Towards Noise-Enhanced Augmented Cognition

Alexander J. Casson

Department of Electrical and Electronic Engineering,
Imperial College London, SW7 2AZ, UK
acasson@imperial.ac.uk

Abstract. Workload classification Augmented Cognition systems aim to detect when an operator is in a high or low workload state, and then to modify their work flow and operating environment based upon this knowledge. This paper reviews state-of-the-art electroencephalography (EEG) recorders for use in such systems and investigates the impact of EEG noise on an example system performance. It is found that adding up to 15 μV_{RMS} of artificially generated noise still leaves EEG signals that have correlations in-line with the correlations found between conventional wet EEG electrodes and new dry electrodes. The workload classification system is found to be robust in the presence of small amounts of noise, and there is initial evidence of small stochastic resonance effects whereby better performance can actually be obtained in the noisy case compared to the traditional noise-less case.

Keywords: EEG, Augmented Cognition, Workload classification, Noise-enhanced signal processing.

1 Introduction

Augmented Cognition is a recent research concept focusing on creating the next generation of Human-Computer Interaction devices. Closed-loop Brain Computer Interfaces (BCIs) are a classic example of such next generation systems. In these, a human operator uses a computer and interacts with changes on the screen; whilst simultaneously the computer monitors the human and changes its outputs based upon the results. For example, workload monitoring systems aim to detect when an operator is in a high or a low workload state, and use this knowledge to change the speed at which information is presented to the operator. As such the work flow and operating environment can be optimized in a real-time and time-varying manner.

Successful BCI Augmented Cognition intrinsically relies on the availability of portable and easy-to-use brain monitoring technologies. For this there are two practical modalities, functional near-infrared (fNIR) and electroencephalography (EEG). The EEG is the non-invasive recording of *brainwaves* performed non-invasively by placing electrodes on the scalp, and is by far the most commonly used modality. As a result, in recent years there has been a huge amount of research dedicated to improving the EEG unit and the overall recording experience. [1]–[6] represent a small selection of such papers.

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Although both have seen considerable process in recent years the two principle focuses in EEG unit research are well known, and remain: power consumption and dry electrode design. In Section 2 this paper presents a brief review of state-of-art EEG technology for use in Augmented Cognition, highlighting the recent improvements on these two fronts. An in-depth analysis on the impact of recording noise on Augmented Cognition performance is then presented in Section 3. Excess noise in the EEG recording is related to the use of dry electrodes through the correlation coefficients obtained as *clean* EEG signals are corrupted by artificially generated noise. By injecting small amounts of artificial noise into the EEG collected from a workload monitoring task it is shown that the task performance is robust under noisy EEG recordings. Further, initial evidence of small stochastic resonance effects, where the system performance actually improves in noisy conditions, is found.

2 Portable EEG for Augmented Cognition

2.1 EEG Recorders

Table 1 summarises the features of state-of-the-art low channel count EEG systems that are potentially suitable for non-obtrusive EEG brain monitoring in Augmented Cognition applications. Low channel counts are sufficient for many applications, and for Augmented Cognition the need for recorders that are discrete, socially acceptable, and quick to set up, places a strong emphasis on the use of a low number of channels.

From Table 1 it can be seen that a number of high quality, highly miniaturised units are now available commercially. These can easily offer over 8 hours of recording time, likely sufficient for any individual protocol in an Augmented Cognition experiment. Nevertheless, one day of recording, allowing a complete sleep-wake cycle to be captured, should be the aim for future high-quality units. (In any case, even the best clinically attached wet electrodes begin to fall off after this time.) This 24 hour level of power consumption is starting to be met by research stage units.

However this still falls far short of *pick up and use* devices. Substantial improvements in system power consumptions will be required to realise units that can be trusted to be re-usable session after session. Although current batteries guarantee that a wanted protocol is feasible, it remains a common experience to have to worry about battery charge, or to have to adjust experiment timings after discovering that a unit was not adequately charged. Tackling this is essential for engendering user trust and reliability in Augmented Cognition systems. Onboard signal processing for providing the first level analysis of the EEG data is a promising approach for further power consumption reductions, but implementing complete and accurate algorithms within the limited power budget available remains a major challenge [1].

Looking further ahead, the EEG technology itself is evolving. For example, [4] reported the use of very small, flexible, textile based EEG units. These are applied directly to the scalp as a *tattoo* and, if forehead only channels are required,

Table 1. Approximate specifications of state-of-the-art low channel count EEG systems for use in Augmented Cognition. Many devices come in different models and configurations; only one potential configuration is reported here. Physical sizes are as given by the manufacturer and are not directly comparable: some are for the recorder unit alone while others are for the complete EEG system.

Device	Channels	Sampling frequency / Hz	Resolution / bits	Size / mm	Weight / g	Battery life / hours	Wireless?	Dry electrodes?	Status
Actiwave [7]	4	128	8	37× 27× 8.5	8.5	13	No	No	Commercial
Emotiv [8]	14	128	14	–	116	12	Yes	No	Commercial
B-Alert [9]	4	256	16	127× 57× 25	110	8	Yes	No	Commercial
NeuroSky [10]	1	512	12	225× 115× 165	90	8	Yes	Yes	Commercial
Sleep zeo [11], [12]	1	128	12	–	24	8 (1 night)	Yes	Yes	Commercial
Enobio [13]	8	500	24	225× 115× 165	65	8	Yes	Yes	Commercial
Quasar [14]	12	240	16	–	500	24	Yes	Yes	Commercial
IMEC [15], [16]	8	1000	12	35× 30× 5	100	22	Yes	Yes	Research
MINDO [17]	4	512	16	165× 145× 50	100	20	Yes	Yes	Research

eliminate much of the wiring involved in the EEG collection and are very inconspicuous. [18] presented a new approach for recording the EEG from the ear canal using a modified hearing aid. This is a very interesting development because the recording location is accessible, it intrinsically holds the electrodes in place, and hearing aids are already very socially acceptable. It also allows a single unit that can collect free-running EEG and auditory steady state responses, while simultaneously collecting a heartbeat record and providing classic hearing aid functionality. Both of these developments are at an early stage, but hold significant promise for future use in Augmented Cognition applications.

2.2 Electrode Technologies

Also apparent from Table 1 is the increasing availability of dry EEG electrodes which do not require a conductive gel to operate. Most of these electrodes are now based upon having *fingered* electrodes, rather than *discs*, for easier penetration through the hair (see for example [19]). It is clear that making a fundamentally gel free recording is no longer a major challenge. However, there are outstanding challenges in how to actually keep the electrodes in place without a cap or tight headband. Furthermore, electrode availability does not mean that these electrodes get comparable performance to conventional wet Ag/AgCl EEG recording electrodes.

In-depth measurements of dry electrode performance have been presented [6], [20], [21] but most studies only report a correlation coefficient between EEG recorded at nearby locations with wet and dry electrodes. Typical values reported are: >0.93 [3]; 0.89 [22]; 0.83 [23]; 0.81–0.98 [15]; 0.68–0.90 [16]; 0.39–0.85 [24]. For greater acceptance of dry electrodes the wider reporting of the second order electrode properties is essential. In particular: the half-cell potential, the long term stability and the contact noise. The latter is known to be a function of electrode contact area [25], which is decreasing with the move to fingered electrodes. To begin to evaluate the impact of this, the remainder of this paper investigates the effect of excess recording noise on a workload monitoring Augmented Cognition task.

3 Noise-Enhanced Augmented Cognition

3.1 Noise Correlation

Noise robustness is a clear requirement of Augmented Cognition systems that must operate in non-controlled environments. Excess recording noise from any source cannot be allowed to have a substantial detrimental effect on the system performance. To investigate this, Fig. 1 shows the correlation coefficient calculated between a raw recorded EEG trace and the same EEG trace after it has had artificial white Gaussian noise deliberately added to it. The additive noise generation procedure is detailed in [26]. In Fig. 1, the artificial noise is added to a complete 12.5 hour EEG recording (using the publicly available data from [27],

[28]). This long EEG record is then split into multiple shorter duration EEG sections, and the correlation in each section plotted against the duration of these shorter sections. This allows the maximum, minimum and median correlation coefficients over time to be found.

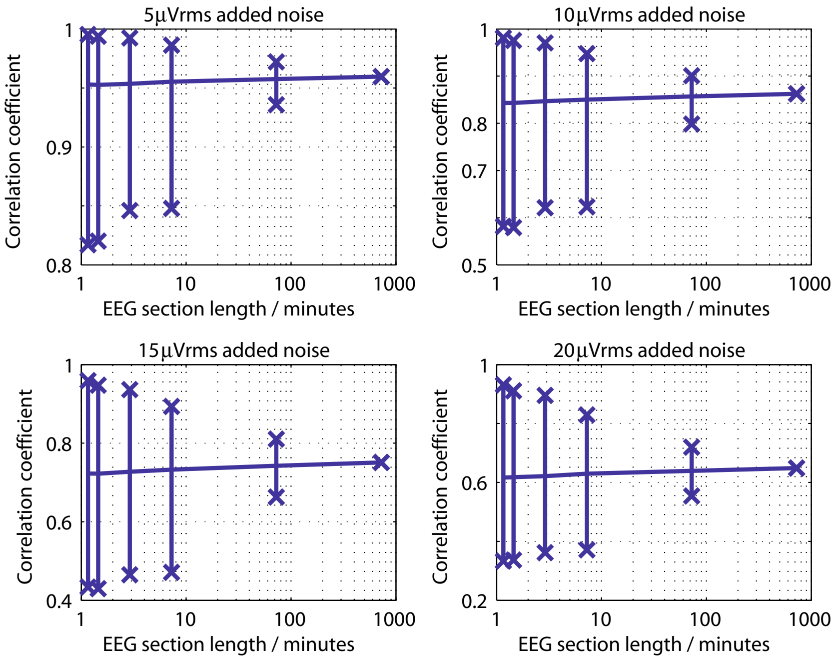

Fig. 1. Correlation coefficients between a raw EEG trace and a noise corrupted copy of the same EEG trace as the EEG section length used for calculation is changed. Vertical lines show the maximum, minimum and median correlation values found over a complete 12.5 hour EEG recording.

From Fig. 1 it is clearly seen that the underlying correlation present is not accurately estimated when very short sections of data are analysed. There is a consistent tendency for the median correlation to be underestimated at the cost of much larger variances. As a result, in some cases only testing the correlation in short EEG records will lead to a significant overestimation of the true correlation present. Importantly, even with up to 15 μV_{RMS} of artificial noise added to the raw EEG traces, correlations in-line with those reported for dry electrodes are found.

It is therefore essential to investigate the impact of this noise on Augmented Cognition system performance. Moreover, recent results have shown that some EEG applications are not only robust in the presence of more noise, but actually get better performance [26]. Such *stochastic resonance* has been observed in many physical systems [29] and could have a big impact on EEG in Augmented

Cognition. For example, is it necessary to design electrodes to have the minimum contact noise anyway?

3.2 Noise-Enhanced Processing

These effects are investigated here using an EEG workload classification system based upon the publicly available data from the 2011 Cognitive State Assessment Competition [30], [31]. In this, participants were asked to perform a workload engagement task [32], [33] which altered the difficultly and required attention level between high and low workload states. Nineteen channels of EEG data were recorded, and the experiment was run on each person multiple times on the same day, and on different days. The objective is to use only the EEG data to recognise the operator's state as either high or low workload.

Fig. 2 shows the performance of a new Artificial Neural Network based workload monitor on the data from two subjects. The used network is a simple feed-forward patternnet with 10 hidden neurons with features from standard FFT frequency bands and time domain features including line-length. These are calculated from all 19 EEG channels. The used Artificial Neural Network is trained using the first recording session from day 1. The test data is then taken as the two other recording sessions on day 1, and the three from day 2. Fig. 2 shows that the Artificial Neural Network performs well on day 1, the same day as the

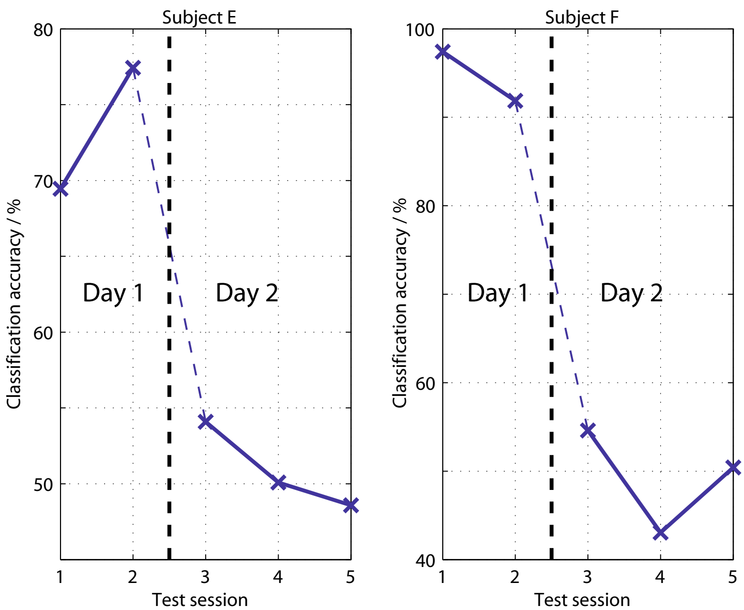

Fig. 2. Performance of an Artificial Neural Network workload monitor using data from two subjects recorded on two subsequent days. Data is taken from the 2011 Cognitive State Assessment Competition [30], [31].

training data is from. However, by day 2 (the next day) the network performance has degraded substantially and is no better than chance.

This result, using a different Artificial Neural Network, replicates the results reported in [30], [31] which demonstrated that the performance of some workload classification systems degraded significantly as the time gap between the training and testing sessions increased. Clearly such systems are not reliable and reusable. Re-training of the network is required each day and this comes with a high time cost. There are now open research questions over the causes of these performance decreases, and potential approaches for mitigating them.

The impact on this situation from adding artificially generated noise to the raw EEG traces is shown in Fig. 3. *Training with noise* is a common technique used to increase the accuracy of Artificial Neural Networks by adding small levels of noise to the training data before training the network [34]. The aim is to do this multiple times and make the available training data more variable and more representative of future unknown data. *Testing with noise* is a novel approach introduced here where independently generated noise is also added to the EEG data used for testing. This therefore simulates the use of a more noisy EEG recorder for obtaining the test data. It also simulates the potential use of low-power, low-accuracy circuit structures in the EEG unit in place of conventional higher-accuracy, higher-power structures. As such the noise results here are useful for creating even low power consumption EEG processing electronics.

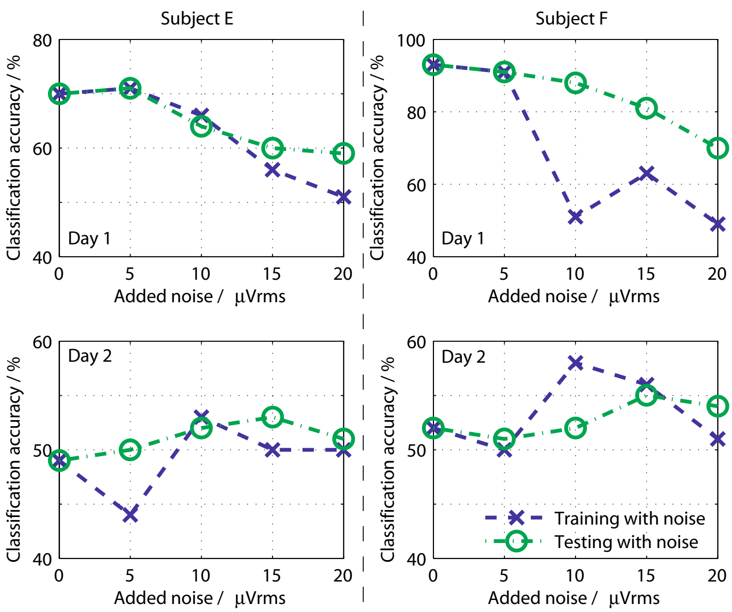

Fig. 3. Performance of an Artificial Neural Network workload monitor as artificial noise is deliberately added to the training and test data. Plotted results show the average performance the test sessions on each day (two on day 1 and three on day 2).

From Fig. 3, in both subjects the presence of excess noise in the EEG recording does not intrinsically stop the workload classification process. Robust performance is maintained when small amounts of noise are present. Moreover, several instances of performance improvements are present. Considering day 1, in Subject E a small performance resonance is present with better classification accuracies being obtained when 5 μV_{RMS} of noise is deliberately added to the EEG signals. In Subject F no resonance is seen, but there is no substantial decrease in performance. On day 2, better classification performance is obtained at many different noise levels compared to the no noise case. This effect is small, and the issue with performance degradation over time is not fixed: in neither of the cases considered here does the performance improve to a level substantially above chance classification. Nevertheless, this demonstration of stochastic resonance effects is an important new result for Augmented Cognition systems. If this effect can be isolated and improved upon, noise enhanced processing could be an important new tool for creating robust and reusable Augmented Cognition systems that can work autonomously over a number of days.

4 Conclusions

Stochastic resonance is an effect whereby noise embedded in a signal leads to better overall performance compared to a no noise case. This paper has demonstrated that EEG systems are now readily available with dry EEG electrodes for quick and easy set ups. These electrodes produce EEG signals with high correlations when compared to conventional wet electrodes, but similar correlations can be obtained when using EEG signals which have been artificially corrupted by up to 15 μV_{RMS} of noise. Using an EEG based Artificial Neural Network workload classification system as an example this paper has shown that the system performance is maintained under such noise levels. Indeed there is initial evidence of stochastic resonance effects, with consistently better performance being obtained on next day workload classifications tests as more noise is added to the EEG data. At present these stochastic resonance effects are very small, but suggestive, and future work investigate their full exploitation.

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