ORIGINAL RESEARCH PAPER

Volume-7 | Issue-5 | May-2018 | PRINT ISSN No 2277 - 8179

INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH

PARALLEL PROCESSING OF EEG SIGNALS OF PEDIATRIC PATIENTS FOR EPILEPTIC SEIZURE PREDICTION

Pediatrics

Samed Jukić International Burch University, Sarajevo, Bosnia and Herzegovina

Dino Kečo* International Burch University, Sarajevo, Bosnia and Herzegovina *Corresponding Author

Jasmin Kevrić International Burch University, Sarajevo, Bosnia and Herzegovina

ABSTRACT

Objective of this study is to parallelize and apply distributed system paradigm to the whole process of EEG signal analysis including the signal segmentation, signal processing, feature extraction, and classification. This study is focused only on time required for execution of every signal processing part within real-time epileptic seizure prediction. CHB-MIT database, containing 22 pediatric patients, is used for this purpose. Based on the achieved results, parallelization has significantly decreased the execution time for more than 50 %.

KEYWORDS

Parallel Processing, EEG signals, Real-time Epilepsy Prediction

Epilepsy has been characterized as a neurological disorder. It has been claimed that it is a brain's inclination to cause sudden bursts of abnormal electrical activity that might interfere with normal brain functions [1]. More than 1% of world's population is affected by epilepsy, which makes it second most frequent neurological disorder after stroke [2].

Observing patients during the long-time period includes storing EEG and related signal from 30–100 channels and requires effective storing of the observed huge data files. It can produce between 5 and 10GB of data, if we record signals of patient over 24 hours using 100 or more channels. So, an effective and user-friendly tool for signal analysis and visualization is crucial for research staff and clinicians to evaluate these huge signal datasets.

The automated processing of EEG signals is time consuming and quite practical at the same time. The needed quantities of data for individual patient to progress are usually high, however, one of the ways to spare the time of progress is by using parallel signal processing technique.

There are a lot of research done about epilepsy prediction [2], but most of those researches are not about real-time prediction, because of enormous amount of data and time-consuming processing.

Dutta et. al [3] in their research study presented chronological data mining tasks and through that they showed that chronological algorithms are tremendously time consuming. They present a parallel architecture for task parallelism proposed to scale on multi-center machine and group situations [3].

Catherine, et. al [4] in their paper introduced the Cloudwave platform that emphasized a Web-based instinctive signal analysis interface relates to a Hadoop-based data dispensation module. Results from the evaluation of the Cloudwave Hadoop data dispensation module reveal one order of magnitude improvement in performance over 77GB of patient information [4].

Our proposed method will include existing MATLAB code, but adapted for running on parallel system, being able to process huge amount of data, and give output in real-time. Ensemble machine learning methods is involved in order to achieve high rate of accuracy, which is one of major aspects for real-time prediction.

METHODOLOGIES

There is an available online CHB-MIT database that was assembled by the Children's Hospital of Boston. To test and evaluate effectiveness and scalability of the developed algorithms, we used it as implementing health monitoring services. It contains EEG recordings of 198 seizures, obtained from pediatric subjects who had intractable seizures. These recordings were collected from 22 subjects (5 males, ages 3 to 22 years and 17 females, ages 1.5 to 19 years) [5].

MSPCA

A substantial conclusion in PCA is to select the most suitable number of principal components which capture the essential relationship and remove the errors. PCA ability to distribute the relationship or cross correlation within variables is combined by Multiscale PCA (MSPCA) [2, 6]. Applying orthonormal wavelet for each variable, the measurements are decomposed to its wavelet coefficients to accomplish the advantages of PCA and wavelets [2, 6].

Wavelet Packet Decomposition (WPD) – Discrete Wavelet Transformation (DWT)

For analyzing various non-stationary signals, there is an effective time-frequency technique which belongs to a group of wavelets-based methods.

Procedure for DWT decomposition starts with the selection of the number of wavelet decomposition levels denoted as *j_max*. For the first decomposition level $j = 1$, discrete-time EEG signal, $X[K]$, is passed through the high-pass filter, $I[']$, and then down sampled by 2. The corresponding outputs are Detail, D_$_j$, and Approximation, A_$_j$, respectively:

$$D_j[i] = w_{high}[i] = \sum_k x[k] \cdot h[2 \cdot i - k] \quad (1)$$

$$A_j[i] = w_{low}[i] = \sum_k x[k] \cdot l[2 \cdot i - k] \quad (2)$$

After D_$_j$ and A_$_j$ have been obtained, the approximation A_$_j$ is set as $x[k]$ and j is set as 2 (increased by 1), and the procedure is repeated until j exceeds j_*max* [7].

WPD is identical to DWT except that the detail coefficients D_$_j$ are further decomposed as well. For a *k*-level wavelet decomposition, WPD will produce 2^k different sets of wavelet coefficients, whereas DWT generates $k+1$ sets of wavelet coefficients (each level has its own detail coefficient plus one final approximation) [8].

ROTATION FOREST

Rotation Forest (RF) is another newly presented effective ensemble classifier generation algorithm, where the training set for every base classifier is designed by applying PCA to rotate the initial attribute axes. Exactly, to create the training data for a base classifier, the attribute set F is randomly divided into K subsets and PCA is applied to every subset. The main point of Rotation Forest is to simultaneously motivate diversity and individual accuracy inside the ensemble [9].

PROPOSED METHOD

In this experiment, seizure number for every patient in database is checked. Based on that, we choose one patient for this experiment. With chosen signals, applying signal processing methods we create new one which include 48 minutes of preictal signals and ictal length. Applying MSPCA matrix is denoised and wavelet packet decomposition features will be extracted from every 8-seconds long denoised segment and put into training database. For tuning machine learning algorithm parameters, we perform 10-fold cross validation on the training database.

In code (explicit) parallelization technique we apply parallel code in every part where it is possible. Therefore, parallelization is applied in in raw signals loading and in signals segmentation where chunks of 8 seconds is made.

We used MATLAB GUI application for training model which we save. Saved model is latter loaded for testing. In test phase, all interictal signals and one preictal and ictal are loaded. On every chunk is applied de-noising and feature extraction, and trained model is used for test data. Based on that result we found prediction value, and we get result about execution time.

RESULTS

Parallelization for signal processing is introduced in this experiment. Applying this method, we decrease time of execution which is presented in Table 1. Applying code parallel way of execution, time needed to execute code is two times less than when we are applying normal (serial) method or MATLAB parallel execution. This way of execution plays important roles for testing, because time of execution for testing cases is high. Using code parallel method for testing reduce execution time more than two times compared to normal or MATLAB parallel way of execution.

Difference of execution time for every part of signal processing is also presented in Table 1. As we see from the table, for every part of signal processing execution time is two times less applying code parallel than when we used normal or MATLAB parallel way of execution.

TABLE – 1 EXECUTION TIME COMPARISON IN SECONDS

Patient 3	Normal execution	MATLAB parallel	Code parallel
Interictal signal processing	534.97	529.75	422.38
Preictal signal processing	375.65	372.51	268.95
Signal processing total	910.61	902.26	691.33
Test	8840.87	8789.65	3339.82

Figure 1 better representing this difference.

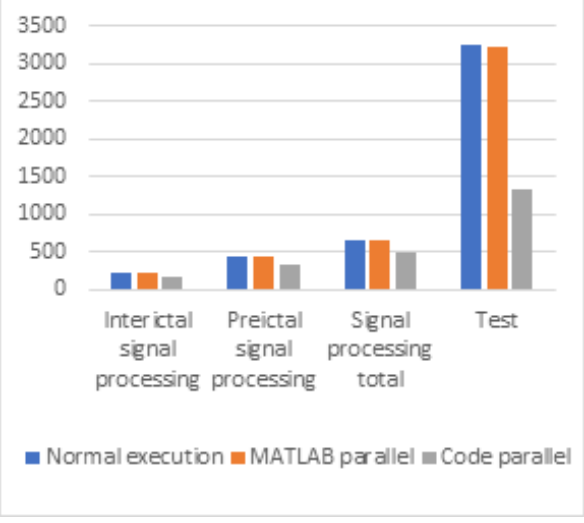

Figure 1: Execution time comparison

DISCUSSION

This section discusses the findings and the results of the analysis and organization of the particularly selected studies. Additionally, an overview of the selected studies and some interactions among the taxonomy categories are presented as well.

Applying parallel processing we achieved significant difference in execution time for processing EEG signals and it is the most important thing which is related to our experiment. Normal (serial) execution is two times slower than execution when we applied code parallelization Comparison of execution time is presented in Figure 1 and Table 1. Tables with results for every segment of signal processing with different execution type is presented in result part. Based on presented result, we can see that execution of serial type (normal) and parallel MATLAB execution method is achieving very similar time of execution. But if we check code parallel, we can see that it achieves time of execution which is two times better than other two methods.

Comparing this work with previous experiments, it is obvious that there is no similar work where author combines parallel signal processing with real-time epilepsy prediction. Because of that, our work is compared with research which are focused on parallel or distributed way of signal processing. Dutta, et al., [3] in their study introduced method for distributed signal processing. In this research they decrease executin time from half of an hour processing to 12 minutes. Comparing to this study, our result proves that execution time using code parallelization is three times faster than normal (sequence) execution time. Beside faster processing, our method did not reduce accuracy for epilepsy prediction. Catherine, et. al [4] in their research used Cloudwave as tool for distributed signal processing. Applying this tool, they achieve significant time reduction of dataset which contain 77 GB of data. Comparing to this research, in our experiment we prove that it is possible to achieve great accuracy result, even if we include parallel method for signal processing.

CONCLUSION

Applying parallelization for EEG signal processing for prediction of epileptic seizure is the main contribution of this study. It is demonstrated how to significantly improve the signal processing execution time for massive EEG data applied for algorithm for real-time prediction of epilepsy seizure. The accomplished experimental results prove that the execution time of normal (serial) processing is high. By introducing our proposed algorithm, the time for execution is decreased by more than 50%. Based on the presented results we can see that our proposed method can successfully (1) increase effectiveness of real-time epilepsy prediction system and (2) optimize execution time for massive EEG data signal processing. Finally, the proposed method can be directly used to decrease execution time of big EEG data within other application domains, such as BCI, brain disease prediction, mind control system and other similar applications.

REFERENCES

[1] E. Waterhouse, "New horizons in ambulatory electroencephalography," Engineering in Medicine and Biology Magazine, IEEE, vol. 22, no. 3, pp. 74-80, 2003.
[2] S. Jukic and A. Subasi, "Localization of the epileptogenic foci using Support Vector Machine," Southeast Europe Journal of Soft Computing, vol. 2, no. 2, pp. 26-30, 2013.
[3] H. Dutta, H. Fiorletta, M. Pooleery, H. Diab, S. German and D. Waltz, "A Case-Study on Learning from Large-scale Intracranial EEG Data using Multi-core Machines and Clusters," Proceedings of the Third Workshop on Large Scale Data Mining: Theory and Applications, 2011.
[4] P. J. Catherine, C. Chien-Hung, B. Alireza, D. L. Samden, Z. Guo-Qiang and S. S. Satya, "Electrophysiological Signal Analysis and Visualization using Cloudwave for Epilepsy Clinical Research," Stud Health Technol Inform, vol. 192, p. 817–821, 2013.
[5] M. Adel Serhani, M. El Menshawy, A. Benharref, S. Harous and A. Nujum Navaz, "New algorithms for processing time-series big EEG data within mobile health monitoring systems," Computer Methods and Programs in Biomedicine, p. 79–94, 2017.
[6] B. R. Bakshi, "Multiscale PCA with Application to Multivariate Statistical Process Monitoring," AIChE Journal, vol. 44, no. 7, p. 1596–1610, July 1998.
[7] P. Ghorbanian, D. M. Devilbiss, A. J. Simon, A. Bernstein, T. Hess and H. Ashrafiuon, "Wavelet Transform EEG Features of Alzheimer's Disease in Activated States," in 34th Annual International Conference of the IEEE EMBS, San Diego, California USA, 2012.
[8] N. Rafiuddin, Y. Khan and O. Farooq, "Feature extraction and classification of EEG for automatic seizure detection," in International Conference on Multimedia, Signal Processing and Communication Technologies, 2011.
[9] Z. Chun-Xia and Z. Jiang-She, "RotBoost: A technique for combining Rotation Forest and AdaBoost," Pattern Recognition Letters, vol. 29, p. 1524–1536, 2008.