Generalized Dynamic Instance Activation for Activity Recognition

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***Abstract*— Activity recognition (AR) is a promising field of research aiming to develop solutions in domains such as healthcare, context-aware computing, ambient assisted living, among others. This research presents the initial results from a new AR algorithm that considers the large amounts of data required to recognize activities as well as the incompleteness and inconsistency related to that data.**

I. Introduction

One of the simplest forms of Smart Environments are those consisting solely of binary sensors, which are activated when an action relating to a certain object occurs. In such environments, sequences of one or more sensor activations provide an insight into the various activities being performed. When these sensor activations and their associated class label (activity) are collected within a dataset, a data-driven machine learning (ML) algorithm can be utilized to identify new occurrences of such activities [1]. New occurrences, however, may lie outside of the generalization abilities of the ML model due to timescale, sensor failure or different order of sensor activations. In this regard, this research presents the Dynamic Instance Activation (DIA) approach: a generalized version of the Dynamic Rule Activation (DRA) [2]. DIA optimizes the set of similar activities compared to the sequence of activated sensors to maximize the AR accuracy.

II. Ongoing Research

In recognition that data-driven AR solutions require large datasets [1], DIA was developed in the Scala programming language using Spark (and Spark SQL) [3], a popular Big Data cluster computing engine that allows the development of software specialized in large-scale data processing. Initially, DIA is based on reducing the data and algorithmic complexity of the previously developed DRA-H approach [2]. In this regard, DIA does not require an Extended Belief Rule-Base system, and the Hamming-based distance function described in [2] (Eq. (3)) was generalized, using the traditional Hamming distance, hence avoiding the ad-hoc weights used to maximize performance used in DRA-H. The activation weight equation of [3] was generalized as follows:

$$w_k = \frac{\sum_{i=0}^{N} d_H(\alpha_i, A_{ik})}{N} \quad (1)$$

where w_k is the activation weight of the k^{th} sample of the dataset, N is the number of sensors used to describe an activity, α_i is the input recorded for the i^{th} sensor and A_{ik} is the actual value of the i^{th} sensor in the k^{th} sample. d_H returns the value 1 if α_i and A_{ik} have the same value and returns the value 0 otherwise. DIA then uses the w_k of each sample in the same process as DRA-H to optimize an λ value to select a suitable set of samples from the dataset to recognize an activity from the input sensor data.

III. Preliminary Results

The initial tests performed with DIA are promising. Compared to its predecessor, DRA-H, and other state-of-the-art methods, DIA performed better than any other in terms of accuracy. The tests were performed using a popular activity recognition dataset, presented in [4]. The dataset contains 245 observations of 7 different ADLs, generated using 14 binary sensors placed across a home setting.

Table 1 summarizes the first results obtained for DIA after running the same cross-validation (CV) tests for the 2 optimizations included in [5] (Tables 2 and 3):

TABLE I. Activity Recognition Dataset Results

	AR Method	**Tests run**			**Mean**
		CV10	***CV4***	***CV2***	
Opt. 1	SVM	**96.73**	**97.14**	95.10	96.32
	NB	96.33	95.92	94.69	95.65
	NN(k=10)	94.69	91.84	91.84	92.79
	R+DRA-H	93.47	95.51	92.24	93.74
	DIA	**96.73**	**97.14**	**95.51**	**96.46**
Opt. 2	SVM	95.10	94.29	93.47	95.78
	NB	95.51	95.92	95.92	94.97
	NN(k=10)	93.88	93.88	90.20	94.29
	R+DRA-H	**98.37**	95.92	94.69	96.33
	DIA	95.92	**96.73**	**96.33**	**96.33**

References

[1] Chen L., Hoey J., Nugent C.D., Cook D.J. and Yu Z.W., (2012), "Sensor-Based Activity Recognition". *IEEE Transactions on Systems, Man, and Cybernetics – Part C*, 42(6): 790-808.

[2] Calzada, A., Liu, J., Nugent, C., Wang, H., Martinez, L., (2014), "Sensor-based activity recognition using extended belief rule-based inference methodology", *36th Annual Intl Conf. of the IEEE Eng. in Med. and Biol. Soc. (EMBC)*, pp. 2694–2697.

[3] Armbrust M., Xin R.S., Lian C., Huai Y., Liu D., Bradley J.K, Meng X.R., Kaftan T., Franklin M.J., Ghodsi A., Zaharia M., (2015), "Spark SQL: Relational Data Processing in Spark" *SIGMOD 2015*.

[4] Van Kasteren T., Englebienne G. and Krose B., (2010), "Transferring knowledge of activity recognition across sensor networks". *Pervasive Computing*, Springer Berlin Heidelberg: 283-300.

[5] Espinilla M., Quesada F.J., Moya F., Medina J., Calzada A., Liu J., Martinez L., Nugent C., (2016), "Optimizing the configuration of a

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