Utrecht University

Doctoral Thesis

Human Acitivity Recognition Using Accelerometer Data

Author:
R.Q. Vlasveld

Supervisor:
Dr. James Smith

A thesis submitted in fulfilment of the requirements for the degree of Master of Science

in the

Research Group Name
Department or School Name

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Declaration of Authorship

I, R.Q. Vlasveld, declare that this thesis titled, 'Human Acitivity Recognition Using Accelerometer Data' and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
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- I have acknowledged all main sources of help.
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"Thanks to my solid academic training, today I can write hundreds of words on virtually any topic without possessing a shred of information, which is how I got a good job in journalism."

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Abstract

Faculty Name
Department or School Name

Master of Science

Human Acitivity Recognition Using Accelerometer Data

by R.Q. Vlasveld

The Thesis Abstract is written here (and usually kept to just this page). The page is kept centered vertically so can expand into the blank space above the title too...

Acknowledgements

The acknowledgements and the people to thank go here, don't forget to include your project advisor…

Contents

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Abbreviations

LAH **L**ist **A**bbreviations **H**ere
PCA **P**rinciple **C**omponent **A**nalysis

Physical Constants

Speed of Light $c = 2.997\ 924\ 58 \times 10^{8}\ \mathrm{ms}^{-\mathrm{S}}$ (exact)

Symbols

a	distance	m
P	power	W (Js^{-1})
ω	angular frequency	$rads^{-1}$

For/Dedicated to/To my…

Chapter 1

Introduction

1.1 Outline

- Context of research (human activity recognition), real-world applications
- Current methods, wrapper vs. filter methods
- Problem statement with current filter methods (which follows from Chapter 3 which goes in-depth with methods).
- Purpose of this research. E.g. "Find a better algorithm for short-activity segmentation"
- Relate to real-world applications

Chapter 2

Literature review

2.1 Outline

- Literature review about Temporal Segmentation (previous draft was more about classification)
- Consider methods for the context of filter-methods for classification
- Take a loot at 3-4 different kind of methods for change detection:
  - Dimensionality reduction
  - Density-ratio estimation
  - Support Vector Machines (?) - if there are more sources about this
  - CUSUM - or other more traditional methods
- With each method, shortly look at characteristics, strengths and weaknesses and consider applicability to accelerometer sensor data

2.2 Statistical framework

Many applications require the detection of time points at which underlying properties of a system change. This problem thus has received a lot of attention in the fields of data mining, etc... *** list and refs ***.

Some methods, such as the CUSUM (cumulative sum) [1] and GLR (generalized likelihood ratio) [2, 3] formulate this problem in the statistical framework in the following sense. A time series is represented by an underlying probability distribution generating the data. The PDFs (probability distribution function) of two consecutive segments around a target point are compared. When they differ significantly, the target point is considered as a change point [4].

2.3 Change-detection by Dimensionality Reduction / Covariance structure

2.4 Change-detection by Density-Ratio Estimation

Formulate the problem of detecting change in the statistical framework. Consider the probability distributions from which two consecutive segments of time series around a target time point are generated. When the disitrubtions differ significantly the target time point is regarded as a change point.

CUSUM (cumulative sum) [1] and GLR (generalized likelihood ratio)

The distribution over the values of time series data can be represented with a probability density function (pdf). Two sections of a time series data can be generated with the same underlying pdf or each with a different.

2.5 Change-detection by Support Vector Machines

Introduced by Vapnik [5, 6], Support Vector Machines offer a way to segment, and classify, linear separable data. When combined with a mapping function, which maps the data from the input space I to a higher dimension feature space F, the input data can be non-linear separable. The linear hyperplane, which segments the data in the feature space F, yields to a non-linear segmentation in the lower-dimensional input space I. Instead of explicitly mapping the input data to the higher dimensional space, a kernel function can be used. This kernel function can calculate values of the feature space directly, without the need to first map the input values to this space. This process is referred to as the kernel trick.

*** Let sigma be a mapping from I to F such that the dot product in F can be computed using some simple kernel ***

2.5.1 One-class Support Vector Machine

The proposed method of Camci [7] uses a one-class support vector machine to segment time series data. One-class SVMs are used to describe the current data under consideration, by assuming all data points are from the same class [8]. The class is described by a spherical boundary around the data with center c and radius r, such that the volume is minimized. Following the definition of Camci [7], the class description is obtained by minimizing r^2:

$$\text{Min } r^2 \tag{2.1}$$

$$\text{Subject to} : \|\mathbf{x}_i - \mathbf{c}\|^2 \leq r^2 \ \forall i, \ \mathbf{x}_i : i\text{th data point} \tag{2.2}$$

To be able to handle outliers in the input data, a penalty cost function ε_i for each outlier can be added.

*** Add new function and constraints? ***

Using this one-class SVM formulation, differences between two (consecutive) windows of data points with size w can be obtained. The first window is used as the input set, h_1 and the second as the test set h_t. For the first window a one-class SVM is constructed, yielding in a representation by c_1 and r_1. When the data points of the second window belong to the same class, the representation of that one-class SVM would equal the first:

$$c_1 = c_2, r_1 = r_2 \tag{2.3}$$

*** First tell more about (underlying) probability density functions, to relate to other methods ***

In case the second window of data points does not belong to the same class, i.e. the probability density function that describes the data differs from the first, the describing values of the second window will differ from the first. The amount of difference can be expressed by a dissimilarity measure over the representations. When the dissimilarity between the two windows exceeds some predefined threshold th, there exists a change point between the windows.

This process can be visualized as done in *** insert figure of four circles ***. The second window, h_2 can be constructed from the first by e.g. a shift of one data point. *** explain data point positions by circle ***.

Note that a difference in the SVM center c or radius r represent a change in the mean and variance, respectively.

2.6 Change-detection by Cumulative Sum

Chapter 3

Change detection by Density-Estimation

3.1 Outline

- In-depth analysis on one of the methods of Chapter 2
- This method (e.g. Density-Ratio estimation) will be the basis for the real research
- Explain why this methods seems worthy and interesting
- Look at problems when applied to accelerometer sensor data
- *The problems discovered here will give rise to the problem statement at the Introduction / beginning of research*
- Opens the possibility for own method

Chapter 4

Proposed method

4.1 Outline

- Based on the problem statement with current research as stated in Chapter 3
- Adjust method to needs
- Explain using graphs, pseudo-algorithms. Make clear distinction in origin of ideas and why to apply

Chapter 5

Result

5.1 Outline

- Compare proposed method with methods of Chapter 2
- Provide plots, tables, graphs, error rates, precision, etc.
- Apply to a multiple of data, to compare to previous research - use that data
- Give theoretical analysis about performance. Big-O, memory, run-time, precision.
- This sections needs programmed implementations of own method and the ones compared

Chapter 6

Real-world applications

6.1 Outline

- Apply proposed method to real-world applications, such as
  - Daily life activity recognition (as the original context of this thesis is)
  - PowerHouse sensor data
  - Stock data?
- Relate back to filter vs. wrapper methods - give results with different methods?

Appendix A

Appendix Title Here

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