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Emotion Assessment from Physiological Signals for Adaptation of Games Difficulty

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Abstract—This paper proposes to maintain player's engagement by adapting games difficulty according to player's emotions assessed from physiological signals. The validity of this approach was first tested by analyzing the questionnaires responses, EEG signals and peripheral signals of players playing a Tetris game at three difficulty levels. This analysis confirms that the different difficulty levels correspond to distinguishable emotions, and that playing several times at the same difficulty level gives rise to boredom. The next step was to train several classifiers to automatically detect the three emotional classes from EEG and peripheral signals in a player independent framework. By using either type of signals the emotional classes were successfully recovered, with EEG having a better accuracy than peripheral signals on short periods of time. After fusion of the two signal categories the accuracy raised up to 63%.

Index Terms—Emotion assessment, Electroencephalography, Games, Signal analysis, Pattern classification.

I. INTRODUCTION

Due to their capability to present information in an interactive and playful way, computer games have gathered increasing interest as tools for education and training [1]. Games are also interesting from a human-computer interaction (HCI) point of view, because they are an ideal ground for the design of new ways to communicate with machines. Affective computing [2] has opened the path to new types of human-computer interfaces that adapt to affective cues from the user. As one of the main goals of games is to provide emotional experiences such as fun and excitement, affective computing is a promising area of research to enhance game experiences. Affective information can be used to maintain involvement of

a player by adapting game difficulty or content to induce particular emotional states [3]. For this purpose, automatic assessment of emotions is mandatory for the game to adapt in real time to the feelings and involvement of the player, without interrupting his / her gaming experience (like it would be the case by using questionnaires). The present work thus focuses on emotion assessment from physiological signals in the context of a computer game application.

Physiological signals can be divided into two categories: those originating from the peripheral nervous system (e.g. heart rate, ElectroMyogram - EMG, Galvanic Skin Response- GSR), and those coming from the central nervous system (e.g. ElectroEncephalograms - EEG). In recent years interesting results have been obtained for emotion assessment with the first category of signals. Very few studies however have used the second category, even though the cognitive theory of emotions states that the brain is heavily involved in emotions [4].

One of the pioneering work on emotion assessment from peripheral signals is [5] where the authors detected eight self-induced emotional states with an accuracy of 81%. In [6] six emotional states, elicited by film clips, were classified with an accuracy of 84%. In a gaming context, Rani et al. [7] proposed to classify three levels of intensity for different emotions. The emotions were elicited by stimulating participants with a Pong game and anagrams puzzles. The best average accuracy obtained with this method was of 86%. The classifiers developed in this study were used in [3] to adjust game difficulty in real time based on anxiety measures. In this case the accuracy dropped to 78% but a significant improvement of player experience was reported compared to difficulty adjustment based on performance. This demonstrates the interest of using affective computing for the purpose of game adaption. In [8] the authors proposed to continuously assess the emotional state of a player using an approach based on fuzzy logic. The obtained results showed that the emotional state evolved according to the events of the game but no exact measure of performance was reported. Nevertheless, this tool could be used to include the player experience in the design of innovative video-games. In [9] three emotional states were detected from peripheral signals with an accuracy of 53%. The emotions were elicited by using a Tetris game. The current paper is a significant extension of this work, which in particular now takes into account the analysis of EEG signals.

There is an increasing amount of psychological literature pointing towards the hypothesis that emotions are resulting

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from a series of cognitive processes [10, 11]. There is also evidence of different patterns of brain activity during the presentation of emotional stimuli. For instance, depending on the nature of reactions (approach or withdrawal), Davidson [12] showed prefrontal lateralization of alpha waves as well as distinct activations of the amygdala. Aftanas et al. [13] reported differences in Event Related Desynchronization / Synchronisation (ERD/ERS) during the visualization of more or less arousing images. In the emotional recall context, Smith et al. [14] showed an augmentation of activity in the connections between the hippocampus and the amygdala during the recollection of negative events compared to neutral events. These works emphasize the importance of using brain signals to improve temporal resolution and classification accuracy in emotion assessment. Among the studies that recognize emotional states from EEG, Takahashi [15] obtained an accuracy of 42% to recognize five emotional states elicited by film clips. In [16] three self-induced emotional states were recognized with an accuracy of 68%. Other works tried to infer operator's engagement, fatigue and workload by using EEG signals in order to adapt the complexity of a task [17-21]. To our knowledge, however, the present article is the first to report on the use of EEG signals for emotion assessment in a gaming paradigm.

Games can elicit several emotional states but knowing all of them is not necessary to maintain involvement in the game. Many representations of the player's affective state have been used in previous studies like anxiety, frustration, engagement, distress scales and the valence-arousal space [22, 23]. According to emotion and flow theories [10, 24] strong involvement in a task occurs when the skills of an individual meet the challenge of a task (Fig. 1). Too much challenge would increase workload which would then be appraised by the player as anxiety. Similarly, not enough challenge would induce boredom. Both these situations would restrain the player's ability to achieve a "flow experience", leading to less involvement, engagement and possibly interruption of the game [25].

<Figure 1>

In a game, the change from an emotional state to another can occur due to two main reasons. First, the difficulty is increased because of progression in the different levels but the increase is too fast compared to the competence increase of the player (potentially giving rise to anxiety, see Fig. 1). Secondly, the competence of the player has increased while the game remained at the same difficulty (potentially giving rise to boredom). In both cases, the challenge should be corrected to maintain a state of pleasure and involvement, showing the importance of having games that adapt their difficulty according to the competence and emotions of the player. Based on this theory, we defined three emotional states of interest that corresponds to three well separated areas of the valence-arousal space: boredom (negative-calm), engagement (positive-excited) and anxiety (negative-excited).

This work attempts to verify the validity and usefulness of

the three defined emotional states by using a Tetris game where the challenge is modulated by changing the level of difficulty. Self-reports as well as physiological activity were obtained from players by using the acquisition protocol described in Section II. Using those data, three analyses were conducted. The first aims at validating the applicability of the flow theory for games (see Section III). In the second analysis, detailed in Section IV, physiological signals were used for the purpose of classification of the different states. In this case, since one of the goals of this study is to go toward applications, particular attention was paid to designing classifiers that could be used for any gamer without having to re-train it.

II. DATA ACQUISITION

A. Acquisition protocol

A gaming protocol was designed for acquiring physiological signals and gathering self-reported data. The Tetris game was chosen in this experiment for the following reasons: it is easy to control the difficulty of the game (speed of falling blocks); it is a widely known game so that we could expect to gather data from players with different skill levels (which occurred); and it is playable using only one hand, which is mandatory since the other hand is used for placement of some data acquisition sensors.

The difficulty levels implemented in the Tetris game were adapted to have a wider range of difficulties than in the original game. The new levels ranged from 1 to 25 with the blocks going down a line every 0.54 seconds at level 1 and 0.03 seconds at level 25. The speed of the falling blocks at the intermediate levels increased exponentially with the level. Other modifications to the original Tetris allowed playing without change of the difficulty level for a given amount of time. Each time the blocks reach the top of the Tetris board, a game over event was reported, the board was cleared and the participant could continue to play.

Twenty participants (mean age: 27, 13 males, all right handed) took part in this study. After signing a consent form, each participant played Tetris several times to determine the game level where he/she reported engagement. This was done by repeating three times the threshold method, starting from a low level and progressively increasing it until engagement was reported by the participant or starting from a high level and decreasing it. The average of the obtained levels was then considered as the participant skill level. Depending on this skill level, three experimental conditions were determined: medium condition (game difficulty equal to the player's skill level), easy condition (lower difficulty, computed by subtracting 8 levels of difficulty from the player's skill level), and hard condition (higher difficulty, computed by adding 8 levels). The participants to the study reported to be engaged at different levels ranging for most of them from 11 to 16, confirming that they had different Tetris skills.

Participants were then equipped with several sensors to

measure their peripheral physiological activity: a GSR (Galvanic Skin Response) sensor to measure skin resistance, a plethysmograph to record BVP (Blood Volume Pulse), a respiration belt to estimate chest cavity expansion and a temperature sensor to measure palmar changes in temperature. Those sensors are known to measure signals that are related to particular emotional activations as well as useful for emotion detection (see Section II.B). In addition, an EEG system was used to record central signaling from 14 of the 20 participants. In this study 19 electrodes were positioned on the skull of participants according to the 10-20 system [26]. As demonstrated in other studies, EEG's can help to assess emotional states and is also useful to provide an index of task engagement and workload [17-20]. Peripheral and EEG signals were recorded at a 256Hz sampling rate using the Biosemi Active 2 acquisition system¹. This sampling rate allows keeping the frequency bands of interest for this study.

Once equipped with the sensors, the participants took part in 6 consecutive sessions (Fig. 2). For each session the participants had to follow 3 steps: stay calm and relax for at least one minute and 30 seconds, play the Tetris game for 5 minutes in one of the three experimental conditions (difficulty level) and finally answer a questionnaire. The first step was useful to let the physiological signals return to a baseline level, to record a baseline activity and to provide a rest period to the participants. For the second step, each experimental condition was applied twice and in a random order to account for side effects of time in questionnaires and physiological data. The goal of participants was to perform the highest possible score. To motivate them toward this goal, a prize of 20 CHF was offered to three of the participants having the highest score (the participants were divided in three groups according to their competence). The questionnaire was composed of 30 questions related to both the emotions they felt and their level of involvement in the game. The answer to each question was given on a 7 points Likert scale. Additionally, participants rated their emotions in the valence-arousal space using Self-Assessment Manikin (SAM) [27] scales.

<Figure 2>

B. Feature extraction

Once the data is acquired, it is necessary to compute features from the signals in order to characterize physiological activity for the different gaming conditions. The features were generally computed over the complete duration of a given session, except in Section IV.D where the features were computed on shorter time windows to analyze the effect of time on emotion assessment accuracy. Two sets of features were computed: the first set includes the features computed from the EEG signals and the second those computed from the peripheral signals.

In this study the collected data are not analyzed for each participant separately but as a whole. It is thus necessary that

the patterns of emotional responses remain stable across participants. Although different patterns of emotional responses have been found in psycho-physiological studies, Stemmler [28] argues that they are due to context deviation specificity. Since in the current study the emotions are elicited in the same context (the video game) this should reduce inter-participant variability. Nevertheless, to further reduce this variability, the physiological signals acquired during the last minute of the rest period were used to compute a baseline activity for each session (6 baselines per participant) that was subtracted from the corresponding physiological features.

1) EEG features

Prior to extracting features from EEG data, we need to remove noise by pre-processing the signals. Environment noise and drifts were removed by applying a 4-45Hz bandpass filter. The signals were visually checked in order to ensure that remaining artifacts did not exceed 5% of the signal. The second step was to compute a local reference by applying a local Laplacian filter [29] to render signals independent of reference electrodes position and to reduce artifacts contamination. For the Laplacian filter computation, the neighbours electrodes where considered as lying in a radius of 4cm from the filtered electrode.

The set of features described in this section was defined to represent the energy of EEG signals in frequency bands known to be related to emotional processes [12, 13]. For each electrode i , the energy in the different frequency bands displayed in Table I was computed for a session, using the Fast Fourier Transform (FFT) algorithm. Moreover, the following EEG_W feature (1) was computed from the N_e electrodes. This feature is known to be related to cognitive processes like workload, engagement, attention and fatigue [20], which are cognitive states of interest in our study. In many studies, the EEG_W feature is computed from only 3 to 4 electrodes [17, 18, 20]. However, there is high discrepancy among studies in the electrodes used. Moreover, the playing of a video game can stimulate several brain areas (for instance the occipital lobe for visual processing, the auditory cortex of the parietal and temporal lobes, and the frontal lobe for emotional processing). For those reasons all the electrodes were included in the computation of the EEG_W feature.

$$EEG_W = \log\left(\frac{\sum_{i=1}^{N_e} \beta_i}{\sum_{i=1}^{N_e} \theta_i + \alpha_i}\right) \quad (1)$$

The EEG_FFT feature set thus contains a total of $3 \times 19 + 1 = 58$ features (3 frequency bands and 19 electrodes plus the EEG_W feature).

TABLE I
THE ENERGY FEATURES COMPUTED FOR EACH ELECTRODE AND THE ASSOCIATED FREQUENCY BANDS.

Feature for electrode i	Frequency band
θ_i	4-8 Hz
α_i	8-12 Hz

¹ Technical details available on <http://www.biosemi.com>

β_i

12-30 Hz

2) Peripheral features

Many studies in psychophysiology have shown correlations between signals of the peripheral nervous system and emotions; effectiveness of such signals in emotion assessment is now fully demonstrated as detailed in the introduction. All data were first filtered by a mean filtering to remove noise. For this purpose we used a rectangular filter of length 128 for GSR, 128 for temperature, and 64 for chest cavity expansion.

GSR provides a measure of the resistance of the skin (electrodermal activity) by positioning two electrodes on the distal phalanges of the index and middle fingers. This resistance decreases due to an increase of sudation, which usually occurs when one is experiencing emotions such as stress or surprise. Moreover, Lang *et al.* discovered that the mean value of the GSR is related to the level of arousal [30]. The number of GSR falls was also computed by identification of the signal local minima. The features extracted from electrodermal activity are presented in Table II.

TABLE II
FEATURES EXTRACTED FROM PERIPHERAL SIGNALS

Peripheral signal	Feature name	Extracted feature	Comment
GSR	μ_{GSR}	Mean skin resistance	Estimate of general arousal level
	δ_{GSR}	Mean of derivative	Average GSR variation
	$f_{GSR}^{DecRate}$	Mean of derivative for negative values only	Average decrease rate during decay time
	$f_{GSR}^{DecTime}$	Proportion of negative samples in the derivative vs. all samples	Importance and duration of the resistance fall
	$f_{GSR}^{NbPeaks}$	Number of resistance falls in the signal	-
BVP	μ_{BVP}	Mean value	Estimate of general BVP
	σ_{BVP}	Standard deviation	BVP variation
Heart rate	μ_{HR}	Mean of heart rate	-
	δ_{HR}	Mean of heart rate derivative	Estimations of heart rate variability
	σ_{HR}	Standard deviation of heart rate	
	f_{HR}^{LF}	Energy in 0.05Hz-0.15Hz band	Parasympathetic and sympathetic activity
	f_{HR}^{HF}	Energy in 0.15Hz-1Hz band	Parasympathetic activity
	$f_{HR}^{LF/HF}$	Ratio of energy in the LF and HF bands	Ratio of parasympathetic and sympathetic activity
Chest cavity expansion	f_{Resp}^{Rate}	Frequency with the highest energy	Respiration rate
	σ_{Resp}	Standard deviation	Variation of the chest cavity expansion signal
	f_{Resp}^{DR}	Maximum value minus minimum value	Dynamic range or greatest breath
Skin Temperature	μ_{Temp}	Mean value	-

 δ_{Temp}

Mean of derivative

Estimation of temperature variability

A plethysmograph was placed on the thumb of the participant to evaluate Blood Volume Pulse (BVP). This signal is not only used as a measure of BVP but also to compute Heart Rate (HR) by identification of local minima (*ie.* foot of the systolic upstroke) and interbeat periods. Blood pressure and HR variability are variables that correlate with defensive reactions [31], pleasantness of a stimuli [30], and basic emotions [32]. The HR signal energy in low frequencies (0.05Hz-0.15Hz) and high frequencies (0.15Hz-1Hz), as well as the ratio of these energies were computed because they are indicators of parasympathetic and sympathetic activity [33].

Chest cavity expansion was measured by tying a respiration belt around the chest of the participant. Slow respiration is linked to relaxation while irregular rhythm, quick variations, and cessation of respiration corresponds to more aroused emotions like anger or fear [32, 34]. To characterize this process we rely on features from both the frequency and time domains (Table II).

Skin temperature was measured by placing a sensor on the distal phalange of the ring finger. Ekman *et al.* [35] found a significant increase of skin temperature for anger compared to his five other basic emotions (sadness, happiness, fear, surprise and disgust). McFarland [36] found that stimulating persons with emotional music led to an increase of temperature for calm positive music and a decrease for excited negative pieces.

III. ANALYSIS OF QUESTIONNAIRES AND OF PHYSIOLOGICAL FEATURES

In this section the data gathered from the questionnaires and from the computed physiological features is analyzed to control the applicability of the flow theory for games. For this purpose the validity of the following two hypotheses were tested:

- H1: playing in the three different conditions (difficulty levels) will give rise to different emotional states;
- H2: as the skill increases, the player will switch from an engagement state to a boredom state (see Fig. 1).

A. Elicited emotions

1) Questionnaires

To test for hypothesis H1, a factor analysis was performed on the questionnaires to find the axes of maximum variance. The first two components obtained from the factor analysis account for 55.6% of the questionnaire variance and were found to be associated with higher eigenvalues than the other components (the eigenvalues of the first 3 components are 10.2, 8.2 and 1.7). The questionnaire answers given for each session were then projected in the new space formed by the two components and an ANOVA test was applied to those new variables to check for differences in distributions of judgment for the different conditions. By looking at the weights of the two components it was found that:

- the first component was positively correlated with questions related to pleasure, amusement, interest and motivation;
- the second component was positively correlated with question corresponding to levels of excitation and pressure and negatively correlated with calm and control levels.

<Figure 3>

The ANOVA test, applied on the data projected on the first component (see Fig. 3), showed that participants felt lower pleasure, amusement, interest and motivation for the easy and hard conditions than for the medium one ($F=46$, $p<0.01$). Differences in the three distributions obtained from the second component demonstrated that increasing difficulty led to higher reported excitation and pressure as well as lower control ($F=232$, $p<0.01$). This demonstrates that an adequate level of difficulty is necessary to engage players in the game so that they feel motivated and pleased to play. Moreover those results also validate hypothesis H1 since they show that the different playing difficulties successfully elicited different emotional states with various levels of pleasure and arousal. According to the self-evaluations those states were defined as boredom for the easy condition, engagement for the medium condition and anxiety for the hard condition.

2) Peripheral features

The physiological features were subjected to an ANOVA test to search for differences in activations for the different conditions and analyze the relevance of those features for emotion assessment. For this purpose the ANOVA test was applied on the three distributions and the F-values and p-values are reported in Table III. Moreover, the ANOVA test was also applied to check for differences between the easy and medium conditions as well as between the medium and hard condition. If a difference is significant (p-value < 0.1) the trend of the mean from a condition to another is reported in Table III.

TABLE III.

F-VALUES AND P-VALUES OF THE ANOVA TESTS APPLIED ON THE PERIPHERAL FEATURES FOR THE 3 DIFFICULTY LEVELS. ONLY THE RELEVANT FEATURES ARE PRESENTED (P-VALUE < 0.1). THE "TREND OF THE MEAN" COLUMN INDICATES THE DIFFERENCES BETWEEN TWO CONDITIONS. FOR INSTANCE ↘↘ INDICATE A SIGNIFICANT DECREASE OF THE VARIABLE FROM THE EASY TO THE MEDIUM CONDITION (FIRST ↘) AND FROM THE MEDIUM TO THE HARD CONDITION (SECOND ↘), WHILE →↗ INDICATE NO SIGNIFICANT DIFFERENCES BETWEEN THE EASY AND MEDIUM CONDITION AND A SIGNIFICANT INCREASE TO THE HARD CONDITION.

Feature	F-value	p-value	Trend of the mean
μ_{GSR}	4.4	0.01	↘→
δ_{GSR}	2.7	0.07	↘→
$f_{GSR}^{DecRate}$	3.1	0.05	↘→
$f_{GSR}^{DecTime}$	6.7	< 0.01	→↗
$f_{GSR}^{NbPeaks}$	18.3	< 0.01	↗→
μ_{HR}	3.4	0.04	→↗
f_{HR}^{LF}	2.4	0.09	↘↗
σ_{Resp}	5.8	< 0.01	→↗
μ_{Temp}	9.4	< 0.01	↘↘

δ_{Temp}	10	< 0.01	↘↘
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The decrease observed for the μ_{GSR} , δ_{GSR} , $f_{GSR}^{DecRate}$ features and the increase of the $f_{GSR}^{NbPeaks}$ between the easy and medium conditions indicate an increase of electrodermal activity when progressing from the easy to the medium difficulty level. Between the easy and medium conditions a significant decrease of temperature is also observed. Those results are in favor of an increase of arousal between the easy and the medium condition. More specifically, the increase in the number of GSR peaks indicates that the changes in arousal are not only due to workload increase but also to some specific events that triggered emotional reactions. When analyzing the GSR features changes between the medium condition and the hard condition, only the $f_{GSR}^{DecTime}$ feature (percentage of negative samples in the GSR derivative) is significantly increasing. An increase of mean HR and a decrease of temperature are also observed between the same conditions. Those results suggest that there is also an increase of arousal between the medium and hard conditions but to a lesser extent than between the easy and medium conditions. In summary, an increased arousal is observed for increasing game difficulty, supporting the results obtained from the analysis of the questionnaires.

As can be seen from Table III a total of ten features were found to have significantly different distributions among the three difficulties. This suggests that the conditions correspond to different emotional states and demonstrates the interest of those features for later classification of the three conditions. One feature of particular interest is f_{HR}^{LF} , the HR energy in low frequency bands, because it has a lower value for the medium condition than for the two others, showing that this condition can elicit particular peripheral activation. This is also one of the only features that can help to distinguish the medium condition from the two others.

3) EEG features

An ANOVA test was also performed on each EEG feature to test for differences between the three conditions. Table IV gives a list of the EEG features that are relevant (p-value < 0.1). No feature corresponding to the energy in the alpha band was significantly different among the three conditions. However, several features in the theta and beta bands were significantly different; which shows their interest for automatic assessment of the three conditions. To illustrate the EEG activity we focused on the EEG_W feature since it is a combination of the other features and is known to be related to cognitive processes such as engagement and workload [20].

TABLE IV

LIST OF THE RELEVANT EEG FEATURES (P-VALUE < 0.1) GIVEN BY FREQUENCY BAND AND ELECTRODE.			
	Left electrodes	Midline electrodes	Right electrodes
Theta band	C3, T7, P3, P7, O1	Fz, Cz	F4, C4, T8, O2
Beta band	Fp1, P7, O1	Cz	C4, T8, P8, O2

Significant differences were observed for the EEG_W feature between the three conditions ($F=5.5$, $p<0.01$). Fig. 4 shows the median and quartiles of the EEG_W values for each condition. Since for the medium difficulty the participants reported higher interest and motivation than for the easy and hard conditions, it was expected that the mean of the EEG_W values would be significantly higher for the medium condition. However, as can be seen from Fig. 4, there is increase in the median of the EEG_W values as the difficulty increases. The differences between the medium and hard conditions as well as between the easy and hard conditions are significant according to the ANOVA test. In our view this reflects the fact that the EEG_W feature is more related to workload than to engagement. The participants involved more executive functions in the hard condition than the medium one, even if they were less engaged.

<Figure 4>

B. Evolution of emotions in engaged trials

Hypothesis H2 was tested by focusing on the data of the two sessions corresponding to the medium condition where the participant is expected to be engaged. Both physiological and questionnaire data were analyzed using a pairwise t-test to verify that there was a decrease of engagement from the first to the second session.

The pairwise t-test on the variables of the questionnaire showed a significant decrease from the first to the second medium condition for the questions “I had pleasure to play” ($t=-1.8$, $p=0.09$) and “I had to adapt to the interface” ($t=-3$, $p=0.06$). From peripheral signals, a decrease in the number of GSR peaks $f_{GSR}^{NbPeaks}$ ($t=-2.4$, $p=0.02$) as well as an increase in the average of temperature μ_{Temp} ($t=2.6$, $p=0.02$) and in the average of temperature derivative δ_{Temp} ($t=2.3$, $p=0.03$) was found.

Those results are indicative of a decrease of arousal and pleasure while playing twice in the same condition, thus supporting hypothesis H2. The result obtained for the question “I had to adapt to the interface” gives a cue that this decrease could be due to an increase of player’s competence. However the competence changes were not measured with other indicators to confirm this possibility. In any case, those results demonstrate the importance of having automatic adaptation of game’s difficulty when the challenge of the game remains the same.

IV. CLASSIFICATION OF THE GAMING CONDITIONS USING PHYSIOLOGICAL SIGNALS

A. Classification methods

In this section, the classification accuracy that can be expected from emotion assessment is investigated. For this purpose classification methods were applied on the data gathered from the gaming protocol. The ground-truth labels were defined as the three gaming conditions, each one being

associated to one of three states: boredom (easy condition), engagement (medium condition) and anxiety (hard condition).

Three classifiers were applied on this data set: a Linear Discriminant Analysis (LDA), a Quadratic Discriminant Analysis (QDA) and a Support Vector Machine (SVM) with Radial Basis Functions (RBF) kernel [37, 38]. The diagonalized versions of the LDA and the QDA were employed because of the low number of samples, which sometimes gives rise to the problem of singular covariance matrices. The size of the RBF kernel was chosen by applying a 5-fold cross-validation procedure on the training set and finding the size yielding the best accuracy. The tested size values belonged to the $5 \cdot 10^{-3}$ to $5 \cdot 10^{-1}$ range with a step of $5 \cdot 10^{-3}$.

The following cross-validation method was employed to compute the test accuracy of the classifiers. For each participant a classifier was trained using features of the other participants; accuracy was then computed by applying the trained model on the physiological data of the tested participant. Since the classifier is tested on the data of participants that are not present in the training set, this method allows evaluating the performance of the classifier in the worst case where the model is not user-specific, i.e. no information about the specificity of the user’s physiology is required for emotion assessment, except for a baseline recording of 1 min. Due to the inter-participant variability that remains in physiological activity after baseline subtraction, player independent classifiers will certainly yield a lower accuracy than player dependant classifiers. However, this approach allows designing applications where it is not necessary to train a classifier for each user which is drastically time consuming [3].

Three feature selection algorithms were applied on this problem to find the features that provide good generalization across participants. All those algorithms were applied on the training set to select features of interest and only the selected features were used for classification of the test set. An ANOVA feature selection was applied to keep only the features that are relevant to the class concept (p -value < 0.1). The Fast Correlation Based Filter (FCBF) [39] was applied to select relevant features and remove redundant ones. The δ_{FCBF} threshold was set to 0.2 because (i) it was shown in [40] that this value is relevant for FCBF EEG features selection and (ii) the number of features that have a correlation with the classes higher than 0.2 (7 for peripheral features and 23 for EEG features) is similar to the number of relevant features found using the ANOVA test (10 for peripheral features and 20 for EEG features). Finally, the SFFS algorithm [41] was also used to select features of interest, including potentially interacting features. To search for features that have good generalization across participants, the accuracy of a feature subset was estimated by computing the participant cross-validation accuracy on the training set. The maximum size of a feature subset for the SFFS algorithm was set to 18 for peripheral features and 20 for EEG features.

The fusion of the EEG and peripheral information was performed to improve classification accuracy. This fusion was performed at the decision level [42], by combining the outputs of the classifiers using the Bayes belief integration [43]. For Bayes belief integration, the errors produced by the classifiers are expressed by the probabilities $P(y | \hat{y}_q)$ that a classifier q estimates a class as being \hat{y}_q , while the true class was y . These probabilities can be computed from the confusion matrices obtained from the training set. The fusion is then performed by assuming classifiers independency and choosing the class y that maximizes the following probability:

$$P(y | \hat{y}_1, \dots, \hat{y}_{|Q|}) = \frac{\prod_{q \in Q} P(y | \hat{y}_q)}{P(y)^{|Q|-1}} \quad (2)$$

where Q is the ensemble of classifiers used for the fusion.

Since the EEG signals were recorded only for 14 out of the 20 participants, the available number of samples for EEG based classification is not the same as for peripheral based classification. For this reason the results obtained from EEG and peripheral features are separated in two sections with classification algorithm applied on 14 participants for EEG and 20 participants for peripheral features. In Section IV.D the classification accuracies obtained with EEG and peripheral features on different time scales are compared while the fusion of peripheral and EEG modalities is investigated in Section IV.E. In both cases, the classification accuracy was computed only on the 14 participants having EEG recorded.

B. Peripheral signals

Fig. 5 presents the accuracies obtained by applying the classification methods on the features extracted from the peripheral signals. Without feature selection the LDA obtained the best accuracies of 54% showing its ability to find a boundary that generalizes well across participants. In any case, the accuracies are higher than the random level of 33%. Except for the ANOVA, the feature selection methods always improved the classification accuracies. The best accuracy of 59% is obtained with the QDA combined with SFFS feature selection. However the FCBF results (58%) are not significantly different from those obtained with the SFFS algorithm because of the high variance of the accuracies. Moreover, the variance of the accuracies obtained with SFFS tends to be higher than those obtained with the FCBF which shows that the FCBF is more stable than the SFFS algorithm in selecting the proper features. According to the results and considering that the FCBF is much faster than the SFFS, the FCBF can be considered as the best feature selection algorithm for this classification scheme.

<Figure 5>

Since the participant cross-validation method was used, the feature selection algorithms were applied 20 times on different training sets. For this reason, the features selected at each iteration of the cross-validation procedure can be different. The histograms of Fig. 6 show for each feature the number of

times it was selected by a given feature selection algorithm. The average number of selected features is 3.5 for the FCBF, 9.35 for the ANOVA feature selection and 4.8 for the SFFS. The ANOVA nearly always selected the features that were found to be relevant in Section III.A but with poor resulting accuracy (Fig. 5). Thanks to the removal of redundant features, the FCBF strongly reduces the original size of the feature space with a good resulting accuracy. Moreover this algorithm nearly always selected the same features independently of the training set showing its stability. The SFFS also obtained good performance but as can be seen from Fig. 6, some of the features were selected only on some of the training sets, showing that this algorithm is less stable than the FCBF.

<Figure 6>

By inspecting the SFFS, FCBF and ANOVA selected features, the $f_{GSR}^{DecTime}$ and $f_{GSR}^{NbPeaks}$ features were always selected which shows their importance for classification of the three conditions from physiological signals. To our knowledge similar features have been used only in [44] for emotions assessment despite of their apparent relevance. The μ_{HR} feature was frequently selected by the FCBF but never by the SFFS and vice-versa for the σ_{Resp} feature. The σ_{Resp} feature was removed by the FCBF because it was correlated with μ_{HR} . However the SFFS kept the σ_{Resp} feature based on its predictive accuracy which suggests that this feature may be better than μ_{HR} for classification. Finally, the temperature features were also found to be frequently relevant.

Because of its good accuracy and low computational time the FCBF algorithm coupled with QDA classification was used for further analyses involving the peripheral modality. Table V presents the confusion matrix for the 3 classes: it can be seen that the boredom condition was well classified, followed by the anxiety condition. Samples from the engagement condition tend to be classified mostly as bored samples and also as anxious samples. This is not surprising since this condition lies in between the others. Notice that 21% of the samples belonging to the anxiety class are classified as bored samples; this can be due to fact that some participants completely disengaged from the task because of its difficulty, reaching an emotional state close to boredom. In this case, the adaptive game we propose would increase the level of difficulty since the detected emotion would be boredom, which is not the proper decision to take. A solution to correct this problem could be to use contextual information such as the current level of difficulty and the direction of the last change in difficulty (i.e. increase or decrease) to correctly determine the action to take.

TABLE V
CONFUSION MATRIX FOR THE QDA CLASSIFIER WITH FCBF FEATURE SELECTION.

Estimated True	Easy (Boredom)	Medium (Engagement)	Hard (Anxiety)
Easy (Boredom)	80%	10%	10%
Medium (Engag.)	37%	33%	30%
Hard (Anxiety)	21%	19%	60%

C. EEG signals

All the classification methods obtained accuracy higher than the random level of 33% (Fig. 7). Without feature selection the LDA had the best accuracy of 49%, followed by the RBF SVM with 47%. As with the peripheral features, these results demonstrate the ability of linear and support vector classifiers to well generalize across the participants. The best result of 56% was obtained by the LDA coupled with ANOVA feature selection. The ANOVA feature selection method always had a better performance than the other methods. To our knowledge these are the first results concerning the identification of gaming conditions from EEG signals, especially considering that the classifiers were trained using a cross-participant framework.

<Figure 7>

As can be seen from Fig. 8, the FCBF selected less features than the two other feature selection methods. It selected 3.1 features in average compared to 20.3 for the ANOVA and 13.0 for the SFFS coupled with the LDA. This explains the low accuracy obtained with the FCBF and shows that good accuracies on this problem can be obtained only by concatenating several features. The ANOVA algorithm often selected the features described in Section III.A. The SFFS coupled with the LDA had accuracies close to those of the ANOVA with LDA but by selecting less features in average. For this reason the features selected by this method are of particular importance for accurate classification of the three gaming conditions. The more often selected features (selected more than 8 times) were the theta band energies of the T7, O1, Cz, P4 and P3 electrodes and the beta band energies of the P7, Pz and O2 electrodes. This result shows that the occipital and parietal lobes were particularly useful for differentiation of the three gaming conditions.

<Figure 8>

The confusion matrix displayed in Table VI for the LDA and FCBF methods shows that the different classes were detected with similar accuracies. The medium condition still has the lowest accuracy but is better detected than when using the peripheral features. On the other hand, the easy condition is detected with less accuracy than with peripheral features. This indicates that the fusion of the two modalities should increase the overall accuracy.

TABLE VI
CONFUSION MATRIX FOR THE LDA CLASSIFIER WITH ANOVA FEATURE SELECTION.

Estimated True	Easy (Boredom)	Medium (Engagement)	Hard (Anxiety)
Easy (Boredom)	57%	43%	0%
Medium (Engag.)	21%	50%	29%
Hard (Anxiety)	19%	19%	62%

D. EEG and peripheral signals

In order to compare accuracies obtained using either EEG or peripheral signals, the best combinations of classifiers and feature selection methods were applied on the physiological database with the same number of participants for both modalities (the 14 participants for whom EEG was recorded).

Moreover, the comparison was conducted for different time scales to analyze the performance of each modality as a function of the signal duration used for the features computation. For this purpose, each session (see Fig. 2) was divided into 1 to 10 non-overlapping windows of $300/W$ seconds, where W is the number of windows and 300 seconds the duration of a session. EEG and peripheral features were then computed from each window and the label of the session was attributed to these features. By using this method, a database of physiological features was constructed for each window size ranging from 30 to 300 seconds.

For a database in which the features were computed from W windows, the number of samples for each class is $20 \times 2 \times W$ (20 participants, 2 sessions per class and W windows per session). Thus the number of samples per class increases with W . Since the number of samples can influence classification accuracy and the goal of this study is to analyze the performance of EEG and peripheral features at different time scales, it is important that this comparison be conducted with the same number of samples for each window's length. To satisfy this constraint one sample was chosen randomly from each session using a uniform distribution to have $20 \times 2 = 40$ samples per class. The classification algorithms were then applied on this reduced database. This was repeated 1000 times for each value of W to account for the different possible combinations of the windows (except for $W=1$). Notice that it is not possible to perform classification for all windows combinations since there are W^{40} such combinations.

By using this method the average accuracies over the 1000 iterations are displayed in Fig. 9. The small accuracy oscillations that can be observed for small time windows (less than 100 seconds) are likely due to the increase of the number of possible combinations of windows. As can be seen from Fig. 9 the accuracy obtained for the peripheral signals with the original duration of the sessions (300 seconds) is not significantly different from the one obtained with all of the 20 of participants (See Section IV.B). Thus having 13 or 19 participants for classifiers training (because of participant cross-validation) does not significantly change the classification performance. This suggests that adding more participants to the current database would not increase classification accuracies and that recording 14 to 20 participants is enough to obtain reliable accuracy estimations.

<Figure 9>

For both modalities, decreasing the duration of the window on which the features are computed leads to a decrease of accuracy. However, this decrease is stronger for peripheral features than for EEG features. For the EEG features, the accuracy drops from 56% for windows of 300 seconds to around 51% for windows of 30-50 seconds. For the peripheral features the accuracy is 57% for windows of 300 seconds and around 45% for windows of 30-50 seconds. Moreover, the EEG accuracy remains approximately the same for windows having duration inferior to 100 seconds while the peripheral accuracy continues to decrease. All those results demonstrate

that the EEG features are more robust on short term assessment than the peripheral features. For our application, adapting the difficulty of the Tetris game based on the physiological signals gathered during the 5 precedent minutes may be undesirable since there is a high probability that the difficulty of the game has changed during this laps of time due to usual game progress. Having modalities, like EEG, that are able to estimate the state of the user on shorter time periods is thus of great interest.

E. Fusion

As can be seen from the confusion matrices obtained from the classification based on the peripheral and EEG features (Table V and Table VI), the errors made with these two feature sets are quite different. The Bayes belief integration is well suited for this type of problem, and thus was employed for fusion of the best classifiers found for each feature set (the LDA couples with ANOVA for EEG features and QDA coupled with FCBF for peripheral features). Another advantage of the Bayes belief integration is that the probabilities $P(\omega_i | \hat{y}_q)$ of (3) can be estimated independently for the two classifiers. It was thus possible to use the training data of 19 participants to compute probabilities for the peripheral features while only 13 participants were used for the EEG features. The resulting accuracy and confusion matrices were obtained by using the participant cross-validation applied on the 14 participants for whom both EEG and peripheral activity were recorded.

TABLE VII
CONFUSION MATRIX FOR THE “BAYES BELIEF INTEGRATION” FUSION.

Estimated	Easy (Boredom)	Medium (Engagement)	Hard (Anxiety)
True			
Easy (Boredom)	82%	14%	4%
Medium (Engag.)	29%	39%	32%
Hard (Anxiety)	4%	27%	69%

The accuracy obtained after fusion was 63% which corresponds to an increase of 5% compared to the best accuracy obtained with the peripheral features. Table VII presents the confusion matrix obtained after fusion. By comparing this table to Table V and Table VI it can be observed that the detection accuracy of the easy and the hard classes was increased by 2% and 7% respectively compared to the accuracy obtained with the best feature set (peripheral features for the easy class and EEG features for the hard class). The accuracy obtained on the medium class with fusion (39%) is lower than the one obtained with EEG features (50%) but higher than with peripheral features (33%). When performing classification based either on EEG or peripheral features many of the hard samples were classified as easy while this problem was solved after fusion. All these results demonstrate the interest of peripheral and EEG fusion at the decision level for a more accurate detection of the three conditions.

The accuracy obtained in the present study is 15% lower than the one obtained in [3]. However, according to the confusion matrix presented in Table VII, the adjusted level of difficulty using the current method should oscillate around the

true difficulty level where the participant experiences engagement. It is thus expected that our method will also improve player experience. Moreover, as stressed before, the current method only requires a baseline recording of 1 min for each new player, compared to the recording of six 1 hour training game sessions for each participant in [3].

V. CONCLUSION

This study investigated the possible use of emotion assessment from physiological signals to adapt the difficulty of a game. A protocol was designed to record physiological activity and gather self-reports of 20 participants playing a Tetris game at three different levels of difficulty. The difficulty levels were determined according to the competence of the players on the task. Two types of analysis were conducted on the data: first a statistical analysis of self-reports and physiological data was performed to control that different cognitive and emotional states were elicited by the protocol, secondly classification was conducted to determine whether it is possible to detect those states from physiological signals.

The results obtained from the analysis of self-reports and physiological data showed that playing the Tetris game at different levels of difficulty gave rise to different emotional states. The easy difficulty was related to a state of low pleasure, low pressure, low arousal and low motivation which was determined as boredom. The medium difficulty elicited higher arousal than the easy difficulty, as well as higher pleasure, higher motivation and higher amusement. It was thus defined as engagement. Finally the hard condition was associated to anxiety since it elicited high arousal, high pressure and low pleasure. Moreover, the analysis of consecutive engaged trials showed that the engagement of a player can decrease if the game difficulty does not change. These results demonstrate the importance of adapting the game difficulty according to the emotions of the player in order to maintain his / her engagement.

The classification accuracy of EEG and peripheral signals to recover the three states elicited by the gaming conditions were analyzed for different classifiers, feature selection methods and durations on which the features were computed. Without feature selection the best classifiers obtained an accuracy around 55% for peripheral features and 48% for EEG features. The FCBF increased the best accuracy on the peripheral feature to 59% while the ANOVA selection increased the accuracy to 56% for EEG features. The analysis of the classification accuracy for EEG and peripheral features computed on different durations demonstrated that the EEG features are more robust to a decrease in duration than the peripheral features, which confirms the importance of EEG features for short term emotion assessment.

Future work will focus on the improvement of the detection accuracy. Fusion of physiological information with other modalities such as facial expressions, speech and vocal signals would certainly improve the accuracy. Including game information such as the evolution of the score can also help to

better detect the three states. Another question of interest is to determine the number of classes to be detected. Since boredom and anxiety are detected with higher confidence than engagement it might be enough to use those two classes for adaptation to the game difficulty. Moreover, from the observation of Fig. 1, one can conclude that it is more interesting to adapt the difficulty of the game solely based on the increase of competence because it leads to a stronger change of state in the flow chart and stimulates learning. In this case only the detection of boredom is of importance to modulate difficulty. This also implies to more clearly define what are the relations between emotions and competence changes. A future study would be to implement an adaptive Tetris game and verify that it is more fun and enjoyable than the standard one. Finally, analysis of physiological signals for different types of games is also required to see if the results of this study can be extended to other games.

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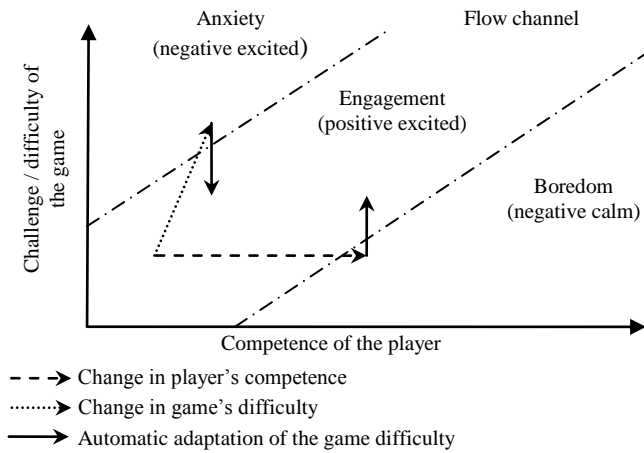


Fig. 1. Flow chart and the suggested automatic adaptation to emotional reactions.

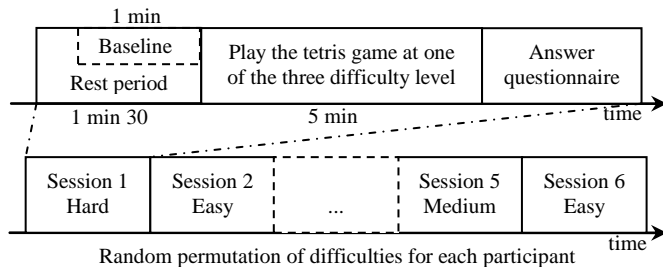


Fig. 2. Schedule of the protocol.

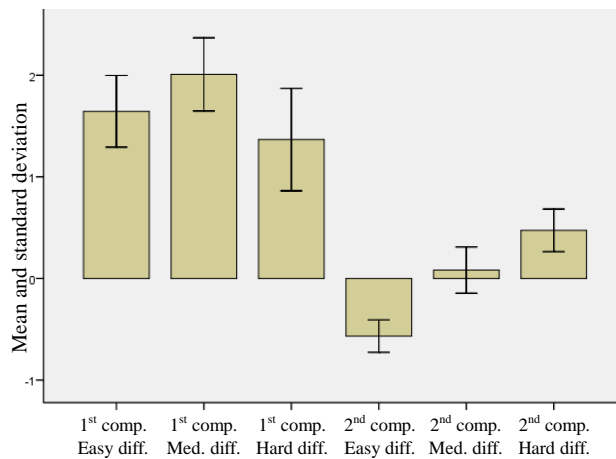


Fig. 3. Mean and standard deviation of judgments for each axis of the two components (comp.) space and the different difficulties (diff.): easy, medium (med.) and hard.

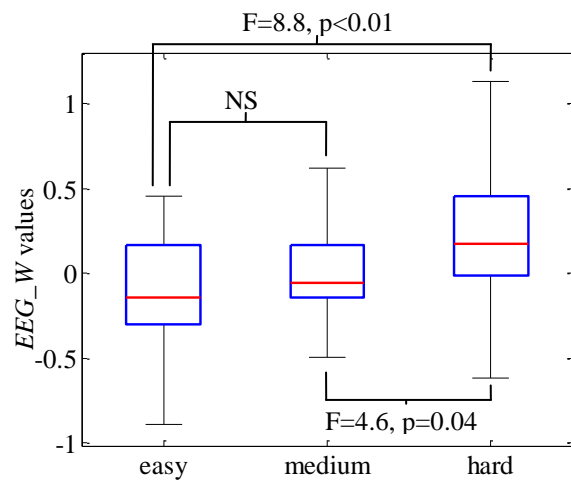


Fig. 4. Boxplot of the EEG_W values for the three conditions. The middle line represents the median of the EEG_W values, the box the quartile and the whiskers the range. NS: non significant.

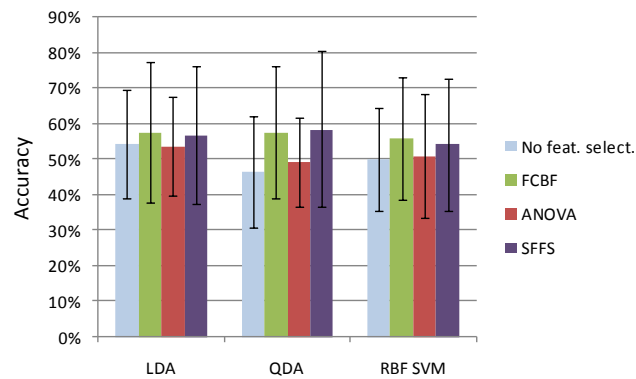


Fig. 5 Accuracies of the different classifiers and feature selection methods on the peripheral features.

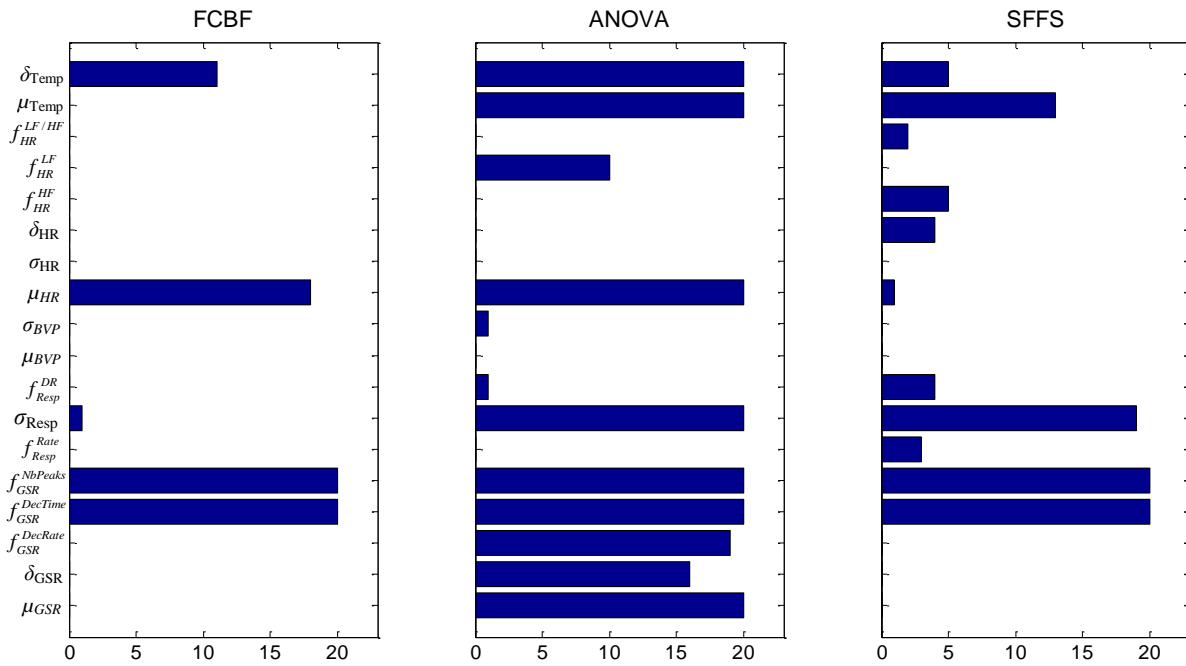


Fig. 6. Histograms of the number of cross-validation iterations (over a total of 20) in which features have been selected by the FCBF, ANOVA and SFFS feature selection algorithms. The SFFS feature selection is displayed for the QDA classification.

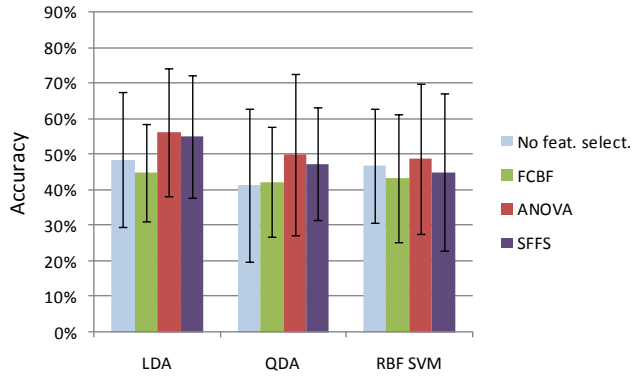


Fig. 7. Accuracies of the different classifiers and feature selection methods on the EEG features.

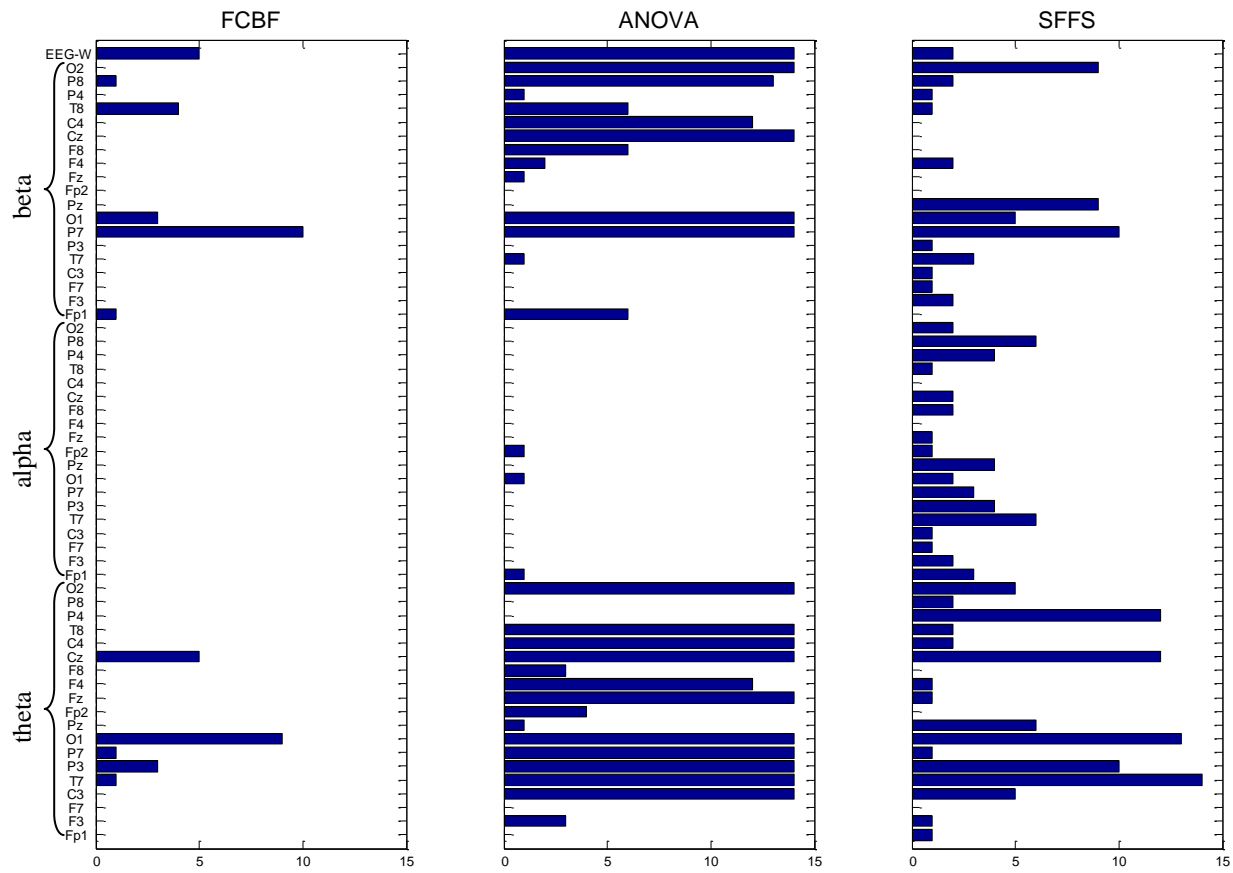


Fig. 8. Histograms of the number of cross-validation iterations (over a total of 14) in which features have been selected by the FCBF, ANOVA and SFFS feature selection algorithms. The SFFS feature selection is displayed for the LDA classification.

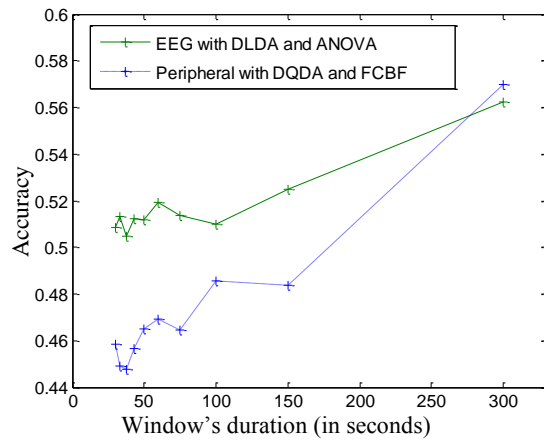


Fig. 9 Classification accuracy as a function of the duration of a trial for EEG and peripheral features.