[15] K. Turetschek, S. Huber, and E. Floyd *et al.*, "MR imaging characterization of microvessels in experimental breast tumors by using a particulate contrast agent with histopathologic correlation," *Radiology*, vol. 218, pp. 562–569, 2001.
[16] S. C. L. Deoni, B. K. Rutt, and T. M. Peters, "Rapid combined $\boldsymbol{T}_1$ and $\boldsymbol{T}_2$ mapping using gradient acquisition in the steady state," *Magn. Reson. Med.*, vol. 49, pp. 515–526, 2003.
[17] G. Brix, F. Kiessling, R. Lucht, S. Darai, K. Wasser, S. Delorme, and J. Griebel, "Microcirculation and microvasculature in breast tumors: pharmacokinetic analysis of dynamic MR image series," *Magn. Reson. Med.*, vol. 52, pp. 420–429, 2004.

A Fully On-Line Adaptive BCI

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***Abstract*—A viable fully on-line adaptive brain computer interface (BCI) is introduced. On-line experiments with nine naive and able-bodied subjects were carried out using a continuously adaptive BCI system. The data were analyzed and the viability of the system was studied. The BCI was based on motor imagery, the feature extraction was performed with an adaptive autoregressive model and the classifier used was an adaptive quadratic discriminant analysis. The classifier was on-line updated by an adaptive estimation of the information matrix (ADIM). The system was also able to provide continuous feedback to the subject. The success of the feedback was studied analyzing the error rate and mutual information of each session and this analysis showed a clear improvement of the subject's control of the BCI from session to session.**

***Index Terms*—AAR, adaptive classification, BCI, on-line adaptation, QDA.**

I. Introduction

A brain computer interface (BCI) is a system which enables people to control devices using electroencephalogram (EEG) patterns, and it is specially helpful to assist patients who have highly compromised motor functions, such as completely paralyzed patients with, e.g., amyotrophic lateral sclerosis, [1]–[11].

In each new BCI application, the user has to be trained over a number of sessions. Often, the EEG patterns change with time. Possible reasons for these changes are the direct or indirect influence of the feedback, changes in concentration, attentiveness, motivation, etc. A BCI system needs to adapt to such changes. In practice, a new "classifier" [4], [12] or new thresholds [10], [13]–[15] are obtained from the data; the classifier is updated after some runs or some sessions. So far, the update of the classifier was done manually, using more or less sophisticated analysis tools and the experience of the experimenter. In [16]–[20], the adaptation is automated, although it was not tried yet during feedback experiments.

In this paper, an on-line adaptive classifier is investigated. This continuously adaptive classifier has been implemented in our on-line cue-based 2-class BCI system and allows an update of the classifier with each trial. The system was tested during feedback experiments with 9 naive subjects to prove the robustness and stability of this BCI.

II. Methods

A. The Adaptive Classification Algorithm (ADIM)

ADIM is an adaptive version of the quadratic discriminant analysis (QDA) that can be on-line estimated. QDA is a statistical classifier based on the Mahalanobis distance $d_i(\mathbf{x})$ of the observation $\mathbf{x}$ to class i

$$d_i(\mathbf{x}) = (\mathbf{x} - \boldsymbol{\mu}_i)^T \cdot \boldsymbol{\Sigma}_i^{-1} \cdot (\mathbf{x} - \boldsymbol{\mu}_i) \tag{1}$$

where $\boldsymbol{\Sigma_i}$ is the covariance matrix for class i, $\boldsymbol{\mu}_i$ is the mean vector for class i, and $\mathbf{x}$ is the feature vector.

For two classes, QDA can be obtained using the Mahalanobis distance of the feature vector to each class, as follows:

$$D(\mathbf{x}) = d_1(\mathbf{x})^{1/2} - d_2(\mathbf{x})^{1/2}. \tag{2}$$

If $D(\mathbf{x})$ is greater than zero, then the input is classified as class 2, and if the output is equal or less than zero, then the input is classified as class 1.

As it can be seen in (1), QDA is based on the inverse of the covariance matrix. This matrix can be adaptively estimated through the Matrix Inversion Lemma [21]. Accordingly, ADIM is obtained through the following update equation:

$$\boldsymbol{\Sigma}_{n,i}^{-1} = (1 + UC) \cdot \boldsymbol{\Sigma}_{n-1,i}^{-1} - \frac{1 + UC}{1 - UC + \mathbf{x} \cdot \mathbf{v}} \cdot \mathbf{v} \cdot \mathbf{v}^T \tag{3}$$

where:

$\mathbf{v}$	$\boldsymbol{\Sigma_{n-1,i}^{-1}} \cdot \mathbf{x}$;
$\mathbf{x}$	current feature vector;
UC	update coefficient;
n	actual sample;
i	class label.

The starting matrices $\boldsymbol{\Sigma}_{0,i}$, which we called "initial classifier," were computed from 1620 trials recorded from 7 subjects in different sessions. The data were recorded using different paradigms, [12].

Some other parameters, like the length of the adaptation window or the time when the adaptation should start, are needed to complete the description of the classifier and to explain how the adaptation works.

1) Mutual Information (MI): MI is a measure of the quality of the signal to be separated into different classes, and it is measured in bits, [22], [23]. It was used because of its robustness compared to the error rate.

2) Initial Time, $Tini$: Is the Initial Time when the adaptation starts within each trial. There are two ways to compute it. One method consists of updating $Tini$ every 3 runs (120 trials) and selecting the moment when the maximum MI occurs. In this case, the MI is computed

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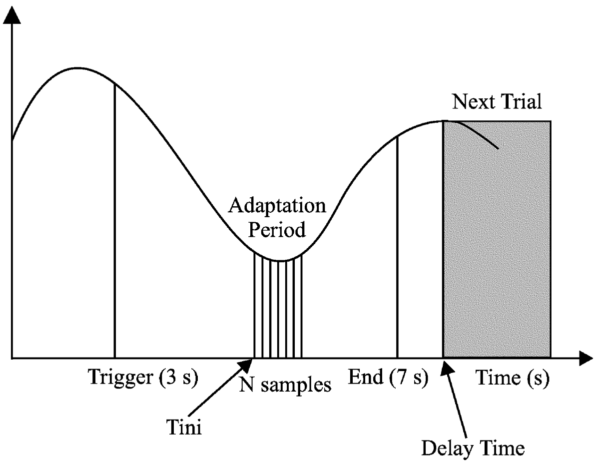

Fig. 1. Classifier adaptation in a trial, the classifier is adapted N samples beginning in $\boldsymbol{Tini}$ and applied after the delay time in the next trial.

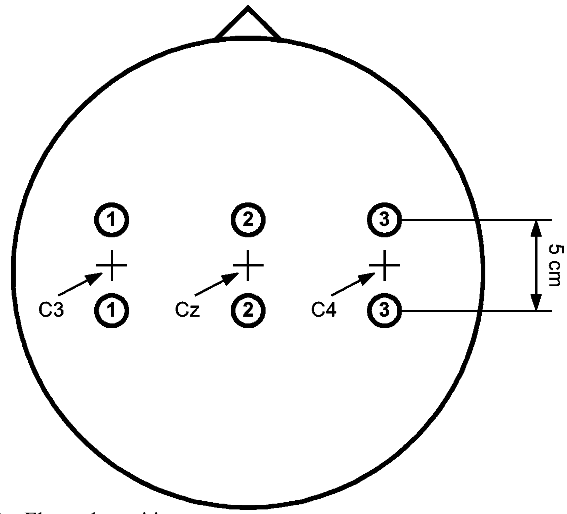

Fig. 2. Electrode positions.

using the recorded output of the classifier of the last 3 runs and it is discontinuously updated. This method was used for subjects S1 to S6. The second method allows a continuous and automatic update of $Tini$, so that all the adaptation process is done in a trial basis. We developed an on-line estimation of the MI, $\widehat{\mathbf{MI}}_t$, using a moving average algorithm, shown in (4)

$$\widehat{\mathbf{MI}}_t = \mathbf{mi} \cdot UC_{tini} + \widehat{\mathbf{MI}}_{t-1} \cdot (1 - UC_{tini}) \quad (4)$$

$$Tini = t|_{\max(\widehat{\mathbf{MI}}_t)} \quad (5)$$

where mi is the output of the classifier multiplied with the class label of the current trial, and UC_{tini} is the one used for ADIM. The time when the maximum of $\widehat{\mathbf{MI}}_t$ appears, it is selected as $Tini$ for the next trial. This method was applied to subjects S7–S9.

3) Window Length, N: Is the Number of samples of the adaptation period, and it varies in a range from 0.25 to 1 s. These values were found optimizing the parameters of the classifier and using data from several subjects, as described in Section II-B.

4) Update Coefficient, UC: Is the update coefficient for the adaptation, given in samples. In fact, we are interested in knowing the number of trials that the classifier will remember, but the update coefficient has to be given in samples to the classifier. For this reason, we define two update coefficients and both are related through a formula that involves N. We define UC_2 as the intertrial update coefficient. This means that $UC_2 \approx 1/NTRIALS$, where $NTRIALS$ is the number of trials that the classifier takes into account. Now UC is defined as the intra-trial update coefficient. UC is a coefficient whose unit is samples instead of trials, and it is the one that we apply in the calculations. The formula that relates them is: $UC_2 = 1 - (1 - UC)^N$ or equivalently $UC = 1 - (1 - UC_2)^{1/N}$. For these experiments UC is fixed to 120 trials, or 3 runs. This value is again result of optimizing the parameters of the classifier, see Section II-B.

5) Delay Time: In order to avoid over-fitting problems, a delay time is applied. The updated classifier starts after the end of the current trial; therefore, the samples used for the adaptation are independent from the ones when the classifier is applied.

Fig. 1 is a scheme of the adaptation within a trial, and it is repeated in every trial of each run.

B. Optimization of ADIM Parameters

An optimization was performed to find proper values of UC and N. Previous data from 6 subjects, performing feedback training, were used. It was a two classes system (left- and right-hand movement imagery) and all subjects were naive. The total amount of trials was 4320. The range of UC was from 8 to 440 000 trials, changing in logarithmic scale in 25 steps. The range of N was from 1 to 128 samples also in logarithmic scale and changing in 7 steps. Since the total number of parameter combinations was not very high, each parameter set was analyzed. With each combination, the on-line model was simulated and as performance measure the MI and error rate (ERR, percentage of error in the classification) were computed. The set of values that provided the maximum MI was selected for performing on-line experiments.

C. Description of the Experiments

The experiment started with 12 able-bodied subjects without previous BCI experience. Only results of 9 of them are presented. The rest were rejected because artifacts were present during the feedback period.

The recording was made using a g.tec amplifier (Guger Technologies OEG Austria) and Ag–AgCl electrodes. Three bipolar EEG channels were measured over the positions C3, Cz, and C4 (see Fig. 2). The EEG was filtered between 0.5 and 30 Hz and sampled with 125 Hz.

The experiment consisted of 3 sessions for each subject. Each session was conducted on a different day and 9 runs were recorded. One run consisted of 40 feedback trials. Between runs there was a break of some minutes (between 1 and 15 min). For each subject the total number of trials is 1080.

The experiment was based on the basket paradigm [24]. The subjects sat on a relaxing chair with armrests. In each trial, the subject saw a black screen for a fixed length pause (3 s). Then, two different colored baskets (green and red) appeared at the bottom of the screen. At this moment, also a little green ball appeared at the top of the screen. After 1 s more, the ball began to fall downward with constant speed. The horizontal position of the ball was directly controlled by the output of ADIM classification. The subject's task was to control the green ball by the imagination of left- or right-hand movements, [25], [26], and try to keep it as long as possible in the side where the green basket appeared. The duration of each trial was 7 s, with a random interval between trials from 1 s to 2 s. The order of left and right cues was random. The subjects were instructed to only imagine the movements and they were said that real movements were forbidden. A camera mounted in front of the subject was used to check that he/she kept still. Also during the experiment, the recorded signals were displayed in a screen to visually detect artifacts and to check if the subjects used them to control the system, although in [26] it was published that EEG patterns of performed and

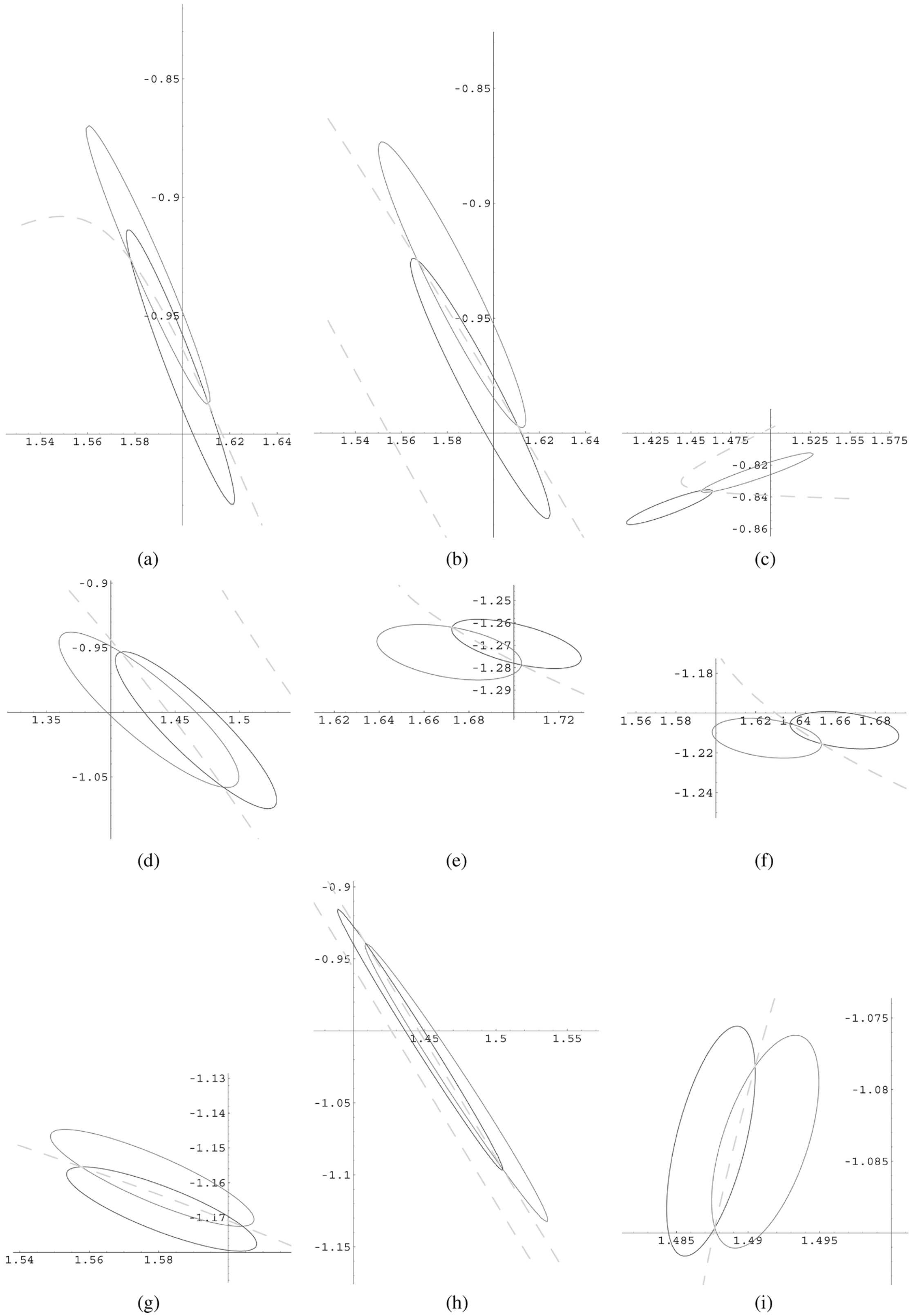

Fig. 3. Two-dimensional projection of the features distribution of both classes calculated using ADIM at the end of each experimental session. (a) S2, session 1; (b) S2, session 2; (c) S2, session 3; (d) S6, session 1; (e) S6, session 2; (f) S6, session 3; (g) S8, session 1; (h) S8, session 2; (i) S8, session 3.

imagined movements are similar. No automatic artifacts rejection was applied during the experiments.

The basket paradigm was designed to motivate trained subjects during the experimental sessions. We decided to use this "game like" feedback with untrained subjects to keep their motivation high, but due to their lack of experience we did not instruct them to try to hit the basket with the ball, but to keep the green ball in the side where the green basket appeared, as long as possible, in order to find at which moment of the trial the separation between classes was the best. In fact, the instructions given to the subject depended on the person. When the feedback was good, i.e., they showed fast some kind of control of the ball, the subject paid attention to the feedback and to the moment of best separation of classes. If the feedback was not good, it might have been because his/her data was not easily separable for a statistical classifier or because the general classifier did not represent well enough the subject's data. In this case, we instructed the subjects to pay more attention to the imagination than to the feedback.

Features were computed based on Adaptive Autoregressive AAR parameters of order 3 [27]–[31] from the bipolar channels C3 and C4, see Fig 2. The order of the AAR parameters was found by optimization, selecting the order which yielded the maximum MI after the classification of the features, using left- and right-hand motor imagery data from different subjects.

The BCI system used is based on the traditional cue-based Graz BCI ([8], [32]) where the classification part was modified to make it on-line adaptive. As seen in Section II-A, ADIM estimates the inverse of the covariance matrices of each class in order to combine the AAR parameters with a QDA.

From the first trial adaptation and feedback were running. The initial sessions without feedback, carried out to calculate a subject-specific classifier, were not needed anymore. Instead of them, an initial and general classifier (matrices $\mathbf{\Sigma_{0,\mathit{i}}}$), was applied in the first trial and then updated trial by trial resulting in a continuously adaptive classifier (ADIM). The performance of the initial classifier was 0.0717 bits of MI and 37.16% of ERR, and the first initial time ($Tini$, see Fig. 1) for the adaptation was at second 4.425, which was the moment of maximum MI of the initial classifier. The output of ADIM was recorded in each sample time for the analysis of its on-line performance during the sessions. During the experimental sessions classical analyses were performed to control the stability of the system. The functions used are freely available in [33].

D. *Off-Line Comparison of Continuous and Discontinuous Adaptation*

A comparison between the continuous trial-based adaptation of the classifier presented in this paper and the traditional discontinuous run-based adaptation, was performed using previously recorded training data (without feedback) of three subjects (R1 to R3). 9 runs were recorded for each them (180 trials for each class). The discontinuous adaptation was performed every three and four runs, with 60 and 80 trials for each class respectively like follows: using 3 runs, runs 1–3 were classified with the general classifier, runs 4–6 with the classifier trained on runs 1–3 and runs 7–9 classified with the classifier trained on runs 4–6. Using 4 runs, runs 1–4 were classified with the general classifier, runs 5–8 with the classifier trained on runs 1–4 and run 9 with the classifier trained on runs 5–8. Features were AAR parameters and classifiers QDA or linear discriminant analysis (LDA). For the continuous adaptation, features were AAR parameters and classifier was ADIM. The parameters of ADIM were the ones used in the experiments and the initial time was continuously estimated (CTini).

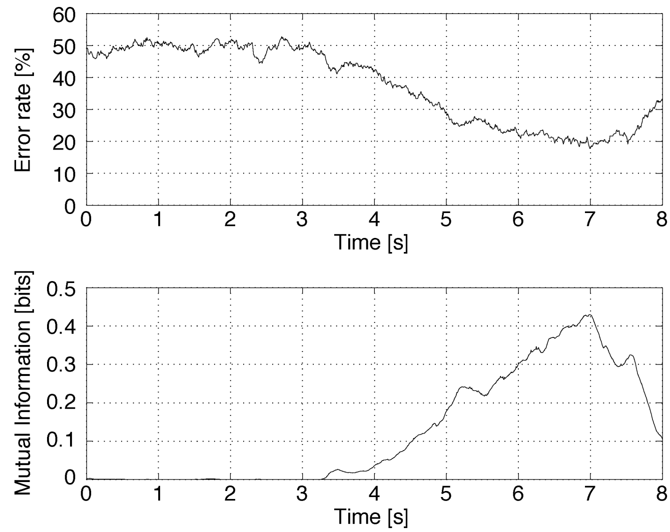

Fig. 4. Subject S6, session 3: time course of ADIM error rate and MI obtained with single trial analysis.

TABLE I
MINIMUM ERROR RATE AND MAXIMUM MI OF TIME COURSE OF EACH SESSION FOR SUBJECTS S1 TO S9 OBTAINED WITH SINGLE TRIAL ANALYSIS

Subject	Session	ERR[%]	Time[s]	MI[bit]	Time[s]
S1	Sess. 1	32.50	4.73	0.105	4.73
	Sess. 2	31.39	5.35	0.101	6.31
	Sess. 3	29.44	6.85	0.156	6.74
S2	Sess. 1	33.61	4.69	0.105	4.69
	Sess. 2	23.61	4.74	0.251	4.70
	Sess. 3	19.17	4.70	0.301	4.62
S3	Sess. 1	27.78	6.18	0.156	6.22
	Sess. 2	26.25	5.18	0.205	5.54
	Sess. 3	25.00	5.45	0.237	5.48
S4	Sess. 1	30.28	4.45	0.145	4.47
	Sess. 2	28.06	4.56	0.186	4.87
	Sess. 3	22.22	4.76	0.294	4.70
S5	Sess. 1	35.56	6.04	0.014	5.72
	Sess. 2	22.50	6.94	0.140	6.97
	Sess. 3	23.33	6.37	0.160	5.78
S6	Sess. 1	36.67	6.44	0.037	3.58
	Sess. 2	28.06	5.06	0.177	6.56
	Sess. 3	17.78	7.00	0.430	6.99
S7	Sess. 1	33.89	4.14	0.105	4.32
	Sess. 2	21.94	4.18	0.248	4.25
	Sess. 3	20.56	4.20	0.335	4.19
S8	Sess. 1	32.22	4.29	0.115	4.51
	Sess. 2	27.50	4.32	0.135	4.34
	Sess. 3	23.89	6.80	0.256	7.00
S9	Sess. 1	25.00	6.28	0.161	6.06
	Sess. 2	22.78	6.22	0.253	6.03
	Sess. 3	18.33	5.95	0.381	5.86

III. RESULTS

A. *Experimental Results*

The nonstationary nature of EEG data makes necessary some kind of adaptation of the system, which in previous BCIs was done by discontinuous adaptation of the classifier. As introduced in [17] the nonstationarities of the features can be illustrated by two–dimensional (2-D) projection of the feature space. Fig. 3 tries to show the shifting distribution of the features in three different time points: at the end of Sessions 1, 2, and 3. Each projection was calculated by consecutive cuts with hyperplanes which contain the mean points of both classes, are perpendicular to a mixed subset of eigen vectors of the covariance matrices of each class and to the LDA hyperplane. This method depicts similar figures to the one in [17], but the technique how tho find the proper 2-D projection is not the same. It is important remark that the planes used to obtain the previous figures are different in each of them, but the implemented method is identical in all cases. The hyper ellipsoids were estimated by ADIM at end of each experimental session of subject S2,

TABLE II
MINIMUM ERR AND MAXIMUM MI OF THE TIME COURSE OF DISCONTINUOUS AND CONTINUOUS ADAPTIVE CLASSIFIERS OBTAINED WITH SINGLE TRIAL ANALYSIS

Subject	AAR+QDA				AAR+LDA				AAR+ADIM	
	3 Runs		4 Runs		3 Runs		4 Runs		CTini	
	ERR[%]	MI[bits]	ERR[%]	MI[bits]	ERR[%]	MI[bits]	ERR[%]	MI[bits]	ERR[%]	MI[bits]
R1	35.83	0.044	30.00	0.172	39.44	0.082	25.28	0.184	23.60	0.244
R2	39.72	0.010	37.22	0.031	35.00	0.017	29.17	0.125	25.83	0.156
R3	36.39	0.062	28.33	0.135	30.28	0.136	28.61	0.189	25.56	0.230

TABLE III
MEAN VALUE AND SEM OF ERR AND MI IN SESSIONS ACROSS SUBJECTS (SEE TABLE I)

	ERR[%]	MI[bit]
Sess. 1	31.95±1.24	0.105±0.017
Sess. 2	25.79±1.08	0.188±0.019
Sess. 3	22.19±1.24	0.283±0.031

TABLE IV
MEAN VALUE AND SEM OF DISCONTINUOUS AND CONTINUOUS ADAPTIVE CLASSIFIERS WHOSE RESULTS WERE SHOWN IN TABLE II

		Mean value ± SEM	
		ERR[%]	MI[bits]
AAR+QDA	3 Runs	37.31±1.21	0.038±0.015
	4 Runs	31.85±2.73	0.113±0.042
AAR+LDA	3 Runs	34.91±2.64	0.078±0.034
	4 Runs	27.69±1.21	0.166±0.020
AAR+ADIM		25.00±0.70	0.210±0.027

S6 and S8. Red color represents class one (left motor imagery), blue represents class two (right motor imagery) and green is the separation surface.

Fig. 4 displays ERR [%] versus time [s] and MI [bit] versus time [s] for subject S6 in the third session. It is obtained computing a single trial analysis of the session. The subfigure above shows the mean ERR and the subfigure below is the mean MI over all trials of the session.

In Table I, we present the result for all subjects and sessions, where the minimum ERR and the maximum MI are shown, together with the time when they take place. For each subject and session a single trial analysis, as shown in Fig. 4, was performed using the recorded output of the ADIM classifier. Then, the minimum ERR and maximum MI were selected to describe the performance of the classifier.

B. Discontinuous versus Continuous Adaptation

Table II illustrates the result of off-line comparing discontinuous and continuous adaptation of the classifier with training (no-feedback) data of three subjects, and shows the minimum ERR and maximum MI. In the Graz BCI, the classifier was typically updated after 3 or 4 runs and we compare such an adaptation with the continuous ADIM classifier. In Table II, results show that ADIM obtains better ERR and MI than these discontinuous classifiers and that the use of 4 runs instead of 3 also improves the performance.

IV. DISCUSSION

A. Experimental Results

Fig. 3 depicts the shifting distributions of the features of subject S6 at the end of each session, and tries to show the need of adaptation in a BCI system, showing how the statistical properties of the data can change with the time.

Looking at the time points in Table I, we see that ADIM not always has maximum MI and/or minimum ERR at second 7 (at the end of the trial). The experiments are based on the basket paradigm, and at first sight it could be interpreted that a minimum ERR in the beginning of the trial has no relevance when the classifier is random in the end of the trial (meaning that the ball can fall in the wrong basket without the subject being able to control it), but this depends on how the operator instructs the subjects in the lab. As it was explained in Section II-C our subjects were encouraged to try to control the ball where they felt more comfortable and not necessarily in the end of the trial.

Table III displays the mean value and standard error of the mean (SEM) from the ERR and MI shown in Table I.

By means of the presented algorithm the subjects were able to learn to control their own brain activity and, therefore, to operate a BCI. In Table III, the improvement of the subjects from session to session is clear. This demonstrates the success of the feedback and that it is possible to do successful experiments using a fully on-line adaptive BCI. There are not initial sessions without feedback, which were needed to compute a subject-specific classifier, and feedback is applied from the very first moment. Therefore the subject is able to learn to control the BCI directly with feedback and can find a strategy, learning from the answer of the system to his/her motor imagery.

B. Discontinuous Versus Continuous Adaptation

Table IV displays the mean value and SEM of the results presented in Table II. These results, although illustrative, are not enough to demonstrate whether continuous adaptation is better than discontinuous adaptation or not. Nevertheless, an improvement in ERR and MI can be seen when comparing results of ADIM and discontinuous QDA or LDA for all subjects. We also see an improvement with the use of 4 runs instead of 3. LDA is better than QDA, probably because with LDA all trials can be used to estimate the common covariance matrix, whereas in QDA only the half of them is useful to calculate the covariance matrix of each class. However, ADIM does not show this behavior although only 20 trials are available for each class in a run.

V. CONCLUSION

An adaptive BCI system has been implemented enabling a fully automated update of the classifier. To our knowledge, this is the first on-line implementation of an adaptive classifier in BCI. The results demonstrate that this BCI is stable and robust. Based on the feedback of this system, the subjects were able to improve their performance. As a consequence of the design of this BCI, training sessions without feedback are not needed and the subject can find a strategy based only on the response of the system.

Nevertheless, this adaptive classifier requires a cue-based BCI, which is typically used to train new subjects. Cue-based BCIs are, therefore, important in BCI research but noncue-based BCIs are real systems that interpret the wishes of the users and adapting them is one of the goals of our future work.

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REFERENCES

[1] G. Pfurtscheller, D. Flotzinger, and J. Kalcher, "Brain-computer interface—a new communication device for handicapped people," *J. Microcomput. Applicat.*, pp. 293–299, 1993.

[2] N. Birbaumer, N. Ghanayim, T. Hinterberger, I. Iversen, B. Kotchoubey, A. Kubler, J. Perelmouter, E. Taub, and H. Flor, "A brain-controlled spelling device for the completely paralyzed," *Nature*, vol. 398, pp. 297–298, 1999.

[3] T. M. Vaughan, J. R. Wolpaw, and E. Dochin, "EEG-based communication: prospects and problems," *IEEE Trans. Rehab. Eng.*, vol. 4, no. 4, pp. 425–430, Dec. 1996.

[4] B. Blankertz, G. Curio, and K. R. Müller, "Classifying single trial EEG: toward brain computer interfacing," in *Advances in Neural Information Processing Systems*, T. G. Diettrich, S. Becker, and Z. Ghahramani, Eds. Boston, MA: MIT-Press, 2002, vol. 14, pp. 157–164.

[5] J. R. Wolpaw and D. J. McFarland, "Multichannel EEG-based brain-computer communication," *Electroencephalogr. Clin. Neurophysiol.*, vol. 90, pp. 444–449, 1994.

[6] J. R. Wolpaw, N. Birbaumer, W. J. Heetderks, D. J. McFarland, P. H. Pekham, G. Schalk, E. Dochin, L. A. Quatrano, C. J. Robinson, and T. M. Vaughan, "Brain-computer interface technology: a review of the first international meeting," *IEEE Trans. Rehab. Eng.*, vol. 8, no. 2, pp. 164–173, Jun. 2000.

[7] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control," *Clin. Neurophysiol.*, vol. 113, pp. 767–791, 2002.

[8] G. Pfurtscheller, C. Neuper, G. Müller, B. Obermaier, G. Krausz, A. Schlögl, R. Scherer, B. Graimann, C. Keinrath, D. Skliris, M. Woertz, G. Supp, and C. Schrank, "Graz BCI: state of the art and clinical applications," *IEEE Trans. Neural Syst. Rehab. Eng.*, vol. 11, no. 2, pp. 177–180, Jun. 2003.

[9] K. R. Müller, C. W. Anderson, and G. E. Birch, "Linear and nonlinear methods for brain-computer interfaces," *IEEE Trans. Neural Syst. Rehab. Eng.*, vol. 11, no. 2, pp. 165–169, Jun. 2003.

[10] N. Birbaumer, T. Hinterberger, A. Kubler, and N. Neumann, "The thought-translation device (TTD): neurobehavioral mechanisms and clinical outcome," *IEEE Trans. Neural Syst. Rehab. Eng.*, vol. 11, no. 2, pp. 120–123, Jun. 2003.

[11] J. del R. Millan, "Brain-Computer Interfaces," in *The Handbook of Brain Theory and Neural Networks*, M. A. Arbib, Ed., 2nd ed. Cambridge, MA: MIT Press, 2002, pp. 178–181.

[12] G. Pfurtscheller, C. Neuper, C. Guger, W. Harkam, H. Ramoser, A. Schlögl, B. Obermaier, and M. Pregenzer, "Current trends in Graz brain-computer interface (BCI) research," *IEEE Trans. Rehab. Eng.*, vol. 8, no. 2, pp. 216–219, Jun. 2000.

[13] J. R. Wolpaw, D. J. McFarland, D. J. Neat, and C. A. Forneris, "An EEG-based brain-computer interface for cursor control," *Electroencephalogr. Clin. Neurophysiol.*, vol. 78, pp. 252–259, 1991.

[14] D. J. McFarland, A. T. Lefkowicz, and J. R. Wolpaw, "Design and operation of an EEG-based brain-computer interface with digital signal processing technology," *Behav. Res. Methods, Instrum., Comput.*, vol. 29, pp. 337–345, 1997.

[15] J. R. Wolpaw, D. J. McFarland, and T. M. Vaughan, "Brain-computer interface research at the Wadsworth Center," *IEEE Trans. Rehab. Eng.*, vol. 8, no. 2, pp. 222–226, Jun. 2000.

[16] P. Sykacek, S. J. Roberts, and M. Stokes, "Adaptive BCI based on variational bayesian kalman filtering: an empirical evaluation," *IEEE. Trans. Biomed. Eng.*, vol. 51, no. 5, pp. 719–727, May 2004.

[17] M. Kraudelat, P. Shenoy, B. Blankertz, R. P. N. Rao, and K.-R. Müller, "Poster: Online adaptation for CSP based BCI systems," presented at the Brain-Computer Interface Technology 3rd Int. Meeting, Rensselaerville, NY, Jun. 14–19, 2005.

[18] J. del R. Millan, "On the need for on-line learning in brain-computer interfaces," in *Proc. Int. Joint Conf. Neural Networks*, 2004, pp. 2877–2882.

[19] T. Nykopp, J. Heikkonen, and M. Sams, "Sequential classification of finger movements from MEG recordings," in *Biomedisinische Tecknik, Proceedings of the 2nd International Brain-Computer Interface Workshop and Training Course (Graz)*, U. Boenick and A. Bolz, Eds., 2004, pp. 77–79.

[20] A. Buttfield, P. W. Ferrez, and J. del R. Millan, "Toward a robust BCI-error recognition and online learning," *IEEE Trans. Neural Syst., Rehab. Eng.*, 2005, submitted for publication.

[21] S. Haykin, *Adaptive Filter Theory*. , NJ: Prentice-Hall, 1996.

[22] A. Schlögl, C. Neuper, and G. Pfurtscheller, "Estimating the mutual information of an EEG-based brain-computer interface," *Biomed. Technik*, vol. 47, pp. 3–8, 2002.

[23] A. Schlögl, C. Keinrath, R. Scherer, and G. Pfurtscheller, "Information transfer of an EEG-based brain computer interface," in *Proc. 1st Int. IEEE EMBS Conf. Neural Engineering*, 2003, pp. 641–644.

[24] G. Krausz, R. Scherer, G. Korisek, and G. Pfurtscheller, "Critical decision-speed and information transfer in the graz brain-computer-interface," *Appl. Psychophysiol. Biofeedback*, vol. 28, pp. 233–240, Sept. 2003.

[25] G. Pfurtscheller and C. Neuper, "Motor imagery and direct brain-computer communications," *Proc. IEEE*, vol. 89, no. 7, pp. 1123–1134, Jul. 2001.

[26] ——, "Motor imagery activates primary sensorimotor area in humans," *Neurosci. Lett.*, vol. 239, pp. 65–68, 1997.

[27] A. Schlögl, D. Flotzinger, and G. Pfurtscheller, "Adaptive autoregressive modeling used for single-trial EEG classification," *Biomed. Technik*, vol. 42, pp. 162–167, 1997.

[28] G. Pfurtscheller, C. Neuper, A. Schlögl, and K. Luger, "Separability of EEG signals recorded during right and left motor imagery using adaptive autoregressive parameters," *IEEE Trans. Rehab. Eng.*, vol. 6, no. 3, pp. 316–325, Sep. 1998.

[29] C. Guger, A. Schlögl, C. Neuper, C. Walterspacher, D. Strein, T. Pfurtscheller, and G. Pfurtscheller, "Rapid prototyping of an EEG-based brain-computer interface (BCI)," *IEEE Trans. Neural Syst., Rehab. Eng.*, vol. 9, no. 1, pp. 49–58, Mar. 2001.

[30] C. Neuper, A. Schlögl, and G. Pfurtscheller, "Enhancement of left-right sensorimotor EEG differences during feedback-regulated motor Imagery," *J. Clin. Neurophysiol.*, vol. 16, pp. 373–382, 2000.

[31] A. Schlögl, *The Electroencephalogram and the Adaptive Autoregressive Model: Theory and Applications*. Aachen, Germany: Shaker Verlag, 2000.

[32] R. Scherer, A. Schlögl, G. R. Müller-Putz, and G. Pfurtscheller, "Inside the Graz-BCI: rtsBCI," in *Biomedizinische Technik: Proc. of the 2nd International Brain-Computer Interface Workshop and Training Course (Graz)*, U. Boenick and A. Bolz, Eds., 2004, pp. 81–82.

[33] A. Schlögl, The BIOSIG Project. 2004-2005 [Online]. Available: http://biosig.sf.net/