HMM-based Activity Recognition with a Ceiling RGB-D Camera
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Introduction

The main goal is to classify and predict the probability of an analysed subject action. We perform activity detection and recognition using an inexpensive RGB-D camera. Human activities, despite their unstructured nature, tend to have a natural hierarchical structure; for instance, generally making a coffee involves a three-step process of turning on the coffee machine, putting sugar in the cup and opening the fridge for milk. Action sequence recognition is then handled using a discriminative hidden Markov model (HMM).

The innovative aspects are in proposing an adequate HMM structure and also the use of head and hands 3D positions to estimate the probability that a certain action will be performed, which has never been done before, for the best of our knowledge, in ADLs recognition in indoor environments.

ADLs Model

Figure 1: Block diagram of the recognition process.

Information provided by head and hands detection algorithms can be used as input for a set of HMMs. Each of these recognise different actions sequence. After training the model, we consider an action sequence

\[ s = \{s_1, s_2, \ldots, s_n\} \]

and calculate its probability \( P(s|\lambda) \) for the observation sequence. Then we classify the action as the one which has the largest posterior probability. Figure 1 depicts the general scheme of the recognition process. In particular, we used three different HMMs, which have as observations 3D points of: the head; the hands; both head and hands together. Finally, the classification module provides the action \( x_j \) that maximizes \( P_{HMM} \). It is the HMM trajectory probability that follows the activity sequence \( s \) given the sequence of \( n \) observations, i.e.:

\[ x_j = \arg \max \ P_{HMM}(X_{1:n} \in \text{seq}_k(s)|o_{1:n}) \]

Experimental Results

Five models were used to recognize activities in the RADiAL dataset and correspond respectively to the activities “other” (this action contains all the other activities performed in a kitchen environment), “coffee” (making a coffee), “kettle” (taking the kettle), “tea/sugar” (making tea or taking sugar), and “fridge” (opening the fridge). The results were obtained using two different validation techniques.

Setup and Acquisition

Figure 2: Snapshots of RADiAL session registration.

To evaluate the usefulness of our approach for activity recognition, we built a new dataset (RADiAL) that contains common daily activities such as making coffee, making tea, opening the fridge and using the kettle. The RGB-D camera was installed on the ceiling of L-CAS laboratory at approximately 4m above the floor (Figure 3).

Figure 3: Reconstructed layout of the kitchenette where RGB-D camera is installed.

The RADIAL dataset1 was collected in an open-plan office of the Lincoln Centre for Autonomous Systems (L-CAS). The office consists of a kitchenette, resting area, lounge and 20 working places that are occupied by students and postdoctoral researchers. We installed a ceiling RGB-D camera (Figure 3) that took a snapshot (with dimensions of 320 x 240 pixels) every second for 5 days, and we hand-annotated activities of one of the researchers over time. Furthermore, the RADIAL dataset contains the 3D positions of the head and hands for each person with a minute-by-minute timeline of 5 different activities performed at the kitchen over the course of days. RADIAL contains 100 trials. Each trial includes the actions related to one person.

Experimental Results

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Table 1: Classification Results Cross Validation.

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<th>HMM2</th>
<th>HMM3</th>
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<td>TPR</td>
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</table>

1 http://vrai.dii.univpm.it/radial-dataset