Handling Unbalanced Data in Nocturnal Epileptic Seizure Detection using Accelerometers

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Abstract: Data of nocturnal movements in epileptic patients is marked by an imbalance due to the relative small number of seizures compared to normal nocturnal movements. This makes developing a robust classifier more difficult, especially with respect to reducing the number of false positives while keeping a high sensitivity. In this paper we evaluated different ways to overcome this problem in our application, by using a different weighting of classes and by resampling the minority class. Furthermore, as we only have a limited number of training samples available per patient, additionally it was investigated in which manner the training set size affects the results. We observed that oversampling gives a higher performance than only adjusting the weights of both classes. Compared to its alternatives oversampling based on the probability density function gives the best results. On 2 of 3 patients, this technique gives a sensitivity of 95% or more and a PPV more than 70%. Furthermore, an increased imbalance in the dataset leads to lower performance, whereas the size of the dataset has little influence.

1 INTRODUCTION

Epileptic seizures mainly occur as paroxysmal events, which means that they occur at a sudden, unexpected timing. The frequency of the seizures varies from patient to patient.

25% to 30% of epileptic patients can not be treated by medication or surgery, they suffer from so called refractory epilepsy (Chapman et al., 2011) (Dalton et al., 2010). To be able to track the progress of the disease and to alarm caregivers during a seizure, these patients should be monitored.

The type of epileptic seizures we focus on are hypermotor seizures, which manifest themselves as violent, uncontrolled movements of the arms and or legs, e.g. by making a pedalling movement (Azar et al., 2008)(Rémi et al., 2011). The movements can last from a couple of seconds to multiple minutes. Due to the possible heavy movements the patients can injure themselves or even die (Husain and Sinha, 2011). Patients may suffer from confusion after a seizure, and when they don't, they often recall the seizure as a 'strange feeling' and need comforting (Tinuper et al., 2005)(Tinuper et al., 2007). Therefore our aim is to develop an automated system which can detect seizures during sleep to alarm the parents or caregivers if a seizure occurs. A second aim is to keep track of the number of seizures the patient has during the night.

Much more normal movements occur compared to seizure data which leads to very unbalanced data when modeling the movements of these patients. In this paper we compare techniques compensating for the highly unbalanced seizure data, to generate a classification model that is able to detect epileptic seizures. The patient group we focus on are children as the prevalence of epilepsy in children is higher and parents want to know when their child has a seizure during the night. Furthermore during sleep the convulsions occur more or less in a controlled reproducible manner without too much interference of other noise sources such as voluntary movement. For recording the motion, the acceleration of the arms and legs is recorded using 3D accelerometers. We want to have a high sensitivity (preferably close to 100%) with as little false positives as possible. But for our

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Table 1: Overview of data available in the dataset.

Patient number	Nights of monitoring	Hypermotor seizures	Normal movements
A	2	9	287
B	5	26	784
C	2	7	381
Total	*9*	*42*	*1452*

application a high sensitivity is more important, as we do not want to miss a possible violent movement.

To overcome the issue of imbalance, we evaluated the following approaches

- use a weighting factor to train the SVM model,
- resample the training data by estimating the probability density function of the seizure data,
- resample the seizure data based on the SMOTE technique (Chawla et al., 2002).

Note that undersampling of the majority class was not considered due to the very limited number of minority class samples that were available. Furthermore we evaluated the linear and the radial basis function (RBF) kernel and the influence of the balance and the number of training points on the performance of our classifier.

He et al. (He, 2009) give an overview of the state-of-the-art techniques that are used to overcome the issue of imbalance. Next to the sampling methods that we discuss in our paper, cost-sensitive methods that give a different cost value to misclassifying instances of different classes, and kernel-based methods are reviewed. But the former two dominate the research efforts.

2 METHODS

2.1 Dataset Overview

In this study, we use a dataset of patients suffering from hypermotor seizures, similar to what we already described in previous studies (Cuppens et al., 2009)(Cuppens et al., 2012), but in this study we only selected patients with at least 4 hypermotor seizures in our dataset, because for training and testing of the classification model, we need at least 3 and 1 seizures respectively. An overview of the dataset is shown in Table 1. From the raw data, five features are extracted to represent the data: the maximal resultant over both arms, the mean standard deviation over all channels, the length of the epoch, the mean root mean square over all the channels and the minimal power in the frequency band 1-3 Hz over all the channels.

The acquired data contains EEG and video which is used for labeling of the data by the neurologists, and 12 channel acceleration data sampled at 250 Hz measured with 3D accelerometers at the four limbs. Also ECG, EMG, EOG and audio are recorded, but these modalities are not used in this study.

2.2 Test Outline

Different classification models are estimated using state-of-the-art Support Vector Machine (SVM) inference. For this purpose the freely available libsvm (Chang and Lin, 2011) implementation was adopted[1]. Two groups of related application specific tests were setup in order to investigate: a) which alternative to adjust model inference for the high class imbalance performed best, b) the influence of the degree of class imbalance on the classification results c) the influence of the training set size on the results.

All the tests we perform, are conducted in a 10 fold randomization with different combinations of seizures and normal movements. The tests are evaluated using sensitivity (measure that indicates the percentage of seizures that is detected, also indicated as recall), the positive predictive value (PPV, a measure that indicates the percentage of true detections over all detections, also indicated as precision) and specificity (measure that indicates the number of true negatives over all normal movements). The sensitivity and PPV values are averaged over the 10 randomizations and the standard deviation is calculated. Thanks to this randomization the obtained results are less biased.

2.2.1 Methods for Coping with Class Imbalance

To overcome the issue of imbalance, we explored: a) different weight factors the first applied to the error term in the SVM learning objective corresponding to the positive examples and the second to that corresponding to the examples of the negative class. For this purpose a weight factor T is introduced which balances the weights of the error terms for both classes in the SVM objective. b) Resampling of the minority class, using 1) sampling from a probability density function estimated using the available minority examples 2) generating new minority class examples using the SMOTE technique.

Resampling based on the estimation of the probability density function estimates the distribution of the seizure data points along every feature using a non-parametric kernel density estimation, with a Gaussian

[1] http://www.csie.ntu.edu.tw/~cjlin/libsvm/

function as kernel and a bandwidth equal to the standard deviation of the seizure data. Based on this estimated distribution, new points are randomly sampled. The SMOTE technique generates new data points by introducing synthetic examples along the line segments that connect minority class examples with their k minority class nearest neighbors.

In a first series of tests, we used the same number of seizures s and normal movements n for each patient in the training ($s = 4, n = 190$) and testing phase ($s = 2, n = 95$), to investigate the performance of the different approaches, and to be able to compare them over all the patients. These movements were randomly chosen from each patient but with a strict separation between training and test set. We used this specific number of normal movement and seizures based on the smallest numbers available for each patient, i.e. 7 seizures for patient C and 287 normal movements for patient A. For each patient, we used two thirds of the data for training and one third for testing.

In the training phase, we used a three-fold cross-validation to find the optimal hyper-parameters for the SVM classifier. These parameters include the regularization parameter C, kernel parameter σ and weight factor T. C affects the trade-off between complexity and proportion of nonseparable samples (Cherkassky and Mulier, 1998). If it is too large, we may overfit and consequently store many support vectors, if it is too small, too much smoothing may be applied giving an underfit (Alpaydin, 2004). The kernel parameter σ denotes the kernel width parameter. A larger σ leads to a smoother fit. The weight factor T gives a lower or higher weight to the error cost of the negative class, in such a way that $C_- = C \cdot T$ and $C_+ = C \cdot (1 - T)$. The different values we tested for the parameters are:

- $C : e^{-3,-2,\ldots,6}$
- $\sigma : \frac{1}{\sqrt{2}} e^{-2.5,-2,\ldots,2}$
- $T \in \{0,\ 0.01,\ 0.02,\ 0.05,\ 0.1,\ 0.2,\ 0.5,\ 0.7,\ 1\}$

The cost function gives a higher weight to the sensitivity compared to the PPV more specific: $cost = -(2 \cdot sens + PPV)$.

2.2.2 Influence of Class Imbalance

In the second series of tests, we use the optimal approach found in the first tests, and investigate the influence of the number of training examples and the balance on the performance of the classification model. To investigate the influence of the balance, we keep the number of seizures in the training set fixed (4), and increase the number of normal movement from 4 (equally balanced) to 190. The same ratio is used in the test set.

2.2.3 Influence of Training Set Size

For the investigation on the influence of the number of training samples, we keep the balance the same (1 seizure for 33 normal movements), and we test this for 2, 3 and 4 seizures in the training set, and 2 seizures and 66 normal movements in the test set.

3 RESULTS

Table 2 shows the results of the SVM classifier using the different methods compensating for the imbalance. To be able to compare the different methods, we calculated a cost value for each test, using the same cost function for model selection $cost = -(2 \cdot sens + PPV)$. This cost value is shown in the last column of Table 2. Notice that the cost values have a negative value, as a lower cost implies a better performance. The higher the absolute value, the better the classifier performs. In general, we can observe that the oversampling techniques work better than only using a different weighting for both classes, although this is mainly due to the low performance on patient B. Furthermore, the density estimation oversampling gives better results than the SMOTE technique, although the PPV values of using SMOTE are higher compared to the density estimation oversampling. But the sensitivity of the latter is higher and this sensitivity has a higher weight in the cost function. For this density estimation oversampling, the linear kernel performs a little better than the RBF kernel, as the absolute cost value of the former is higher.

To investigate the influence of the size of the training set and the balance in the data, we used the oversampling based on the probability density estimation with the linear kernel. In the first test, we evaluated three different sizes of training set with the same balance, and a test set with a fixed amount of data. Table 3 shows the results of this test. We do not observe a clear trend when a larger set of data is used. Although there is a difference in performance in each test with respect to the sensitivity and PPV for each patient, the overall cost stays more or less the same.

Table 4 shows the results of the second test, where we tested the influence of the balance of the dataset on the performance. These results show that the balance of the dataset has a large influence on the performance. When the number of seizures and normal movements is equal, the performance is best, with a sensitivity and PPV of 100.00% for patient A and C. For patient B and for all patients combined, the values are around 50.00% for the sensitivity and 85.00% or higher for the PPV. But when the imbalance increases,

Table 2: Results of performance of SVM classifier using different methods to overcome the problem of imbalance.

Balance factor									
linear	n°	**sens.**(%)	std.	**PPV.**(%)	std.(%)	spec.(%)	std.(%)	-cost	
kernel	A	**80.00**	25.82	**93.33**	14.05	99.79	0.44	253.33	
	B	**0.00**	0.00	**0.00**	0.00	99.37	1.66	0.00	
	C	**80.00**	42.16	**89.58**	19.80	99.68	0.71	249.58	
	all	**10.00**	21.08	**16.67**	25.82	98.95	1.57	36.67	**134.90**
RBF	n°	**sens.**(%)	std.(%)	**PPV.**(%)	std.(%)	spec.(%)	std.(%)	-cost	
kernel	A	**90.00**	21.08	**90.00**	16.10	99.68	0.51	270.00	
	B	**5.00**	15.81	**25.00**	50.00	99.68	0.51	35.00	
	C	**50.00**	52.70	**100.00**	0.00	100.00	0.00	200.00	
	all	**15.00**	24.15	**14.29**	20.25	98.21	1.79	44.29	**137.32**
Probability density estimation oversampling									
linear	n°	**sens.**(%)	std.(%)	**PPV.**(%)	std.(%)	spec.(%)	std.(%)	-cost	
kernel	A	**90.00**	21.08	**68.67**	29.15	98.63	1.41	248.67	
	B	**70.00**	34.96	**12.44**	6.50	88.95	3.92	152.44	
	C	**100.00**	0.00	**83.33**	22.22	99.37	0.89	283.33	
	all	**65.00**	24.15	**12.90**	5.84	89.47	4.30	142.90	**206.84**
RBF	n°	**sens.**(%)	std.(%)	**PPV.**(%)	std.(%)	spec.(%)	std.(%)	-cost	
kernel	A	**95.00**	15.81	**74.00**	23.98	98.95	1.11	264.00	
	B	**60.00**	39.44	**12.99**	10.08	91.05	4.25	132.99	
	C	**100.00**	0.00	**80.00**	26.99	99.05	1.44	280.00	
	all	**45.00**	36.89	**19.41**	13.27	95.79	3.33	109.41	**196.60**
SMOTE oversampling									
linear	n°	**sens.**(%)	std.(%)	**PPV.**(%)	std.(%)	spec.(%)	std.(%)	-cost	
kernel	A	**90.00**	21.08	**83.33**	22.22	99.47	0.74	263.33	
	B	**45.00**	36.89	**9.84**	8.18	91.68	3.27	99.84	
	C	**85.00**	33.75	**87.04**	20.03	99.58	0.74	257.04	
	all	**55.00**	28.38	**17.22**	10.35	92.21	5.39	127.22	**186.86**
RBF	n°	**sens.**(%)	std.(%)	**PPV.**(%)	std.(%)	spec.(%)	std.(%)	-cost	
kernel	A	**90.00**	21.08	**75.67**	26.44	99.05	1.16	255.67	
	B	**30.00**	25.82	**15.59**	19.47	95.68	3.42	75.59	
	C	**80.00**	34.96	**87.04**	20.03	99.58	0.74	247.04	
	all	**45.00**	28.38	**16.58**	14.53	94.00	3.75	106.58	**171.22**

Table 3: Results of performance using resampling based on a density estimation and a linear kernel in the SVM classifier. This table shows the influence of different sizes of the training set.

Training: 2 seizures, 66 normal Test: 2 seizures, 66 normal								
n°	**sens.**(%)	std.	**PPV.**(%)	std.(%)	spec.(%)	std.	-cost	
A	**95.00**	15.81	**81.67**	19.95	99.09	1.06	271.67	
B	**65.00**	33.75	**18.15**	9.38	90.30	6.32	148.15	
C	**100.00**	0.00	**83.33**	17.57	99.24	0.80	283.33	
all	**70.00**	34.96	**22.65**	11.18	92.73	3.96	162.65	**216.45**
Training: 3 seizures, 99 normal Test: 2 seizures, 66 normal								
n°	**sens.**(%)	std.(%)	**PPV.**(%)	std.(%)	spec.(%)	std.(%)	-cost	
A	**90.00**	21.08	**76.67**	21.08	98.79	1.20	256.67	
B	**75.00**	35.36	**14.70**	7.00	87.27	2.49	164.70	
C	**100.00**	0.00	**66.67**	19.25	98.18	1.20	266.67	
all	**65.00**	33.75	**22.99**	14.18	92.12	5.09	152.99	**210.26**
Training: 4 seizures, 132 normal Test: 2 seizures, 66 normal								
n°	**sens.**(%)	std.(%)	**PPV.**(%)	std.(%)	spec.(%)	std.(%)	-cost	
A	**90.00**	21.08	**76.67**	22.50	98.94	1.02	256.67	
B	**70.00**	34.96	**15.82**	11.21	86.82	7.92	155.82	
C	**100.00**	0.00	**70.00**	21.94	98.33	1.33	270.00	
all	**70.00**	25.82	**21.03**	12.13	89.85	4.90	161.03	**210.88**

we see a gradual reduction of the performance, which is also reflected in the cost value for each test, which increases from -244.72 when the dataset is balanced, to -207.04 when the imbalance is largest (4 seizures compared to 190 normal movements).

Table 4: Results of performance using resampling based on a density estimation and a linear kernel in the SVM classifier. This table shows the influence of a different balance between seizures and normal movements in the training and test set.

	n°	**sens.**(%)	std.(%)	**PPV.**(%)	std.(%)	spec.(%)	std.(%)	-cost	
Training:	A	**100.00**	0.00	**100.00**	0.00	100.00	0.00	300.00	
4 seizures, 4 normal	B	**50.00**	47.14	**88.89**	17.21	90.00	21.08	188.89	
Test:	C	**100.00**	0.00	**100.00**	0.00	100.00	0.00	300.00	
2 seizures, 2 normal	all	**45.00**	28.38	**100.00**	0.00	100.00	0.00	190.00	**244.72**
Training:	A	**95.00**	15.81	**100.00**	0.00	100.00	0.00	290.00	
4 seizures, 10 normal	B	**60.00**	45.95	**68.75**	33.85	88.00	13.98	188.75	
Test:	C	**100.00**	0.00	**100.00**	0.00	100.00	0.00	300.00	
2 seizures, 5 normal	all	**55.00**	36.89	**74.07**	35.46	92.00	10.33	184.07	**240.71**
Training:	A	**95.00**	15.81	**90.00**	16.10	98.00	3.22	280.00	
4 seizures, 30 normal	B	**65.00**	41.16	**45.67**	34.10	88.00	8.78	175.67	
Test:	C	**100.00**	0.00	**100.00**	0.00	100.00	0.00	300.00	
2 seizures, 15 normal	all	**65.00**	33.75	**63.70**	29.03	92.00	9.32	193.70	**237.34**
Training:	A	**95.00**	15.81	**90.00**	16.10	99.14	1.38	280.00	
4 seizures, 70 normal	B	**70.00**	34.96	**27.21**	15.16	87.14	7.77	167.21	
Test:	C	**100.00**	0.00	**78.33**	23.64	97.71	2.63	278.33	
2 seizures, 35 normal	all	**65.00**	24.15	**48.61**	23.98	94.29	6.46	178.61	**226.04**
Training:	A	**90.00**	21.08	**76.67**	22.50	98.94	1.02	256.67	
4 seizures, 132 normal	B	**70.00**	34.96	**15.82**	11.21	86.82	7.92	155.82	
Test:	C	**100.00**	0.00	**70.00**	21.94	98.33	1.33	270.00	
2 seizures, 66 normal	all	**70.00**	25.82	**21.03**	12.13	89.85	4.90	161.03	**210.88**
Training:	A	**90.00**	21.08	**68.67**	29.15	98.63	1.41	248.67	
4 seizures, 190 normal	B	**70.00**	34.96	**13.16**	8.36	88.95	4.16	153.16	
Test:	C	**100.00**	0.00	**83.33**	22.22	99.37	0.89	283.33	
2 seizures, 95 normal	all	**65.00**	24.15	**13.02**	5.77	89.47	4.57	143.02	**207.04**

4 DISCUSSION

The oversampling methods give the best results. However, we still observe that with an increasing unbalance, the performance gets worse. It should be noted that thanks to the oversampling, the SVM model is still trained with an equally balanced training set, and that only the test set remains unbalanced.

When we test the statistical significance of the difference in methods to overcome the issue of imbalance, we observe that in patient A non of the methods or type of kernel in the SVM approach give a significant difference for either sensitivity or PPV. In patient B there is a significant difference (with p-values lower than 0.05) between methods and kernels, except for the difference in PPV for the type of kernel. For patient C only the difference in sensitivity for the method (not the kernel) is significant.

In most of the trials, the performance on patient B is lower. This is due to the different clinical manifestation of the seizures of this patient, which are clearly shorter in time and lower in intensity.

Note that for the calculation of the performance on all patients, the varying number of seizures per patient is not taken into account. This means that the influence of patient B is higher than those of patient A en C as 62% of the total seizures belong to patient B (26 on a total of 42). This explains why the performance of all patients combined is most of the time very similar to the performance on patient B.

In the real setting the balance between epileptic and normal movements can differ from patient to patient, and therefore influence the patient-specific performance.

The number of seizures we collected is small for some patients, which makes the training of an SVM classifier more difficult if we want to make patient-specific models. Although the results of the tests on the influence of the dataset size indicated that there is no big difference when changing the amount of data. However, this statement needs to be interpreted carefully since the number of seizures was too small to draw any conclusions about the relation between seizure set size and classification performance.

Due to the limited number of seizure examples, the weighting method does not give very good results. This can be explained by the fact that the number of the support vector candidates is small, which reduces the flexibility of setting the decision hyperplane. We also noticed that the cost of most of the different parameter combinations (C, σ, T) was the same when using only the weighting of the classes. This means that due to the limited number of training examples, the hyper-parameters only have a small influence on the decision hyperplane.

In our tests we used 2 seizures in the test set using 10 randomizations. Therefore, the resolution of the sensitivity is only 5%. This is also visible in the tables showing the results.

For using the SMOTE technique, we have only a limited number of seizures in our setup when using the 3-fold cross-validation in determining the optimal parameters for the SVM. The new data points are generated on the line segments connecting the minority class examples, but sometimes there is only one nearest neighbor (for determining the line segments) for generating new data points. This can explain why the SMOTE technique gives lower results, although it also works well for patient A and C.

We also evaluated a cost function taking into account the decision values of the SVM classification (indicating the distance from the data points to the decision plane). However, this did not give any better results compared to our original cost function, in most cases the performance was even lower.

5 CONCLUSIONS

We have tested different approaches to overcome the imbalance problem in our application of detecting nocturnal epileptic seizures in children using accelerometers. Oversampling of the minority class seems to give the best results, especially the density estimation oversampling. On 2 of 3 patients, this technique gives a sensitivity of 95% or more and a PPV more than 70%.

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