Before you can be fitted with your Braincap, you have to be completely bald. . . . A faint drumming sound accelerated until it became the lowest of audible Cs, then raced up the musical scale until it disappeared beyond the range of the human hearing. . . . He presumed that his neuromuscular control was being tested. . . . (Clarke 1997)

The braincap, as described in *3001: The Final Odyssey*, the concluding edition of Arthur C. Clarke’s science fiction classic, is the ultimate human-computer interface: it connects the brain to a system that is able to read thoughts and upload new information. The wearer can in minutes acquire new skills that would otherwise take years to master.

Currently, however, a system that uploads information into the brain cannot exist outside the realm of science fiction, although machines that can read signals from the brain are becoming present-day reality. Furthermore, we should soon be able to control all sorts of devices by our thoughts alone. In 1998, a paper presented at the 9th European Congress of Clinical Neurophysiology already reported impressive advances in research on an electroencephalogram-based system to control a prosthetic hand (Guger and Pfurtscheller 1998). More recently, scientists at Brown University reported the development of a brain-computer interface for a system whereby a monkey controlled a cursor on a computer screen (Turner 2002). At first, the monkey used a joystick to move the cursor. After a while, the joystick was disconnected, and the monkey, who had not realized this, continued moving the cursor by means of tiny electrical signals emanating from an electrode implanted on the monkey’s motor cortex (the main brain area for motor control).

We are interested in developing thought-controlled musical devices, and to this end we are currently working on the design of a musical braincap. We are developing technology to interface the brain with music systems and compositional techniques suitable for thought control.

This article focuses on extracting and harnessing tiny electrical brain signals from electroencephalograms (EEGs) that can be captured with electrodes on the scalp. We present three experiments whose results provide the basis for building systems to automatically detect information in the electroencephalogram associated with musical mental activities. Then, we describe how these results are currently being embedded in the design of the musical braincap. Before we present the experiments, we briefly introduce the growing field of Brain-Computer Interfaces (BCI), followed by an introduction to the EEG and the signal processing techniques we employed to harness it.

Before we continue, it is necessary to clarify the meaning of the expression “thought control.” In
thought control should not evoke the idea of a person imagining a specific piece of music that is then magically generated exactly as imagined. This is beyond the capabilities of current science and technology. By thought control, we mean simply using brain signals associated with specific mental activities to interact with musical devices. The sophistication of this interaction will depend upon the nature of the mental activities that one is able to identify in the EEG, the efficiency of the EEG signal-processing techniques employed, and above all, the design of the system in question. We are by no means proposing the naive scenario of a “high-tech Mozart” who would simply imagine music that the technology then creates.

**Brain-Computer Interfaces and Music**

Generally speaking, a brain-computer interface (BCI) is a system that allows one to interact with a certain device by means of signals emanating directly from the brain. There are basically two ways of tapping brain signals: invasively and non-invasively. Whereas invasive methods require the placement of sensors connected to the brain inside the skull, non-invasive methods use sensors that can read brain signals from the outside the skull. Invasive technology is becoming increasingly sophisticated, but brain prosthetics is not a viable option for this research. The most viable non-invasive option for tapping the brain for BCI currently is the EEG. It is a well-known phenomenon that brain activity produces a range of electrical signals in the cerebral cortex, generating electrical fields that can be captured using electrodes placed on the scalp. These signals are generally referred to as the EEG. There is a growing number of people developing EEG-based BCI, as could be witnessed at the first international meeting *Brain-Computer Interface Technology: Theory and Practice*, held at the New York State Department of Health, in June 1999. (Unfortunately, no proceedings were published.)

It is possible to identify three categories of BCI systems: user-oriented, computer-oriented, and mutually-oriented.

**User-Oriented Systems**

In user-oriented BCI systems, the computer adapts to the user. Metaphorically speaking, these systems attempt to “read” the mind of the user to control a device. For example, Anderson and Sijercic (1996) reported on the development of a BCI controller that learns how to associate specific EEG patterns from a subject to commands for navigating a wheelchair. The prosthetic hand and the monkey experiment mentioned earlier also fit into this category.

**Computer-Oriented Systems**

With computer-oriented BCI systems, the user adapts to the computer. These systems rely on the capacity of the users to learn to control specific aspects of their EEG, affording them the ability to exert some control over events in their environments. Examples have been shown where subjects learn how to steer their EEG to select letters for writing words on the computer screen (Birbaumer et al. 1999).

**Mutually-Oriented Systems**

Finally, mutually-oriented BCI systems combine the functionalities of both categories, where the user and computer adapt to each other. The combined use of mental task pattern classification and biofeedback-assisted online learning allows the computer and the user to adapt. Prototype systems to move a cursor on the computer screen have been developed in this fashion (Peters, Pfurtscheller, and Flyvberg 1997; Penny et al. 1999). Co-evolving systems of humans and computers belong in this category.

**BCI Music Controllers**

To date, most efforts of BCI research have been aimed at developing ways to help severely impaired people communicate via computer systems and/or control mechanical tools, such as a wheelchair or a prosthetic organ. However, very little has been done to address the use of BCI technology for musical applications; such applications could undoubtedly improve the life quality of physically impaired
people in many forms, ranging from entertainment to therapy.

Those who have attempted to employ EEG as part of a music controller have done so by associating certain EEG characteristics, such as the power of the EEG alpha waveband to specific musical actions. These are essentially computer-oriented systems, as they require the user to learn to control their EEG in a certain way. This is very difficult to achieve without appropriate training. An effective method for learning to achieve specific mental states is based upon the notion of biofeedback. Biofeedback is a therapeutic technique whereby patients are trained to improve their condition by altering body functions that are involuntary, such as blood pressure, body temperature, and EEG (Robbins 2000).

The idea of thought-controlled music can be traced back to the 1960s, when Alvin Lucier composed *Music for Solo Performer*, a piece for percussion instruments played by the vibrations produced from the performer’s EEG (Lucier 1976). Lucier placed electrodes on his scalp, amplified the signals, and relayed them onto loudspeakers that were coupled to cymbals, gongs, and drums. The sounds emitted by the loudspeakers set the surfaces and membranes of the percussion instruments into vibration.

It was David Rosenboom, however, who in the early 1970s began systematic research into the potential of EEGs to generate art works, including music (Rosenboom 1990a). Drawing on concepts from electroencephalography (Niedermeyer and Lopes da Silva 1987) and cybernetics (Wiener 1948), he developed EEG-based musical interfaces associated with a number of compositional and performance environments that used the latest EEG technology at the time. In particular, Mr. Rosenboom explored the hypothesis that it should be possible to detect the occurrence of certain aspects of our musical experience in the EEG signal. For example, he introduced a generative music system whose parameters were driven by EEG components believed to be associated with shifts of the performer’s selective attention (Rosenboom 1990b).

We have tried to replicate the system described in Mr. Rosenboom’s 1990 article, but we found it extremely difficult to establish whether our system was really detecting shift of attention in the EEG. In the case of Mr. Rosenboom’s work, however, this was not necessarily a problem. On the contrary, his objective was to allow the performing subject’s EEG to influence the evolving musical forms, regardless of whether they were always aware of the events. All the same, his work is undoubtedly a landmark in the field of BCI for musical applications, as it indicates that the notion of thought-controlled musical systems is indeed possible. The core idea is to control or influence generative musical processes using EEG information about the musical experience of a performer during the unfolding of the piece. The sophistication of such a system is largely dependent upon its ability to harness the EEG signal and to devise suitable generative music strategies. We believe that we can push Mr. Rosenboom’s initial ideas much further by taking the progress made in the last decade in the fields of artificial intelligence, EEG analysis technology, and digital signal processing.

Several commercial systems can play music from EEG data. These normally consist of a headband furnished with two or three electrodes intended to read the EEG from the forehead of the subject. The signal is sent to a computer running software that allows associations of notes or musical events to incoming EEG data. For example, if the EEG’s predominant frequency components are lower than 10 Hz, then the system might play sound 1, otherwise play sound 2, and so on. As an excellent example of such a system, we cite the IBVA system designed by IBVA Technologies (refer to Miranda 2001 for a succinct description).

On the whole, these systems do a good job of capturing the EEG from the forehead, but they are rather limited when it comes to using the EEG in meaningful ways. The problem is that the raw EEG data is a stream of unsystematic, “random-like” numbers of little musical interest. Sophisticated analysis tools are needed to decipher the complexity of the EEG before any attempt is made to associate it with musical parameters, and this is a very difficult problem. Apart from breaking the EEG signal into different frequency bands, such systems lack the ability to detect useful information in the EEG. Consequently, they are unable to offer generative music strategies that would take advantage of such information. Our objective is to go beyond...
simplistic EEG waveband associations and computer-oriented BCI systems in a variety of important ways.

The Electroencephalogram (EEG)

As previously mentioned, neural activity generates electric fields that can be recorded with electrodes placed on the scalp [Misulis 1997]. The EEG is the visual plot of this signal, but today people normally use the term “EEG” to refer to the electric fields themselves. These electric fields are extremely faint, with amplitudes on the order of only a few microvolts. To be displayed and/or processed, these signals must be amplified. The EEG is measured as the voltage difference between two or more electrodes on the surface of the scalp, one of which is taken as a reference. Normally, this reference is an electrode placed in a location that is assumed to lack brain activity, such as the earlobe or the nose. It is also common practice to calculate the EEG of an electrode by averaging the signal from all electrodes and then subtracting it from the signal of each electrode. As far as BCI research is concerned, most of the important EEG activity lies below 40 Hz.

The EEG expresses the overall activity of millions of neurons in the brain in terms of charge movement, but the electrodes can detect this only in the most superficial regions of the cerebral cortex. The EEG is a difficult signal to handle, because it is filtered by the meninges (the membranes that separate the cortex from the skull), the skull, and the scalp before it reaches the electrodes. Although experts can often diagnose brain malfunctioning from raw EEG plots, this signal must be further scrutinized with signal processing and analysis techniques in order to be of any use for our research.

There are three fundamental approaches to EEG analysis: power spectrum analysis, event-related potential analysis, and correlation analysis. A brief introduction to EEG power spectrum analysis is given below owing to its relevance to BCI research in general. Event-related potential analysis and correlation analysis lie beyond the scope of this article. More information on how these have been employed in neuroscience of music research can be found in Besson and Faith [1995]; Janata and Pet-sche [1993]; Koelsch, Schröger, and Gunter [2002]; Näätänen [1990]; and Tervaniemi [1999].

Table 1. Bands of EEG activity and associated mental states for a healthy young adult

<table>
<thead>
<tr>
<th>EEG Rhythm</th>
<th>Frequency Band</th>
<th>Mental Association</th>
</tr>
</thead>
<tbody>
<tr>
<td>Delta</td>
<td>( \delta \leq 4\text{Hz} )</td>
<td>Sleep</td>
</tr>
<tr>
<td>Theta</td>
<td>( 4\text{Hz} &lt; \theta \leq 8\text{Hz} )</td>
<td>Drowsiness, trance, deep relaxation, deep meditation, hypnosis</td>
</tr>
<tr>
<td>Alpha</td>
<td>( 8\text{Hz} &lt; \alpha \leq 13\text{Hz} )</td>
<td>Relaxed wakefulness, (normally generated by closing the eyes)</td>
</tr>
<tr>
<td>Low Beta</td>
<td>( 13\text{Hz} &lt; \beta (-) \leq 20\text{Hz} )</td>
<td>Awake, alertness, moderate mental activity</td>
</tr>
<tr>
<td>Medium Beta</td>
<td>( 20\text{Hz} &lt; \beta (m) \leq 30\text{Hz} )</td>
<td>High alertness, intense mental activity</td>
</tr>
<tr>
<td>Gamma (also referred to as High Beta)</td>
<td>( \gamma &gt; 30\text{Hz} )</td>
<td>Hyper-awareness, stress, anxiety</td>
</tr>
</tbody>
</table>

Power Spectrum Analysis

Spectrum analysis is primarily based on Fourier techniques, such as the Discrete Fourier Transform (DFT), familiar to many electronic musicians (e.g., Miranda 1998). In short, DFT analysis breaks the EEG signal into different frequency bands and reveals the distribution of power among them. This is useful, because the distribution of power in the spectrum of the EEG can reflect certain states of mind. For example, a spectrum with salient low-frequency components is associated with a state of drowsiness, whereas a spectrum with salient high-frequency components is associated with a state of alertness.

There are six recognized bands of EEG activity, also referred to as EEG rhythms, each of which is associated with specific mental states. Experts disagree about the exact frequency boundaries of these bands and the mental states that are associated with each. Table 1 gives what the authors perceive to be consensual values and plausible associations.
Figure 1 shows two EEG spectral plots taken while a subject was watching television ([Figure 1a]) and while the same subject was relaxed, listening to ambient music with closed eyes ([Figure 1b]). Notice the broad band of beta activity in Figure 1a, which indicates that the subject is focusing attention and engaged in intense mental activity. The plot in Figure 1b shows moderate delta and theta activity, and a very narrow band of beta activity, which indicates a deep relaxation with a moderate degree of mental activity.

EEG rhythms clearly are a good source of information about mental activity, but they reveal only the “tip of the iceberg.” We must find new meth-
ods for extracting other types of features from the EEG. One such alternative is to track the variation in the density of the overall EEG spectrum. In the experiments described herein, we employed auto-regression (AR) analysis to represent the EEG in terms of estimations of its spectral density over time. Auto-regression analysis is further explained in a subsequent section.

Experimental Procedures

The objective of our experiments was to test whether variations in the spectral density of the EEG associated with different mental musical activities can be detected and classified automatically. The problem is that we do not know in advance which mental musical activities to target.
Hence, a significant part of our research is dedicated to the discovery of the various mental musical activities that generate distinct EEG patterns.

These experiments focus primarily on brain activity related to the perception of music rather than brain activity related to the control of music. An in-depth discussion of whether one should distinguish between perception and control is beyond the scope of this article. At this stage, we measure only the EEG where explicit control is not included in the mental task. We then use this knowledge to design control situations that could be used for performance. The experimental procedure consists of six steps: EEG acquisition, pre-processing, feature analysis, data preparation, classification, and statistical assessment (see Figure 2).

In short, we begin by extracting spectral dynamics information from the EEG obtained while subjects perform prescribed mental tasks. This generates a corpus of information that is divided into two sets: a training set and a test set. The training set is used to train a neural network to recognize the mental tasks associated with the remaining elements in the test set.

**EEG Acquisition**

We employed a 128-channel Geodesic System, manufactured by Electrical Geodesics, for EEG acquisition. It uses a network of 128 electrodes forming a geodesic structure, referred to as a Geodesic Sensor Net, or GSN (see Figure 3).

The advantage of the GSN over a simple headband with just two or three electrodes is that the GSN covers the entire upper brain. It allows us to capture a maximum amount of the brain’s electrical activity generated during the musical mental...
tasks, improving our chances of detecting useful information. The GSN is entirely non-invasive: it uses electrodes embedded in sponges that are soaked in a saline electrolyte solution to provide good conductivity on the scalp. Only the surfaces of the soaked sponges touch the skin.

The EEG data are greatly amplified and digitized at a sample rate of 250 Hz with a 12-bit resolution analog-to-digital (A/D) converter (Tucker 1993). An additional computer manages the presentation of the musical passages and trial-onset markers. A good-quality active loudspeaker relays monophonic audio at a distance of one meter from the subjects in the first two experiments. A pair of professional headphones was used to relay stereophonic audio to the subjects in the third experiment. Electric Geodesic’s Net Station software allowed raw EEG data to be saved as a segmented binary data file compatible with MATLAB, the software used in the next stages of the experimental procedure (see Figure 4).

Pre-Processing
Artifact Removal and Low-Pass Filtering
Raw EEG signals contain unwanted artifacts derived from muscle activity. Eye movement, blinking, swallowing, and other spurious limb movements generate strong EEG components that mask the components we are interested in analyzing.

Even though our subjects were instructed to sit still and close their eyes during the experiments, small involuntary eye movements still produced unwanted artifacts. These artifacts are detected and eliminated by comparing fast and slow running averages of the differences among signals from the electrodes placed near the eyes. This algorithm is given in appendix A.

Also, with dense electrode arrays like those used in our experiments, some electrodes may be faulty or become misplaced in the course of the experiment. When this happens, the EEG from the respective electrodes is excluded from further analysis.

We then apply a low-pass filter (LPF) to attenuate signals higher than 40 Hz, with the objective of reducing AC line noise (mains hum) and minimizing equipment interference. An eighth-order Butterworth LPF filter (Hamming 1989) with a cut-off frequency of 40 Hz is applied to individual channels of EEG data.

The representation of a subject’s EEG data is given by

\[ x_{c,n,k}(t), t = 1, \ldots T \]

where
- \( c \) is the index of the EEG channels \( c = 1, \ldots, 128 \);
- \( n \) is the set of segments (generated according to the number of trials, one segment per trial);
- \( k \) represents the classes (i.e., the mental tasks associated with the segments according to the experimental conditions at hand);
- \( t \) represents discrete time; and
- \( T \) is the trial length in units of the sample period (e.g., \( T = 250 \) for 1 sec trials and \( T = 500 \) for 2 sec trials; recall that the EEGs are digitized at 250 Hz).
**Laplace Filtering**

A Laplace spatial filter is employed to boost the manifestation of individual channels by separating the local EEG from larger global effects [Peters, Pfurtscheller, and Flyvberg 1997; Roberts and Penny 2000]. This filter simply works by subtracting the average of the signals of its nearest neighbors from the signal of each electrode:

\[ x_{c,k}^{n,k}(t) = x_{c,k}^n(t) - \frac{1}{|\Omega_k|} \sum_{i \in \Omega_k} x_{i,k}^n(t) \]

where \( \Omega_k \) is the neighborhood of channel \( c \) for all channels, and \( |\Omega| \) is the cardinality of \( \Omega \). Note that \( \Omega \) can vary according to the location of different electrodes [see Figure 5].

**Feature Analysis**

Feature analysis attempts to create a manageable and meaningful representation of raw original EEG data to maximize the potential success of the classification stage. Feature analysis also tries to compress the data to reduce the number of input variables of the neural network. We employed a linear AR algorithm for representing the EEG data in terms of estimations of its spectral density in time [Anderson and Sijercic 1996; Peters, Pfurtscheller, and Flyvberg].

Auto-regression models a time series \( u(t) \), \( t = 1, \ldots, T \), as the linear combination of \( N_o \) earlier values in the series. \( N_o \) is referred to as the order of the auto-regression, which is given by

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The process of transformation by AR modeling reduces the EEG time series \( x^{i,k}[t], t = 1, \ldots, T \) to \( N_s \) AR coefficients \( \{ a[i] \}, i = 1, \ldots, N_s \), which gives the feature set \( \{ f^{c,k}[m], m = 1, \ldots, N_s \} \). This can be represented as the feature set vector \( f^{c,k} \), which consists of the AR coefficients.

**Data Preparation**

The feature set is then presented to the neural network (see the next section), whose weights are adjusted during an iterative training process that minimizes the network error. Before presentation to the neural network, the feature vectors are organized into patterns of vectors

\[
p^{n,k} = \begin{bmatrix} f^{1,k}_{0} \\ f^{1,k}_{1} \\ \vdots \\ f^{n,k}_{0} \\ f^{n,k}_{1} \\ \vdots \end{bmatrix}
\]

of length \( N_s \times N_o \), where \( N_s \) is the number of available channels.

For each pattern vector, a target vector \( t^{c,k} \) is constructed to represent the desired output of the network. The form of the target vector depends on the number of output units in the neural network, and its construction depends on the number of outputs of the classification task, the number of classes in question (represented below as \( c \)), and the number of output units being used (see Table 2).

To train and test the neural network, the complete set of pattern vectors and their associated target vectors are split into a training set \( E = \{ [p^{n,k}, t^{c,k}], n \in \Psi, k \in \zeta \} \) and a test set \( T = \{ [p^{n,k}, t^{c,k}], n \in Y, k \in \zeta \} \). Here, \( \Psi \) is a random subset of segments from the total set of segments \( I \), where \( Y \cap \Psi = \emptyset \) and \( Y \cup \Psi = I \), and \( \zeta \) is the set of classes in question. Considering that the size of \( I \) is \( N_i \) and \( \zeta \) is \( N_o \), then the size of the whole set of patterns and target vectors is \( N_{ts} = N_i \times N_o \). The size of the training set can be calculated as \( N_{ts} = N_{tr} \times N_o \) and the size of the test set as \( N_{ts} = N_{T} \times N_o \).

Finally, all pattern vectors are linearly scaled within the range \([-1, 1]\) to limit the range of values presented at each input of the neural network. This scaling is useful, because it reduces the number of training iterations required to train the network by limiting the range of values presented to any of the network inputs. Sets of target vectors

_"Figure 5. Examples of neighborhood for electrodes F3 and Pz. (Note that this is only a didactic example using an electrode configuration that does not correspond to the GSN configuration used in the experiments.)"_
Table 2. Target vector formats for various 2- and 3-way classification tasks

<table>
<thead>
<tr>
<th></th>
<th>1 output</th>
<th>2-way</th>
<th>3-way</th>
</tr>
</thead>
<tbody>
<tr>
<td>class (1)</td>
<td>[0]</td>
<td>[1 0]</td>
<td>[1 0 0]</td>
</tr>
<tr>
<td>class (2)</td>
<td>[1]</td>
<td>[0 1]</td>
<td>[0 1 0]</td>
</tr>
<tr>
<td>class (3)</td>
<td>n/a</td>
<td>n/a</td>
<td>[0 0 1]</td>
</tr>
</tbody>
</table>

A single-output neural network is used in the Auditory Stimulus experiment, whereas the two- and three-output networks are used in the Active Listening and Musical Focusing experiments.

Classification

A classic, single, hidden-layer static Multi-Layer Perceptron (MLP) neural network with variable number of hidden units and between one and three output units (depending on the task at hand) is used for the classification task (see Figure 6). The network is trained in batch mode using a scaled conjugate gradient algorithm, as described by Bishop (1995), and the following logistic sigmoid transfer function:

\[ \phi(v) = \frac{1}{1 + e^{-v}} \]

where \( \phi(v) \) is the neuron's output for input \( v \).

Patterns in the test set are propagated forward through a trained network to assess its classification fitness. Patterns presented in this manner are awarded “1” for a correct classification and “0” for an incorrect classification:

\[ \text{award}(p) = \begin{cases} 1: f(y) = \text{true} \\ 0: f(y) = \text{false} \end{cases} \]

where \( f(y) \) is a post-processing function that converts the continuous output of the sigmoid output units into a binary form comparable to the target vectors. The exact nature of \( f(y) \) depends on the number of output units in the network and how the target vectors are constructed. Two post-processing functions are employed for the two types of output/target vector regimes: single output and multiple output functions. The single-output function is used in the first experiment. The two-way classification is encoded as a single bit target vector, where “0” represents class(1) and “1” represents class (2). When presented with a test pattern, the trained network produces a single-valued output within the range \([0, 1]\). The post-processing function used here is a simple threshold rule:

\[ f(y) = \begin{cases} 1: y > 0.5 \\ 0: y \leq 0.5 \end{cases} \]

The multiple-output function is used in the second and third experiments. In this case, two-way and three-way classifications are encoded as two- and three-bit target vectors, respectively. For instance,
the three-class target vectors \([1 \ 0 \ 0], [0 \ 1 \ 0], \text{ and } [0 \ 0 \ 1]\) represent \text{class}(1), \text{class}(2), \text{ and } \text{class}(3), \text{ respectively.} \) When presented with a test pattern, the trained network produces three continuous outputs within the range \([0, 1]\). The post-processing function used in this case is a competitive transfer function that returns a vector in which the bit with the highest value is allocated “1” and the others “0.”

\section*{Statistical Assessment}

To measure the effectiveness of a classification, we calculate its fitness \((\text{fit})\) by averaging the awards for the test set \(T\) as follows:

\[
\text{fit} = \frac{1}{N_k N_y} \sum_{k \in \mathcal{C}} \sum_{y \in \mathcal{Y}} \text{award}\ (p^{*}\ k)
\]

where \(N_y\) is the cardinality of \(\mathcal{Y}\).

To assess the accuracy of the classification, the process is repeated a number of times for a number of permutations of training sets \(E\) and test sets \(T\). Then, the average fitness \(\bar{\text{fit}}\) is taken to represent that particular classification. For example, if a two-class classification exercise gives results of 40\% fitness for a batch of 100 test patterns, the probability of the random classifier getting 40 or more hits in 100 is 0.00966 (i.e., almost 1\% probability). In this case, the classification task in question does not perform better than random choices. Such classification would outperform random choices only when this probability dropped to less than 5\%. In cases where the fitness is high (e.g., 70\% or higher) and/or when there are many trials in the test set, then the probability that random choices will match the performance of the neural network classification becomes negligible. For example, suppose that a three-class classification run gives an average fitness of 50\%. If there were only ten test patterns (i.e., \(N_y = 10\)), then the probability of guessing five trials correctly would be approximately 21\%, considering \(1 - F(n, k - 1, p)\), where \(n = 10, k = 5, \) and \(p = 0.333\) (refer to appendix B). However, if \(N_y\) is on the order of 50 or more, then the performance of a random classifier becomes insignificant (i.e., less than 1\%). In this case, the resulting 50\% is in fact statistically superior to random guessing.

\section*{The Experiments}

We performed three different experiments, referred to as \textit{auditory stimulus, active listening,} and \textit{musical focusing.} The subjects were three adult men, not professional musicians, but with some knowledge of music theory and/or practice.

To avoid sensor misplacement problems and to minimize artifacts from muscular activity and sensor misplacement, subjects were asked to sit still and keep their eyes closed during the experiments.

\section*{Auditory Stimulus Experiment}

\section*{Objective}

The objective of the auditory stimulus experiment was to test the hypothesis that information exists in the EEG that allows the automatic distinction between segments recorded immediately preceding and immediately following a simple auditory stimulus heard over silence. The classification task was to determine, on a segment-by-segment basis, the class of 1-sec multi-channel EEG segments, where class(1) represented the \textit{pre-stimulus onset}, and class(2) represented the \textit{post-stimulus onset}.

\section*{Procedure}

Subjects performed a single recognition task while listening to a sequence of auditory stimulus trials, each consisting of one of four tones. The experiment consisted of four blocks of 100 1-sec trials, each with a random inter-stimulus interval between three and nine seconds (see Figure 7). Each trial played one of four sinusoidal tones at 300 Hz, 400 Hz, 420 Hz, and 600 Hz from a pseudo-random play-list. There were 25 trials of each tone per block. Subjects were asked to listen to the tones and think about which of the four they had just heard. To maintain the subjects’ interest in the trials, we presented four tones in random order and with varying inter-stimulus intervals. A rest period of approximately 1 min was allowed between the blocks.

The trials were divided into pre-stimulus onset and post-stimulus onset segments of 1 sec each,
labeled class[1] and class[2], respectively \([N_1 = 2]\). Each subject yielded an average of 190 valid trials, resulting in \(N_f = 380\) segments. The set \(N_f\) was randomly partitioned into training sets and testing sets with split ratio 9:1, resulting in 342 training segments and 38 testing segments, respectively.

We used an MLP neural network with two hidden units and one single output unit. We tested neural networks with up to 16 hidden units, but those with a greater number performed only marginally better than those with only two units. In total, there were 768 inputs to the network \([N_s = 128 \times N_f = 6]\), and the training was performed in batch mode for 50 epochs. The network was reset, retained, and re-assessed ten times with different permutations of training and testing segments.

Results

Table 3 presents the average classification scores for each subject. The results demonstrate that it is possible to build a system to differentiate between pre- and post-auditory stimuli in multi-channel EEG signals with a considerably high degree of accuracy. Moreover, this can be achieved using a fairly standard correlation feature-detection method combined with a rather simple MLP neural network.

The fact that subjects were asked to identify the tone that they had just heard probably helped the accuracy of the classification, as this required some extra mental effort added to the listening activity. This is a positive phenomenon, because it leads us to challenge whether we can distinguish between the mental task of imagining music (i.e., hearing music in the “mind’s ear”) and passive relaxed listening.

The Active Listening Experiment

Objective

In this experiment, we attempted to test the hypothesis that information exists in the EEG that allows for the detection of whether a subject is engaged in active listening or passive listening. In this context, the active listening task was to replay the experience of hearing some music, or part of that music, in the “mind’s ear.” Conversely, the task of passive listening was to listen to music without making any special mental effort. In day-
to-day life experience, we are likely to be listening passively if we are relaxing to peaceful music or engaged in some other task while listening to light music in the background.

**Procedure**

The experiment was divided into six blocks of trials, giving the subject the chance to relax in between. Each trial lasted for 8 sec and contained two parts: a rhythmic part, lasting for the entire trial, and a melodic riff part, lasting for the first half of the trial. (A riff is a short, catchy musical passage that is usually repeated many times in the course of a piece of music.) During the second half of each trial, the mental task was performed. The rhythmic part comprised four repetitions of a one-bar rhythmic loop. Two repetitions a one-bar riff loop starting at the beginning of the trial and terminating halfway through were superimposed on the rhythmic part (see Figure 8).

In total, there were 15 unique riff loops: five played on a synthesized piano (General MIDI preset 1, “acoustic grand piano”), five using an “electronic” timbre (General MIDI preset 55, “synth voice”), and five on an actual electric guitar. The music was in the style of a pop club-like dance tune at 120 beats per minute with four beats per bar. The background rhythm looped seamlessly for the entire duration of each trial block. Blocks were named after the task the subject was instructed to perform on that block, ordered as shown in Table 4. Each of the 15 riff parts is presented four times in each block in random order.

Participants were instructed to perform one of three mental tasks while listening to a continuous sequence of trials. In the first task, active listening, subjects were asked to listen to the looped riff that lasts for two bars, and then immediately after it finishes, imagine that the riff continues for another two bars until the next trial begins. During the passive listening task, subjects were asked to listen to the entire four-bar trial with no effort and to just

<table>
<thead>
<tr>
<th>Block</th>
<th>Subject 1</th>
<th>Subject 2</th>
<th>Subject 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>active</td>
<td>passive</td>
<td>counting</td>
</tr>
<tr>
<td>2</td>
<td>passive</td>
<td>counting</td>
<td>active</td>
</tr>
<tr>
<td>3</td>
<td>counting</td>
<td>active</td>
<td>passive</td>
</tr>
<tr>
<td>4</td>
<td>active</td>
<td>passive</td>
<td>counting</td>
</tr>
<tr>
<td>5</td>
<td>passive</td>
<td>counting</td>
<td>active</td>
</tr>
<tr>
<td>6</td>
<td>counting</td>
<td>active</td>
<td>passive</td>
</tr>
</tbody>
</table>

Notes: The active listening experiment is divided into six blocks of trials. Blocks are named after the mental task the subjects are instructed to perform.

**Table 4. The Active Listening experiment**

**Figure 8. Subjects listen to four-bar trials containing a looped riff that lasts for two bars.**
relax and focus on the continuing background part. Finally, for the counting task test, subjects were asked to listen to the looped riff that lasts for two bars, then immediately after it finishes, mentally count the following self-repeating sequence of numbers: 1, 10, 3, 8, 5, 6, 7, 4, 2, 1, 10, and so forth. (Timing was unconstrained in the sense that there was no beat to perform the counting.)

The classification task here was to determine the class of 2-sec multi-channel EEG segments, where class(1) represents active listening, class(2) represents passive listening, and class(3) represents the counting task \( N_c = 3 \).

The rationale for including the counting task was as a control to determine whether the EEG features that might allow for the differentiation between the imagery and relaxed listening tasks are merely a function of a concentrating versus a non-concentrating state of mind. The hypothesis here is obvious: the ability to classify these three classes—two of which require mental effort—is an indication that effort-related tasks involving different mental faculties produce different EEG patterns.

Only the last 4 sec [i.e., the second half of each trial] were considered for analysis. These 4-sec segments were further divided into two 2-sec segments. Thus, each trial yielded two segments. There were 120 trials for each of the three conditions, and each subject produced a total of 720 segments \( N_i = 720 \). 240 segments for each condition.

The MLP neural network with eight units in the hidden layer was trained in batch mode for 50 epochs. In total, there were 768 inputs to the network \( N_i = 128 \times N_c = 6 \). The network was reset, re-trained, and re-assessed ten times with different permutations of training and testing segments.

**Results**

Classifications were made between 2-sec multi-channel segments belonging to pairs of conditions \( N_c = 2 \) for two-way classification] and to all three conditions \( N_c = 3 \) for three-way classification]. The average classification scores, including confidence limits and standard deviations for each subject, are shown in Table 5.

The figures in Table 5 are outstanding, with mean classification scores of no less than 95% accuracy. This experiment supports our hypothesis that it is possible to build a system to efficiently infer from the EEG whether a subject is actively listening to music or passively listening to it without any special mental effort. In this experiment, the notion of active listening is associated with the task of imagining or mentally re-creating a previously heard musical passage. In the next experiment, we expanded this notion by testing whether we could distinguish the EEG of a person who is focusing attention on a certain aspect of a musical passage from the EEG of a person who is listening holistically, that is, not focusing attention on any particular aspect of the music.

**The Musical Focusing Experiment**

**Objective**

The objective of the musical focusing experiment was to test the hypothesis that information exists in the EEG that allows identification of whether a subject is engaged in one of two mental tasks: musical focusing or holistic listening. We also attempted to test whether we could identify which side of the stereo field, left or right, on which the subject was focusing.

In this experiment, musical focusing required the subject to pay attention to a particular part of the music to which they were listening. For instance, consider a piece of pop music in which many instruments play different parts placed apart in a stereo mix. Suppose a clarinet part is hiding somewhere amidst the other parts, and the subject deliberately steers their attention toward the clarinet. We hypothesize that information in the EEG indicates whether the subject is performing such focusing mental tasks or simply listening holistically, in a relaxed, non-focused manner. Moreover, the EEG can also tell whether the subject is focusing on a part of the music that is panned to the left, right, or center. To simplify this experiment, however, we
Table 5. Average classification accuracy scores for the Active Listening experiment

<table>
<thead>
<tr>
<th>Subject</th>
<th>Classification Task</th>
<th>Mean</th>
<th>Min.</th>
<th>Max.</th>
<th>Deviation</th>
<th>Confidence</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>active × passive</td>
<td>0.998</td>
<td>0.979</td>
<td>1.000</td>
<td>0.007</td>
<td>+/- 0.007</td>
</tr>
<tr>
<td></td>
<td>active × counting</td>
<td>0.996</td>
<td>0.979</td>
<td>1.000</td>
<td>0.009</td>
<td>+/- 0.009</td>
</tr>
<tr>
<td></td>
<td>passive × counting</td>
<td>0.994</td>
<td>0.979</td>
<td>1.000</td>
<td>0.010</td>
<td>+/- 0.010</td>
</tr>
<tr>
<td></td>
<td>active × passive × counting</td>
<td>0.998</td>
<td>0.958</td>
<td>1.000</td>
<td>0.015</td>
<td>+/- 0.016</td>
</tr>
<tr>
<td>2</td>
<td>active × passive</td>
<td>0.994</td>
<td>0.979</td>
<td>1.000</td>
<td>0.010</td>
<td>+/- 0.010</td>
</tr>
<tr>
<td></td>
<td>active × counting</td>
<td>0.973</td>
<td>0.896</td>
<td>1.000</td>
<td>0.031</td>
<td>+/- 0.032</td>
</tr>
<tr>
<td></td>
<td>passive × counting</td>
<td>0.954</td>
<td>0.896</td>
<td>1.000</td>
<td>0.038</td>
<td>+/- 0.039</td>
</tr>
<tr>
<td></td>
<td>active × passive × counting</td>
<td>0.951</td>
<td>0.903</td>
<td>0.986</td>
<td>0.023</td>
<td>+/- 0.024</td>
</tr>
<tr>
<td>3</td>
<td>active × passive</td>
<td>0.973</td>
<td>0.958</td>
<td>1.000</td>
<td>0.014</td>
<td>+/- 0.014</td>
</tr>
<tr>
<td></td>
<td>active × counting</td>
<td>0.992</td>
<td>0.979</td>
<td>1.000</td>
<td>0.011</td>
<td>+/- 0.011</td>
</tr>
<tr>
<td></td>
<td>passive × counting</td>
<td>0.994</td>
<td>0.958</td>
<td>1.000</td>
<td>0.014</td>
<td>+/- 0.014</td>
</tr>
<tr>
<td></td>
<td>active × passive × counting</td>
<td>0.985</td>
<td>0.958</td>
<td>1.000</td>
<td>0.015</td>
<td>+/- 0.016</td>
</tr>
</tbody>
</table>

did not attempt to classify cases where the subject is focusing on the center of the stereo field.

The classification task therefore is twofold. It must be able to determine whether a 2-sec multichannel EEG segment corresponds to musical focusing or holistic listening, and within the musical focusing, it must be able to determine whether the subject is focusing on music heard though the left or the right ear. As with the previous experiment, we also included the counting task here. In total, there were four different classes to classify, namely musical focusing to the left, musical focusing to the right, holistic listening, and counting ($N_c = 4$). However, to use the same MLP neural network architecture as the previous experiment, the classification exercise involved subsets of two and three classes.

**Procedure**

Subjects were instructed to perform one of three mental tasks [musical focusing, holistic listening, and counting] while listening to a continuous sequence of trials. Starting with a vocal cue, each trial continued with a 16-sec musical passage composed of four parts: a rhythmic part plus three instrumental parts. During the musical portion of each trial, one of the three mental tasks was performed. The experiment was divided into four blocks of trials, thus giving the subject the opportunity to rest. Before the experiment began, subjects were given the following instructions as to the nature of the tasks.

For musical focusing, they were asked to listen to the looped riffs while focusing especially hard on the target part, which belongs to the instrument that is defined during the cue at the beginning of the trial. For holistic listening, subjects were asked to listen to the entire 4-bar trial with no effort. Finally, for the counting trial, subjects were asked to count the following self-repeating sequence: 1, 10, 3, 8, 5, 6, 7, 4, 9, 1, 10, and so on, until the end of the trial.

Each trial lasted for 19 sec. The trials started with a 3-sec vocal cue that informed the subject which task they must perform during the trial. For focusing trials, subjects heard the names of the three instruments and an indication of the target instrument on which they should focus. The subjects were not informed that we were interested in classifying the stereo panning. In the case of the passive listening or counting tasks, they heard the words “relax” or “count,” respectively. This was followed by 16 sec of music, during which the subject performed one of the three basic tasks. As soon as the 16-sec musical portion of the current trial finished, the next trial began (see Figure 9).

The musical portion of each trial was composed of four parts. The music was in the style of a moderate “dance-pop” tune at 120 beats per minute,
part comprises eight repetitions of a one-bar riff played on one of three instruments.

Figure 9. The musical portion of each trial is composed of four instrumental parts. Each instrumental part comprises eight repetitions of a one-bar riff played on one of three instruments.

Table 6. The Musical Focusing experiment

<table>
<thead>
<tr>
<th>Trial</th>
<th>Hard-left</th>
<th>Center</th>
<th>Hard-right</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Synth-1</td>
<td>Guitar-1</td>
<td>Piano-3</td>
</tr>
<tr>
<td>2</td>
<td>Synth-2</td>
<td>Piano-1</td>
<td>Guitar-3</td>
</tr>
<tr>
<td>3</td>
<td>Guitar-1</td>
<td>Synth-1</td>
<td>Piano-4</td>
</tr>
<tr>
<td>4</td>
<td>Guitar-2</td>
<td>Piano-2</td>
<td>Synth-3</td>
</tr>
<tr>
<td>5</td>
<td>Piano-1</td>
<td>Synth-2</td>
<td>Guitar-4</td>
</tr>
<tr>
<td>6</td>
<td>Piano-2</td>
<td>Guitar-2</td>
<td>Synth-4</td>
</tr>
<tr>
<td>7</td>
<td>Synth-5</td>
<td>Guitar-3</td>
<td>Piano-5</td>
</tr>
<tr>
<td>8</td>
<td>Synth-6</td>
<td>Piano-3</td>
<td>Guitar-5</td>
</tr>
<tr>
<td>9</td>
<td>Guitar-6</td>
<td>Synth-3</td>
<td>Piano-6</td>
</tr>
<tr>
<td>10</td>
<td>Guitar-7</td>
<td>Piano-4</td>
<td>Synth-7</td>
</tr>
<tr>
<td>11</td>
<td>Piano-7</td>
<td>Synth-4</td>
<td>Guitar-8</td>
</tr>
<tr>
<td>12</td>
<td>Piano-8</td>
<td>Guitar-4</td>
<td>Synth-8</td>
</tr>
</tbody>
</table>

Note: The trials are played randomly so three instruments are always playing with different panning.

four beats per bar, comprising a background part formed by eight repetitions of a 1-bar drum rhythm loop, an instrumental part panned hard left, a second instrumental part centrally panned, and a third instrumental part panned hard right. Each instrumental part comprised eight repetitions of a one-bar riff played on one of three instruments, identical to those used in the active listening experiment. Altogether, there were 24 different riffs, split between the three instruments, resulting in eight piano riffs, eight “synth-voice” riffs, and eight electric guitar riffs. The instrumental parts were played randomly so that three instruments were always playing with each one panned either hard left, center, or hard right [see Table 6]. We chose different riffs for each instrument to provide variety for the subjects.

Altogether, there were four blocks, each consisting of 12 focusing trials (six with left-target and six with right-target parts), 12 holistic listening trials, and 12 counting trials. This makes a total of 36 trials lasting 19 sec each, and an equal number of trials from each of the three main conditions were presented. The trials were played within each block in a pseudo-random order so that the subject did not learn to predict the next type of trial. Before the experiment started, subjects were given an opportunity to become familiar with the trial format.
and mental tasks with a short practice session. The subjects listened to the trials on headphones.

Each trial was segmented into eight non-overlapping 2-sec segments. Each subject produced $N_1 = 1152$ segments comprising 384 holistic listening segments, 384 counting segments, and 384 musical focusing segments, where the latter group was divided into 192 focusing on the left and 192 focusing on the right segments. The data were randomly partitioned into training sets and testing sets with split ratio 9:1, resulting in 346 training segments and 38 testing segments for each class per subject (or 173 and 19 segments, respectively, when distinguishing left- and right-focusing).

The MLP neural network with eight units in the hidden layer and either two or three units in the output layer (for 2- and 3-way classification tasks, respectively) was trained in batch mode for 50 epochs. As with the previous cases, there were 768 inputs to the network [$N_s = 128 \times N_o = 6$]. The network was reset, re-trained, and re-assessed ten times with random permutations of training and testing segments.

**Results**

Classifications were made between 2-sec multi-channel segments belonging to pairs and triplets of conditions [$N_c = 2$ for 2-way classification and $N_c = 3$ for 3-way classification, respectively]. The average classification scores, including confidence limits and standard deviation for each subject, are shown in Table 7.

The scores in Table 7 are slightly less encouraging than the scores for the previous experiment, but we should bear in mind that the classification task was far more difficult here. Still, the mean scores are far better than random guessing, and the confidence limits are within a reasonably good range. The results indicate that it is possible to build a system that is able to infer from the EEG whether the subject is performing a mental focusing task of listening holistically. It is also possible to infer whether the subject is focusing on a part of the music that is panned to the left or to the right of the stereo field.

**Practical Use of the Results**

As mentioned earlier, the objective of our research is twofold: we are developing techniques for harnessing the EEG for the musical braincap and compositional techniques suitable for thought control. A thorough report on the compositional techniques that have been developed so far is beyond the scope.
of this article. However, to provide a good idea of how we are using the results from our experiments in practice, we briefly introduce below two of the schemes that are currently being tested: b-soloist and b-conductor.

The active listening experiment led to the development of the b-soloist ("brain soloist") technique, where the EEG is taken from a performer's brain (see Figure 10). First, the neural network is trained to identify when the incoming EEG corresponds to active or passive listening, as described in the experimental procedure. We used the same musical scheme as the one in the active listening experiment (see Figure 8), except that the riff part is produced by a transformational rule [Miranda 2000] that generates slight variations on an original two-bar riff.

The composition works as follows: the rhythmic part is continuously played and a riff is played sporadically. Immediately after a riff is played, the system checks the subject's EEG. If it detects active listening behaviour, then the system activates a transformation rule to generate a variation of the riff that has just been played. Otherwise, it does not generate anything and waits for the subject's response to the next sporadic riff. Sporadic riffs are always a repetition of the last played riff; in other words, it does not change until the system detects active listening behavior. The initial riff is given by default. The subject who plays the music should be the same person as the one who trained the system.

The b-conductor ("brain conductor") technique was devised following the focusing experiment. It is inspired by the metaphor of the conductor who steers the expressive performance of a musical score by an orchestra. Here, we use EEG to steer expressive aspects of a musical score performed by a computer. In this case, the score constitutes four tracks of recorded music, identical to the music used in the experiment (see Figure 9). All four tracks were recorded with equal volume levels. The idea is to let the subject steer the loudness of the left and the right tracks by focusing on the part that is being played in the respective channel (see Figure 11).

First, the neural network is trained to identify whether the incoming EEG corresponds to focusing on the music panned to the left or to the right side of the stereo field, as explained in the experimental procedure. The music is then played back, and the system checks the subject's EEG. If it detects a mental focus on the musical part that is panned to the left of the stereo field, then the system will increase the amplitude of the left channel track. Conversely, if it detects a mental focus on the part that is panned to the right, then the system will increase the amplitude of the right channel track. There is a confidence measure whereby the degree of confidence determines the amount of volume increase. After a few seconds, the volume of the modified track returns to the initial default level.

Concluding Remarks

The idea of interfacing the brain with computers is no longer a science fiction fantasy, but one should not overstate what has been achieved so far. Much research is still needed to test hypotheses, discard those that are impractical, and build upon those that are feasible.

There have been a few attempts to build systems that generate music from the EEG, but these systems are very limited in the sense that raw EEG data is merely used to trigger MIDI notes in a random-like fashion. We believe that this scenario can be much improved by finding ways to harness the EEG signals and extract meaningful musical information from them. In this article, we introduced three experiments whose results suggest that it is possible to train a system to detect and harness EEG components associated with musical mental activity. Then, we discussed how these results might be put into practice.

This article described the use of fairly standard signal-processing algorithms for handling the EEG signal. Although one of our intentions was to use the simplest signal-processing methods possible, we are aware that a compromise between simplicity and efficiency must be found. But what is encouraging here is that, once the neural network is trained, the classification of a testing vector is very fast (it is based on 1-sec segments).

We tested a number of methods for feature analysis and classification, other than auto-regression coefficients and MLP neural networks, to handle the
Figure 10. The overall functioning of the b-soloist scheme whereby the brain plays variations of imagined riffs.
Figure 11. Block diagram for the b-conductor scheme whereby the performer steers the faders of a mixer with the brain.
data from the experiments above, including ARMO (auto-regression model order) and correlation for feature extraction, and GLM (generalized linear model) and the Fisher discriminant for classification [Duncan 2001]. Different combinations of these methods sometimes produced better scores than the ones presented here, suggesting that the best approach would perhaps be to use competing multiple alternatives associated with some sort of selection mechanism to automatically choose the best solutions.

Two other fundamental areas must be addressed. It is vital to devise generative music strategies tailored to the kinds of information we can extract from the EEG. Ideally, one should try to adapt standard compositional techniques, but new compositional techniques may—and should—emerge from this work. The other area that must be addressed is EEG acquisition. The Geodesic Sensor Net is a great device for research, but it is impractical for the musical braincap: so many electrodes and wires do not facilitate the design of an ergonomic and easy-to-wear device. New, noninvasive EEG-acquisition technology must be devised. The recently announced system for recording EEGs without placing electrodes in contact with the scalp [Harland, Clark, and Prance 2002] is a promising development.

Another alternative that we are considering is the magnetoencephalogram (MEG), either as a complementary brain activity reading or as a replacement of EEG altogether. MEG records the magnetic field generated by neural activity. At the moment, MEG technology is more expensive and cumbersome to use than EEG, but the resulting measurements are better, especially when it comes to identifying localized activity in specific brain areas.

References

Anderson, C., and Z. Sijercic. 1996. “Classification of EEG signals from Four Subjects During Five Mental Tasks.” Solving Engineering Problems with Neural Networks: Proceedings of the Conference on Engineer-

### Appendix A: Artifact Removal Algorithm

This algorithm is applied twice to detect eye-blink and eye movement artifacts (once for each pair of channels near the eyes). It compares the deviation between fast and slow running averages of a pair of eye channels with a threshold. An eye blink is detected when the deviation exceeds the threshold level of 70 μV.

1. **Fast = 0**
2. **Slow = average of difference of first 10 samples**
3. **FOR each sample DO:**
   - **Diff = difference in voltage of eye channels**
   - **Fast = (Fast * 0.8) + ((Diff − Slow) * 0.2)**
   - **Slow = (Slow * 0.975) + (Dif * 0.025)**
4. **IF |Fast| > eye_blink_threshold THEN reject segment**

The same algorithm is used for detecting eye movement, with the exception that it uses the two horizontal channels near the eyes.

### Appendix B: Random Classifier

The expected performance of a random classifier that guesses the classes for each trial is used as a means of gauging the performance of our classification strategy. Suppose there is a problem with *c* classes. For each trial, a random classifier chooses one of these classes at random. Assuming that the underlying classes in the observation data are equally probable, the probability of a success is *p = 1/c* and failure 1 − *p*. The probability of *k* successes over *n* independent trials in one particular sequence of successes and failures is given by

\[
\binom{n}{k} = p^k(1 - p)^{n-k}
\]

The following equation therefore calculates the total probability of any *k* success in *n* trials:

\[
f(n,k,p) = \frac{n!}{k!(n - k)!} p^k(1 - p)^{n-k}
\]

The distribution function is then computed as follows:

\[
F(n,k,p) = \sum_{q=0}^{k} f(n,q,p)
\]

The distribution function gives the probability that the random classifier will have *k* or less success in *n* trials, but we can calculate the probability of getting more than *k* success simply by subtracting 1 − *F(n, k − 1, p).*