**Introduction:**  
Identifying a person’s current location and recognizing what he or she is doing—is a key functionality in many pervasive computing applications. Activity recognition using inertial sensing is a well-established research field with considerable amount of work being done to analyze sensor data to detect the activity. Our research began with studying the feasibility of identifying the dependence between activity being performed and the location at which it is performed. If an inter-dependence exists, then the inertial sensing data could be exploited to train models which can identify what kind of place the person currently is. Our research has produced promising results with the classifier working with an accuracy of 79%

\*We believe that this is a new approach towards location identification and can be implemented as an additional feature in wearable devices to provide location context tags based on inertial sensing data\*

**Prior and related work /Motivation:**  
Location sensing using inertial data has been a widely researched field. In several mobile computing studies [1], sound beaconing has been employed to estimate relative positions to other devices. Kunze et al. [2] propose an absolute positioning method that estimates where a phone is placed combining vibration and short, narrow frequency beeps to sample the response of an environment. Rossi et al. [3] propose a positioning method using smartphones based on the background sounds. The authors measure impulse response at each indoor position and train a classifier that predicts a user’s current position using the observed impulse response. In contrast, our study attempts to predict a location class by using only the data obtained from the user such as accelerometer, gyroscope, skin temperature and heart rate. Tung et al. [45] also employ active sound probing for indoor location tagging and achieve 1cm resolution.

Our research in contrast to these was oriented towards using inertial data collected only from the user without using any infrastructure mediated sensing. Our idea was to analyze whether the activity being performed has a correlation to the location where it is being performed. If there does exist this correlation, then we can predict the location context without collecting any location depending data. This can considerably reduce privacy concerns related to using cameras or microphones to collect location dependent data. Also, we wanted to differentiate between locations where the activities being performed are quite similar for eg. attending a lecture and reading at a library. We ran studies to estimate accuracies in these cases too.

**Description of work**

Data collection

Device used: Initially, we used mobile phone for collecting inertial sensor data. We created an android application in order to extract accelerometer and gyroscope data from a smartphone. 8 participants volunteered for our study. On analysis of the data collection process and the outcomes, we observed that the phone data is not the true representative of energy pattern for a particular place. This was even supported by a research paper [2].  
The participants had their mobile phone either in a bag or pocket during the entire duration of the activity under consideration for example, in gym, the participants kept the mobile phone at a distant place like their locker. Hence, we acquired a Microsoft band for our study and carried out the experiments again. The results (as shown in the plots) were in favour of our analysis, and we decided to go ahead with using the Microsoft Band for our further data collection process.

App: Sensus Application  
Locations targeted and the kind of activity performed there:  
Number of participants: 10 volunteers helped us in data collection at the following places:

* Classroom: The volunteer was asked to wear the Microsoft band on the dominant hand and attend a 75 min lecture.
* Library: 2 different activities were performed by the volunteers- Studying and stacking books. Both the activities were performed for 60 min duration.
* Grocery Store: The volunteer used a shopping cart around the store and shopped for around 45 mins.
* Recreation center/Gymnasium: The volunteer were asked to perform activities like weight training, treadmill, playing squash, racquetball etc. for around 60 min.

Data which is being collected:   
a. Accelerometer b. Gyroscope c. Skin Temperature d. Heart Rate

Preprocessing

The data collected was pre-processed by applying a variety of filters before choosing the apt one. We tried the following filters: FIR filter(Rectangular), Filt Filter, Median Filter, L Filter as shown in the figure. We decided to use FIR Filter for Gyroscope data and Median Filter for Accelerometer values. This decision was made after analyzing the accuracy of the Random forest classifier. The accuracy was 91% when median filter was used for both accelerometer and gyroscope data and 95% when we use median filter for accelerometer and FIR for gyroscope data. L filter and Filt filter performance wasn’t as good as the other filters as required by our application.

Training the classifier:  
To extract features from the collected data, we chose a range of frame size and step size by means of trial and error.   
Range: frame size 50 to 200, at increments of 5  
 step size 25 to 100 at increments of 5.

Since it was difficult to zero down on a fixed value of frame size and step size from this range,  
For each of the combination of frame size and step size, we extracted the features.  
Next, we separated the training data from the test data using split train test technique. To select a test dataset from the available data, we randomly chose a point within the dataset, and extracted a block of data from this point. The size of the block was 1/10th of the total size of each dataset. We deleted this test data block from the training data, thereby making sure that there is no overlap at all between training and testing data. The training data was then labeled and shuffled completely.   
We then trained and tested using different classifiers iteratively for different combinations of frame size and step size.

For choosing the correct classifier we tried different possible classifiers.  
1. SVM:  
Kernel used: RBF (non-linear)  
Kernelized SVMs require the computation of a distance function between each point in the dataset, which is the dominating cost of (n features× n2 observations). The storage of the distances is a burden on memory, so they're recomputed on the fly. We got an accuracy of 58%, but the full simulation could not be completed due to computational intensity.

2. KNN  
N\_neighbors: 4 ( 5 different classes of data)  
With KNN we got an accuracy of 72.28 % for frame size of 105 and overlap of 75.  
  
3. Random Forest  
n\_estimators: 10 (trial and error)  
We got an accuracy of 79.04% for frame size of 90 and overlap of 80.

**Discussion**:

We learnt that feature selection is an important criterion in activity recognition. Changing the classifier to obtain accuracy works upto certain threshold beyond which the accuracy becomes constant. But accuracy depends a lot on the feature vector used. We studied how each feature affected the accuracy of the classifier. We learnt which \_\_\_\_\_\_\_\_ play a dominant role for our application.

**Future Work: What remains to be done for your project**

In this project, we have trained the model and conducted studies with a limited number of locations and volunteers. The project can be extended for more locations with data collected by more volunteers to see how well it performs with increased number of locations with similar activities being performed. The accuracy of the classifier should go up with more data from different persons coming in but at the same time, we expect the addition of more locations to reduce the accuracy.

Currently, the wearable device we used did not have a barometer sensor. If we add barometer sensor, it can be used to find out the exact floor in the building based on those readings. Also, these readings will improve the accuracy of the user location as different locations have different barometric readings.

We can further improve upon the location if include the wifi triangulation as well. Using  the fingerprinting for the wifi signals that we encounter at a certain location we can improve upon the location accuracy as different locations will have different wifi signals.

Paper in the readings employing sensors to differentiate between locations like lift and also such things

mention this in references.

combined with wifi triangulation.

**Conclusions**

**References**  
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