Human activity recognition in RoboCup@home: Inspiration from online benchmarks

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Abstract—**Human activity recognition is an important aspect of many robotics applications. In this paper, we discuss how well the RoboCup@home competition accounts for the importance of such recognition algorithms. Using public benchmarks as an inspiration, we propose to add a new task that specifically tests the performance of human activity recognition in this league. We suggest that human-robot interaction research in general can benefit from the addition of such a task as RoboCup@home is considered to accelerate, regulate, and consolidate the field.**

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. Many applications benefit from a sophisticated robot perception that is able to detect human activities [1]. This entails learning, recognition, and potentially prediction of human postures, gestures, actions, and emotions in real-world scenarios. Our work investigates the current role of human activity recognition (HAR) in the *RoboCup@Home* competition [2] and identifies a benefit of adding a task that emphasises benchmark of HAR in human-robot interaction (HRI). We thus propose to introduce a new task in *RoboCup@Home* that is inspired by established activity recognition benchmarks.

II. RoboCup@home Competition

RoboCup is a global project to advance progress in artificial intelligence and robotics. Besides its flagship league RoboCupSoccer, it has established a number of other competitions that are not related to football but evolve around other robotics application domains. One of these competitions, the *RoboCup@Home* league, is focusing on HRI in everyday situations at home and in other indoor spaces to promote and foster the development of service and assistive robotics [3]. Robots must autonomously solve a wide range of tasks to support the human in their activities such as navigation in unknown environments, people recognition, object picking and placing, or verbal interaction. Prior to each year's competition, a predefined set of up around 20 tasks is designed by a technical committee to evaluate the robot's abilities. The exact set varies and is published in the annual rulebook [2]. In this paper we focus on those tasks that are related to HAR.

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TABLE I
Overview of HAR tasks in RoboCup@Home

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

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 only a small number of tasks test HAR-related 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 identify what people present and do, there is no explicit identification of HAR tasks in this league at all. More than half of of the tasks that contain any activity recognition can be solved by recognising waving gesture as a signal for the robot to continue its operation. Likewise, pointing, nodding and rising were usually required only at specific points in time and not as general function where the robot would need to distinguish between different set of activities during a longer period of interaction or observation.

[1]Online resource: robocupathome.org/rules

Crowd identification and asking them to move away were actions needed to accomplish the *Navigation Test* from 2016 to 2018. Some state-of-art recognition challenges, such as describing a person and learning actions from demonstrations have been introduced in the *Enhanced Endurance General Purpose Service Robot (E2GPSR)* task and the *Demo Challenge*. In these two tasks, no team has yet achieved the maximum score. In 2017 and 2018, for example, none of the teams attempted the *Demo* challenge and the highest achieved score in *E2GPSR* these years was 70 out of 250 in the open platform competition [4]. The recognition of individual, very specific events like a dropping blanket, littering, or a fire hazard were a part of some tasks. The detection of general human activities such as falling, sitting, walking, lying, and awakening were only essential in *Emergency Situation* (2014), *Robo-Nurse* (2015), and *Person and Speech Recognition* (2018).

III. Activity recognition benchmarks

A wide range of HAR benchmarks has been developed to compare the performance of activity recognition algorithms on standardised datasets. The recognition is thereby 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 [5]. 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*. The *HASC Challenge*, orchestrated by Nagoya University [6], is also similar and involves data collected from a large number of subjects by 20 teams. The *BSN Contest* [7], 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 many research groups have prepared datasets, only some of these are designed to evaluate the accuracy. *ActivityNet* [8], 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 [9] 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).

IV. Suggestions for Improving RoboCup@Home

Inspired by these publicly available benchmarks, we propose to include a new task in the competition that puts an exclusive focus on general HAR to further advance activity recognition in HRI and further acknowledge its importance in the field. We suggest to add a task that accounts for both types of HAR benchmarking, vision- and sensor-based. Ideally, the task would combine the use of the robot's integrated sensors and sensors from a smart environment to facilitate a competition within an interactive scenario. Motion detectors, door sensors, wearables (e.g. smartwatches) or cameras could be used to gather information about a person to recognise postures and activities in different locations. Moreover, we propose a complementing online simulation, which could alleviate hassles and costs. The task could, for example, be set in an assistive robotics scenarios where HAR plays a crucial role.

V. Conclusion

We reviewed tasks in *RoboCup@Home* and revealed that activity recognition only plays a limited role within this competition. We also provided an overview of activity recognition benchmarks in home environments to use as an inspiration to better account for the importance of HAR in HRI. With this background, we proposed a task for *RoboCup@Home* that focuses on HAR benchmarking. Using a combination of vision and other sensors, this task will allow to evaluate activity recognition during interaction to further advance HRI research.

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