Epileptic Seizure Detection

Identification of Ictal and Pre-Ictal States Using RBF Networks with Wavelet-Decomposed EEG Data

BY RONALD SCHUYLER, ANDREW WHITE, KEVIN STALEY, AND KRZYSZTOF J. CIOS

Despite advances in the development of drugs for the control of seizures, there are still many individuals with pharmacoresistant epilepsy [1]. Recent conferences suggested the use of animal models of chronic epilepsy to facilitate the development and testing of more efficacious drugs [2]. Because seizures are intermittent and behavioral manifestation of seizures is quite subtle in rats, the electroencephalogram (EEG) is used. Because of the volume, human review of the data is impractical. An automated system is required to increase accuracy and speed of analysis. Artificial neural networks have been used for EEG analysis for disease diagnosis [3], [4], sleep-stage classification [5], mental-state classification [6], artifact recognition [7], and the detection of epileptiform discharges [8], [9].

In this study radial basis function (RBF) neural networks are used to identify seizure or preseizure states. As input to the RBF networks we used raw EEG data, coefficients from a Fourier transform, and wavelet decomposition of the raw data. An RBF network consists of an input layer, a single hidden layer, and an output node[25]-[27].

In addition to demonstrating a reliable seizure identification method, the possibility of predicting an impending seizure before clinical onset is also investigated. The period during a seizure is known as the ictal state, while the periods of normal brain activity between seizures are called interictal. A third state, referred to as pre-ictal, has been defined [10]–[12] as the period just before seizure onset. If this state can be identified in the EEG [10]–[17] seizures can effectively be predicted, resulting in an early warning to the patient. This would also facilitate the use of implantable devices that would abort a seizure [10]–[12], [17]–[19], eliminating the need for prophylactic drug treatment [11].

Review of Previous Work

The field of seizure identification has been around for many years [20], [21] and many techniques have been refined to accurately identify either focal or generalized seizures. These methods can directly employ use of the EEG data or may involve transformations (Fourier or wavelet analysis). The attempt to identify a pre-ictal state began much more recently and has been shown to be a much greater challenge [10], [12], [13], [22].

Early attempts at identifying seizures used the EEG data directly [20]. These attempts met with some success, but more subtle seizures and those associated with a noisy signal were often missed. More recently, more sophisticated algorithms have been used, yielding increasingly accurate results. For example, visual inspection of wavelet-transformed EEG from an epileptic patient was used [23], where the Daubechies wavelet decomposition was found superior to the short-time Fourier transform for its ability to localize and identify the transient signals associated with epileptic discharges.

There is extensive literature concerning the use of neural networks in EEG interpretation.

One approach described in [30] uses a 31-node input layer that characterizes a 2-second epoch. Input parameters include amplitude, slope, etc., and the eight output nodes identified seizure versus muscle versus noise or normal patterns. When 78 files containing seizures were examined, it was able to detect 76% of those showing seizures. It did find three seizures in files that had none.

Seizure prediction is somewhat controversial because it has not been proven that there is a "pre-ictal state" during which the brain functions differently than in the inter-ictal state. It is further uncertain whether or not this proposed difference in functioning is evident on an EEG. Most methods of seizure prediction employ nonlinear techniques. A review of seizure pre-ictal state identification research was published in [10]. One parameter that has been used is the fractal dimension of the EEG [10], [13]–[15], [24], based on the observation that brain activity just prior to a seizure focus becomes more correlated, while physiologic electrical activity decreases [22]. It is pointed out in [22] that estimates of fractal dimension of EEG data are almost certain to be incorrect; however, relative differences between estimates using the same method may be useful in distinguishing between states. In [13], a dimensionality decrease was noted in human EEG data hours before seizure onset, indicating an increase in the correlated neural activity. This finding has not been reproduced by other authors.

The earliest study of pre-ictal state identification to use wavelet decomposed data with a neural network was reported in [12]. They used recurrent neural networks with one or two inputs, ten or 15 recurrent hidden neurons, and one output neuron. Daubechies wavelets were used to decompose the raw

 0739-5175/07/$25.00©2007IEEE

data, and only data from the most relevant intracranial probe were used. Separate networks were trained with raw data, wavelet approximation coefficients, and detail coefficients. As there were only four seizures in the study, the criterion used to evaluate accuracy was visual inspection of a plot of network output when presented with 170 seconds of data immediately preceding a previously unseen seizure.

Data

Data used here were collected at Colorado State University and at the University of Colorado at Denver and Health Sciences Center, during a project funded by the NIH. The analyzed data consist of approximately 50 billion data points taken from raw EEG readings acquired from three-channel radiotelemetry units of nine rats. Five rats were treated with kainate to induce seizures. Four other rats served as controls. Two of the rats did not survive long enough to collect sufficient data. More than 100 days of data were recorded from electrodes placed in each hippocampus and one placed on the surface of the brain. The data sampling rate was 250 Hz. Representative plots of normal and ictal EEG are shown in row 1 of Figure 1. In addition to the raw EEG data, the time of day and duration of 2,462 seizures was available. Of these, 106 were truncated or corrupted in the recording process.

Data Preparation Methods

The goal of data preprocessing is to generate well-defined feature vectors of lower dimension than the original data. In our case, preprocessing involves the extraction of relevant sections of data and the additional preparation necessary before the data are used to train the RBF network. The dimensionality of these extracted segments is further reduced by: performing a Fourier transform, wavelet decomposition, selecting a smaller window of raw data from within the segment, or some combination of the above.

The first step in preparing the raw EEG data for presentation to the neural network was to locate the relevant segments based on the known seizure times. Extracted segments are 230 seconds long, slightly longer than the longest seizure duration in the study. The total number of data points per extracted

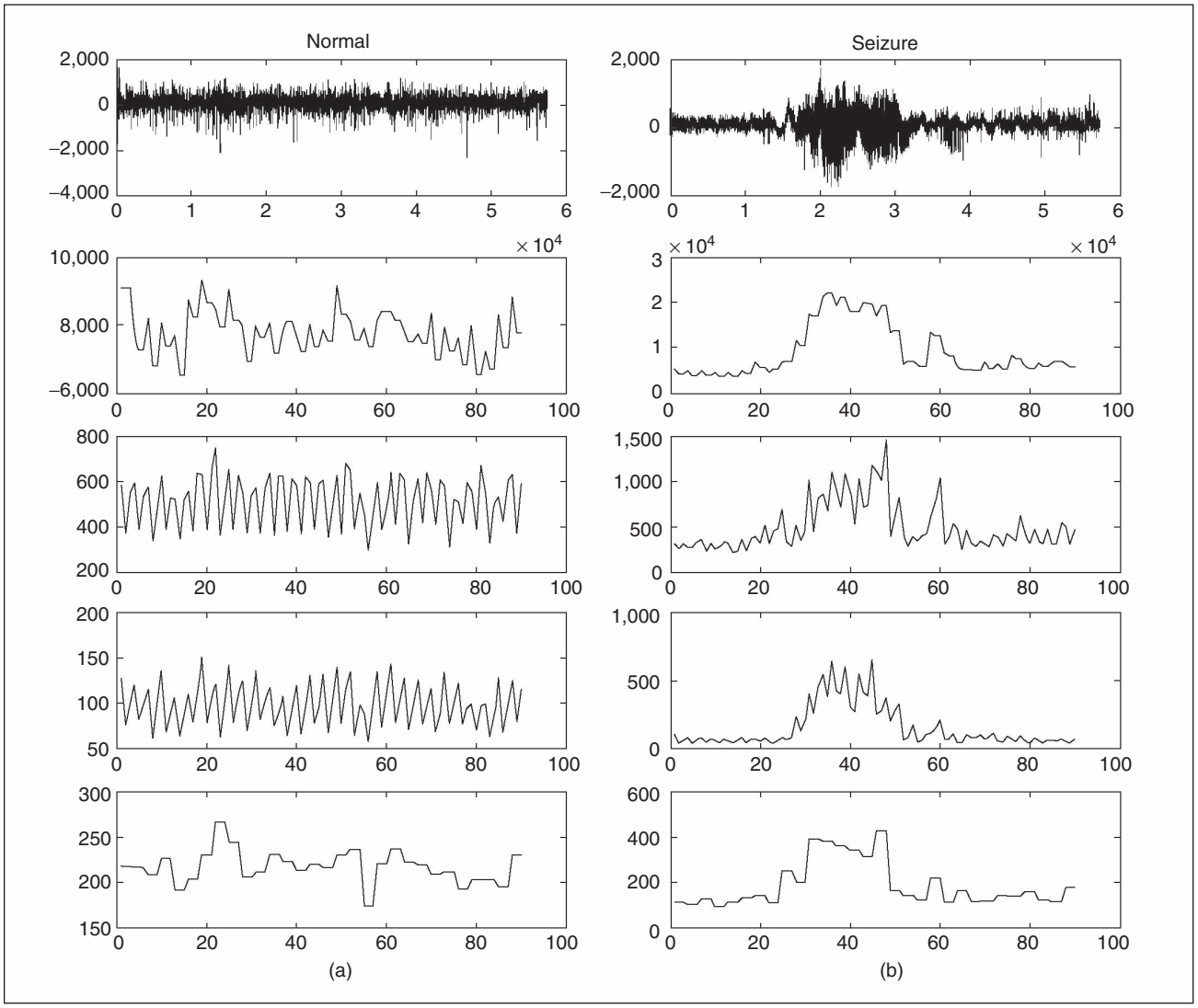

Fig. 1. Transformation examples. Row 1: raw data for one normal and one seizure segment at 250 Hz for 230 seconds. Rows 2–5: FFT, wavelet approximation, wavelet details, and mean raw transformations. Transformations in column 1 are applied to a normal segment; transformations in column 2 are applied to a seizure segment.

Seizure prediction is somewhat controversial because it has not been proven that there is a "pre-ictal state" during which the brain functions differently than in the inter-ictal state.

segment using all three available data channels is: 230 seconds × 250 points per second × 3 channels = 172,500 points per segment. We used 2,356 seizure segments for training and testing.

In our study, data from two normal (nonepileptic) rats and five abnormal (epileptic) rats were used. Normal EEG signals were obtained from both epileptic rats and nonepileptic rats with the restriction that each segment start and end time must not be within five minutes of the start or end of any existing segment. The total number of normal segments was greater than or equal to the number of seizure segments for each day and for each rat. An additional 336 normal segments were extracted randomly from each of the nonepileptic rats.

Windowing

In order for an RBF network to generalize from a set of training vectors, the number of training samples available must be much greater than the dimension of each sample vector. Given the extracted segment length of 172,500 points, 2,356 seizures, and 3,106 normal samples, the length of the vector presented to the network must be significantly reduced. The most straight-forward technique, called windowing, is to chop the vector into smaller segments, taking only a few seconds, or fractions of a second worth of nonoverlapping raw data, rather than the whole segment.

Pre-Ictal Slices

The problem of seizure prediction can be approached in the same way as the problem of seizure identification. The only difference is the location of a data slice of interest relative to seizure onset. Short slices for pre-ictal state identification were extracted from between two minutes and one second before seizure onset. In order to avoid having to mark explicitly when normal data ended and pre-ictal data began, normal data for training were taken from several minutes (around 40 minutes in most cases) before the start of any pre-ictal data. In cases where there were only a few minutes between seizure occurrences, it is possible that brain activity did not return fully to an interictal state, so it was not required that a normal segment be extracted from directly before each pre-ictal period. Normal segments were extracted from periods when the EEG was in a consistent interictal state. All slices up to two minutes before seizure onset were considered pre-ictal and treated equally.

Table 1. Classification of seizures using the seizure-at-once method.

Feature Set	Number of Neurons	Sensitivity	Specificity	Accuracy
FFT	20	79.5	89.6	85.27
FFT	200	83.6	90.3	87.45
Wavelet Details	20	77.3	93.3	86.38
Wavelet Details	200	83.2	94.1	89.40
Wavelet Approx.	20	79.9	83.5	81.97
Wavelet Approx.	200	82.0	83.2	82.67
Mean Raw	20	74.1	80.5	77.77
Mean Raw	200	74.5	87.9	82.11

Data Mining

Two methods are used for distinguishing between segments of EEG recordings containing seizures and those containing only normal data. In both, an RBF network is trained and tested using samples from two classes of data (normal and abnormal). The first method, referred to as the seizure-at-once method, attempts to determine whether a given 230-s segment of data contains a seizure. This segment size was chosen to cover the duration of the longest seizure in this study. (Average duration was around two minutes.) In order to compare data preparation methods, each 230-s segment is preprocessed using either a Fourier transform or wavelet decomposition. An RBF network is then trained to distinguish between the two classes. The second method (short-slice) focuses on a few-second slice representative of the seizure activity in each abnormal segment. Each data slice is preprocessed using wavelet decomposition with a range of wavelet bases before being used to train and test the RBF network. Consecutive short-slices output are compared in order to improve overall seizure identification accuracy by requiring that some threshold number of abnormal slices be identified before declaring an abnormal segment.

Seizure-at-Once Method

Each segment was divided into 30 equal slices across the three channels of data. Either a fast Fourier transform (FFT) or a level-three wavelet decomposition using the Daubechies two base wavelet was then applied to each slice. Wavelet approximation and detail coefficients were used separately. The mean amplitude within a slice was also used. The values were averaged within each slice, resulting in 30 values per channel for each data segment, or a 90-dimensional vector.

An RBF network could easily be trained to distinguish between the 90 point vectors in the left column of Figure 1 from those in the right column. These examples were chosen to illustrate how these preprocessing methods looked in the best case; unfortunately, it was not always this clear.

Short-Slices Method

Slices of raw EEG data from less than one second to approximately 22-s in duration were extracted from random locations between the indexed seizure start

and end times. The use of shorter slices allowed several vectors to be obtained from each indexed seizure. This also eliminated the need to average over multiple values and consequent loss of information, as was necessary to reduce the length of the vectors representing the full 230-s segments. This method resulted in the availability of several thousand seizure examples for the RBF network, depending on the length of slice used, from only 555 indexed seizures.

To have a valid comparison of RBF networks, it is necessary to use vectors of the same length. Applying wavelet decompositions with different bases and at different levels to a constant-width signal results in transformed vectors of different lengths. Raw data slices of different widths were used to maintain a constant transformed vector length of 152 or 171 points. In this way, the use of slices over the range of one to 22-s can be fairly compared.

The RBF neural network was trained using slices of wavelet-transformed or raw data from normal and seizure segments and validated using a testing set of vectors not used in training. Network responses above the threshold of 0.5 indicate that the network believes the input vector causing this response came from within a seizure. This trained network was then tested further by feeding it a full day of data, slice by slice. False positives were minimized by requiring that eight of ten consecutive network responses be above the threshold before declaring a seizure (eight of ten heuristic). The RBF networks trained using the short-slice method were specific to each rat. Each network was trained to recognize seizures from one rat only. This improved accuracy but decreased generalization to other rats.

Evaluation of Discovered Knowledge

Seizure-at-Once Method

The most effective neuron radius value was determined for each feature set based on the accuracy of the resulting trained network when tested using another data set. All results in this section were obtained using 5-fold cross validation. Table 1 gives the results of using the *k*-means cluster centers as neuron centers method for 20 and 200 neurons.

Additional neurons improved performance at the cost of increased computation time, and 200 neurons seemed to be nearing the point of diminishing returns. The results show that using wavelet detail coefficients or applying the FFT transform to the raw data before using it to train the network improves accuracy. Comparing networks using only 20 neurons, the wavelet approximation coefficients give much better results than using raw data. When neuron count is increased to 200, results using raw data are comparable to using the wavelet approximation. The use of wavelet detail coefficients with a relatively high neuron count produces the best results here with 89.5% accuracy.

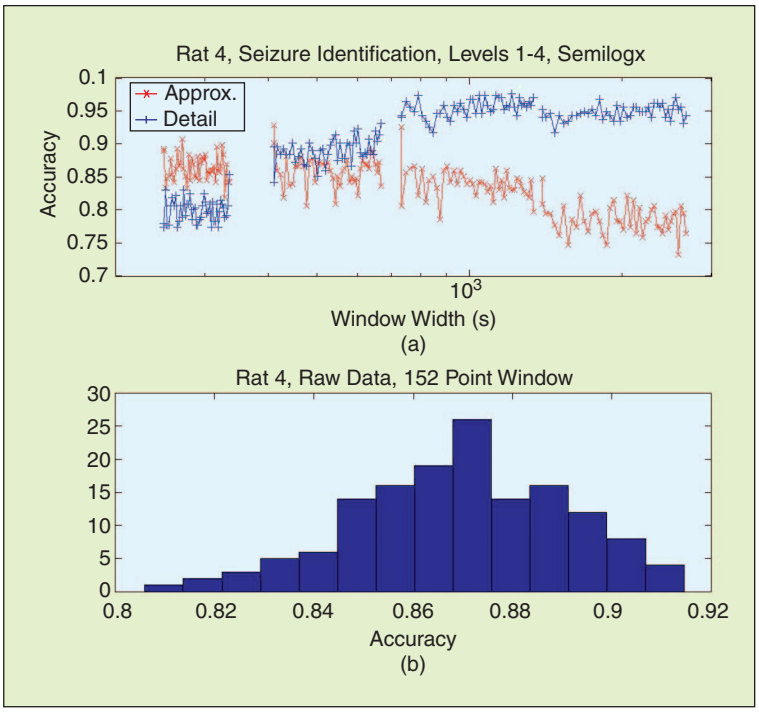

Fig. 2. Per-slice seizure identification accuracies using short slices. Using (a) wavelet detail coefficients (blue) and approximation coefficients (red) at levels 1–4, and (b) raw data with 152 data points or 0.6 seconds per slice.

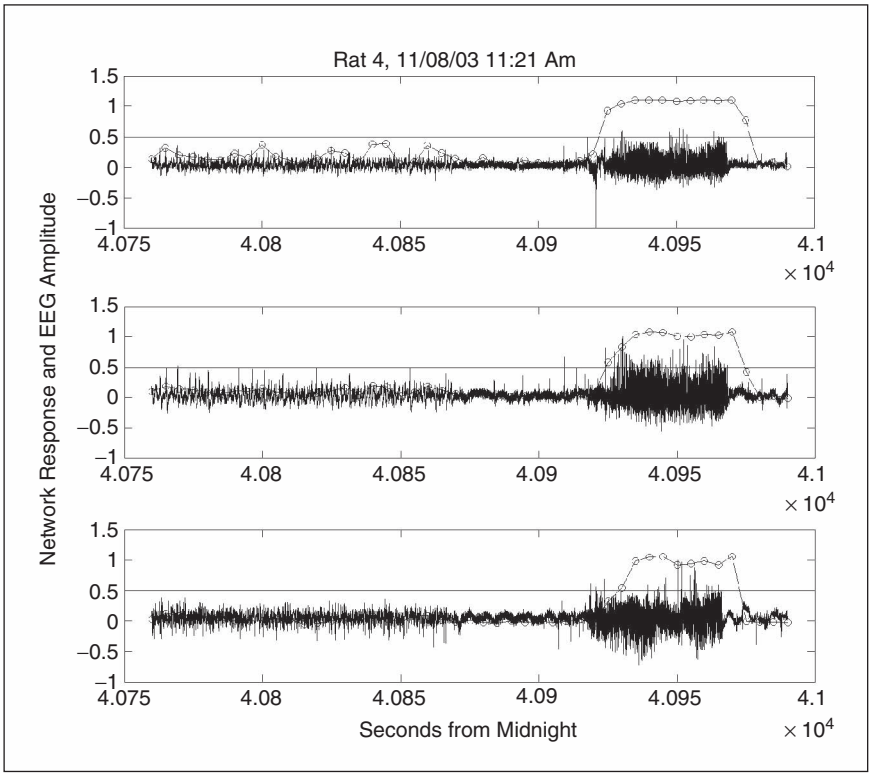

Fig. 3. Seizure identification for rat 4. Three channels of raw data, with network responses to 4.8 second slices superimposed (circles). X-axis is time in seconds.

Short-Slices Method

For the short slices method only one rat was considered. RBF networks with 200 neurons trained using short slices for one rat at a time outperformed those trained using whole seizures for all rats. For this method, half of the available vectors were used for training and half for testing. Training and testing sets were swapped, and the results were averaged. Data slices from all three channels were used for seizure identification. For each trial, raw data were extracted from random starting positions within the ictal or interictal data, decomposed into wavelet coefficients, and used to train the neural network. A data set of equal size was used for testing. Figure 2 compares the results of using wavelet detail and approximation coefficients at decomposition levels one through four. A histogram of 146 trials using 0.6-second slices of raw data is also shown for comparison. The histogram of raw data accuracies in Figure 2 shows that an average per-slice accuracy of 87% was obtained using untransformed narrow windows of raw data. Results using wavelet decompositions clearly show that detail coefficients do a better job of extracting relevant information from longer slices of raw data than approximation coefficients. The best results for rat 4 come from using the details of a level-three decomposition, with an average per-slice accuracy of 95%. This corresponds to a window width of 1,000 to 1,300 points. Increasing the width of the window beyond 1,300 points shows a decreased accuracy of the resulting neural network.

Once the most accurate preprocessing parameters are identified for a given rat, a network can be trained and applied to longer stretches of data, slice by slice. Figure 3 shows three channels of raw data from rat 4 for approximately four minutes with network responses to 4.8-second slices. The neural network was trained with detail coefficients at level three using wavelet base db1. The seizure is clearly identified by the network responses above the threshold of 0.5. Plots using the 8 of 10 heuristic (i.e., 8 out of ten consecutive slices must exceed a threshold value) for the days 11/7/03 and 11/8/03 are shown in Figure 4. No seizure occurred on 11/5/03 and 11/6/03 for rat 4, and none was identified by the network.

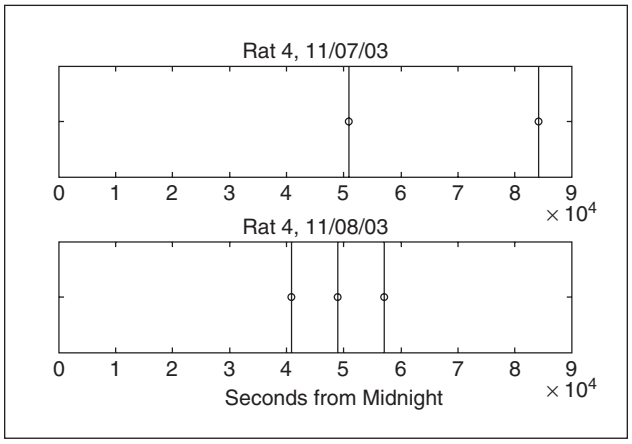

Fig. 4. Rat 4 seizure identification for two days. Circles indicate actual observed seizures. Lines are seizures identified by the neural network. X-axis is time in seconds from midnight.

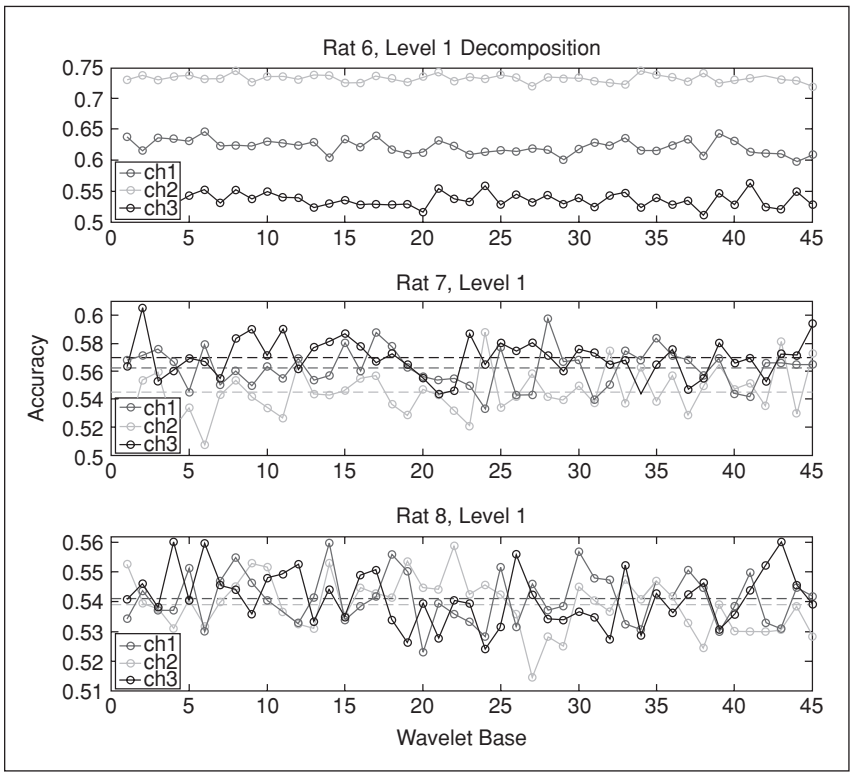

Fig. 5. Seizure prediction on different channels for different rats. Accuracy versus wavelet base at level 1 decomposition. For rat 6 there is a clear difference in the accuracy achieved across channels (around 74%, 62%, and 53% for channels 2, 1, and 3, respectively). For rats 7 and 8 this is less clear. Some data channels perform better than others, possibly due to electrode placement.

Seizure Prediction

Because seizures often originate from a single epileptic focus at a different location within the brain for different individuals, it is reasonable to suspect that the probe closest to the focus would have a higher fraction of predictive signal. Probes further from the focus would have a lower signal-to-noise ratio and less accurate predictive capabilities. If a preictal state can be identified, it is likely that data from one probe will be more useful than the others. For rat 6, channel two shows much better predictive capabilities than the other channels. For rats 7 and 8, the most relevant channel is less clear. This is shown in Figure 5. For seizure prediction, wavelet approximation coefficients perform better than detail coefficients, indicating that relevant preictal information is contained in the lower frequencies. Figure 6 illustrates this with a representative example from rat 6. Given the 74% per-slice accuracy for channel two of rat 6, it seems that fairly accurate seizure prediction should be possible. Figure 7 shows three channels of raw data for rat 6 with slice classification responses from a network trained to identify the preictal state from channel two only. This seizure could have been predicted approximately four minutes in advance. This

result becomes clearer when the heuristic requiring 8 of 10 consecutive network responses above the threshold is applied. A different seizure from rat 6 is used to illustrate this point in Figure 8, with two plots showing raw data and network responses for channel two before and after applying the heuristic for identification. The impending seizure is identified approximately two minutes in advance in this case. When applied to a full day of data, seizure prediction is less successful. All seizures were predicted for the three days, but specificity is poor.

Conclusions

Two types of RBF seizure classifiers have been tested. One attempted to identify an entire seizure at once, while the other used a two-stage approach by looking at several consecutive network responses to short time slices of the data. An average of 89% accuracy was achieved across all rats using the seizure-at-once method combined with detail coefficients of wavelet decomposition preprocessing. This method has the advantage of not needing to explicitly localize a seizure within the 230-second data segment before training the network but may be less accurate due to the averaging of seizure and nonseizure times. By limiting the focus to just a few seconds of data and a single rat, the short-slice method demonstrated consistent per-slice accuracies of 95% using wavelet decomposed data. Training and testing the networks to generalize for multiple rats resulted in lower accuracies. This suggests that individual rats exhibit different identifiable characteristics in their seizure EEG.

The results obtained for seizure prediction suggest that an identifiable pre-ictal state exists, at least in some circumstances. Because seizure origins are localized at a stationary point within the brain in at least some cases, it was expected that if a pre-ictal state were identifiable, it would be more evident in data from one probe than from the others. In three of the five rats, prediction was significantly more effective using data from one channel than from the others, particularly for rats 4 and 6. It seems likely that the probe providing the best data for seizure prediction was very near the seizure origin.

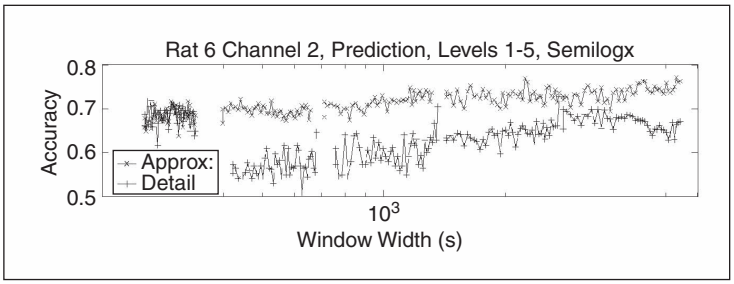

Fig. 6. Seizure prediction for rat 6.

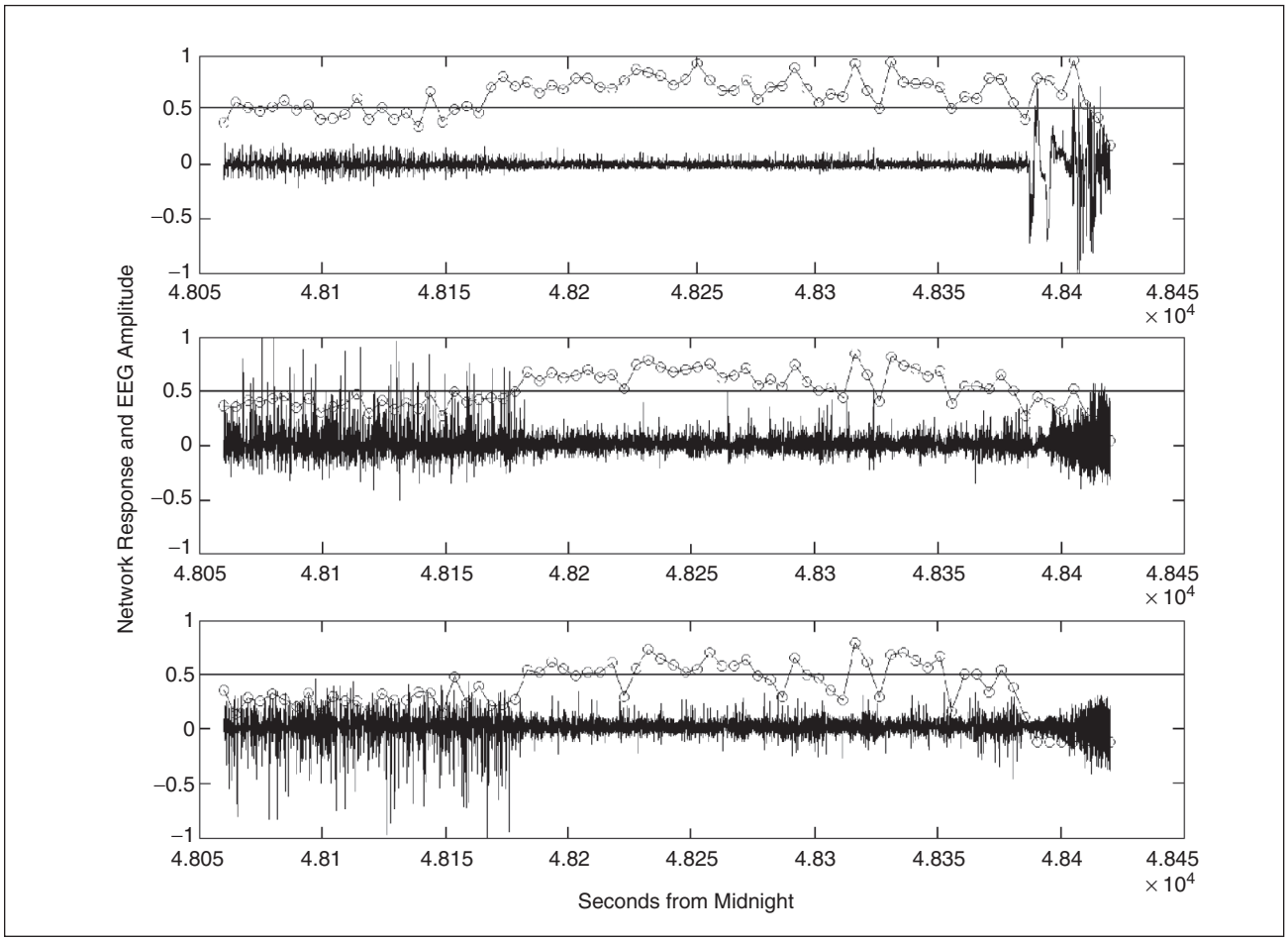

Fig. 7. Prediction of one seizure. Three channels, six minutes of raw data for rat 6 and responses (circles) from a network trained for prediction on channel 2.

The analyzed data consist of approximately 50 billion data points taken from raw EEG readings acquired from three-channel radiotelemetry units of nine rats.

The results reported in [12] using human EEG data suggest that it is the signal's high-frequency components that contain the information relevant for seizure prediction. The results obtained here contradict those findings. While the wavelet details were most useful for seizure identification, it was the approximation coefficients that provided the most accurate results for prediction.

The use of half-second windows of raw data as input demonstrates the ability of the RBF network to learn differences in the patterns of ictal and interictal EEG data without feature extraction. Wavelet decomposition of the narrow window of raw data improves performance while transformation of a wider window, up to about five seconds, improves it even further. The ability of wavelet decomposition to transform five seconds of raw data into a vector of manageable length without substantial loss of relevant information makes it an effective tool for preprocessing EEG data.

Acknowledgments

The authors would like to thank F. Edward Dudek, Ph.D., for the use of his data in this work, which he collected through his NIH project (No. NS34360).

Ronald Schuyler received his M.S. degree in Computer Science from the University of Colorado at Denver and Health Sciences Center, with a Computational Biology option. He is currently enrolled in the Computational Bioscience Ph.D. program at the UCDHSC

Andrew White received his B.S. degree from the University of Michigan. He received M.S. and Ph.D. degrees from the University of Wisconsin in the field of Nuclear

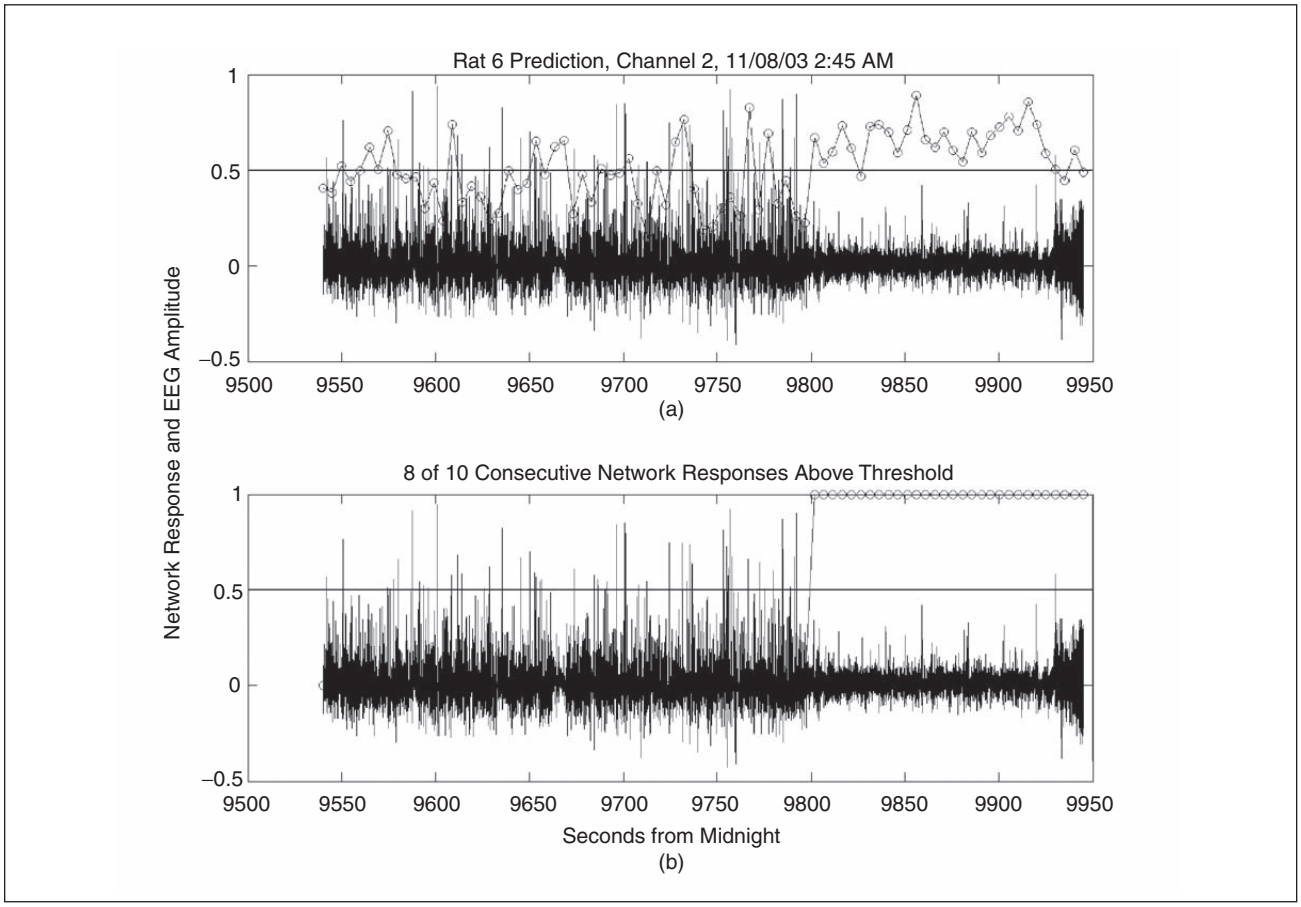

Fig. 8. Prediction refinement with heuristic for rat 6, channel 2, 6.6 minutes of data. Circles represent (a) raw network output and (b) predictions after application of an 8 of 10 heuristic.

Engineering. He received his M.D. degree from the University of Illinois and performed his residency in child neurology at the University of Colorado. He is currently an Assistant Professor at the University of Colorado where he works in the fields of numerical analysis and epileptogenesis. He is currently receiving funding from the NIH. He is a member of the American Epilepsy Society and the Society for Neuroscience.

Kevin Staley received the B.S. degree in physics from Loyola Marymount University, Los Angeles and the M.D. degree from the University of California, San Diego. He is currently a Professor of Neurology at the Massachusetts General Hospital and Harvard Medical School, and the Director of the Staley Lab. His research interests include synaptic physiology and network properties of CA3 hippocampal area, spontaneous network activation in epileptic seizures, and neuronal ion transport.

Krzysztof J. Cios received the M.S. and Ph.D. degrees from the AGH University of Science and Technology, Krakow, the MBA degree from the University of Toledo, Ohio, and the D.Sc. degree from the Polish Academy of Sciences. He is currently a professor at the University of Colorado at Denver and Health Sciences Center, and Associate Director of the University of Colorado Bioenergetics Institute. He directs Data Mining and Bioinformatics Laboratory. Dr. Cios is a well-known researcher in the areas of learning algorithms, biomedical informatics and data mining. NASA, NSF, American Heart Association, Ohio Aerospace Institute, NATO, US Air Force and NIH have funded his research. He published three books, about 150 journal and conference articles and 12 book chapters; serves on editorial boards of *Neurocomputing, IEEE Engineering in Medicine and Biology Magazine, International Journal of Computational Intelligence*, and *Biodata Mining* and edited five special issues of journals. Dr. Cios has been the recipient of the Norbert Wiener Outstanding Paper Award, the Neurocomputing Best Paper Award, the University of Toledo Outstanding Faculty Research Award, and the Fulbright Senior Scholar Award. Dr. Cios is a Foreign Member of the Polish Academy of Arts and Sciences

References

[1] S. Shinnar and J. Pellock, "Update on the epidemiology and prognosis of pediatric epilepsy," *J. Child Neurol.*, vol. 17, suppl. 1:S4-17, Jan. 2002.

[2] J. Stables, E. Bertram, F. Dudek, G. Holmes, G. Mathern, A. Pitkanen, and H. White, "Therapy discovery for pharmacoresistant epilepsy and for disease-modifying therapeutic: Summary of the NIH/NINDS/AES Models II Workshop," *Epilepsia*, vol. 44, no. 12, pp. 1472–1478, 2003.

[3] N. Hazarika, J. Chen, A. Tsoi, and A. Sergejew, "Classification of EEG signals using the wavelet transform," *Signal Process.*, vol. 59, no. 1, pp. 61–72, 1997.

[4] S. Walczak and W. Nowack, "An artificial neural network approach to diagnosing epilepsy using lateralized bursts of theta EEGs," *J. Medical Systems*, vol. 25, no. 1, pp. 9–20, Feb. 2001.

[5] A. Mutapcic, T. Shimayama, and A. Flores, "Automatic sleep stage classification using frequency analysis of EEG signals," in *Proc. XIX Int. Symp. Information and Communication Technologies,* Sarajevo, 2003.

[6] C. Anderson, S. Devulapalli, and E. Stolz, "EEG signal classification with different signal representations," in *Proc. IEEE Workshop Neural Networks for Signal Processing V*, Aug., Cambridge, MA, 1995, pp. 475–483.

[7] R. Bogacz, U. Markowska-Kaczmar, and A. Kozik, "Blinking artefact recognition in EEG signal using artificial neural network," in *Proc. 4th Conf. Neural Networks and Their Applications*, Zakopane, Poland, 1999, pp. 6–12.

[8] C. James, R. Jones, P. Bones, and G. Carroll, "Detection of epileptiform discharges in the EEG by a hybrid system comprising mimetic, self-organized artificial neural network, and fuzzy logic stages," *Clin. Neurophysiol.*, vol. 110, pp. 2049–2063, Dec. 1999.

[9] W. Webber, R. Richardson, and R. Lesser, "A seizure detector based on a neural network for EEG recordings from scalp," *Electroencephalogr. Clin. Neurophysiol.*, vol. 95,no. 2, p. 28P, 1995.

[10] B. Litt and J. Echauz, "Prediction of epileptic seizures," *Lancet Neurol.*, vol. 1, pp. 22–30, May 2002.

[11] B. Litt, R. Esteller, J. Echauz, M. D'Alessandro, R. Shor, T. Henry, P. Pennell, C. Epstein, R. Bakay, M. Dichter, and G. Vachtsevanos, "Epileptic seizures may begin hours in advance of clinical onset: A report of five patients," *Neuron*, vol. 30, pp. 51–64, Apr. 2001.

[12] A. Petrosian, D. Prokhorov, R. Homan, R. Dasheiff, and D. Wunsch II, "Recurrent neural network based prediction of epileptic seizures in intra- and extracranial EEG," *Neurocomputing*, vol. 30, no. 1, pp. 201–218, 2000.

[13] K. Lehnertz, F. Mormann, T. Kreuz, R. Andrzejak, C. Rieke, P. David, and C. Elger, "Seizure prediction by nonlinear EEG analysis," *IEEE Eng. Med. Biol. Mag.*, vol. 22, pp. 57–63, Jan./Feb. 2003.

[14] T. Maiwald, M. Winterhalder, R. Aschenbrenner-Schiebe, H. Voss, A. Schulze-Bonhage, and J. Timmer, "Comparison of three nonlinear seizure prediction methods by means of the seizure prediction characteristic," *Physica D*, vol. 194, pp. 357–368, Sept. 2003.

[15] P. McSharry, L. Smith, and L. Tarassenko, "Comparison of predictability of epileptic seizures by a linear and a nonlinear method," *IEEE Trans. Biomed. Eng.*, vol. 50, pp. 628–633, May 2003.

[16] J. Paul, C. Patel, H. Al-Nashash, N. Zhang, W. Ziai, M. Mirski, and D. Sherman, "Prediction of PTZ-induced seizures using wavelet-based residual entropy of cortical and subcortical field potentials," *IEEE Trans. Biomed. Eng.*, vol. 50, pp. 640–648, May 2003.

[17] S. Schiff, "Forecasting brain storms," *Nature Med.*, vol. 4, no. 10, pp. 1117–1118, Oct. 1998.

[18] C. DeGiorgio, S. Schachter, A. Handforth, M. Salinsky, J. Thompson, B. Uthman, R. Reed, S. Collins, E. Tecoma, G. Morris, B. Vaughn, D. Naritoku, T. Henry, D. Labar, R. Gilmartin, D. Labiner, I. Osorio, R. Ristanovic, J. Jones, J. Murphy, G. Ney, J. Wheless, P. Lewis, and C. Heck, "Prospective long-term study of vagus nerve stimulation for the treatment of refractory seizures," *Epilepsia*, vol. 41, no. 9, pp. 1195–1200, 2000.

[19] E. Waterhouse, "New horizons in ambulatory electroencephalography," *IEEE Trans. Biomed. Eng.*, vol. 50, pp. 74–80, May/June 2003.

[20] J. Gotman, "Automatic recognition of epileptic seizures in the EEG," *Electroencephalogr. Clin. Neurophysiol.*, vol. 54, no. 5, pp. 530–540, Nov. 1982.

[21] R. Esteller, "Detection of seizure onset in epileptic patients from intracranial EEG signals," Ph.D. dissertation, Dept. Electrical Eng., Georgia Inst. Tech., Atlanta, GA, 1999.

[22] A. Galka, *Topics in Nonlinear Time Series Analysis*. Singapore, World Scientific, 2000.

[23] H. Adeli, Z. Zhou, and N. Dadmehr, "Analysis of EEG records in an epileptic patient using wavelet transform," *J. Neurosci. Methods*, vol. 123, no. 1, pp. 69–87, 2003.

[24] M. D'Alessandro, R. Esteller, G. Vachtsevanos, A. Hinson, J. Echauz, and B. Litt, "Epileptic seizure prediction using hybrid feature selection over multiple intracranial EEG electrode contacts: A report of four patients," *IEEE Trans. Biomed. Eng.*, vol. 50, pp. 603–615, May 2003.

[25] K. Cios, W. Pedrycz, and R. Swiniarski, *Data Mining Methods for Knowledge Discovery*. Norwell, MA: Kluwer, 1998.

[26] D. Wedding II and K. Cios, "Certainty factors versus parzen windows as reliability measures in RBF Networks," *Neurocomputing*, vol. 19, no. 1–3, pp. 151–165. 1998.

[27] D. Wedding II and K. Cios, "Time series forecasting by combining RBF neural networks and the Box-Jenkins model," *Neurocomputing*, vol. 10, no. 2, pp. 149–168, 1996.

[28] H. Demuth and M. Beale, *Neural Network Toolbox for Matlab*. Natick, MA: The Mathworks Inc., 1998.

[29] I. Daubechies, "The wavelet transform, time-frequency localization and signal analysis," *IEEE Trans. Inform. Theory*, vol. 36, pp. 961–1004, Sept. 1990.

[30] W.R.S. Webber, R.P. Lesser, R.T. Richardson, and K. Wilson, "An approach to seizure detection using an artificial neural network (ANN)," *Electroencephalogr. Clin. Neurophysiol.*, vol. 98, no. 4, pp. 250–272, 1996.

Address for Correspondence: Krzysztof J. Cios, Dept. of Computer Science and Engineering, University of Colorado at Denver and Health Sciences Center, P.O. Box 173364, Campus Box 109, Denver, CO 80217-3364 USA. E-mail: krys.cios@cudenver.edu.