The EggLink Brain-Computer Interface: Engineering and Performance Evaluation

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Abstract

Brain-computer interfaces, systems that operate electronic or mechanical systems using imaged brain events as operational input commands, have gained much ground in the research world over the last two decades, as they potentially provide rehabilitative and restorative functionality to several clinical populations. The EggLink is an electroencephalography-based brain-computer interface that is being developed to operate common household computers based on machine learning classifications of fine motor signals generated in the brain. At this stage, the project involves designing and building the prototype system that will classify fine motor activity (the flicking of each of 10 fingers) to as high a degree of accuracy as possible. Future stages will involve classifying eye movements for computer cursor control, real-time processing, and other functional additions to the overall system design.
The EggLink Brain-Computer Interface: Engineering and Performance Evaluation

Introduction

Brain-computer interfaces (BCIs), also known as brain-machine interfaces or neural interfaces, are systems that image neurological signals in some capacity for the purpose of operating computers or robots, or convert physical stimuli into neurological information through surgically-implanted circuits (Wolpaw, Birbaumer, McFarland, Pfurtscheller & Vaughan, 2002). Non-invasive BCIs, those that do not involve surgical operations or direct contact with the nervous system, rely on such technology as functional near-infrared spectroscopy (Kamran & Hong, 2013), electroencephalography (EEG), or functional magnetic resonance imaging to translate patterns of physiological behavior into digital signals that can then be processed by computational means (Lebedev & Nicolelis, 2006). Invasive BCIs involve such as cortical microelectrode implants that can record neurological systems activity or deliver signals to neuronal populations, thereby allowing dysfunctional nervous circuitry to be bypassed or supplemented in its function (Guitchounts, Markowitz, Liberti & Gardner, 2013). But because these invasive types require strict medical oversight for research and implementation, which was beyond the resources available for this project, the project described herein was oriented around the design of a non-invasive BCI.

A preponderance of BCIs have been constructed by neural engineers that allow for the operation of proprietary computer interfaces, largely oriented about the function of communication for physically disabled or otherwise locked-in medical patients (Mussa-Ivaldi & Miller, 2003). These systems tend to exist solely within the laboratory in which they were created, thereby making them largely inaccessible to the very population that they were constructed to aid (Tonet et al., 2008). Continuing efforts are being made to standardize and distribute these systems, at least in the clinical context, but by and large there is no easy access to a neural interface to date. Further, the average healthy person has no legitimate use for such BCI technologies, as even commercially-available products are severely inefficient and cumbersome to operate compared to normal computer interfacing technology (mouse, keyboard, touchscreen, etc.)
(Mussa-Ivaldi & Miller, 2003). While medical conditions often drive both the funding and innovative thinking in this realm, public interest in this technology has reached a level of demand worthy of addressing (BCI in Health care).

EEG is supported by BCI researchers such as Millán, Ferrez, Galán, Lew and Chavariagga (2008) as the most ideal technology for practical applications of neural interfacing due to comparatively low-cost hardware and ease of use. Studies have found that control of typing and cursor-control programs enabled through EEG-based BCIs have met with legitimate success, albeit such interfaces are hindered by low-bandwidth throughput (the speed at which data is transferred from the BCI to the computer being controlled) and rigid control mechanisms (Tonet et al., 2008). This suggests that consistent signals in the brain underlying motion, intention, and attention are indeed available within EEG waveforms, but that significant considerations in methodology and technology are needed to make use of them.

As EEG signals are functionally independent of spatial source (Srinivasan, 1999), it is unlikely that the mathematical sophistication to isolate any single EEG signal to a particular cortical or subcortical site is worthwhile to investigate for BCI use in the near future. Thus, all research examined here for informing BCI construction takes into account the modulatory effects of neurological processes that may manifest in EEG electrodes at any site on the scalp. This information demanded that I design scalp-wide analyses conducted by all machine learning techniques seeking to identify relevant brain signals, even when doing so amplified the amount of data being processed.

The largest problem in the use of this technology for such purposes is the sheer lack of distinguishable signals embedded within noisy EEG waveforms (Müller, Tangermann, Dornhege, Krauledat, Curio & Blankertz, 2008). Static signal processing algorithms have been found to be unfeasibly slow and inaccurate in reading users’ neurological activity (Lotte, Congedo, Lécuyer, Lamarche & Arnaldi, 2007), thus researchers (e.g. Pires, Nunes, & Castelo-Branco, 2012) have introduced machine learning programs for BCI operation to allow for greater adaptation to the user. This allows for the BCI to adapt to the particular neurological activity of individuals with different brains by means of creating unique operating environments (mathematically-speaking) during the system’s
calibration period.

Support-vector machines (SVMs) dominate BCI research as the standard for the algorithmic processing of brain signals (Müller, Krauledat, Dornhege, Curio & Blankertz, 2004; Wissel et al., 2013). The primary means of processing the recorded brain signals via the EggLink involves submitting a number of transformed data sets to SVM algorithms for classification training. The EggLink also implements a number of experimental machine learning techniques and data analysis operations, such as using wavelet decompositions (Ting, Yan, Yang & Hong, 2008), alpha- and gamma-band oscillatory time-locking (Buzsáki & Draguhn, 2004), and so on, thus to form a meta machine learning system that incorporates overlapping signal classifications so as to improve performance accuracy. A final dimensionality-reducing clustering neural network (cNN) (Lincoln, 1992) dictates the singular command output of the entire system.

The ideal state of functionality for the EggLink would be to host real-time neurological analyses, as anything less than immediate system responses to ongoing brain activity would be generally useless to computer operators. However, due to resource limitations, the EggLink is currently designed for offline analyses, such that recorded brain activity is examined by machine learning techniques with no regard to the time required to complete each computation. This permits ongoing work to refine the system’s accuracy rather than speed in terms of correctly classifying fine motor movements. After a satisfactory level of classification accuracy has been achieved at approximately 95% per distinct motor signal, my efforts will shift towards reducing the computational load of the design so as to improve performance speed in anticipation of eventual real-time operation. Further, this system could allow locked-in or otherwise medically-disadvantaged individuals to have computer-operating capabilities equivalent to a healthy person, thereby restoring substantial life functionality with regards to communication and entertainment.

Overall, in an attempt to compensate for the limited-use nature of non-invasive BCIs, I focused on the development of a new system, named the EggLink Brain-Computer Interface, which was intended to host a greater level of applicability for a non-medical population. This required the use of EEG neural
imaging technology in combination with machine learning computational systems in order to build a BCI that could permit any common household computer to be operated by the brain signals that manifest during simple motor actions. The EggLink was constructed to take advantage of the robust neurological signals that arise during actual or imagined finger movements, while being flexible enough to incorporate any fine motor operation that the user of the system would deem appropriate for any given application. The EggLink’s use of as many distinct motor operations as possible allows for a greater breadth of versatility in application compared to established BCI technology. While many stages of development will yet be required to develop this system to the point where it is clinically or commercially viable, the overall goal to engineer a BCI that can discriminate between subtle motor signals has been completed.

Methods

Participants

A total of eight participants were recruited by convenience from a small liberal arts college located in the Intermountain West (5 male, 3 female). No preference was given to any demographic quality in recruiting these participants. No prior experience operating BCIs was required, however, participants were confirmed to be computer-literate by self-report. Participants were also free of any known major neurological conditions such as stroke damage, severe autism, etc. by self-report.

Materials

Hardware and software. All neurological recordings was conducted with a 128-channel Dense Sensor Array HydroCel Geodesic Sensor Net (Electrical Geodesics, Inc.) combined with the paired E-Prime and NetStation software set to record at 1000Hz (1000 samples per second). All head recordings required the user to have their hair saturated with a solution of potassium chloride (KCl) and baby shampoo (Shopko) so as to improve electrical conductance across their scalp. Recorded data was processed by machine learning programs through MATLAB (Mathworks) software on an 8-core 32GB
RAM laptop (Alienware) running Windows 8.1 (Microsoft).

**Calibration.** After being fitted with an EEG net, participants in this study conducted calibration training for the EggLink. This involved sitting in a chair in a comfortable position, with each finger resting on one key on a common keyboard. The left hand used keys (from pinky finger to thumb) “1,” “2,” “3,” “4,” and “v,” and the right hand used keys (from thumb to pinky finger) “b,” “7,” “8,” “9,” and “0.” Participants were prompted by a program running in E-Prime to push any of the 10 available keys whenever they feel that they should do so, and were given an unlimited amount of time per trial to push a key. After a keystroke had been recorded, a five-to-six second inter-trial interval indicated that no motion should be conducted, followed by another prompt for a keystroke. A total of 500 keystrokes were recorded per participant.

**Data pre-processing transformations.** Data is recorded at 1000Hz from 128 electrode sites across the entire scalp, and is band-passed from 0.1Hz to 100Hz as it is recorded. The users’ keystroke values are used to generate a set of labels for the EEG data that corresponds to user activity, and windows of 800ms surrounding a keystroke event are labeled as a finger movement. Portions of the data that do not correspond to a keystroke are down-sampled to 100Hz so as to reduce the overall computational load of the system.

The raw EEG voltage data then undergoes 49 independent transformations, all performed using MATLAB default algorithms: Set (1) is the raw data. Set (2) is the positive-definite version of the raw data. Sets (3-8) are in the frequency domain and analyze varying frequency bands from .01Hz to 100Hz in terms of power amplitudes. Sets (9-18) are formed by running the raw data through 10 iterations each of Daubechies wavelets 1 through 10. Set (19) is formed by running the raw data through 10 iterations of a Discrete Meyers wavelet. Sets (20-24) are formed by running the raw data through 10 iterations each of coiflets 1 through 5. Sets (25-35) are formed by running the raw data through 10 iterations each of Symlets 1 through 11. Sets (36-42) are formed by running the raw data through 10 iterations each of Biorthogonal x.y wavelets ($x, y = 1.1, 1.3, 1.5, 2.2, 2.4, 2.6, 2.8$). Sets (43-49) are formed by running the raw data through 10 iterations each of Reverse Biorthogonal x.y wavelets ($x, y = 1.1, 1.3, 1.5, 2.2, 2.4,$
Each of these 49 data sets are then duplicated into 20 copies each, 2 copies for each finger, with the accompanying label set modified to reflect binary action (finger-on or finger-off). 10 of the copies are unaltered, while 10 undergo centroid normalization. All copies of each of the 49 data sets are then segmented into 500 finger-on samples and 500 finger-off samples for machine learning training. In total, 980 data sets are produced along with their corresponding label set.

**Classification-oriented machine learning ensemble.** A combination SVMs are used to generate classification prediction on the recorded data. SVMs use what is known as the “kernel trick” to embed data into higher dimensional space in an effort to make collections of data points linearly separable from each other. The SVMs used in the EggLink operate with three kernel functions: Radial basis, linear, and polynomial. In order to generate a linear separation, SVMs solve an optimization problem with a given set of constraints. Here I use two optimization operations: L1 soft margin minimization and sequential minimal optimization. Each optimizing algorithm can use any of the kernel functions, so there are a total of six SVM types available for classification on each of the 980 data sets.

Each SVM is provided 1000 samples of data from its respective data set, which is partitioned into 500 finger-on and 500 finger-off samples. All SVMs are permitted a maximum of 10,000 iterated attempts to solve their respective optimization convergence problem before being forcefully rejected from the system. Each successfully trained SVM is then used to make predictions on the remaining data in each data set via binary classification of each sample across all 128 electrode channels. The binary outputs of all SVMs are combined to form a prediction matrix consisting of 5880 binary prediction arrays.
Support-Vector Machine Kernel Functions:

- Radial Basis Function: \( G(x_1, x_2) = e^{-\frac{||x_1 - x_2||^2}{2\sigma^2}} \)
- Linear: \( G(x_1, x_2) = x_1^T x_2 \)
- Polynomial: \( G(x_1, x_2) = (1 + x_1^T x_2)^p \)

Support-Vector Machine Optimizers:

- L1 Soft Margin Minimization:
  \[
  \min_{w,b,s} \left( \frac{1}{2}w^Tw + c \sum_i s_i \right) \\
  \text{with constraints:} \\
  y_i(w^T x_i + b) > 1 - s_i \\
  s_i > 0 \\
  \text{and} \\
  \max_{\alpha} \left( \sum_i \alpha_i - \frac{1}{2} \sum_i \sum_j y_i y_j K(x_i, x_j) \alpha_i \alpha_j \right) \\
  \sum_i \alpha_i y_i = 0 \\
  0 \leq \alpha_i \leq C
  \]

Table 1: The kernel functions and optimizing equations used in the EggLink. The optimization equations are restricted by their constraint variables as defined. Each optimization equation is combined with each of the kernel functions, permitting 6 total SVM types to be applied to each data set. Variables: \( x_i \) is a sample of data across 128 electrode channels, \( \sigma \) is the mean value of the data points between two samples, \( P \) is an arbitrary positive real number, \( w \) is a weight vector determined algorithmically, \( c \) is a step-rate variable usually equal to 1, \( s_i \) is a slack variable that permits non-discrete determination of an output, \( y_i \) is an updatable prediction, \( \alpha_i \) is the growth-rate limiter, and \( C \) is the growth-rate cap.

The output prediction matrix is then used as the input data for a second tier of the same SVM operations. This data set is similarly parsed into 10 data sets, one for each finger, with respective binary label sets. This is again operated on by six SVM types, and so produced a second prediction matrix consisting of 60 binary prediction arrays. This output prediction matrix is then used as the input data for a third tier of machine learning.

The third and final tier of the machine learning ensemble uses a clustering neural network to reduce the data from 60 dimensions to 11 (one for each of the fingers-on and one for all fingers-off). Whereas the SVMs in the previous tiers operate on a binary prediction system, and so can generate multiple positive predictions per sample of data in parallel, the cNN forces only one positive prediction per data sample instance. In other words, the cNN restricts the output of the EggLink to a single command at any given millisecond, rather than having multiple overlapping commands that need to be processed.
further. This is achieved through the competitive update function
\[ w_i(q) = w_i(q - 1) + \alpha (p(q) - w_i(q - 1)), \]
where \( w_i \) is the weight vector that determines which dimension received the positive prediction, \( \alpha \) is a growth-rate limiter, \( p \) is a posterior placement of a positive prediction, and \( q \) is the data sample being predicted on.

The final output of the EggLink is then an \( 11 \times n \) matrix of binary (0 or 1) predictions, where \( n \) is the number of samples of data. This matrix can then be statistically analyzed for machine learning ensemble performance values by comparing positive and negative predictions to the known labels (see results below). In a real-time system, these final outputs would be sent to the user’s computer and used as the command inputs for executing interface operations.

**Procedures**

Participants were welcomed into the lab and given a brief explanation of the requirements of the study. They were then fitted with an EEG net, which was measured for acceptable impedance values (the electrical resistance each electrode on the EEG net has as it records data). The participants then underwent the calibration recording session, in which they were asked to randomly strike a pre-determined set of keys at timing left to their discretion. They were required to submit 500 keystrokes before the recording session ended. Following this, the EEG net was removed, they were thanked for their participation, offered one of several snacks available, and then ushered out of the lab.

The recorded data sets were then run through all data transformations and processed by the machine learning algorithms mentioned above so as to determine the accuracy of motor signal classifications made by the EggLink. Portions of the data set for each of the 10 fingers from each participant were partitioned out so as to provide training data (approximately 50 trials for each finger, depending on the total number of keystrokes per finger that were recorded) for the machine learning algorithms. The remaining data for each keystroke type was submitted to the learning machine ensemble without known solutions so as to verify the accuracy of the classifiers produced by the algorithms. The final results came in the form of percentage of correctly identified keystrokes given only the neurological
data without keystroke labels.

**Results**

Machine learning cross-validation (see Table 2) yields the following four values: Positive predictive value (PPV), negative predictive value (NGV), sensitivity (SN), and specificity (SP). The PPV is the ratio of correctly predicted instances to total predicted instances for a given finger. NGV is the ratio of correctly unpredicted negative instances to total finger-off instances for a given finger. SN is the ratio of correctly predicted instances to total labeled instances for a given finger. SP is the ratio of correctly unpredicted negative instances to total finger-off instances for a given finger.

<table>
<thead>
<tr>
<th>Value</th>
<th>L. Pinky</th>
<th>L. Ring</th>
<th>L. Middle</th>
<th>L. Index</th>
<th>L. Thumb</th>
<th>R. Pinky</th>
<th>R. Ring</th>
<th>R. Middle</th>
<th>R. Index</th>
<th>R. Thumb</th>
</tr>
</thead>
<tbody>
<tr>
<td>PPV</td>
<td>6.54%</td>
<td>4.13%</td>
<td>4.33%</td>
<td>4.31%</td>
<td>5.21%</td>
<td>4.58%</td>
<td>2.57%</td>
<td>3.30%</td>
<td>4.68%</td>
<td>3.66%</td>
</tr>
<tr>
<td>NPV</td>
<td>96.62%</td>
<td>95.15%</td>
<td>95.94%</td>
<td>95.94%</td>
<td>94.43%</td>
<td>95.31%</td>
<td>96.65%</td>
<td>96.19%</td>
<td>94.63%</td>
<td>96.09%</td>
</tr>
<tr>
<td>SN</td>
<td>13.01%</td>
<td>3.31%</td>
<td>16.05%</td>
<td>11.32%</td>
<td>9.97%</td>
<td>4.55%</td>
<td>1.39%</td>
<td>2.94%</td>
<td>1.99%</td>
<td>3.04%</td>
</tr>
<tr>
<td>SP</td>
<td>0.63%</td>
<td>0.17%</td>
<td>0.74%</td>
<td>0.41%</td>
<td>0.50%</td>
<td>0.22%</td>
<td>0.05%</td>
<td>0.13%</td>
<td>0.11%</td>
<td>0.13%</td>
</tr>
</tbody>
</table>

Table 2: The cross-validation results of the EggLink machine learning ensemble by finger.

<table>
<thead>
<tr>
<th>Value</th>
<th>L. Pinky</th>
<th>L. Ring</th>
<th>L. Middle</th>
<th>L. Index</th>
<th>L. Thumb</th>
<th>R. Pinky</th>
<th>R. Ring</th>
<th>R. Middle</th>
<th>R. Index</th>
<th>R. Thumb</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correct</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Instances</td>
<td>569.8</td>
<td>205.8</td>
<td>1213.8</td>
<td>415.3</td>
<td>561.9</td>
<td>345.6</td>
<td>78.8</td>
<td>148.0</td>
<td>136.3</td>
<td>171.6</td>
</tr>
<tr>
<td>Correct %</td>
<td>0.0060</td>
<td>0.0016</td>
<td>0.0071</td>
<td>0.0039</td>
<td>0.0047</td>
<td>0.0021</td>
<td>0.0005</td>
<td>0.0012</td>
<td>0.0010</td>
<td>0.0012</td>
</tr>
</tbody>
</table>

Table 3: The distribution of correct predictions and percentages by finger.
Figure 1: Graphs of the cross-validation results of the EggLink machine learning ensemble by finger. Not that each graph has a different scale for the vertical axis.

Further results come from direct accuracy measures (see Table 3) in which the predictive strength for each finger is calculated by determining the ratio of correctly predicted instances to total labeled instances by finger.

Discussion

This study was oriented around the design and construction of an EEG-based BCI that uses fine motor signals recorded as minute electrical fluctuations exuding from the brain to control computer operating systems. The intent for this stage of the project was to produce an offline BCI that could theoretically be applied to any common computer or program, thus to use a 10-finger control scheme to
replace a physical keyboard. The EggLink differs from other BCIs in that it was intended to be a tool that will be easily applicable to any computer and usable by almost any person, rather than being a proprietary system that supports limited clinical applications. Following that, the EggLink was intended to produce a superior signal classification system compared to previously-constructed BCIs, in that the subtle difference between the movement of fingers could be resolved with a great deal of accuracy.

**Performance**

The cross-validation yields that the average PPV of the system is 4.3%, the average NPV is 95.7%, the average SN is 6.8%, and the average SP is 0.3% across all fingers on an average of 385 positive predictions per finger with 0.3% overall average accuracy. Taking into account finger-off periods, the total system accuracy of the EggLink is 25.2% by instance-by-instance. However, these techniques are intended to measure the performance of binary-classifying machine learning rather than multi-classifiers such as the cNN, as is used in the final tier of the EggLink’s machine learning ensemble. No statistical methods currently exist to measure the performance of multi-classifying machine learning systems, so these results must be taken as is.

As such, these results indicate that the EggLink’s machine learning ensemble performs quite poorly, with its legitimate value in that it can correctly classify each finger’s movements independently and with some minor accuracy. This serves as proof-of-concept in that the EggLink can function as intended, even if its strength currently lies in negative prediction accuracy.

**Limitations**

As offline BCI systems are generally unavailable for real-world applications due to the disconnect between calibration and actual use, this incarnation of the EggLink is absent of immediate function. The cost of equipment and software needed to transition the EggLink to a real-time system is prohibitive for the involved researchers, thus this system design must remain as is for the time being.
The emphasis of this project was on establishing extremely high accuracy in neurological signal classification. In doing so, a great deal of computational overhead was generated which resulted in prohibitively slow computation speeds. While this issue can be mostly resolved with faster computers or more computational equipment, the EggLink as proposed cannot perform as a real-time BCI unless it can achieve imperceptible response times (10-50ms). Further investigations into improving the efficiency of the involved machine learning algorithms and data transformations may be the only way to bring the temporal cost of data processing down given no further financial or technological resources.

The EggLink was intended to be a BCI for home-computer-use, but the research-grade EEG system used in its construction is beyond the budget of most consumers (approximately $100k). Besides this, most EEG manufacturers will sell equipment only to research labs or clinicians, thus accessing the required hardware may be unfeasible for most. Upon reaching the desired level of performance, the EggLink could serve as a foundation for functionally advanced BCIs that have a place outside of the research laboratory. However, the first stage of this project necessarily neglected the involvement of eye movement signals for computer cursor control. Lastly, reasonable developments to the involved hardware setup (dry EEG, portable EEG, electrodes with improved signal-to-noise ratio during recording, etc.) could see this trend in technology reaching a mass market.

**Future Research**

The most pertinent research needed to further develop the EggLink will be the conversion of the entire BCI from an offline system to a real-time system. This will permit the EggLink to become a functional BCI as intended for home-use, allowing users to supplement normal computer interface devices. On the medical side, clinical patients cannot be aided by offline systems. Real-time calibration and operation is a necessity for locked-in individuals to be able to use the system with any legitimate function.

Optical tracking for on-screen cursor movement is paired in priority with the above. Substantial investigations into classifying eye movements using electrooculograms and eye-trackers paired with EEG may allow the EggLink to combine motor-based content control via the fingers with spatial navigation.
operations permitted by shifts in gaze. The completion of this aspect of the BCI would allow the EggLink to fully replace the mouse and keyboard setup common to almost all computers.

Research-grade EEG hardware requires liquid preparations and a third party in order to attach a net to an individual’s head. This further limits the convenience of the EggLink, as in order for it to function as a simple computer interfacing tool it would need to be simple to put on the head, maintain, and remove when desired. Current EEG equipment that departs from the normal arrangement suffers from lower performance with BCIs (Popescu, Fazli, Badower, Blankertz & Müller, 2007; Zander et al., 2011), thus further research into the related material sciences for dry and portable EEG technology will help to establish this as a valid form of computer interaction.

As the EggLink is intended for common computer systems, it must be considered that no common computer system is equipped from the manufacturer to interact with a BCI. Future endeavors should be focused on how to quickly and easily integrate the EggLink into any of the many available computer systems on the public market so that it can be used as a primary interfacing tool via USB connection or the lik. Similarly, technical and industrial computing systems should be considered, as the EggLink may have desired applications in particular circumstances that I cannot predict. As such, a convenient user interface should be designed so that customizable control schemes can be developed on-the-fly by users regardless of the involved programs or computers.

Finally, and without the prompt of this project, research into superior machine learning techniques may find that an even greater level of functionality can be achieved with the EggLink or a similar BCI. I am content with using fine motor classifications for the control of computers, but this does not mean that newly-developed machine learning techniques may be able to readily identify and work with extremely subtle neurological phenomena. This could most easily aid in treating medical conditions in which individuals may only be able to produce a limited set of brain responses.

Predictive analysis systems are needed to further complement the EggLink’s background functionality. Numerous neurological phenomena have been found to be available for classification several seconds prior to the event that is otherwise thought to generate a signal of interest (Bai et al.,
2011). This, then, begs for two waves of data analysis during offline and forthcoming real-time processing: Predictive algorithms that look forward to determine when a signal is going to occur and what that signal might be, followed by more rigorous signal analyzers at time sequences identified to contain relevant signals.

However, the EggLink should also implement a number of experimental machine learning techniques and data analysis operations beyond those currently in place, such as using hidden Markov machines (Wissel et al., 2013), Kolmogorov entropy analysis (Gao, Wang & Chen, 2013), and so on, thus to permit a meta machine learning system that incorporates overlapping signal classifications so as to improve performance accuracy as by boosting theory (Saberian & Vasconcelos, 2011). An automated weighting system should also be considered for implantation so as to dictate how valued each machine learning system is according to the particular incoming brain data and the corresponding signal classifications, such that the entire system will alter its set of conducted operations based on the conditions of the user.
References


