An Incremental Learning Mechanism for Human Activity Recognition

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***Abstract*—This paper proposes an incremental mechanism for the automatic recognition of physical activities performed by humans. The specific research field has become quite relevant as it may offer important information to areas such as ambient intelligence, pervasive computing, and assistive technologies. The works in the related literature so far assume the a-priori availability of the dictionary of activities to be recognised. This work is focused on relaxing that assumption by learning and recognizing the human activities in an incremental manner based on the acquired datastreams. To this end, we designed a learning mechanism based on hidden Markov models for recognising human activities among those of a dictionary. The major novelty of the proposed mechanism is its ability to detect the occurrence of new activities and update the dictionary accordingly. We conducted experiments on a publicly available dataset of six human activities, i.e. *walking*, *walking upstairs*, *walking downstairs*, *sitting*, *standing*, and *laying*, where the efficiency of the proposed algorithm is demonstrated.**

Keywords*—Human activity recognition; hidden Markov models; online dictionary learning.

I. Introduction

During the last decades, there has been an exponential growth in the development of wearable devices able to support novel ranges of applications [1], [2]. In this context, an important application is the recognition of human activities (i.e. cycling, running, walking, etc) [3], [4]. by using wearable sensors, such as accelerometers, gyrometers, etc. Human Activity Recognition (HAR) gains increased importance when the focus is placed upon medical, military, and security applications, e.g. to have knowledge of the activities performed by a soldier in the battlefield for providing strategical advices, monitor the activities of a patient who may suffer from high blood pressure, make informed decisions in combats, etc.

The literature about HAR based on wearable devices includes a great and diverse gamut of methods and approaches[1]. A thorough review is provided in [10]. Typically, HAR systems are based on machine learning technologies able to learn and subsequently recognise activity patterns. A great variety of input signals have been used for HAR, such as environmental characteristics (temperature, audio level, etc.), acceleration, location, psychological signals, etc. These may be used either in raw format or after a feature extraction phase, and then combined with pattern recognition algorithms. Time and frequency domain features have been proposed [11], [12] along with both generative and non-generative modelling tools [10]. The majority of the authors have employed learning-based classification algorithms, such as neural networks [13] and support vector machines [14], [15], decision trees [16], k-nearest neighbours [17] or classifier ensembles [18]. Hidden Markov models (HMMs) have also been considered for HAR. [19] extracts features from the low-frequency components of the acceleration signals for feeding a HMM. However, details regarding the training of the HMM are not provided. The authors of [20] fused data obtained from two wearable inertial sensors. An hierarchical HAR system composed of an HMM operating on the outputs of two neural networks each one processing data belonging to a single sensor, is proposed. In both works the behaviour of the signals in time is not explicitly incorporated in the HMMs.

Despite the different considered machine learning technologies, all these approaches implicitly assume the a-priori availability of the dictionary of activities. In fact, they assume the a-priori knowledge of all the activities to be classified and the availability of data (to be used for learning) for each of them. Even though they do offer satisfactory results in static conditions, it is practically impossible to adapt them to evolving conditions (where new classes need to be incorporated) since full system retraining is required. This limitation hardens substantially their application on real world dynamic scenarios.

This work, which is inspired by [21], proposes a new mechanism for HAR dealing with the activity recognition and the incremental learning of the dictionary online. The proposed mechanism processes the incoming datastreams and is able to associate them to an activity existing in the dictionary, or understand whether a new activity is encountered through a change detection technique. In case a novel activity has appeared, the mechanism learns its characteristics online and inserts it into the dictionary of activities automatically. The only assumption made by the proposed system is that each activity lasts for at least a specific amount of time as it is usual that a user will not rapidly change his/her activity status. Performance assessment is made on the database used in [22] which includes measurements of a tri-axial accelerometer and gyrometer embedded on a smartphone device.

The rest of this paper is organised as follows. Section II formulates the problem, while Section III details the proposed mechanism for HAR and incremental dictionary learning. Section IV analyses the experimental set-up and results, while our conclusions drawn in Section V.

II. Problem Formulation

The technological scenario refers to a wearable device including M sensors, each of which generates a scalar in time

[1]It should be mentioned that HAR based on external sensors, i.e. sensing units attached to predefined points of interest such as smart homes [5], [6], cameras [7]–[9], is outside the scope of this work.

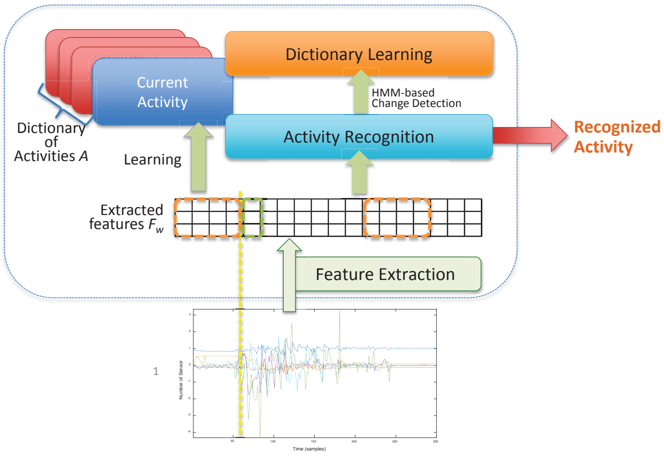

Fig. 1. The block diagram of the proposed HAR mechanism. After feature extraction, the mechanism recognises automatically the performed activity by consulting the dictionary $\mathcal{A}$. In case a new one is detected by the change detection component, the mechanism learns its distribution and incrementally updates the dictionary $\mathcal{A}$.

measurement $X_i(t)$, $i = 1 \ldots M$. The sampling frequency has been suitably identified in a preliminary sensor configuration phase. The sensors could be homogeneous (e.g. accelerometers) or heterogeneous measuring different physical quantities (e.g. both accelerometers and gyrometers).

Traditional approaches assume a fixed and a-priori known activity dictionary $\mathcal{A} = \{A_1, \ldots, A_N\}$, where A_i denotes the i-th activity and N the total number of activities. Acquired measurements are partitioned into overlapping windows of data (of length K) each one classified into an action among those present in the dictionary. Moreover, they assume availability of a training set $X_i(t)$, $i = 1 \ldots M, 1 \leq t \leq T_0$. These are partitioned into windows $[X_i(t_1), \ldots, X_i(t_2)]$, $i = 1 \ldots M$ of length $w = t_2 - t_1$. Every window of data is annotated with an action belonging to the dictionary $\mathcal{A}$.

Instead, this work makes no assumption regarding the dimensionality of $\mathcal{A}$, nor requires an annotated training set. Our only assumption is that each activity lasts t_a samples. Obviously, the worst case scenario would be rapid changes of novel activities, i.e. a scenario where activities not present in $\mathcal{A}$ occur and change swiftly. Nonetheless that is unrealistic since a user tends to perform the same activity for a reasonable amount of time due to practical and physical constrains.

The goal of the proposed system is to exploit the availab raw signals for a) performing HAR, i.e. associating the mea- surements obtained at time $t > t_a$, i.e. $X_i(t)$, $i = 1 \ldots M, t$ t_a, with a human activity A_i, which may be recurrent, and l learning the dictionary $\mathcal{A}$ over time.

III. The Proposed Solution for HAR and Dictionary Learning

This section describes the proposed algorithm realizin the activity recognition and the learning of the dictionar The proposed embraces the following steps (see Fig. 1): a recognition of the ongoing activity, and b) dictionary learning. These steps are explained in the following two subsections.

A. HMM-based Human Activity Learning

The first step is to extract features which may reveal characteristic information for HAR. To this end, windows of raw signals $[X_i(t_1), \ldots, X_i(t_2)]$, $i = 1 \ldots M$, $w = t_2 - t_1$ are transformed to the vector of features $F_w = \{F_w^1, \ldots F_w^f\}$, where f is the total number of features. Principal Component Analysis (PCA) is applied onto F_w for retaining the l components with the highest variance. HMM learning is conducted on these components. Moreover we rely on a training set TS to learn the first action A_1 and a validation set VS to estimate two thresholds T_l and T_u as described below.

An HMM H is characterized by the following set of components, i.e. $H = \{S, P, T, \pi\}$, where

1) S comprises the the number of states,
2) P is the the probability density function associated with each state. In this work it is modelled as a mixture of Gaussians (GMM), $P(y|x) = \sum_{k=1}^{K} p_k p(y|x_{(k)})$, where $p_k s$ are the mixture weights, y is a continuous-valued data vector, i.e. the features, $x_{(k)}$ represents the $k-th$ component of the vector, $x = [\sigma, \mu]$, $p(y|x_{(k)}) = \frac{1}{(2\pi)^{d/2}|\sigma|} e^{-\frac{1}{2}(y-\mu_k)^t \sigma_k^{-1}(y-\mu_k)}$.
3) T is the state transition probability matrix $T = \{\tau_{ij}\}$ where entry τ_{ij} represents the probability of moving from state j at time t to state i at time *t+1*. For example, the transition probability of moving from state 1 to state 2 is represented by τ_{12}, and
4) π is the initial state distribution defined as $\pi = \{\bar{\pi}_i\}$, where $\bar{\pi}_i$ corresponds to the probability that the HMM starts in state i, i.e. $\pi_i = P[q_1 = S_1], 1 \leq i \leq N$.

In order to learn the components of and HMM we employ the Baum-Welch algorithm [23]. During evaluation, the Viterbi algorithm [24] is used to find the most probable path taken across the states in the HMM. It uses dynamic programming and a recursive approach to find the path. Its outcome is a log-likelihood demonstrating the statistical affinity between the novel data and the one used during training.

The cornerstone of the proposed HAR framework is detector of changes in the performed activity since it allows to activate the procedure for identifying a new activity or recognizing an activity among those existing in $\mathcal{A}$. The change

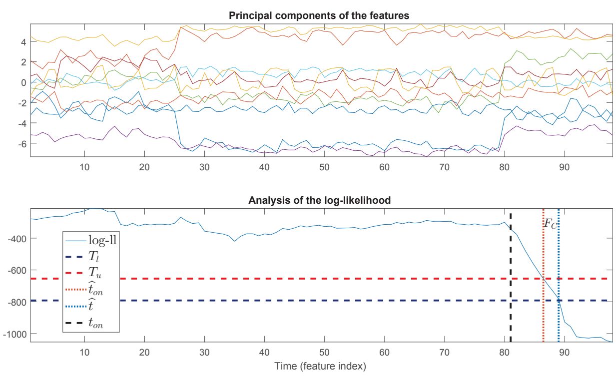

Fig. 2. The way the proposed HAR framework determines the onset time instance of a change in the performed activity.

1. Input: feature sequence representing activity i, γ_1, γ_2, W_b;
2. Partition the sequence into TS and VS;
3. Build H_i on TS;
4. Compute detection threshold $T_l = min(ll_v) - \gamma_1(\overline{ll}_v - min(ll_v))$, where ll_v are the log-likelihoods computed on VS and $\overline{ll}_v$ its average value;
5. Compute the onset detection threshold $T_u = min(ll_v) - \gamma_2(\overline{ll}_v - min(ll_v))$;
while (1) **do**
    6. Compute the log-likelihood $L_t = P(F_w^t|H_i)$;
    7. **if** $L_t < T_l$ **then**
        8. Change detected at time $t = \widehat{t}$;
        9. $\widehat{t_0} = \{min(t|L_t < T_u), t \geq \widehat{t} - W_b\}$;
        10. $F_C = \{F_w|\widehat{t_0} < t < \widehat{t}\}$;
        11. Activation of the identification module on F_C, Alg. 2;
    end
end

Algorithm 1: The algorithm for detecting activity changes and estimating the time instance the change started.

1. Input F_C, $\mathcal{A}$, t_a;
2. **for** k=*1:N* **do**
    3. $L(k) = P(F_C|\mathcal{A}_k)$;
    4. **if** $L(k) > T_l^k$ **then**
        5. $C = [C; k]$;
    end
end
6. **if** *isempty(C)* **then**
    7. Appearance of new activity;
    8. Partition $F_C + t_a$ into TS and VS;
    9. Learn H_{N+1} on TS;
    10. Compute T_l^{N+1} and T_u^{N+1} on VS;
    11. Add H_{N+1} to $\mathcal{A}$;
else
    12. Find max(C), i.e. k_{max} and associate F_C with activity $\mathcal{A}_{k_{max}}$;
end

Algorithm 2: The activity recognition and dictionary learning algorithm.

detection test (CDT), which is inspired by [25], inspects the statistical behaviour of the observed features, while including two phases: a) detection of a change in the incoming features, and b) estimating the time instance the new activity started.

In more detail, the CDT operates as follows: the inputs of the CDT algorithm depicted in Alg. 1 are the feature sequence F_w, γ_1, γ_2, and W_b, while $\gamma_2 < \gamma_1$. γ_1 is a parameter responsible for change detection, γ_2 for detecting the initiating point, and W_b is the buffer size in samples that represents the maximum number of samples that the algorithm can go back in time, i.e. the maximum difference between the change detection $\widehat{t}$ and initiation point $\widehat{t_0}$. The algorithm divides the features extracted from the training sequence to training TS and validation sets VS (line 2, Alg. 1). During this process we employ 90% of the data for training and 10% for validation purposes. Then it learns H_i using TS (line 3, Alg. 1) and computes the lower threshold T_l as $T_l = min(ll_v) - \gamma_1(\overline{ll}_v - min(ll_v))$, where ll_v are the log-likelihoods computed on VS and $\overline{ll}_v$ the average value (line 4, Alg. 1). The following step calculates the onset detection threshold $T_u = min(ll_v) - \gamma_2(\overline{ll}_v - min(ll_v))$ (line 5, Alg. 1).

During operation the algorithm evaluates the feature vector at time t, i.e. F_w^t, using H_i by means of log-likelihood L_t (line 6, Alg. 1). L_t comprises a degree of resemblance between the observed features, i.e. F_w^t, and the one used for learning H_i. In case L_t falls below T_l the algorithm detects a change (line 8, Alg. 1) and goes back in the previously computed feature vectors to find the sample where the change started $\widehat{t_0}$ (line 9, Alg. 1). The feature sequence between theses two points is gathered, i.e. $F_C = \{F_w|\widehat{t_0} < t < \widehat{t}\}$, (line 10, Alg. 1) and the human activity identification module is activated (line 11, Alg. 1). The way the proposed algorithm detects the initiating point a new activity if demonstrated in Fig. 2. F_C represents a new sequence of feature vectors that can be associated to the recently detected action. In the next phase the mechanism will discriminate between already known activities (among those present in the dictionary) and a new activity (to be included in the dictionary that is initially empty).

B. HAR and Learning of the Activities Dictionary

The proposed mechanism performs HAR and dictionary learning based on the following logic: once a change is detected and F_C has been established by Alg. 1, we control whether the features in F_C can be associated with one of the activities in $\mathcal{A}$, i.e. we evaluate $\mathcal{A} = \{A_1, \ldots, A_N\}$. We retain all the HMMs producing log-likelihoods above the respective lower thresholds, i.e. T_l^i, while the one producing the maximum log-likelihood comprises the identified activity. In case there is no HMM satisfying that condition, the algorithm detects a new class, learns the respective HMM, and updates the dictionary $\mathcal{A}$.

The inputs to Alg. 2 are the feature sequence F_C, the dictionary $\mathcal{A}$, and t_a. The algorithm evaluates all the HMMs in $\mathcal{A}$ (line 2, Alg. 2) and retains in C the ones having a log-likelihood above the respective lower threshold T_l (line 4-5, Alg. 2). In case C is not empty the algorithm assigns to F_C the class with the highest log-likelihood (line 12, Alg. 2). On the contrary, the algorithm detects a activity not existing in $\mathcal{A}$ (line 7, Alg. 2) and learns the respective distribution H_{N+1} (line 9, Alg. 2). After computing the corresponding thresholds T_l^{N+1} and T_u^{N+1} (line 10, Alg. 2), it adds H_{N+1} to $\mathcal{A}$ (line 11, Alg. 2).

IV. Experiments

This section aims at providing a thorough evaluation of the proposed solution. To this end we considered the SBHAR dataset [22], which is publicly available and includes six basic activities, i.e. *walking*, *walking upstairs*, *walking downstairs*, *sitting*, *standing*, and *laying*. It includes data coming from 30 participants generating approximately 5h of data at a sampling rate of 50Hz. Following the literature [22], we employed the features tabulated in Table II leading to a feature vector F_w of dimensionality equal to 156. The selection of this dataset

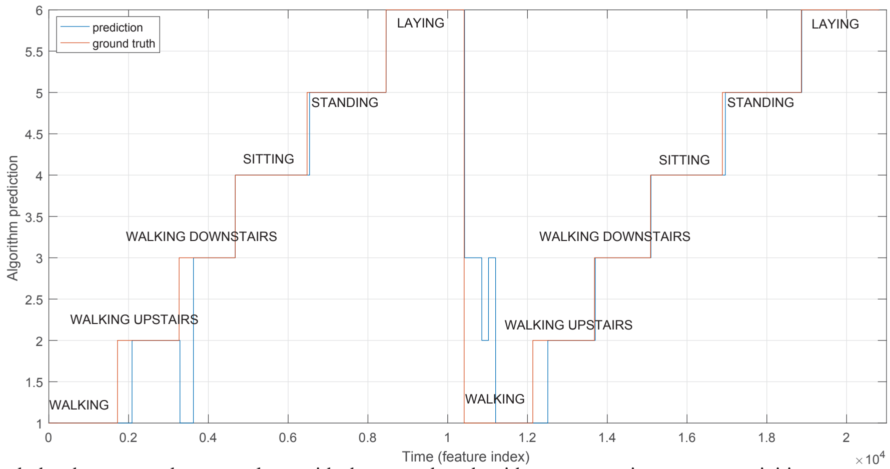

Fig. 3. The predictions made by the proposed system along with the ground truth with respect to six recurrent activities.

facilitates comparison between the different methodologies which is a common issue in the HAR literature as each system works with a different dataset, while there is no standard dataset [10]. Moreover, to fully exhibit the capabilities of the proposed system we address the issue of *recurrent* activities.

a) Figures of merit: The works performing HAR simply consider the recognition rate per activity as a performance metric, i.e. r_i, which is computed as

$$r_i = \frac{\#ofcorrectlyIdentifiedFeatureVectors}{\#totalNumberofFeatureVectors},$$

where i is the activity. This figure aims at measuring the ability to correctly associate the incoming feature sequence with an activity present in the dictionary $\mathcal{A}$.

In this article, we need to evaluate as well the ability of the system to discover correctly the dimensionality of $\mathcal{A}$, i.e. to enumerate the observed activities. To this end we introduce the enumeration rate v measuring the ability of the proposed algorithm to correctly identify the true number of activities N present in the experiment (in percentage).

b) Algorithm parametrization: The parameter t_a was set equal to 300 subsequent feature observations. The number of states of the HMM was selected from the set $s \in \{3,4,5,6\}$ and the number of Gaussian functions from the set $g \in \{2,4,8,16,32,64,128\}$. After an exhaustive exploration in the interval [0,1] with step 0.1, we set $\gamma_1 = 0.4$, $\gamma_2 = 0.1$. The buffer size was set $W_b = 20$ after searching the space [0,100] with step 5. Finally the number of retained principal components was 10.

c) Human activity recognition and enumeration: During evaluation we acquired the data with respect to all the activities and presented them to the proposed system, while each activity appeared twice in the incoming stream. The experiment was iterated 100 times and the final rates were averaged. The sequence of activities was the following: *walking*, *walking upstairs*,*walking downstairs*, *sitting*, *standing*, and *laying*. The algorithm had both to enumerate the number of occurred activities, i.e. 6, as well as learn the distribution exhibited by the features of each one online.

Two iterations of the operation of the proposed algorithm, one with recurrent activities and one without, are depicted in Fig. 3 and Fig. 4 respectively. The final rates per activity are 84.5%, 76.1%, 86.5%, 99.6%, 96.5%, and 99.6%, for *walking*, *walking upstairs*, *walking downstairs*, *sitting*, *standing*, and *laying* respectively, as we can see in the confusion matrix shown Table I. The overall average rate is 90.5%, while $v = 99.8\%$. As we can see the largest amount of misclassifications concerns the family of walking activities, i.e. *walking*, *walking upstairs*, and *walking downstairs* which is similar to [22]. There, the average recognition rate is higher (96.7%) than the one reached by the proposed mechanism. However the dictionary is assumed to be a closed and known a-priori set, while data with respect to every activity is available for SVM training. Overall, we infer that the performance demonstrated by the proposed algorithm is quite encouraging.

V. Conclusions

This work analysed an novel mechanism for HAR and online dictionary learning. The proposed algorithm operates in the feature space, where the distribution of each activity is modelled by means of HMMs. Each HMM is accompanied by a CDT responsible for detecting new classes of activities and updating the dictionary of human activities on-the-fly. A carefully designed experimental protocol was followed, which

TABLE II. The features employed in this work computed over window of size w.

Feature	***Description***
mean(X_i)	arithmetic mean
std(X_i)	standard deviation
mad(X_i)	median absolute deviation
max(X_i)	the maximum value
min(X_i)	the minimum value
skewness(X_i)	the skewness of the signal
kurtosis(X_i)	the kurtosis of the signal
maxFreqInd(X_i)	largest frequency component
energy(X_i)	average sum of squares
sma(X_i,$i = 1, \ldots, 3$)	signal magnitude area
entropy(X_i)	the entropy of the signal
iqr(X_i)	interquartile range
autoregression(X_i)	4th order Burg autoregression coefficients
correlation(X_i,$i = 1, \ldots, 2$)	Pearson correlation coefficient
meanFreq(X_i)	frequency signal weighted average
energyBand(X_i, $[a, b]$)	spectral energy of a frequency band with limits $[a, b]$
angle(X_i,$i = 1, \ldots, 3$,mean)	angle between signal mean and vector

TABLE I. THE CONFUSION MATRIX PROVIDING THE RESULTS OF THE PROPOSED HAR ALGORITHM. THE HIGHEST RATES ARE EMBOLDENED

Presented \ Responded	*Walking*	*Walking Upstairs*	*Walking Downstairs*	*Sitting*	*Standing*	*Laying*
Walking	**84.5**	5.3	10.2	-	-	-
Walking Upstairs	23.9	**76.1**	-	-	-	-
Walking Downstairs	12	1.5	**86.5**	-	-	-
Sitting	-	-	0.4	**99.6**	-	-
Standing	-	-	-	3.5	**96.5**	-
Laying	-	-	-	-	0.4	**99.6**

illustrated the appropriateness of the proposed algorithm to the specific problem. In the future we plan to integrate a fault diagnosis component for isolating a potentially faulty sensor(s) and perform HAR relying only on the healthy ones.

ACKNOWLEDGMENT

This work was supported by the Politecnico di Milano International Fellowship Program.

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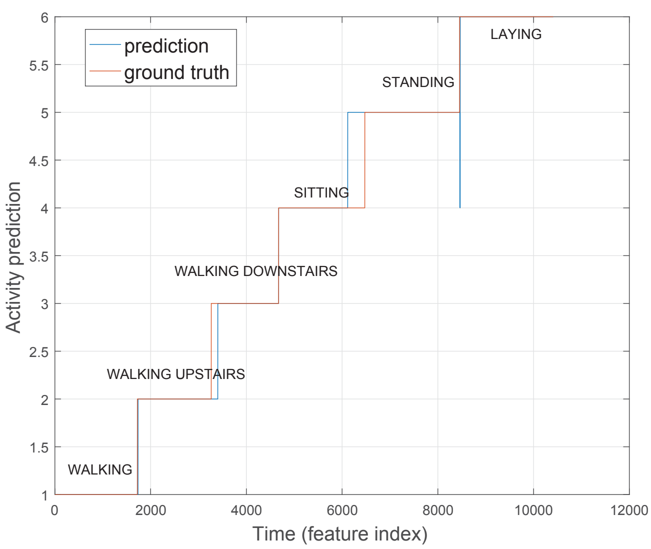

Fig. 4. The predictions made by the proposed system along with the ground truth with respect to six activities.

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