Human Activity Recognition

Human Activity Recognition integrates the emerging area of sensor networks with novel data mining and machine learning techniques to model a wide range of human activities.Mobile devices (e.g. smartphones) provide sufficient sensor data and calculation power to enable physical activity recognition to provide an estimation of the energy consumption during everyday life. Sensor-based activity recognition researchers believe that by empowering ubiquitous computers and sensors to monitor the behavior of agents (under consent), these computers will be better suited to act on our behalf.

Dataset Description:
The experiments have been carried out with a group of 30 volunteers within an age bracket of 19-48 years.Each person performed six activities (WALKING, WALKING_UPSTAIRS,WALKING_DOWNSTAIRS, SITTING, STANDING, LAYING) wearing a smartphone(Samsung Galaxy S II) on the waist. Using its embedded accelerometer and gyroscope, we captured 3-axial linear acceleration and 3-axial angular velocity at a constant rate of 50Hz. The experiments have been video-recorded to label the data manually. The obtained dataset has been randomly partitioned into two sets, where 70% of the volunteers was selected for generating the training data and 30% the test data.The sensor signals(accelerometer and gyroscope) were pre-processed by applying noise filters and then sampled in fixed-width sliding windows of 2.56 sec and 50% overlap (128 readings/window). The sensor acceleration signal, which has gravitational and body motion components, was separated using a Butterworth low-pass filter into body acceleration and gravity.
The gravitational force is assumed to have only low frequency components, therefore a filter with 0.3 Hz cutoff frequency was used. From each window, a vector of features was obtained by calculating variables from the time and frequency domain.
For each record it is provided:

- Triaxial acceleration from the accelerometer (total acceleration) and the estimated body acceleration.
- Triaxial Angular velocity from the gyroscope.
- A 561-feature vector with time and frequency domain variables.
- Its activity label.
- An identifier of the subject who carried out the experiment.

Subsequently, the body linear acceleration and angular velocity were derived in time to obtain Jerk signals (tBodyAccJerk-XYZ and tBodyGyroJerk-XYZ). Also the magnitude of these three-dimensional signals were calculated using the Euclidean norm (tBodyAccMag, tGravityAccMag, tBodyAccJerkMag, tBodyGyroMag, tBodyGyroJerkMag). Finally a Fast Fourier Transform (FFT) was applied to some of these signals producing

fBodyAcc-XYZ, fBodyAccJerk-XYZ, fBodyGyro-XYZ, fBodyAccJerkMag,
fBodyGyroMag,
fBodyGyroJerkMag (Note the 'f' to indicate frequency domain signals).
These signals were used to estimate variables of the feature vector for each pattern:'-XYZ' is used to denote 3-axial signals in the X, Y and Z directions.
● tBodyAcc-XYZ
● tGravityAcc-XYZ
● tBodyAccJerk-XYZ
● tBodyGyro-XYZ
tBodyGyroJerk-XYZ
● tBodyAccMag
● tGravityAccMag
● tBodyAccJerkMag
● tBodyGyroMag
● tBodyGyroJerkMag
● fBodyAcc-XYZ
● fBodyAccJerk-XYZ
● fBodyGyro-XYZ
● fBodyAccMag
● fBodyAccJerkMag
● fBodyGyroMag
● fBodyGyroJerkMag
The set of variables that were estimated from these signals are:
● mean(): Mean value
● std(): Standard deviation
● mad(): Median absolute deviation
● max(): Largest value in array
● min(): Smallest value in array
● sma(): Signal magnitude area
● energy(): Energy measure. Sum of the squares divided by the number of values.
● iqr(): Interquartile range
● entropy(): Signal entropy
● arCoeff(): Autoregression coefficients with Burg order equal to 4
● correlation(): correlation coefficient between two signals
● maxInds(): index of the frequency component with largest magnitude
● meanFreq(): Weighted average of the frequency components to obtain a mean frequency
● skewness(): skewness of the frequency domain signal
● kurtosis(): kurtosis of the frequency domain signal
● bandsEnergy(): Energy of a frequency interval within the 64 bins of the FFT of each

window.
● angle(): Angle between two vectors.
Additional vectors obtained by averaging the signals in a signal window sample. These are used
on the angle() variable:
● gravityMean
● tBodyAccMean
● tBodyAccJerkMean
● tBodyGyroMean
● tBodyGyroJerkMean