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Research paper

Embedded system on high performance data for wearable augmented reality of eye blinks, muscle stress detection movement and observation

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Abstract

Eyes blinking and its movement can portray many reasons of the body and health state. Eyes can blink intentionally and sometimes ran-dom-ly even in sleeping mode. Thus, the aim of this paper is to discover and observe the relationship between the frequency of eye blink and the level of eye muscle stress. The eye track data is fed directly into the electroencephalogram (EEG) record for parameter classifica-tion and identification. The EEG signal might have an artifact that has been analyzed and converted the observation into the mathemati-cal library and repository software (HPC). The artificial neural network (ANN) is integrated with EEG digital data by the derivation of the mathematical modelling. The function of ANN is to train a large sparse digital data for future prediction of eye condition associated with the stress lev-el. In order to validate the model and simulation, the numerical analysis and performance evaluation are compared to the real data set of eye therapy industry, IC Herbz Sdn Bhd. A library and repository software of mathematical model using EEG record data is developed to inte-grate with wearable augmented reality (WAR) based on EEG sensor device for predicting and monitoring the real time eye blinks, move-ment and muscle stress.

Keywords: *Wearable Augmented Reality; Eye Blinks, EEG; ANN; Embedded System.*

1. Introduction

The digital eye blinks are fully realized universe of WAR. The blinks of an eye, muscle stress and brain activity are simultaneous-ly connected to an interactive technology of augmented reality. The normal human eye conditions show that some temperature distribution of the human eye with an ambient temperature of 20oC and blood temperature 37oC. Under normal conditions, intraocular pressure is distributed evenly throughout the eye at the average 15 mm Hg. The majority of the eye's workings are still a mystery. In achieving the characteristic of the standard normal eye, this paper obtains the mathematical model to explain the relation-ship between eye blinks, movement and muscle stress. The eye and muscle activity can be measured using the signal detection of EEG sensor device, body temperature and blood flow and other parameter characterizations. The main objective of this research is linking these signals with a specific activity, such as activating motor function or solving mathematics equation using mental calculation. It is even harder to generalize the interpretation of these associations, since brain activity can differ between different persons. The aim of this paper is to detect and observe the eye blinks of one test subject and correlate eye blink frequency with the level of stress. Some parameter identifications are eyed blinks, movements, muscle stress, pressure distribution and body temper-ature. The integrated EEG and WAR are able to obtain eye blink and brain activity for car driving simulation. During the driving experiment, stressful emotions of the driver had been triggered, through steep curves and attention-seeking billboards. The record of the EEG sensor device contains the combination of stress detec-tors, lead to other applications in improving the transportation safety and other support areas. The stress level of eye muscle needs to be monitored and will be organized in an HPC library and repository. The eye track data set is recorded using a digital-to-analogue converter card in the EEG sensor device, and the output produces an analogue signal. A copy of the eye track is fed direct-ly into the EEG record based on meaningful analyses of simulta-neously parameter reaction. The methodologies involve the trans-formation of some parameters into miniature augmented reality displays. The HPC platform of the large sparse mathematical sim-ulation is based on single instruction and multiple data stream (SIMD) architecture using the distributed computer systems. The output of the complete simulation is the trained data set will pre-dict and monitor the real time eye blink, movement and muscle stress. The output of this research is a software development in-volving high-performance library and repository, HPC of the mathematical modeling for observing a big data EEG record. The table and graph are the important output and visualization tool for embedded system of WAR. The validation and analysis of this system are based on numerical analysis and some performance evaluations.

2. Literature review

The human brain is considered a black box by many scientists. This paper presents the methodology to transform some parameter involve into miniature augmented reality displays. Although we are able to model and explain some phenomena, the majority of the brain's workings is still a mystery. The brain's activity can be measured using detection of electrochemical signals, blood flow and possibly others. When looking at the electrochemical signals, a large problem is linking these signals with a specific activity, such as activating motor functions or solving math equations using mental calculations. It is even harder to generalize the interpretation of these associations, since brain activity can differ between different persons. The aim of this proposal is found on detecting eye blinks of one test subject and correlate eye blink frequency with the experienced level of stress. We also present our findings on mental calculations with open and closed eyes, and their effect on brain activity. This line of research may be very useful to society. Human activities like driving vehicles could be made safer when being able to sense that the driver has an irregular or fast eyes blinks, indicating drowsiness or stress. There are numerous other applications where eye blink detection may be used to enhance stress monitoring. It's also useful for the scientific EEG community since eye blink artifacts contaminate the EEG signal [1]. For our experiment, we chose the EEG sensor device as the technique to capture brain action. Its detection technique is based on the electrochemical brain activity. The high temporal resolutions together with the low-cost make EEG device is produced great solution for our research.

In our experiment, we acquire brain activity using EEG equipment, convert and remove artifacts using software, extract and select features characteristic for eye blinks and finally classifies the signal, using the selected features as an eye blinks in the signal. Some parameters involve are eye blink, eye movement, pressure distribution and body temperature.

Eye-blinks is an often unwanted feature found in EEG measurements, due to the eye lid muscles' proximity to the posterior sensors FP1 and FP2 [3]. The signals measured from the muscles have a magnitude 2 much greater than the signals from the brain, and as such they often occlude essential data. Although several methods are available for detection and removal of eye-blinks, their greater magnitude makes them more easily detectable than other features, both visually and analytically – they occur mostly in the 0.5-3 Hz range across the power spectrum [4].

A lot of research has been done on detecting eye blinks using specific features from the data, such as, Cross Correlation [3]; this method is capable of detecting and removing eye-blink artifacts through average and cross-correlation features of the independent EEG components, Power spectrum analysis [4]; this method exploits the lower amplitude signature coming from the FP1 and FP2 sensors, EMCP [5] and ICA; the EMCP method is based on regression while ICA is a blind source separation algorithm assuming statistically independent components. The areas of EEG research concerning eye-blinks to have been done in clinical research, mental state identification, brain computing interfaces, and computer games [6].

3. Methodology

Based on the integrated embedded system and sensor device in [7], the methodologies to display the augmented reality of the prediction and visualization of eye blinks are as follows:

1) Methodology of integrated mathematical modeling involving ANN is based on EEG techniques will be applied to train the discretized data for easy interpretation. The results will be compared to the exact solution from a big data set of eye therapy industry, IC Herbz Sdn Bhd.
2) Discretization of finite different method using some numerical scheme of AGE and RBGS will emphasize to simulate a large sparse linear system of equations (LSE) in (1).
3) The large sparse simulation in (2) is supported by a parallel computing system based on distributed parallel computer systems The four stages of parallel algorithm development on distributed parallel computer systems can be summarized as follows,

a) Partitioning. The computation that is to be performed, and the data operated on by this computation are decomposed into smaller tasks. Practical issues such as the number of processors on the target computer are ignored, and focus attention on recognizing opportunities for parallel execution.
b) Communication. The communication required to coordinate task execution is determined, and appropriate communication structures and algorithms are defined.
c) Agglomeration. The task and communication structures defined in the first two stages of a design are evaluated with respect to performance requirements and implementation costs.
d) Mapping. Each task is assigned to a processor in a manner that attempts to satisfy the competing goals of maximizing processor utilization, minimizing communication costs and determining load-balancing algorithm.

The outcome of the design process will be a SIMD parallel program focuses on tasks dynamically and loads balancing techniques to control the mapping of tasks to processors. Parallel algorithm computation will be supported by a distributed parallel computer system involving heterogeneous computing components connected together through local area network (LAN). These HPC platforms will support the larger computational, enhance a huge memory space and increase the speed up. The software will also be designed and analyzed for the feature of efficiency, distribution, robustness, adapts and stability of the algorithms. the feature of efficiency, distribution, robustness, adapts and stability of the algorithms.

4) Based on [8], the methodology of HPC Library and repository software for the modeling and observation process will be built upon a Linux platform which is open source technology. The algorithm will be programmed with C language while the web development tools will be Perl-CGI, HTML, PHP and MySQL database. The software will also be designed and analyzed for its efficiency, distribution, robustness, adaptive ness and stability of the algorithms.
5) Methodology of numerical analysis, performance evaluations and validation of the sequential and parallel algorithm in (3) is investigated in terms of run time, convergence rate, accuracy, consistency, stability, convergence criterion, root means square error and maximum error. Validation of numerical results, the visualization of (4) and interpretations are based on the real data set from IC Herbz Sdn Bhd.

Implementation and Outcome

This paper focuses on the implementation of ANN algorithms to optimize the observation of EEG record from the sequential and parallel of some numerical methods and its performance analysis. The computing platform of the mathematical simulation is based upon a SIMD architecture of distributed computer systems. The outcome of the training data will predict and monitor the eye blink, movement and muscle stress. The output of this research is a software development involving high-performance library and repository (HPC) software of a big data of EEG record. The function of HPC software is to support the embedded system of WAR (Figure 1). The table and graph are the important output visualization of the high-performance software system.

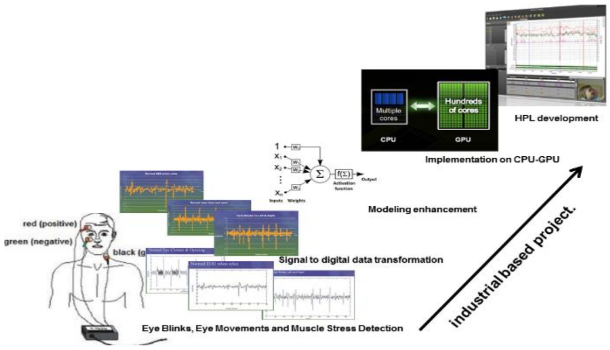

Fig. 1: Methodology Involved for HPL Development.

The validation and analysis of this system are based on numerical analysis and performance evaluations as referred to [8]. Figure 2 (a) shows the sequential algorithm involves computing the mathematical modelling integrated with ANN and EEG signal data. However, the wearable augmented reality is a grand challenge application and involves a large sparse matrix. Thus, an HPC with multiprocessors/CPUs is used to support the huge computation, to reduce computational time and to increase the performance of the programming. The parallel algorithm is presented in Figure 2(b). This figure shows the message passing activity among processors in CPU-GPU computing software.

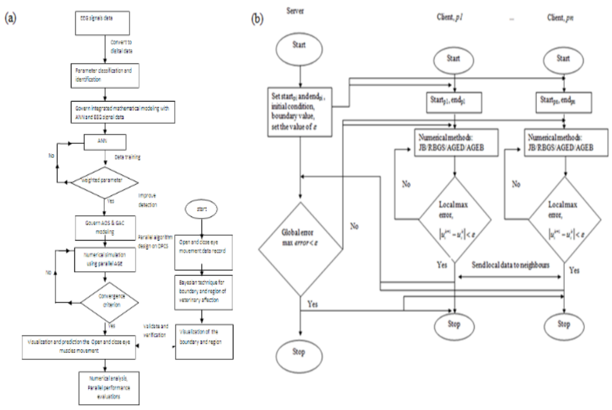

Fig. 2: Sequential and Parallel Algorithm.

4. Results and discussion

The results were divided into two phases. The first is the numerical analysis on the EEG data, and the second is applying ANN of the discretized data. This process has been done using Get Data Graph Digitizer and ANN algorithm. Then, performance analysis has been checked for the absolute error and the accuracy of the integrated algorithm. Figure 3-5 show the graph of digital data from the EEG signal when eyes moved upward and downwards, eye closure and opening and eye move toward the left and right.

No	x	y
1	9.7143	-0.59
2	25.172	0.65
3	38.2948	-0.75
4	50.5314	0.65
5	66.8242	-0.75
6	97.9611	1.03
7	88.9626	-0.58
8	114.0152	0.39
9	120.6448	-0.53
10	142.306	1.14

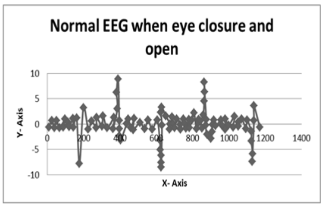

Fig. 3: Graph of Digital Data for Normal EEG Signal with Eye Closure and Opening.

No	x	y
1	8.7379	-0.57
2	17.4757	0.86
3	43.6893	0.19
4	64.0777	-0.046
5	66.9903	0.5256
6	84.466	-0.14
7	93.2039	0.7168
8	110.6796	-0.57
9	125.2427	0.81
10	136.8932	-0.52

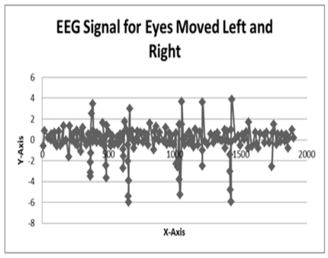

Fig. 4: Graph of Digital Data for Eyes Moved to Left and Right.

No	X	Y
1	-1.6671	0.36
2	15.555	0.6
3	18.7981	-0.54
4	39.57	0.36
5	49.7361	-0.48
6	60.1988	0.42
7	80.7151	-0.17
8	91.1267	0.42
9	90.9426	-0.65
10	115.2021	0.54

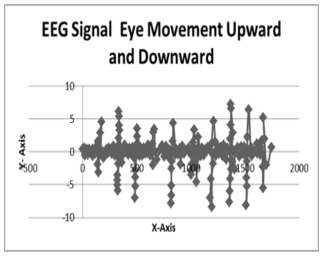

Fig. 5: Graph of Digital Data for Eyes Movement Upwards and Downwards.

4.1. Numerical analysis of EEG signal

Some numerical analysis measurements are applied to analyse the performance of digital EEG data observation. Four measurements are included in this process. There are a number of iterations, time execution, maximum error and root mean square error (RMSE). The performance analysis is compared two numerical methods: Jacobi (JB) and Gauss Seidel (GS). Table 2 shows the numerical analysis of EEG signal for three types of eye conditions, which are: (a) eye open and close, (b) eye moved toward the left and right, and (c) eye moved upwards and downwards.

Table1: Numerical Analysis of EEG Signal for Three Types of Eye Conditions

Conditions	Measurements	GS	JB
(a) EEG signal with eye closure and opening	Time Execution (s)	33084.83	44503.14
	Number of iteration	70	110
	Maximum Error	6.25113e-003	6.18310e-003
	RMSE	1.29159e-005	1.27754e-005
(b) EEG signal when eye moved to the left and right	Time Execution (s)	30811.5	23513.53
	Number of iterations	80	110
	Maximum Error	6.28004e-003	4.89048e-004
	RMSE	1.49622e-005	1.16515e-006
(c) EEG signal when eye moved upwards and downwards	Time Execution (s)	25166.85	85742.84
	Number of iteration	85	130
	Maximum Error	4.9249e-004	4.79184e-004
	RMSE	9.72430e-007	9.46147e-007

Based on Table I, the execution time for GS method is faster than JB method for the condition (a) and (c). However, in the condition (b), GS is faster than JB method. Meanwhile, GS proposed a smaller number of iterations compared to a JB method for all types of eye conditions. Another measurement for numerical analysis is the accuracy. JB gives a smaller value of RMSE compared to the GS. Thus, JB is more accurate than GS. For maximum error, it shows that the maximum error of JB is lower than the maximum error of GS. It is because the number of iterations of JB is much higher than GS.

4.2. Results for ANN method

ANN method focuses on back propagation algorithm as learning algorithm for training process. For this learning phase, the network learns by adjusting the weights so as to be able to predict the correct class label of input samples. Therefore, by using Microsoft Visual C++ Version 2012, the training output was attained. Figure 6 shows the example of the output of normal EEG when relaxes. The assuming is difference condition of the eye has a different value of the output, weight and the predicted values.

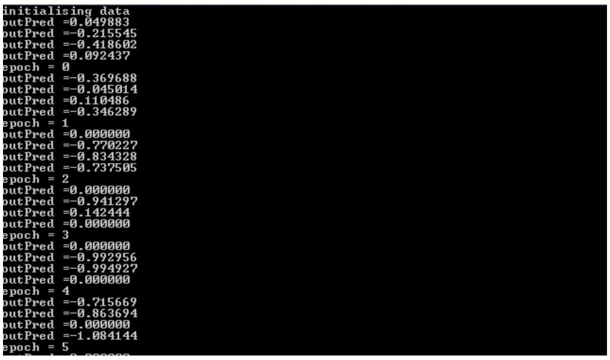

Fig. 6: Some Output for Eye Close and Open Condition.

The comparisons of value were between digital data and ANN output. Digital data are from first part has been listed in ANN data in Table 2-4. An absolute error has been calculated by using the root mean square error. Table 2 indicates the data comparison with the eye close and open. Based on the table, the errors are varying between iteration. The error at iteration two has the least error which is 0.006532. The highest error is at iteration five, which is 0.598984. Then, the following Table III shows the data comparison for left and right eye's condition. At iteration seven, the error is 0.001285. It is the smallest compared to another iteration. The highest error is 0.304367 at iteration six. Last but not least, Table IV is for upwards and downwards condition. The lowest error is 0.021816 while the highest error is 0.397236 at iteration four and nine respectively.

Table2: Accuracy of Eye Close and Open Condition between Digital Data and ANN

N=10	ANN	Digital Data	RMSE
i = 0	-0.418602	-0.59107	0.054539
i=1	0.110486	0.647	0.169661
i= 2	-0.770227	-0.74957	0.006532
i=3	0.142444	0.649479	0.160339
i=4	-0.994927	-0.74678	0.078471
i=5	-0.863694	1.03046	0.598984
i=6	-1.060599	-0.58332	0.150929
i=7	-0.771897	0.386868	0.366434
i=8	-0.788667	-0.52646	0.082917
i=9	0.696522	1.142322	0.140974

Table3: Accuracy of Eye Left and Right Condition between Digital Data and ANN

N=10	ANN	Digital Data	RMSE
i = 0	-0.029323	-0.5712	0.171357
i=1	0.184608	0.85761	0.212822
i= 2	0.223125	0.19163	0.00996
i=3	0.372355	-0.04592	0.13227
i=4	0.155508	0.52558	0.117027
i=5	-0.146562	-0.14062	0.001879
i=6	-0.245742	0.71675	0.304367
i=7	-0.572565	-0.5685	0.001285
i=8	0.00000	0.81284	0.257043
i=9	-0.840946	-0.52019	0.101432

Table 4: Accuracy of Eye Upwards and Downwards between Digital Data and ANN

N=10	ANN	Digital Data	RMSE
i = 0	-0.004134	0.357143	0.114246
i=1	0.0000	0.595238	0.188231
i= 2	-0.630761	-0.53571	0.030058
i=3	-0.364147	0.357143	0.228092
i=4	-0.545177	-0.47619	0.021816
i=5	0.0000	0.416667	0.131762
i=6	-0.621412	-0.17857	0.140039
i=7	-0.687429	0.416667	0.349146
i=8	-1.061997	-0.65476	0.12878
i=9	-0.720458	0.535714	0.397236

Table 5: Execution Time and Number of Iteration for ANN

Conditions	Eye close and eye open	Eye move upwards and downwards	Eye move left and right
Execution time (s)	0.007	0.004	0.006
Iteration	10	10	10

Table 5 indicates the execution time and number of iterations for three types of eye conditions. Based on the result, the fastest condition is eye move upwards and downwards which is 0.004 seconds. For the slow condition is eye close and eye open condition with 0.007 seconds. However, most of the execution time is quite fast because it is less than 1 second. This can show that ANN is a good method. The training process of neural network is efficient and well suited for parallel computing with SIMD architecture because this method can be learned from sample data.

The partial differential equation of mathematical modelling based on the finite difference method (FDM) proposes the parabolic curve to predict the early detection of eye muscle stress problems as shows in Figure 7. This model is using the digital data of EEG as the initial condition of FDM discretization.

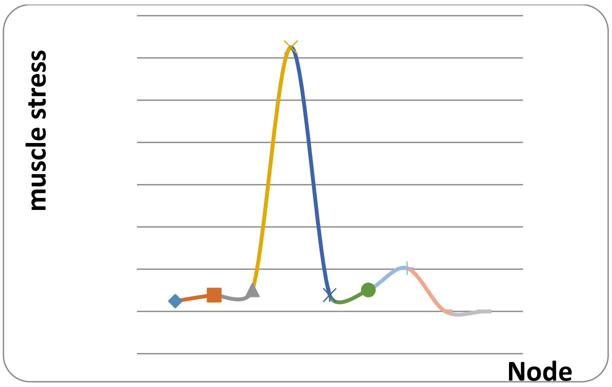

Fig. 7: Parabolic Curve for Visualizing the Early Detection of Eye Muscle Stress.

The visualization of HPC software is presented in Figure 8 below. The data training of EEG record are high potential to observe the future prediction of an eye blink and movement and the level of eye muscle stress.

Fig. 8: The Visualization of HPC Software.

5. Conclusion

The WAR of the eye blinks, movement, and muscle stress are detected and recorded using a digital-to-analogue converter card embedded with the integration of library and repository software. The eye track data is fed directly through the EEG record for the simulation of parameter classification and identification. The governing mathematical modelling integrated with ANN and EEG signal data is solved using some numerical schemes such as JB and GS methods for the numerical comparison by analyzing proven. Based on the results, the integrated ANN for a big EEG data record is considered as an alternative method to produce a set of data training procedure. A high-performance library and repository software, HPC based on the mathematical model using EEG record data is developed for early detection and observation by the real time eye blinks, movement and muscle stress problems.

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