Active Human Detection with a Mobile Robot

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Abstract

The problem of active human detection with a mobile robot equipped with an RGB-D camera is considered in this work. Traditional human detection algorithms for indoor mobile robots face several challenges, including occlusions due to cluttered dynamic environments, changing backgrounds, and large variety of human movements. Active human detection aims to improve classic detection systems by actively selecting new and potentially better observation points of the person. In this preliminary work, we present a system that actively guides a mobile robot towards high-confidence human detections, including initial simulation tests that highlight pros and cons of the proposed approach.

Introduction

Mobile robots are already sharing environments with humans, especially for indoor applications. Providing services to and interacting with people are the most important tasks for such robots. Therefore, research in sensing methods and algorithms for human detection has received considerable attention in the last decades.

Human detectors for autonomous mobile robots encounter several challenges. Humans can assume a variety of poses (standing, sitting, etc.) and be observed from different views [1]. Another challenge is detecting occluded humans, which is one of the most difficult problems, though a few attempts have been proposed to deal with it [2]. Determining whether there is an occlusion or not is a key issue in itself [3]. The authors in [4] proposed a method to find the best robot pose for human observation. First, the robot locates the human using colour segmentation and then it moves around him/her to select the best observation pose. Although their work improved the detection confidence, it's still challenged by occlusions and human motion.

Active Perception (AP) seeks to control and guide the acquisition of sensor data in order to improve the performance of the input process and maximise the information acquisition [5]. The robot has to decide the optimal sensing configuration based on the current situation. AP systems therefore include a dynamic control of the robot behaviour, key for applications in real, changing environments. Recently, AP has been proved useful in many different scenarios [6, 7, 8]. However, to our knowledge, there are no AP systems for human detection with a mobile robot, as proposed in the current work. Active human detection is a particular AP system that seeks to overcome some of the previous challenges. The AP can guide the observation process and move the robot to the best available poses for human detection.

In our system, the best available poses are selected according to the human detection confidence, using a pre-learnt observation model. The latter is a distribution of the detection confidence values for multiple robot-human pose configurations, as shown in Fig. 1. In order to build this model, we collect a set of human confidence measurements and apply a 2D polynomic regression model to obtain the expected confidence for any new human-robot pose. The human detection method used in our system is a real-time RGB-D based upper body detector [9].

In this preliminary work, our system is tested in a ROS simulation environment, shown in Fig. 3. The architecture of the proposed active human detection system is shown in Fig. 2. The system starts with an initial human detection. Then, the robot moves to find the best available view for human detection, based on the known confidence model, and taking into account the motion cost. If the human changes his pose, the system adapts by selecting a new robot pose accordingly, at least as long as the human remains in the robot's field of view. In case of occlusion, instead, the robot selects a new pose from the set of available poses and avoids the area of the previous occlusion.

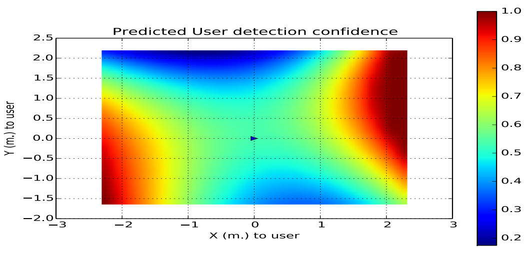

Figure (1) The pre-observation model

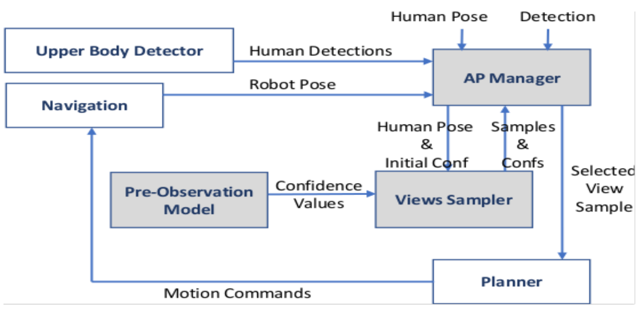

Figure (2) System architecture

System Design

The system design has a simple and modular structure, compatible with a standard ROS stack, which facilitates future developments and improvements. Fig. 2 shows the full system architecture. The gray modules implement the key contributions of this work. The system starts with an RGB-D upper body detection, which provides an initial human position and observation confidence. The human orientation is computed from the shoulders using the method proposed in [10]. Combining this information with the pre-observation model of detection confidence, the views-sampler generates several viewpoints randomly distributed around the person. These viewpoint samples are such that the expected human detection confidence is better than the previous one. Finally, the AP manager selects the next best viewpoint from the available samples that maximizes the expected detection confidence and minimizes the robot's moving cost.

Testing Results

The active human detection system continuously tries to improve its confidence. If the person moves or is occluded by an obstacle, the robot moves as well to find a more suitable position for high-confidence human detection. We performed some simulations (Fig. 3) to test our method against a typical passive approach in case of occlusion (Fig. 4) along with human motion. For the latter, in particular, it is clear that with a static robot (passive approach) the human detection confidence decreases as the human moves, as shown in Fig. 5. In contrast, Fig. 6 shows that our active approach can guide the robot towards good observation viewpoints. It is worth noting that the current implementation is not able to cope with a relatively fast-moving person, therefore it can only provide high-confidence detections for very short time intervals.

Conclusions

In this work, we have presented some preliminary work on active human detection, which has the potential to succeed in many situations where passive detection approaches usually fail. Initial simulation tests, however, highlighted the difficulty of dealing with fast moving humans. Our future work will focus on new strategies for active human detection that can prevent occlusions and take into account the limitations of a mobile robot platform, such as its limited field of view. We will also validate our approach in new real-world experiments.

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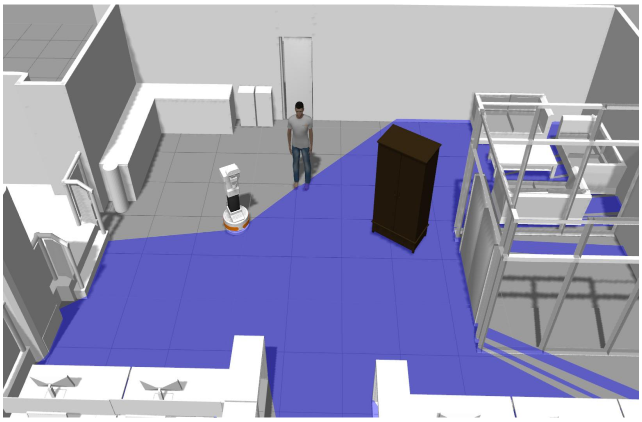

Figure (3) Simulation environment

Figure (4) Occlusion example

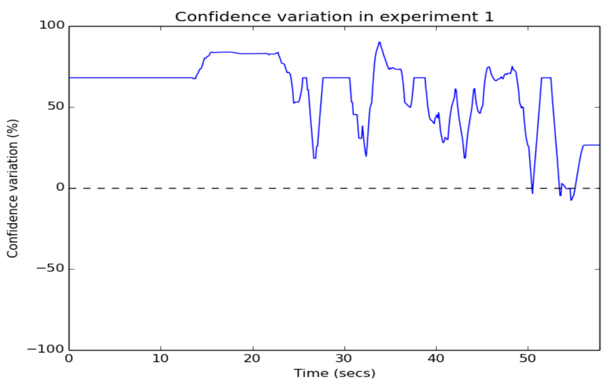

Figure (5) Human motion (passive system)

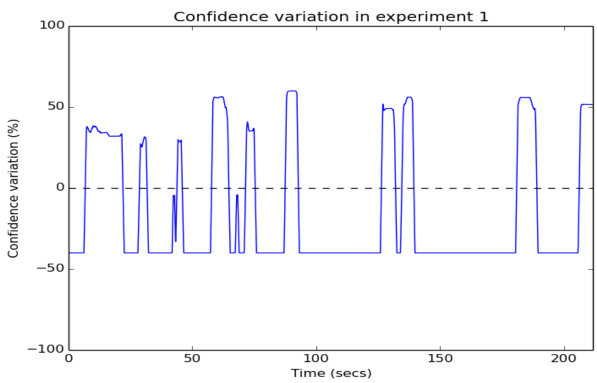

Figure (6) Human motion (active system)

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