LJMU Research Online

Karran, AJ, Fairclough, SH and Gilleade, K

A Framework for Psychophysiological Classification within a Cultural Heritage Context Using Interest

https://researchonline.ljmu.ac.uk/id/eprint/587/

Article

For more information please contact researchonline@ljmu.ac.uk

A Framework for Psychophysiological Classification within a Cultural Heritage Context Using Interest

ALEXANDER J. KARRAN, Liverpool John Moores University
STEPHEN H. FAIRCLOUGH, Liverpool John Moores University
KIEL GILLEADE, Liverpool John Moores University

This paper presents a psychophysiological construct of interest as a knowledge emotion and illustrates the importance of interest detection in a cultural heritage context. The objective of this work is to measure and classify psychophysiological reactivity in response to cultural heritage material presented as visual and audio. We present a data processing and classification framework for the classification of interest. Two studies are reported, adopting a subject-dependent approach to classify psychophysiological signals using mobile physiological sensors, and the support vector machine learning algorithm. The results show that it is possible to reliably infer a state of interest from cultural heritage material using psychophysiological feature data and a machine learning approach, informing future work for the development of a real-time physiological computing system for use within an adaptive cultural heritage experience designed to adapt the provision of information in order to sustain the interest of the visitor.

1. INTRODUCTION

The introduction of digital technology has the capability of increasing the amount of information provided to visitors at a museum or art gallery [Ott & Pozzi, 2011] and to enhance cultural heritage patrons' enjoyment and interaction with heritage sites and material [Holzinger et al. 2011] . Cultural heritage (CH) in all its forms is unique and irreplaceable, and the current generation holds the responsibility of preserving it for the benefit of future generations. The challenge for digital technologies and technology design is to provide tools that will play a leading role in key issues such as providing access, increasing interaction, sharing knowledge and increasing the commercial viability of heritage institutions.

In order to understand how the experience of the visitor may be augmented by technology, we must consider the nature and quality of CH experience. Previous research described CH experience in terms of satisfaction, which in turn is determined by positive expectations of the visitor being fulfilled [De Rojas & Camarero, 2008]. The optimal CH experience has been defined in conceptual terms as a "total experience" that incorporates aspects of leisure, culture and social interaction [De Rojas & Camarero 2008, Pine & Gilmore 1998].

The analysis of cultural heritage experience described by Pine and Gilmore (1998) describes four crucial drivers of visitor experience:

1. entertainment (leisure, narrative)
2. educational (knowledge transfer)
3. aesthetics (pleasure)
4. escapist (immersion)

The first factor refers to capacity of cultural heritage artefacts to engage the visitor in a cognitive and affective manner. The educational component of the CH experience represents the process of knowledge transfer by which the visitor is informed about

artefacts. The aesthetic aspect of cultural heritage is perhaps the most difficult to understand because cultural artefacts are capable of evoking a range of aesthetic responses. Previous definitions of aesthetic experience have emphasised both information processing and emotional responses [Leder et al. 2004], i.e. a cognitive perceptual process accompanied by a dynamic affective state. The final factor (escapist) is associated with the degree to which the visitor is immersed within a mixed reality (i.e. past – present, new technology – ancient artefact). The concept of immersion is often associated with a sense of presence in a three-dimensional virtual reality (VR) [Russell 2003]; however, the same concept may be applied to mixed reality systems such as augmented reality [Smithsonianmag 2012]. Immersion has clear implications for creating memorable experiences in CH contexts, particularly using technology to engage and engross the visitor in a particular artefact.

This paper is concerned with technology that is designed to improve the CH experience via the adaptive provision of information. Physiological computing systems monitor the physiology of the user and use these data as input to a computing system [Fairclough 2009]. The passive monitoring of spontaneous changes in psychophysiology indicative of the cognitive and emotional underpinnings of CH experience can be used to adapt information provision in real time. These systems are constructed around a biocybernetic loop [Fairclough & Gilleade, 2012] that describes the data processing pipeline from the translation of raw physiological data into control input at the interface. Passive monitoring of psychophysiology can be used to inform intelligent adaptation, allowing software to respond to the context of the user state in a personalised fashion.

A physiological computing system could be created to monitor the CH experience in real-time by quantifying the state of the visitor and using these data to personalize the provision of information via a process of "adaptive curation". To perform this act of personalization, the physiological computing system must be sensitive to those psychological dimensions underpinning the four facets of the CH experience. It is proposed that activation, cognition and valence are essential elements of the CH experience with cognitive stimulation playing a primary role in the educational aspect and activation and valence capturing the emotional aspect of visitor experience. Engagement of both cognitive stimulation and emotional processes may interact in order to yield the escapist or immersive facet of the experience.

2. BACKGROUND

The psychological conceptualisation of affective experience falls into two distinct theoretical domains. Theories of basic emotions, e.g. happiness and fear, argue that emotional experience may be divided into discrete and independent categories [Ekman 1992]. This theoretical model contrasts with the circumplex model developed by Russell [Russell 1980, 2003] that represents emotional experience within a two-dimensional space consisting of arousal/activation (alert - tired) and valence (happy - sad). Unlike the basic emotions theory, the circumplex model emphasises the association between different categories of emotional experience via the common dimensions of activation and valence. It is assumed that cultural artefacts that are stimulating, both in a cognitive and an emotional sense, will increase the activation level of the visitor and responses will span the range of positive or negative affect.

The experience of a cultural heritage environment, regardless of whether it is a museum or gallery, is shaped by exploratory behaviour driven by the interest and curiosity of the visitor. A physiological computing system must build upon the

psychological foundations of curiosity in order to capture the experience of the visitor. The concept of interest as a psychological entity was described by Berlyne [Berlyne 1960] in terms of increased arousal and sensation-seeking, i.e. objects inspire curiosity via novelty and emotional conflict. This concept was expanded by Silvia [Silvia 2008, 2010] to incorporate a cognitive dimension, i.e. interest driven by stimulus complexity and a need to comprehend the stimulus. Both cognitive and emotional facets of interest were explored by Hidi and Renninger [Hidi & Renninger, 2000] who referred to the former as a perceptual/representational processes accompanied by a sense of positive emotion derived from intellectual engagement.

To encompass the affective and aesthetic aspects of the CH experience a conceptual model of interest was developed based upon a review of the literature. This conceptual model consisted of six sub-components of perceptual representational processes, three of which are cognitive in nature and three emotional factors. The cognitive sub-components are derived from Silvia [2010] and consist of:

- *Novelty*, i.e. whether the object or exhibit was familiar or unexpected/unconventional/different
- *Comprehension*, i.e. whether the representation/function of the object was clearly understood
- *Complexity*, i.e. whether the perceptual complexity of the object is high or low

The emotional components of interest owe much to the work of Berlyne [Berlyne 1960] and are described as follows:

- *Activation/Arousal*, i.e. whether consideration of the object was stimulating or not
- *Attraction*, i.e. whether the object was viewed as either attractive or repellent
- *Valence*, i.e. whether viewing the object made the person feel happy or sad

The proposed model of interest distils the four elements of the Pine and Gilmore into two important elements, cognitive factors (education and knowledge transfer) and affective influences (aesthetics). Cognitive factors are defined here as stimulus features that drive the curiosity of the viewer, such as novelty and complexity, whereas affective influences are defined in a two dimensional space [Russell 1980].

The complexity of the model was reduced into a simple form consisting of three dimensions for the purpose of operationalisation into psychophysiological measures, which were:

- *Cognition*, which captures the novelty and complexity of the stimuli i.e. familiarity vs. unexpectedness and intricacy vs. simplicity
- *Activation*, which captures how stimulating the stimuli is
- *Valence*, to capture the level of emotional experience as positivity or negativity towards the stimuli

Speaking purely in terms of a physiological computing system constructed around an inference of user "interest" towards cultural heritage artefacts, understanding the underlying neural pathways, and their connections to psychophysiological states, during cultural heritage experiences is therefore important to the development of a functional biocybernetic loop. The inference of interest in this context concerns the creation of a one-to-many relationship in which two or more physiological elements or

measures are associated with one psychological element or construct [Cacioppo et al, 2007].

Cognitive engagement (as cognition) can be quantified using Electroencephalography (EEG), particularly using alpha waves which have been associated with changes in cognitive load, i.e. a higher cognitive load is indicative of greater cognitive engagement (Goldman et al, 2002). Furthermore, recent studies in the field of neuroaesthetics have used functional magnetic resonance imaging (fMRI), functional near infrared spectroscopy (fNIRS) and EEG to investigate the relationship between brain activity and cultural heritage experiences, in particular the perception of beauty and aesthetics [Nadal & Pearce, 2011]. This research contends that the prefrontal cortex (PFC), in particular Brodman's area (BA) 10 located in the dorsal PFC, plays an important part in the evaluation of artworks through attentional top-down feedback that is the interpretation of sensory processing through cognitive engagement with the stimuli [e.g. Cupchik et al, 2009; Vessel et al, 2012; see Hahn et al, 2006 for a review]. In addition BA10 has also been associated with a wide range of cognitive process, ranging from the selection and judgment of stimuli held in short term memory [Petrides 1994] and working memory and attentional control [Ramnani & Owen, 2004] to reversal learning and stimulus selection [Dobbins et al 2002]; of specific import to the interest model is the association between BA10 and the 'elaboration encoding' of information into episodic memory [Henson et al. 1999, Wagner et al. 1998]. Another area of the prefrontal cortex relevant to the inference of interest is BA9, a part of the orbitofrontal cortex that has been associated with the motivational or emotional value of incoming information [Tataranni 1999, Rolls 2000] and has been linked to frontal EEG asymmetry [Davidson 1993].

Moreover, it has also been noted that alpha activation in the PFC is reduced during aesthetic experiences[1], particularly during the judgment of beauty [Cela-Conde et al, 2011], making EEG an appropriate measure to encapsulate cognitive engagement in cultural heritage settings. Cognitive engagement can therefore be captured and quantified using spontaneous EEG measures of electrocortical activation in CH contexts. Additionally, the aspect of arousal or activation described by Berlyne (1960) and Russell (1980) can be captured through changes in the visitor's psychophysiology. Thus, cognitive engagement can be quantified through changes in psychophysiology and brain activation. In addition it has been hypothesised that greater activation of the left hemisphere of the PFC is associated with positive emotions whereas greater activation of the right hemisphere is linked to negative emotions [see Coan & Allen, 2004 for a review], thus the emotional response (as valence) to cultural heritage artefacts could also be captured using spontaneous EEG measures of electrocortical activation.

The level of physiological stimulation (as activation) associated with the construct of interest can be captured via the level of skin conductance (SC) and supplemented by the measurement of heart rate (HR); SC is highly sensitive to sympathetic nervous system activity [Boucsein, 1992] and HR captures both sympathetic and parasympathetic components of the autonomic nervous system. Both SC and HR have been found to be appropriate measures to be used in CH environments [Tschacher et al, 2011].

---

[1] EEG alpha activation has a converse relationship with brain activity (Goldman et al, 2002), i.e. higher alpha activity is associated with reduced brain activation.

Operationalising the conceptual model of interest as psychophysiological measurement is a key step in the development of a physiological computing system. Using the insights gained from this previous research to inform our choice of variables, we elected to operationalise the cognitive and valence components of the interest model via EEG monitoring of four cortical locations. Cognitive activation was represented by EEG activity at FP1 and FP2 corresponding anatomically with BA10, for valence F3 and F4 were used to represent BA9. The measurement of cognition was captured using spontaneous measures of electrocortical activation and it has been shown that there is an inverse relationship between the level of alpha activity and brain activation [Goldman et al. 2002], i.e. higher alpha activity is associated with reduced brain activation, thus cognition becomes a ratio derived from activity in the beta band (12-30Hz) divided by activity in the alpha band (7-11Hz) at each site. Valence, generally measured in psychophysiology using facial EMG [Cacioppo et al. 1990], was deemed too intrusive for our needs, hence we captured valence by measuring the level of frontal hemispheric asymmetry expressed as a ratio, subtracting right from left hemispheric alpha band activity. It has been hypothesized that greater left activation of the prefrontal cortex is associated with positive affect whereas greater right side activation is linked to negative affect [Davidson et al. Lang 1995, Silbermann & Wiengartner 1998, Davidson 2004]. The activation component is measured via the level of skin conductance (SCL) and supplemented by measuring heart rate (HR); SCL is highly sensitive to sympathetic activity [Boucsein 1992] and HR captures both sympathetic and parasympathetic components of the autonomic nervous system. This array of physiological measures is designed to deliver a multidimensional representation of the psychological state of interest and to quantify the interest level of an individual in a dynamic fashion.

To test this concept, two experimental studies were designed to record and classify psychophysiological responses to CH material. Our approach combines the interest model with psychophysiological data and a machine learning algorithm in order to distinguish between stimuli that are high or low with respect to the level of interest provoked in the viewer.

3. DATA PROCESSING PIPELINE: THE IBIS FRAMEWORK

In order to integrate the quantification of interest into a real-time adaptive system suitable for use in a cultural heritage context, the model must be proceduralised. Whereby, psychophysiological measurements are taken and features processed at one end (see Novak et al. [2012] for a survey of methods) and interest is classified as a binary determinant and/or scale then output to an adaptive process at the other. This process then determines the level of automation or interaction required based upon the goals of the CH institution or user, such as information provision determined by were the user sits on the interest scale or a steady state of "edutainment" determined by consistent high interest classifications. Figure 1, displays the framework outlining the procedural flow of data, through measurement, processing and classification, from which classifier outputs can represent Interest as a Binary state or Interest as a Scale (IBIS) or both concurrently.

Figure 1 The IBIS procedural framework
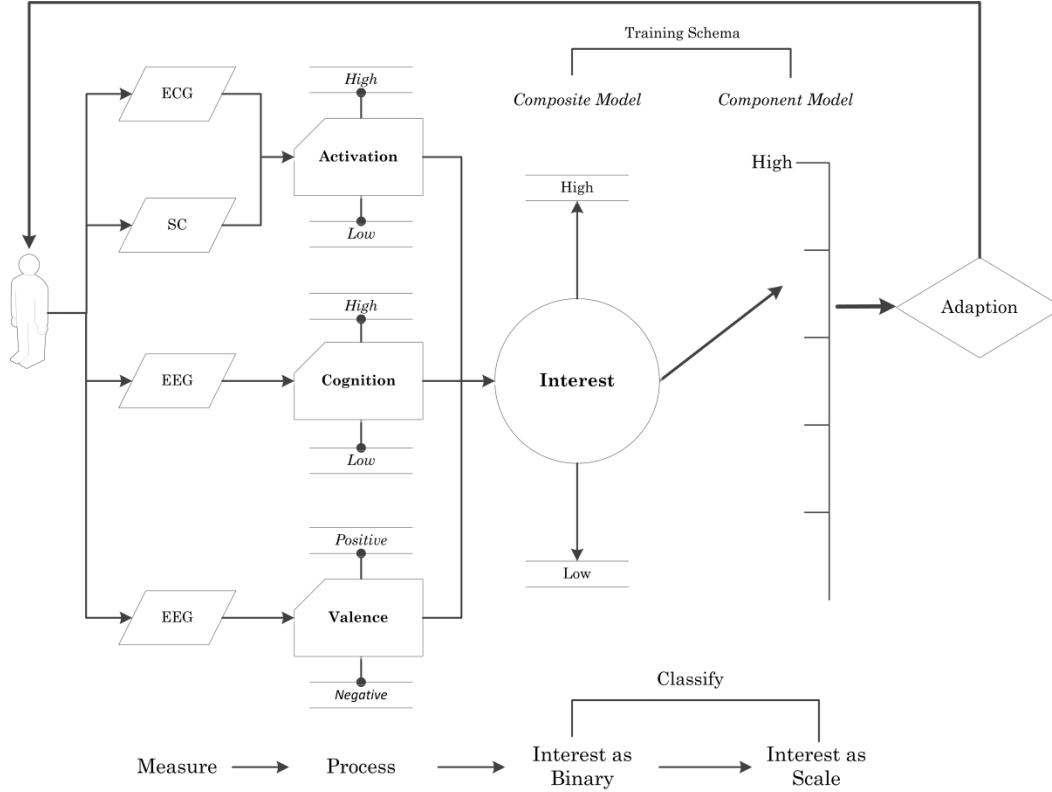
Procedurally, inputs from the physiological sensors are forwarded to component processors. The processors derive features (activation, cognition and valence) from the raw sensor data. These features are forwarded to a classification engine, which then forks to create two classification processes. One classifies interest as a binary state, by fusing the physiological feature data into a single classification vector and training an SVM classifier using a composite class label derived from subjective judgments. The output from this is a representation of interest as either low or high.

The second mode classifies interest as a scale by separating the physiological feature data into multiple classification vectors, representing each component of the interest model. These features are then associated with the subjective judgments given for each component. A classifier is trained for those components. The outputs from those classifiers can then be combined with propositional logic to represent interest on a scale ranging from very low to very high, i.e. IF activation = Low AND cognition = Low AND valence = Negative: INTEREST = Very Low.

The procedural framework allows both classification models of a user's interest state to be completed concurrently, as a composite model (single classification vector) and a component model (multiple classification vectors). Thus, the IBIS framework outputs either a single binary high or low determination of interest, in the case of the composite model; or an interest in the case of the component model.

Both forms of classification output can therefore be made available in real-time, as input to an adaptive engine which can perform system adaptions which have a concomitant effect on the measures of physiological activity, which are then classified as part of the biocybernetic loop.

4. EXPERIMENTAL STUDIES: ELICITATION OF INTEREST USING CULTURAL HERITAGE MATERIAL

The first study set out to create a virtual heritage installation that replicated in part, a late 18th century Valencia kitchen mosaic (installed at the Museo Nacional de Artes Decorativas in Madrid). The second study was undertaken in situ at the Foundation for Art and Creative Technology (FACT) in Liverpool. The former allowed participants in the study to stand in a natural fashion, while simultaneously viewing the mosaic and listening to audio narratives, specific to elements of the visual representation. The latter study was designed to present participants with audio and video content associated with a CH artefact. The studies were designed with the following goals:

- To measure and classify psychophysiological reactivity in response to CH content presented as visual and audio stimuli
- To define the psychophysiological variance as a two condition level of interest (high and low) consisting of three dimensions: activation, cognition and valence
- To determine the optimum method of gathering subjective response data and observe its effect on classifier performance
- To evaluate the performance of the Support Vector Machine (SVM) classification algorithm [Cortes & Vapnik 1995, Burges 1998, Platt 1999] for real-time application and the precision of the classifier, when compared to subjective response data
- To evaluate the effect of differing feature sampling rates on classifier performance

4.1. Study one: A virtual heritage installation

In this first study participants were asked to stand in a natural relaxed manner approximately 2 meters in front of a 3*2 meter projection screen, giving an image size of approximately 103 inches in width and 78 inches in height, giving a 130 inch 4:3 aspect-ratio screen. This was followed by the audio-visual presentation of the Valencia kitchen, lighting was dimmed throughout the presentation and audio was reproduced via a Dolby 5.1 surround sound speaker arrangement, at moderate easy listening volume (approx. 70dB). The presentation of the kitchen stimulus was linear and timed to progress through the narrative, giving four stories (average 17s in length) consisting of 3 factual elements. The audio commentary was divided into four 'stories' consisting of three discrete 'facts'. The four stories were composed around elements in the still image, refreshments; the Lady of the House; the ceramics; and the dog. To draw the gaze of the viewer specific fragments of the mosaic were highlighted (see Figure 2.). When the presentation was completed each participant was asked to rate which two stories were perceived to be the most interesting out of the four that were presented. Stimulus presentation was performed to be analogous with common in use cultural heritage audio tour guides and all stimulus content was supplied by the participating cultural heritage institution (MNAD).

Figure 2. The stimulus image, highlighted sections correspond to the audio narration. (Image courtesy of the Museo Nacional de Artes Decorativas, Madrid)

4.1.1. Procedures

Instruction about the experimental procedure was given and participants were asked to complete a consent form in accordance with the approval of the University Research Committee, and then fitted with a mobile pouch to hold the Nexus sensor hardware at the hip. Electrodes for ECG and SCL were placed on the torso and fingers, a Biosemi sensor cap was fitted to the participant to ensure correct sensor placement (see Table 1.) and electrodes attached. Participants were asked to stand in a relaxed position in front of the projection screen (shown in Figure 3.). This was followed by the audio-visual presentation of the Valencia kitchen.

Figure 3. Participant wearing sensor hardware

In this study ten participants 2 male 8 female, aged 19-75 took part, physiological responses from the autonomic system were measured during experimental sessions, using the Electrocardiogram (ECG, sampled from the torso) and SCL (second and forth finger, non-dominant hand) channels of the Mind Media Nexus X Mk II (sampled at 512Hz). Four channels of electroencephalographic (EEG) data were recorded using the Enobio (Starlab) wireless 4-channel sensor (sampled at 250Hz) with ground contacts on left ear lobe and inner ear. An EEG cap was fitted and

aligned to ensure sensor placement, electro-conductive gel was added to sites Fp1, Fp2, F3 and F4 [Jasper 1958] and electrodes attached.

4.1.2. Feature extraction and classifier training schema

Prior to commencing classification analysis of the physiological data, features were derived from measures of heart rate, skin conductance and EEG. For study one this resulted in a total of 9 features (Table 1) for each of the 12 stimulus events (average 17s). These features were further subdivided into the three components of the interest model, such that each feature set created a unique classifier feature vector for each element.

- *Activation* : Heart rate mean and standard deviation as inter-beat interval (iBi), and for skin conductance level, mean and standard deviation
- *Cognition* : Where the ratio :x is expressed as β (power 12-30Hz) divided by α (power 8-12Hz) at Fp1, Fp2, F3, F4 (1)
- *Valence* : Where the ratio :x is expressed as log natural of α (power), subtracting right from left hemispheric activity at sites (Fp1, Fp2) and (F3, F4) (2)

$$:x = \left(\frac{y_\beta{}^i}{y_\alpha{}^i}\right) \qquad\qquad (1)$$

$$:x = ln(z_\alpha{}^i) - ln(y_\alpha{}^i) \qquad\qquad (2)$$

Component	Measure	Derivative			
Activation	HR	iBi-Mean	iBi-Stdev		
	SC	Mean	Stdev		
Cognition	EEG	Ratio β /α FP1	*Ratio* β /α FP2	Ratio β /α F3	Ratio β /α F4
Valence		Ratio α FP1-FP2			

Table 1 Features derived from each measure for each component of the interest model

To train the classifier, class labels were derived from subjective judgments given by participants after each stimulus event and represented a "forced" choice, in that, subjects were asked to pick 2 stories from the 4 presented as most interesting. These Subjective judgments (as high interest) were then associated with the psychophysiological data for six facts (2 stories) the remaining data were associated with a label of low interest, these labels were subsequently used for both the "composite" and "component" model classifications.

4.2. Study two: Liverpool FACT study

For study two, participants were asked to view a heritage presentation which took the form of multimedia presentations (audio, text, images and video) of the work of three living film directors, the stimulus content was developed by the participating heritage institution (FACT) as part of a developing exhibit. The presentation of each directors work lasted an average of 2 minutes 24 seconds; director one, 4 segments; director two, 6 segments; director three, 5 segments, for a total of 15 segments (approx. 7 minutes). The presentations were displayed on a 22" computer LCD screen and audio was reproduced through stereo speakers at an easy listening volume of 70 dB [Arts 2010] placed on the floor approximately 45" in front of the participant. The presentation took the form of a documentary narrative, detailing the context, work and style of each director. Each narrative lasted approx. 30 seconds. After each director presentation was complete, participants were asked to provide subjective judgments using a provided questionnaire consisting of three Likert scales ranked 1 – 10. These scales aligned to the 3 dimensions of the interest model; *Activation: tired*

passive 0 to activated alert 10; *Cognition: low 0 to high 10*; and *Valence: sad angry 0 to happy cheerful 10.* The presentation order of the director narratives was counterbalanced within director; the first narrative presented was used to prime participant physiology and not included in the classification analysis.

Director	Context			Work			Style	
Krzysztof Wodiczko	Video Audio	Video Audio		Video Audio	Audio	Video Audio	Video Audio	Video Audio
Content	Artist work			Artist work	Interview	Interview	Interview	Artist work
Length(sec)	30			30	30	30	30	
Ken Loach	Video Audio	Video Audio	Video Audio	Image Audio	Image Audio	Image Audio	Audio	Audio
Content	Interview	Interview	Interview	Artist work	Artist work	Other films	On realism	On politics
Length(sec)	30			30	30	30	30	30
Apichatpong Weerasethakul	Video Audio	Video Audio		Audio	Video Audio	Audio	Video Audio	Video Audio
Content	Artist work			Artist work	Artist work	Artist work	Interview	
Length(sec)	30			30	30	30	30	

Table 2 Stimulus types FACT study

4.2.1. Procedures

After instruction, participants were asked to complete a consent form, and then fitted with the Nexus sensor technology for ECG and SCL. The Enobio headset was then fitted for comfort and the dry sensors aligned for signal quality using the mobile headband supplied with the device; for this study no Biosemi sensor cap was required to guide correct sensor placement, all EEG recording was performed using frontal sites from the forehead. Participants were asked to sit in a relaxed position approximately half a meter in front of a large computer screen, following which counterbalanced stimulus content was presented. To determine the memorability of the material and provide class labels for the psychophysiological response data, participants were asked to complete a questionnaire consisting of three Likert scales ranked 1 – 10. These aligned to the 3 dimensions of the interest model; Activation: tired passive 0 to activated alert 10; Valence: sad angry 0 to happy cheerful 10; Cognition: low 0 to high 10. Participants were offered access to the content to aid in recall if needed during the subjective judgment period.

For this second study 8 participants 5 male 3 female, aged 20-40 took part; psychophysiological response data was collected in a similar way to study one with the notable exception of EEG data. As this was an in-situ study, it was necessary to dispense with the EEG cap to allow for the ergonomic considerations of participants and speed of fitting. To this end, three channels of EEG data were recorded using the Enobio EEG sensor (StarLab) with mobile headband fitted and three dry electrodes placed at sites FP1, FP2 and FPz.

4.2.2. Feature extraction and classifier training schema

For this study, as with study one, features were derived from measures of heart rate, skin conductance and EEG, resulting in a total of 8 features (Table 3) for an average of 10 stimulus events (approx. 30 seconds), data from the stimulus events that were used to prime participants psychophysiology were not included in the feature extraction. These features were then further subdivided into the components of the interest model.

- *Activation* : For heart rate (iBi), mean, and standard deviation; for skin conductance level, mean and standard deviation extracted every 2 seconds for each content stimulus epoch
- *Cognition :* EEG data was derived from a fast Fourier transform of total amplitude spectra using a 2 second Hanning window for each stimulus epoch, where the ratio :x is expressed as β (power) divided by α (power) at sites FP1, FP2, FPz (1)
- Valence : Where the ratio :x is expressed as lognormal of α (power) subtracting right from left hemispheric activity at sites (FP2,FP1) (2)

Component	*Measure*	*Derivative*		
Activation	HR	iBi-Mean	iBi-Stdev	
	SC	Mean	Stdev	
Cognition	EEG	Ratio β /α FP1	*Ratio* β /α FP2	Ratio β /α FPz
Valence		Ratio α FP1-FP2		

Table 3 Features derived from each measure for each component of the interest model

After each stimulus event participants were asked to complete a questionnaire consisting of three Likert scales ranked 1 – 10. These scales aligned with the 3 dimensions of the interest model; Activation: tired passive 0 to activated alert 10; Cognition: low 0 to high 10; Valence: sad angry 0 to happy cheerful 10.

To train the SVM classifier(s), two forms of class labels were derived from the questionnaire data, one which represents the "composite" model (i.e. overall level of "interest") towards the stimulus material and one that represents the "component" model (i.e. individual component response), both ranked high or low. To derive the binary class labels for the composite model classifications, the Likert scores for each participant and each stimulus event were normalised to the form:

$$y^i = \sum_{i=3} x_i \left(\frac{x_i - minC}{maxC - minC} \right)$$

Where x_i is the sum of subjective scores for each dimension of the interest model (activation, cognition and valence) combined, minC and maxC are the minima and maxima of the population of scores for each stimulus segment. The result y^i is a population of normalised scores. To set the threshold for class assignation, the median of this population was calculated. Above the median was labelled as high and below as low interest. Class labels for the component model, were derived by modifying the above method to remove the sum component, thus x_i becomes the population of normalised scores for each of the components.

The result, in the first instance is a class label (either high or low), that represents a single subjective judgment as a composite "interest" score for each stimulus segment. In the second instance, the class label (high or low) represents the level of response for each component (cognition, activation and valence) of the interest model individually. These labels are then associated with the psychophysiological data for that stimulus event and once combined, these data become the feature vectors used to train and test the classifiers for the composite and component modes.

4.3. Classification of the psychophysiological response: Cross-validation and Classifier Parameterisation

For the two studies reported here, a subject dependent approach was taken to analysing and classifying the psychophysiological data to determine the recall accuracy of a support vector machine (SVM) classifier. The SVM classifier implemented for this study was part of the bioinformatics module within the Matlab (2011Rb) environment. To evaluate classifier performance, the derived feature data were grouped according to the three components of the interest model; such that each feature set created unique vectors for training the SVM classifier. Each component of the interest model has corresponding psychophysiological measures and feature derivatives of those measures (Table 1, 3) and class labels (either as "composite" or "component" model training labels, Figure 1). This approach has a number of advantages, each feature vector is identified as a separate component of the model; feature sets can be combined as a fusion of features; thus the effect of each feature set or fusion of features on classifier class recall can be evaluated. For study one, a single classification trial was completed, consisting of subject dependent classifications using the composite training schema to determine classifier accuracy for individuals. For study two, in addition to the composite training schema a second classification trial using the component training schema was completed.

Recall accuracy in the context of interest state classification for these studies is determined by cross-validating the SVM models over the training data, using the holdout method [Isaksson et al. 2008]. This method of cross-validation uses the entire dataset as both training and testing data by splitting the data arbitrarily according to criteria; that is, data is randomly assigned to either training or testing sets according to a "set size" determined before classification (in this case 60% training, 40% testing). The training dataset contains both the classification vectors (physiological observations) and its associated class labels (subjective judgments), testing the SVM model involves classifying the remaining (40%) unknown instances of test data, to determine recall accuracy. In a laboratory context, the labels (subjective judgments) associated with the test vectors (observations) are known to the experimenter but unknown to the SVM model, thus recall accuracy is calculated by comparing SVM model classification output (in terms of class) and with the known class labels, the result is how well the SVM model recalled the class of the observation.

Recall accuracy is determined by the number of true classifications plus the number of true negative classifications divided by the number of true plus false negative classifications plus the number of true negative classifications in the form of:

$$accuracy = \frac{number\ of\ true\ positives + number\ of\ true\ negatives}{number\ of\ true\ positives + false\ positives + false\ negatives + true\ negatives}$$

Parameters for creating the SVM model for classification of the data consisted of the sequential minimal optimisation (SMO) [Platt 1998], to reduce the processing overhead associated with the minimisation problem, and the Gaussian radial basis function (RBF) kernel to provide a non-linear classifier (suitable for physiological data). To provide optimal values for the RBF kernel a loose grid search algorithm was developed and applied outside of the hold-out cross-validation procedure, see Algorithm 1. The hold-out cross-validation method has been shown to provide a more accurate assessment of classifier performance in comparison to k-fold cross-validation when applied to small datasets, such as those gained from real-time applications [Isaksson et al. 2008].

ALGORITHM 1. Holdout Cross-validation using *n* by *n* grid search (*loose*)

Input: *Physiological data, Class labels, max Box-constraint, max Sigma*
Output: *Optimal Box-constraint; Sigma; accuracy*
sigma = 0.1;
box-constraint = 0.1;
Counter = 1;
Create array for box-constraint; sigma and accuracy values
[*optimalValues*] ;
for *n* to max *box-constraint* **do**
        for *n* to max *sigma* **do**
                Create two class problem
                Create a 60/40 split of *Physiological Data* as training and test data with
                associated *Class labels:* [*train*, *test*]
                Initialise a performance tracker
                Get instances of training data: *trainIdx* = [*train*];
                Get instances of test data: *testIdx* = [*test*];
                Train SVM using training data, current value of *box-constraint* and *sigma*
                Test the SVM model using test instances of training data
                Gather performance statistics
                optimalValues = [*box-constraint*, *sigma*, *accuracy*]
                Counter = Counter + 1;
                sigma = sigma + 0.1;
        end
        sigma = 0.1
        box-constraint = box-constraint + 0.1
        Store performance statistics
        Optimal = [*optimalValues*]
end
Find optimal settings
Criteria = max[Optimal(*accuracy*)]
Output optimal settings
Parameters = [*box-constraint*, *sigma*, *accuracy*]

---

5.   RESULTS

The results obtained from study one (the virtual heritage installation) are summarised in Table 4. These data represent the classifier recall accuracies from the subject-dependent classification of the feature data. The feature sets (activation, cognition and valence) were classified alone and in combination, to determine which permutation of features provided the best class recall accuracy over all participants. The data table indicates that the combination of activation and valence features afforded the best mean classification recall accuracy of 95% (σ 7.8). Similarly, the combination of activation and cognition or all three components together performed well with 92% (σ 11.2) and 93% (σ 8.3) respectively, showing a negligible difference in recall accuracy between these three feature vectors. However, a standard deviation above 10 shows the combination of activation and cognition to be moderately unstable across participants. Standard deviation in this context represents the inherent variability of mean classification accuracy across individuals, and can be seen as a measure of classifier stability, thus a low deviation value represents a more stable classifier across individuals. This resulted in lower class recall accuracies for some participants, highlighting the influence of individual differences in physiological responses towards the heritage material.

Features	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	Mean Recall	Range σ
A	83	83	83	100	100	83	83	83	100	100	90	8.3
C	100	83	83	83	67	83	67	83	83	100	83	10.4
V	100	83	67	83	83	67	67	100	100	100	85	13.7
A,C	83	67	83	100	100	100	100	83	100	100	92	11.2
A,V	100	83	83	100	100	83	100	100	100	100	95	7.8
C,V	100	83	83	83	100	67	83	83	83	100	87	10.0
A,C,V	100	83	100	100	100	83	83	83	100	100	93	8.3

Table 4 Classification recall accuracy (%) for all participants (P) presented across each source of psychophysiological data (activation (A), cognition (C), valence (V))

These significant classification rates offer strong evidence, that combining components of the interest model (such as activation and valence or the full component model) as feature vectors represents an effective method to classify level of interest in a cultural heritage setting. Comparing classifier recall accuracies from other feature sets, it can be seen that the combined features of activation and cognition are only 3% less accurate overall than those of the combined activation and valence feature sets, with a maximum of 92% mean recall accuracy.

The results from the second experimental study carried out at FACT, are summarised in Table 5. These results represent the subject-dependent classification of the feature data from classifiers trained, using the composite model training schema of the IBIS framework. Similar to study one the combination of activation and valence presents with the highest mean recall accuracy, reporting 84.7% (σ 8.5). However, in this instance there can be seen a negligible increase in inter-subject classification accuracy variation for some participants, when compared to the previous study (95% σ 7.8).

Training Schema *Composite Model*									
Features	P1	P2	P3	P4	P5	P6	P7	P8	Mean Recall	Range σ
A	96.5	93.6	95.2	80.0	87.0	73.8	84.2	88.0	87.3	7.4
C	66.7	69.4	67.7	67.0	70.0	60.7	73.7	72.0	68.4	3.7
V	61.4	66.1	66.1	67.0	62.0	62.3	68.4	63.0	64.6	2.5
A,C	73.7	88.7	95.2	69.0	68.0	62.3	79.0	82.0	77.3	10.4
A,V	93.0	91.9	95.2	82.0	85.0	67.2	79.0	84.0	84.7	8.5
C,V	68.4	62.9	64.5	67.0	68.0	62.3	71.9	70.0	66.9	3.2
A,C,V	71.9	88.4	93.6	69.0	68.0	60.7	80.7	84.0	77.0	10.6

Table 5 Classification recall accuracy (%) for all participants (P) presented across each source of psychophysiological data (activation (A), cognition (C), valence (V))

Interestingly, in this classification trial the features of activation alone present the highest mean recall accuracy and classifier stability across participants (87.3%, σ 7.4). The classifier created to combine activation, cognition and valence which represents the full interest model, achieves a mean recall accuracy of 77.0% (σ 10.6) and this high variation in accuracy is indicative of a classifier that is unstable across individuals. It is worth noting however, that the lowest reported accuracy still remains above chance levels.

Training Schema *Component Model*									
Features	P1	P2	P3	P4	P5	P6	P7	P8	Mean Recall	Range σ
A	89.5	98.4	95.2	90.2	71.7	78.7	96.5	82.5	87.8	8.8
C	66.7	66.1	67.7	67.2	69.8	60.7	75.4	73.7	68.4	4.3
V	66.7	64.5	66.1	65.6	62.3	63.9	70.2	66.7	65.7	2.2

Table 6 Classification recall accuracy (%) for all participants (P) presented across each source of psychophysiological data (activation (A), cognition (C), valence (V))

Table 6 displays the results from the second classification trial, in which classifiers were trained using the component model training schema of the IBIS framework. In this trial a classifier was created and trained for each component of the interest model using class labels specific to that component. The results show that in this instance the classification of the features of activation present a favorable mean recall accuracy (87.8%, σ 8.8). However, in this instance a degree of accuracy variation can be observed, indicative of minor instability across participants. The classifiers created for the features of cognition and valence both report low recall accuracy when compared to activation of 68.4% (σ 4.3) and 65.7% (σ 2.2) respectively. However, despite the lower accuracy output, both classifiers report above chance level classifications coupled with exceptionally low accuracy variance across participants, creating stable, if inaccurate classifiers.

6. DISCUSSION

The results from these studies provide evidence that the combination of psychophysiological features, coupled with a SVM classifier and a subject-dependent classification approach can reliably infer the "knowledge emotion" interest in response to cultural heritage material. The results from the two studies indicated that the IBIS framework, which outlines a subject-dependent approach to psychophysiological measurement, data processing and two modes of classification, can achieve high classification accuracies coupled with low accuracy variance across participants when using the composite classification model. These results indicate, that participants responded physiologically to the content of the cultural heritage material. Moreover, these features when combined appear to add a larger degree of separation within the classification vector space between the two classes, allowing for more consistent classifications and an inference of a state of interest indicative of greater variation within the psychophysiological responses.

A surprising finding was the lack of comparable classification accuracies between the classifiers created for the component model of the IBIS framework. Our expectation that the accuracy of the component classifiers would be analogous or superior for the FACT study was proven to be unfounded, with the component classifiers showing a marked decrease in classification accuracy when compared to study one. A possible explanation for this disparity could be the different methods used to assess subjective judgment during each study. In study one subjective judgment represents a "forced" choice, which although blunt and with little consideration given to any detailed introspective assessment, may have been more representative of the recorded psychophysiological response. In study two, participants were given the opportunity to review the stimulus material post-hoc after each stimulus segment before giving subjective judgments about their levels of stimulation upon a Likert scale. It is possible that the reported judgments are dissimilar to those represented by the psychophysiological data due to the process of subjective estimated provoked by the Likert scale. This difference could also account for the moderate drop in mean

classification accuracies between the two studies, as supervised learning algorithms only gain improvements in performance when trained with accurate training data [Ranni et al. 2007].

A possible limitation within the studies reported which may have affected the component level classification accuracies for valence is one of handedness, which was uncontrolled for within both experiments. The effects of handedness on hemispheric lateralization as a means to measure affective response have not been thoroughly investigated and existing literature is inconclusive [Rodway et al. 2003]. One of the most consistent findings has been through studies using dichotic-listening paradigms. Handedness-related hemispheric lateralization differences have been noted in studies using music, words, and speech prosody as stimuli [McFarland & Kennison 1989; Bryden et al. 1991; Perria et al. 2001]. These dichotic listening studies have shown that right-handers' affective lateralization corroborates with the common "valence hypothesis" (i.e. right hemisphere for negative affect, left hemisphere for positive), but that left-handers have opposite lateralization. These studies point to a possible confound which may have had an effect on the ratio measurement used as an index of affective response. A further limitation of the work concerns sample size, due to the complexity of the experimental procedures and length of data analysis, the pool of participants per study was small. This makes the results less generalisable than if a larger population of participants were used. However, the IBIS framework posited here is as a subject dependent methodology and is designed not for generalisability but rather for systems trained for individuals by individuals within the same session.

This lack of comparable or increased classification accuracy appears to indicate that the component training schema is the less effective of the two modes of classification in terms of raw mathematical accuracy. Indeed, in the case of the FACT study, component level classification accuracies suffered significant decline of accuracy when compared to the first study. However, in theory the component model classification approach appears superior, as it offers a more nuanced inference of a user's level of interest, whereas the composite model offers a much less granular binary inference. Here we report only on the mathematical output accuracy of classifications using the SVM algorithm, and these classifications can be used "as is" within a system that can utilise the binary (composite) inference of interest. However, to realize this potential and output interest upon a scale ranging from very low to very high; the component model classification output of the IBIS framework requires a secondary processing stage.

Propositional Logic : Interest as a Scale			
IF	AND	AND	Inferred Interest
Activation +	Cognition +	Valence +	Very High
Activation +	Cognition +	Valence -	High
Activation +	Cognition -	Valence +	High
Activation +	Cognition -	Valence -	Moderate
Activation -	Cognition +	Valence +	Moderate
Activation -	Cognition +	Valence -	Low
Activation -	Cognition -	Valence +	Low
Activation -	Cognition -	Valence -	Very Low

Table 6 Propositional logic representing eight states of the interest scale

This secondary processing stage would utilise the binary classification output from each component of the interest model, and apply propositional second order logic [De Morgan 1847] to map the series of binary outputs into an eight state model (Figure 6), representative of an interest scale or "experience". Such that, IF activation = High

AND cognition = High AND valence = Positive: INTEREST = high. These eight states of interest transpose well onto the IBIS framework, the states can be processed in parallel with composite model classifications and used separately or combined to inform an adaptive decision component to make changes to an interface or content in real-time. Furthermore, the transposition of three binary classifications into eight states could potentially be used as the basis for a more comprehensive interaction and adaption model. This enhanced interaction and adaption model could allow CH institutions to aggregate more detailed visitor "interest" statistics about installations and associated content and to create more memorable heritage experiences. Adaptions based on the scale level of interest, would inform adapt-no-adapt decision level logic leading to variable levels of content adaption that insert or take away content in order to elicit favourable high interest responses; for example, if the level of cognitive engagement is consistently low, insert more intellectually stimulating content to the interaction context (via the monitoring media tags and meta-level information about content). Not only would the IBIS framework drive an adaption model via a bio-cybernetic loop, but externally it would drive the content creation process, allowing CH institutions to monitor the impact of content on museum patrons and feedback into the system with content demographically apropos to knowledge transfer and entertainment goals.

The accuracy floor, below which interactive systems using this approach within a bio-sensing component would become unusable, is a topic of speculation at this point in our research. Finding the optimum balance between synthetic classification accuracy and quality of user experience is a topic worthy of further research, one which requires implementing the IBIS framework as a real-time bio-sensing component within an interactive system, then evaluating its performance using receiver operator characteristic techniques and real-time user feedback. This is currently work in progress and a real-time interactive heritage application is in development.

We envision many possible applications of this approach within the context of cultural heritage, such as automated or semi-automated recommendation of cultural heritage content informed by real-time psychophysiological assessment (a digital curator) or "interest" profiling involving implicit tagging of heritage material to build up heat maps that use interest as a basis to inform future interactions and build cultural heritage installations that imbue artefacts with a sense of modernity, whilst at the same time preserving any cultural and historical significance. The possibility of further commercialization also exists in the form of "big data" i.e. bioinformatics processing; in that psychophysiological data coupled with survey data (such as nationality of user), gathered over an extended period from multiple users could be used for targeted advertising or demographic profiling purposes. However, to use these data in commercial projects, either a formally or informally would require both the consent of every user and careful consideration of the ethical implications of their use.

The overarching goal of this research was to answer the questions "Can we use physiological computing for adaptive information provision in a CH context?", "Will a sustained state of interest using personalised information provision enhance the CH experience?" we tentatively posit an answer of yes. The results from the two studies presented here show that it is possible to reliably infer a state of interest from psychophysiological signals. However, in order for an interactive and adaptive CH physiological computing system to be fully realised, the proposed framework and approach we have discussed must be applied outside of the laboratory and restricted simulated environments and tested in the field. To this end a real-time interest state

classification and information adaption system is under development. The success of this system will be contingent on overcoming a number of technical and user experience issues, such as those arising from naturalistic visitor behaviour, such as detecting artifacts within physiological signal acquisition caused by movement patterns (walking, acceleration and hand gestures etc.) and determining the effects of the relationship between the mathematical accuracy of the classifiers within the system and the perceived accuracy of the system by the user.

7. CONCLUSION

In this paper, we distil research in the field of cultural heritage experience to create a model of the "knowledge emotion" interest, we operationalise the interest model as three components; activation, cognition and valence and detail subject-dependent methods for the measurement and capture of psychophysiological responses towards cultural heritage material. We introduce IBIS, a procedural framework which details the procedures involved inferring a users' interest state from measurement to classification using two classification schemas (composite and component) that can be run in parallel as part of a real-time bio-cybernetic loop. Two studies are reported here which utilise the elements of the IBIS framework and genuine cultural heritage material in an offline context, the results from study one (95% σ 7.8) and study two (87.3%, σ 7.4) show that it is possible to infer with a fair degree of accuracy a users' state of interest in cultural heritage material. We discuss the potential of the IBIS framework for use within a real-time adaptive information provision system and detail an interest scale which transposes the output from three binary classifiers onto an eight state scale using propositional logic.

ACKNOWLEDGEMENTS

REFERENCES

A. Isaksson, M. Wallman, H. Göransson & M.G. Gustafsson. 2008. "Cross-validation and bootstrapping are unreliable in small sample classification". Pattern Recognition Letters, Volume 29, Issue 14, Pages 1960-1965

A. D. Wagner, et al. 1998. "Building memories: remembering and forgetting of verbal experiences as predicted by brain activity." Science 281, 1188–1191

Arts HA. 2010. "Sensorineural hearing loss in adults." In: Cummings CW, Flint PW, Haughey BH, et al, eds. Otolaryngology: Head & Neck Surgery. 5th ed. Philadelphia, Pa: Mosby Elsevier; chap 149

B. Hahn, T. J. Ross, E. A. Stein. 2006 "Neuroanatomical dissociation between bottom-up and top-down processes of visuospatial selective attention." Neuroimage, 32, pp. 842 – 853

C. Cortes, V. Vapnik. 1995. in Machine Learning, pp. 273-297

C. De Rojas, & C. Camarero. 2008. "Visitors' experience, mood and satisfaction in a heritage context. Evidence from an interpretation center". Tourism Management. 29, 525-537

C. J. C. Burges. 1998. "A tutorial on support vector machines for pattern recognition." Knowledge Discovery and Data Mining, 2

C. Jennett, A. L. Cox, P. Cairns, S. Dhoparee, A. Epps, T. Tijs & A. Walton. 2008. "Measuring and defining the experience of immersion in games". International Journal of Human-Computer Studies, 66, 641-661

C. J. Cela-Conde, G. Marty, F. Maestú, T. Ortiz, E. Munar, A. Fernández, M. Roca, J. Rosselló, F. Quesney. 2004. "Activation of the prefrontal cortex in the human visual aesthetic perception." Proceedings of the National Academy of Sciences of the United States of America, 101(16), pp.6321–5

D. E. Berlyne. 1960. "Conflict, Arousal, and Curiosity". London: McGraw-Hill Book Company

D. Novak, M. Mihelj, M. Munih. 2012. "A survey of methods for data fusion and system adaptation using autonomic nervous system responses in physiological computing". Interacting with Computers, 24, 3, 154-172

De Morgan, Augustus. 1847. "Formal Logic." London: Walton and Maberly.

E. T. Rolls. 2000. "The orbitofrontal cortex and reward." Cereb. Cortex 10, 284–294

E. K. Silberman, H. Weingartner. 1986. "Hemispheric lateralization of functions related to emotion." Brain Cognit 5:322–353

E. A.Vessel, G. G. Starr, N. Rubin 2012 "The brain on art: intense aesthetic experience activates the default mode network." Frontiers in human neuroscience, 6(April), p.66

G. C. Cupchik, O. Vartanian, A. Crawley, D. J. Mikulis. 2009 Viewing artworks: contributions of cognitive control and perceptual facilitation to aesthetic experience. Brain and cognition, 70(1), pp.84–91

H. H. Jasper. 1958. "The 10–20 electrode system of the International Federation". Electroenceph. clin. Neurophysiol.10, p370–375

H. Leder, B. Belke, A. Oesberst, & D. Augustin. 2004. "A model of aesthetic appreciation and aesthetic judgement". British Journal of Psychology, 95, 489-508

I. G. Dobbins, H. Foley, D. L. Schacter, A. D. Wagner. 2002. "Executive control during episodic retrieval: multiple prefrontal processes subserve source memory." Neuron 35:989–996.

J. Pine. & J.H. Gilmore. 1998. "Welcome to the experience economy." Harvard Business Review, 97-107

J. A. Russell. 1980. "A circumplex model of affect". Journal of Personality and Social Psychology, 39, 1161-1178

J. C. Platt. 1999. "Fast training of support vector machines using sequential minimal optimization." In Advances in kernel methods, Bernhard Schlkopf, Christopher J. C. Burges, and Alexander J. Smola (Eds.). MIT Press, Cambridge, MA, USA 185-208

J. T. Cacioppo, L.K. Bush, L.G. Tassinary. 1990. "Microexpressive facial actions as a function of affective stimuli: Replication and extension". Personality and Social Psychology Bulletin 18, 515-526

J. T. Cacioppo, L. G. Tassinary, and G. Berntson. 2007. eds. Handbook of Psychophysiology. 3rd ed. Cambridge: Cambridge University Press.

J. A. Coan, J. J. B. Allen. 2004 "Frontal EEG asymmetry as a moderator and mediator of emotion." Biological psychology, 67(1-2), pp.7–49

J. A. Russell. 2003. "Core affect and the psychological construction of emotion". Psychological Review, 110, 145-172

K. Holzinger, M. Lehner, M. Fassold, A. Holzinger. 2011. "Archaeological Scavenger Hunt on mobile devices: from Education to e-Business: A triple adaptive mobile application for supporting Experts, Tourists and Children." ICEB-2011, pp. 131-136. SciTePress INSTICC, Sevilla.

M. Ott, & F. Pozzi. 2011. "Towards a new era for Cultural Heritage Education: Discussing the role of ICT". Computers in Human Behaviour, 27, 1365-1371

M. Petrides. 1994. "Frontal lobes and behaviour." Curr. Opin. Neurobiol. 4, 207–211

M. P. Bryden, T. Free, S. Gagne, and P. Groff. 1991. "Handedness Effects in the Detection of Dichotically-presented Words and Emotions." Cortex 27.2: 229-35

M. Nadal, M. T. Pearce. 2011 "The Copenhagen Neuroaesthetics conference: Prospects and pitfalls for an emerging field." Brain and Cognition, 76, 172 – 183

N. Ramnani, & A. M. Owen. 2004. "Anterior prefrontal cortex: insights into function from anatomy and neuroimaging". Nat Rev Neurosci. 5, 3: 184-94

O. Villon. C. Lisetti. 2007. "Toward Recognizing Individual's Subjective Emotion from Physiological Signals in Practical Application." Computer-Based Medical Systems, CBMS '07. Twentieth IEEE International Symposium on, vol., no., pp.357,362, 20-22 June 2007 doi: 10.1109/CBMS.2007.112

P. Ekman. 1992. "An argument for basic emotions". Cognition and Emotion, 6: 169-200

P. J. Silvia. 2010. "Confusion and interest: The role of knowledge emotions in aesthetic experience". Psychology of Aesthetics, Creativity, and the Arts, 4(2), 75-80

P. J. Silvia. 2008. "Interest—The Curious Emotion". Current Directions in Psychological Science, 17(1): 57-60

P. Rani, C. Liu, N. Sarkar, E. Vanman. 2006. "An empirical study of machine learning techniques for affect recognition in human–robot interaction." Pattern Anal. Appl. 9, 1 (May 2006), 58-69. DOI=10.1007/s10044-006-0025-y

P. A. Tataranni, et al. 1999. "Neuroanatomical correlates of hunger and satiation in humans using positron emission tomography." Proc. Natl Acad. Sci. USA 96, 4569–4574

P. Rodway, P. L. Wright, and S. Hardie. 2003. "The Valence-specific Laterality Effect in Free Viewing Conditions: The Influence of Sex, Handedness, and Response Bias." Brain and Cognition 53.3: 452-63

P. Perria, G. Rosadini, and G. F. Rossi. 1961. "Determination of Side of Cerebral Dominance with Amobarbital." Archives of Neurology 4

R. I. Goldman, J.M. Stern, J. Engel & M.S. Cohen. 2002. "Simultaneous EEG and fMRI of the alpha rhythm". Neuroreport 13, 2487-2492

R. J. Davidson. 2004. "What does the prefrontal cortex "do" in affect: perspectives on frontal EEG asymmetry research". Biological Psychology 67, 219-233

R. J. Davidson, J. P. Chapman, L. J. Chapman, & J. B. Henriques. 1990. "Asymmetrical brain electrical activity discriminates between psychometrically-matched verbal and spatial cognitive tasks."

Psychophysiology, 27, 528-543

R. A. Mcfarland, and R. Kennison. 1989. "Handedness Affects Emotional Valence Asymmetry." Perceptual and Motor Skills 68.2: 435-41

R.P.W. Duin, P. Juszczak, P. Paclik, E. Pekalska, D. de Ridder, D.M.J. Tax, S. Verzakov. 2007. "PRTools4.1, A Matlab Toolbox for Pattern Recognition", Delft University of Technology

R. N. Henson, T. Shallice, & R. J. Dolan. 1999. "Right prefrontal cortex and episodic memory retrieval: a functional MRI testof the monitoring hypothesis." Brain 122, 1367–1381

S. H. Fairclough. 2009. "Fundamentals of Physiological Computing". Interacting With Computers, 133-145

S. H. Fairclough, and K. Gilleade. 2012. "Construction of the biocybernetic loop: a case study". In Proceedings of the 14th ACM International Conference on Multimodal Interaction (Santa Monica). ACM

S. Hidi & K. A. Renninger. 2006. "The four-phase model of interest" development. Educational Psychologist, 41(2), 111–127

W. Boucsein. 1992. "Electrodermal Activity". Plenum Press, New York

W. Tschacher, S. Greenwood, V. Kirchberg, S. Wintzerith, K. van den Berg, M. Trondle. 2011 "Physiological Correlates of Aesthetic Perception of Artworks in a Museum." Psychology of Aesthetics, Creativity, and the Arts, 18

Smithsonianmag. 2014. "Augmented reality livens up museums"- http://blogs.smithsonianmag.com/ideas/2012/08/augmented-reality-livens-up-museums/ - accessed January 2014.