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Trajectory planning based on activity recognition and identification of low-level process deviations

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Abstract

Improving work efficiency and ensuring safety of the human worker while the human worker and robot simultaneously perform the tasks in close proximity is one of the key research topics in human-robot cooperation. Given a process which contains a set of tasks or process steps performed within the shared human-robot workspace, a methodology for the robot's trajectory planning will be mentioned in this concept paper. The methodology will be based on activity recognition and identification of low-level process deviations. Here, the low-level process deviations which occur from the robot assistant side are mainly focussed.

1. Introduction

A key requirement in the field of human-robot cooperation is to realize the process execution in a safe and time-efficient manner. Here, process refers to a list of process steps/tasks performed simultaneously by the human worker and robot assistant. To achieve safe execution of shared human-robot tasks, a process monitoring component which identifies low-level process deviations is a pre-requisite. In the context of shared human-robot tasks, deviations are often classified into robot assistant side deviations and human worker side deviations. Robot assistant side deviations are defined as unexpected events like unreachable goal configuration, grasp failure reported by the robot's tool and high probabilistic existence of collision-prone trajectories with the nearby static or dynamic objects while the robot performs an object manipulation task in the shared workspace. Human worker side deviations are defined as expected events like performing spatial sequence of actions or activities and unexpected transition between the tasks or process steps. Process deviations from the human worker side are not considered within this work. The motivation behind this research work is to come up with a trajectory planning framework which can identify and handle low-level process deviations with respect to the simultaneous recognition of human activities and process steps/tasks. In this research work, the handling of process deviations will also be mentioned.

1.1. Related Work

Recent work which deals with trajectory planning is based on prediction of human actions and activities to achieve spatio-temporal synchronization in shared human-robot tasks. The manipulation planning framework presented in [3], [9], [16], [5], and [1] considered the trajectory planning problem from the normal operation of a manipulation task. A time-series classification algorithm was presented in [3] to perform the online prediction of human reaching motion by applying a motion capture camera system. Partial segments of actual motion variables are compared with the subset of motion variables which represent the optimally time aligned human motion demonstrations. In [9], the predicted motion trajectories are represented as 3D voxels which infers the workspace occupancy information. Similar approaches were adopted in [16], [5] for human motion prediction. In [6], human-object interactions in combination with human motion trajectories were used to build temporal conditional random fields for anticipating human activities. In [1], a human worker's intent was estimated by computing the probabilistic representation of workspace segmented areas to which the human is heading.

Task and motion planners were integrated in [13] and [4] to identify and handle low-level process deviations such as collision-prone trajectories with the neighbouring objects. Here, the process addressed is a pick and place operation performed by a robot on a cluttered table and a payload carried by two robots respectively. During the process execution, the interface layer in between the task and motion planners determines the presence/absence of obstructions by identifying the collision-prone trajectories from the trajectory planner as low-level process deviations. Based on these deviations, the task planner is updated with a new state and sends a variation of the initial task plan to the trajectory planner. An alternative way to handle these kinds of deviations is to replace object grasping with multiple push-grasps in a cluttered environment [10]. With our work we intend to enhance the state of the art by cascading activity recognition and task recognition to identify low-level process deviations and perform task level trajectory planning. In this work, we also intend to realize activity recognition by estimating the skeletal joint positions with a higher sampling rate.

1.2. Paper Organization

Section 2 deals with the methodology proposed for trajectory planning based on activity recognition and identification of low-level process deviations. Section 3 will present the experimental setup including a static process plan where the human worker and robot performs process steps/tasks within their shared workspace. Section 4 will detail the expected contributions.

2. Methodology

In this section, the methodology behind the trajectory planning based on activity recognition and identification of low-level process deviations will be described along with the system architecture. Figure 2 depicts the system architecture which consists of 7 major building blocks 1) Object tracking 2) Skeletal joints estimation 3) Action recognition 4) Activity recognition 5) Task recognition 6) Trajectory planner and 7) High-level planner. The algorithms applied for object tracking and action recognition components have already been realized and evaluated in [14] and [15] respectively and will not be mentioned in this research work. Therefore, the methods required for the remaining major blocks will be mentioned here.

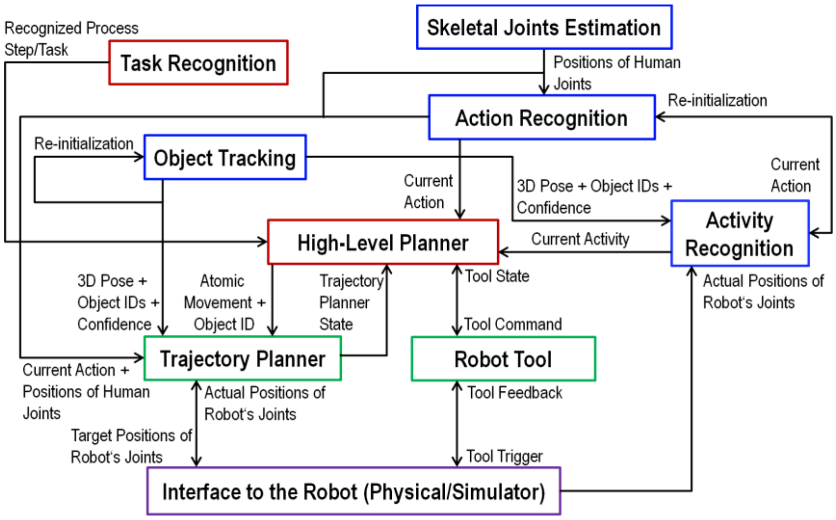

Figure 2: System architecture

2.1. Skeletal Joints Estimation

Estimation of skeletal joints is a crucial pre-requisite to overcome real-time data loss. The sampling rate of currently affordable RGB-D sensors is 30 fps. Recent works [3, Section 1.1], [9, Section 1.1] indicates that this sampling rate is not sufficient to recognize human activity in less than 1s. This leads to the motivation of estimating the skeletal joints data with a higher sampling rate. In the first stage, mathematical modelling of skeletal joints of left and right hands with respect to *Head*, *Neck* and *Spine Shoulder* skeletal joints will be performed in offline. In the second stage, the measured skeletal joints will be fed to a zero order hold (ZOH) component to provide the k^{th} sample at time instant $k*T_s$ with repeated values until the $k+1^{th}$ sample appears at time instant $(k+1)*T_s$. To overcome real-time data loss at time instant $k*T_s$, extrapolated values for skeletal joints of the left and right hands will be generated from the mathematical model. In the third stage, the samples with the higher sampling rate resulting from the ZOH and the extrapolated values resulting from the mathematical model will be used for estimating the desired skeletal joints positions. A forward Markov model describing the desired skeletal joints positions will be assumed and a stochastic subspace realization algorithm [8] will be applied to estimate the desired skeletal joint positions.

2.2. Activity and Task Recognition

Activity is defined as the sequence of actions or a single action performed by a human and his/her interactions with the objects of interest within an arbitrarily short time window. During the offline stage, probabilities of the recognized actions, human-object interactions and actual positions of robot's joints are considered as activity specific features and are collected with respect to *M* activity demonstrations by *L* individuals. Here, human-object interactions are represented by human motion trajectories and 3D position information, IDs and probability values of tracked objects. The recorded *M**L* demonstrations are then fed to a classifier for activity classification. A Markov model will be adopted to represent the temporal relationship between human activities over time. During the online stage, partial segment of the activity specific features are used as inputs to compute the probability for states which represents human activities. The state with the highest probability will then be the recognized activity [12]. The activity recognition approach mentioned in this section will be extended for task recognition using a Hidden Markov model (HMM) to represent the process steps/task as its states. In the case of task recognition, the probability values of human actions and his/her activities, robot's planned trajectories and positions of the robot's tool will be considered as task relevant features to model the states of the HMM [2].

2.3. Trajectory Planner

The trajectory planner considers the static workcell, actual skeletal joint positions, detected human activities and 3D locations of the objects of interest as an input and computes a collision-less trajectory for the robot. These activity dependent collisions-less trajectories will result in process-specific object manipulations like Grasp, Lift, Place, and Present. During the execution of the process, trajectory planner will send status updates about the object manipulations which will be requested by the high-level planner. Path planning algorithms which were applied in [11], [7] will be investigated to verify which one of them would be ideal for safe execution of the considered process.

2.4. High-Level Planner

High-Level Planner is an intermediate layer which receives the status updates continuously from major building blocks and robot's tool positions to monitor the process execution. The High-Level Planner will be included with the static description of sequential order of process steps/tasks involved within a process. During the execution of the process, the High-Level Planner will compare the actual state of the process with its desired state and identify the low-level process deviations from the robot assistant side. Based on these deviations, the trajectory planner will then compute a collision-free trajectory which will lead to successful completion of the previously failed process steps/tasks. Here, High-Level Planner will continuously send the same process step/task to the trajectory planner until the identified deviation vanishes.

3. Experimental Setup

The process of assembling a Steam cooker device using its individual objects is considered here. The individual objects of the steam cooker are present on the worktable as depicted below.

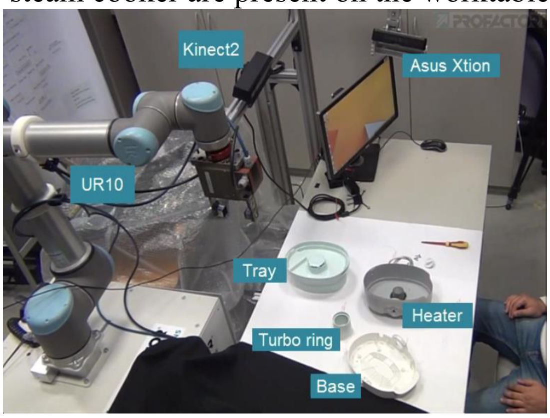

Figure 3: Experimental setup included with individual objects of a steam cooker device

In Figure 3, UR10 is the universal robot which is placed on a movable platform. This movable platform is clamped to the worktable where the human worker and ur10 robot will share the workspace. A Kinect v2 sensor is applied for the human action and human activity recognition and an Asus Xtion sensor provides the scene data for the localization and tracking of objects of interest. The following static work plan related to the assembly process of a Steam cooker will be assumed.

- Step 1: Human worker picks the base object and robot grasps and lifts the heater object
- Step 2: Human worker holds the base object and robot shows the heater object to the human
- Step 3: Human worker attaches the base object to the heater object and inserts the timer cap on the side of heater object and performs the screwing

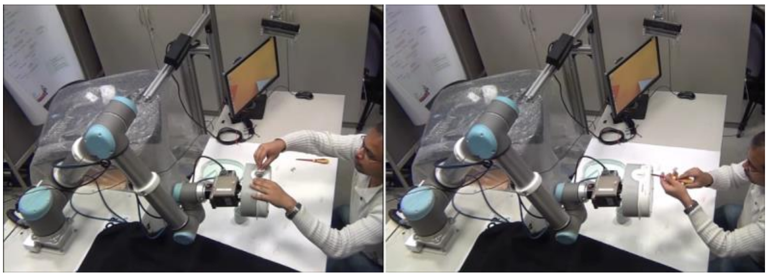

Figure 3.1.2: Human worker performing step 3

- Step 4: Robot lifts and places the compound object resulted from step 3
- Step 5: Human picks the turbo ring object and places it inside the compound object while the robot grasps and lifts the tray object
- Step 6: Robot presents and hands over the tray object to the human worker
- Step 7: Human worker inserts the tray object into the compound object resulted from step 5

Figure 3.1.3: Left image => step 6 and Right image =>step 7

4. Expected Contributions

The expected contributions resulting from this research work will be 1) Identification of low-level process deviations from the robot assistant side 2) task level trajectory planning based on simultaneous task and activity recognition to handle such process deviations 3) estimation of skeletal joints positions with a higher sampling rate.

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