Development of an Epileptic Seizure Detection Application based on Parallel Computing

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***Abstract*—Epileptic seizure detection in a large database of Electroencephalography (EEG) signals needs to be a time constrained process for real-time analysis. Epileptic seizure detection algorithms are designed to obtain and analyze a group of neural signals and recognize the presence of seizure occurrence. The computational cost of the algorithms should be minimized to reduce the processing time and memory consumption. Automated epileptic seizure detection using optimized feature selection improves the classification accuracy, but it occupies more processing time during the Artifact Removal (AR) stage. So, the execution time is greatly reduced by introducing task parallelism in the artifact removal stage. By harnessing parallel computing the computational overhead and processing time are decreased. An epileptic seizure detection application is developed and analyzed with respect to execution time, speedup, and parallel efficiency. The application was developed in Intel Pentium(R) Dual-core CPU with processor clock rate of 2.60 GHz, memory of 1.96 GB, and operating system of Windows XP Professional Service Pack 2.**

Index Terms—Artifact Removal (AR), Ensemble Empirical-Mode Decomposition (EEMD), Epileptic seizure, Local Worker (LW), Parallel efficiency, and Speedup.

I. INTRODUCTION

Time consumption in epileptic seizure detection application is vital especially in large medical databases. The detection process needs to be a real-time instant process rather than recording the Electroencephalography (EEG) readings and taking additional time for producing the detection results.

The previous automated epileptic seizure detection method used optimized feature selection to enhance the classification accuracy. But it involves more processing time while removing the artifacts. This can be efficiently decreased by utilizing parallelism during the artifact removal (AR) process. Parallel processing technique, accesses the memory and process the data simultaneously thereby it provides an increased computational speed and the processing time and computational overhead are reduced. The epileptic seizure detection application is implemented and tested with respect to execution time, speedup, and parallel efficiency, and it is noted that its performance is good.

The remaining part of the paper is organized as follows: Section II involves a brief overview of the existing method –Optimized feature selection for enhanced epileptic seizure detection and the computational constraints involved in it. Section III involves the works related to the probable solutions for minimizing the processing time in the epileptic seizure detection using parallel computing. Section IV involves the outline of the epileptic seizure detection application. Section V involves the architecture and working of the epileptic seizure detection application. Section VI involves the performance evaluation. The paper is concluded in Section VII.

II. OPTIMIZED FEATURE SELECTION FOR ENHANCED EPILEPTIC SEIZURE DETECTION

The existing method for epileptic seizure detection involves a feature selection method, which is an important aspect that improves classification accuracy. The artifacts and noise in the EEG dataset are removed and the features of the input data are constructed. The features are selected and validated. Finally, the input samples are divided into multiple classes. This optimized feature selection technique consumes more processing time during the AR stage. This processing time needs to be minimized for real-time epileptic seizure detection analysis.

III. RELATED WORK

This section deals with various epileptic seizure detection methods using parallel computing for faster processing. *Tang* and *Durand* designed an epileptic seizure detector using a tunable support vector machine assembly (SVMA) classifier [1]. Some of the difficulties during the seizure detection occur due to the diverse EEG morphologies, artifacts, and varying EEG recordings from a single patient. The SVMA contains a set of SVMs used for the selective control of the classifier which is trained with various sets of data weights. The training on huge problem sets can be parallelized to simplify the process. Various multi-channel EEG signal analysis methods for signal denoising, signal segmentation, and feature detection are reviewed in [2]. The segmentation process is considered over parallel observations of multi-channel data. The conventional computational models are combined with parallel data processing tools to handle the large amount of data. The resultant pattern vectors are classified using a statistical criterion based self-organizing neural networks (NNs). These pattern vectors are used to compute the distances of separate feature vectors from the related cluster centers.

Case and *Soltesz* analyzed the biological basis for the development of a computational seizure detection model [3]. This computational model can also be modified based on parallel computing to quicken the seizure detection process. *Raimondo*, *et al* optimized the Graphics Processing Unit (GPU) of Infomax-ICA (Independent Component Analysis) based EEG analysis [4], where Infomax is an efficient optimization technique for information processing systems and NNs. The optimized version employing Compute Unified Device Architecture (CUDA) is hereby known as CUDAICA. Various extensions of the primitive Instruction Set Architecture (ISA) for vector processing enable parallel execution of similar operations on multiple data. Massively parallel processors are added in the GPUs for reducing the ICA computation time. Faster parallelization is achieved through a common shared memory.

Dan, *et al* proposed an Ensemble Empirical-Mode Decomposition (EEMD) based on General-Purpose computing on the GPU (GPGPU) for EEG analysis during anesthesia [5]. An adaptive time-frequency analysis method like EEMD is mainly used to obtain the useful information from noisy non-stationary or non-linear data, but it does not support larger scale of computations and real-time applications. A parallelized EEMD technique was developed using GPGPU is known as G-EEMD. The real-time estimation of the Depth of Anesthesia (DoA) is facilitated by a spectral entropy function and G-EEMD. *Dan*, *et al* also performed neural signal processing on a multi-core platform [6]. [7] suggests the source reconstruction, evaluation, and visualization of EEG/MEG (Magneto encephalography) signals can be performed using a source analysis tool box known as Neuro dynamic Utility Toolbox for Magneto encephalography and Electroencephalography (NUTMEG). The estimation of source neural activity can be speedup by running the batch scripts on a parallel computing cluster to decrease the computation. Similarly, the computation time for huge datasets and searching the links among brain voxels can be reduced via parallel computations on Linux clusters.

Yadav, *et al* proposed a model-based automatic seizure detection method for intracranial EEG recordings [8]. This technique is based on a set of primitive functions and statistically optimal null filters (SONFs) for the detection of similar seizures. The seizure detection process involves template seizure pattern segmentation, elimination of recursive and noisy segments, feature extraction, selection of the most efficient seizure model, and classifier training. Finally, the trained classifier detects the similar seizures in the remaining data. A SONF can be implemented as a group of parallel branches to reduce the computational cost. EPILAB is a software package for the early detection of epileptic seizures [9]. The epileptic seizure detection is performed by cellular neural networks which involve the parallel processing of the input matrix to reduce the computation time. Other epileptic seizure detection methods using parallel processing include Higher order spectra to identify Epileptic EEG[10], Automated diagnosis of epileptic EEG using entropies[11], and Parallel algorithm to analyze epileptic spikes [12].

IV. FLOW OF EPILEPTIC SEIZURE DETECTION APPLICATION

Epileptic seizure detection based on parallel computing is developed as an application file. The working flow of this application is described in this section.

*A. **Basic layout of the application***

The layout of the application consists of four signal displays namely, Mixed Signal, constrained ICA Signal, Stationary Wavelet Transform (SWT) Signal, and AR Signal. Next, it contains two tabular columns for displaying the values of the extracted features and the values of the selected features. Finally, the epileptic seizure detection result is displayed. The basic layout of the application is shown in Fig. 1.

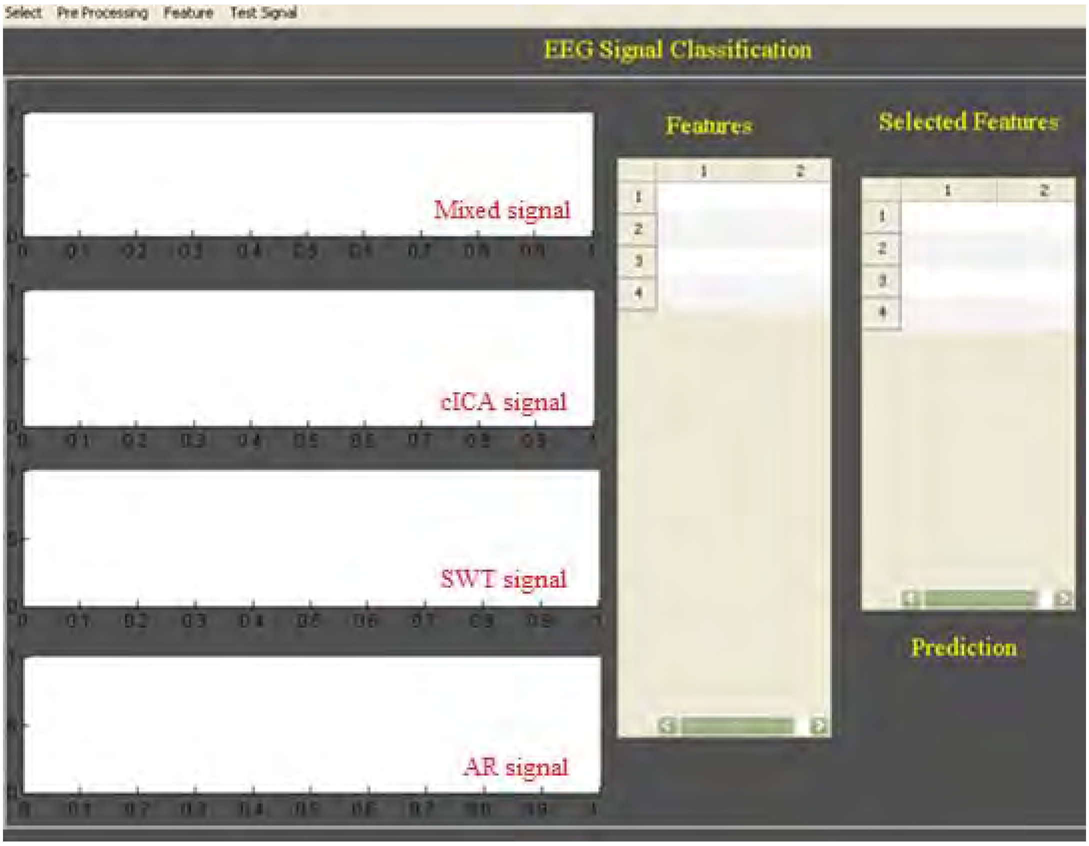
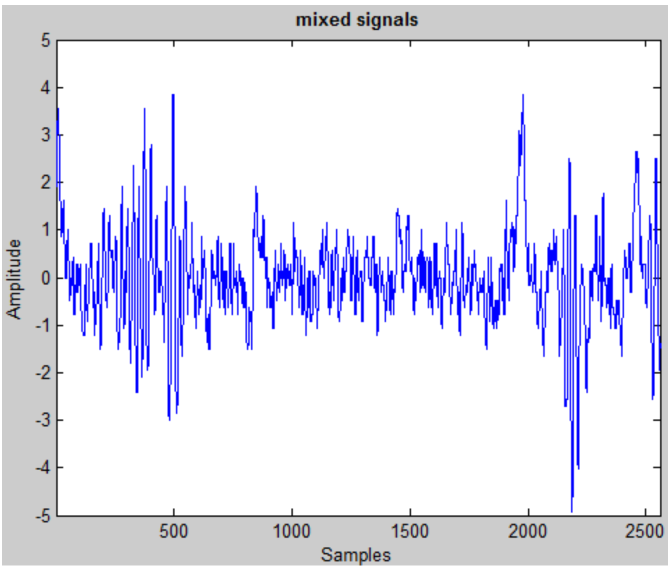


Fig. 1. Basic layout of the epileptic seizure detection application.

B. *Acquisition of mixed EEG signals*

The mixed EEG signals are obtained for a specific channel out of the 948 channels. The mixed signals for a particular channel with 2560 samples are acquired as shown in Fig. 2.



. Fig. 2. Acquisition of mixed EEG signals

C. *Process of epileptic seizure detection*

An approximate extraction of the desired source signal constitutes the reference signal for the AR process. The extraction procedure involves the maximization of the mean delay autocorrelation of the desired source signal at multiple time delays. Constrained ICA (cICA) also known as ICA with a reference which is used for the AR process[13].

A SWT signal is a shift invariant, linear, and redundant signal for wavelet denoising based on thresholding, wavelet basis function and decomposition level. Artifact removal is performed by subtracting the SWT signal from the original EEG signal[14].

The features for the epileptic seizure detection process are extracted using the FastICA algorithm [15]. The set of feature values of a dataset is grouped into a *feature vector*.

$$\tilde{s}(t) = \tilde{S}\, E^{-1/2}\, V^T s(t)$$

The FastICA algorithm computes the ICA feature vectors $\tilde{s}(t)$, where $\tilde{S}$ is a separation matrix trained by the FastICA algorithm, E is the matrix of eigen values, V is a matrix of eigenvectors, and $s(t)$ is the combination of n statistically independent signals.

The features are selected using an optimized feature selection method. This method uses Genetic Algorithm (GA) [16] for optimized feature selection and multi-class SVM [17] for validation of the selected features. A Linear Discriminant Analysis (LDA) classifier is used to calculate the fitness function[18]. The layout of the process/results occurring in the epileptic seizure detection application is shown in Fig. 3.

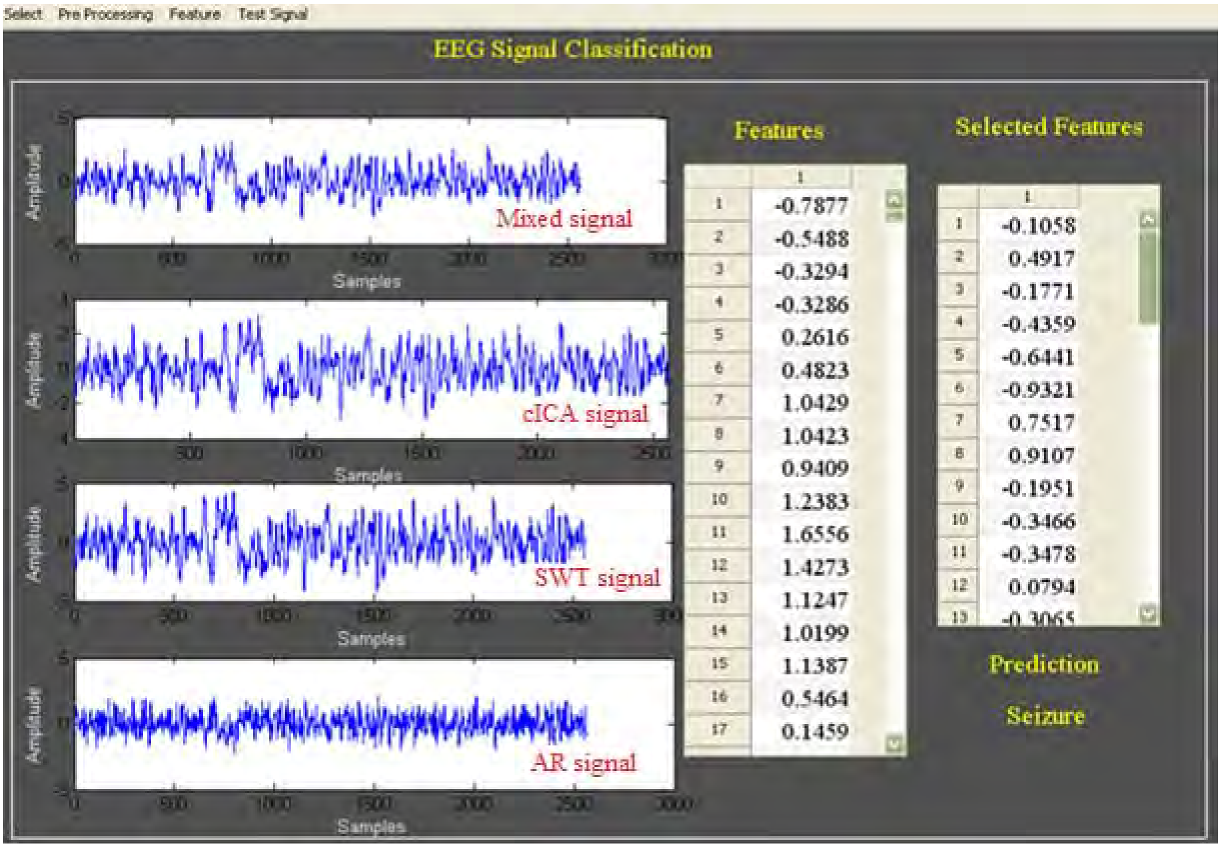


Fig. 3. Process of epileptic seizure detection.

V. PARALLELIZED EPILEPTIC SEIZURE DETECTION

A parallelized epileptic seizure detection application is developed to reduce the processing time. This section describes the architecture and the working of the parallelized epileptic seizure detection based on shared memory and task parallelism.

A. *Architecture of parallelized epileptic seizure detection*

The working of parallelized epileptic seizure detection application is illustrated in Fig. 4. It is seen that the EEG signal dataset is given to the AR model. From the previous work it is observed that the time consumption in AR process is high. So, a parallelized computing model is introduced during the AR process to decrease the execution time and thereby attain a linear speedup.

The AR process is divided among four local workers (LWs) to reduce the processing time. The processes in the four LWs are simultaneously executed to save more time. After the AR process, feature extraction, feature selection, and NN classification processes are followed.

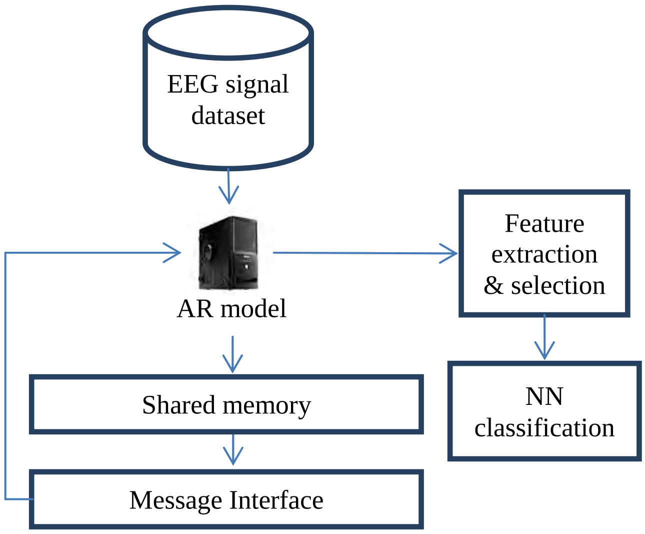


Fig. 4. Working of parallelized epileptic seizure detection application.

B. Process of parallelized epileptic seizure detection

The optimized feature selection for epileptic seizure detection involved serial computations. To reduce the time consumption and solve a common computational problem, parallel computing has been applied using multiple computational resources.

The clock time can be significantly decreased by considering multiple processors and task parallelism. The parallel tasks are divided among four LWs, where a worker is a computational engine. The parallel tasks are coordinated in real-time and this process is known as synchronization. A problem of size *X* is divided into *N* sets. The time consumption can be considerably reduced by partitioning the tasks (or) instructions of each problem set. A processor is assigned to each problem set, where *N* in this work is equal to 4. and the problem is solved simultaneously by the multiple processors.

A shared memory is regarded based on the process interaction and task parallelism is considered based on the problem decomposition. The interaction of the processes in the system refers to the mechanisms by which the parallel processes communicate with each other. The outline of the shared memory architecture is shown in Fig. 5. Multiple processors access the entire shared memory as a single global address space. This enables quicker data sharing.

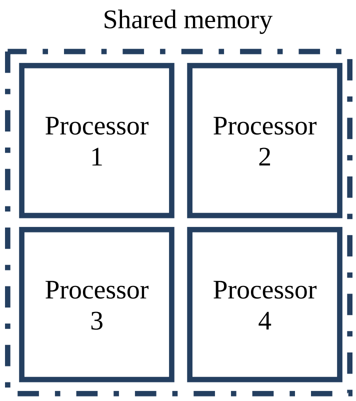


Fig. 5. Shared memory architecture.

The shared memory is simultaneously accessed by multiple processors with an aim to provide communication among them, avoid redundant data, and decrease the computation time. The memory space is conserved by directing the accesses to a single instance using virtual memory mappings or explicit program support. The programs can be simplified since the communication between the tasks need not be explicitly specified.

VI. PERFORMANCE ANALYSIS

The epileptic seizure detection application is analyzed with respect to execution time, speedup, and parallel efficiency.

A. Execution time

The execution time of epileptic seizure detection is analyzed by including up to four local workers. The execution time is observed by measuring the period between start clock time and stop clock time. The clock is started and stopped by the MATLAB® commands *tic* and *toc* respectively. The analysis is shown in Fig. 6. It is observed that the execution time decreases from 31.28s to 19.32s when the number of workers is increased from one to two. The decrease in execution time is low after the number of workers is increased from two to four. The highest execution time is 31.28s, while the lowest execution time is 17.86s.

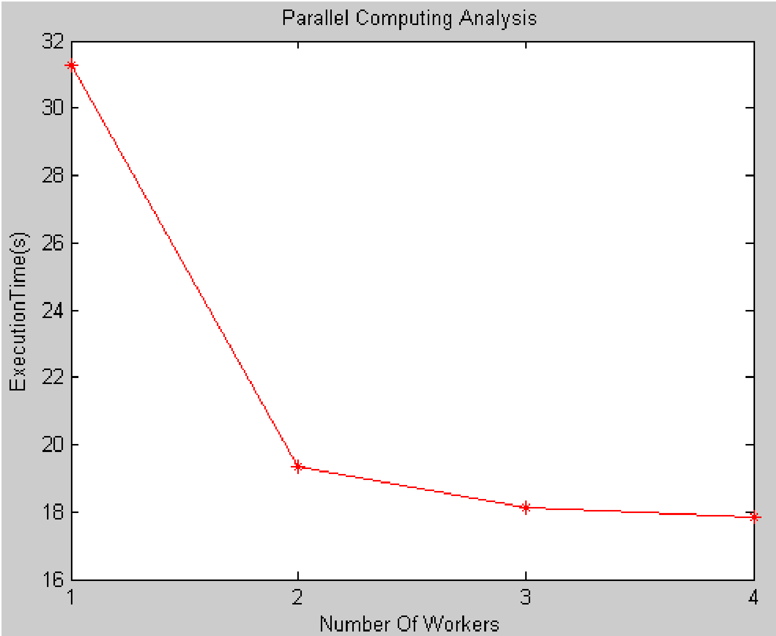


Fig. 6. Execution time of epileptic seizure detection application with respect to number of workers.

B. Speedup

Speedup is the ratio of sequential execution time to the parallel execution time[21]. The analysis of speedup for an increasing number of workers from one to four is shown in Fig. 7. It is seen that the increase in speedup is almost a linear response. The minimum speedup attained is unity, while the maximum speedup attained is 1.75.

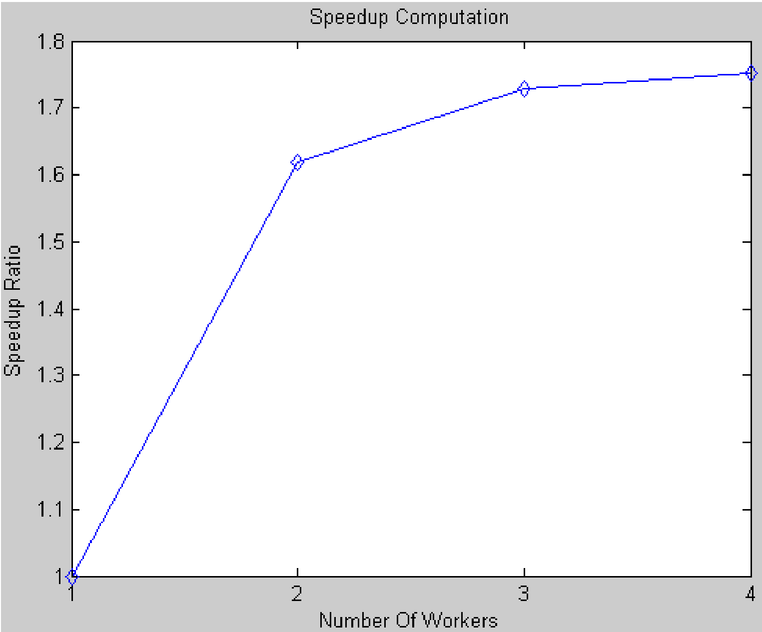


Fig. 7. Speedup ratio of epileptic seizure detection application with respect to number of workers.

C. *Parallel efficiency*

Parallel efficiency is defined as the speedup ratio achieved per number of cores on the system[22]. The analysis of individual parallel efficiency for an increasing number of workers from one to four is shown in Fig. 8.

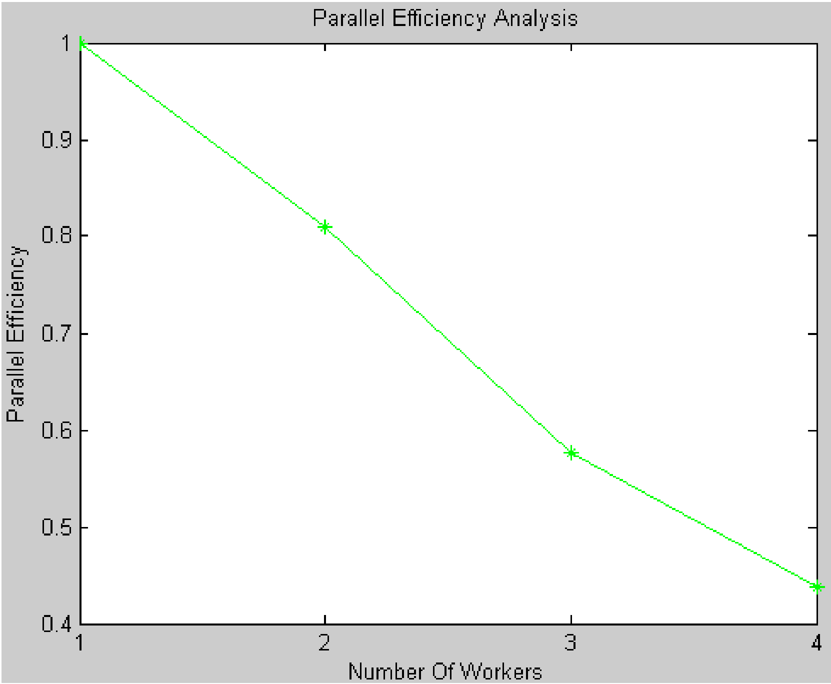


Fig. 8. Parallel efficiency of epileptic seizure detection application with respect to number of workers.

VII. Conclusion

An important objective of epileptic seizure detection algorithms is the quick, efficient, and accurate transformation of neural signals input into seizure detection output indicator. Real-time epileptic seizure detection is required for the online analysis of neural signal data points as soon as they are available. The detection process should have negligible delay without any dependence on future information. The previous development of automated epileptic seizure detection using optimized feature selection enhanced only the classification accuracy, but did not reduce the processing time considerably during the Artifact Removal (AR) stage. This demerit is overcome in this work by designing artifact removal process based on task parallelism. An application is developed for epileptic seizure detection based on parallel computing, which uses a shared memory that may be accessed by multiple processor synchronously, so it can avoid the redundant data copies and reduce the computational time.

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