Enhancing Automatic Detection of Frustration Induced During HCI with Moment-based Biosignal Features

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***Abstract*—Enhancing HCI systems with the capability to detect user's frustration and respond appropriately is a significant challenge. In this line, biosignal features based on the theory of orthogonal Krawtchouk and Legendre moments are assessed in the present work over their ability to enhance accuracy in automatic detection of frustration, which is induced through HCI, during video-game playing. Experimental evaluation, conducted over a multi-subject dataset over frustration detection showed that conventional features, typically extracted from Galvanic Skin Response and Electrocardiogram in the past, achieved correct classification rate (CCR) of 83.59%. Fusing these conventional features with moment-based ones extracted from the same modalities resulted to significantly higher accuracy, at the level of 93%. Furthermore, moment-based features lead also to over 10% increase in CCR when the aim was to identify both bored and frustrated cases, within a 3-classs affect detection problem.**

Keywords- automatic frustration detection, biosignals, moment-based features, video game-playing

I. INTRODUCTION

Negative emotional states like frustration are likely to be induced during Human - Computer Interaction (HCI). Frustration is an emotional state commonly associated with anger. During HCI, it can cause a negative disposition of the user towards the machine [1]. In the context of video games, frustration is typically induced when game difficulty is in mismatch with the capabilities and/or preferences of the player [2]. It can lead to player's disassociation from the game, dissatisfaction and resign. This is a case that may occur even in modern video-games, which, although carefully designed, do not take into account the player's current emotional state and its specifics [2].

Future game-playing systems can be augmented with the capability to automatically detect the player's affective state and monitor user experience [3]. When needed, these systems will be capable to adjust playing context appropriately [4], so as to maintain entertainment through a closed biocybernetic loop [5]. Frustration is an emotional state that can play a key role in this context [6], since as it has been shown in the past, machines responding to player's frustration can lead to improved gaming experience [1,2]. However, a pre-requisite for building such future game-playing systems, is to provide machines the capability to detect frustration effectively.

A. Related Work

During the past years, significant progress has been made in the field of automatic affect detection (e.g. [9,10,21]). This progress is important for a large variety of future HCI applications, ranging e.g. from affective games [7] to affective intelligent tutoring systems [12] that can be based on emotion sensitive e-learning models [8]. In this context, important efforts have been made so far towards enabling machines to automatically detect frustration. These studies utilized biosignals [11,12,14], video [12], or other data types [11,12] recorded during frustration induction, so as to build classifiers appropriate for detecting this negative emotional state.

Features extracted from the Galvanic Skin Response (GSR) and Blood Volume Pulse (BVP) were used in [14], leading to frustration detection accuracy of 67.39% among a multi-subject (MS) dataset, having a computer game as stimuli. In [12], the focus was towards an affective learning companion, and frustration was predicted with accuracy of 79% (MS), by utilizing features extracted from a face tracker, a posture sensing chair, a pressure mouse and GSR. Physiological features merged with contextual ones, extracted during students' interaction with a tutoring system, lead in [11] to 88.8% frustration detection accuracy. In [15], using features extracted from biosignal (GSR, temperature and heart rate) modalities, frustration was recognized from five further emotion classes with accuracy of 78.3%. Focusing on HCI in respect of video games, biosignal (e.g. GSR and Respiration) features were found to correlate in [3] with frustration induced from video-game playing, whereas in [4] frustration was detected from biosignals and gameplay data with accuracy around 85%.

From the above it is clear that in general, biosignals have good potential towards automatic frustration detection. However, although affect detection has significantly advanced during the recent years [16], frustration detection accuracy levels as well as in general emotion recognition (ER) ones have remained relatively limited, i.e. only rarely exceeding 90%. Therefore, evident is the need for new biosignal processing techniques, which will lead to more effective ER systems. Working towards this direction, [13] proposed biosignal features extracted from GSR and Inter-

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Beat-Intervals (IBI) time series (calculated from the Electrocardiogram (ECG)), which are based on the theory of orthogonal Legendre [17] and Krawtchouk [18] moments. These moments have been widely used in the past for the purposes of image analysis and reconstruction. Such a typical example can be found in [18], where it was shown that based on weighted Krawtchouk moments, effective image reconstruction and object recognition can be achieved. However, before [13], features based on Legendre and Krawtchouk moments had not been considered as an option in biosignals-based affect detection. The use of these features, together with conventional, not-moment based ones typically utilized in the past, was found in that work to significantly increase effectiveness of automatic boredom recognition.

B. *Contribution*

Boredom and frustration are both negative emotions of high significance in the context of HCI applications. Therefore, the present work aims to enhance effectiveness of automatic frustration detection, by using moment-based biosignal features. Moreover, taking a step further from [13], we assess whether the moment-based features can deal with the problem of detecting whether the subject is getting both bored and frustrated during HCI. As explained in the following, it was found that combining moment-based features with conventional ones can significantly enhance the effectiveness of automatic frustration and also joint boredom/frustration detection, compared to the case where conventional features are used alone.

II. BIOSIGNAL FEATURES EXTRACTION

Various biosignal features were examined in the present study over their effectiveness in the given context. All features presented in the following were extracted from GSR and IBI time series recorded during rest periods and game-playing trials of the dataset described in Section 3.

A. *Conventional features*

A set of "conventional" features was first extracted from all game-playing trials. These features, summarized in Table I, have proved in the past capable to form the basis for systems targeting automatic frustration detection, and ER in general. More details regarding the specifics (e.g. formulas) for the extraction of these features in the present study can be found in [13].

TABLE I. FEATURES EXTRACTED FROM THE GSR SIGNAL AND THE INTER BEAT INTERVALS (IBI) TIME SERIES

Signal	Conventional Features Extracted
GSR	Mean, Standard Deviation (SD), 1st derivative average, 1st derivative RMS, Number of SCRs, Average Amplitude of SCRs, Average Duration of SCRs, Maximum Amplitude of SCRs, δ(gsr), δ_{norm}(gsr), γ_{norm}(gsr), f_d(gsr)
IBI	Mean, SD, LF/HF, RMSSD, pNN50, δ(ibi), δ_{norm}(ibi), γ_{norm}(ibi), f_d(ibi)

Moreover, all features of Table I were also extracted from only the first and last 10 seconds of each trial or resting period; then, the ratio between each feature's value calculated from the first 10 seconds to the corresponding value calculated of the last 10 seconds was extracted as an extra feature (marked in the rest of the paper with the extension "***_FL***"). These ratios were calculated for all features that were applicable, similarly to [13]. In total, 37 conventional features were extracted, 9 from IBI, 12 from GSR, and 16 as the feature value ratio between the first and last 10 secs of each trial.

B. *Biosignal Features Based on the Theory of Moments*

Legendre moments [17] are based on projecting a signal onto Legendre polynomials, which form a complete orthogonal basis set defined over the interval [-1,1]. For a 1D discrete signal $f(x_i)$, $1 \le i \le N$, the 1D Legendre moment of order p is given by:

$$L_p = \frac{2p+1}{N-1}\sum_{i=1}^{N} P_p(x_i)\, f(x_i) \tag{1}$$

where $x_i=(2i-N-1)/(N-1)$ and $P_p(x)$ is the p^th order Legendre polynomial given by:

$$P_p(x) = \frac{1}{2^p}\sum_{k=0}^{p/2}(-1)^k \frac{(2p-2k)!}{k!(p-k)!(p-2k)!}x^{p-2k} \tag{2}$$

where x belongs in the span [-1,1]. Legendre polynomials were calculated with appropriate recursive relation [13]. Legendre moments of orders 0-39 were calculated for the GSR and IBI signals (features ***gsr_LgXX*** and ***ibi_LgXX*** respectively, where ***XX*** is the moment order), taken from the first 25 seconds of each trial so as to ensure uniformity in the extraction process. Prior to feature extraction, signals were sub-sampled at 4Hz and normalized to their subject-specific global min and max values by $\overline{X}(i) = (X(i) - X_{\min})/(X_{\max} - X_{\min})$, where X is either the GSR or IBI signal, $X(i)$ is a GSR or IBI sample, X_{min} and X_{max} are the GSR or IBI signal's min and max values recorded during all the specific subject's game-playing trials. Only the first 40 orders were extracted as features; the use of higher ones would increase complexity and was not expected to provide added value. As shown in [10], these orders were capable to capture information conveyed through signal frequencies approximately up to 0.5Hz.

Krawtchouk moments are based on a set of orthonormal polynomials; the n-order Krawtchouk classical polynomials are defined as:

$$K_n(x;p,N) = \sum_{k=0}^{N} a_{k,n,p}x^k = {}_2F_1(-n,-x;-N;\frac{1}{p}) \tag{3}$$

where x,n=0,1…N, N>0, p belongs in the span (0,1) and ${}_2F_1$ is the hypergeometric function [18]. Weighted Krawtchouk polynomials ($\overline{K}_n(x;p,N)$) were introduced in [18]. For a 1D signal $f(x_i)$ of length N, the weighted Krawtchouk moments $\overline{Q}_n$ are defined as:

$$\overline{Q}_n = \sum_{i=1}^{N} \overline{K}_n(i-1;p,N-1)\, f(x_i) \tag{4}$$

where $x_i=i$-1. In our case p was taken equal to 0.5, in order for the region-of-interest of the feature extraction process to be centered at the half of each trial's first N samples. The 40 first Krawtchouk moments (0-39) were calculated with (4) for the GSR and IBI time series (features ***gsr_KrXX*** and ***ibi_KrXX*** respectively, ***XX*** is the moment order), by following the same specifics as in the afore-described Legendre moments case. The analysis was restricted to the first 40 orders; in this case information conveyed through signal frequencies approximately up to 0.8Hz was captured.

The moment-based feature variations proposed in [13] were also extracted and assessed over their effectiveness in the present work's context. These moment-based feature variations have the rationale of suppressing the static parameter of the original moments calculation; i.e. the area between the projection polynomial and the x axis, which is always identical. By using (5) and (6) instead of (1) and (4) respectively, these features are defined as:

$$L_p^{\mathrm{mod}} = (2p+1)\sum_{i=1}^{N} P_p(x_i)(f(x_i)-1) \quad (5)$$

$$\overline{Q}_n^{\ \mathrm{mod}} = \sum_{i=1}^{N} \overline{K}_n(i-1; p, N-1)(f(x_i)-1) \quad (6)$$

Based on the first 40 Legendre polynomials, 40 features were extracted from GSR and IBI signals (features **gsr_Lg**$_{\mathbf{mod}}$**XX** and **ibi_Lg**$_{\mathbf{mod}}$**XX**), by following the same procedure as in the original Legendre moment-based features case, and using (5) instead of (1). Similarly, by using (6) instead of (4), 40 further Krawtchouk-based features were extracted from each signal (features **gsr_Kr**$_{\mathbf{mod}}$**XX**, **ibi_Kr**$_{\mathbf{mod}}$**XX**).

III. FRUSTRATION INDUCTION THROUGH REPETITIVE VIDEO GAME PLAYING

All aforedescribed features were extracted from biosignals recorded through the experimental process described in [13]. The specific experiment had the purpose of naturally inducing negative emotions like boredom to subjects, by the repetitive playing of the same video-game. The game utilized was an easy "3D Labyrinth" one. In each repetition (trial), the subject started from the same point and had to find the exit of the labyrinth, which was always located at the same place. The "3D Labyrinth" resembled on its gameplay basis to modern commercial games played by vast amounts of gamers worldwide (i.e. 3D-based first person role playing games). At the same time, the overall repetitive playing procedure lacked in all three of Malone's intrinsic qualitative factors for engaging game play (challenge, curiosity and fantasy) [19]. As a result, although at the beginning the game could be considered somewhat exciting, as soon as the subject had learned the shortest path to the labyrinth exit, boredom and negative emotions due to loss of interest were naturally induced.

Taking into account the appraisal theory [20], the main factor manipulated during the experimental session was novelty, the absence of which is a key factor for boredom induction. Furthermore, low novelty may result to the induction of further emotions, such as irritation / cold anger. Therefore, it was rational to expect the appearance of frustration in subjects during the session, an emotional state that was monitored by self-reports (mid-trials questionnaires) throughout the experiment. After each trial, the subject answered a few questions directly assessing her/his emotional state. Among these questions were Likert-scaled (1-5, with labels in the range "Not at all"-"Very Much") ones regarding the self-assessment of boredom and frustration that the subject experienced during the last trial, as well as one asking whether s/he wanted to play the game again.

Data was collected from 19 subjects (14 male, 5 female) who frequently used computers in their work. These were between 23 and 44 years old, and their average age was 29. In total, 221 trials were recorded. The collected biosignals data was annotated as "Not Frustrated" (NF) or "Frustrated" (F) on the basis of the subjects answers to the frustration self assessment question. Each trial after which the answer to this question was "1" or "2" was labeled as belonging to the NF class. If this answer was "4" or "5", the trial was assigned to the F class. Trials after which the respective answer was "3" were excluded from further analysis. As a result, an annotated dataset (A) consisting of 195 trials, 149 belonging to the NF and 46 to the F class, was obtained. Moreover, one further annotated dataset (B) was deployed, formulating a 3-class ER problem, where trials were labeled as "not bored" (NB), "bored and not frustrated" (B/NF), or "bored and frustrated" (B/F). The idea behind dataset B was to evaluate the given biosignal GSR and IBI features over their capability to differentiate between cases of subjects who are 1) not bored, 2) bored, but not frustrated, 3) bored, to the extent where frustration has also appeared during HCI. For this purpose, all trials after which the subject's answer to the boredom self-assessment question was "1" or "2" (denoting absence of boredom) were annotated as NB. The rest of trials were annotated as B/NF or B/F, in respect to the answer to the frustration self-assessment question, similarly to the annotation of dataset A. Trials for which the answer either to the boredom or the frustration self-assessment question was "3" were excluded. As a result, dataset B consisted of 168 trials in total, 55 NB, 70 B/NF and 43 B/F.

IV. RESULTS

Initially, the subjects' answers to the mid-trials questionnaires were analyzed on the basis of Kendall's tau correlation coefficient, examining correlations between boredom, frustration and the tendency to resign from game playing. Boredom correlated inversely to the subject's willingness to continue playing (τ = -0.784, $p<0.001$, N=195). Inverse correlation was also found between the latter and the player's frustration (τ = -0.208, $p<0.001$, N=195); frustration and boredom were also found to correlate (τ = 0.325, $p<0.001$). These results support the fact that boredom and frustration are two negative emotional states of great importance in the context of video-games. Their efficient automatic recognition from future game-playing systems could contribute towards ensuring game-playing quality and player satisfaction.

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In order to examine whether the moment-based features under consideration can improve automatic recognition of frustration that is induced during HCI, an LDA-based classifier was utilized, trying to solve classification problems related to frustration detection, which were formulated by the annotated data sets described above. Following leave-one-out cross validation, the LDA weights as well as the class centroids were calculated on the basis of the train set, and each test case was classified as belonging to its less distant class, similarly to [13,21]. Classification accuracy was assessed in terms of the correct classification rate (CCR = number of all cases correctly classified / total number of cases). In order to find features with the best discrimination capabilities between emotional classes, a Sequential Backward Search (SBS) [21] feature selection process was employed, using the CCR as the feature selection criterion. SBS was applied on several initial feature sets (some of them described in Table II), as explained in the following.

TABLE II. DESCRIPTION OF FEATURE SETS WHERE SBS WAS APPLIED, CONSISTING OF BOTH GSR AND IBI FEATURES

Feature Set	Features
CONV	All conventional features extracted from GSR and IBI
M	***gsr_KrXX*** and ***ibi_LgXX*** features (XX=0-39)
M_{mod}	***gsr_Kr***$_{mod}$***XX*** and ***ibi_Lg***$_{mod}$***XX*** features (XX=0-39)
CM	*CONV* and ***gsr_KrXX*** and ***ibi_LgXX*** features (XX=0-39)
CM_{mod}	*CONV* and ***gsr_Kr***$_{mod}$***XX*** and ***ibi_Lg***$_{mod}$***XX*** features (XX=0-39)

A. Frustration Detection with Conventional Features

Using initially only GSR or IBI conventional features as initial feature sets for SBS, max average CCRs of 67.69% (132/195; NF: 102/ 149, F: 30/46) and 78.46% (153/195; NF: 115/149, F: 38/46) were respectively achieved. By fusing the GSR and IBI conventional features, feature set *CONV* was formed, from which SBS selected features: GSR {Mean, SD, 1st Deriv avg, 1st Deriv RMS, # of SCRs, Avg SCR Amplitude, δ, δ_{norm}, f_d, γ_{norm}_FL, f_d_FL}, IBI {SD, LF/HF, RMSSD, pNN50, γ_{norm}, f_d, Mean_FL, LF/HF_FL, RMSSD_FL, δ_FL, δ_{norm}_FL}. These features achieved a max CCR of 83.59% in dataset A (Table III). In line with findings of previous works, the joint use of conventional GSR and IBI features was found effective towards automatic frustration detection, yet at a relatively limited accuracy level.

TABLE III. CONFUSION MATRIX AFTER SBS ON *CONV* FEATURE SET

Annot ated as	Classified as NF	Classified as F	Total	CCR per Class
NF	**126**	23	149	84.56%
F	9	**37**	46	80.43%

B. Frustration Detection with Moment-based Features Only

Krawtchouk and Legendre moment-based features were found in [13] the most descriptive transformations of the GSR and IBI modalities respectively. Following this line, SBS was applied in the present study to feature sets *Kgsr* and *Libi*; the first contained the 40 ***gsr_KrXX*** features and the second the 40 ***ibi_LgXX*** ones. With *Kgsr*, a max CCR of 77.44% (151/195; NF: 123/149, F: 28/46) was achieved in dataset A, whereas *Libi* produced a 68.21% (133/195; NF: 104/149, F: 29/46) CCR. Then, feature set *M* was formed by fusing *Kgsr* and *Libi*. With this feature set, a max CCR of 80.51% (157/195; NF: 124/149, F: 33/46) was obtained.

Applying similar analysis for the moment-based feature variations, two further feature sets were fed to the SBS, $K_{mod}gsr$ and $L_{mod}ibi$, consisting of all ***gsr_Kr***$_{mod}$***XX*** and ***ibi_Lg***$_{mod}$***XX*** features extracted respectively. $K_{mod}gsr$ produced a max CCR of 75.90% (148/195; NF: 122/149, F: 26/46) and $L_{mod}ibi$ achieved 71.79% (140/195; NF: 116/149, F: 24/46). A further initial feature set was formed (M_{mod}) by fusing the above features, over which the SBS procedure produced a max CCR of 82.56% (161/195; NF: 129/149, F: 32/46). Concluding, by completely replacing conventional features with moment-based ones, frustration detection accuracies close to the initial one (of the *CONV* feature set) were achieved in dataset A.

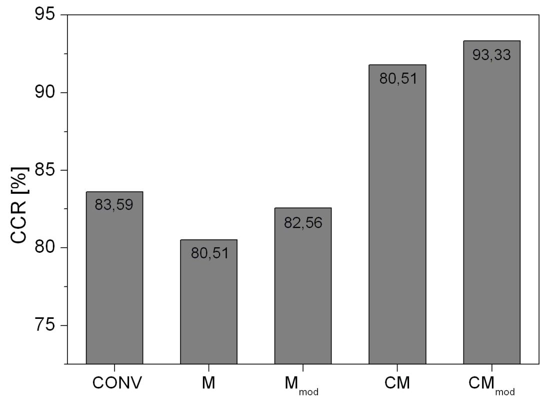

Figure 1. Max average CCRs obtained over Dataset A from the best features selected.

C. Fusion of Conventional and Moment-based Features

SBS was then applied to feature sets built from fusing the conventional features with the moment-based ones. Feature set *CM* consisted of the conventional features, together with all ***gsr_KrXX*** and ***ibi_LgXX*** ones. In the CM_{mod} feature set, the ***gsr_Kr***$_{mod}$***XX*** and ***ibi_Lg***$_{mod}$ ***XX*** moment-based feature variations were fused with the conventional features. SBS over *CM* produced a CCR of 91.79% (179/195; NF: 142/149, F: 37/46), significantly higher (by 8.2%) than the result obtained from *CONV*. Moreover, SBS over CM_{mod} achieved even higher frustration detection accuracy (Table IV); the best model built after SBS contained in this case features: GSR{*gsr_Kr*$_{mod}$***XX*; *XX***=2,4,5,8,9,14,19,20-22,26, 27,39}, IBI{Mean, SD, LF/HF, pNN50, γ_{norm}, f_d, Mean_FL, LF/HF_FL, δ_{norm}_FL, γ_{norm}_FL, *ibi_Lg*$_{mod}$***XX***; ***XX***=3-6,11,20, 27,36,39}.

TABLE IV. CONFUSION MATRIX OF SBS ON CM_{mod} (CCR=93.33%; 182/195)

Annotated as	Classified as NF	Classified as F	Total	CCR per Class
NF	**140**	9	149	84.56%
F	4	**42**	46	80.43%

As shown in Figure 1, fusing conventional features with moment-based ones significantly increased the accuracy of frustration detection among dataset A. Both *CM* and CM_{mod} feature sets increased the max average CCR compared to *CONV*; by a maximum 9.74% in the latter case. The significance of this increase in performance was proved by a two-tailed paired t-test ($p<0.001$). Within the best final feature set (selected from CM_{mod}), all conventional GSR features were replaced by moment-based ones, indicating the significance of the GSR moment-based feature variations in the context of automatic frustration detection. Such an example is the GSR SD, which although selected from *CONV*, it was discarded from SBS in the CM_{mod} case and replaced by moment-based GSR features, despite the fact that the specific feature has been found in the past [4] particularly significant towards automatic frustration detection. Regarding the IBI signal, several moment-based features were selected in the final best model built; however they were not capable to totally replace conventional ones. Some of the latter (e.g. pNN50) were kept in the best model, and this underlines their significance towards automatic frustration detection. Nevertheless, it has to be noted that another such feature, RMSSD, was replaced by moment-based features in the best final model built.

D. Joint Automatic Detection of Boredom and Frustration

The effectiveness of moment-based features was assessed also on the basis of a three-class ER problem, towards building a system capable to detect either not-bored, bored, or subjects being bored and frustrated as well. In order to do so, SBS was applied over feature sets *CONV* and CM_{mod}, in respect of the afore-described dataset B. As shown from Table V, the joint use of moment-based features with conventional ones significantly increased (by 11.91%) the total accuracy of the LDA-based classifier over the given 3-class ER problem.

It has been shown in the past that more-than-two-class ER problems can be effectively split down into simpler binary ones, so as to increase ER efficiency [21]. Following this line, the afore-described original 3-class joint boredom/frustration recognition problem was also split into two binary ones; boredom and frustration detection. Two binary LDA classifiers were used in cascade, the first regarding boredom (LDA-b) and the second regarding frustration recognition (LDA-f). Cases were first classified as B/NB by LDA-b. Then, cases classified as B were fed to LDA-f, which decided whether the subject was also frustrated (B/F) or not (B/NF). Again, two feature set types were examined, *CONV_bf* and CM_{mod}*_bf*. For *CONV_bf*, the best features selected from *CONV* in Section 4.1 and *F_Set_C* in [13] were used for the LDA-f and the LDA-b classifiers respectively. For CM_{mod}*_bf*, the best combinations of conventional and moment-based features reported in Section 4.3 and [13] were used for the LDA-f and the LDA-b classifiers respectively.

TABLE V. CONFUSION MATRICES PER FEATURE SET FOR THE 3-CLASS ER PROBLEM

Feature Set	Cases Annotated as	Cases Classified as			Total Cases Nr	CCR	
		NB	B/NF	B/F		Per Class	Total
CONV	NB	**41**	10	4	55	74.55%	70.83% 119/168
	B/NF	14	**44**	12	70	62.86%	
	B/F	1	8	**34**	43	79.07%	
CM_{mod}	NB	**45**	9	1	55	81.82%	82.74% 139/168
	B/NF	8	**55**	7	70	78.57%	
	B/F	1	3	**39**	43	90.70%	

Following this approach allowed conventional features to achieve an average CCR of 76.19% (128/168) among the 3 classes, significantly increased (by 5.36%) compared to the respective result shown in Table V. Similarly, in the case of CM_{mod}*_bf*, accuracy reached a CCR of 88.69% (149/168), increased by 5.95% compared to Table V. These results further depict the contribution of moment-based features in the domain of automatic ER; automatic multi-class ER systems based on conventional features can be enhanced towards increased efficiency by various techniques proposed in the past (e.g. [21]), and augmenting them with moment-based features can lead to even increased effectiveness.

V. CONCLUSIONS

In this work, experimental evaluation showed that augmenting conventional biosignal features with moment-based ones, significantly enhances the efficiency of binary frustration detection (NF vs. F), which is induced during HCI. Moment-based features were also found effective over a joint frustration and boredom detection ER problem, regarded from a 3-class perspective (NB vs. B/NF vs. B/F). When this problem was split into simpler binary ones, the accuracy of conventional features increased. However, the highest CCR was once more obtained by conventional features fused with moment-based ones.

Biosignal sensors are anticipated to become wireless, smaller and less obtrusive in the future. This will pave the way for future practical HCI systems augmented with biosignals-based automatic affect detection capabilities. Such a case could be an affective game playing system that will be capable to understand in real-time whether negative emotions like frustration have appeared and subsequently adapt, so as to ensure game-playing quality. Similar rationale can be followed in further HCI constructions as well, like e-learning systems etc. It has to be noted however, that in the present study, the real-time monitoring of frustration was not the immediate target, and off-line processing was applied to biosignals. Nevertheless, the on-line calculation of biosignal features based on the theory of moments can be regarded as feasible in future developments, since the processing power of modern PCs, along with multi-threading techniques already allow the simultaneous real-time extraction of large sets of biosingal features.

The results of the present analysis clearly show that moment-based features are significantly helpful towards enhancing effectiveness in automatic detection of negative emotions like frustration induced during HCI, which is in turn expected to be of great importance towards future affective game-playing systems and other HCI applications as well.

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