CLASSIFICATION OF BODY POSTURES/MOVEMENTS USING SUPPORT VECTOR MACHINES

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ABSTRACT. In this paper we consider the task of identifying certain body movements and postures through accelerometer data. This is very important in the field of Human Activity Recognition which has, recently, seen much development. We make use of support vector machines in order to accomplish this task.

1 Introduction

Facial recognition can be accomplished using only a multi layered perceptron[1], which is a relatively simple algorithm for supervised learning. How about body recognition? That is, how can we classify body movements and postures? There is a lot of information in how people position themselves, how people walk, how people sit, etc. With advancements in machine learning algorithms, we have been able to accomplish many things, including the aforementioned.

We aim to present a method of classification used to identify some body postures and movements. The data we examined is from the UCI Machine Learning Repository. In particular, it is the "Wearable Computing: Classification of Body Postures and Movements (PUC-Rio) Data Set."[2] It is, essentially, just a collection of accelerometer data. We predicted the body postures/movements which produced this data with LIBSVM[3]

Of the many experiments which have been done with predicting body movements/postures with accelerometer data, it seems that the best accuracy was attained through the use of neural networks [1]. Neural networks have been gaining popularity once again with advancements in hardware which allow us to construct deeper nets.

1.1 The Dataset

The dataset is given as a csv. A single line is of the form: *user,gender,age,height,weight,body mass index, x1,y1,z1,x2,y2,z2,x3,y3,z3,x4,y4,z4,class*. Accelerometer 1 was placed on the subject's waist, accelerometer 2 was placed on the subjects left thigh, accelerometer 3 was placed on the subjects right ankle, and the last accelerometer was placed on the subjects right bicep. The xi,yi,zi values refer to the readings from the i^{th} accelerometer. There are 165,633 samples from 2 women and 2 men. For this dataset, there were five classes: sitting down, standing up, walking, standing, and sitting. One thing to note about this dataset is that we have many more samples of 3 of the classes (namely walking, standing, and sitting) than we do of the other 2 (See Table 1.).

Table 1.

CLASS	FREQUENCY
sitting down	11,827
standing up	12,414
walking	43,390
standing	47,370
sitting	50,361

Since the data given was already in numerical form for the most part, determining the features for the SVM was trivial; the features would simply be the numbers. The names are irrelevant so those were discarded. As a measure of performance of our classifier, the following ratio is computed:

$$Accuracy = \frac{\#correctlypredicteddata}{\#totaltestingdata} * 100\%$$

2 Predictive Task

As was previously mentioned, we aimed to classify the postures/movements of the subjects using the accelerometer data and the data on their heights, weights, age,and BMI. A labeling scheme was devised for the 5 classes mentioned earlier; essentially, each class (sitting, sittting-down, etc) was mapped to an integer (5 categories were mapped to {1,2,3,4,5}. We also mapped the Woman/Man feature to integers (0 for man 1 for woman). An SVM was appropriate for this task as this was a classification task, however, a neural network would probably get similar accuracy. LIBSVM implements multi class classification by use of the ”one against one” strategy [4]. This strategy essentially consists of constructing c(c-1)/2 classifiers to classify two classes. Then, for training data from two classes, i and j, the problem becomes the two-class classification problem:

$$\min_{w^{ij},b^{ij},\xi^{ij}} \frac{1}{2}(w^{ij})^T w^{ij} + C\sum_{t\in T}\xi_t^{ij}$$

with the constraints:

$$(w^{ij})^T\phi(x_t) + b^{ij} \geq 1 - \xi_t^{ij}$$

, if x_t is in the ith class,

$$(w^{ij})^T\phi(x_t) + b^{ij} \leq -1 - \xi_t^{ij}$$

, if x_t is in the jth class,

$$\xi_t^{ij} \geq 0$$

.

A voting strategy is then utilized. Each classification is then considered as a vote for a class and the class with the highest number of votes wins. As a baseline, we trained our data using a 75/25 split. So we used 75% for training and 25% for testing. No preprocessing was done for this baseline. We then scale our features to the range [-1,1]. This is, quite often, a preprocessing measure utilized in classification problems. The general formula for doing this is given by:

$$x' = \frac{x - min(x)}{max(x) - min(x)}$$

We then performed 5-fold cross validation on the training set in order to estimate the parameters that would give us the best fit. In general, what k-fold cross validation does is split the training data into k equal sized subsets. I then uses one of the subsets as a validation set for the other k-1 subsets. It does this for each of the k subsets, using each one as the validation set once. Using these methods, we were able to obtain a 98% validation accuracy and a 98.12% test set accuracy with the pre computed parameters.

3 Literature

The dataset used for this project came from UCI's machine learning repository. It was originally used for exactly the same thing I used it for except they used Adaboost instead for classifying the postures. Also they used 10 fold cross validation for parameter estimation as well. See the table on the next page for a summary of research conducted on the classification of body movements that has been done using accelerometer data courtesy of Ugulino et al [2]. So this is clearly not a new type of data to analyze, but, it is also clear that, it has become a very popular field relatively recently. Most of the accuracy rates from the table are above 90% which suggests that this task is actually not an extremely difficult task to accomplish. However, there are many different configurations possible for this data. For example, they could have placed the accelerometer anywhere on the subjects body. They also could have collected different attributes of the subjects (for example, some sort of metric on the healthiness of the individual or if the individual had even had any difficulty walking i.e injury.) Of course adding in more relevant features would surely make our classifier more accurate, however, this would also make the task of constructing the hyperplanes needed for classification more difficult for our SVM.

Table 2

Research	# of sensors	Accelerometers' position	Solution	# of users	Learning mode	Test mode	Correct (%)
Liu et. al. (2012) [6]	1	hip, wrist (no info about orientation)	SVM	50	Super-vised	leave-one-out	88.1
Yuting et al. (2011) [7]	3	chest and both thighs (no info about orientation)	Threshold-based	10	--	--	98.6
Sazonov et al. (2011) [8]	1	foot	SVM	9	Super-vised	4-fold cross validation	98.1
Reiss & Stricker (2011) [9]	3	lower arm, chest and foot	Boosted Deci-sion Tree	8	Super-vised	8-fold cross validation	90.7
Min et al., (2011) [10]	9	torso, arms and legs	Threshold-based	3	--	Comparison with k-means	96.6
Maekawa & Watanabe (2011) [11]	4	wrists of both hands, waist, and right thigh	HMM	40	Unsu-pervised	leave-one-out	98.4
Martin et al. (2011) [12]	2	hip, foot and chest	Threshold-based	5	--	--	89.4
Lei et al. (2011) [3]	4	waist, chest, thigh, and side of the body	Naive Bayes	8	Super-vised	Several, w/ no cross validation	97.7
Alvarez et al. (2011) [13]	1	centered in the back of the person	Genetic fuzzy finite state machine	1	Super-vised	leave-one-out	98.9
Jun-ki & Sung-Bae (2011) [14]	5	forehead, both arms, and both wrists	Naive Bayes and SVM	3	Super-vised	leave-one-out	**99.4**
Ioana-Iuliana & Rodica-Elena (2011) [15]	2	right part of the hip, lower part of the right leg	Neural Networks	4	Super-vised	66% trainning vs 33% test	**99.6**
Gjoreski et al. (2011) [2]	4	chest, waist, ankle and thigh	Naïve Bayes, SVM, C4.5, Random Forest	11	Super-vised	Leave-one-person-out	90.0
Feng, Meiling, and Nan (2011) [16]	1	Waist	Threshold-based	20	--	--	94.1
Czabke, Marsch, and Lueth (2011) [17]	1	Trousers' Pocket	Threshold-based	10	--	--	90.0
Chernbumroong, et al. (2011) [18]	1	Non-dominant wrist (watch)	C4.5 and Neural Networks	7	Super-vised	5-fold cross-vali-dation	94.1
Bayati & Chavarriaga (2011) [19]	--	Simulations instead of real accelerometers	Expectation Maximization	--	Unsuper-vised	Not mentioned	86.9
Atallah et al (2011) [20]	7	ear, chest, arm, wrist, waist, knee, and ankle	Feature Selection algorithms*	11	Super-vised	Not applied	--
Andreu et al. (2011) [21]	1	Not mentioned	fuzzy rule-based	--	Online learning	--	71.4

4 Results and Conclusions

The resulting accuracy of the SVM when used without any preprocessing of the data was 77.8%. With the aforementioned preprocessing steps we were able to get a much better accuracy than that baseline which demonstrates that support vector machines are, indeed, a successful way to analyze this dataset. Furthermore, our model resulted in an accuracy better than most of the accuracies given in the table on the previous page. A confusion matrix is given which nicely summarizes our results (See table

3). From the confusion matrix, it is not surprising that the most mistake class was walking for standing. This is why we need more feature so that our SVM could also identify the *way* certain people walk (i.e. they might be bobbing their heads). Overall, though, the results are quite amazing. The SVM is a great classifier for this task as it has been shown. Although, I believe that any model used for classification could be adapted for this task given the right features. However, given these features, it would seem that an SVM would be the best classifier to choose for this task, if not, a neural network would also be just as good of a choice, perhaps even better as it has been demonstrated (table 2).

TABLE 3

		PREDICTED CLASS				
		SITTING	SITTING DOWN	STANDING	STANDING UP	WALKING
ACTUAL CLASS	SITTING	12748	7	0	11	0
	SITTING DOWN	1	2849	3	76	24
	STANDING	0	25	11759	73	319
	STANDING UP	12	40	39	2917	54
	WALKING	0	37	46	11	10358

References

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