

AN ABSTRACT OF THE THESIS OF

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presented on January 1, 2013.

Title: Activity Detection on Free-Living Data Using Change Point Detection

Abstract approved: _____

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(Abstract text)

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Activity Detection on Free-Living Data Using Change Point Detection

by

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A THESIS

submitted to

Oregon State University

in partial fulfillment of
the requirements for the
degree of

Master of Science

Presented January 1, 2013
Commencement June 2013

Master of Science thesis of Michael M. Anderson presented on January 1, 2013.

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I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Michael M. Anderson, Author

ACKNOWLEDGEMENTS

(Acknowledgement text)

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Chapter 1: Introduction

1.1 Motivation

1.2 Previous Research

Chapter 2: Experimental Setup

2.1 Featurization

2.2 Base Classifiers

2.3 Datasets

2.4 Performance Metrics

Chapter 3: Top-Down Approach

3.1 Change Point Detection

For this approach, the data was split into non-overlapping segments for featurization using techniques from the statistical field of change point detection. Change point detection has found application in many problem domains that require analysis of time series data from dynamic systems, including failure detection [1], quick detection of attacks on computer networks [7], and monitoring of heartbeat fluctuations during sleep [5]. Change point detection assumes that each tick of a time series is a draw from some process, but that the process may suddenly change as time passes. The goal is to predict when these changes have occurred. A *score* is generated for each time tick, and if the score is above a given threshold a change is predicted to have occurred between that tick and its immediate predecessor. To generate a score at a time tick, a window of data that immediately precedes it (the *reference data*) is compared to it along with a window of data that immediately follows it (the *test data*).

Model-based approaches to change point detection assume that each tick in a time series is a draw from some underlying probability distribution. Scores are generated by estimating the distribution of the reference data and the test data, and then by calculating the likelihood that the two distributions are different. Where it is reasonable to assume that the data belongs to a particular family of distributions then parametric estimation methods have been employed [8]. If no such modeling assumptions are reasonable then non-parametric methods have also been found to be viable [3]. Finally, distance-based approaches such as Singular Spectrum Analysis generate scores through other metrics of dissimilarity or difference between the reference data and the test data [4]. Notationally, we say that for each tick i in a time series:

$$s_i = D(x_{r,i}, x_{t,i})$$

Where s_i is the score of the i th tick, $x_{r,i}$ is the reference data associated with the i th tick, $x_{t,i}$ is the test data associated with the i th tick, and $D(A, B)$ is a function

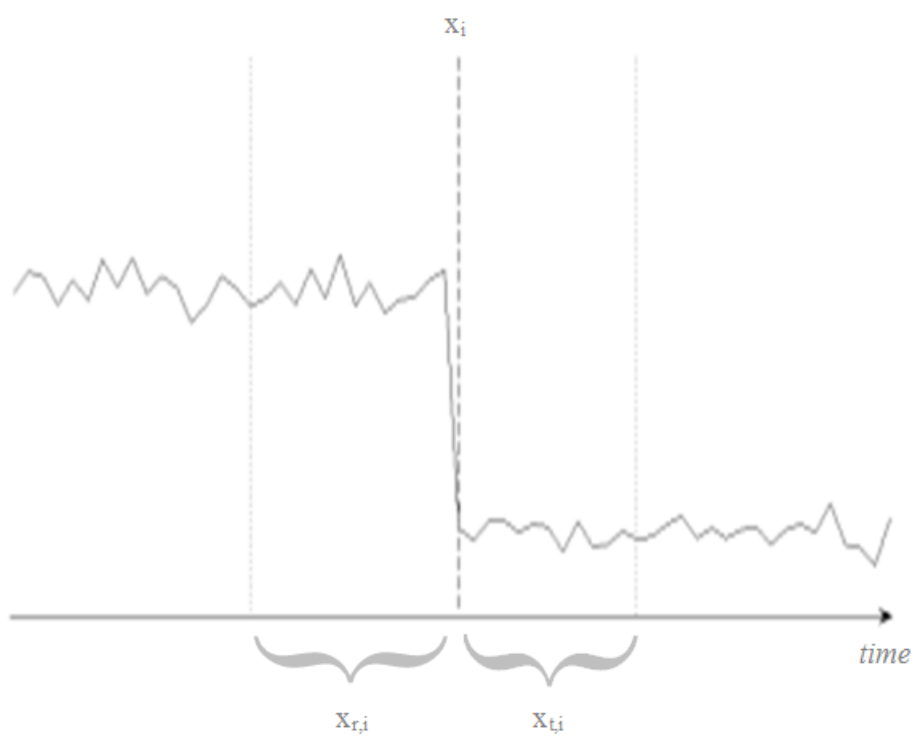


Figure 3.1: Change Point Detection

that computes the dissimilarity between a matrix of data A and matrix of data B , and is particular to the given change point algorithm. Note that for a given algorithm it may not be possible to generate scores right at the very beginning of the time series (insufficient reference data) or at the very end of a time series (insufficient test data).

3.2 Methodology

There are many different modeling assumptions and associated algorithms for generating change point detection scores, and one simple baseline approach that we wanted to test was the Shewhart Control Chart. This approach assumes that the reference data is drawn from a multivariate normal distribution, and that scores are calculated by the Mahalanobis distance of the target time tick from the estimated multivariate normal:

$$s_i = \sqrt{(\bar{x}_{r,i} - x_i)^T S_{r,i}^{-1} (\bar{x}_{r,i} - x_i)}$$

where $\bar{x}_{r,i}$ is the sample mean of the reference data, $S_{r,i}$ is the sample covariance matrix of the reference data, and $x_i = x_{t,i}$ is the i th data point [?].

We were also interested in testing the performance of a newer and more sophisticated change point detection algorithm: the Kullback-Leibler Importance Estimation Procedure (KLIEP), introduced by Kawahara and Sugiyama [2] [6]. This approach generates scores using the Kullback-Leibler (KL) divergence between the reference data and the test data. One method of doing this is to estimate the density of the reference distribution and test distribution separately, and then compare them using a likelihood ratio (known in the change point detection literature as *importance*). Instead, KLIEP estimates the importance directly using a non-parametric model.

Let the estimate of the importance \hat{R} be represented by this model:

$$\hat{R} = \frac{p_t}{\hat{p}_r} = \sum_{j=1}^{n_t} \alpha_j K_G(x, x_{t,j})$$

Where p_r and p_t are the probability densities of the reference data and the test data, n_t is the number of ticks in the test window, α is a vector of model parameters to solve for, x is the concatenation of the reference and the test data, $x_{t,j}$ is the j th element of the test data, and $K_G(A, B)$ is the Gaussian kernel with width σ :

$$K_G(A, B) = \exp\left(-\frac{\|A - B\|^2}{2\sigma^2}\right)$$

Now solve for α so that the empirical KL divergence between \hat{p}_t and $p_t = p_r \hat{R}$ is minimized, which is equivalent to the following convex optimization problem:

$$\begin{cases} \max_{\alpha} & \sum_{j=1}^{n_t} \log\left(\sum_{k=1}^{n_t} \alpha_k K_G(x_{t,j}, x_{t,k})\right) \\ \text{s.t.} & \frac{1}{n_r} \sum_{j=1}^{n_r} \sum_{k=1}^{n_t} \alpha_k K_G(x_{r,j}, x_{t,k}) = 1 \\ & \text{and } \alpha_1 \dots \alpha_{n_t} \geq 1 \end{cases}$$

Finally, the scores that we wish to generate are just the estimate of the importance given by the solution to the complex optimization problem, i.e. $s_i = \hat{R}_i$.

Since this approach uses a Gaussian kernel, it requires the selection of a kernel width σ for each time tick. We used an implementation of KLIEP that is available at Sugiyama's website, which included a cross-validation procedure for the value of σ . The CV procedure chooses a number of disjoint splits of the test data along with a number of different candidate σ 's, and runs KLIEP with each combination of split and candidate σ . Then it chooses the candidate σ that, on the average across all of the splits, maximizes the KL divergence (the \max_{α} equation above) the most.

For the OSU Hip dataset, we used this CV to choose the the kernel width at each individual time tick. This computationally- intensive approach was impractical for the UQ dataset because it is orders of magnitude larger, so instead of running it on every tick of that data, we ran the CV procedure on a number of random ticks drawn from the data. From this we were able to empirically identify 0.01 as a plausible σ , and so fixed σ at that value for our experiments on this dataset. Our reference windows were fixed at a length of 10 seconds, and our test windows were fixed at a length of 1 second.

Once scores were generated, we chose a number of threshold values to determine which scores were considered high enough to predict a changepoint. Threshold values were chosen by considering the false positive rates of change prediction for the change point detection algorithms. A smaller false positive rate corresponded to a higher and more conservative threshold, which split the time series into fewer segments for featurization.

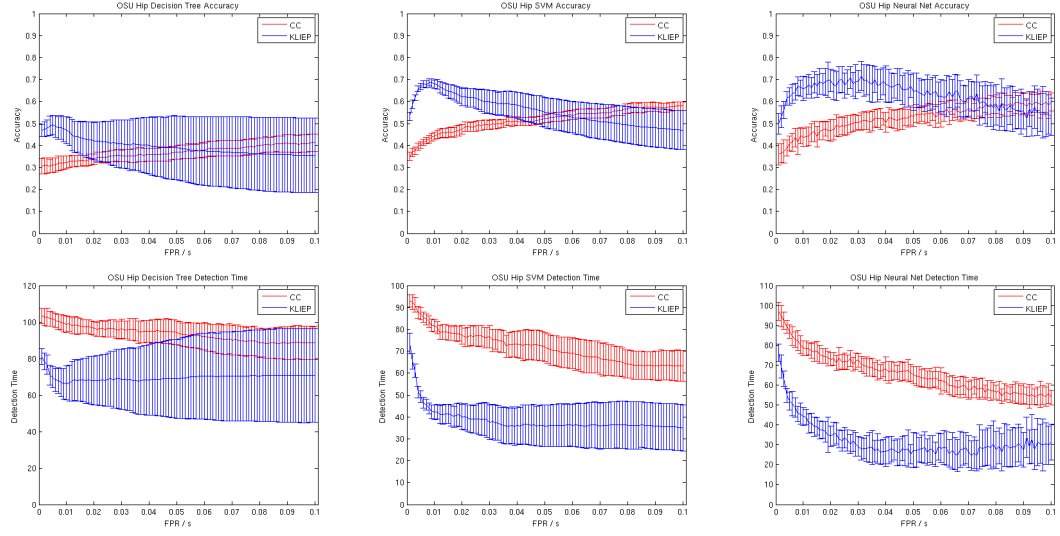


Figure 3.2: CPD-Based Classification Performance

A larger false positive rate corresponded to a lower threshold, which split the time series into more segments.

3.3 Results

Figure 3.2, shows accuracy and detection time as a function of the false positive rate per second, for the OSU Hip dataset, for each of the SVM, Decision Tree, and Neural Net base classifiers.

3.4 Discussion

Chapter 4: Bottom-Up Approach

4.1 HMMs

4.2 Methodology

4.3 Results

4.4 Discussion

Chapter 5: Conclusion

5.1 Discussion

5.2 Directions for Future Research

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