Improving Physiological Signal Classification Using Logarithmic Quantization & a Progressive Calibration Technique

Anonymized Authors
Anonymized Institution
Anonymized Institution
Anonymized Emails

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Abstract: Physiological signals vary widely between persons, and even within individuals, over time. As a result, applications with physiological inputs usually require repeated calibration. Application designers face a tradeoff between computational complexity, calibration time, and classification accuracy. In this paper, we describe a data quantization technique that increases the computational speed associated with calibrating of power spectrum time series data. We test this technique on electroencephalograph (EEG) signals by simulating the calibration of a binary brain-computer interface (BCI). We find that we can increase the computational speed associated with training a machine-learning based classifier 4.5 times without a significant detriment to the system's accuracy. A progressive calibration strategy achieves high accuracy in 86.6% of subjects with under five minutes of quantized calibration data, and in 100% of subjects with under 15 minutes. We discuss implications for consumer BCI devices and for physiological computing applications generally.

1 INTRODUCTION

Physiological data do not carry universal meanings. While the movement of a computer mouse can be mapped to the position of a cursor in a straightforward manner, the expression of bio-signals varies widely between individuals, and often changes within individuals over time. Brain-computer interface (BCI) serves as a good example of this phenomenon: regular calibration and re-calibration are essential due to the personal and non-stationary nature of neural signals (Dornhege, 2007; McFarland and Wolpaw, 2011).

Supervised learning algorithms have enabled systems to adapt to users' personal physiology after a calibration period. In BCI, this approach has yielded proof-of-concept systems ranging from brain-controlled keyboards and wheelchairs to prosthetic arms and hands (Blankertz et al., 2007; Millan et al., 2010; D. Mattia, 2011; Hill et al., 2014; Campbell et al., 2010).

Moving from laboratory settings into the real world, these systems have fewer and less sensitive sensors due to cost, ergonomic and aesthetic considerations. They also process noisier signals as data acquisition increasingly occur while people are engaged in everyday activities: walking, talking, sleeping, and so on. As an additional challenge, computational complexity, measured by both storage and processing requirements, may be limited by the mobile and wearable computing architectures, on which these systems are deployed.

In this paper, we study how the processing of physiological signals and the strategy for user calibration can impact the performance of a machine-learning based bio-signal classification system. We use signals acquired from a low-cost, mobile electroencephalograph (EEG) device with a single sensor. Prior to classification, how can we characterize the tradeoff between computational complexity and classification accuracy at the signal processing step? Given a well-tuned classifier, is it possible to achieve user calibration on the order of minutes rather than hours or days?

We propose a novel signal quantization technique that applies logarithmic binning to power spectrum data from a single EEG electrode. We find that this technique can increase the computational speed of a classification-based BCI by 450% compared to uncompressed data without significant detriment to system accuracy. In conjunction with a progressive user-calibration protocol, in which candidate mental gestures are tested "on demand" in order to minimize calibration time, we calibrate 86.6% of users to a threshold of BCI control in under five minutes of training data, and 100% of users in under 20 minutes.

This paper is organized as follows. We discuss related works in Section 2, and provide a summary of the dataset in Section 3. We describe our signal quantization method in Section 4, and quantify its effect on classifier speed and accuracy in Section 5. We evaluate a user calibration strategy in Section 6 before concluding.

2 RELATED WORK

2.1 Calibrating EEG-based BCI

Generally, BCI systems aim to recognize a user's mental gestures as one of a finite set of discrete symbols, a problem that can be framed as a pattern recognition task (Lotte et al., 2007). The difficulty of this task stems primarily from the variable and nonstationary nature of neural signals: the "symbols" are expressed differently between individuals, and even vary within individuals based on mood, stress, and other factors (Vidaurre et al., 2011).

In order to compensate for variability in BCI signals, recent work has leveraged adaptive classification algorithms to distinguish between mental gestures (Lotte et al., 2007; Vidaurre et al., 2011; Friedrich et al., 2013). Automated calibration procedures have turned BCI novices into competent users over the course of hours instead of days or weeks, and without manual calibration (Vidaurre et al., 2011). During calibration, users perform "labeled" (that is, known) mental gestures in order to produce samples for the classifier.

2.2 Statistical Signal Processing in EEG-based BCI

To account for the nonstationarity of EEG signals and the need for regular calibration, recent work has leveraged machine learning algorithms capable of adapting to their inputs. Support vector machines (SVM) are a set of supervised machine learning methods that take labeled example data to create a model. This model can be used to predict the classes of unlabeled data. SVMs use a hyperplane (an n-dimensional construct in an n+1 dimensional space) to draw discriminatory boundaries between classes.

Past work has used linear SVMs in BCI applications (Garrett et al., 2003; Grierson and Kiefer, 2011). SVMs select the hyperplane that maximizes distance from the nearest training points, which has been shown to increase the model's generalizability (Burges, 1998).

SVMs suffer from a property known as "the curse of dimensionality": larger feature vectors require an exponential increase in the amount of data needed to describe classes (Jain et al., 2000). Traditionally, BCI applications rely on dense, high-dimensional feature vectors produced by multi-electrode scanning caps with high temporal resolution (Lotte et al., 2007), which threatens the responsiveness of BCI from a user experience standpoint and places high requirements on end users' hardware.

2.3 Brain-Computer Interface "in the Wild"

Recent years have seen the emergence of a consumer market for inexpensive, mobile EEG devices. Compared to medical-grade scanning devices, these headsets have significantly fewer electrodes and therefore much lower spatial resolution. Most of them employ dry contact electrodes, which produce noisier signals (De Vos and Debener, 2014). Nonetheless, researchers have demonstrated several mobile-ready BCI systems that use these devices to detect emotional states, event-related potentials (ERP), and demonstrate the feasibility of brainwave-based biometric authentication (Crowley et al., 2010; Grierson and Kiefer, 2011; Chuang et al., 2013; Johnson et al., 2014).

However, the use of consumer EEGs for the direct, real-time control of software interfaces has proven more difficult, as the number of electrodes on these headsets limit the spatial resolution required to discriminate between mental gestures (Carrino et al., 2012; Larsen and Hokl, 2011). Even with improvements over successive generations of consumer-grade EEG devices, the signal from these devices will remain noisier than professional scanning devices, as users will be wearing and using them in everyday settings, with ambient electromagnetic signals interfering with endogenous bio-signals.

3 DATA

We obtained an anonymized dataset of EEG recordings from 15 subjects, all students at UC Berkeley, performing seven mental gestures in a sitting position over two sessions (Chuang et al., 2013). The signals were recorded using a consumer-grade EEG headset, the Neurosky MindSet, with a dry contact EEG sensor over the Fp1 position. The power spectrum time series data were recorded using the Neuroview Software. Participants performed each of the seven mental gestures ten times. Each of the ten trials lasted ten seconds. The seven mental gestures were: (i) breathing with eyes closed; (ii) motor imagery of right index finger movement; (iii) motor imagery of subject's choice of repetitive sports motion; (iv) mentally sing a song or recite a passage; (v) listen for an audio tone with eyes closed; (vi) visual counting of rectangles of a chosen color on a computer screen; and (vii) any mental thought of subject's choice as their chosen "password".

The power spectrum time series data consists of one power spectrum every 0.5 seconds. Therefore, for a 10 second recording, we have a sequence of 20 power spectra. Each power spectrum contains frequency components from 0 Hz to 256 Hz at 0.25Hz intervals. Therefore there are 1024 values reported for each power spectrum.

The dataset was further cleaned by removing all readings marked as having suboptimal signal quality by the Neuroview Software. The Neuroview Software delivers a signal quality value that is greater than zero when signal quality is suboptimal. Factors causing this value to be greater than zero include lack of contact between the electrode and skin, excessive non-EEG noise (e.g., EKG, EMG, EOG, electrostatic), and excessive motion.

At this point, each mental gesture is represented by ten trials, each trial consisting of a time series of 20 power spectra. Each power spectrum is comprised of 1024 frequency readings.

4 SIGNAL QUANTIZATION FOR RAPID CLASSIFICATION

Our objective is to maximize the accuracy of the classifier while minimizing its computational expense. One way to reduce the computational requirements of a classifier is to reduce the size of the feature vectors on which it is trained and tested. We propose a signal quantization method that allows us to directly adjust the size of feature vectors by changing the signal's resolution. This allows us to operationalize a tradeoff between the running time and accuracy of the classifier.

We compress the power spectrum time series in the temporal dimension. Given a sequence of 20 power spectra (from a 10 second trial), with 1024 frequency components per spectrum, we compute a discrete probability density function (pdf) in which each component is the mean of its corresponding frequency components through time. This results in a discrete pdf with 1024 components for each trial.

4.1 Logarithmic Binning

Since EEG activity is associated with frequencies from 1-40Hz, we presume this range contains the majority of relevant signal. However, this frequency range can be polluted with non-neural signals (Ball et al., 2009), and we do not rule out the possibility that useful signal exists in other frequency ranges as well. Muscular activity, for example, might be correlated with mental gestures in some cases. In order to exploit the entire frequency spectrum while preserving our bias toward known sources of useful signal, we select a logarithmic spacing of the data bins through the pdf. Figure 1 shows an example of logarithmic binning with 100 bins. It offers a 10x compression ratio while still preserving the structure of the original 1024-point pdf.

We apply the quantization step by performing data binning on the probability density function. Data binning offers a simple way to "quantize" the information contained in the full signal. By taking the mean of several adjacent points in the pdf, we are left with a single bin that compresses the information contained in its local area of frequencies. For instance, four contiguous frequencies (1Hz, 1.25Hz, 1.5Hz, 1.75Hz) of the values (4, 4, 5, 5) could be combined into a single bin with the value 4.5. The number of bins can be chosen to provide a desired level of resolution on the signal.

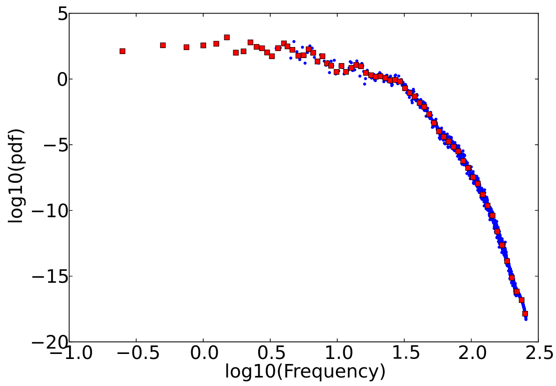

Figure 1: In double logarithmic scale, the original 1024 bins (blue dots) of the probability density function (pdf) obtained from averaging the n power spectra of one recording, and the resulting "quantized" pdf with a resolution of 100 log-bins (red dots). The quantized pdf preserves very well the structure of the original, 1024-point pdf.

The output of the logarithmic binning step is a single feature vector, whose size is controlled by the number of bins. This vector can now be used as an input into the classifier.

4.2 Binary BCI Classifier

To test the performance of the quantization method, we build a binary BCI using a support vector machine (SVM) classifier, which we train individually on each subject's recordings while varying the bin size. We use LinearSVC (Fan et al., 2008), a wrapper for LibLinear exposed in Python through the scikit-learn library (Pedregosa et al., 2011). We chose LinearSVC because BCI classification problems are generally presumed to be linear (Garrett et al., 2003; Lotte et al., 2007), and because LibLinear's underlying C implementation boasts among the fastest train- and test-time performance among state-of-the-art solutions (Fan et al., 2008). We use a hyperparameter of 100, found through a "grid search", or an exhaustive search through a randomly-selected sample of our dataset. We use scikit-learn's built-in cross-validation toolkit, which performs seven cross-validation steps using different splits of data in each round.

Out of the seven mental gestures in the dataset, we want to identify and select, for each individual subject, the two best gestures for that subject. This results in a personalized binary (two-class) classifier, where the SVM can discriminate between two mental gestures performed by the subject with the highest classification accuracy. The gesture-pairs may vary from subject to subject. For example, one subject's best-case pair may be *song* and *sport* while another's may be *color* and *finger*.

5 EFFECT OF QUANTIZATION ON CLASSIFIER SPEED AND ACCURACY

We hypothesize that both the SVM training time and accuracy increase with signal resolution, i.e., the greater the number of bins, the higher the accuracy but also the longer the training time.

For each subject, we generate every pair of two mental gestures and cross-validate our SVM on the recordings for this pair. Given seven candidate gestures, we have a total of 21 possible gesture pairs. For every pair, we vary the signal resolution by varying the number of bins from 1 to 1024. For every pair processed, we record mean classification accuracy across all rounds of cross-validation. For each subject, we record the best-performing pair, which corresponds to our estimation of optimal performance of the BCI for that subject.

As an additional performance audit, we measure the time needed to fit an SVM to the data for two randomly selected gesture pairs across all subjects. We repeat this process ten thousand times at different resolutions, collecting the minimum time observed in each series of attempts.

Figure 2 shows the mean best-case accuracy of the classifier versus the number of bins. We can see that the accuracy level remains above 90% even as we reduce the signal resolution down to 100 bins. Although classifier accuracy is positively correlated with signal resolution (Slope = 0.0013, R-squared = 0.773, p $<$0.001), this effect appears only at resolutions lower than 100 bins. We find no significant difference in SVM accuracy at resolutions over 100 bins.

Figure 3 shows, in log-log scale, the SVM training time versus the number of bins. We see that the log of the classifier training time is positively correlated with the log of signal resolution (Slope = 0.5, R-squared = 0.947, p $<$0.001). We also observe an increase in variance in the data, possibly due to variability in memory read and write times, which exacerbates SVM training time at larger vector sizes (as more reads and writes are being performed).

Combining these two results, Figure 4 confirms the tradeoff between classifier accuracy and classifier training time. It also points to the existence of a threshold resolution at around 100 bins that provides a 450% speed improvement over a non-quantized baseline of 1024 bins without a significant detriment to classifier accuracy.

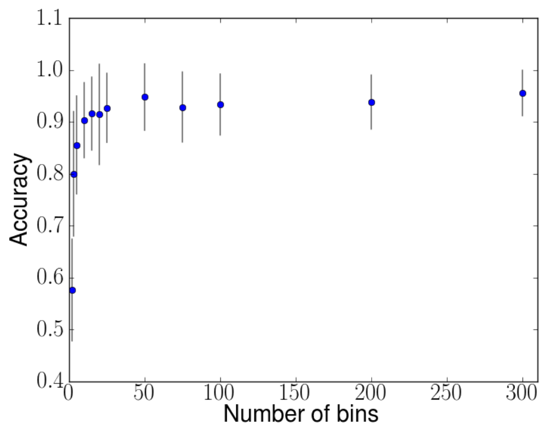

Figure 2: Mean best-case accuracy among all subjects compared to signal resolution. At resolutions of 100 points (bins) and greater, we find no evidence of an increase in classification accuracy.

Overall, we find that relatively small feature vectors produced with our method (100 values) yield classifiers as accurate as full-resolution samples (1024 values), and that reducing vector size in this way can dramatically increase computational speed.

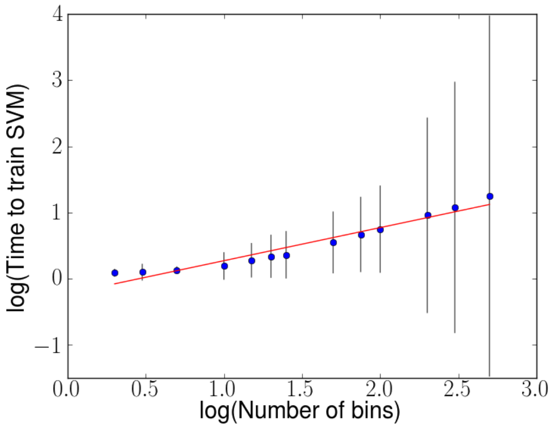

Figure 3: Log of mean classifier training time compared to log of data resolution. The slope is 0.5, indicating that the time needed to train the classifier increases as approximately the square root of the signal resolution.

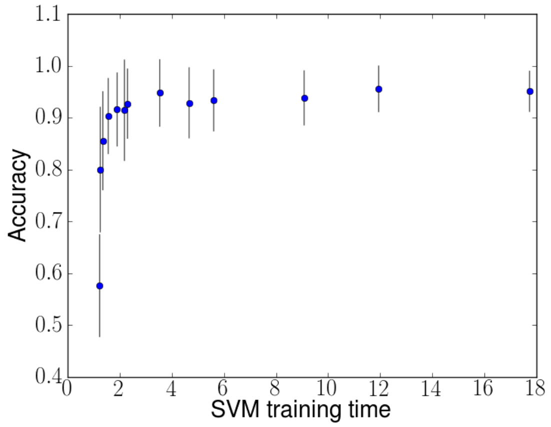

Figure 4: Best-case accuracy compared to the time needed to train the classifier. By decreasing the number of bins in the EEG data, we can decrease the time needed to train the support vector machine up to nine times without without significant detriment to classifier accuracy.

6 PROGRESSIVE STRATEGY FOR CALIBRATING A BINARY BCI

In the previous section, we found that our compression technique can speed up an SVM classifier without significant detriment to BCI accuracy. However, it must also allow users to quickly calibrate the system to their personal physiological signals.

In this section, we evaluate a strategy for user calibration in which mental gestures are recorded progressively on an "as needed" basis. Using quantized signals with a resolution of 100 bins, we measure user calibration time (the time it takes a user to achieve a threshold accuracy with the BCI) and the classification accuracy each user achieves after calibration.

Our calibration strategy takes sixty-second sample recordings of mental gestures and splices them into 120 $1/2$-second chunks. By performing sevenfold cross-validation on sample data from a pair of mental gestures, we make an estimate of how easily discriminable these gestures are by our classifier. With this technique, we only need to identify the most promising (highest-performing) of candidate gesture pairs for further testing

In addition, we seek to minimize the amount of time users spend recording samples of mental gestures. One way to minimize this time is to first test the subset of gestures most likely to yield strong performance. For each subject, we perform an exhaustive search of the 21 best-performing gesture pairs and record the frequency of each gesture's occurrence in a best-case pair (Table 1). Assuming that we can establish a consistent ordering of best-performing mental gestures for a target population, we use this data to inform the order in which our calibration strategy prompts the user to perform gestures.

Gesture	Frequency
color	10
breathing	5
pass	4
sport	3
finger	2
song	2
audio	2

Table 1: Frequency of each mental gestures's occurrence in a pair that achieves highest classification accuracy for a subject.

The progressive strategy starts with three gestures most commonly associated with best-case performance (*color*, *breathing*, *pass*) for an initial user calibration time of 180 seconds (60 seconds per gesture). We then cross-validate every permutation of two of these gestures (i.e., *color* versus *breathing*, *color* versus *pass*, *breathing* versus *pass*). The gesture pair with the highest mean score across cross-validation rounds is selected for an additional testing session, in which the remaining 80 seconds of recordings for both gestures are used to generate an estimate of the classifier's accuracy on new EEG signals.

If the score on this additional testing procedure is below 75%, a commonly used threshold for BCI literacy (Vidaurre and Blankertz, 2010), the user will be prompted to record sixty seconds of the next candidate mental gesture (e.g. *sport*). We repeat the above process on unexplored pairs until a pair achieves over 75% accuracy on post-calibration data, or until all combinations have been evaluated.

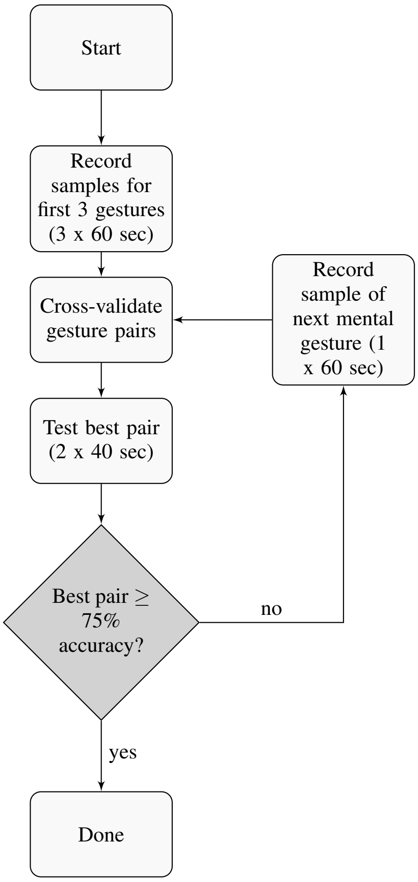

Figure 5: Progressive calibration routine. We begin with 60 second recordings of the three best-performing gestures (Table 1). We then perform seven-fold cross-validation on each pair of gestures. The pair that scored highest on cross-validation is selected for testing on an additional 80 seconds of data, 40 from each gesture. If this test fails to reach 75% accuracy, we prompt the user to record a 60 second sample of the next highest-scoring gesture and repeat the cross-validation process on all new (unexplored) gesture pairs.

For the given set of seven candidate gestures, the baseline exhaustive search strategy requires 2100 seconds of calibration time (60 seconds times 7 gestures plus 80 seconds times 21 gesture pairs) and produces an average accuracy of 92.5% across subjects (σ = 0.09). Our progressive strategy takes an average of 374.6 seconds of calibration time (σ = 52.2) and produces an average accuracy of 88.3% (σ = 0.11).

Figure 6 shows the results from a subject's perspective. Out of 15 subjects, the progressive calibration strategy allows 66.7% (10 subjects) to be calibrated in under 5 minutes, and 86.7% (13 subjects) in under 6 minutes. The remaining two subjects were calibrated in 11 minutes and 22 minutes, respectively. All 15 subjects achieve a minimum of 75% classification accuracy. Six subjects (40%) achieve 100% accuracy.

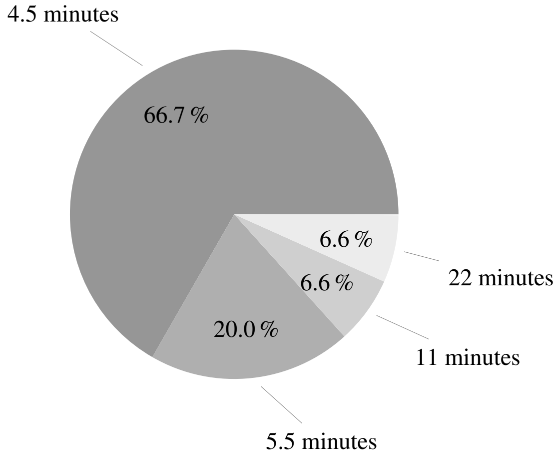

Figure 6: Calibration time across subjects (top) and classifier accuracy (bottom). The vast majority of subjects achieve acceptable accuracy in under five minutes of training, and all subjects achieve BCI literacy in under 22 minutes.

Our strategy calibrates users to BCI control significantly more quickly than an exhaustive search, and we do not find a significant difference in per-user accuracy between our progressive strategy and an exhaustive search.

7 CONCLUSION

In this study, we investigated the effect of a signal quantization technique on the performance of a binary BCI that uses a low-cost, single-channel EEG headset as input. We find that our technique allows for a computationally efficient BCI, which can achieve good simulated accuracy for all subjects in our dataset, and boasts quick user calibration times.

Specifically, we find that our quantization method decreases the computational expense of EEG-based calibration (from 18 ms to 2 ms for SVM training time) without a significant detriment to accuracy and, using quantized data, our progressive user calibration strategy achieves an average of 88.3% accuracy across all subjects. All subjects require under 22 minutes of calibration time, and 86.6% of these subjects require 6 minutes or fewer"

The conclusions to be drawn from this study are limited in a few regards. First, calibration and classification are performed offline, so factors involving the user interface (such as feedback) are not taken into account. We cannot be sure, for instance, that our findings based on the splicing of 10-second-long recorded data will persist when a system solicits recordings of only a second or under. Furthermore, a few of the gestures (e.g., the *color* labeled gesture) relied on exogenous stimuli, which may be impractical in naturalistic settings for ergonomic reasons.

Our study implies that practical BCI can be achieved with as few as one inexpensive EEG sensor, minimal processing power, and a only a few minutes of user calibration. Future work could build usable, online BCI systems to test this claim more rigorously, especially in mobile and out-of-lab environments.

Since many types of physiological data can be represented as power spectra (e.g., electrocardiography, electromyography), future work could test our quantization technique in other classification-based physiological applications, such as heart sensing, gesture recognition, or systems with heterogeneous sensors.

Logarithmic binning dramatically decreases the size of physiological data in memory. This technique could allow developers to more easily ship bio-signals to remote servers. Future work could explore the design space associated with the storage and transmission of physiological signals. BCI calibration, for example, could occur "in the cloud" where the client would quantize power spectra data using our method before shipping these compressed data to a more powerful server in the network.

Alternatively, the small size of quantized feature vectors could enable long-term, pervasive recording of mental states. The data would be small enough to ship and store on a centralized server, or to store locally in a decentralized fashion. Monitoring mental and other biophysical activity continuously in everyday settings could yield novel observations about human activity & physiology.

REFERENCES

Ball, T., Kern, M., Mutschler, I., Aertsen, A., and Schulze-Bonhage, A. (2009). Signal quality of simultaneously recorded invasive and non-invasive eeg. *Neuroimage*, 46(3):708–716.

Blankertz, B., Krauledat, M., Dornhege, G., Williamson, J., Murray-Smith, R., and Mller, K.-R. (2007). A note on brain actuated spelling with the berlin brain-computer interface. In Stephanidis, C., editor, *Universal Access in Human-Computer Interaction. Ambient Interaction*, number 4555 in Lecture Notes in Computer Science, pages 759–768. Springer Berlin Heidelberg.

Burges, C. (1998). A tutorial on support vector machines for pattern recognition. *Data Mining and Knowledge Discovery*, 2(2):121–167.

Campbell, A., Choudhury, T., Hu, S., Lu, H., Mukerjee, M. K., Rabbi, M., and Raizada, R. D. (2010). NeuroPhone: brain-mobile phone interface using a wireless EEG headset. In *Proceedings of the second ACM SIGCOMM workshop on Networking, systems, and applications on mobile handhelds*, page 38. ACM.

Carrino, F., Dumoulin, J., Mugellini, E., Khaled, O., and Ingold, R. (2012). A self-paced BCI system to control an electric wheelchair: Evaluation of a commercial, low-cost EEG device. In *Biosignals and Biorobotics Conference (BRC), 2012 ISSNIP*, pages 1–6.

Chuang, J., Nguyen, H., Wang, C., and Johnson, B. (2013). I think, therefore i am: Usability and security of authentication using brainwaves. In Adams, A., Brenner, M., and Smith, M., editors, *Financial Cryptography and Data Security*, volume 7862 of *Lecture Notes in Computer Science*, pages 1–16. Springer Berlin Heidelberg.

Crowley, K., Sliney, A., Pitt, I., and Murphy, D. (2010). Evaluating a brain-computer interface to categorise human emotional response. In *ICALT*, page 276278.

D. Mattia, F. Pichiorri, M. M. R. R. (2011). Brain computer interface for hand motor function restoration and rehabilitation. In *Towards Practical Brain Computer Interfaces*. Springer, Biological and Medical Physics, Biomedical Engineering.

De Vos, M. and Debener, S. (2014). Mobile eeg: towards brain activity monitoring during natural action and cognition. *International journal of psychophysiology: official journal of the International Organization of Psychophysiology*, 91(1):1–2.

Dornhege, G. (2007). *Toward Brain-computer Interfacing*. MIT Press.

Fan, R.-E., Chang, K.-W., Hsieh, C.-J., Wang, X.-R., and Lin, C.-J. (2008). LIBLINEAR: a library for large linear classification. *J. Mach. Learn. Res.*, 9:18711874.

Friedrich, E. V., Neuper, C., and Scherer, R. (2013). Whatever works: A systematic user-centered training protocol to optimize brain-computer interfacing individually. *PloS one*, 8(9):e76214.

Garrett, D., Peterson, D., Anderson, C., and Thaut, M. (2003). Comparison of linear, nonlinear, and feature selection methods for eeg signal classification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 11(2):141–144.

Grierson, M. and Kiefer, C. (2011). Better brain interfacing for the masses: progress in event-related potential detection using commercial brain computer interfaces. page 1681. ACM Press.

Hill, N. J., Ricci, E., Haider, S., McCane, L. M., Heckman, S., Wolpaw, J. R., and Vaughan, T. M. (2014). A practical, intuitive braincomputer interface for communicating yes or no by listening. *Journal of Neural Engineering*, 11(3):035003.

Jain, A. K., Duin, R. P. W., and Mao, J. (2000). Statistical pattern recognition: A review. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 22(1):437.

Johnson, B., Maillart, T., and Chuang, J. (2014). My thoughts are not your thoughts. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication*, UbiComp '14 Adjunct, pages 1329–1338, New York, NY, USA. ACM.

Larsen, E. A. and Hokl, C.-s. J. (2011). *Classification of EEG Signals in a Brain- Computer Interface System*.

Lotte, F., Congedo, M., Lcuyer, A., Lamarche, F., Arnaldi, B., et al. (2007). A review of classification algorithms for EEG-based braincomputer interfaces. *Journal of neural engineering*, 4.

McFarland, D. J. and Wolpaw, J. R. (2011). Brain-computer interfaces for communication and control. *Commun ACM*, 54(5):60–66.

Millan, J. D. R., Rupp, R., Muller-Putz, G. R., Murray-Smith, R., Giugliemma, C., Tangermann, M., Vidaurre, C., Cincotti, F., Kubler, A., Leeb, R., Neuper, C., Muller, K.-R., and Mattia, D. (2010). Combining brain-computer interfaces and assistive technologies: State-of-the-art and challenges. *Front Neurosci*, 4.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., and Duchesnay, . (2011). Scikit-learn: Machine learning in python. *J. Mach. Learn. Res.*, 12:28252830.

Vidaurre, C. and Blankertz, B. (2010). Towards a cure for BCI illiteracy. *Brain topography*, 23(2):194198.

Vidaurre, C., Sannelli, C., Mller, K.-R., and Blankertz, B. (2011). Machine-learning-based coadaptive calibration for brain-computer interfaces. *Neural Computation*, 23(3):791–816.