Bayesian Recognition of Motion Related Activities with Inertial Sensors

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ABSTRACT

This work presents the design and evaluation of an activity recognition system for seven important motion related activities. The only sensor used is an Inertial Measurement Unit (IMU) worn on the belt.

For classification, we applied Bayesian techniques, based on relevant features of the IMU raw data which are calculated in real time. Based on a complete labelled data set, i.e. supervised by an observing human judge, a K2 learning algorithm by Cooper and Herskovits was used to construct the Bayesian Network (BN) of the features.

Our comparison of dynamic and static inference algorithms, based on the evaluation of the labelled data sets recorded from 16 male and female subjects show that a Hidden Markov Model (HMM) based on a learnt BN provides the best results.

Author Keywords Activity Recognition, Context Inference, Bayesian Networks, Inertial Navigation.

ACM Classification Keywords I.2.3 Deduction and Theorem Proving - Deduchtion, Inference engines, Nonmonotonic reasoning and belief revision, Uncertainty, ``fuzzy," and probabilistic reasoning; I.2.6 Learning – Induction, Knowledge acquisition, Parameter learning

General Terms Algorithms, Performance, Reliability

INTRODUCTION

Knowledge about the current activity of a person, in particular motion related activities, is helpful in many domains:

In indoor positioning, the current activity may be used as an information source. For example, if the activity is known as ‘climbing stairs’, the probability of the user being in the staircase would increase tremendously. It limits the possible locations in combination with the integration of floor plans (see for instance [1], just like walls act like constraints that aid localization.

For first responders or fire fighters, knowledge about the current or recent physical activity or status is very relevant. The controlling agency can react more quickly to unforeseen events and is alerted if personnel are endangered.

UbiComp’10, September 26–29, 2010, Copenhagen, Denmark.
ACM 978-1-60558-843-8/10/09.

In domains like Ambient Assisted Living knowledge of a person’s physical activity can be used as early warning systems in the case, say, that they are showing signs of reduced activity, more frequent falls or a fall not followed by getting up.

In all these use cases, a set of requirements becomes obvious. The recognition of activities has to work in real time, without long learning phases during usage, the system must not depend on infrastructure, and last, the system must be easy to wear, be compact and unobtrusive.

To serve the above described use cases, we focused on a set of seven important motion related activities. Activities with a repetitive pattern, such as “walking” and “running”, the static activities “standing”, “sitting” and “lying”, as well as important short-time activities “falling” and “jumping”.

APPROACH

We recognise these seven activities based on the data provided by one Inertial Measurement Unit (IMU). But in contrast to the work in [2,3,4,5,6,7] our approach assumes data being measured at one point of the body. Our IMU is worn on the belt, close to the centre of gravity of the human body. This provides us most relevant information, both about the upper part of the body, as well as about the movement of the legs.

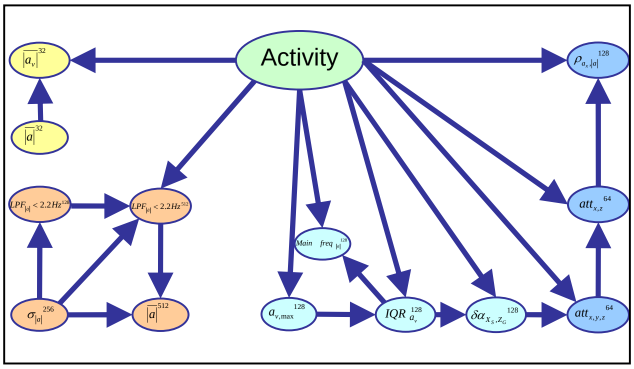

Figure 1. Static Bayesian Network for recognition of human motion related activities, learnt from the recorded data set. Yellow nodes represent short term features regarding vertical and overall acceleration, orange ones represent the jerk in long windows. The other nodes represent medium term features about the attitude of the sensor (blue) or vertical acceleration and the acceleration’s main frequency component (turquoise).

Based on the 3D turn rates and accelerations provided by the IMU we analysed characteristic features for each target activity with their physical or bio-mechanical explanation, their discriminative power between activities and their computation complexity. The features span different window lengths from 32 to 512 samples (at 100 Hz), which represent the different natures of instantaneous activities (like "jumping") to longer term, repetitive activities like "running". All features are calculated in real time with a frequency of 4 Hz and discretised into states meaningful to distinguish between activities. These have been defined manually in our set up, but this could be automated easily with data clustering algorithms. In our implementation, the set of features is easily extendable and would also cover the integration of more sensors into the system seamlessly.

For the classification, we decided to apply Bayesian techniques. With the discretised value ranges of all features, we applied a modified learning algorithm for discrete Bayesian Networks (BNs), the Greedy Hill Climber with Random Restarts based on the Cooper and Herskovits Log score (see [8]) and Dirichlet distributions of the conditional probability tables, on our 270 minutes activities data set. We limited structure learning to a fixed number of parents per node and imposed causal direction to learnt arcs. The learnt structure is shown in Figure 1.

For evaluation, we calculated the posterior probability of the node "Activity" and selected the most probable value given the evidence from the finally selected features.

In order to further improve the classification results, we decided to add the temporal domain to the learnt BN, by defining a first order Hidden Markov Model (with Activity being the hidden node). The transition model was defined manually and evaluated with a Grid-Based Filter [9].

RESULTS

Our results are based on the evaluation with our data set, recorded from 16 different persons (6 female, 10 male, aged from 23 to 50 years) under semi-naturalistic conditions. Our results show that Bayesian evaluation leads to very good results. As expected, the incorporation of the temporal history in the HMM provides the best results.

	SIT	STD	WLK	RUN	JMP	FAL	LYG
Recall	1	0.98	1	0.93	0.93	1	0.98
Precision	0.97	1	0.98	1	0.93	0.8	1

Table 1: Precision and recall for every activity with dynamic inference from a learnt BN. Features are computed at 4 Hz, with sliding windows and recognition delay taken into account

A four-fold cross validation (learning data from 3 persons and evaluating for a fourth person), taking into account the recognition delay of 0.5 s (due to the window lengths and the 4 Hz evaluation frequency) provides very good results with a recall rate between 93% and 100%, see Table 1. Precision is almost as high as recall, but with an outlier for the activity "falling". This is caused by the transition probabilities and the recognition delay, again, but optimised in this way in order not to miss any fall.

With these 0.5 seconds of delay, activities can be recognised in time for the applications mentioned in the introduction. The computation time is negligible, as feature computation takes 1.5 ms on average, inference with the Grid-Based Filter on the learnt BN 7.7 ms (averaged on 780 runs on an Intel Core 2 Duo E8400 microprocessor with 3 GHz and 2 GB RAM).

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