Determining Granger Causality in multi-channel EEG recordings with Support Vector Regression

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1. Introduction

Epilepsy is a neurological disorder in which patients suffer from seizures, or brief periods of excessive electrical activity in the brain. (Epilepsy Foundation) The majority of patients can have their seizures held in check by anti-seizure medication, or, in more extreme cases, surgery to remove the area where the seizures originate. For a minority of patients, however, none of these measures are effective, and they suffer from frequent seizures which can be debilitating and cause permanent brain damage. For patients such as these, and indeed all epileptics, an early warning system to predict the onset of a seizure and perhaps provide appropriate intervention before the seizure begins would greatly increase their quality of life.

Strong evidence exists that seizures are often predictable. Various studies have shown that over 50% of patients interviewed experience auras, or pre-seizure sensations. (Litt and Echauz) This points to changes in brainwave patterns before a seizure. If these changes can be detected, the probable onset of a seizure can be predicted and an appropriate intervention, or even a simple warning, initiated. Researchers have been working on this complex problem for decades, and many methods for analyzing the brainwave data have been proposed. (Litt and Echauz) Most of these, however, have fallen short of the accuracy and reliability required of such a system. (Morman)

2. Project Goals

One subset of the seizure-prediction problem is the problem of determining causation in the spread of a seizure. Seizures generally start in a particular part of the brain, different in each patient, known as the epileptogenic area. From there, the abnormal activity spreads through the brain as neurons fire in tandem, setting off neurons in other areas and sending a wave of electricity ripping across the brain. Determining whether neurons firing in one area of the brain affects the activity of another region can be crucial in charting the development pattern of a seizure.

In our work, we used Support Vector Regression and Granger Causality to measure the likelihood of electrical activity in one part of the brain (represented by a particular channel in an EEG recording) affecting brainwave patterns in another. Our results are incomplete and therefore inconclusive, but seem promising.

3. Methods

3.1. Support Vector Regression

Support Vector Regression (henceforth SVR) is a method of using Support Vector Machines, a common classification algorithm, to solve linear regression problems. In SVR, the goal is to find the line that best fits the data points in a series, using the equation

$$Minimize \quad \frac{1}{2}\left\|w\right\|^2 + C\sum_{i=1}^{l}(\varepsilon_i + \varepsilon_i^*)$$

$$Subject\ to \begin{cases} y_i - (w,\ x_i) - b \ \leq \ \varepsilon + \varepsilon_i \\ (w,\ x_i) + b - y_i \ \leq \ \varepsilon + \varepsilon_i^* \\ \varepsilon_i, \varepsilon_i^* \ \geq \ 0 \end{cases}$$

(Vapnik, Smola and Scholkopf)

Often, such a line is not easily drawn in a linear plane, so a kernel function is used to convert the data into a higher-dimension plane where linear regression can be easily performed. (Muller, et al) This line can then be extrapolated to predict the next value or values in the series, in our case a time series of EEG recordings. (Parella) The cost parameter c determines the tightness of the margin and the tradeoff between accuracy and inclusion of all possible values. (DTREG)

3.2 Granger Causality

Granger Causality (GC) is a method for measuring causality between time series developed by Clive W. J. Granger. (Granger Causality, Wikipedia**)** A series x is said to *Granger-cause* another series y if the prediction error for x obtained using only values of x is improved by adding values from y. That is, if the variance of the error of x is lower when including some values from y in the prediction, it is likely that y had some effect on x. (Hess, et al) Granger Causality is not absolute causation; there are many factors that can cause a correlation between x and y. If the causality goes in only one direction (that is, x granger-causes y but y does not granger-cause x) and the "causing" variable occurs earlier in time than the "caused" variable, one can say that there is a strong likelihood that x caused y, but no more. (Sorenson) The converse is slightly more reliable: if x does *not* Granger-cause y, it probably doesn't cause it either. (Lion)

The equation for determining whether x Granger-causes y is:

$$F_{x\rightarrow y} = \ln\left(\frac{var(y)}{var\ \ (x\rightarrow y)}\right)$$

where x and y are time series, var(y) is the variance of the error of y alone, and var(x -> y) is the variance of the error of y with values of x used in the prediction. (Hess, et al)

3.3 Dataset

The dataset used was that of the University of Freiburg, Germany. (data set) Data from a 15-year old female patient with simple partial and complex partial seizures originating in the frontal lobe was used in our work. While ictal (before and during a seizure) and inter-ictal (between seizures, normal) recordings were available, we were primarily interested in the pre-ictal (immediately preceding the onset of a seizure) recordings included in the ictal set, and therefore used only those. The patient's data consisted of several sets of files containing recordings from seizures, as well as at least 50 minutes of pre-ictal recording, the most significant part for us. Each file set was composed of 6 files, corresponding to the 6 channels of the EEG recording. Each file contained 921,600 data values, recorded at a sampling rate of 256 Hz.

3.4 Computation and Calculation of Granger Causality

The program used to process the data was written in Java and makes extensive use of the open source Machine Learning code of Weka, a Java ML program. The program read the data values from text files and converted them in the .arff files required by Weka, with 100 data values in each sample. Then it used the various classification classes provided by Weka to perform support vector regression on the time-series in the file. The regression generated a numeric prediction for the 100th value in each sample, then calculated the error for the sample; that is, the difference between the actual and predicted values.

We then calculated the variance of the error over the entire data set, using the formula

$$V = \frac{\sum e^2}{n}$$

where V is the variance, e is the error for each instance, and n is the total number of instances in the data set. This process was repeated four times for every pair of files in the dataset: for every pair of files x and y, the regression was done on x, y, x with values of y added, as above, and y with values of x added.

We then used the equation for Granger Causality given in section 3.2 to calculate the Granger causality for x → y and y→ x. This process was repeated for each pair of files in the set of 6 channels: 30 pairs in all, with the resulting Granger Causality values forming a 6 x 6 matrix.

4. Results

The program was run once for each of the following C – values: .001, .01, .1, 1.0, 10.0, and 100.00. sampling of the results can be found below.

	1	2	3	4	5	6
1	0	0.026	-0.009	-0.01	-0.016	-0.008
2	-1.057	0	-0.008	-0.007	-0.001	0.009
3	1.801	1.816	0	-0.004	-0.014	-0.004
4	0.241	0.238	0.25	0	0	-0.012
5	0.143	0.153	0.165	0.167	0	0.024
6	-0.057	-0.073	-0.044	-0.028	-0.034	0

Table 1. Granger Causality, C-value 0.1

The 0's on the diagonal are the GC value for a time-series added to itself: 0. All other 0's are the result of the regression. Values above 0 are highlighted.

	1	2	3	4	5	6
1	0	0.068	0.193	0.013	0.16	0.103
2	-1.098	0	0.086	0.214	0.067	0.088
3	1.665	1.668	0	-0.045	-0.07	-0.088
4	0.168	0.208	0.153	0	-0.053	-0.021
5	0.086	0.098	0.091	0.081	0	-0.027
6	-0.013	-0.03	-0.018	-0.011	-0.016	0

Table 2. Granger Causality, C-value 1.0 The 0's on the diagonal are the GC value for a time-series added to itself. Values above 0 are highlighted.

5. Conclusions

The summer ended long before our program finished testing even one patient, so our results are severely limited. However, as can be seen from the figures above, several of the channel pairs had high Granger-Causality values (close to or even above 1), suggesting that electrical activity in one of the channels influenced that of the other. As such, this seems to be a promising direction for future research in the genesis of epileptic seizures.

Figure 1. Granger Causality values for each pair of files; C-values 0.1 and 1.0. The notation on the x-axis is: "influencing file -- influenced file." For instance, 2-- 1 means "channel 2 influencing channel 1."

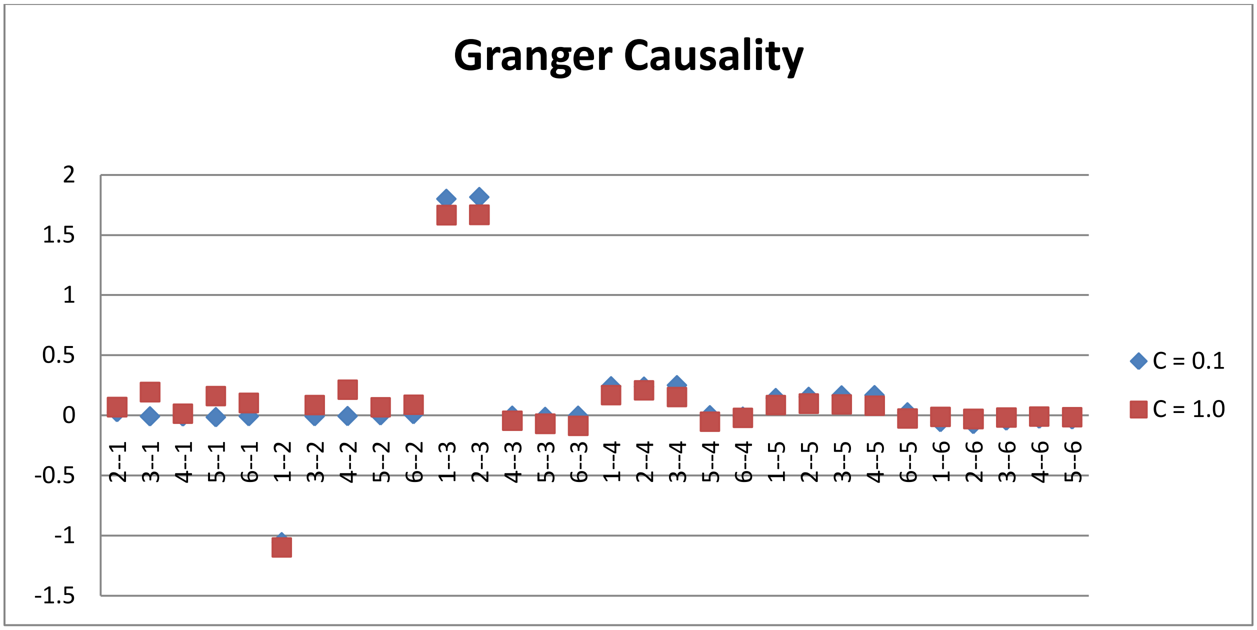
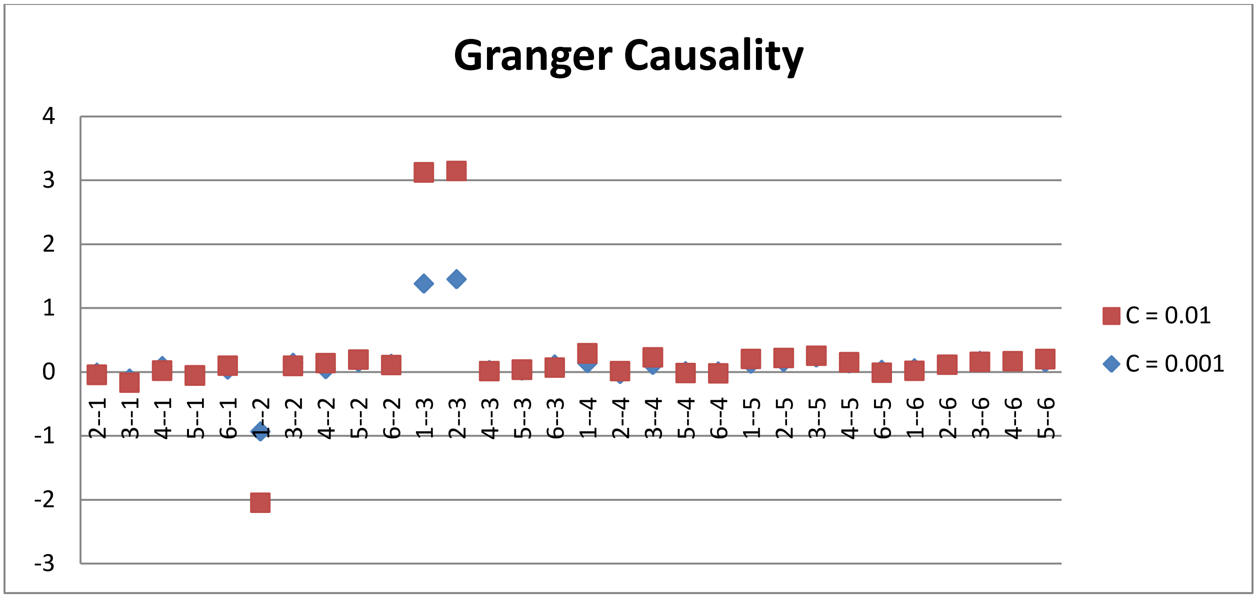


Figure 2. Granger Causality values for each pair of file; C-values .001 and .01. Notation same as above.



References

"About Epilepsy." The Epilepsy Foundation. <http://www.epilepsyfoundation.org/about/>

Hess, W, Moller, E, Arnold, M, Schack, B. "The Use of Time-Variant EEG Granger Causality for Inspecting Directed Interdependencies of Neural Assemblies", Journal of Neuroscience Methods 124, (2006)

"Introduction to Support Vector Machine (SVM) Models", DTREG.com, <http://www.dtreg.com/svm.htm>

Lion, Guy. "Granger Causality" (slideshow). December 2005.

< http://www.slideshare.net/gaetanlion/granger-causality-presentation>

"Linear Regression." *Wikipedia, The Free Encyclopedia*. 17 May 2009, 20:43 UTC. 1 Sep 2009 <http://en.wikipedia.org/w/index.php?title=Linear_Regression&oldid=290579919>.

Litt, B and Echauz, J. "Prediction of Epileptic Seizures", Lancet Neurology 1 (2002)

Mormann, F, Andrezejak, R. G., Elger, C.E., Lehnertz, K. "Seizure Prediction: the Long and Winding Road', Brain 130 (2007)

Muller, K.R., Smola, A.J., Ratsch, G., Scholkopf, B. , Kohlmorgen, J., Vapnik, V. "Predicting Time Series with Support Vector Machines". Artificial Neural Networks – ICANN '97. (1997)

"Nonlinear regression." *Wikipedia, The Free Encyclopedia*. 6 Nov 2009, 14:14 UTC. 9 Nov 2009 <http://en.wikipedia.org/w/index.php?title=Nonlinear_regression&oldid=324277993>.

Parella, Francesco. “An Introduction to Support Vector Machines.” Online Support Vector Regression. 7 Sep 2009. <http://onlinesvr.altervista.org>

"Regression Analysis." *Wikipedia, The Free Encyclopedia*. 9 Dec 2007, 19:44 UTC. 1 Sep 2009 <http://en.wikipedia.org/w/index.php?title=Regression_Analysis&oldid=176833299>.

Smola, A.J and Scholkopf, B. “A Tutorial on Support-Vector Regression”. For Statistics and Computing, 2003

Sorenson, Brent E. “Granger Causality”. 1 Mar 2005. <http://www.uh.edu/~bsorense/gra_caus.pdf>

University of Freiburg Epilepsy Data Set. <https://epilepsy.uni-freiburg.de/freiburg-seizure-prediction-project/eeg-database>

Vapnik, V. “The Nature of Statistical Learning Theory”. Springer, New York, 1995.