Human activity recognition at home: benchmarks and competition

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***Abstract*—The use of benchmarks and competitions is generally considered to accelerate, regulate and consolidate new research into robotics in home environments. While several high-profile robotics competitions are held annually, only a limited number of them are relevant to human activity recognition tasks. In this paper, we discuss how well the RoboCup@home league and other publicly available benchmarks account for human activity recognition tasks and identify areas for improvement and extension.**

***Index Terms*—Human activity recognition, robotics competitions, benchmarks.**

I. Introduction

It is likely that technological progress will soon result in a greater prevalence of robots and intelligent systems within human living and working environments. Robots are thereby expected to assist people in their daily life, for example, by helping with the housework or serving food. For many of these tasks, the robot needs a sophisticated perception system that is able to detect human activities. This entails learning, recognition, and potentially prediction of human postures, gestures, actions, and emotions in real-world scenarios. Our work investigates the role of human activity recognition (HAR) in the *RoboCup@Home* competition [1] and characterises some important benchmarks in HAR for future extensions. We propose to introduce a new task in *RoboCup@Home* that dedicates to HAR evaluation in human-robot interaction (HRI).

II. RoboCup@home Competition

RoboCup is a global project to advance progress in artificial intelligence and robotics in different application domains. One of its competitions, the *RoboCup@Home* league, is in the context of service and assistive robotics to advance technologies in indoor companion robotics domain. The competitors thereby solve a given set of tasks (test) that are designed by a technical committee to evaluate the robot's abilities in supporting daily activities [2]. The individual tasks might vary from year to year and are recorded in the rulebook [1]. The league includes a wide range of challenges from navigation to adaptive behaviour but in this paper we focus on those tasks that are related to HAR.

A. Human Activity Recognition in RoboCup@Home

A glimpse at rulebooks[1] of the 2009 to 2020 competitions illustrates that most tasks are in HRI and object detection and recognition, while a small number of tasks are related to the HAR functions. Table I lists all tasks that include human activities from every year's rulebook from 2009 to 2020. With the exception of 2014, in which the technical challenge was explicitly dedicated to what people present and do, there is no explicit identification of HAR tasks in this league at all. If the tasks contains HAR, more than half of the cases focus on recognising waving gesture as a signal for the robot to continue its operation. Likewise, pointing, nodding and rising were usually required at specific points in time as opposed to a general activity recognition task where the robot would need to distinguish between different set of activities during a longer period of interaction/observation.

TABLE I
Overview of HAR tasks in RoboCup@Home

Year	Task	Activity
2009	Who Is Who?	Waving
	Enhanced Who Is Who?	Waving
	Shopping Mall	Pointing
	Demo Challenge (In the bar)	Waving
2010, 2011	Who Is Who?	Waving
	Enhanced Who Is Who?	Waving
	Shopping Mall	Pointing
2012	Who Is Who?	Waving
2013	Emergency Situation	Fire event
2014	Emergency Situation	Fall over, waving
	Technical Challenge: People Activity Detection	Standing, Sitting, Laying, Confused, Happy, Bored
2015	Robo-Nurse	Waving, fall, sit, walk
	Wake me up test	human awakening
	Demo Challenge	Learning actions on-the-fly
2016	Navigation Test	Crowd
	Demo Challenge	Learning actions on-the-fly
2017	Cocktail Party	Waving
	Navigation Test	Crowd
	E2GPSR	Describing a person
	Demo Challenge	Learning actions on-the-fly
2018	Cocktail Party	Rising and waving
	Navigation Test	Crowd
	Person and Speech Recognition	Crowd, waving, rising, standing, siting, laying
	E2GPSR	describing a person
	Tour guide	Waving
	Demo Challenge	Learning actions on-the-fly
2019	Hand Me That	Pointing
	Stickler for the Rules	Littering
2020	What is That?	Nodding

Human activities such as falling, sitting, walking, lying, and awakening were only essential in the *Emergency Situation* task (2014), the *Robo-Nurse* tasks (2015), and in *Person and Speech Recognition* (2018). Crowd identification and asking them to move away were actions needed to accomplish the navigation task from 2016 to 2018. Specific activities such as identifying a dropping blanket, littering, or a fire hazard were part of some tasks. Some state-of-art activity recognition challenges, such as describing a person and learning actions

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[1]Online resource: robocupathome.org/rules

on the fly have been introduced in the *Enhanced Endurance General Purpose Service Robot (E2GPSR)* task and the demo challenge. No team has yet achieved the maximum score. For example, in 2017 and 2018, none of the teams attempted the *Demo* challenge and the highest achieved score in the *E2GPSR* task was 70 out of 250 in the open platform competition of these years [3].

III. Activity recognition benchmarks

A wide range of HAR benchmarks has been developed but the inherent variety means that a direct comparison of the approaches is not always feasible. Activity recognition is typically vision- or sensor-based, or a combination of the two.

A. Sensor-based Benchmarks

The *OPPORTUNITY* challenge is an example for the use of public benchmarks for sensor-based activity recognition [4]. A wide range of locomotion models and gestures were collected using onboard robot sensors, and environmental sensors. These were classified by *k-NN, NCC, LDA and QDA* techniques then evaluated using standard approaches such as *Weighted F-measure, Area under the ROC curve* and *Misalignment measures*. This challenge focused on four critical tasks in activity recognition: multimodal activity recognition, automatic segmentation, multimodal gesture recognition, and robustness to noise. The *HASC Challenge*, orchestrated by Nagoya University [5], is also similar and involves data collected from a large number of subjects by 20 teams. The *BSN Contest* [6], was a competitive benchmark based on body-attached sensors. The *BDA Challenges*[2], which aim to recognize daily physical activity from phone sensors, are another example of HAR competitions that aim to recognise six basic activities.

B. Vision-based Benchmarks

Although research groups have prepared many datasets, only some of these are designed to evaluate the accuracy of the recognition model. *ActivityNet* [7], for example, is an international challenge on activity recognition that have been held since 2016 in conjunction with the CVPR conference. It includes a diverse set of tasks each emphasising a different aspects of activity recognition to develop the visual perception of videos and natural human language. Three challenges were based on *ActivityNet*'s own dataset and some other tasks were based on other large-scale activity and action datasets, including Kinetics, AVA, ActEV, HACS, and ActivityNet Entities. The *SPHERE* challenge [8] is another activity recognition competition in the context of a smart environment utilising data including RGB-D, accelerometer, and environment sensor. Two main challenges are predicting posture and daily living activities with the aim of creating a reliable model to enhance physical well-being. The *VISUM challenge*[3] is third benchmark that uses the *KTH dataset* with six type of human actions (walking, jogging, running, boxing, hand clapping and hand waving).

[2]Online competition: kaggle.com/c/bda-2020-physical-activity-recognition
[3]Online competition: kaggle.com/c/visum-activity-recognition

TABLE II
Comparison between RoboCup@Home and online benchmarks

RoboCup@Home	**Online Benchmarks**
One set of specific rules	Different rules per benchmark
Real-world competition	On-line evaluation
Equipment (robot) necessary	Implementation only
No specific HAR task included	Many different HAR challenges

IV. Suggestions for Improving RoboCup@Home

Many of the HAR functions in *RoboCup@Home* are not mandatory, and there is a lack of a specific HAR task. We propose to include a new task in the competition that puts an emphasis on benchmarking HAR. We suggest a task that allows a combination of smart environment sensors, gadgets, and robots, to facilitate a competition around HRI at home. Sensors like motion detectors, door sensors, wearables (e.g. smartwatches) or cameras could be used to gather information about a person within with the goal of recognising postures and activities in different locations. The task could, for example, be set in companion and assistive robotics scenarios where HAR plays a crucial role.

V. Conclusion

We provided an overview of the common competitions and public benchmarks that provide an evaluation of HAR in home environments. A comparison of the two forms of evaluation can be found in Table II. The representation of several related tasks in *RoboCup@Home* reveals that there is only a limited emphasis on activity recognition in this competition. Unlike this competition, online benchmarks do not benefit from specific rules, that hinders comparative evaluation. To combine some advantages of the two approaches, we propose a *RoboCup@Home* task that focuses on HAR benchmarking. With this task that benchmarks high-level activity recognition in practice, we believe, HRI research can be further advanced in the community.

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