Adaptive Classification of Arbitrary Activities Through Hidden Markov Modeling with Automated Optimal Initialization

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Abstract An adaptive method for classification of arbitrary activities is presented that assesses continuously the activity in which a subject is engaged, thus providing contextual information facilitating the interpretation of any continuous data gathered from an (unsupervised) applied wearable robotics device and its bearer. Specifically the effect of a novel adaptive and fully automated initialization method using Potts energy functionals is discussed. Exemplary data suggests that this method very likely improves overall performance equally or better than more traditional methods. This includes state of the art methods based on segmental k-means initialization that do require substantial recurrent manual intervention.

1 Introduction

To interpret all detailed kinematic, kinetic and muscle activation and system control data gathered from a wearable robotic device and its wearer in a real life unsupervised application, contextual information is very valuable. Specifically there is a need for continuous contextual information on the activity in which the subject is engaged.

The ideal method for contextual data assessment recognizes any activity in which a person is engaged in from data that is already gathered by the wearable robotic device.

As there are many activities in which a subject could be engaged and given the many specific ways in which a given activity can be performed by a subject, a method that can adapt to the situation is required.

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One such an adaptive method is presented earlier by authors and is built around Hidden Markov Modeling, This method is capable of adapting to the activity classification challenge at hand by learning to recognize a given set of activities from a given set of relevant data channels performed in a specific way [3]. This paper discusses how to improve application of this method by optimizing the initialization of the used HMMs with a newly developed adaptive method.

2 Methods

A. *Data preparation*

From 3 IMMUs (Xsens Mtw) placed on pelvis, lumbar back section and sternum only 3D linear acceleration and 3D angular velocity data were used. To make data more independent from the occasion, subject and sensor placement, all sensor data was transformed to body segment through a body segment calibration procedure [1].

Transformation of the data to a more mutually independent vector base was done by applying Principal Component Analysis (PCA).

B. *HMM initialization*

3 different types of HMM initialization were tested. 'Flat start' (or no) initialization, an initialization using k-means clustering and an initialization through a custom algorithm developed using Potts energy functionals:

1. 'Flat start initialization' (standard approach)
   - All activities are represented by 8 states representing segments of equal duration
   - Each state has a normal data distribution with the same overall mean and variance for the whole activity as initial mean and variance
2. 'Segmental K-means initialization'
   - Each activity has a manually chosen number of states representing segments of equal duration
   - Each state has an estimate for initial mean and average determined through a K-means clustering procedure [2].
3. 'Potts Initialization'
   - For each activity the number of states and the duration of each state was estimated by a variation on Potts algorithm and each state was then given the mean and variance of the data in the interval of each state

The classical Potts problem to be solved to find the optimal number and duration of states is formulated as:

$$P_\gamma = \gamma\|\nabla \upsilon\|_0 + \|\upsilon - f\|_2^2 \rightarrow \min.$$

$$\gamma \in \mathbb{R}$$

where f(t) = u(t) + noise(t) is the measured signal where u(t) is the state function. Here a successful optimization run delivers u(t) and the number of jump discontinuities in it: the initial number of states. Gamma controls the sensitivity of this process in adding extra states.

The Hidden Markov Models for activity λ = (**A**, **B**, **π**) were optimized in a training sequence with a the Baum-Welch algorithm [3], i.e. solving:

$$\lambda *_{\mathrm{i}} = \arg\max(\lambda_{\mathrm{i}})(\mathrm{P}(\mathrm{Activity}_{\mathrm{i}}|\lambda_{\mathrm{i}}))$$

Here **A** is a transition probability matrix, **B** the signal probability distribution matrix and **π** the initial state distribution.

3 Results

Figure 1 shows the HMM training results for the 3 methods of initialization applied to an artificial signal. It is clear that flat initialization performs badly and the other 2 perform quite good, where the Potts has a more correct segment start, end and duration estimate.

In another example Fig. 2 shows in the left graph the original set of the trunk acceleration z-channel instances for one activity and their average (Black). In the right graph the mean and the resulting state function u(t) with estimated state segment durations, means and variances. Note the different durations of the state segments.

Finally Fig. 3 shows in the top row classification results for a set of typical activities for an order picker for applying the full method with all three initialization methods. Clearly the K-means method performed better than the flat initialization method. The Potts method failed badly. It turned out that this was caused by the

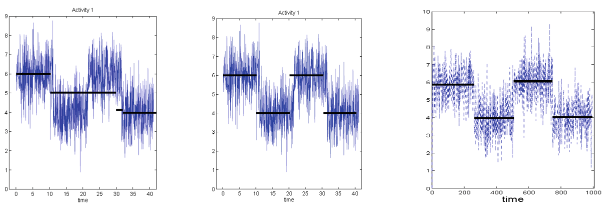

Fig. 1 Results after HMM training for three methods of initialization applied on an artificial one dimensional signal with 4 states with duration average 25 and variance of 1 and amplitude average (6, 4, 6, 4), with variance (1, 1, 1, 1). *Left* Flat, *middle* K-means and *right* Potts initialization

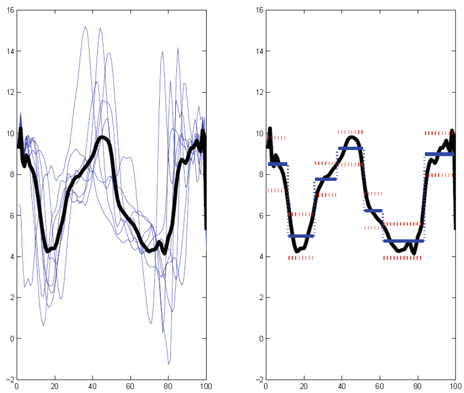

Fig. 2 Results of Potts method of initialization applied on actual thorax z channel acceleration signal of a squat lift activity. *Left* Original signal, *right* depiction of states with duration, amplitude mean and variance as estimated by the Potts initialization method. (arbitrary units on both axes)

ori\pred	Down	Left	Right	Sit	Squat	Stand	Stoop	Walk	D	# originals
Down	32	0	1	0	0	0	0	0	0	33
Left	0	9	0	0	0	0	0	0	0	9
Right	0	0	7	0	0	0	0	0	0	7
Sit	0	0	0	4	0	0	0	0	0	4
Squat	0	0	0	0	8	0	0	0	0	8
Stand	0	0	0	0	0	14	0	1	0	15
Stoop	0	0	0	0	0	0	9	0	0	9
Walk	0	0	0	0	0	0	0	37	0	37
I	0	0	0	0	0	3	0	0	Total:	3

Fig. 3 Results when applying to set of activities. *Top* classification results for all three initialization methods, *bottom* classification table with predicted versus original activities segmental k-means initialization

HMM software not being adapted for the new nuance in initialization, introduced by the Potts method, of state segments possibly having different initial lengths. At the time of writing this abstract it is not clear how the Potts method will perform when this 'software bug' is corrected.

4 Discussion and Conclusion

Although statistically more powerful analysis results are not yet available, the exemplary data presented in this paper strongly suggests that optimizing the HMM initialization with the k-means method improves the systems classification capabilities. As the Potts method performed n better than the k-means method in estimating initial state parameters it is expected that this method will perform similar or better in classification, specifically in situations of states with different segment durations.

If this indeed proves true the fully automated Potts method is strongly preferred over the k-means method that requires manual human intervention for each activity to be trained every time it is applied.

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