Masterthesis in Informatik

Exposé

1 General information

Working title:	Multi-Cue Person Tracking using RGB-Depth Camera and Laser Range Finder
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2 Goals

Remove implementation details, focus on LRF - optional support from rgbd

The goal of this project is to implement and evaluate a tracking approach using a Laser range finder which is supported with additional tracking with a RBG-D camera. The object to be tracked is a person, who at start of the experiment is standing in front of the sensors. The sensors are mounted on a Tiago Robot. To enable the tracking, the person will be positioned in a 2D coordinate system measured relative to the position of the robot. This is tracked using the 2D LRF data, supported by the tracking from the 2D image data. Multiple scenarios will be devised where the position of the object to be track changes, the object either is occluded from the field of view of the sensors, or it exits and re-enters the frame. The data provided to evaluate the tracking efficiency will be provided through a simulation initially. Following which the experimental set-ups will be recreated in a lab environment. The Tiago robot will be used as the sensor platform to record cases similar to the ones deployed in the simulation.

Assuming the above-mentioned method is successful in tracking, another approach can be devised. This will involve tracking, using LRF data to be supported by point cloud data from the Kinect (RGBD) sensor. The LRF data will be used to reinforce the tracking of the object in a 3D coordinate frame.

Finally, the aim of the project is to compare and illustrate the results of the different methods implemented in it to the previous methods in use by the research group at Uni Bielefeld. [1][2]

3 Related work

For the case of applications such as assistant and companion robots, a good human following ability is needed. There are robots which are meant to carry loads of different weights and follow people autonomously. Such robots can be deployed in a variety of fields. There can be a load bearing robot for use alongside first responders, which may bear weights that might hamper the mobility of the person in a disaster response scenarios. The situation of use of such robots can lead to problems of their own, such as loss of tracking due to presence of static and dynamic obstacles. Such obstacles can cause a loss of target object. The challenged posed by such an application are: detection of human, tracking of the human and the successful following of that human. The path of the robot is based on the path of the target being followed. The robot must also navigate the environment successfully, avoiding collisions. Many works have been published in the field of person tracking with robots [3]. Many of these implementations are based on laser range finder data as many models of autonomous robots are equipped with LRF's. The LRF data is presented as 2D image. Also as the LRF sensors are usually placed at a lower height most of these tracking methods use the geometric data of legs to track humans. There exist implementations [4][5] of person tracking through laser itself, but it is not very reliable in a cluttered environment.

The paper published by Chebotareva Et. al. [6]. deals presents a human-following algorithm for an autonomous robot, which has a monocular camera and a 2D Laser Range finder. The use case for both this project and the one mentioned in [6] is an indoor, office/university environment. Usually, the head and upper body is used for this form of object tracking, but this paper proposes a method which does not need to have the full human figure in frame at initialization and can track based on the lower body and does not place restrictions on the nature of clothing worn. Their implementation was compared by simulating experiments in Gazebo for the use cases of a corridor and office/lab room environment.

Their method was to take the LRF data at initialization, the human to be tracked is closest to the robot. These are a collection of points, which are connected to the nearing points to create a curve. This approach allowed them to record the position of the legs and track it easily. Several trackers were deployed such as: KCF, TLD, Median Flow, MOSSE and MIL. The most promising results of the LRF based tracking were from MIL and MOSSE. Even though all the used trackers had their shortcomings, to overcome this, they supported it using the data from a monocular camera.

Another approach is a method like one mentioned in [7]. Their implementation of Multi-Object-Tracking uses deep learning, DeepSort. In the MOT algorithm, simple online and real-time tracking (SORT) adopts the Kalman filter and Hungarian matching algorithm to track the objects, which obtains fast and great tracking performance.

4 Approach

chapter could be more concise

The initial approach is based on a paper [6], which deals with a weight carrying robot and its movement based on the person tracked.

can add subsection: dataset: describe needed datasets, simulated and real etc

4.1 Data-set

The data for the experiments conducted will be provided through two primary methods.

1. Through simulation data provided by Gazebo.
   - Firstly, a generic scene will be composed, which can be replicated within the lab facilities which are present. The 3D models those approximate to furniture in the lab environment present in Gazebo will be used.
   - This project will use simulation data, which is recorded by the sensors in Gazebo.
2. Through the recording of similar scenarios using the Tiago robot.
   - The experimental set-ups created within Gazebo will be recreated.
   - Recordings of tentative cases(mentioned below) will be made.

We assume that at start time, the person directly in front of the sensors is our tracking object. As the individual is walking away from the sensor array, the objective is to include occlusion (such as another person walking in between the line of sight, other cases will be devised) and observe if the tracking holds. The laser range finder data is used as the primary tracking method under this implementation, where the data from the RBG camera is used to reinforce the tracking efficacy of the system. To set up the different tracking methods, using both the RGB-Depth camera and the LRF, a setup will be created in Gazebo. Trackers such as MIL, MOSSE. This will be supplemented by the data from the Kinect, a 2D image of scene with the person in front of it.

This will involve:

- The transformation of the laser data points to create a 'curve' (2D Image) of the person standing start time.
- Upon which MIL tracking methods will be initialized to create a region of interest rectangle.
- The RBG camera data serve as another 2D image on which the laser tracking data will be projected upon.
- Along with the reinforcement of the RBG camera data with the LRF data MIL and MOSSE tracking methods will be initialized.

A further implementation is the deep learning-based tracking of multiple objects through YOLO and DeepSORT. Here even though it is a method used for multi object tracking, it deals with point clouds and the re-identification of object target once it is occluded, making it a good case for our project. The 2D laser data will be used to support the tracking object identified with the help of the 3D point cloud. The trackers used for the laser data would be KCF, MIL and an implementation of DeepSORT for the point could.

The 'fusion' of sensor data will be thought of. For the first implementation, it is like the method used by ref paper (1). In the other case, the actual way to incorporate both data sets to create a successful tracking algorithm will be devised. This is provided through Bayes tracker.

This prototype will provide a good starting goal. It will be easy to run the algorithms created for Gazebo simulation in the real world as well. Different cases will be tried, and results will be demonstrated.

4.2 Equipment Used

The equipment at the university lab includes a Tiago robot, which has a Kinect as an RGB-Depth sensor located where the 'head' of the robot is and an LRF located close to the ground. The Robot Operating System is what Tiago runs on; this is what will be used to provide data from the sensors.

4.3 Tentative cases

think about which features the tracker has. e.g. reinitialization after lost tracking and scenario to test this e.g. move around corner

1. Robot following human down a straight line.
   - Evaluate the efficacy with no interruptions, just the scene and the target object.
   - Introduce occlusion to the scene, between the field of view of the sensors and the object tracked.
   -
2. Robot following human who walks straight initially then turns to the left or right.
   - Induce the loss of tracking object from the FOV, forcing reinitalisation of tracked object
3. Introduce similar objects into the FOV of the sensors.
   - Other legs with similar orientation
   - Other objects with similar LRF profiles.

remove indepth explanation, add occlusion etc. as list items

4.4 Schedule

Task	Completion Date
Handing in of Expose	21st August
Start of creation of prototype in Gazebo.	22nd August
Initialization of LRF based tracker on the generated curves from laser scan data.	29th August
Initialization of camera based tracker for the experimental setup.	5th September
Evaluation of tracking approach with simulation data.	
Different scenarios for tracking situations recorded.	
Evaluation of tracking approach with synthetic data.	
Other approach algorithms implemented after successful first algorithm	

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