Defining Activities through Continuous Motion Analysis using Wearable Sensors

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Wearable sensors are quickly becoming a ubiquitous and nearly invisible technology. Anyone who carries a smart phone or wears a smart watch is a rich source of motion data. In many cases, this data is available as long as the person is awake and moving around, particularly in the case of smart watches. This allows for continuous motion tracking applications, such as step counters, which use activity classification algorithms. In August of 2017, a colleague[1] and I recognized that while activity classification has been thoroughly researched [5, 6, 7, 8], there have not been applications of continuous activity recognition using wearable sensors beyond counting steps or heart rate. Fitness tracking applications require the user to stop and start recordings, identify the activity manually, and record separately for different activities [3]. Classifying an activity moment by moment is useful in a step counter, but it does not tell you when you started walking, or when you stopped. It also does not tell you the duration or the intensity of an activity. To remedy this, we began a project to detect changes in the person's level of activity, determine what the person is doing based on the context, and then define when the activity started and when it stopped. Once high impact physical activity is detected and defined, other health sensors can be triggered awake to better assess the level of activity and the overall health of the individual.

To this end I will leverage new advances in capacitive stretch fabrics and apply them to measuring pulmonary function using a chest strap. There has been some research in this area [15], and products which use mechanical capacitive stretch sensors to measure respiratory rate in fitness scenarios are available to the public [16]. I will compare the responsiveness of the new materials to medically proven methods of measuring pulmonary function including respiratory rate, lung capacity, and blood oxygenation. There are medical applications to be explored, from elderly care [17] to emergency trauma situations where large medical equipment is unavailable and a lightweight low energy option for measuring pulmonary function could be ideal. The chest strap could be used in a continuous motion scenario to provide additional health metrics for quantifying performance in high impact activities. Over time, not only would it assess performance during physical activities, but also provide feedback to improve it.

1 Mission Alignment

Similar to a prolonged bed rest, it has been well established that the reduced gravity conditions of long endurance space flight have a detrimental effect on bone and muscle mass in humans [11, 12, 13, 14]. This can cause health problems when they return to higher gravity conditions. One method of alleviating the effects of reduced gravity on the body is to perform regular aerobic exercise and resistance training [9, 10]. The International Space Station currently has a number of large machines for maintaining and tracking physical fitness [2]. An unobtrusive device, like a watch or a chest band, that detects activities automatically throughout the day would be a useful tool for mission members and medical personnel. The resulting data could lead to a more thorough understanding of health issues caused by reduced gravity. Light weight, low energy devices for assessing an individual's medical condition would also be useful in situations where large or heavy equipment is an issue, electrical infrastructure is scarce, or visible measurement of an individual's life signs, such as breathing, are made impossible by bulky suits or helmets. These sensors could be incorporated into a garment worn under a suit.

2 Background and Previous Work

Continuous Motion: I currently have 2 hours of accelerometer and gyroscope data collected using an Apple Series 3 watch. 45 minutes of that data was used to train a Support Vector Machine(SVM) learning algorithm to determine what category of activity a segment of data falls under. The categories the SVM trained on included running, cycling, and what we call 'transition', defined as lower impact activities like walking, drinking water, tying their shoes, often conducted in the transition period between high impact activities. 1hr 15 min of the data was comprised of simulated biathlons. We had each of the 3 volunteers either run and transition to cycling, or bike and transition to running. During the biathlon, the volunteers wore a GoPro on a chest harness. This provided the ground truth for start and stop times for each activity. The data from the sensors is viewed using a sliding window technique, with the SVM classifying the activity in each window. This gives a time line of classifications that can be fed into a second algorithm which analyzes each

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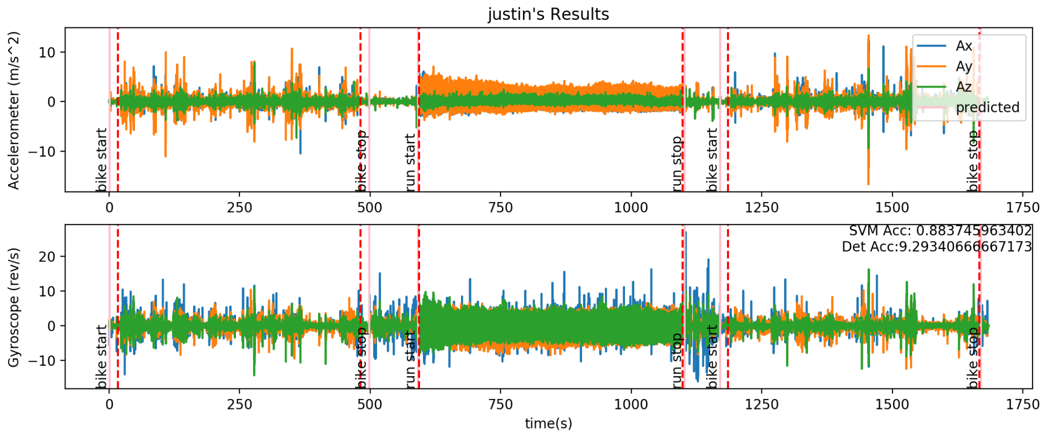

Figure 1: Predicted start and stop times for each activity are labeled and represented by pink vertical lines. The red lines represent the ground truth determined by the GoPro video.

classification event in the context of what came before. The algorithm focuses on trends in the time series data, allowing recognition of the difference between a temporary interruption, like stopping to tie a shoe or navigating around an obstacle, and completion of an activity. For each volunteer, the algorithm correctly determined the number and type of sustained activity, and was able to define a start and stop time within 14 seconds of ground truth. The preliminary set of features that we extracted from our data includes: the root mean square of the amplitude, the standard deviation, the mean, and the median of the amplitude, the avg distance between peaks, the standard deviation of the distance between peaks, the average amplitude between peaks and the standard deviation of the amplitude between peaks. After the first iteration of our results, we noticed that there was a difference between the accuracy of the predicted start and stop times for running and cycling. The runs were within 8.5 seconds of ground truth and the rides were within 19.5 seconds of ground truth. Upon review of the video, we saw that each of the volunteers walked the bicycle several feet before mounting and after dismounting the bicycle. We were then able to correlate the predicted start and stop times to when the subjects began/stopped walking the bicycle, rather than when they mounted/dismounted the bicycle. I intend to study distinguishing features for the classifier, so that it can differentiate between riding and walking a bicycle. This may prove challenging as the difference may be very subtle. The wrist is in a similar fixed position in both cases. The vibration from the tires on the pavement passed through the frame of the bike would also be very similar. I also intend to gather training data for the running activity. The SVM classifier did not recognize portions of the run where the user was looking at the watch to check their time, due to an interruption in the rhythmic motion being captured by the accelerometer. When this occurred during the run, the time line algorithm was able to filter it out as an interruption, but when the user held up the wrist with the watch at the end of the run, the algorithm would end the run activity early, with the times correlating to when the volunteer raised their wrist rather than when they stopped running. In one case, the difference was nearly 30 seconds.

We also recorded a session where I biked, ran, then biked again. The algorithm found all three sustained activities, seen in Figure 1, predicting start and stop times on average within 9.8 seconds of the ground truth. In this case we were trying to simulate a full triathlon which is comprised of 3 consecutive activities. In a real triathlon, one of those activities would be a swim. Adding more activities to the SVM classifier will require additional data collection.

Figure 2: StretchSense sensor attached to a chest strap. Capacitive fabric is the gold portion, bottom left of the logo.

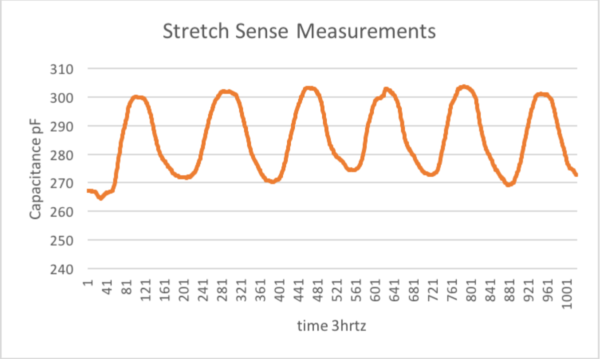

Figure 3: Breathing Data from the StretchSense sensor while the subject was at rest.

Pulmonary Measurement: I have a sensor made by StretchSense [1] which collects capacitance data using a capacitive stretch fabric. When the fabric is stretched, the capacitance increases, and when the fabric relaxes, the capacitance returns to the ground state. When incorporated into a chest strap, as seen in Figure 2, the expansion of the sensor, as a subject breathes, may be used to determine respiratory rate, and also the deepness of each breath. The data collected from the sensor, seen in Figure 3, suggests a pattern of breathing while a subject is sitting still, and a similar pattern is apparent when the subject is moving, but there are also artifacts in the data associated with upper body movement which can drown out the smaller movements I have associated with breathing. This makes measuring respiratory rate difficult unless the subject is perfectly still, which would not be practical for continual motion analysis for a subject that was not asleep or comatose. In order to extract the respiratory rate of an ambulatory user, the upper body movements must be filtered out of the data. It is also possible that the artifacts themselves can be classified to determine certain types of upper body motion.

3 Plan of Study

Task One: To improve the accuracy and capabilities of the activity detection algorithm I will collect data from a larger group of volunteers:

- To refine the current activity predictions and improve the accuracy of the start and stop predictions. This will involve collection of data from specific scenarios such as walking a bicycle or running with the wrist up. I will also study various feature descriptors to identify the most distinguishing features for activity classification.
- To expand the range of activities. Activities will include swimming, core intensive exercises, weight lifting, and running/biking indoors on stationary equipment. With the increase in the number of activities, I will also explore various supervised learning techniques to improve the performance of the system.
- Of many different ages and levels of fitness for each activity. Everyone has different running styles and habits, but there may also be differences in range of movements based on height or fitness level. This could lend itself to tailored training sets for individuals. I will assess that possibility and determine if a tailored approach lends itself to higher accuracy in the predictions.

Task Two: Task two, which may be done in conjunction with Task one, will involve:

- Building models for chest expansion during respiration by collecting data using the capacitive sensing chest strap while ambulatory and at rest. This model will allow us to measure respiratory rate and deepness of breath.
- Developing filtering techniques for the capacitive sensor data to aid us in isolating breathing data (signal to be measured) from the noise caused by user's upper body motion. Since body movements have higher magnitude than chest expansion during breathing, this task will be particularly challenging.
- Comparing the accuracy and precision of the resulting model to current fitness sensors as well as medical guidelines and methods for measuring pulmonary function. I will use a device similar to the Easy One Pro^{R} [4], a portable spirometer used by medical professionals to measure pulmonary function, as ground truth for measurements taken by the capacitive sensing chest strap.
- To correlate the upper body movement filtered from the sensor data with certain activities or motions

Task Three: Task Three will be to incorporate the capacitive sensing chest strap into the continuous motion analysis, measuring respiratory rate and deepness of breath for activity confirmation and fitness metrics.

4 Expected Outcomes

Currently, I have a working model and a time series filtering algorithm that can classify 2 high impact activities, running and cycling, and determine their start and stop times within 14 seconds. I also have some data in regards to the efficacy of the capacitive fabric as a pulmonary measurement device. The goal of this research is to develop a system for continuous motion analysis for accurately identifying activities from a users daily time line using wearable sensors. It will also evaluate the capacitive fabric sensor as a means of measuring pulmonary function. This would allow more detailed activity monitoring than current applications. The results will be developed into a manuscript for submission to a research conference or journal.

References

[1] General information about StretchSense sensors and purchase options. *StretchSense*, https://www.stretchsense.com/

[2] @NASA "Exorcising in Space" *Tumblr*, 5 Jan 2016, https://nasa.tumblr.com/post/136706596374/exercising-in-space

[3] A popular athletic tracker which gives a user the ability to edit their workout and manually split it into multiple activities after its been posted. *STRAVA*, https://www.strava.com/

[4] General information about the Easy One Pro and purchase options. *NDD Med*, https://www.nddmed.com/en-us/product/easyone-pro.html#details

[5] Juha Pärkkä, Miikka Ermes, Panu Korpipää, et al. *Activity Classification Using Realistic Data From Wearable Sensors* IEEE Transactions on Information Technology in Biomedicine, Vol. 10, No. 1, January 2006. Available: http://ieeexplore.ieee.org/abstract/document/1573714/

[6] Muhammad Shoaib, Stephan Bosch, Ozlem Durmaz Incel, et al. *Complex Human Activity Recognition Using Smartphone and Wrist-Worn Motion Sensors* Sensors 2016. Available: http://www.mdpi.com/1424-8220/16/4/426/htm

[7] Seon-Woo Lee, Kenji Mase. *Activity and Location Recognition Using Wearable Sensors* IEEE Pervasive Computing (Vol. 1, No. 3, July-Sept 2002. Available: http://ieeexplore.ieee.org/abstract/document/1037719/

[8] Andrea Mannini, Stephen S. Intille, Mary Rosenberger, et al. *Activity recognition using a single accelerometer placed at the wrist or ankle* Med Sci Sports Exerc. Nov. 2013. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3795931/

[9] Smith, S. M., Heer, M. A., Shackelford, L. C., Sibonga, J. D., Ploutz-Snyder, L. and Zwart, S. R. (2012). *Benefits for bone from resistance exercise and nutrition in long-duration spaceflight: Evidence from biochemistry and densitometry* J Bone Miner Res, 27: 18961906. doi:10.1002/jbmr.1647. Available: http://onlinelibrary.wiley.com/doi/10.1002/jbmr.1647/full

[10] Jörn Rittweger, Harold M. Frost, Hans Schiessl, et al. *Muscle Atrophy and Bone Loss after 90 days' bed rest and the effects of flywheel resistive exercise and pamidronate: Results from the LTBR study* Bone vol. 36, issue 6, June 2005 pages 1019-1029. Available: http://www.sciencedirect.com/science/article/pii/S8756328204004648

[11] A. LeBlanc, V. Schneider, L. Shackelford, et al. *Bone mineral and lean tissue loss after long duration space flight* J Musculoskel Neuron Interact 2000; Available: http://www.ismni.org/jmni/pdf/2/leblanc.pdf

[12] V.S. Oganov, A.I. Grigor'ev, L.I. Voronin, et al. *Bone mineral density in cosmonauts after flights lasting 4.56 months on the Mir orbital station* Aviakosm. Ekol. Med., 26 (1992), pp. 20-24. Available: https://www.scopus.com/record/display.uri?eid=2-s2.0-0026988861&origin=inward&txGid=8c31fa09d66290dffe087faf63b9f76f

[13] J.M. Vogel, M.W. Whittle. *Bone mineral changes: the second manned Skylab mission* Aviat., Space Environ. Med., 47 (1976), pp. 396-400. Available: https://www.scopus.com/record/display.uri?eid=2-s2.0-0017288026&origin=inward&txGid=450c76f5bbf910a42632b0796c41d609

[14] V. Schneider, V. Organov, A. LeBlanc, et al. *Space flight bone loss and change in fat and lean body mass* J. Bone Miner. Res., 117 (1992), p. S122. Available: https://www.scopus.com/record/display.uri?eid=2-s2.0-0001449741&origin=inward&txGid=86fa520c8ee9da7a32f481ecad58f100

[15] Josip Grlica, Toni Martinović, Hrvoje Džapo.*Capacitive Sensor for Respiration Monitoring* Sensors Applications Symposium (SAS), 2015 IEEE. Available: http://ieeexplore.ieee.org/document/7133567/

[16] J.-H. Kim, R. Roberge, J.B. Powell, et al. *Measurement Accuracy of Heart Rate and Respiratory Rate during Graded Exercise and Sustained Exercise in the Heat Using the Zephyr BioHarnessTM.* International journal of sports medicine 34.6 (2013): 497501. PMC. Web. 22 Jan. 2018. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4620538/

[17] Ho, S.-W., Teng, Y.-H., Yang, S.-F., Yeh, H.-W., Wang, Y.-H., Chou, M.-C., Yeh, C.-B. (2017). *Risk of pneumonia in patients with isolated minor rib fractures: a nationwide cohort study* BMJ Open, 7(1), e013029. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5253567/