# Activity Recognition in Construction Sites Using 3D Accelerometer and Gyrometer

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#### Abstract

Accelerometer and gyrometer data were collected from 3 construction workers during regular work days in order to distinguish between different activities. These activities - hammering, sawing, sweeping and drilling - were collected with a smart watch attached to the worker's dominant hand, with a sampling rate of 25Hz. The dataset was divided into training and test set with two different partitions - 50/50 and 80/20 (training/test). A preprocessing stage was first performed in order to minimize three main sources of problems - noise, gravity influence, and outliers. Then, 46 features, including time and frequency domain, were extracted from a window of 40 samples (1.6 seconds). Five different algorithms were tested in order to verify their performances. The tests were conducted using the two different partitions of training and testing. A feature selection algorithm was performed in order to reduce the dimensionality of the feature space and evaluate the models performance. Finally, a last test was conducted by comparing the performance of each algorithm using both sensors' data and using only accelerometr data. The best performance measured by the number of correctly classified activities was 91%.

## 1. Introduction

We have seen in the last few years a significant increase in the wearables industry. Many new devices are coming to market every year. And the main reason is because the price of sensors such as accelerometers and gyrometers are getting cheaper every year due to the smart phone industry push. Therefore, the possibility of collecting continuous data and perform further analysis can be a powerful tool in many different applications. Nowadays we are seeing many applications of wearable devices in fitness and health industry. However, no application was found by the author, until this date,

where wearable devices are being used to classify work-related activities of construction workers. By being able to better quantify direct work - job hours spent doing activities related to work - and indirect work - activities not related to work (e.g. waiting and preparing material), general contractors can bid projects with more confidence, increase their profit margin, find bottlenecks on workflow and so on. In this paper, a first step was taken towards the goal of increasing and understanding productivity in construction sites. We evaluate different machine learning algorithms that aim to classify construction activities such as hammering, sawing, sweeping, and drilling based on accelerometer and gyrometer data.

### 2. Previous Work

There has been a large variety of works trying to identify user activities based on accelerometers and gyrometers. A high number of papers are focused on fitness by classifying activities such as walking, running, cycling etc. Some examples are found in [1] and [2]. However, in a much smaller number, papers focused in different applications can also be found. In [3], accelerometer data is used to identify posture orientation, periods of activity and rest and when important events happen with patients such as fall. [4] uses accelerometer data to identify user traits such as sex, height, and weight. In [5], accelerometers are used to identify anomalies in an helicopter transmission system. This adds a new layer of information that is crucial for making sure the system is in good conditions. In [6], accelerometer and microphone data are used to track the progress of maintenance or assembly tasks in a workshop. In [7], a wilmote is used to detect a dictionary of 18 basic hand gestures. In addition to the referenced works, commercial systems are available, with open APIs, where users can develop applications on top of the classifiers. However, they are limited in the number of activities it can recognize. The lack of research in applying machine learning techniques to construction environments motivated this work.

### 3. Data Set and Preprocessing

Data from a 3D accelerometer and 3D gyrometer was collected using the GearLive smart watch from Samsung with sampling rate of 25Hz. Previous research has shown that frequencies between 20-100Hz are enough to capture human movements [8]. An app running on the watch (and phone) was developed in order to collect data and send it to a paired phone via Bluetooth. The app running on the phone was responsible to send the data

to a webserver where it could be accessed. The data was collected from 3 subjects in three different days and labeled during each activity. This data set comprises of approximately 55 daily repetitions of each movement done by each subject. This provided us with a total of approximately 500 repetitions of each movement.

After collecting the data, signal processing techniques were performed in order to minimize noise, gravity influence and outliers. Thus, two different type of filters were used. First a third order Butterworth with cutoff of 10Hz was used to remove high frequency noise and then a third order elliptic filter with an edge frequency of 0.3Hz was used to remove gravity's influence [9].

### 4. Feature Extraction and Feature Selection

Raw data coming from accelerometers and gyrometers very rarely can be used directly. Thus, after a preprocessing step, features were extracted from the raw data within a time frame, in order to characterize user's physical activity. In [9], a survey of the most common activities used in context-recognition is presented.

For this work, a total of 46 features (time and frequency domain) were extracted with a 50% overlap window of 40 samples. Among this 46 features, 26 were related to accelerometer and 20 to gyrometer. Common time-domain based metrics such as mean, variance, percentiles, max, min, correlation coefficients, rotation angle, and signal magnitude area were extracted, partially from each of the three axes, partially from the magnitude. Frequency domain features such as spectral energy and entropy was computed for both, magnitude and axes.

A feature selection algorithm [2] was used in order to evaluate the potential of reducing the dimensionality of the feature set with respect to the model's accuracy. This algorithm performs a forward-backward search where it alternately adds features to the feature vector with the current best quality and remove features based on a minimal threshold gain (thus examining subsets of combinations that have not been considered before). A map showing the four different classes and all features is shown in figure 1.

## 5. Results

Five different algorithms were used in order to compare their performances - Naive Bayes (NB), Multinomial Logistic Regression (MLR), Multi Class Support Vector Machine (SVM), Linear Discriminant Analysis (LDA),

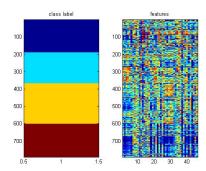


Figure 1: Colored features map for each class label.

and Quadratic Discriminant Analysis (QDA). For each algorithm, two different partitions between training and test data were performed (50/50 and 80/20). Within each partition, accelerometer-only and accelerometer and gyrometer data were used in order to evaluate the effect of the gyrometer sensor with the accuracy of the different models. Subsets of the feature set were also evaluated.

Table 1:								
	Accel		Accel+Gyro					
	Full feat(26)	15 feat	Full feat (46)	30 feat	20 feat			
NB	73%(74%)	63%(69%)	74% (73%)	72.5% (73%)	69% (70.4%)			
MLR	83% (99%)	67%(76%)	82.6% (99.7%)	79%~(88%)	72%~(83%)			
SVM	15.4%(100%)	17%(100%)	16%(100%)	$20\% \ (100\%)$	20%~(98%)			
LDA	85%(93%)	68%(74%)	87% (93%)	81% (87%)	$74\% \ (79\%)$			
QDA	88%(100%)	77% (91%)	90% (100%)	84% (100%)	84% (96%)			

Table 1: This table shows the percentage of test and training (in parenthesis) cases correctly identified by each classifier using a partition of 50/50 training and test set. The first two columns corresponds to accelerometer data-only for the full set of features and a subset selected using the feature selection algorithm.

Table 2: This table shows the percentage of test and training (in parenthesis) cases correctly identified by each classifier using a partition of 80/20 training and test set. The first two columns corresponds to accelerometer data-only for the full set of features and a subset selected using the feature selection algorithm.

Table 3: This table shows the confusion matrix for the best case (QDA).

Table 2:								
	Accel		Accel+Gyro					
	Full feat(26)	15 feat	Full feat (46)	30 feat	20 feat			
NB	71%(72%)	68%(68%)	73%(75%)	70%(74%)	64%(73%)			
MLR	86% (96%)	68%(73%)	88%(97%)	81% (88.5%)	72% (82%)			
SVM	70%(100%)	46% (97%)	70.3% (100%)	48.7%(97%)	65%~(99%)			
LDA	87%(91%)	68%(71%)	87.5%(90.53%)	78%~(86%)	70%~(80%)			
QDA	90%(100%)	83% (88%)	91% (100%)	90%~(98%)	85% (95%)			

Table 3: Confusion Matrix							
	Hammering	Sawing	Sweeping	Drilling			
Hammering	<b>97.2</b> %	0	2.8%	0			
Sawing	3.6%	<b>96.4</b> %	0	0			
Sweeping	12.9%	1.7%	<b>85.4</b> %	0			
Drilling	13%	0	0	87%			

The diagonal elements are the percentage of correct classified activities and the off diagonal are the misclassification percentage.

## 6. Conclusions and Future Work

The results show that from the five models we tested the one that provided the best results was QDA (91%) followed by MLR (88%) and LDA (87.5%). Also the performance of all models were increased when they were trained with more data. In addition, the number of features used degrade the performance of all models differently. Finally, the addition of the gyrometer did not considerably improve the accuracy thus not justifying it's use due to added cost and higher computational effort.

Some attempts can be made to improve model's accuracy. The first one is increasing the dataset size and adding more workers so the classifiers can become more general. Next, adding new features such as wavelets coefficients, time between peaks in a window, and performing data segmentation has shown to help improve accuracy.

This project will keep being developed as a part of a bigger tool that is currently being develop by the company the author works. Thus the next steps will be testing new algorithms such as Hidden Markov Models. Also more classes will be added. The final goal is being able to classify activities as being direct work (e.g. hammering), indirect work (e.g. material preparation), and no work (e.g. lunch time). Lastly, we want to understand

the relation between workers, e.g. worker 1 is not working because he/she depends on workers 2 finalizing his/her job.

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