**MIST.6160 Advance Data Mining**

**Project Proposal Document**

This document will provide a brief of the course project on which I will be working and presenting.

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**Recognizing Human Activity**

The challenge of identifying sequences of accelerometer data captured by specialized harnesses or cellphones into recognized, well-defined movements is known as "human activity recognition." Traditional methods involve manually creating features from observations and using machine learning models, which is quite different because acquiring features from data requires a high level of knowledge. Instead of doing this, we can use Deep Learning Algorithms, which can create features automatically from Raw Time Series data.

Sensors Used –

* Accelerometer is an electronic sensor that measures the acceleration forces acting on an object, to determine the object’s position in space and monitor the object’s movement.
* A gyroscope is a device that can measure and maintain the orientation and angular velocity of an object. These are more advanced than accelerometers. These can measure the tilt and lateral orientation of the object whereas an accelerometer can only measure linear motion.

The recordings of 30 study participants engaging in activities of daily living (ADL) while wearing a smartphone strapped on their waist with inertial sensors were used to create the Human Activity Recognition database. *The goal is to assign activities to one of the six done activities*.

The trials were conducted on a group of 30 volunteers ranging in age from 19 to 48. Each participant used a smartphone (Samsung Galaxy S II) while doing six tasks **(walking, climbing stairs, walking downstairs, sitting, standing, and lying)**. Data has been recorded with 3-axial linear acceleration and 3-axial angular velocity at a constant rate of 50Hz using integrated accelerometer and gyroscope. These experiments were also videotaped so that the data could be manually labeled. The resulting dataset was divided into two sets at random, with 30% of the volunteers chosen to create test data and 70% of the participants chosen to create training data. After applying noise filters as a pre-processing step, the accelerometer and gyroscope sensor data were sampled with fixed width sliding windows of 2.56 seconds and 50% overlap (128 readings/window). A Butterworth low-pass filter was used to separate the gravitational and body motion components of the sensor acceleration data into body acceleration and gravity. Since it is believed that the gravitational force solely consists of low frequency components, a filter with a cutoff frequency of 0.3 Hz was employed in the dataset. A vector of features was generated from each window by calculating variables in the time and frequency domain.

For every signal, now we have 128 dim vectors.  Domain specialists have also contributed some other Engineered Features in addition to the six time-series data. Using a low pass filter with a corner frequency of 0.3 Hz, the acceleration signal was divided into Body and Gravity acceleration signals (tBodyAcc-XYZ and tGravityAcc-XYZ).

Then, in order to obtain jerk signals, the body's linear acceleration and angular velocity were determined (tBodyAccJerk-XYZ and tBodyGyroJerk-XYZ).

These three-dimensional signals' magnitude was determined using the Euclidian norm. With names like tBodyAccMag, tGravityAccMag, tBodyAccJerkMag, tBodyGyroMag, and tBodyGyroJerkMag, these magnitudes are expressed as features.

Data Attributes:

Frequency domain signals from some of the available signals by applying an FFT (Fast Fourier Transform). These signals obtained were labeled with **prefix ‘f’** just like the original signals with **prefix ‘t’**.

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| --- | --- | --- | --- |
| **'-XYZ' is used to denote 3-axial signals in the X, Y and Z directions.** | | | |
| **Attribute** | **Definition** | **Data Type** | **Data Range** |
| tBodyAcc-XYZ | Body Acceleration | Numeric (float) | (-1,1) |
| tGravityAcc-XYZ | Gravity Acceleration | Numeric (float) | (-1,1) |
| tBodyAccJerk-XYZ | Body Acceleration Jerk Signals | Numeric (float) | (-1,1) |
| tBodyGyro-XYZ | Body Angular Acceleration | Numeric (float) | (-1,1) |
| tBodyGyroJerk-XYZ | Body Angular Acceleration Jerk Signals | Numeric (float) | (-1,1) |
| tBodyAccMag | Body Acceleration Magnitude | Numeric (float) | (-1,1) |
| tGravityAccMag | Gravity Acceleration Magnitude | Numeric (float) | (-1,1) |
| tBodyAccJerkMag | Body Acceleration Jerk Magnitude | Numeric (float) | (-1,1) |
| tBodyGyroMag | Body Angular Acceleration Magnitude | Numeric (float) | (-1,1) |
| tBodyGyroJerkMag | Body Angular Acceleration Jerk Magnitude | Numeric (float) | (-1,1) |
| fBodyAcc-XYZ | Body Acceleration | Numeric (float) | (-1,1) |
| fBodyAccJerk-XYZ | Body Acceleration Jerk Signals | Numeric (float) | (-1,1) |
| fBodyGyro-XYZ | Body Angular Acceleration | Numeric (float) | (-1,1) |
| fBodyAccMag | Bod Acceleration Magnitude | Numeric (float) | (-1,1) |
| fBodyAccJerkMag | Body Acceleration Jerk Magnitude | Numeric (float) | (-1,1) |
| fBodyGyroMag | Body Angular Acceleration Magnitude | Numeric (float) | (-1,1) |
| fBodyGyroJerkMag | Body Angular Acceleration Jerk Magnitude | Numeric (float) | (-1,1) |
| subject | Volunteer ID | Categorical | (1,30) |
| Activity | Target Variable (Acitvity doing) | String | SITTING, LAYING, WALKING, WALKING\_UPSTAIRS, WAKLING\_DOWNSTAIRS |

**Data source:** The data source used for this practice/project can be found [here](https://www.kaggle.com/datasets/uciml/human-activity-recognition-with-smartphones?resource=download&select=test.csv).