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Physical activity recognition using accelerometer data is a rapidly emerging field with many real-world applications. Much of the previous work in this area has assumed that the accelerometer data has already been segmented into pure activities, and the activity recognition task has been to classify these segments. In reality, activity recognition would need to be applied to "free-living" data, which is collected over a long, continuous time period and would consist of a mixture of activities. In this thesis, we explore two approaches for segmenting realistic free-living time series data. In the first approach, we apply a top-down strategy in which we segment free-living data using change-point detection algorithms and then classify the resulting segments using supervised learning techniques. In the second approach, we employ a bottom-up strategy in which we split the time series into small fixed-length windows, classify these windows, and then smooth the predictions using an HMM. Our results clearly show that the bottom-up approach is far superior to the top-down approach in both accuracy and timeliness of detection.

# Physical Activity Recognition of Free-Living Data Using Change-Point Detection Algorithms and Hidden Markov Models

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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

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# Chapter 1: Related Work

As mentioned in the previous chapter, sensor systems may consist of environmental or wearable devices. Some examples of environmental sensors that activity detection researchers have used to gather data are microphones [7], weight detection panels [14], cameras [6], and water usage detectors [7]. Researchers will generally place environmental sensors inside of a house, have subjects live in the house for a period of time, and attempt to predict for activity types like cooking, watching TV, etc.

Various wearable devices have been tried as well, such as RFID gloves [14], but the most popular wearable for activity detection purposes is the accelerometer. Besides being inexpensive, accelerometers tend to be small and lightweight, and so are fairly unobtrusive and user-friendly. Accelerometers also gather data at a high frequency, and as such may be used to collect a sizeable amount of data in a relatively short amount of time.

Whether or not an accelerometer will be discriminative for a set of activity types depends partially on where the accelerometer is worn on a subject's body. For example, an accelerometer worn on the ankle will be more discriminative for the activity of cycling than it would be if it was worn on the hip, and different types of arm movements will likely be discriminated only by an accelerometer worn on the arm. For this reason some researchers have opted to use multiple accelerometer systems to capture movement information from different parts of the body [2] [5]. However, this approach can be cumbersome for the wearer, so a single accelerometer is preferred when it is reasonable to assume that it will be discriminative over the relevant set of activities. Further research has leveraged the accelerometers found in smart phones that subjects are likely to carry with them anyway as data collection devices [2] [4] [10]

Activity sensor data tends to be noisy and not amenable to a deterministic or rule-based analysis, so activity types are typically modeled probabilistically, and activity detection is usually formulated as a supervised learning problem. The various common supervised learning algorithms are all familiar to the activity detection literature, though neural networks are especially popular, such as in [1] [15] [16]. More complicated metamodeling approaches have also been tried, such as plurality voting with bagged, boosted, and stacked classifiers [13]; conditional random fields [3] [8] [18] [19]; and HMMs [8] [11] [12] [19].

In the past few years researchers have started to focus on the feasibility of online activity detection [8] [9] [19], and have started to recognize the need to test on realistic free-living data [10] [17]. Our contribution is to compare different change-point detection techniques for window segmentation with the state-of-the-art (in terms of accuracy) HMM approach on free-living data in an online setting.

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