

An Intuitive Interface for designing Social behaviors based on Human motions

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Abstract. Humans interacting with intelligent robots has been seen as a potential game changer of the future. In scenarios where robots coexist with humans in a social environment, understanding not only verbal communication, but also non-verbal communication is extremely inevitable. The non-verbal communication carries information such as intention, emotion and health of a human, that adds value to the way robots participate in an interaction. Additionally, the people who design interaction scenarios are from diverse fields who do not essentially have the required robot programming skills. In this paper we propose an easy to use and intuitive programming paradigm which gives the power to design robot behaviors taking into account human motions. We propose a distributed architecture which gives the capability to plug and play multi-modal motion recognition systems and diverse class of robots. We present results of Nao humanoid robot performing actions understanding human motions using kinect motion recognition system.

Keywords: human robot interaction, motion recognition, robot behaviors, kinect, nao

1 Introduction

Human Robot Interaction (HRI) is a challenging research field at the intersection of psychology, cognitive science, social sciences, artificial intelligence, computer science, robotics, engineering and human-computer interaction[9]. Goodrich[11] in his extensive survey proposed two main types of HRI namely Remote interaction or Teleoperation and Proximate interaction. The latter is particularly important where the humans and the robots are co-located (for example, service robots may be in the same room as humans). Proximate interaction has gained importance due to the successful encounters of putting robots to work with human beings. It has led to the development of a new class of robots called Social Robots. Fong et al. [10] define that social robots are able to recognize each other and engage in social interactions; Breazeal et al.[5] explain that a social robot is a robot which is able to communicate with humans in a personal way; Bartneck and Forlizzi [4] describe that a social robot is an autonomous

or semi-autonomous robot that interacts with humans by following some social behaviors; Hegel et al. [13] define that a social robot is a combination of a robot and a social interface. Summarizing all these Yan et al. [26] defines *A social robot is a robot which can execute designated tasks and the necessary condition turning a robot into a social robot is the ability to interact with humans by adhering to certain social cues and rules.*

The Social robots already entered the human spaces as entertainers[2], educators[2], caring agents[1] and personal assistants[3]. Given that social robotics has emerged as a promising field, designing and developing interaction systems need to be approached in a systematic manner wherein the robots should be able to understand the human motions and intentions in order to interact in a better way. To make it possible it is necessary to develop robotic systems with essential cognitive skills for efficient and natural interaction. Most often the on-board sensors on the robots fail to satisfy this demanding requirement due to various constraints like space, power and computational requirements. Hence consideration of augmenting exteroceptive sensors that are commonly available in the smart home/public environments to this purpose is important.

Another important aspect in HRI is the fact that the users of such systems are from diverse backgrounds. So the tools needed to design behaviors of a social robot should be intuitive and user friendly. With increased availability of social robots and cost effective motion recognition sensors, we could observe a huge void which inhibits the exploitation of available technology for designing human motion driven robot behaviors. More efficient tools are needed which could tackle this issue.

The main contribution of this work will be to develop an application independent experimental platform wherein a social robot will be augmented with essential perceptual ability to understand human motions. The behavior design of such a social robot will be made possible by an easy to use behavior design interface. The experimental platform will be used to design and evaluate the interaction between the social robot and the human driven by his/her motion.

2 Related work

2.1 Human Pose Detection

Vision based motion capture and analysis has been studied widely and a summary of all the approaches developed during the past three decades have been presented in the surveys [18] [19][20]. All these studies have investigated vision based human motion capture and analysis in general, however our particular focus is to use low cost RGB-D sensors like Microsoft Kinect[14] to this purpose. Vision based human pose estimation has traditionally suffered from the requirement to adopt an initialization pose and losing track after a few frames. These problem has been addressed by the approaches by Xbox[14] team which are capable of accurately predicting the 3D positions of body joints using single depth images without using any temporal information[23][24]. Unlike the approaches used in the Kinect SDK, the approach presented in [6] uses both the

depth and color(RGB-D) data for human body detection and pose estimation using a customizable human kinematic model.

Understanding of human motion is not complete if the gesture of the human could not be understood. Hidden Markov models (HMM) which had been widely used for speech recognition[21] also inspired to be used for the gesture recognition applications. In the survey by Microsoft research[12], a background study on various algorithms used for human activity analysis is presented. Recently data-driven machine learning approaches like neural networks, Support vector machines, clustering, decision trees and bayesian networks are being used to this purpose[15].

The localization of humanoid robots is a challenging issue, due to rough odometry estimation, noisy onboard sensing, and the swaying motion caused by walking[7]. Tracking rectangular fiducial markers using augmented reality toolkits like ARToolKit[16] can be interesting if we could embed those markers on the humanoid robot. This is one of the simplest and cheapest solution in terms of the computational power as it can provide position and orientation relative to physical markers in real time. The Point cloud library[22] which is one of the most widely used 3D perception software library, implements ready to use probabilistic tracking algorithms[25]. This could be readily used to track an object of known geometry and this information has to be fed to the PCL through a point cloud mesh of the object. Studies on robot localization, obstacle mapping, and path planning in multilevel 3D environments by equipping Nao with a consumer-level depth camera has been reported in [17]. Localization and motion planning in smart home environment using an external Kinect sensor have been proposed in [7]. In [8] a robust particle filter parallelized on a GPU that can track a known 3D object model over a sequence of RGB-D images is proposed.

2.2 Behavior Design Frameworks

3 System Architecture

4 Implementation

5 Experimentation

6 Conclusions

For the moment we have evaluated our system only for the Kinect motion capture system working seamlessly with the Nao humanoid robot for a set of predefined gestures and robot behaviors. We are planning to develop an extensive database containing commonly encountered gestures and also an extensive set of primitive robot actions. These will be made available to the end user through the intuitive programming interface which could be then used for defining complex motion driven behaviors. Additionally we are also planning to integrate our system to

work with other modes of motion recognition like IMU, Accelerometers and Gyroscopes that are available in smart-phones and wearable devices. Similarly we would like to integrate other system with other robots like Pepper which we expect to receive soon.

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