCCL middleware platform is implemented with the integration of Aldebaran NAO humanoid robot [15] and the Big Data Analytics tools of Apache Ecosystem. NAOqi is the software framework that runs on and controls the Aldebaran NAO humanoid robot. The NAOqi framework provides rich programming libraries and tools to develop sophisticated robot applications. The Big Data data storage facilities are provided by the Apache HBase and Apache Hive. Apache Mahout is a set of well established and scalable machine learning and data mining libraries, which support Big Data analytic applications, running on an Apache Hadoop platform. Recommendation, clustering and classification are the main machine learning techniques implemented by the Mahout libraries. As illustrated in Figure 1, three are three main parts (A, B and C) in the architecture: the Part A is the functional modules inside a NAO robot; the Part B is the main messaging system; and Part C is data store and Big Data Analytics Service in the Cloud.

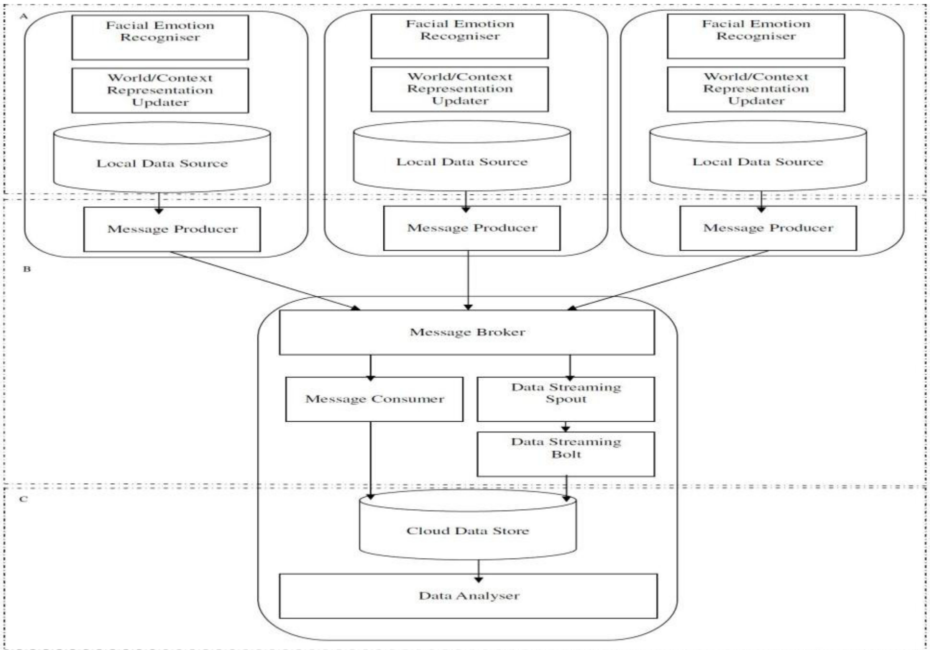

Figure 1 Big Data Analytics based Distributed Collaboration and Continuous Learning Middleware Platform.

Part A of Modules of NAO Humanoid Robot includes the following components. *Facial Emotion Recogniser*: on the recognition of a facial emotion expression of the interested human character, the Recogniser generates an event of updating world/context representation database. *World/Context Representation Updater*: ALWorldRepresentation is a module of NAOqi the update and access to the long-term storage of data about generic objects. The World/Context Representation Updater subscribes to the database update event generated by the Facial Emotion Recogniser and uses the API of ALWorldRepresentation module to update the World/Context Representation with the recognised emotion state embedded in the event content accordingly. *Local Data Sourece:* It is a SQLite database for persistent data store on the NAO robot and supports generic queries with intelligent criterions via a C/C++ API library. ALWorldRepresentation provides a wrapper on this library.

Part B of Modules of the Messaging System includes the following components. *Local Data Source*: although the Local Data Source of Part A is embedded on the robot side, form the viewpoint of message source, the Local Data Source is also considered as part of the messaging system which connecting the a robot to the Big Data Analytics Service in the Cloud. *Message Broker*: Apache Kafka is an open source message broker to manage the message exchange between Message Producers, Message Topics and Message Commuters. *Message Producer*: A Java program that uses the SQLite API to access the data stored in the World Representation databases and uses the Apache Kafka API to construct and publish well-formatted messages into the predefined topic inside the Kafka Message Broker. *Message Consumer*: an Apache Kafka API based Java program for subscribing messages from Kafka "FusedWorld" message topic and store them into the Big Data Store in the Cloud. *Data Streaming Subsystem (as a Configurable Plug-in)*: for the case of a large-scale data transfer application, a Data Streaming Subsystem can be configured to capture data from Kafka Producer into Apache Storm Spout. This data will be processed in real time. Apache Storm Spout will read data from Kafka "FusedWorld" message topic. Spout passes streams of data to Apache Storm Bolt, which processes and passes it to the Big Data Store in the Cloud.

Part C of Modules of the Big Data Analytics Service in the Cloud includes the following components. *Big Data Store*: Apache Hive and Apache HBase tables are created to store the data from the Message Consumer or configurable Data Streaming Subsystem. *Big Data Analyser*: A set of data analysis and processing functionalities, which include a Subjective Logic Consensus Operator [18] based information fusion process and an Apache Mahout scalable data mining libraries based high-level decision support system. As the recommendation library of Apache Mahout is integrated with the NAO robot on the DCCL platform, a NAO humanoid service robot is able to access a remote recommendation service hosted in the Cloud.

4.4 Use Case Study Design and Preliminary Simulation

In this section, the design of a use case in preference based recommendation application is introduced. In this use case, humanoid service robot companions are required to recommend appropriate toys to children by taking their emotion states and behaviours into accounts. These humanoid service robot companions are to be deployed to play together with a group of children hosted in classroom. Children's emotion state is inferred with their facial expressions, when playing with a toy. The emotion state is interpreted as preference feedback on the recommendations of toy and are collected and shared by the individual robot companion to adjust the overall recommendation decision making at runtime. The preference of a child to a toy is inferred from the emotion state change and scored by the intensity of the emotion state.

The relationship between children ID, toys ID and preferences are generated and stored into a common ‘preferences’ database table as part of the context representation. The remote recommendation service accesses a fused representation to build a recommendation model. At run time, a humanoid service robot updates the preference values according to recognised emotion change and invokes the remote recommendation service to recommend a toy to a child.

In a preliminary simulation study of the fused emotion detections by multiple robots over a period of time, the facial emotion state recognised by three humanoid robots are to make a final consensus. The simulation results of individual recognition result and the consensus of a *happy* type facial emotion detections on a particular facial emotion by the three robots over 5 minutes, in which 3 snapshots are taken for every 1 second and 180 snapshots in total for very minute by each robot. Among the 180 snapshots, each classified *happy* type facial emotion expression is used as positive evidence and the other emotion types such as *sad*, *surprise* and *neutral* etc. are all used as negative evidence; the expectation of a detected type is a real value between 0 and 1 as a confidence value. The interpretation of positive and negative evidence and related opinion consensus on the fused expectation calculation are based on the Subjective Logic Consensus Operator [18].

5 Conclusion and Future Work

This paper envisages that as the increasing participations of humanoid service robot companions in human society, new challenges are emerging from even more complicated (both physical and intelligent demanding) application scenarios, such as children education, ageing society and smart home. A Big Data Analytics as a Service based Distributed Collaboration and Continuous Learning middleware Platform is developed to support advanced capabilities of cooperative humanoid service robots that are able to conduct affective interactions with human characters. Thanks to the stability of messaging system, the DCCL middleware platform is able to support multiple types of message producers, consumers and topics, which collectively support data transfers of different contexts or scenarios. For example, in future, for the recognition of the mood of a child, the emotion stability features, such as arousal and valence, define a complex world representation. These features can be collected and analysed over the time by using the platform. Based on the recognition on the mood, the change of a child's preference to a toy is inferred from a child's relatively long-term mood change rather than the short-term emotion state intensity variation during playing a toy.

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