Project proposal

**Human Activity Recognition**

**Cognitive Computing**

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Report By:

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# Description of the topic

Human activity recognition plays a significant role in human-to-human interaction and interpersonal relations. Because it provides information about the identity of a person, their personality, and psychological state, it is difficult to extract. The human ability to recognize another person’s activities is one of the main subjects of study of the scientific areas of computer vision and machine learning. As a result of this research, many applications, including video surveillance systems, human-computer interaction, and robotics for human behavior characterization, require a multiple activity recognition system.

As we understand the importance of human activity recognition, have you ever wondered how your smartphone, smartwatch or wristband knows when you’re walking, running or sitting?

Well, your device probably has multiple sensors that give various information. GPS, audio (i.e. microphones), image (i.e. cameras), direction (i.e. compasses) and acceleration sensors are very common nowadays.

We will use data collected from accelerometer sensors which was built from the recordings of 30 study participants performing activities of daily living (ADL) while carrying a waist-mounted smartphone with embedded inertial sensors. The objective is to classify activities into one of the six activities performed viz WALKING, WALKING\_UPSTAIRS, WALKING\_DOWNSTAIRS, SITTING, STANDING, LAYING.

Virtually every modern smartphone has a tri-axial accelerometer that measures acceleration in all three spatial dimensions. Additionally, accelerometers can detect device orientation.

In this part of the series, we will train an LSTM Neural Network (implemented in TensorFlow) for Human Activity Recognition (HAR) from accelerometer data.

# Background Research of related work

In 2001, Paul Viola and Michael Jones invented an efficient algorithm for face detection. Their demo that showed faces being detected in real time on a webcam feed was the most stunning demonstration of computer vision and its potential at the time. Soon, it was implemented in OpenCV and face detection became synonymous with Viola and Jones algorithm.

Every decade or so a new idea comes along that is so effective and powerful that you abandon everything and wholeheartedly embrace it. Deep Learning is that idea of this decade. Deep learning models have crushed other classical models on the task of image classification and they are now state of the art in object detection as well.

One of the first advances in using deep learning for object detection was [OverFeat](https://arxiv.org/abs/1312.6229) from NYU published in 2013. They proposed a multi-scale sliding window algorithm LSTM Neural Network.

We want to apply these learnings about these advances in algorithms for human activity recognition as currently it is a fundamental problem in perception that is receiving increasing attention.

# Data sources

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.

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.

The dataset includes the following files:

* README.txt
* features\_info.txt: Shows information about the variables used on the feature vector.
* features.txt: List of all features.
* activity\_labels.txt: Links the class labels with their activity name.
* train/X\_train.txt: Training set.
* train/y\_train.txt: Training labels.
* test/X\_test.txt: Test set.
* test/y\_test.txt: Test labels.

The following files are available for the train and test data.

* 'train/subject\_train.txt': Each row identifies the subject who performed the activity for each window sample. Its range is from 1 to 30.
* 'train/Inertial Signals/total\_acc\_x\_train.txt': The acceleration signal from the smartphone accelerometer X axis in standard gravity units 'g'. Every row shows a 128 element vector. The same description applies for the 'total\_acc\_x\_train.txt' and 'total\_acc\_z\_train.txt' files for the Y and Z axis.
* 'train/Inertial Signals/body\_acc\_x\_train.txt': The body acceleration signal obtained by subtracting the gravity from the total acceleration.
* 'train/Inertial Signals/body\_gyro\_x\_train.txt': The angular velocity vector measured by the gyroscope for each window sample. The units are radians/second.

# Proposed Work

* Creating RNN and use of different activation functions for creating a base model on sequential data.
* Implementation of LSTM and performance comparison between the two
* Create REST API using FLASK to call the model for feature engineering and calling the saved models.
* Develop an Android App to classify the human activity using Accelerometer and Gyro meter data from the phone and call the created REST API.
* Develop a web page to reflect the current activity from the Android App at an interval of a certain time frame.

# Future work

* Create a predictive model to predict the t+1 activity
* Integrate this model with the Android App and the web page

# Use case

* Track Human activity for current knowledge of the person for safety

# Process Outline

* Data preprocessing
* Creating Models for classification
* Creating RestAPI for the model
* Creating RestAPI for the performing feature engineering
* Creating Android App for capturing current data.
* Creating Web App to showing the result.

# References

1. <https://archive.ics.uci.edu/ml/machine-learning-databases/00240/>
2. Davide Anguita, Alessandro Ghio, Luca Oneto, Xavier Parra and Jorge L. Reyes-Ortiz. A Public Domain Dataset for Human Activity Recognition Using Smartphones. 21st European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, ESANN 2013. Bruges, Belgium 24-26 April 2013.