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Information transfer of an EEG-based brain computer interface

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Abstract-**The idea of an EEG-based brain computer interface is to support the communication of locked-in-patients. Thus, it is important to quantify the information transfer. Wolpaw et al. (2000) has proposed a measure which is derived from the classification error rate. In this work, we propose an alternative measure. Both measures are compared and the advantages and disadvantages of both are discussed.**

Keywords **- brain computer interface, adaptive autoregressive parameters, quadratic classifier, communication theory, mutual information**

I. Introduction

In the past, the performance of EEG-based brain computer interfaces (BCI's) were quantified mostly in a percentage of correctly classified results [1]. However, it is reasonable to look at the BCI as an communication channel and to quantify the information transfer of such a BCI system. One attempt relates the accuracy with the bit rate of a BCI system [2].

$$B = \log_2 N + P \log_2 P + (1-P) \log_2[(1-P)/(N-1)] \quad (1)$$

N .. number of possible selection
P .. accuracy (probability that the desired selection will be selected)
B .. bits per trial

Note, the accuracy (or error rate) must be known in order to estimate the bit rate B. An alternative attempt to quantify the amount of information can be derived from the mutual information between the BCI output and the class information [3,4]. In this work, the idea of the latter method is presented and compared with the former.

II. Methodology

Lets assume, the BCI output consists of two components. One component is correlated with the desired output, the second component is completely uncorrelated. In other words, the first components contains the useful signal u_k, the second component is random noise only.

$$D(k) = v_k = u_k + n_k \quad (2)$$

Without loss of generality, we assume the noise n_k is zero mean and variance σ_n^2 and is not correlated with the signal.

$$n_k = N(0, \sigma_n^2) \quad (3)$$

$$E<(u_k - \mu_u)(n_k - \mu_n)> = 0 \quad (4)$$

If the probability for both states is equal, the mean and variance are $\mu_u = (\mu_1 + \mu_2)/2$ and $\sigma_u^2 = (\mu_1 - \mu_2)^2/4$, respectively.

$$u_k = \{\mu_1, \mu_2\} \quad (5)$$

Accordingly, the signal-to-noise ratio (SNR) is

$$SNR = \sigma_u^2/\sigma_n^2 = \sigma_v^2/\sigma_n^2 - 1 \quad (6)$$

or

$$SNR[db] = 10 * \log_{10}(\sigma_u^2/\sigma_n^2). \quad (7)$$

Next, we introduce the entropy of information (short: entropy) according to Shannon [5]. For a continuous stochastic x process, the entropy $H(x)$ is

$$H_x = integral\ \{p(x)\ \log_2(p(x))\ dx\}. \quad (8)$$

It can be shown, the entropy of a stochastic process x with a given variance σ_x^2 is

$$H(x) \leq 0.5 * \log_2(2\pi e \sigma_x^2). \quad (9)$$

The equality holds if x is a Gaussian process, the entropy $H(x)$ is smaller for any other distribution. Therefore, this formula is an approximation of the maximum entropy.

The mutual information I (i.e. entropy difference between the observed process v and the noise process n) is the entropy of the "useful" output, i.e. the signal u.

$$I(u) = H(v) - H(n) \quad (10)$$

Using the approximation that v, n and s are Gaussian, we get

$$I(u) \approx ½ \log_2(2\pi e \sigma_v^2) - ½ \log_2(2\pi e \sigma_n^2) \quad (11)$$

$$I(u) \approx ½ \log_2(\sigma_v^2/\sigma_n^2) = ½ \log_2(1+SNR) \quad (12)$$

Note, the entropy difference, i.e. amount of information in signal *s*, depends on the SNR only. In other words, the ratio between the signal and the noise variance determines the amount of mutual information between the output and the class relation.

A. Simulation

A signal and a noise process are simulated. The noise process is zero mean white noise with a r.m.s. value of $1/\sqrt{SNR}$. The signal is just -1 or $+1$. The standard deviation of this process is 1 (assuming both classes occur with equal probability). The result is shown in Figure 1.

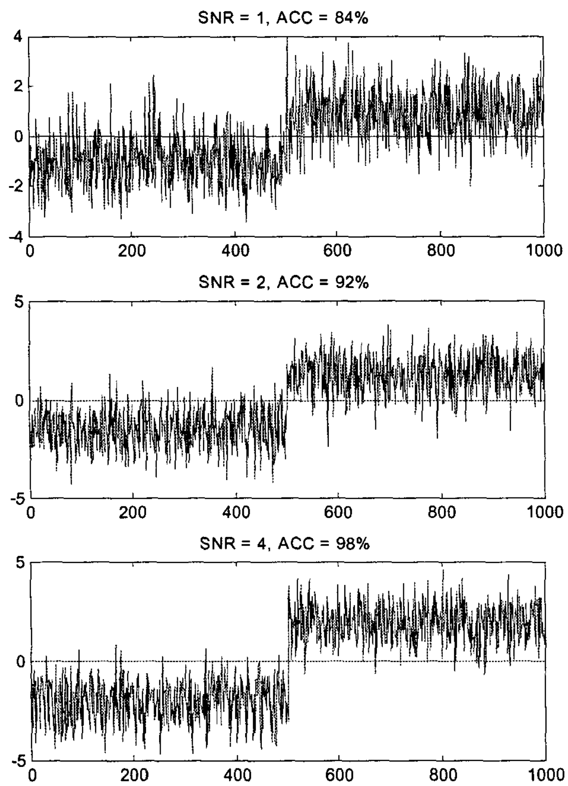

Figure 1: Detection accuracy with different SNR levels. The first 500 samples are for class 1, the second 500 samples represent class 2. The three examples correspond to different levels of SNR and classification accuracy.

It is shown, that the classification accuracy increases with the SNR. For this simple case, the relationship between accuracy and SNR is

$$ACC = \tfrac{1}{2} + erf(-\sqrt{SNR/2})/2 \qquad (13)$$

The information is quantified with two methods. Firstly, the classification accuracy was used to obtain the information transfer according to (1) for N=2 classes and accuracy P. Secondly, the amount of information is estimated with the mutual information (12). Figures 3 and 4 display the relationship between the SNR, the classification accuracy and the amount of information.

B. Experiment

In the next step, some real world BCI data were investigated. For this purpose, we used a similar experiment as described in [4], whereby several modifications were applied. Three bipolar channels over C3, Cz and C4 were recorded. In a first run (training), the subject was asked to perform imagery left or right hand movements. Three training runs (each 20 left + 20 right) trials were used to build a classifier. In the next runs, feedback was provided (Figure 2). The subject was asked to move the bar into the direction of the arrow.

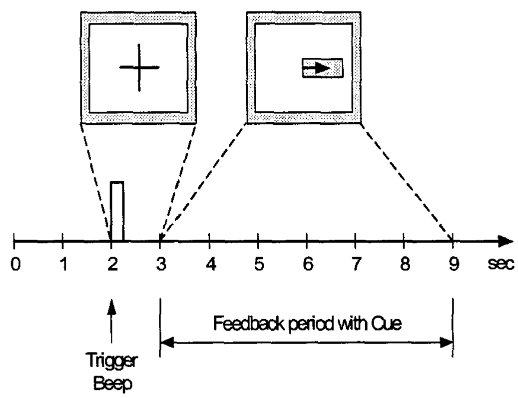

Figure 2: Timing of one trial. At t=2s a tone (beep) and a cross appeared on the computer screen. Beginning with t=3s, the cue (arrows towards left or right) was presented; the continuous feedback was presented as horizontal bar with varying length.

C. Feature extraction

Adaptive autoregressive (AAR) parameters were estimated with Kalman filtering (mode=a2v3, [3]). A model order p=6 and an update coefficient UC= 0.0055 were chosen. The AAR parameters were estimated from two EEG channels (C3 and C4). Thus, 12 parameters (features) were obtained for each sample.

$$x(t) = [a_{1,1}(t), \ldots a_{p,1}(t), a_{1,2}(t), \ldots a_{p,2}(t)] \qquad (14)$$

The AAR estimation algorithm was used offline for estimating the "classifier", as well as for online calculation of the feedback.

D. Combining the features (classification)

In an offline analysis, the ensemble mean $\mu_i(t)$ and the covariances $\Sigma_i(t)$ for both classes and each time point were calculated from the AAR parameters. The means and covariances of 8 sample-segments were averaged. In the next step, the Mahalanobis distance MD between left and right trials were calculated for each time segment.

The Mahalanobis distance d_c of one point x in the feature space to the multivariate normal distribution $N(\mu_c, \Sigma_c)$ of class c is defined by

$$d_c^2(t) = (x(t)-\mu_c) \cdot \Sigma_i^{-1} \cdot (x(t)-\mu_c)^T \quad (15)$$

The differences of the distances $D(t) = d_1(t) - d_2(t)$ can be calculated giving the mahalanobis-based distance:

$$D_{MDA}(x) = d_1(x) - d_2(x) = \quad (16)$$

$$= \sqrt{((x-\mu_1).C_1^{-1}.(x-\mu_1)^T)} - \sqrt{((x-\mu_2).C_2^{-1}.(x-\mu_2)^T)}$$

The segment with the largest distance $d_1(\mu_2) - d_2(\mu_1)$ was used to build the classifier. The experiments with feedback estimated online the AAR parameters (14) and the classification (16). The matrix inversions were be performed offline; this reduced the computational load for online processing. The classification output was used the control the length of the horizontal bar on the computer screen.

In this work, the result from the training session is evaluated. Hence, the training and test set were the same. In order to implement cross-validation, a jackknife method [6], based on leave-one-trial-out, was applied. The error rate, the SNR, the information transfer (1) and the mutual information (12) were calculated for each point in time.

III. RESULTS

A. Simulations

The relationship between SNR and classification error was demonstrated on three examples. In Figs. 3 and 4 the relationship between SNR, error rate (accuracy), mutual information and information transfer are presented in a more general way.

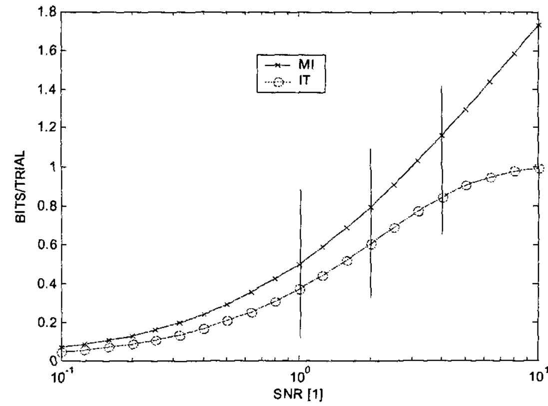

Figure 3: Relation between the SNR, the information transfer (IT), and the mutual information (MI). The vertical lines indicate a SNR of 1, 2 and 4.

The results (Figs. 3 and 4) show that the information transfer according to (1) has an upper limit of 1. An 100% accurate classification would provide 1 bit only. The mutual information become also larger than 1 bit, if the SNR is large enough. The mutual information is, in general, larger then the information transfer.

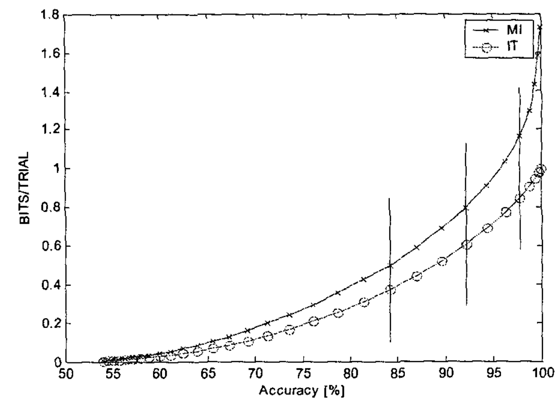

Figure 4: Relation between accuracy, information transfer (IT) and the mutual information (MI). The vertical lines indicate a SNR of 1, 2 and 4 and an accuracy of 84, 92 and 98%.

Fig. 5 shows the time course of the separability of an BCI experiment. The plots display the time courses of: the error rate or accuracy (top), the mean and standard deviation within the classes indicating the signal-to-noise ratio (middle), and the information transfer and the mutual information (bottom). The mutual information is, again, larger than the information transfer.

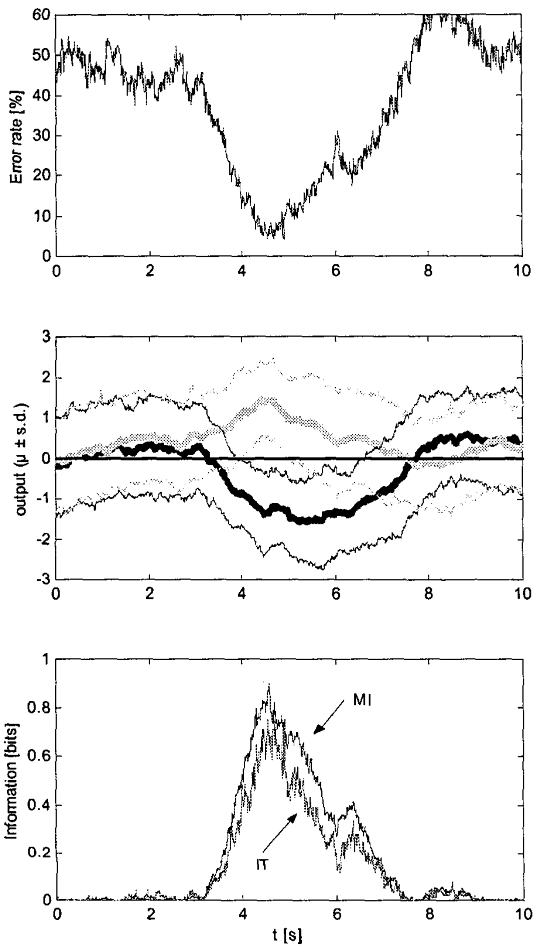

Figure 5: Time courses displaying the separability between two classes. Adaptive autoregressive (AAR) parameters of order p=6 from two bipolar channels (C3 and C4) were estimated with Kalman filtering. The AAR parameters between t = 4.13s and t = 4.25s were used to build the classifier. Cross-validation based on "leave-one-trial-out" (jackknife method) was applied.

(a) In the first plot, the time courses of the error rate is shown. ERR(t) gives the classification error with MDA of the EEG-channels C3 and C4 at time t. AAR(6) parameters were used as EEG features.

(b) The second plot shows the average output for the left (dark) and right (light) trials. The average output (thick lines) clearly show a different pattern between imagined left and right hand movement. The thin lines represent the within-class standard deviation (SD) of the output and indicate the inter-trial variability of the EEG patterns.

(c) The third plot shows the information transfer from the cue to the classification output. The upper and lower curve represent the mutual information and the information transfer, respectively.

IV. Discussion

In this work, two measures for the quantification of information were compared. Both measures, the information transfer [1] and the mutual information [3,4], were derived from Shannon's communication theory [6] and were used to quantify the amount of information of a BCI output.

The differences between both measures are also obvious. Firstly, the results are different. Secondly, the measures are calculated in different way. The mutual information uses the entropy difference of stochastic processes, the information transfer requires the classification accuracy. To classify the BCI output, a threshold must be applied. This causes the rejection of the magnitude, causing a reduction of information.

The magnitude carries information, e.g. about the certainty of a classification. Moreover, if continuous feedback is provided, the subject can also use this information for its training. If the feedback control would be sufficiently accurate the subject would be able to select more than two positions on a one one-dimensional scale.

V. Conclusion

The information transfer can be increased by reducing the noise level or by increasing the signal. If the noise level is sufficiently small, the information transfer rate of a two-class paradigm can be larger than 1 bit per trial.

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