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

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Abstract: This paper exhibits two methods for decreasing the time associated with training a machine learning classifier on biometric signals. Using electroencephalography (EEG) data obtained from a consumer-grade headset with a single electrode, we show that these methods produce significant gains in the computational performance and calibration time of a simple brain-computer interface (BCI) without significantly decreasing accuracy. We discuss the relevance of reduced feature vector size to the design of physiological computing applications.

1 INTRODUCTION

Bio-signals vary widely between individuals, and their expression often changes within individuals over time. Typically, brain computer interfaces (BCI) serve as an excellent example of this phenomenon. Regular calibration and re-calibration are critical to achieving decent BCI accuracy (Dornhege, 2007; McFarland and Wolpaw, 2011).

Supervised learning algorithms have assisted systems in adapting 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).

However, in order to move BCI into broader consumer markets, systems must work with more mobile sensing equipment and wearable computing platforms. Mobile device architectures limit computational complexity relative to lab-based systems, and ergonomic considerations limit the number and quality of sensors on the device.

In this study, we simulate a simple brain-computer interface using signals acquired from a low-cost, mobile electroencephalograph (EEG) device with a single electrode. Using a BCI that takes *mental gestures* as input, we investigate how the processing of bio-signals and the strategy for user calibration can impact the computational performance, reliability and calibration time of a physiological signal classification system.

First, we present a novel signal quantization technique in which we apply logarithmic binning to power spectrum data from an EEG electrode. We find that this technique can speed up the computational performance of a classification-based BCI by 450% without significant detriment to the system's accuracy.

Second, we combine this technique with a progressive user calibration strategy, in which candidate mental gestures are tested in an order designed to minimize calibration time. We calibrate 86.6% of users to a threshold of *BCI literacy* (75% accuracy) (Vidaurre and Blankertz, 2010) with under five minutes of training data, and 100% of users within half an hour.

This paper is organized as follows. We introduce relevant background research in Section 2. We present the power spectrum quantization method in Section 3, and the data used for calibration in Section 4. We then evaluate the quantization method (Section 5), and we present a time-efficient calibration strategy for our BCI apparatus (Section 6). We conclude with limitations and future research directions.

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* (i.e. 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-user 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 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. Since vector size directly impacts the runtime of the classifier, this technique operationalizes the tradeoff between computational speed and accuracy.

We average the power spectrum time series in the temporal dimension and compute a discrete probability density function (pdf) from the resulting power spectrum 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, which can be quantized as described in the following section.

3.1 Logarithmic Binning

Since EEG activity is associated with frequencies from 1-40Hz, it is generally presumed that 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 outside this frequency range 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 log-spaced data bins through the logarithm of the frequency range. Figure 1 shows an example of logarithmic binning with 65 bins. The original, 1024-point pdf is compressed more than 10 times, but its original structure is well-preserved.

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 represents the local area of spectrum. For example, four contiguous frequencies (1Hz, 1.25Hz, 1.5Hz, 1.75Hz) of the values (4, 4, 5, 5) average into a single bin with the value 4.5. The number of bins can be adjusted to produce feature vectors of different sizes. This vector, which highlights the statistical properties of the power spectrum for each mental task, can be used as an input of variable size to the classifier.

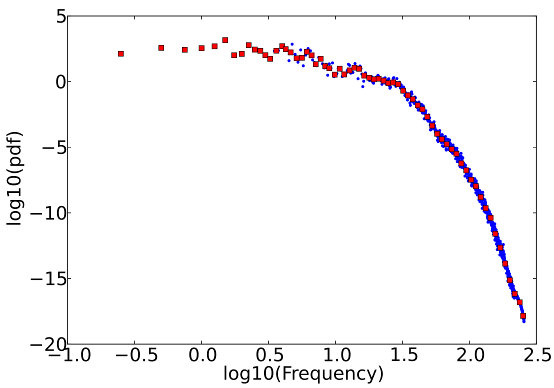

Figure 1: In double logarithmic scale, the original 1024 bins (blue dots) of the probability density function (pdf) obtained from averaging the n power spectra of one recording, and the resulting quantized pdf with a resolution of 65 log-bins (red). The quantized pdf preserves very well the structure of the original, 1024-point pdf.

3.2 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 of a randomly-selected sample of our dataset. We use scikit-learn's built-in cross-validation toolkit, which performs seven cross-validation steps utilizing 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 gestures (or *classes*) that we can most reliably differentiate from one another. This results in a personalized, binary 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*. Subjects can then select one of two options by performing one of the mental gestures in their gesture pair.

4 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 (Chuang et al., 2013).

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, so 1024 values are 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 of the seven mental gesture is represented by ten trials, each trial consisting of a time series of 20 power spectra. 1024 frequency readings comprise each power spectrum.

5 EFFECT OF QUANTIZATION ON CLASSIFIER SPEED AND ACCURACY

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

In order to make an optimal binary BCI for each subject, we must find the two gestures that the SVM distinguishes most reliably. 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 processed, we record mean classification accuracy across all rounds of cross-validation. We record the best-performing gesture pair for each subject, which yields the optimal pair for the binary BCI.

We perform this process multiple times, varying the signal resolution by varying the number of bins from 1 to 1024. 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 number of bins to 50. 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 50 bins. We find no significant difference in SVM accuracy at resolutions over 50 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 50 bins that provides a 450% speed improvement over a non-quantized baseline of 1024 bins without a significant detriment to classifier accuracy.

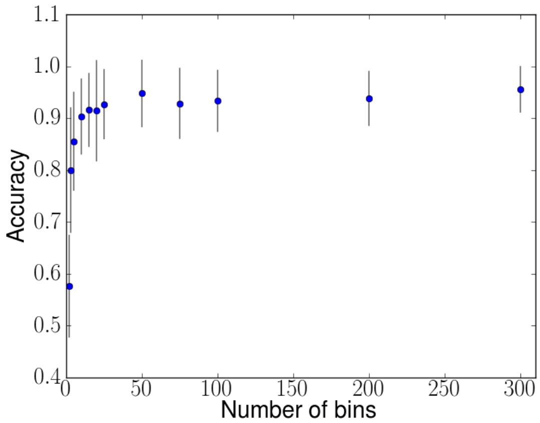

Figure 2: Mean best-case accuracy among all subjects compared to signal resolution. At resolutions of 50 points (bins) and greater, we find no evidence of an increase in classification accuracy.

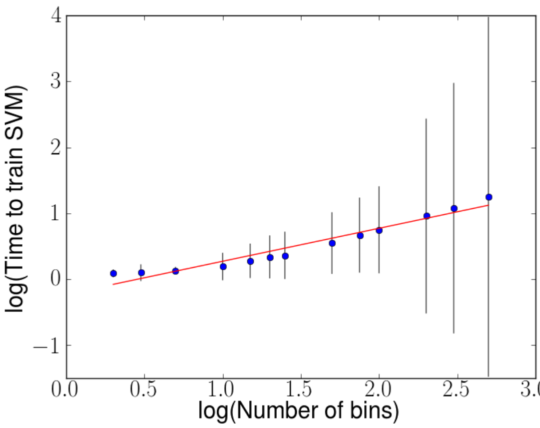

Figure 3: Log of mean classifier training time compared to log of data resolution. The slope is 0.5, indicating that the time needed to train the classifier increases as approximately the square root of the signal resolution.

Overall, we find that relatively small feature vectors produced with our method (50 values) yield classifiers as accurate as full-resolution samples (1024 values), and that reducing vector size in this way can

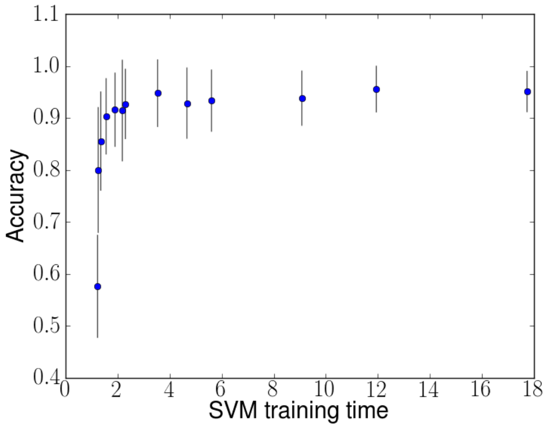

Figure 4: Best-case accuracy compared to the time needed to train the classifier. By decreasing the number of bins in the EEG data, we can decrease the time needed to train the support vector machine up to nine times without without significant detriment to classifier accuracy.

dramatically increase computational speed.

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 50 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.

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 allowed 66.7% (10 subjects) to be calibrated in under 5 minutes, and 86.7% (13 subjects) in under 6 minutes. The system calibrated the remaining two subjects in 11 minutes and 22 minutes, respectively. All 15 subjects achieved a minimum of 75%

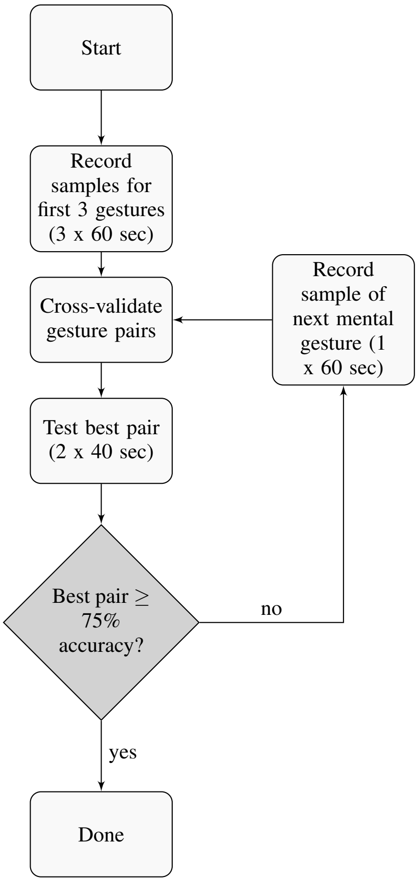

Figure 5: Progressive calibration routine. We begin with 60 second recordings of the three best-performing gestures (Table 1). We then perform seven-fold cross-validation on each pair of gestures. The pair that scored highest on cross-validation is selected for testing on an additional 80 seconds of 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.

classification accuracy. Six subjects (40%) achieve 100% accuracy.

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 single, low-cost EEG electrode as input. We found that our technique allows for a BCI that is computationally efficient at training time,

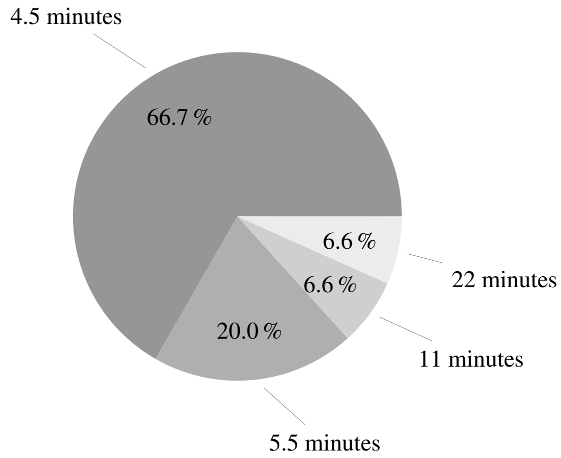

Figure 6: Calibration time across subjects (top) and classifier accuracy (bottom). The vast majority of subjects achieve acceptable accuracy in 4.5 minutes of training, all but one subject in 11 minutes, and the remaining subject in 22 minutes.

which can achieve good simulated accuracy for all subjects in our dataset, and boasts quick user calibration times. Specifically, we showed 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 required under 25 minutes of calibration time, and the system calibrated to all but one of these subjects in 15 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 indicates 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 (e.g. on mobile computing platforms or in naturalistic settings). Since many types of bio-signals can be represented as time series of power spectra (e.g., electrocardiography, electromyography), future work could also test our quantization technique on different types of biometric signals.

Reducing the size of feature vectors in physiological computing applications could confer numerous benefits to application developers. Smaller feature vectors could enable quick, cloud-based processing, reducing the computational load on the end-user hardware. Small feature vectors also lower the boundaries to achieving continuous, pervasive recording. By quantizing signals from physiological sensors, developers can collect large corpa of biometric data without expensive, high-performance server configurations, enabling large-scale observations on physiological data.

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