AN ABSTRACT OF THE THESIS OF

Michael M. Anderson for the degree of Master of Science in Computer Science
presented on June 13, 2013.

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

Abstract approved: ______________________________
Weng-Keen Wong

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

by

Michael M. Anderson

A THESIS

submitted to

Oregon State University

in partial fulfillment of
the requirements for the
degree of

Master of Science

Presented June 13, 2013
Commencement June 2013

Master of Science thesis of Michael M. Anderson presented on June 13, 2013.

APPROVED:

Major Professor, representing Computer Science

Director of the School of Electrical Engineering and Computer Science

---

Dean of the Graduate School

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

I would like to acknowledge and thank my advisor, Dr. Weng-Keen Wong, for providing me with a clear and overarching vision of this project at all stages of its development, as well as for his general expertise and helpfulness with all of the rough patches, sticking points, and unexpected problems that invariably accompany an endeavor of this magnitude. I would also like to thank the other members of my committee, Dr. Prasad Tadepalli, Dr. Raviv Raich, and Dr. Hector Vergara, for giving their time to help supervise the final stages of this project. Finally, thanks go to all of my family and friends who encouraged and stood by me along the way. They are too numerous to name but they know who they are.

TABLE OF CONTENTS

Chapter 1: Introduction

One of the general goals of the field of artificial intelligence is to build computing devices that are "context-aware", that act as more than just passive number-crunching machines that receive input data through very restrictive and wholly human-operated channels such as a keyboard or mouse. Context-aware devices are capable of using sensor data to understand the environment that they are situated in, such as the locations of nearby objects and how the objects are moving [1]. One subfield of context-aware computing that has been receiving considerable attention in recent years is activity detection. The goal of activity detection is to build computer plus sensor systems that are able to determine what activity a human subject is performing at any given moment.

Such systems have a variety of real-world applications. Researchers have been exploring the feasibility of using both wearable and non-wearable sensor systems to monitor the health of elderly patients that have or are at risk of developing degenerative physical and mental diseases [8]. The goal is to eventually build sensor-based monitoring systems that can aid doctors and family members in tracking the decline of subjects over time. Also, detection of an abnormal activity may indicate that a senior is undergoing a serious medical event such as a heart attack or slip-and-fall [21]. Another application of activity detection is to track the energy expenditure of subjects as they go through the course of their day. The traditional method of performing such tracking is with self-reporting by the subject of their activities. Wearable sensors offer an alternative approach that is not susceptible to misreporting due to bias, poor memory, or other confounding factors that a human reporter introduces into the system. One approach is to estimate the vigorousness or metabolic equivalent (MET) of an activity and calculate energy expenditure directly [17], while another is to attempt to predict the type of activity performed, and calculate energy expenditure using knowledge of how vigorous that activity is generally [19].

Activity detection generally assumes that sensor data will be represented as a time series, and that at any given moment in the time series the subject is performing one and only one type of activity. Thus the time series is thought of as being partitioned into a number of non-overlapping intervals (*windows*), which are delimited by moments in time when the subject stopped performing one activity and started performing another. Previous work has treated activity detection as an offline problem, and has rarely considered performance metrics other than accuracy. In this work we are interested in the feasibility of partitioning and classifying a time series on free-living data in real time. In addition to accuracy we will also evaluate our algorithms in terms of the amount of time required to detect that an activity change has occurred.

To predict changes in activity and partition the data, we used change-point detection, which is a field of statistics popular in control theory and other similar applications. We call this our top-down approach, because this method takes as input an initial time series and partitions it into smaller pieces using change-point detection. As an alternate approach we used the well known technique of partitioning the time series into small fixed-length non-overlapping windows, predicting the activity type of each window using a base classifier, treating that prediction as the observable state of an HMM, and finally solving the HMM for its hidden states. We call this our bottom-up approach, because we begin with small windows of fixed-length, and use an HMM to aggregate windows and smooth them together into larger activity intervals.

Chapter 2: 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 [8], weight detection panels [15], cameras [7], and water usage detectors [8]. 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 [15], 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 [3] [6]. 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 [3] [5] [11]

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 [2] [16] [17]. More complicated metamodeling approaches have also been tried, such as plurality voting with bagged, boosted, and stacked classifiers [14]; conditional random fields [4] [9] [20] [22]; and HMMs [9] [12] [13] [22].

In the past few years researchers have started to focus on the feasibility of online activity detection [9] [10] [22], and have started to recognize the need to test on realistic free-living data [11] [18]. 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.

Bibliography

[1] Gregory D. Abowd, Anind K. Dey, Peter J. Brown, Nigel Davies, Mark Smith, and Pete Steggles. Towards a better understanding of context and context-awareness. In *Proceedings of the 1st international symposium on Handheld and Ubiquitous Computing*, HUC '99, pages 304–307, London, UK, UK, 1999. Springer-Verlag.

[2] K. Aminian, P. Robert, E. Jequier, and Y. Schutz. Estimation of speed and incline of walking using neural network. *Instrumentation and Measurement, IEEE Transactions on*, 44(3):743–746, 1995.

[3] Ling Bao and Stephen S. Intille. Activity recognition from user-annotated acceleration data. pages 1–17. Springer, 2004.

[4] Ulf Blanke and Bernt Schiele. Remember and transfer what you have learned-recognizing composite activities based on activity spotting. In *Wearable Computers (ISWC), 2010 International Symposium on*, pages 1–8. IEEE, 2010.

[5] Tanzeem Choudhury, Anthony LaMarca, Louis LeGrand, Ali Rahimi, Adam Rea, Gaetano Borriello, Bruce Hemingway, Karl Koscher, James A. Landay, Jonathan Lester, Danny Wyatt, Dirk Haehnel, and et al. The mobile sensing platform: An embedded activity recognition system, 2008.

[6] S.I. de Vries, F.G. Garre, L.H. Engbers, V.H. Hildebrandt, and S. van Buuren. Evaluation of neural networks to identify types of activity using accelerometers. *Medicine & Science in Sports & Exercise*, 43(1):101, 2011.

[7] T.V. Duong, H.H. Bui, D.Q. Phung, and S. Venkatesh. Activity recognition and abnormality detection with the switching hidden semi-markov model. In *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pages 838–845, June 2005.

[8] James Fogarty, Carolyn Au, and Scott E. Hudson. Sensing from the basement: a feasibility study of unobtrusive and low-cost home activity recognition. In *Proceedings of the 19th annual ACM symposium on User interface software and technology*, UIST '06, pages 91–100, New York, NY, USA, 2006. ACM.

[9] T. Gu, Z. Wu, X. Tao, H. K. Pung, and J. Lu. epsicar: An emerging patterns based approach to sequential, interleaved and concurrent activity recognition. In *Pervasive*

Computing and Communications, IEEE International Conference on, pages 1–9, 2009.

[10] E. Keogh, S. Chu, D. Hart, and M. Pazzani. Online algorithm for segmenting time series. In *ICDM, Proceedings IEEE Internation Conference on*, pages 289–296, 2001.

[11] J. R. Kwapitz, G. M. Weiss, and S. Moore. Activity recognition using cell phone accelerometers. *SIGKDD*, 12(2):74–82, 2010.

[12] Jonathan Lester, Tanzeem Choudhury, Nicky Kern, Gaetano Borriello, and Blake Hannaford. A hybrid discriminative/generative approach for modeling human activities. In *In Proc. of the International Joint Conference on Artificial Intelligence (IJCAI*, pages 766–772, 2005.

[13] D.M. Pober, J. Staudenmayer, C. Raphael, and P.S. Freedson. Development of novel techniques to classify physical activity mode using accelerometers. *Medicine & Science in Sports & Exercise*, 38:1626, 2006.

[14] Nishkam Ravi, Nikhil D, Preetham Mysore, and Michael L. Littman. Activity recognition from accelerometer data. In *In Proceedings of the Seventeenth Conference on Innovative Applications of Artificial Intelligence(IAAI)*, pages 1541–1546. AAAI Press, 2005.

[15] Jim Rowan and Elizabeth D. Mynatt. Digital family portrait field trial: Support for aging in place. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, CHI '05, pages 521–530, New York, NY, USA, 2005. ACM.

[16] Yoonseon Song, Seungchul Shin, Seunghwan Kim, Doheon Lee, and Kwang Lee. Speed estimation from a tri-axial accelerometer. In *Proceedings of the 29th Annual International Conference of IEEE EMBS*, August 2007.

[17] J. Staudenmeyer, D. Pober, S. Crouter, D. Bassett, and P. Freedson. An artificial neural network to estimate physical activity energy expenditure and identify physical activity type from an accelerometer. *Journal of Applied Physiology*, pages 1300–1307, 2009.

[18] Christina Strohrmann, Holger Harms, Gerhard Tröster, Stefanie Hensler, and Roland Müller. Out of the lab and into the woods: kinematic analysis in running using wearable sensors. In *Proceedings of the 13th international conference on Ubiquitous computing*, UbiComp '11, pages 119–122. ACM, 2011.

[19] S.G. Trost, W.K. Wong, K.A. Pfeiffer, and Y. Zheng. Artificial neural networks to predict activity type and energy expenditure in youth. *Medicine and Science in Sports and Exercise*, pages 1801–1809, September 2012.

[20] Tim van Kasteren, Athanasios Noulas, Gwenn Englebienne, and Ben Kröse. Accurate activity recognition in a home setting. In *Proceedings of the 10th international conference on Ubiquitous computing*, UbiComp '08, pages 1–9, New York, NY, USA, 2008. ACM.

[21] Junbo Wang, Zixue Cheng, Mengqiao Zhang, Yinghui Zhou, and Lei Jing. Design of a situation-aware system for abnormal activity detection of elderly people. In *Proceedings of the 8th international conference on Active Media Technology*, AMT'12, pages 561–571, Berlin, Heidelberg, 2012. Springer-Verlag.

[22] Tsu-yu Wu, Yi-Ting Chiang, and Jane Yung-jen Hsu. Continuous recognition of daily activities from multiple heterogeneous sensors. In *Proceedings of the 2009 AAAI Spring Symposium on Human Behavior Modeling*, pages 81–85, March 2009.