A Human Morning Routine Dataset

(Extended Abstract)

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ABSTRACT

To be able to evaluate and compare the quality of different approaches in research, general and publicly available datasets are needed. While in some areas, there exists a variety of such datasets that are constantly used by researchers, in the area of activity recognition and human activity modelling, the number of publicly available datasets is rather small. In this extended abstract, we introduce a new dataset that captures several typical activities of a human morning routine of a single male person that includes motion tracking data for the person and objects from real sensors and a simulation as well as ground truth information in the form of diary notes. The dataset is intended to ease comparison between different approaches in the afrementioned research areas and free researchers from the time-consuming task of recording new datasets.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

Experimentation, Human Factors, Algorithms

Keywords

Datasets, Human Behavior Modelling, Activity Recognition

1. INTRODUCTION

With robots advancing more and more towards working together with humans, the field of activity recognition becomes increasingly important as a key enabler for effective and acceptable human-robot interaction. Recently, different approaches have evolved that use diverse methodologies and algorithms to recognize human activities from sensor data like motion tracking information or RFID readings. The increasing number of approaches makes it necessary to have general datasets about human activities that enable researchers to compare the quality of their approaches using similar sensor modalities. In many cases, such datasets use sensor settings that include RFID sensors, but also approaches using video cameras for human motion tracking data [2] are popular. Other sensor modalities like GPS, pressure sensors, reed switches or waterflow sensors are also used. In our work, we are specifically interested in analyzing human motion tracking data of routine activities. In this extended abstract, we present a new dataset that is designed to support researchers in the fields of activity recognition and human activity modelling by capturing a typical human morning routine of a single male person.

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2. RELATED WORK

The MIT PlaceLab [1] is a sensor-equipped apartment laboratory in Cambridge, MA. The apartment consists of a living room, dining area, kitchen, office, bedroom, full bath and half bath with each room including a micro controller and up to 30 sensors to record audio-visual data. The apartment has been used to perform several studies and record several datasets in which participants were asked to perform common tasks of daily living. Ground truth data is only available for parts of the data due to financial restrictions.

The publicly available TUM kitchen dataset [2] offers several recordings of humans performing two different variations of a table-setting task in a typical kitchen environment in two different ways. The dataset includes video sequences from four cameras, full body motion tracking data of the human, RFID tag readings of objects and magnetic sensor readings from furniture objects like cupboards and drawers in the environment. The data has been manually labeled to provide a ground truth for motion segmentation. The sensor setup used in this dataset is quite complex and expensive, but therefore offers accurate motion tracking data without occlusions.

3. DATA ACQUISITION

The dataset described in this extended abstract has been created with the aim of capturing a typical morning routine of a single person in an apartment. In contrast to other datasets like the TUM kitchen dataset [2] which consists of several persons performing the same task, the focus for this dataset was to capture several activities of daily living performed by the same person at different days during an extended period of time. Furthermore, we specifically focused on a low cost sensor setting using only two Kinect sensors which cost below 250 USD in contrast to relying on complex and expensive motion tracking systems. We think

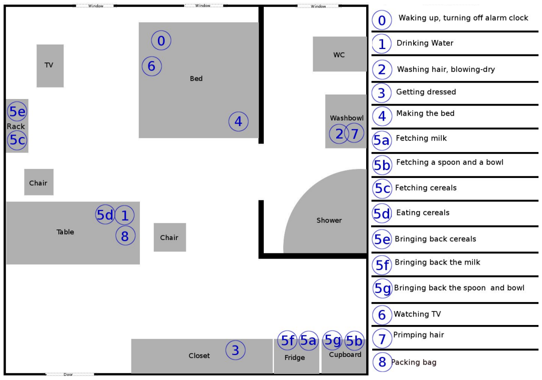

Figure 1: One day of the notes the participant took showing the order of locations he visited during his morning routine.

that a commercial service robot that will be deployed on the consumer market will use rather low cost components in order to be affordable for a wide range of people. Thus our dataset reflects a realistic impression about how such a robot would perceive routine activities of its user when it is deployed in a human apartment. The dataset has been released to the public on September 24th, 2013 and is publicly available for download [1].

We investigated a period of 14 workdays of a voluntary male test person that was living in a rental apartment by himself. We asked the test person to note down the activities that he performed before going to work over 3 weeks (that included one holiday) as well as the locations where he performed each of the actions. The exemplary notes of one day are shown in figure 1.

4. DATA GENERATION

To obtain sensor data of human motion tracking as well as detected objects, the participant was asked to reenact his morning routine according to his notes in a kitchen environment equipped with two Kinect sensors. We use one of the Kinects for human motion tracking using the OpenNI tracker[2] and the second Kinect for object detections based on visual markers using the ar_pose[3] wrapper for ARToolKit. Since the size of the visual markers was of critical importance for the detection, we only used markers on objects that were of a certain size: Cornflakes, Milk, Backpack, Curd cheese, and Bottle. The ar_pose object detection returns the approximate pose of all detected objects in reference to the Kinect as coordinate transformations in the ROS TF framework [4]. Although the motion tracker worked quite well while the test person was walking, it sometimes lost track of the person when parts of the body are occluded or returned incorrect measurements, which resulted in a “jumping” of some joints of the tracked human. While in many cases, the marker-based object detection returned correct object detections, it often happened that objects were detected at wrong places or some detections of objects even were confused.

We also set up a simulated environment of the same kitchen

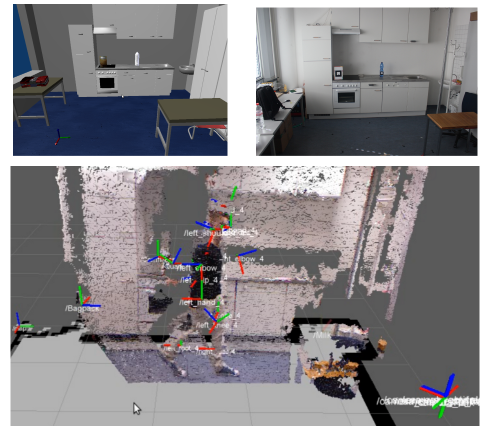

Figure 2: Upper left: Simulated environment in the MORSE simulator, Upper right: Experimental kitchen environment. Lower picture: Sensor input of the real scenario.

using the MORSE simulator[5]. This simulator includes a human avatar that can be controlled by a user to move around and to perform pick- and place tasks in the simulated environment like in 3D computer games. Figure 2 depicts the experimental kitchen in its simulated version as well as the real kitchen environment. Furthermore, the picture shows a visualization of the motion tracking data and object detections that are obtained by the two Kinect sensors. Objects were placed at typical locations in both scenarios (butter in the refrigerator, cutlery in a drawer etc.). We tracked the position of all objects using a simulated object tracker and the human using a simulated person tracker. Instead of eating or drinking, the person was asked to take each object that is part if the corresponding task with the simulated human avatar for a short time and wait for a while.

5. CONCLUSION

This extended abstract introduced the TUM Morning Routine Dataset which provides researchers with data about a typical human morning routine of a single male person in a rental apartment. It includes diary-like information about activities as well as motion tracking data of activities in one real and one simulated kitchen together with ground truth labels. The dataset has been created to ease the comparison of different approaches in different research areas like activity recognition, human behavior modelling or learning.

6. REFERENCES

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[1] `https://hcai.in.tum.de/research/dataset`
[2] `http://ros.org/wiki/openni_tracker`
[3] `http://www.ros.org/wiki/ar_pose`
[4] `http://www.ros.org/wiki/tf`
[5] `http://morse.openrobots.org`