Detecting and Exploiting Periodicity in Activity Classification

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***Abstract*—The technology for activity classification presents new opportunities for control and monitoring of serious games players. Other than for step detection, human activity classification is normally undertaken by calculating features from a fixed interval length of sensor data and comparing them to values expected from a range of activities. It was observed that many human activities, especially vigorous activities, are cyclic. This paper tested the hypothesis that, if features are calculated over an integer number of cycles of a cyclic activity, more accurate activity classifications will be achieved. An algorithm was developed that determines whether an activity is cyclic and if so, identifies the cycles and calculates the feature set over an integer multiple of cycles. If the activity is determined to be non-cyclic, the features are calculated over a fixed time window. The hypothesis that more accurate activity classifications will be achieved was confirmed with a pairwise t-test at the 99% significance level. Knowledge that a cyclic activity is taking place is already informative and can enable generation of features from individual cycles. One of these, cycle length, was added to the feature set which improved recognition rates for activities where the cycle length varied greatly from other activities. For example, brushing teeth improved from 39% with a fixed window to 54% for an adaptive window and 74% for an adaptive window with cycle length. An overall improvement in activity classification success rate was found for this adaptive windowing method compared to a fixed window approach with overall success rates of 54% for a fixed window, 62% for an adaptive window and 64% for an adaptive window with the additional feature.**

Keywords—activity classification; adaptive windowing; accelerometer; cyclic activities

I. Introduction

Activity classification is the identification of a user's activities from analysis of sensor observation. There are various useful applications for activity recognition some of which are: building context aware systems [1], monitoring of elderly when performing activities that may be difficult for them and cause a fall [2], a means of tracking physical fitness and exercise such as in the popular mobile application Google Fit [3], to understand and improve sports technique [4] and as a potential control scheme in some form of games. As such, activity recognition has major applications in healthcare, exercise tracking and wearable technologies. There are various methods for collecting data to perform activity recognition. Environmental or off-body sensors may be used which can track motion, location and object interaction with a user [2]. Off-body sensors however, can be expensive, require maintenance and they limit activity recognition to the location of the sensors. On-body sensors are used in this paper and consist of a sensor located on the body to track tri-axial acceleration. Unlike other methods, they are not limited by the wearer's location. On-body sensors may measure accelerations, orientation and rotational velocities of the part of the body they are attached to. Activity recognition via acceleration data has a higher mean success rate than orientation or rotational velocity data for various feature sets and monitor set ups [4]. When the combined acceleration, orientation and rotational velocity data were used to extract features, the success rate for activity recognition was only slightly better than using the acceleration data alone. As such, only acceleration data from sensors was used in this paper. People have demonstrated a willingness to wear wrist devices in popular commercial systems such as Fitbit watches, Jawbone activity trackers and Garmin Vivosmart. Different body sensor locations provide different success rates in activity recognition and the user's dominant wrist provides the highest success rate making it the preferred location should only one sensor be used [4]. As the dominant wrist location has the highest success rate for activity classification and is a desirable location to wear an accelerometer, one sensor at this body location was used for this paper.

Activity classification via a wrist accelerometer to control a computer game has not been widely explored. Generic control devices such as the keyboard or mouse are being replaced with technologies that involve body motion recognition [5] as they give the user a sense of reality and immersion in a game. The action to perform an activity in the game is closer matched to the activity performed in natural life by these methods. Some examples of these control devices are: the Nintendo Wii, which can sense the location and motion of the handheld remote via an infrared projector and camera [5]; and the HTC Vive, which controls by detecting the location of two handheld controllers and a head-mounted display via laser pointers [6]. A limitation with these control methods is that they require an additional control device which is unnatural and impossible for those who are not able to hold and operate a controller such as those with prosthetic hands. As such, activity classification by a wrist based accelerometer, could allow more active, natural control and an alternative control means.

The longest known and most effective human activity recognition technique is that of peak acceleration detection for identifying heel strikes, most often interpreted as steps. This is used in the simplest waist mounted step counters to the current generation of activity recognition products. More sophisticated systems mostly provide historical logging and improved interfaces to data produced from the same underlying sensing technique as the simplest step counters. Peak accelerations associated with heel strikes are so far removed from accelerations caused by all other body movements that they provide clear delineation and become a feature that can be further interpreted. For more complex activities that aren't as easily characterized, a more complex classification process is used. Activity classification consists of four major steps: segmenting sensor data, feature extraction, training the activity model and classification. Segmentation refers to how the sensor data is segmented or windowed for which features are extracted from. Feature extraction involves determining features of the data that characterize the activity being performed. Training the activity model refers to training the chosen classifier by a training set of the extracted features with activity labels. Classification of the activity is then performed on a test set of extracted features to determine their activity labels by the trained classifier.

Some activities are significantly easier to identify such as walking and running as compared to dusting and watching TV for one sensor location. Some human activities are also found to be highly confusable with each other [4]. It is this confusability that makes it difficult to compare results across the many studies of activity recognition and to predict from these results how effective an activity recognition system will be in everyday use. Acquiring sensor data for the vast range of human activities that is labeled with the activity being undertaken is impractically difficult. All studies use a subset of human activities, most studies employ a very small subset, and the smaller the subset the less confusability there will be. This combines with the problem of discrete versus complex activities to produce the outcome of studies reporting very high success rates but systems built using the methods reported on frustrating users with unacceptably high error rates. This has resulted in almost all commercial systems using only peak accelerations as their feature of interest. Peak accelerations in most body locations (not the head) for walking and running are so much larger than for any other human activities that confusability is acceptably low [7]. Complex activities e.g. walking upstairs or playing soccer are also accepted as correct by users when reported as walking, running or steps.

II. METHODOLOGY

A. Data Collection

Data for 22 activities was collected which could be categorized together to form a core of day to day routines centered around the house as follows:

1. Household cleaning – Vacuuming, sweeping, dusting
2. Laundry – Folding clothes, ironing clothes
3. Kitchen work – Peeling, dicing, grating, stirring, washing dishes, washing hands, washing vegetables
4. Walking on stairs - Walking upstairs, walking downstairs
5. Sedentary activities – Watching TV, talking on the phone, texting on the phone, using PC, writing with a pen
6. Brushing teeth
7. Walking
8. Running

Data for walking and running was collected from 21 subjects, of which 14 were males, 7 were females and were all aged between 14 to 51. The remaining 20 activities were gathered from 17 subjects, of which 14 were males, 3 were females and were all aged from 27 to 52. The data collection was semi-controlled as subjects were not advised how to perform an activity. Sampling of data was performed at 128Hz.

Some of these activities involve gross movement such as walking, running and walking on stairs. The remaining activities, involve fine movements. For implementation as a controller for a game, the gross movements could allow movement of an avatar whereas the fine movements would provide actions to interact with objects in the game.

B. Adaptive Time Windowing

To capture features of an activity, the continuous raw sensor data is segmented into windows of a certain duration known as windows. There are three main segmentation techniques, activity defined windows, event defined windows and fixed size windows [8]. Activity defined windows are partitioned based on a detection of change in activity. The initial and end points of an activity are determined before the activity is actually analyzed and identified. There are various methods to determine a change in activity such as variations in frequency characteristics [9], separation of static and dynamic activities [10] or from user feedback [2]. This windowing technique is rarely used for recognition but more often used as a means of labeling training data. Event defined windows partition data depending on the location of a specific event. An example of this for walking was used by Benocci, et al. [11], where the event of a high acceleration associated with a heel strike event was used to segment data. It is also the method used in most commercial activity trackers, such as Fitbits. This method is not suitable for identifying complex activities that can be made up of varying combinations of simple activities.

The fixed size window technique is a commonly used technique in activity recognition. According to Banos, et al. [8], it is the best suited method for real time applications due to its simplicity and lack of pre-processing. However, this is true only for activity sets other than running or walking which can be identified even more simply using peak accelerations. A range of window sizes have been used in previous studies. The fixed window length used has an impact on the success rate of activity classification. There is an increase in success rate with an increase in window size, with a linear relationship between the success rate and the logarithm of the window length [4]. However, a longer window length impacts the power consumption when sampling discontinuously and results in a lag in a real-time application as the sensors will need to capture more data before recognizing an activity. Larger window sizes may also result in multiple activities falling within that window, providing low activity resolution. If the window is too small, there will not be enough data to characterize the activity.

Many activities we perform are cyclic in nature and thus the use of a fixed time window results in an unpredictable number of cycles of the activity in one fixed time window. To avoid this problem, an adaptive windowing method was explored that sets the window to be an integer number of cycles of the activity which can be accomplished by using autocorrelation.

Autocorrelation is the cross correlation of a signal with itself at varying time lags. The peaks of the autocorrelation function are the points where the signal is highly correlated with itself and thus the period of an activity may be determined by the time between two peaks of the autocorrelation function. The autocorrelation value at this point is a measure of how correlated the two cycles are. A normalized autocorrelation function is used and is described by:

$$r_x[h] = \frac{1}{N-h}\sum_{n=0}^{N-h-1} x^*(n)x(n+h)$$
$$h = 0, 1, \dots, N-1 \quad (1)$$

Where h is the time lag, $x^*(n)$ is the complex conjugate of $x(n)$ [12] and N is the length of x.

Before the autocorrelation is determined, the three axis acceleration sensor data is first combined to give the magnitude of acceleration regardless of direction by (2).

$$a = \sqrt{a_x^2 + a_y^2 + a_z^2} \quad (2)$$

The data is then normalized by subtracting the mean and dividing by the standard deviation. This is necessary as a non-zero mean causes high correlation and this normalization allows comparison of the autocorrelation of signals of different magnitudes. Autocorrelation must be done over a segment and to extract the period, the segment must be long enough to contain at least two cycles of the activity. However, activities can change so a shorter segment is more likely to contain only one activity. Therefore, we want the shortest interval possible that is guaranteed to contain at least two cycles of an activity. Of the 22 activities, the longest period was always less than 1.5 seconds so it was decided that a 3 second segment of sensor data would be suitable to determine the autocorrelation function over. An unbiased estimate of the autocorrelation function is used to ensure the magnitude of the autocorrelation function isn't dependent on the lag.

Not all activities we perform are cyclic, thus to be able to still classify non-cyclic activities, a pre-processing step is needed to determine if the activity is cyclic. If cyclic, the adaptive windowing method is applicable otherwise a fixed time interval is preferable. It was observed that cyclic activities had more energy in the 0-10Hz range of the spectrum. The Fourier transform was squared and summed for frequencies in this range and if the resultant energy was greater than a threshold, was determined to be cyclic. This threshold was chosen qualitatively to minimize the windows from the activities that were known to be non-cyclic and maximize the proportion of windows from activities that were known to be cyclic. An activity will often not be performed constantly and consistently over the entire window and when Sheng, et al. [13] used a similar approach to segment the time window there was an assumption the cycles always began at the beginning of the window which led to segmentation containing a non-integer number of cycles when this did not occur. As well, features extracted from a segment that contains multiple sub-activities that make up an activity are likely to be poor indicators of either sub-activity. Thus, a method was needed to identify windows that contained multiple sub-activities and were not able to be segmented into an integer number of cycles. The autocorrelation function provides a count of the number of cycles in the analyzed window so that the number found can be compared to the number expected for the length of the window analyzed. Where the number found differs from the number expected, the window is abandoned. A graphical representation of this algorithm is illustrated in Fig. 1.

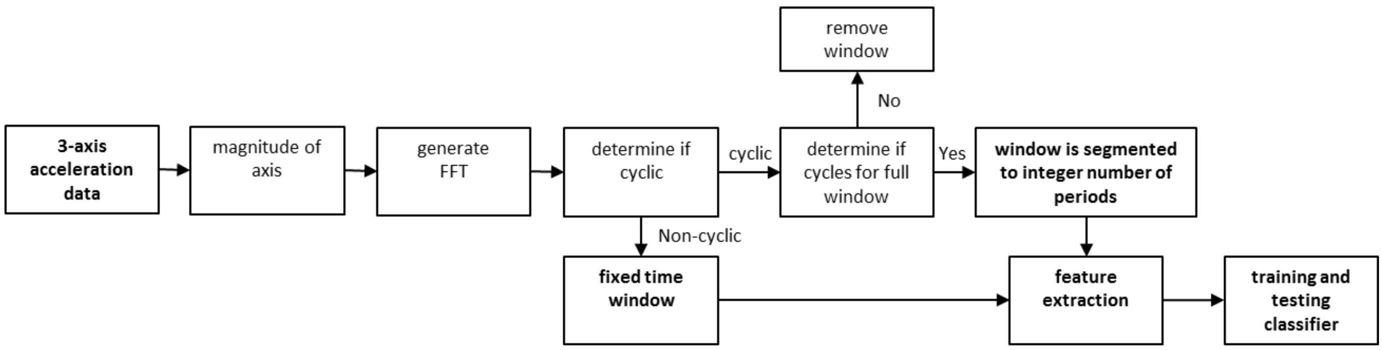

Fig. 1. Adaptive window algorithm

C. *Feature Extraction and Classifier*

Classification algorithms must be applied to features extracted from the raw data that can characterize each activity. The feature set used in this paper was that used by Bao and Intille [14] consisting of the mean of each axis, energy of each axis, frequency domain entropy of each axis and Pearson product-moment correlation features of each pair of sensors. The success rate of the feature sets used by Bao and Intille [14] and Kwapisz, et al. [15] were compared and it was found that the feature set used by Bao and Intille [14] resulted in a higher success rate [4] and so was chosen for this paper. This feature set is then used to train the classifier to achieve the activity recognition model.

The model training method used for activity recognition defines the method in which training and test data are partitioned and used to train the model. Two cross-validation techniques that are commonly used for training and testing data partitioning in activity recognition are *N*-fold cross validation and remove-one-subject cross-validation. *N*-fold cross-validation consists of dividing the data into *N* equal folds. For each test iteration, a fold is randomly selected and used for testing while the remaining folds are used for training. In the remove-one-subject method, for each test iteration, a subject is removed for testing while the remaining subjects are used for training. Remove-one-subject cross-validation method has a reduced success rate [4] which can be explained by inter-subject variability. As there is some similarity between users for the same activity, there is greater similarity between data from the same subject as two different points in time. Thus, if a subject's data exists in the training and test data, a higher success rate will result. These results imply that better activity recognition success rates may be achieved by including the end user's data to train the model. However, remove-one-subject cross-validation provides a more valid representation of what will occur outside the laboratory because in practically deployable systems, training for the specific user requires too much effort. As such, remove-one-subject cross-validation was used to train and test the classifier in this paper.

There are numerous classifier methods utilized in activity recognition including Artificial Neural Networks, Kohonen Self-Organizing Maps, Bayesian Networks, the Hidden Markov Model and decision trees [16]. For the feature set used in this project, a pilot study found [4] decision trees to be the best classifier and so was used in this paper.

The depth of the decision tree impacts the success rate of prediction. A deep decision tree will be very accurate on the training data however may have low accuracy for an independent test set as it is unable to generalize new data due to overfitting of the training data [17]. Pruning is a technique to minimize overfitting by turning branch nodes into leaf nodes and removing the leaf nodes that are below that branch to reduce the size of a tree. Minimal cost-complexity pruning as defined by Breiman, et al. [17] was used to prune the trained decision tree in this paper [18]. This pruning method involves beginning at the lowest subtree and pruning the weakest-link branch. This method is continued recursively moving up the decision tree. The extent of pruning is defined by the pruning level. There is a gradual increase in overall success rate with an increase in pruning level until the pruning level becomes so large that the decision tree is over simplified.

D. *Using Adaptive Windowing characteristics as Additional Features*

It was anticipated that the activity classification success rate could be further improved by using the cycle length of the activity as an additional feature to classify an activity. Different activities have different periods of motion, so it is likely that the period of the activity would improve activity classification. For cyclic activities, the length of a cycle of the activity was added to the feature set. For activities determined to be non-cyclic, the value added to the feature set was set to be 2 orders of magnitude greater than cycle lengths found for cyclic activities to set apart the non-cyclic from cyclic activities in the classifier.

III. Results and Discussion

The overall activity classification success rate was improved by segmenting sensor data adaptively rather than by a fixed window as shown in Fig. 2, with the median indicated in red and the top and bottom edged of the box indicating the 75^{th} and 25^{th} percentiles, respectively. The overall activity classification success rate was further improved by the activity's cycle length as an additional feature. The mean activity success rate was 54% for a fixed window, 62% for an adaptive window and 64% for an adaptive window with the additional feature. A paired difference t-test was performed on the subject's activity success rates for adaptive window and fixed window to determine whether the difference in means was significant. The t-test confirmed a pairwise difference at the 99% significance level.

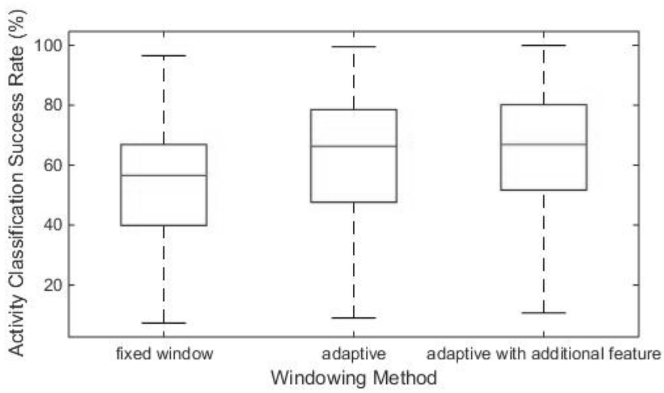

Fig. 2. Overall activity classification success rate for three methods for grouped sub-activities

The confusion matrix for the adaptive windowing method with additional feature is illustrated in Table I. Sedentary activities performed significantly worse than the other activity categories. This is likely due to sedentary activities involving very little movement making the activity hard to characterize by its accelerations.

TABLE I. CONFUSION MATRIX FOR THE ADAPTIVE WINDOW WITH ADDITIONAL FEATURE FOR GROUPED SUB-ACTIVITIES

		Predicted Activity (%)							
		household cleaning	*laundry*	*kitchen work*	*walking on stairs*	*sedentary activities*	*brush teeth*	*walking*	*running*
Actual Activity (%)	***household cleaning***	**69**	11	3	3	5	0	6	3
	laundry	11	**60**	13	9	5	1	1	0
	kitchen work	4	18	**65**	6	6	1	0	1
	walking on stairs	4	9	10	**67**	9	0	0	0
	sedentary activities	14	10	10	13	**39**	1	11	3
	brush teeth	2	11	5	1	3	**76**	1	1
	walking	11	2	2	0	9	0	**76**	1
	running	15	2	4	1	6	0	1	**71**
	Probability of activity prediction (%)	16	15	14	13	10	10	12	10

When these 8 activity categories are broken down to their 22 sub-activities, the overall success rate is decreased to 43% for a fixed window, 47% for an adaptive window and 49% for an adaptive window with the additional feature (see Fig. 3).This is due to an increased set of activities resulting in increased confusability. Further analysis is performed at the sub-activity level.

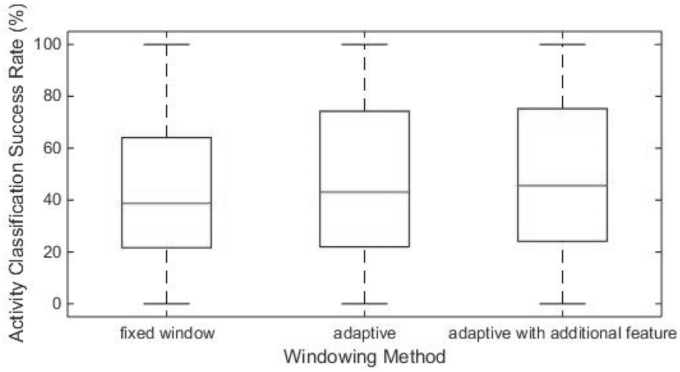

Fig. 3. Overall activity classification success rate for three methods

To evaluate the performance of the adaptive window method compared to the fixed window approach, the false positive rate and true positive rate were analyzed. The true positive rate is:

$$TPR = \frac{TP}{TP+FN} \qquad (3)$$

Where TP refers to the number of true positives and FN is the number of false negatives. The false positive rate is:

$$FPR = \frac{FP}{FP+TN} \qquad (4)$$

Where FP is the number of false positives and TN is the number of true negatives. It is desirable to have a high TPR and a low FPR.

Fig. 4 and Fig. 5 compare the TPR and FPR for the two windowing methods, fixed and adaptive. The horizontal axis is the class of activity and the vertical axis is the evaluation parameter. It can be seen from Fig. 4 that the true positive rate increased for adaptive windowing for most activities.

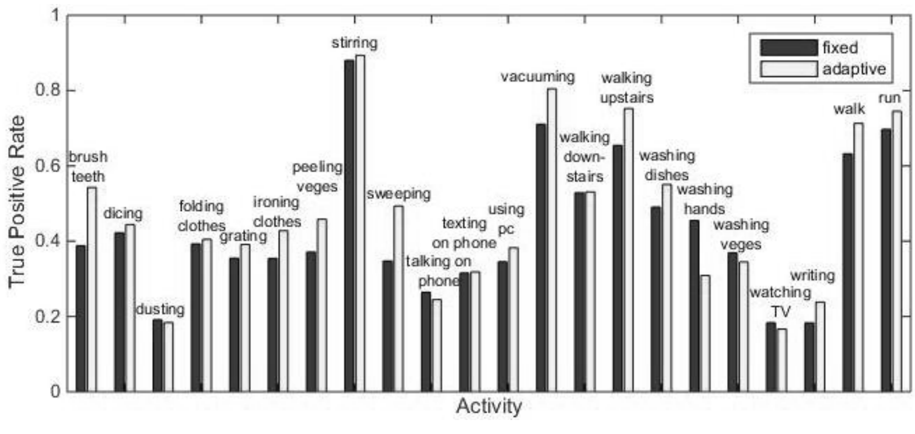

Fig. 4. True positive rate for both windowing methods

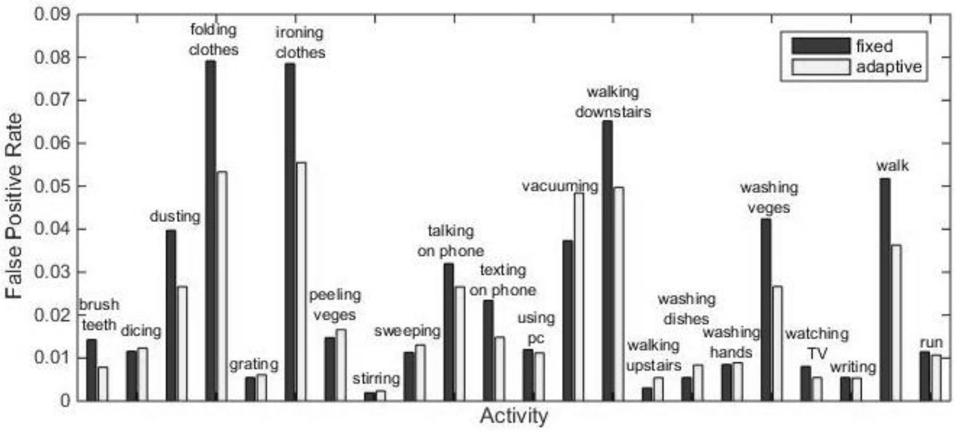

Fig. 5. False positive rate for both windowing methods

A t-test confirmed a pairwise difference at the 95% significance level for 9 of the 22 activities: brushing teeth, ironing clothes, sweeping, vacuuming, walking upstairs, washing hands, writing, walking and running. Of these activities, only washing hands had a lower TPR. Brushing teeth and sweeping had the greatest improvement in TPR as these activities were found to be highly cyclic and were not predicted well by the fixed window approach. The adaptive method had a lower FPR for most of the 22 activities as shown in Fig. 5.

Fig. 6 illustrates the probability of an activity being identified as cyclic and the mean cycle length identified from the adaptive window methodology. Most of the activity's probability of cyclic detection is as expected with activities like running and brushing teeth determined to be highly cyclic and sedentary activities such as using a computer having a lower probability of cyclic detection. Watching TV was determined to be cyclic 43% of the time which suggests the determination of whether an activity is cyclic or not could be further improved. It is likely that for watching TV, which is an activity with little movement and therefore low accelerations, that because the magnitude of the accelerations is normalized, noise becomes the dominant component of the data to be analyzed. This is likely to lead to erroneous artifacts.

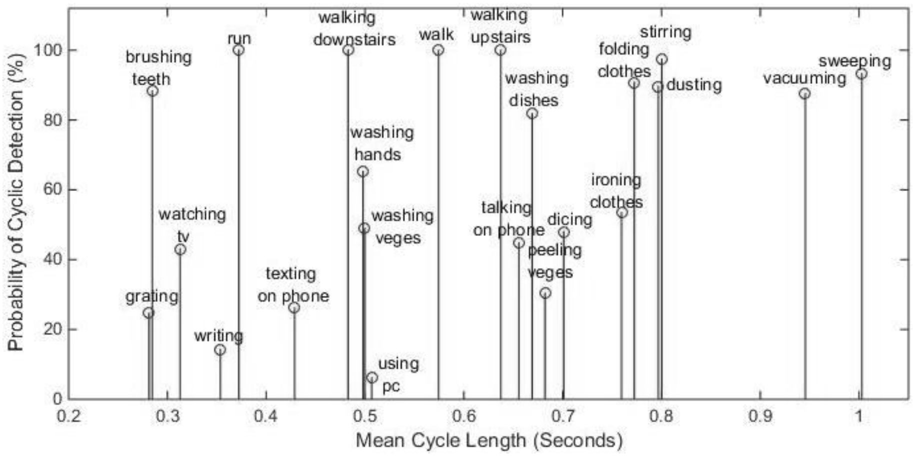

Fig. 6. Probability of cyclic detection and mean determined cycle length

It can be seen that activities have characteristic cycle lengths associated with them such as running having a shorter cycle time than walking. It is this association that further improved classification success rate for most activities when comparing the adaptive window to the adaptive window with the additional cycle length feature as in Fig. 7. Brushing teeth had a large improvement with the additional feature from 54% to 72% which was already much improved on the 39% for a fixed window. This is likely due to brushing teeth having a much lower cycle length as compared to the other activities that have also have a high probability of cyclic detection.

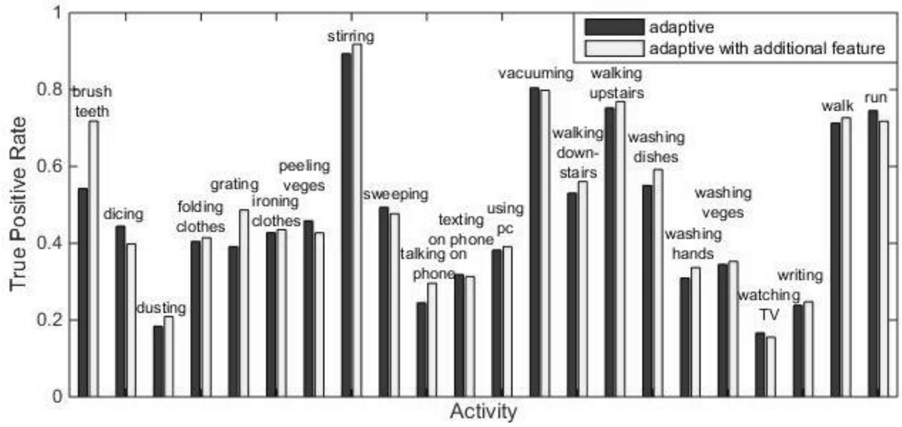

Fig. 7. True positive rate for adaptive windowing with and without the additional cycle length feature

The improvement in TPR wasn't as great as anticipated as activity cycle lengths were not sufficiently distinct from each other for many activities. This could occur even when their mean cycle lengths were quite different as cycle length distributions were sometimes quite broad and overlapped as shown in Fig. 8.

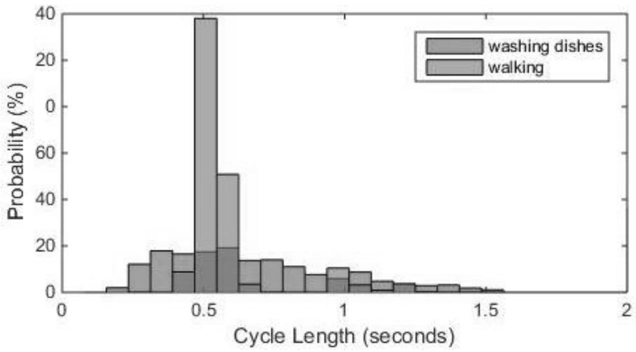

Fig. 8. Distribution of determined cycle lengths for washing dishes and walking

The easily detected heel strike can be used to derive features such as cadence, magnitude of heel strikes, cadence rate changes and number of consecutive heel strikes. These features can be used for delineation into activities that all involve foot movement such as walking, running and dancing. A heel strike is a sub-activity that forms a component of a larger activity like walking where the signal during the rest of the activity is significantly different. We were unable to identify any other acceleration based features so clearly associated with a class of human activity. However, recognizing an activity to be cyclic provides information that is as potentially as useful as the knowledge that there has been a heel strike. Similarly, to heel strikes, a cyclic activity is often a sub-activity that forms a component of a larger activity. For example, with brushing teeth, significant proportions of the activity involve repositioning the brush which produces vastly different acceleration signals to those produced during scrubbing. With time based segmentation, features are calculated indiscriminately over very different signals without these differences being known. Detecting cyclic portions of an activity allows activities to be broken down into sub-activities where the signal pattern is consistent, to calculate features for these sub-activities and then to identify the activity from the combination of sub-activities. Detecting activities by combinations of sub-activities was not attempted in this investigation.

IV. Conclusion

Activity classification is normally undertaken by calculating features from a fixed interval length of sensor data and this paper tested the hypothesis that, for cyclic activities, if features are calculated over an integer number of cycles, more accurate activity classifications will be achieved. This hypothesis was confirmed with a pairwise t-test at the 99% significance level. An overall improvement in activity classification success rate was found for this adaptive windowing method compared to a fixed window approach with success rates of 62% and 54% respectively.

The insight explored in this paper is that, like heel strikes, activities that involve repeated movements are associated with an interesting class of activities. This is a fundamental improvement and opens the way to explorations of the feature sets that can be generated from the knowledge that a cyclic activity is taking place and feature sets that can be generated from individual cycles. One of these features, cycle length, was tested and this improved recognition success rates to 64%. This improvement was not as great as hoped as many activities had overlapping cycle lengths.

V. Future Work

The recognition of cyclic activities and cycle times mostly worked well but further improvement is possible. The frequency spectrum over which the energy was calculated and the cut off energy to determine whether an activity was cyclic was chosen qualitatively and while neither of these parameters were sensitive to small changes they are probably not optimal. Signals were normalized so that they could be compared but this had the effect of reducing signal to noise ratios which was probably what caused one activity that was known to be non-cyclic, watching television, to be identified as cyclic 43% of the time. This could be improved by first determining if the magnitude of the acceleration is low before normalization and identifying that segment as non-cyclic.

There are many new features that can be generated from analyzing complete cycles. Only one of these, cycle length, was tested and there are many more that should be tested. Possibilities include the number of zero crossings per cycle, the number of peaks and troughs per cycle and the number of repeated cycles.

The segmentation of activities into cyclic and non-cyclic sub-activities opens up many new possibilities for development of feature sets that make use of this knowledge. This approach remains unexplored.

Finally, the use of activity classification using the techniques described in this paper as a means of game control has not been implemented and should be explored.

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