Addressing Signals Asynchronicity during Psychophysiological Inference

A Temporal Construction Method

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Abstract: Predicting the psychological state of the user using physiological measures is one of the main objectives of physiological computing. While numerous works have addressed this task with great success, a large number of challenges remain to be solved in order to develop recognition approaches that can precisely and reliably feed human-computer interaction systems. This paper focuses on one of these challenges which is the temporal asynchrony between different physiological signals within one recognition model. The paper proposes a flexible and suitable method for feature extraction based on empirical optimisation of windows' latency and duration. The approach is described within the theoretical framework of the psychophysiological inference and its common implementation using machine learning. The method has been experimentally validated (46 subjects) and results are presented. Empirically optimised values for the extraction windows are provided.

1 INTRODUCTION

The idea of a link between patterns of physiological activity and psychological states is commonly attributed to the American psychologist William James (1842-1910) (Ellsworth, 1994). He suggested that a person's perception of emotion stems from physical sensations caused by a reaction to a stimulus. In the early 1990s, computer scientists broadened this idea to create a new field of research : physiological computing (Allanson and Fairclough, 2004). The goal of physiological computing is to translate bioelectrical signals from the human nervous system into computational data. A wide range of applications in human-computer interactions, from brain-computer interactions to affective computing, require the recording and processing of the user's nervous system activity.

This paper focuses on one subfield of physiological computing that aims to connect physiological measures with psychological states. At a theoretical level, this process is based on the psychophysiological inference (Cacioppo and Tassinary, 1990), and can be defined as follows: let ψ be the set of psychological constructs (e.g. arousal, cognitive load) and Φ be the set of physiological variables (e.g. heart rate, pupil dilation). Cacioppo et al., 2007 now describe the psychophysiological inference according to the following equation:

$$\Psi = f(\Phi)$$

The relationship f could be declined in four ways: 1) one-to-one: a psychological state linked in an isomorphic manner to a physiological variable, 2) one-to-many: a psychological state reflects various physiological variables, 3) many-to-one: various psychological states related to a single physiological variable, or 4) many-to-many: multiple psychological states linked to multiple physiological variables. The regulation of emotions relies at once upon the sympathetic and parasympathetic activity of the autonomic nervous system, whose activity is also integrated in the central nervous system. The regulation of emotion thus requires physiological adjustments stemming from multiple response patterns (Kreibig, 2010). Hence, relationships 1 and 3 have little chance of being sufficiently specific to produce a valid inference. In fact, the relationships 2 and 4 dominate the psychophysiology literature. However, when taking into account the difficulties

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associated with isolating the physiological effects of multiple simultaneous psychological states, most works in physiological computing bring forth the third relationship (many-to-one).

Numerous works have implemented the physiological inference using a machine learning framework (Picard et al., 2001, Christie and Friedman, 2004, Haag et al., 2004, Bamidis et al., 2009, Chanel et al., 2009, Verhoef et al., 2009, Kolodyazhniy et al., 2011). Despite interesting results, reported prediction accuracy rates are still below the level of other machine learning problems and cannot feed large-scale real-world applications (van den Broek et al., 2010a). In a recent series of papers, van den Broek et al. proposed 11 prerequisites to strengthen the foundation of this field, which they coined Affective Signal Processing (ASP) (van den Broek et al., 2009). In this paper, we specifically address one of these problems; temporal construction (van den Broek et al., 2010b). We propose a method to take into account the temporal differences while integrating different physiological signals in a recognition process.

The remainder of the paper is as follows. Section two presents the general inference framework used in this paper and in most ASP approaches. Section three describes the temporal construction problem in the context of the later framework and our approach to address this problem. The experimental validation is presented in Section four and a discussion and a conclusion are in Section five.

2 INFERENCE FRAMEWORK

Most works using the psychophysiological inference follow more or less the six steps pipeline summarised in Figure 1. The main goal is to gather a data set, in which data points have the form [ψ_1, ψ_2, ψ_3, …, Φ], in order to train a recognition model f.

At step 1, the physiological signals Φ_i are selected according to their relation to the psychological construct ψ that is to be inferred. In this paper, three recognition models have been trained to test the temporal construction solution: ψ_1 = emotional valence, ψ_2 = emotional arousal and ψ_3 = cognitive load, and five physiological signals have been selected: Φ_1 = electrodermal activity, Φ_2 = pupil size, Φ_3 = respiration, Φ_4 = electroencephalography, and Φ_5 = cardiovascular activity.

The goal of the elicitation step is to allow subjects to experience different levels of the inferred construct. Elicitation methods can be categorised as being endogenous (relying on voluntary expression) or exogenous (using stimuli) (Cowie et al., 2011).

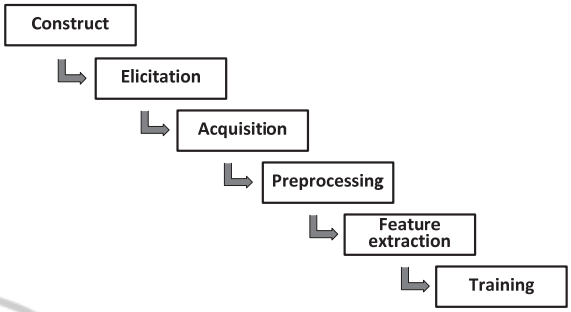

Figure 1: Psychophysiological inference pipeline.

Whatever the method, the objective it to capture the ground truth (G_T) - the real state of the construct for the subject - as precisely as possible. On the other hand, the expected elicitation represents the value that is anticipated and that will be inserted as targets in the training data set (i.e. Φ in a data point). The elicitation error (E_E) can then be defined as $E_E = | G_T - \Phi|$. Since G_T is related to the experiential dimension of the construct, a certain level of elicitation error is inevitable. As E_E can considerably impair the training process by inducing fuzzy targets, different methods are used to minimise it.

The feature extraction step consists in transforming the raw physiological signals in a data representation that will serve as inputs for the training algorithms. The choice of representation can have a significant influence on the training process and it is recommended to use domain knowledge in doing it (Guyon and Elisseeff, 2003). In the field of affective signal processing (ASP), most researches use a feature-based approach, popularised by the work of Picard *et al.* (Picard et al., 2001). As illustrated in Figure 2, this approach consists in three main substeps. First, different underlying features (e.g. Respiratory Sinus Arrhythmia (RSA), heart rate) related to the inferred construct are derived from the raw signal (e.g. Electrocardiogram - ECG). The second substep consists in segmenting these features according to the stimuli presentations. During the last substep, different statistics are calculated over each segment and for each feature (e.g. average, standard deviation, min and max). The latter statistics are the final ψ_i attribute forming a data point.

3 TEMPORAL CONSTRUCTION

Among the 11 prerequisites to improving the field of

ASP presented by van den Broek et al. (van den Broek et al., 2009), one of the most important is temporal construction. More precisely, three main problems are encountered concerning the temporal aspects of physiological signals (van den Broek et al., 2010b).

First of all, the habituation phenomenon implies that the intensity of the physiological reactions to the repeated presentation of a stimulus tapers off in time. From the perspective of the psychophysiological inference this means the relationship $\Psi = f(\Phi)$ between a set of signals and a psychological construct is not fixed in time. Other elements must be considered in order to account for the impact of previous occurrences of Ψ upon the physiological reactions at a specific point in time.

The second problem concerns the law of initial values. This law stipulates that "change of any function of an organism due to a stimulus depends, to a large degree, on the prestimulus level of that function" (Wilder, 1958). The use of this law in psychophysiology is subject to debate and it is recommended to discuss the principle of initial values instead (Jennings and Gianaros, 2007). While this principle cannot be applied integrally and should be nuanced, it remains that we can observe a correlation between the prestimulus baseline of a function and the direction and intensity of a reaction.

The final challenge concerning the temporality of physiological activity is the asynchrony of signals. As each physiological system operates in collaboration with a variety of inputs and outputs from the rest of the organism, the measured signals present various durations and latencies for a given stimulus. Heart rate for example may have a shorter latency than Electrodermal Activity (EDA) for a given stimulus. In this context, **latency** is defined as the time elapsed between the presentation of a stimulus and the beginning of a physiological reaction. **Duration** is defined as the time elapsed between the start and the end of a physiological reaction. It is harder to identify the end of a reaction as opposed to the beginning because the return to the equilibrium of a signal is not necessarily equivalent to the measured pre-stimulus baseline.

According to Gunes and Pantic, 2010, van der Zwaag et al., 2010 and to the best of our knowledge, the current literature on ASP offers no solutions to these three temporal construction problems. We were unable to find methodological approaches or algorithms allowing for the process of inference to take into account these temporal effects and to improve the quality of recognition. Among the three problems, we believe the most critical to be the asynchrony of signals. First, because the relationships 1 and 3 for the psychological inference are not specific enough (see Section 1). Second, because signal integration is at the heart of the problem of triangulation of research tools in this field. Asynchrony of signals is thus one of the main obstacles in using multiple physiological signals within a recognition approach. As can be seen in Figure 2, the feature extraction step segments all the signals at the same time point for a given stimulus. The data vectors forming the training set therefore contain attributes that do not optimally portray the studied construct in regards to latency and duration.

3.1 Windows Optimisation

Our proposed solution for the problem of asynchrony relies upon a flexible feature extraction procedure, which allows modeling of the temporal particularities of the various physiological measures. The main idea is to optimise the latency and duration of extraction windows. Furthermore, as suggested by

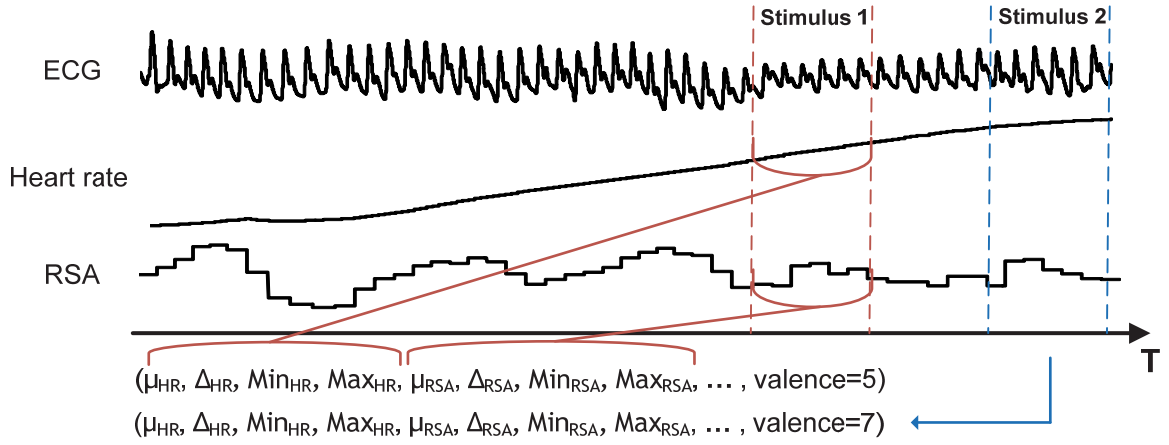

Figure 2: Feature extraction step.

van den Broek *et al.* (van den Broek et al., 2010b),these two parameters should be optimised according to the different constructs. Consequently, an optimal extraction window should be determined for each attribute and for each construct.

The identification of optimal latencies and durations is done using an empirical optimisation process. This optimisation was performed using the data collected in the experiment described in Section 4. Let us take for example the optimisation of the latency of the attribute µ EDA for the construct of emotional arousal. Let n = the number of data points in the training set and L = all possible latencies (e.g. between 0 and 7000 ms, in increments of 100 ms). For each latency L_i, a table of size n x 2 is generated containing n pairs [µ EDA, arousal] using an extraction window with latency L_i. A Pearson correlation coefficient r^2_i is then computed between both columns of the table. The latency L_i that maximises r^2_i will be selected as the optimal latency for the feature extraction window of µ EDA for emotional arousal. Figure 3 illustrates various latency values for three attributes (Δ interbeat interval, µ EDA, and µ pupil size), for the construct of emotional arousal. The latencies with the maximal r^2 are identified with dotted lines (5000ms for µ EDA, 250ms for Δ IBI (Interbeat Interval), and 1000ms for µ Pupil).

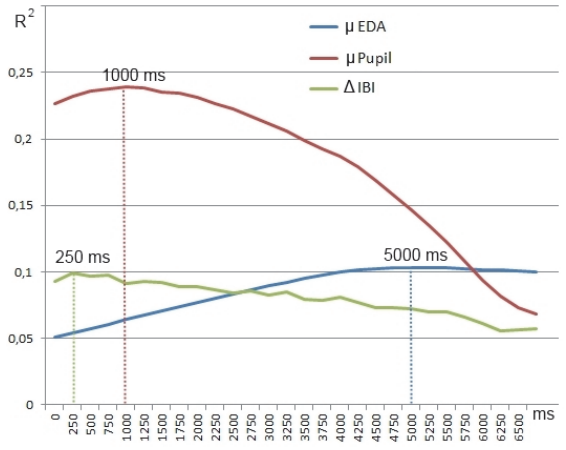

Figure 3: Empirical optimisation of windows latency.

In order to simultaneously optimise both parameters of the extraction windows, the empirical optimisation process is extended to include duration. As illustrated in Figure 4 (for µ EDA), for each latency L_i and each duration D_j, a Pearson correlation coefficient r_{ij} is computed.

The previously obtained optimal latency, 5000 ms, goes up to 7000 ms when jointly optimised with duration for µ EDA. This shift on the optimisation surface results in a slight increase of r of 0.01 (0.33 – 0.32). However, as opposed to the no optimisation point (0, 6000) – stimuli were presented for 6 seconds (see Section 4.1.2) – the impact of the combined optimisation of extraction windows parameters upon r is more substantial (0.33 – 0.23 = 0.1). The average gain for the correlation coefficients brought on by combined optimisation, for all the attributes of the three inference models, are of 0.08 (arousal), 0.06 (valence) and 0.14 (cognitive load).

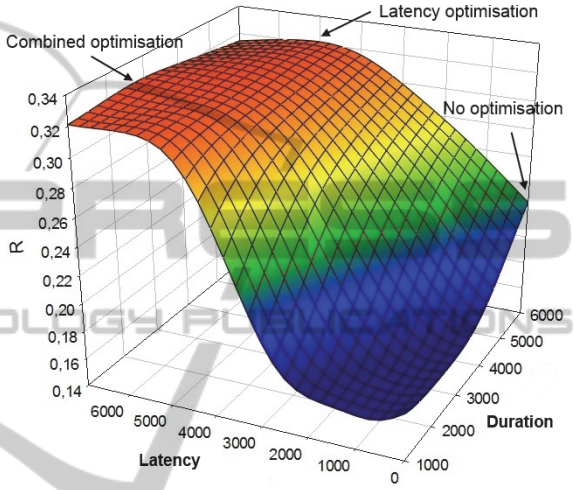

Figure 4: Combined optimisation of latency and duration.

4 VALIDATION

This section presents the experimental validation that was performed in order to assess the impact of the optimisation of the feature extraction windows on recognition performance.

4.1 Protocol

Fifty-two (52) participants (average age = 31) were recruited for this experiment, an equal number of men and women. A compensation of 40$ was offered at the end of the session, which lasted about 1h30.

The physiological signals were collected at 250Hz using a *Procomp Inifinity* amplifier from *Thought Technology*. Electrodermal activity (EDA) was recorded at the phalange site. Cardiovascular activity was recorded through blood volume pressure (BVP) using a photopletismograph placed on the middle finger. A respiration belt placed on the upper chest was used to record respiration activity. Electroencephalographic (EEG) activity was

recorded using four electrodes on the F3, F4, P3 and P4 sites following the 10-20 placement system. These sites were selected in order to measure frontal asymmetry (Coan and Allen, 2004). A 60 Hz notch filter, and low-pass (1 Hz) and high-pass (60 Hz) filter were applied to remove the electrical noise. Finally, pupil size was measured using a *Tobii X-120* eye-tracker. A simple normalisation procedure was applied ($x' = x - \mu_B$) using baseline data collected during a two-minute resting period before acquisition. For this work, 20 features were extracted from the raw signals, for which 7 statistics were calculated (mean, standard deviation, average and absolute values of the first difference, min, max, and kurtosis). Each data point in the training set is initially composed of 140 attributes and one target.

4.1.1 Cognitive Load Elicitation

The first 15 participants did not complete the cognitive load task. Amongst the 37 participants that completed this part of the experiment, data from six was rejected because of technical problems related to the recording of physiological signals. Hence, data from 31 participants was retained.

The protocol used to elicit cognitive load consisted of an immediate serial recall task. Twenty-four sequences of letters, varying between two and seven letters, were presented to the participants. They were asked to retain them for six seconds, before repeating them out loud. The first 12 sequences were repeated in the same order they were presented, while the following 12 were repeated in the inverse order. The memorising was solely mental and repeated voicing strategies were prohibited. The presentation sequence of the stimuli is shown in Figure 5.

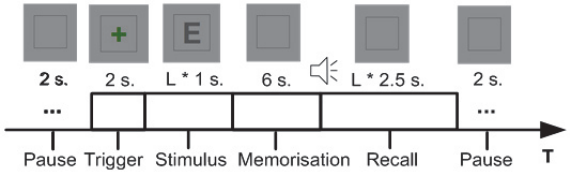

Figure 5: Cognitive load stimuli presentation sequence.

The beginning of the sequence was indicated by the presence of a green cross. Then followed the sequence of letters, each presented for one second, and the period of memorising. An audible beep signaled when the presented sequence should be repeated. This task provided 744 training examples.

4.1.2 Arousal and Valence Elicitation

Standardised stimuli composed of an image and a related sound from the International Affective Picture System (IAPS) (Lang et al., 2008) and the International Affective Digitized Sounds (IADS) (Bradley and Lang, 2007) collections were used to elicit emotional arousal and valence. Forty-six stimuli were presented for a period of six seconds each. A bimodal stimuli approach was chosen in order to confer a stronger ecological validity to the elicitation (Anttonen and Surakka, 2005, Mühl and Heylen, 2009). Self-evaluation using the SAM scale (Bradley and Lang, 1994) has also been used in order to reduce the elicitation error (see Section 2).

All participants performed the affective stimuli task. Data from eight of them were rejected because of technical problems tied to the recording of physiological signals. Hence, data from 44 participants was retained. While relying upon the normalised evaluation of the valence and arousal of the stimuli included in the IAPS, the images were chosen in order to form five groups and uniformly cover all quadrants of the emotional space. Figure 6 shows the distribution of the selected images.

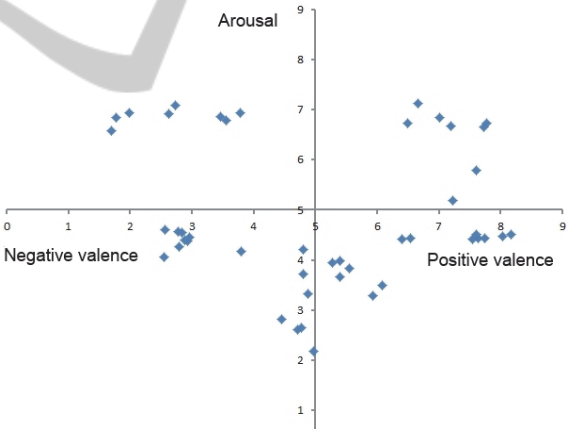

Figure 6: Affective distribution of stimuli.

The distribution includes four non neutral groups composed of eight images each: negative/low, negative/high, positive/low and positive/high, as well as a neutral group composed of 14 images: neutral/very low. The sequence of the affective stimuli presentations is depicted in Figure 7.

The general sequence, at the top of the figure, alternates neutral and non-neutral block with a 20 second break in between each. The neutral and non-neutral blocks respectively include two and four stimuli. The bottom of the figure shows the sequence of presentations within a block. It begins with a

baseline (2 seconds), followed by the presentation of a stimulus (6 seconds) and ends with a rest period (5 seconds). The presentation order of the non-neutral blocks and the presentation order of the images inside of the blocks are random. The images were presented full screen and a green cross was displayed for one second before each image. After all 46 stimuli were presented, a self-assessment interface was introduced showing all the previously shown images in the same order. Underneath each image were two scales based upon the Self-Assessment Manikin (SAM) allowing for the rating of the emotion felt at the time of the original presentation. They were scored on a scale of 1 to 9. This task produced 2024 training examples.

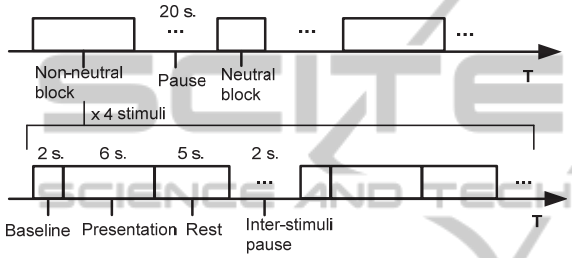

Figure 7: Affective stimuli presentation sequence.

4.2 Results

Prior to model training, a substep of feature selection was performed in order to reduce the data dimensionality and to keep only the more relevant attributes. A variable ranking method based on random probes was used (Guyon and Elisseeff, 2003), and 38 physiological attributes were selected for the arousal model, 10 for the valence model and 51 for the cognitive load model. For emotional arousal and valence, the targets are the average between the subject's self-assessment and the normalised values from the IAPS and IADS guides. For the cognitive load model, the targets are the number of letters to memorise (2 to 7). Since all targets are numbers, the training of each model is a regression problem. As we are interested in assessing the impact of the proposed temporal construction method on recognition performance (and not recognition performance *per se*), three different training algorithms were used: Support Machine Vectors (SVM), k-Nearest Neighbor (KNN) and Artificial Neural Networks (ANN). The *Statistica* software from *Statsoft* was used to perform training.

For machine learning regression problem, the quality of the model's training is assessed using the mean squared error (MSE), which is the average of the squared difference between the predictions and the actual values. Results are presented according to this metric. Training of the SVM and KNN models was executed following a k-fold cross validation procedure with k=10. Training of the ANN model was executed 10 times and the results averaged out to account for the randomized elements involved in the training procedure. In order to assess the impact of temporal construction method upon the capacity of the models to recognise the emotional/cognitive state of a subject, the models were trained with and without extraction windows optimisation. Results are presented in Figure 8.

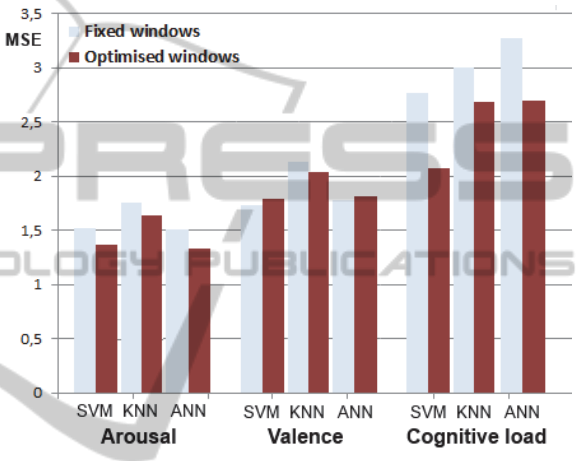

Figure 8: Impact of windows optimisation on MSE.

We can see that the mean squared error (MSE) variation trends for each construct were consistent amongst the different algorithms except for emotional valence where two algorithms (SVM and ANN) suffered a small error increase while one algorithm decreased (KNN). The average variation of MSE (over the three algorithms) for each model is of -0.15 (arousal), 0.0 (valence) and -0.53 (cognitive load). This results in average proportional gains for the prediction performance of 9 % (arousal), 0 % (valence) and 18 % (cognitive load).

5 DISCUSSION / CONCLUSIONS

van den Broek *et al.* proposed 11 prerequisites to strengthen the foundation of affective signal processing (van den Broek et al., 2009). This paper presented a solution to the specific problem of signal asynchrony. We demonstrated a method to circumvent the temporal differences while integrating many different signals in an implementation of the psychophysiological

inference $\Psi = f(\Phi)$. When the relationship f is used on a one-to-many basis (a psychological state reflects various physiological variables), the elements of Φ react according to different temporal scales (e.g. EDA at 4 seconds and ECG at 1 second post stimulus). Until now, the feature extraction methods used in the literature neglected this phenomenon and segmented all signals according to a stimulus using a single window.

Our temporal construction technique provides a solution to the problem of signal asynchrony and allows for a more optimal triangulation of multiple signals and recording instruments by individually optimising each extraction window for both latency and duration. Results from this experiment showed how the technique improved the quality of recognition model of arousal by 9 % and of cognitive load by 18 %. The valence recognition model was not improved (0%) on the average and reduced for two algorithms (SVM and ANN). A possible explanation for this can be found in the bipolar nature of the valence scale. As opposed to arousal and cognitive load which increase in a monotonous way, valence can be conceived as evolving in two directions (positive or negative). Indeed, it has been suggested to replace the bipolar scale with two unipolar scales (van den Broek, 2011). With this in mind it is logical that a unique relationship between values from the bipolar scale and optimal temporal windows is hard to establish. We now believe that different optimal windows can exist for a given physiological signal, depending upon the positivity or negativity of valence. Future works should also include looking for gender, age or personality effects on the value of the optimal windows' latency and duration. It could therefore be possible to tailor more precisely the extraction windows for specific subjects.

Following the large sample size of this study (n=44 for valence and arousal and n=31 for cognitive load), it can be expected that the empirically optimised values for the extraction windows can be used successfully in other studies. To do so, we included in the Appendix (Figure 9) the aforementioned values. Researchers working on the physiological recognition of valence, arousal or cognitive load could use these values while segmenting signals according to their stimuli – being that they are alike – and look for a gain in recognition accuracy. The proposed approach could also be adapted to different recognition contexts by optimising extraction windows for various physiological signals, psychological constructs or stimuli.

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APPENDIX

Signal	Feature	Attribute	Arousal		Valence		CL	
			L	D	L	D	L	D
BVP	Heart rate	μ	0	1000	4750	1000	0	2600
		std	0	5750	0	1000	2200	1000
		μ Δ	3000	1250	2750	2750	5800	3600
		|Δ|	750	4250	0	1000	2200	1000
		min	1000	1250	3000	2750	0	1400
		max	0	5750	6250	1250	7000	3600
		kurtosis	4750	5500	3500	2500	2200	5800
	Interbeat interval (IBI)	μ	7000	2250	0	1000	400	5600
		std	250	6000	6250	1250	2200	1000
		μ Δ	4250	4750	5500	5500	2400	5400
		|Δ|	500	5750	0	1000	2200	1800
		min	7000	1000	0	1000	4000	4600
		max	7000	4000	0	1000	1000	1600
		kurtosis	4750	5500	3500	2500	2200	5600
	Amplitude	μ	0	1000	0	1000	5400	1600
		std	2750	5750	0	1000	1800	1600
		μ Δ	1000	2750	3750	2750	5000	1600
		|Δ|	5750	2000	0	1000	2000	1200
		min	0	1000	0	1000	5200	1000
		max	2750	5500	0	1000	3800	1400
		kurtosis	4250	5000	4000	3000	5800	4800
	VLF (% of total power)	μ	0	1000	0	1000	0	1000
		std	6250	2250	0	1000	0	1200
		μ Δ	6000	1250	7000	1750	0	1000
		|Δ|	6750	1500	0	1000	0	1200
		min	0	1000	0	1000	0	1000
		max	0	1000	0	1000	0	1000
		kurtosis	0	1500	6750	1250	0	3800
	LF (% of total power)	μ	7000	6000	0	1000	0	1200
		std	0	1000	0	1000	200	1000
		μ Δ	7000	2250	0	1000	0	1000
		|Δ|	0	1250	0	1000	200	1200
		min	7000	6000	0	1000	0	1200
		max	7000	6000	0	1000	0	1400
		kurtosis	0	1500	5750	4500	3400	1000
	HF (% of total power)	μ	3750	1000	0	1000	0	1000
		std	0	1000	0	1000	0	1000
		μ Δ	0	1000	0	1000	0	1000
		|Δ|	0	1000	0	1000	0	1000
		min	0	5250	0	1000	0	1000
		max	6000	6000	0	1000	0	1000
		kurtosis	6250	1000	6500	1500	800	1200
	LF/HF (% of total power)	μ	7000	6000	0	1000	0	1200
		std	2750	4750	0	1000	3800	1000
		μ Δ	0	1000	0	1000	0	1000
		|Δ|	4250	2250	0	1000	2800	1000
		min	7000	6000	0	1000	0	1200
		max	7000	6000	0	1000	0	1200
		kurtosis	3250	1250	6500	1750	7000	2800
	VLF (average power)	μ	0	1000	7000	6000	7000	6000
		std	5750	3500	1000	1000	0	1000
		μ Δ	6500	1250	0	1000	0	1000
		|Δ|	5500	4250	1000	1000	0	1000
		min	0	1000	3500	6000	7000	5000
		max	0	1000	1000	1000	7000	6000
		kurtosis	1000	1750	3250	1250	1200	1200
	LF (average power)	μ	0	1000	0	1000	0	1000
		std	0	1000	4250	1250	0	1000
		μ Δ	0	1000	0	1000	0	1000
		|Δ|	0	1000	3750	2750	0	1000
		min	0	1000	0	3000	0	1000
		max	0	1000	0	1000	0	1000
		kurtosis	3750	2000	500	3500	4800	1000
	HF (average power)	μ	1500	6000	0	1000	0	5600
		std	7000	6000	0	1000	1600	4800
		μ Δ	0	1000	0	1000	6800	1000
		|Δ|	7000	6000	0	1000	2000	3800
		min	3000	1000	0	1000	1000	2400
		max	7000	6000	0	1000	2400	1400
		kurtosis	7000	6000	250	3250	400	1400

Signal	Feature	Attribute	Arousal		Valence		CL	
			L	D	L	D	L	D
BVP	LF/HF (average power)	μ	7000	6000	0	1000	0	1200
		std	2750	4750	0	1000	3800	1000
		μ Δ	0	1000	0	1000	0	1000
		|Δ|	5000	1250	0	1000	3800	1000
		min	7000	6000	0	1000	200	1000
		max	7000	6000	0	1000	0	1200
		kurtosis	6750	1750	0	2250	6200	1600
	HR Max-Min	μ	3000	6000	0	1000	0	1000
		std	4500	3000	1000	1000	0	1000
		μ Δ	1000	1500	7000	3750	2800	5800
		|Δ|	4500	2750	750	1000	0	1000
		min	3750	1250	0	1000	6800	1400
		max	2500	4750	0	1000	6000	5000
		kurtosis	6750	3500	6500	6000	6000	4800
EDA	Skin conductance	μ	7000	2750	0	1000	7000	6000
		std	3500	2000	0	1000	7000	6000
		μ Δ	3250	2000	6500	5500	6600	6000
		|Δ|	3750	1500	0	1000	6600	6000
		min	7000	2250	0	1000	7000	4000
		max	5500	4250	0	1000	7000	6000
		kurtosis	0	5000	0	1000	2400	1200
EEG	F3-F4	μ	0	1000	0	1000	0	1000
		std	1000	1500	1500	1000	5400	3800
		μ Δ	3250	5750	3500	3500	5200	1000
		|Δ|	1250	1500	0	2250	4400	5800
		min	0	1000	0	1000	0	1000
		max	7000	4750	1500	1000	6800	5800
		kurtosis	2500	2250	5500	1250	1200	4200
	P3-P4	μ	500	1750	0	1000	0	1000
		std	0	1000	0	1000	3800	1000
		μ Δ	0	3250	7000	2250	1400	1000
		|Δ|	5750	2000	0	1000	2000	1200
		min	0	1000	0	1000	5200	1000
		max	2750	5500	0	1000	3800	1400
		kurtosis	4250	5000	4000	3000	5800	4800
	(F3+P3) - (F4+P4)	μ	750	2250	0	1000	0	1000
		std	0	1250	7000	6000	3800	1000
		μ Δ	1000	3750	3500	5750	1400	1000
		|Δ|	1500	1000	0	1000	4000	2000
		min	750	2500	0	1000	0	1000
		max	250	1500	0	1000	4600	4000
		kurtosis	2750	1750	4250	2750	0	2200
	(F3+F4) - (P3+P4)	μ	3750	1000	6500	1000	2000	6000
		std	7000	6000	0	1000	6600	5000
		μ Δ	1750	2500	2000	5250	0	2600
		|Δ|	6750	3750	0	1000	7000	5200
		min	3250	1500	7000	2250	2600	1000
		max	2250	2500	6500	1000	2200	2600
		kurtosis	2500	1250	5500	1750	800	2200
Resp.	Respiration rate	μ	3000	1000	0	1000	0	1000
		std	750	1000	0	1000	1400	2000
		μ Δ	0	1000	5750	1000	0	1000
		|Δ|	750	1000	750	1500	1600	1600
		min	1750	1750	0	1000	0	1000
		max	3500	1250	6500	5000	0	3200
		kurtosis	2500	3500	6500	1500	5400	5200
	Amplitude	μ	5500	3500	0	1000	0	1000
		std	2750	1250	0	1000	7000	5000
		μ Δ	0	1000	1500	3250	2000	3600
		|Δ|	2750	1000	0	1000	0	1000
		min	1500	3750	0	1000	0	1000
		max	5000	3000	0	1000	3000	1400
		kurtosis	2500	3500	6500	1500	4800	5600
Pupil	Size	μ	4500	1000	7000	2000	7000	3200
		std	0	2000	7000	3750	4600	1400
		μ Δ	500	1000	3000	4500	800	2800
		|Δ|	4750	2500	4750	1000	4000	1400
		min	4500	1000	7000	5500	7000	2400
		max	5000	1750	7000	1250	7000	5200
		kurtosis	1500	5250	2750	6000	5000	6000