Affective Computing and Interaction:

Psychological, Cognitive and Neuroscientific Perspectives

Didem Gökçay
Middle East Technical University, Turkey

Gülsen Yildirim
Middle East Technical University, Turkey

INFORMATION SCIENCE REFERENCE
Hershey · New York

Director of Editorial Content: Kristin Klinger
Director of Book Publications: Julia Mosemann
Acquisitions Editor: Lindsay Johnston
Development Editor: Dave DeRicco
Publishing Assistant: Milan Vracarich Jr.
Typesetter: Milan Vracarich Jr., Casey Conapitski
Production Editor: Jamie Snavely
Cover Design: Lisa Tosheff

Published in the United States of America by
Information Science Reference (an imprint of IGI Global)
701 E. Chocolate Avenue
Hershey PA 17033
Tel: 717-533-8845
Fax: 717-533-8661
E-mail: cust@igi-global.com
Web site: http://www.igi-global.com

Copyright © 2011 by IGI Global. All rights reserved. No part of this publication may be reproduced, stored or distributed in any form or by any means, electronic or mechanical, including photocopying, without written permission from the publisher. Product or company names used in this set are for identification purposes only. Inclusion of the names of the products or companies does not indicate a claim of ownership by IGI Global of the trademark or registered trademark.

Library of Congress Cataloging-in-Publication Data

Affective computing and interaction : psychological, cognitive, and
neuroscientific perspectives / Didem Gokcay and Gulsen Yildirim, editors.
p. cm.
Includes bibliographical references and index.
ISBN 978-1-61692-892-6 (hardcover) -- ISBN 978-1-61692-894-0 (ebook) 1.
Human-computer interaction. 2. Human-machine systems. 3. Affect
(Psychology)--Computer simulation. I. Gokcay, Didem, 1966- II. Yildirim,
Gulsen, 1978-
QA76.9.H85A485 2011
004.01'9--dc22

2010041639

British Cataloguing in Publication Data
A Cataloguing in Publication record for this book is available from the British Library.

All work contributed to this book is new, previously-unpublished material. The views expressed in this book are those of the authors, but not necessarily of the publisher.

Chapter 3
Emotional Axes:
Psychology, Psychophysiology and Neuroanatomical Correlates

Didem Gökçay
Middle East Technical University, Turkey

ABSTRACT

For applications in affective computing, the quantitative representation provided by the dimensional view of emotions is very valuable. The dimensional account of emotions has gained impetus over the last decade, due to the consistent observation of two principal axes, valence and arousal, from several experiments on semantic maps. Interestingly, these two orthogonal components differentially modulate human physiology as measured by skin conductance, startle eyeblink and event related potentials. Furthermore, in the human brain there exists distinct localizations for valence/arousal-related emotion evaluation processes. Our current knowledge regarding these two basic components of emotion is presented in this chapter. The emotional palette varies widely through development and across populations. Two different models (Circumplex and PANA) have been coined to account for the vast distribution of data clustered across emotional categories. In this chapter, these models are also discussed comparatively.

INTRODUCTION

It has been slightly over a decade since the investigations regarding the role of emotions in cognitive functionality has gained popularity. Earlier, 'traditional approaches to the study of cognition emphasized an information-processing view that has generally excluded emotion' (Phelps, 2006). Then Damasio (1999) introduced the Somatic Marker Hypothesis indicating that emotions interfere with the information processing streams of our brain through preserved somatic signals relating to the body-state structure and regulation either consciously or unconsciously. Nowadays the computer metaphor, which has inspired the human cognition studies is definitely augmented by a new player: affect. Although the main areas in the human brain that subserve emotional processing are already identified at the gross level (Pessoa, 2008), the nature of their interaction with

DOI: 10.4018/978-1-61692-892-6.ch003

Copyright © 2011, IGI Global. Copying or distributing in print or electronic forms without written permission of IGI Global is prohibited.

each other, and the nature of their interference with cognitive processes remain elusive. This chapter is an attempt to clarify the dimensional approach to emotional processing, which can be briefly summarized as follows: The representation and expression of emotions is possible through a few orthogonal components. A data point along these components refer to the instantiation of a specific emotion, and emotion instances can be clustered creating emotional categories such as happiness, sadness, fear or anger. In the following sections, details about the main components of emotions will be introduced. However, it is important to mention that other than the dimensional account provided here, there is still ongoing research attempting to identify distinct physiological signatures that represent basic emotions. Most recent reviews in this regard can be found in Kreibig (2010) and Stephens et. al. (2010).

PRINCIPAL COMPONENTS OF AFFECT

The Layout of the Semantic Space

During the course of evolution, humans generated sophisticated responses for communicating the meaning of the situations they encounter. Many of these intentionally coded responses such as gestures, gross body movements and facial expressions are non-linguistic. Together with language, all of these expressions serve a single purpose: communicating the meaning of the complex environment that humans dwell. Through a series of experiments held during 1950's (Osgood, 1957), Osgood and his colleagues shed light on the nature of the redundancy embodied in the semantic space. According to Osgood, the semantic space consists of 2-5 principal components. Although there is some dependency between these components (as discussed later in the section on proposed models), after several decades and a plethora of experiments -not only involving verbal stimuli but also involving sounds and pictures- two principal components prevail: valence (pleasantness) and arousal (activity).

The semantic space seems to be extremely wide, if we initiate voluntary free speech with a question such as: 'What does SOPHISTICATED mean?'

'It's being **clever** *and* **wise** *about people and things… It's sort of* **smooth** *and* **polished***,* **graceful** *but not* **awkward**...**poised***,* **savvy***' (Osgood, 1957, p.18).*

On another front, associations indirectly bring out a somewhat similar response: 'What other things make you think of SOPHISTICATED?'

'Lady, cocktails, music, **educated***,* **clever***,* **smart***' (Osgood, 1957, p.18-19)*

Although free expression is richer in terms of meaning, the overlap between free expression and associations point in the same direction: There exists a limited set of adjectives to be used to attribute meaning to a given verbal input. So Osgood and his colleagues started out to devise a methodology to generate a representative and standardized set of verbal responses across subjects. Needless to say, the ability for the human brain to generalize and think using metaphors helped this cause. 'Cotton' and 'stone' can be easily put on a scale of 'soft-hard' but so does 'mother' and 'bodyguard'. Similarly, 'loss' and 'win' can be directly defined on a scale of 'unfair-fair' but so does 'thunder' and 'breeze', albeit through metaphors. A representative layout of the entire semantic space can then be constructed through these semantic differences.

The 'semantic differential' technique is generated through the use of polar (i.e. opposite in meaning) adjective pairs each serving as an individual semantic dimension. For example in a semantic space of n dimensions, the adjective pairs might be: 1. 'good-bad', 2. 'soft-hard', 3. 'slow-fast',

Table 1. 4 principal factors extracted from the semantic space and some sample adjectives that contribute to these factors

Factor I (Evaluation)	Factor II (Potency)	Factor III (Activity)	Factor IV (Not named)
Good-bad	Hard-soft	Active-passive	Private-public
True-false	Strong-weak	Fast-slow	Small-large
Positive-negative	Opaque-transparent	Hot-cold	Constrained-free

…, n. 'bright-dark'. Each dimension is scaled the same way, for example on a 7 point Likert scale. Therefore, when we are asked to produce a response with respect to a given word (for ex. 'sun'), we will have to evaluate at what locations it would fit in each of these n scales. When several words representative of a vocabulary are evaluated in this manner, some of these n dimensions will group together and receive similar ratings almost all the time. By using factor analysis (or principal component analysis), we can determine which of these n different dimensions are correlated, and reduce the entire n-dimensional semantic space into m orthogonal dimensions such that m<<n. It is important to mention that each of the reduced m dimensions consists of a weighted (rotated) form of the original n dimensions. For example, the 'good-bad', 'bright-dark' dimensions specified above may receive high weightings in one of the emerging two principal components, pleasantness, whereas the 'slow-fast' dimension may receive a weighting close to zero for this component, because it is unrelated to this dimension.

The variance of the entire n dimensional data space may not be captured by the reduced m components. However, when eigenvalues corresponding to the rotated m dimensions are all greater than 1, we can safely assume that the reduced space is representative, although the new semantic space may now reflect approximately 50-80% of the variance of the original space. In one of their studies on 100 subjects, Osgood and his colleagues (Osgood, 1975, p.47-53), collected ratings from 20 new words (as well as those in a previous study) along 76 dimensions. Four major dimensions are obtained which explained 41.1%, 20.5%, 16.0% and 11.5% of the variance respectively. Although these factors are not named, by studying the dimensions that contribute with high weightings to these factors, it becomes clear that the first three factors go along with the original naming of Osgood and his colleagues: Evaluation, Potency, and Activity. Table 1 (sampled from Osgood, 1957 p.53) illustrates a few adjective pairs contributing to these reduced four principal components.

As seen from this table, it is possible to obtain more than 2 principal components, however, among these components, Evaluation and Activity have been repeatedly emerging in follow-up studies whereas the variances represented by the other two components had not been replicated with the same consistency or turned out to be negligible in different samples/studies of the semantic space. There are some adjective pairs such as 'excitable-calm', which receive high weightings from multiple factors. Due to this, it is important to note that the data oriented along the new axes in the reduced space might have interactions. Nevertheless, the basic two components, named as Evaluation and Activity are consistently replicated for subject populations across different ages (Osgood, 1975, p. 58) and cultures (Osgood, 1975, chap. 4).

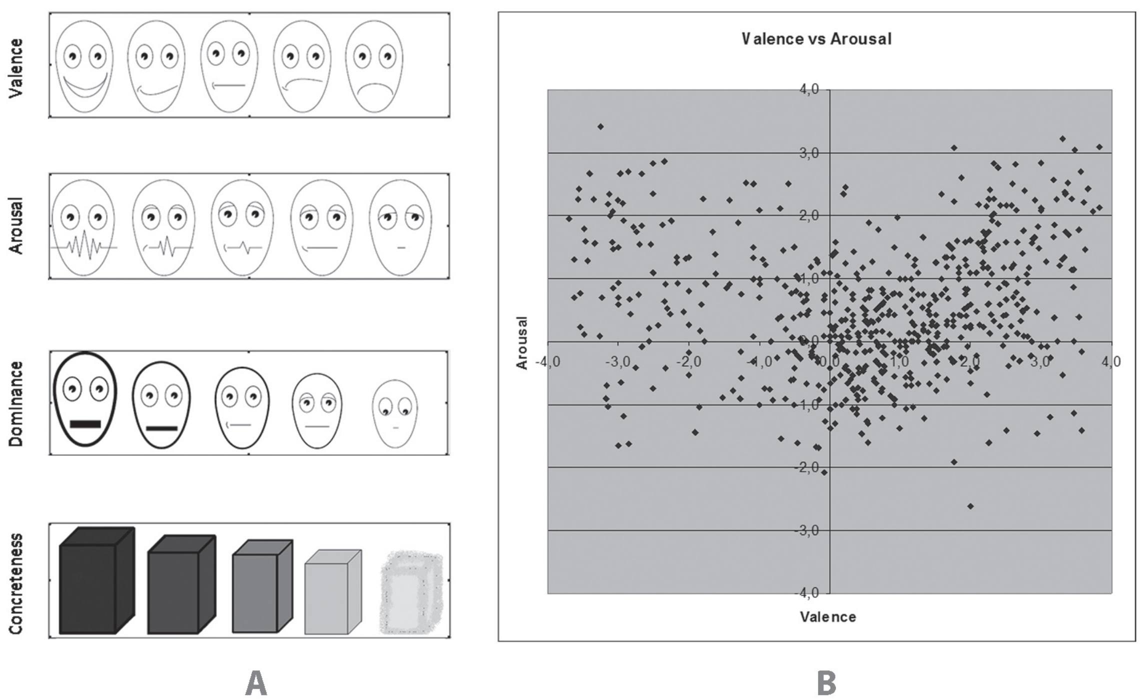
The semantic space studies at our times can be performed with more words and more dimensions, owing to the accessibility of high computing power. One of the most recent extensive vocabulary compilations done by Samsonovic and Ascoli (2010) yielded three axes: ''good-bad'' (valence), ''calm-excited'' (arousal), and ''open-closed'' (freedom). In this study, the dictionary of synonyms and antonyms extracted from the thesaurus of MS Office and Princeton WordNet are used. The word list is constructed by starting from an initial seed word, adding the corresponding synonyms and antonyms to the list in an iterative fashion. Synonyms and antonyms are assembled into bidirectional pairs and words with less than two synonym/antonym links are cleared, yielding with 15000-20000 core words for English. Then varying n from 10 to 100, the location of each word in the core list is computed automatically from a function which measures the word's distance from the given n dimensions through the number of its synonym/antonym links. After all the core words are mapped onto the n dimensional space, the principal components are extracted, once again returning valence and arousal as two prominent factors.

Among all semantic space studies of English, the most widely used one is inarguably ANEW (Bradley and Lang, 1999a). In this study, Bradley and Lang assumed that the three principal components of the semantic map are valence, arousal and dominance. With this assumption, on a 9 point scale, they collected evaluations from the subjects directly on these three principal components, rather than a higher dimensional adjective-pair scale space. A total of 1034 words are evaluated and the evaluation on the three scales are facilitated by the use of an icon named SAM, which contains a range of different expressions at different scale points (a smile … frown on SAM's face to represent the valence scale, a jittery … calm sketch on SAM's body to represent the arousal scale and a small … large SAM figure to represent the dominance scale). The data distribution emerging from this semantic map directly puts the words on the reduced semantic space consisting of three orthogonal axes, so there is no need for factor analysis. Affective word norms can be generated in this fashion, by averaging the ratings of all subjects for each word and scale.

Another study is worth mentioning due to the different technique employed in generating the original n dimensional semantic space. As mentioned above, meaning is a construct derived from not only words but also from gestures and facial expressions. Fontaigne et. al. (2007) created a 144 dimensional affective space by using distinct verbal descriptions derived from the main characteristics of emotions such as: appraisals of events, psychophysiological changes, motor expressions, action tendencies, subjective experiences. Some sample verbal descriptions are as follows: 'treated unjustly', 'irrevocable loss' (appraisal of events), 'felt heartbeat slowing down', 'blushed' (psychophysiological change), 'frowned' (motor expression), 'produced abrupt body movements', 'spoke faster' (action tendency), 'felt nervous', 'felt tired' (subjective experience). On the other hand, 24 emotion words are chosen to be rated along these 144 dimensions on a 9 point Likert scale. These emotion words are: anger, anxiety, being hurt, compassion, contempt, contentment, despair, disappointment, disgust, fear, guilt, happiness, hate, interest, irritation, jealousy, joy, love, pleasure, pride, sadness, shame, stress, surprise. Subsets of emotion words are administered to 198 subjects and their ratings are collected on all 144 dimensions. After factor analysis, 4 principal components are extracted: Evaluation, Potency, Activity and Unpredictability. Altogether, these components explained for 75.4% of the variance of the distribution in the original affective space.

The semantic map studies in English are repeated over the years for other languages as well. BAWL-R (Vo et.al., 2009) contains imageability, valence and arousal ratings for approximately 2900 German words (2,107 nouns, 504 verbs, 291 adjectives). In another study on German words (Lahl et. al., 2009), Internet is utilized to collect concreteness, valence and arousal ratings for 2,654 German nouns from 3,907 subjects. Spanish version of ANEW is made available by Redondo et.

Figure 1. a) Mert icon for data collection along the affective axes, b) The distribution of TUDADEN data across valence and arousal axes



al (2007), providing mean affective ratings on the 3 major axes valence, arousal, dominance from 720 subjects. In our lab, through a joint study with M.A. Smith (Gokcay and Smith, 2007), we used a methodology similar to ANEW for generating mean evaluations for 1240 Turkish words from a subject pool of 170. Parallel sessions technique of MS Access is used to generate 200 word ratings from each subject for 4 dimensions valence, arousal, dominance and concreteness, and all of the ratings are merged into the same database called TUDADEN. Figure 1a illustrates the MERT icon we used for collecting online evaluations for each scale. Mean ratings of the words are plotted in the scatter-plot seen in figure 1b for the valence and arousal scales. In this graph, each point corresponds to a single word's valence and arousal ratings averaged across all subjects. It is important to note that not all the data quadrants are filled when ratings are collected from the subjects directly in the reduced space of principal components. This is an important feature that is discussed below, in the section on models of the principal affective components.

When the adjective lists contributing to the principal affective components are considered, one might think that the principle components extracted from the semantic space are byproducts of verbal/cognitive processes rather than affective processes. This thought might have been agreeable if these principal components were obtained exclusively for the word lists but not for auditory or visual stimuli. However, as discussed in the section on ANS responses below, numerous studies conducted on visual and auditory stimuli reveal that words, pictures and sounds with similar valence and arousal ratings cause similar changes in the autonomic responses of subjects. Therefore the validity of the affective principal components has been verified across multiple stimulus modalities. IAPS (Lang et.al. 2008) and IADS (Bradley and Lang, 1999b, Redondo et.al, 2008), consisting of pictures and sounds respectively, provide two widely used stimulus sets with ratings along the three principal components, valence, arousal and dominance. A study conducted by Faith and Thayer (2001) supports very clearly that the principal components extracted from the semantic space relate to affect because in this study, subjects provided conscious, reflexive evaluations regarding their emotions in response to facial expressions, IAPS pictures, mental imagery and music. The evaluations are made for 15 emotion terms: afraid, agitated, amused, angry, aroused, disgusted, happy, interested, pleasant, relaxed, sad, serene, still, surprised, tired. Principal component analysis revealed 4 factors with eigenvalues above 1, explaining 35.8%, 15.4%, 10.2% and 7.2% of the variance. When emotional categories with high weightings for these factors are investigated, once again, the first two factors are found to be valence and arousal, while the other two factors turned out to be uninterpretable.

It still remains open whether verbal self-reports in response to emotionally loaded stimuli reflect the phenomenological feelings induced on the subjects or reflect just semantic understanding of the emotional words that are being rated. Barett (2004) investigated this aspect by conducting a series of experiments asking each subject to cross-rate emotion words as well as self-report their instantaneous feelings in response to: 1. A set of emotion-laden slides, 2. Pre-designed emotion inducing scenarios in their lab environment, 3. A beeper inquiring the subject's current emotional state for a 60 day period. To obtain a baseline, subjects rated the relationship between 16 emotion words on a 7 point Likert scale. In these semantic ratings, there was an overall bias for differentiation along the arousal axis. Subjects also rated their current emotional feelings in one of the above-mentioned three experimental setups for 88 emotion-related adjectives. For these reflexive ratings, there was an overall bias for more differentiation along the valence axis. In sum, Barett (2004) showed that self-report ratings not only relate to phenomenological feelings, but also identify individual differences between the subjects.

Overall, collection of emotional evaluations over emotional verbal descriptions has proven to be a valid methodology to delineate the major components of our affective map.

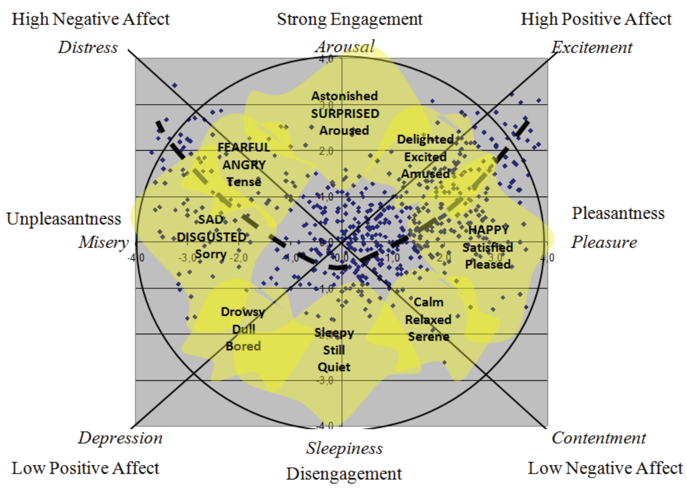
Models for the Principal Affective Components

While the existence of two major emotional axes is inarguable, how to model the data distribution after reducing the original data distribution from n dimensions down to 2 dimensions has been problematic. The controversy created over modeling is centered on multiple issues:

1. Why does the two dimensional data distribution sometimes fill all quarters, but at other times fill only two quarters?
2. Is there a correlation between valence and arousal?
3. How does the data in the two dimensions relate to the six basic emotions: happiness, sadness, fear, anger, surprise and disgust?
4. What is the variability of the data distribution within and between subject populations?

Figure 2 is developed in an effort to answer these questions altogether. In this figure, our sample data distribution from TUDADEN (Gokcay and Smith, 2008) is merged with axes names taken from Russell (1980) and Watson et. al. (1999) along with 24 commonly used emotional categories (including the six basic emotions). Russell (1980) named the two principal emotional axes such that, the horizontal axis measures misery versus pleasure (valence) and the vertical axis measures sleepiness versus arousal (arousal). He also considered that there is another two di-

Figure 2. The axes and emotion categories of the Circumplex model, along with the axes and data distribution of the PANA model



mensional orthogonal coordinate system rotated 45 degrees. In this system, one axis measures depression versus excitement and the other axis measures distress versus contentment. Russell always referred to the main axes as pleasure versus arousal, considering the other pair of axes as a means for explaining the data distribution within quarters. On the other hand, as seen in Figure 2, Watson et. al. (1999) posited that the main axes are the ones rotated 45^{o} CCW. They named the first main axis as: PA (positive affect) which is used to measure low positive affect versus high positive affect. The second axis was named as: NA (negative affect) measuring low negative affect versus high negative affect. The other axes in Watson et.al.'s (1999) coordinate system were used as scales of pleasantness and engagement.

Issue 1: Models of data distribution

According to the **Circumplex model (**Russell 1980), when the original data in the n dimensional emotional space is projected into the two dimensional reduced space along the valence and arousal axes, the data distribution becomes similar to a doughnut shape. Although we are unable to show this in figure 2, we have shown how these data clusters would be distributed within point clouds of discrete emotions. For example, within the vicinity of the arousal axis, we expect a data distribution that reflects emotion terms similar to sleepy, still, quiet when arousal is low and astonished, surprised, aroused when arousal is high. All other point clouds anticipated within the circumplex distribution are observable from Figure 2. There exist several studies in support of this model (Barett, 2004; Terraciano et.al. 2003; Fontaine et.al. 2007, Faith and Thayer, 2001, Sauter, 2006).

According to the **PANA model** (Watson et. al., 1999), the main axes are the positive affect and negative affect axes, obtained by 45 degree rotation of the valence/arousal axes. The data distribution on these axes resemble a bumerang shape as seen from figure 1 b. In this approach, discrete emotional categories are not the main founding factors underlying behaviour, but approach and avoidance is. The points clustered within the vicinity of high positive affect are obtained from responses to stimuli that create approach behaviour. On the other hand, the avoidance behaviour is initiated as a result of the emotional evaluation represented by the points clustered around high negative affect. There are several studies supporting this type of data distribution (Bradley ANEW, Bradley IADS, Lang, 2008, Mikels, 2005; Libkuman, 2007; Rubin, 2009; Redondo2, 2008; Redondo1, 2007; Vo, 2009).

The study conducted by Rubin and Talarico (2009) point out the common methodologies between researches that support the Circumplex model versus PANA model. In studies which return data that comply with the Circumplex model, emotional ratings are done in a high dimensional space where n is varying between 15-140 and then the data distribution in two dimensions is obtained by principal component analysis. On the other hand, in studies which comply with the PANA model, the emotional ratings are collected directly on the two reduced dimensions. This observation indicates that there might be two different processes for evaluating the emotion scales: In the first process, the subjects go through extensive inquiries regarding the stimulus that is currently presented. In the second process, the subjects are presented a limited opportunity to weigh the emotional value of the stimulus (pleasantness versus intensity (arousal)). Therefore in the second process, the subjects have to filter-out all the other factors, deciding only about the importance of the stimulus in regards to a more goal-oriented framework. Needless to say, the evaluations performed weighing more attributes are richer, however the evaluations performed weighing only two attributes is faster and satisfy the crucial approach/avoidance need of humans.

Issue 2: Correlation between valence and arousal

When the Circumplex model is considered, the data does not comply with a specific valence/arousal pattern, so a correlation between the quantities measured by valence and arousal is not supported. However, when the PANA model is considered, there is a clear pattern for the data distribution, indicating an interaction between these two axes. In Vo (2009), the nature of this interaction is revealed by curve-fitting. For this specific study, arousal is found to be related to valence with a quadratic function: $0.15x^2-0.25x+2.53$, $R^2=0.37$ (similar to the dashed line in figure 2). Conceptually, valence is distributed in a bi-polar fashion such that arousal increases when valence extends towards extremely positive or extremely negative values. But for low values of valence, regardless of the polarity, arousal is almost always low.

Issue 3: The relationship of the models with six basic emotions

Given emotional evaluations on either emotional words or valence/arousal axes, emotional categories are clustered into point clouds as illustrated in figure 2 (Among these emotional classes, six basic emotions are shown with capital letters). Unfortunately, the PANA model's ability in capturing emotional categories is limited. The scatter of the data is sparse in the lower quadrants (representing drowsy, dull, bored, sleepy, still, quiet, calm, relaxed, serene) as well as the left hand side of the valence axis (sad, sorry, disgusted). On the other hand, in the Circumplex model, although the data may not always be homogeneously distributed, almost all quadrants are represented. Hence this model supports the existence of six basic emotions, and a much larger emotional palette. As indicated before, the underlying concept behind the PANA model is goal-oriented behavior. If we approach from this direction, the emotional categories which does not reinforce goal-oriented behaviour (such as bored, calm, sad) become obsolete, whereas the emotional categories that support approach (such as excited, happy) and avoidance (such as fearful, angry) are essential. Interestingly, there have been several statistical attempts for predicting the distribution of valence/arousal from emotional categories or vice versa using words (Stevenson et. al., 2007), sounds (Stevenson and James, 2008) and pictures (Mikels et. al. 2005, Libkuman et. al. 2007) as stimuli. However, the predictive power between the principal components and distinct emotional categories is not found to be as high as expected. This might be partially due to the scarce representation of some emotional categories. Another factor prohibiting automatic emotion identification from the emotional axes is the variability involved in the data distribution between individual subjects, as well as populations.

Issue 4: Variability of the data distribution within and between subject populations

Variability of the emotional evaluation within the same individual occurs during the course of the day, or during larger time periods. It is also possible for some subjects to be more arousal oriented while others are more valence oriented. And finally among populations, some trends can be observed due to personality traits or other gross factors such as professional training. Watson et. al. (1999) studied variation of the arousal and valence ratings in their PANA model during the course of the day within 2 hour intervals. The ratings along the negative affect axis did not show much change throughout the day, but the ratings along the positive affect axis changed such that the ratings are low early in the morning and late at night, but higher during the day until the evening. Posner et. al. (2005) investigated the Circumplex distribution in school children, and found that in this population the data is collapsed along the valence axis. Unpleasantness extent of the valence axis coded fear, anger and sadness, while the Pleasantness extent coded excitement, happiness and contentment, without much difference along the arousal axis for these emotions. Terraciano et. al. (2003) studied personality traits based on the data distribution along the Circumplex. In the facet O3 (Openness to Feelings) of the Revised NEO Personality Inventory, individual differences in attentiveness to inner feelings and affective experiences is assessed where high scorers experience deeper and more differentiated emotional states. Subjects with high scores on the O3 returned a wider range of emotions distributed along the Circumplex, while subjects with low O3 returned emotions distributed similar to the PANA model, occupying only the upper two quadrants.

Overall, depending on the population, we can say that when the n dimensional data collected from multiple subjects (or from the same subject over a period of time) is reduced to 2 dimensions by PCA, the scaling of the data distribution across the axes, as well as the location of the specific emotion clusters may differ. Some subjects may have a flatter emotion class distribution across the valence or arousal axis (Barett, 2004), whereas other subjects may have a distribution reflecting the Circumplex in a better way. In addition, the location of the emotional classes might be shifted across quadrants.

NERVOUS SYSTEM RESPONSES TO AFFECTIVE STIMULI

Autonomic Nervous System (ANS) Responses

A while ago, Lang et.al. (1993) showed that our body's autonomic response to emotionally evocative stimuli differs with respect to the valence or arousal content of the stimuli. While arousal modulates sweating as measured by skin conductance response (SCR), valence modulates startle as measured by eyeblink (startle eyeblink reflex). Table 2 summarizes the change of psychophysiology measurements with respect to the major affective components.

In an experimental paradigm which inspired psychophysiology research onwards, Lang et. al. (1993) measured psychophysiological signals in response to affective pictures chosen from IAPS. Pictures are shown for 6 sec, and then the screen goes dark for a variable period between 20-35 sec

Table 2. Psychophysiological measures related to the two principal components, valence and arousal

Emotional Axis	Contributing factor	Observed correlation
Valence	Startle eyeblink magnitude	Negatively correlated with increasing valence
	Startle eyeblink latency	Positively correlated with increasing valence
Arousal	Skin conductance magnitude	Positively correlated with increasing arousal
	Pupil dilation	Increase in dilation for high arousal stimuli with respect to neutral stimuli

while ratings are collected using the affective scales (valence, arousal) printed on the SAM icon. The skin conductance response is measured for the entire 6 sec as well as a baseline period of 2 sec beforehand. This response has a slowly rising and slowly falling pattern. The startle eyeblink response is not collected in this study, but a similar measure, facial muscle activity, (corrugator) is. Other measures such as heart rate, facial muscle response (zygomatic), viewing time are also collected. Recently, a replication of this study is done by Sanchez-Navarro (2008), in which startle eyeblink response is collected. The startle is induced by an acoustic white noise probe which comes on randomly either 3.5 or 4.5 sec after stimulus onset. This response builds up abruptly, hence must be sampled at a high frequency of 900-1000 Hz.

In both studies, factor analysis among all the pschophysiology data as well as the subjects' valence and arousal ratings revealed two principal components: valence and arousal. The valence axis was loaded positively by the valence ratings, and negatively by the corrugator/startle eyeblink magnitude. On the other hand, the arousal axis was loaded positively by the arousal ratings, skin conductance magnitude and viewing time. These findings implicate that even without looking at the individual emotional evaluations from the subjects, by inspecting the startle eyeblink and skin conductance responses, emotional appraisal of the subject can be predicted respectively in terms of valence and arousal.

- **Startle eyeblink response:** The magnitude of the eyeblink response is larger for unpleasant stimuli, and smaller for pleasant stimuli. Therefore there exists a negative correlation between the valence values and eyeblink magnitude (Lang. et. al, 1993). Another study (Sanchez-Navarro, et. al. 2008) which took the startle latency into account returned a high weighting for startle latency along the valence axis after factor analysis. Correlation of startle latency with valence resulted in a positive linear trend causing increased startle latencies for increasing values of valence. Interestingly, a different trend in eyeblink modulation is observed when static pictures are used versus the utilization of dynamic pictures. Lang and Bradley (2010) observed that in a predator prey simulation, when pictures of a closing gun are shown back to back, the startle eyeblink magnitude becomes increasingly inhibited, reversing the negative correlation between startle magnitude and valence.
- **Skin conductance response:** The magnitude of the skin conductance response is larger for intensely arousing stimuli, and smaller for stimuli with less arousal intensity. Therefore there exists a positive correlation between the arousal intensity and skin conductance response (Lang. et. al, 1993). In a recent study (Bradley et. al., 2008) it is observed that pupil dilation is strongly correlated with arousal. After the

presentation of a visual stimulus, a constriction reflex of the pupil occurs due to the intensity change. Successively, as the stimulus is being viewed, the pupil starts to dilate. Pupil dilation is modulated by arousal intensity, as long as the valence values are high in a bipolar fashion: high in pleasantness or high in unpleasantness.

Before concluding this section, it is important to note that the interaction between valence and arousal is observed in psychophysiological data as well. When factor analysis is performed, the measures which load the valence axis with high weights do not receive completely negligible weights along the arousal axis and vice versa. It is commonly observed that valence-related measures load the arousal axes and vice versa with weights approximately in the range of 0.15. It is also worth to mention that, due to the limited space, only a few major autonomic responses are discussed here. Several different measures relating to respiration and cardiac pulsation are also found to be correlated with valence and arousal, as listed exhaustively in Kreibig (2010).

Brain Activation Patterns

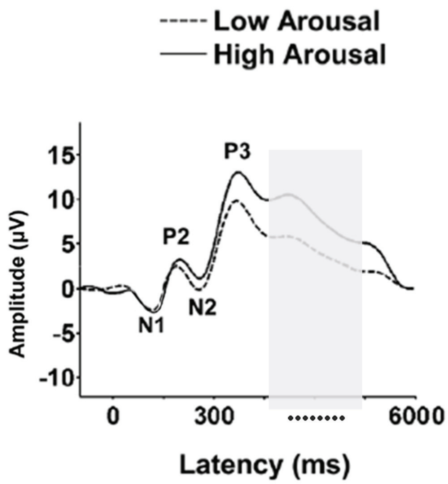
Event Related Potentials (ERP) or functional Magnetic Resonance Imaging (fMRI) reveal the brain's physiological response to emotion-laden stimuli (Please see key terms and definitions for brief descriptions of the ERP signal and fMRI signal). Since in this chapter, we are exclusively interested in how emotional axes are manifested, we will concentrate on the manipulation and localization of brain activity with respect to plain evaluative processing of the principal axes, valence and arousal, leaving out how complex cognitive processes such as memory, decision-making are affected by emotions.

Prediction of Emotional Axes from the ERP Signals

In a most recent review (Oloffson et. al. 2008), ERP results obtained over decades for visual stimuli are compiled together. The literature based on event related potentials (ERP) indicates that the processing of affective stimuli distributed along the two principal components valence and arousal differ. Overall, the results show that the valence component modulates subtly the early part (100-150 msec) of the ERP signal whereas the arousal component modulates strongly the late part (300-1000 msec). In an effort to illustrate how the ERP signal changes, we have devised a sketch in figure 3. Since this type of processing pertains to both subliminally (duration 25-35 msec) and consciously (duration comparable to seconds) presented affective stimuli, affective processing can be considered as being an integral part of perception. (Oloffson et. al. 2008) interpret the early changes in the ERP signal as a reflection of selective attentional processes. However, they believe that the late modulation is due to a demand for attentional resource allocation –caused by appetitive and aversive action requirements as well as enhanced memory processing.

- **Changes in ERP due to valence:** In general, unpleasant stimuli is found to have stronger effects than pleasant or neutral ones, producing larger positive amplitudes around 100 msec (P1). This early modulation points to amygdala focused negativity processing. The ERP processing in this time range is also shown to be affected by stimulus complexity (Bradley et. al 2007), which is in line with the attentional processes in charge with saliency detection.
- **Changes in ERP due to arousal:** An arousal related positivity occurs in the ERP signal within the range of 200 msec (Please see discussion in Oloffson et. al., 2008). Usually 200-300 msec range of the

Figure 3. A sketch of the ERP signal in response to affective stimuli occurring at t=0 (Adapted from Rozenkrants and Polich (2008))



ERP signal is affected by stimulus discrimination and response selection processes, however, a negativity is reported for arousing stimuli in comparison to neutral stimuli in this time frame regardless of valence (for both pleasant or unpleasant pictures) and task (either passive viewing or target detection). Later, starting from 300 msec on, a strong arousal induced positive signal (P300) builds up, and remains potentiated for a long period in the range of seconds. Cutberth et. al (2000) asked subjects to view pleasant and unpleasant highly arousing stimuli, as well as neutral stimuli for about 6 sec and then evaluate the valence and arousal of these pictures. Pleasant stimuli consisted of erotic images and unpleasant stimuli consisted of violence. A negative build up in the ERP signal is observed for unpleasant images approximately 100 msec after picture onset, and a positive increase in the ERP signal is observed for all emotional pictures (regardless of valence) after 300 msec, which remained high for the entire 6 sec. In another study, Rozenkrants and Polich (2008) constructed an emotional visual oddball paradigm. Subjects are asked to press a button when they detect a picture among continually presented images of patches. The patches occurred with a rate of 60% and pictures occurred with a rate of 40%. The pictures consisted of 4 categories: Pleasant and low arousal, unpleasant and low arousal, pleasant and high arousal, unpleasant and high arousal. The results were in alignment with those presented by Cutberth et. al (2000), such that the late positive potential was observed only for the high arousal categories, and was extended in the order of seconds. In an effort to summarize these findings, we have devised the generic transparent box in figure 3, showing that the distinction between the highly arousing versus neutral stimuli persists in the ERP signal for a duration of a few seconds.

In sum, the sustained late positive signal indicates the importance of the intensity of arousal. Interestingly the high ERP signal which extends for seconds persists mostly unhabituated even after 90 repetitions of the same stimulus (Lang and Bradley 2010). As pointed out by Oloffson et. al. (2008) as well as Lang and Bradley (2010), such a strong effect might be due to top-down processes in the production motivational responses.

Localization of Emotional Axes by fMRI

It is of great interest to find out whether the affective principal components are localized on dissociable brain systems. Current research indicates that valence and arousal are processed by distinct brain areas; however, the operation of these areas in the evaluation of emotions does not seem to be entirely separable. fMRI research on emotions center mostly on the localization of joint emotional and cognitive processes within decision making, memory, and attention, or perceptive processes modulated by emotion. Therefore, fMRI studies that focus exclusively on the evaluative processing of the principal axes, valence and arousal, are scarce. Here we will summarize only two studies in this regard.

In one study (Anders et.al., 2004), ANS outputs such as SCR, startle eyeblink are collected along with fMRI, as well as valence arousal ratings from the subjects while they viewed emotional and neutral pictures chosen from IAPS. The fMRI signal of each voxel in the brain is correlated with either ratings of the subjects or ANS responses. The ratings and ANS responses are used as separate regressors for the prediction of the observed fMRI signal (This procedure is called General Linear Model). High correlations of the fMRI signal with the valence ratings are observed within voxels around the Insula. On the other hand, voxels that correlated with the arousal ratings are observed around the Thalamus and Caudate. The startle eyeblink response was centered in the parietal region and Amygdala while the SCR response was centered in the orbitofrontal cortex (OFC).

In another study (Lewis et.al., 2007), fMRI is collected by using words from ANEW such that the words had either highly pleasant or highly unpleasant ratings with arousals ranging from neutral to high. The subjects are asked to perform a self-referential task and indicate with a button whether the presented word could be used to describe themselves. Regressors are defined using the ratings from ANEW. The fMRI signal in each voxel is attempted to be defined with these regressors. The voxels which can be defined with high values of both pleasant and unpleasant words (bipolar valence), are found to be located in the ventral and subgenual parts of the ACC. On the other hand, brain areas defined by the regressor constructed from the intensity of arousal are detected on Caudate, Ventral Striatum, Thalamus, Amygdala, Insula and brain stem (VT).

It is important to note that data acquisition through fMRI has a resolution on the order of seconds. The above reported brain areas responding to valence and arousal are observed to become active within ranges of 3-12 seconds.

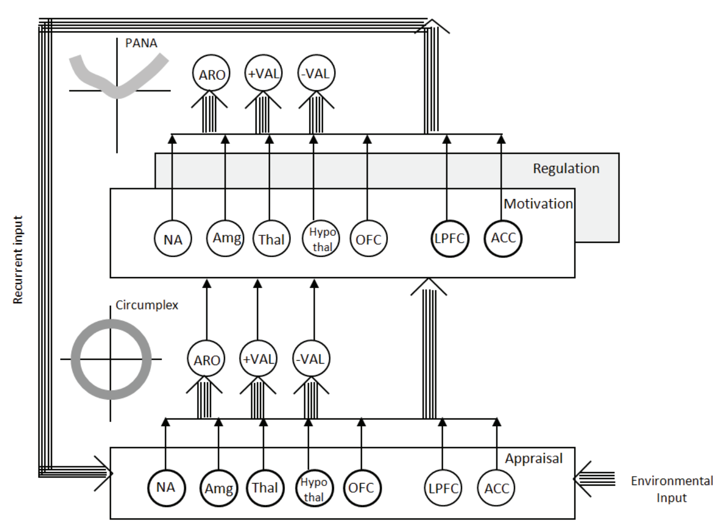
A Neural Network Proposal Based on the Current Emotional Models and Neuroimaging Findings

Earlier, Phillips et.al. (2003, p.505), have suggested a processing pipeline for emotion appraisal and regulation in which stimulus processing occurs iteratively. In this model, initially, the emotional state is determined by appraisal. Then by excitatory or inhibitory modulation of the current emotional state, the next emotional state is determined, and also the appraisal step is reinitiated. This flow is repeated over and over defining successive emotional states through appraisal and regulation. Considering this pipeline, I have generated figure 4, to illustrate how key players in the brain may come together to generate the data distribution across the valence and arousal axes. Some of the key players as we know from the neuroscience and neuroimaging literatures (Posner et.al., 2005; Pessoa, 2008) are: Nucleus Accumbens (NA), Amygdala (Amg), Thalamus (Thal), Hypothalamus (Hypothal), Orbitofrontal Cortex (OFC), Lateral Prefrontal Cortex (LPFC), and Anterior Cingulate Cortex (ACC). Obviously for generality, we should add the Ventral Striatum -not just Accumbens- and Reticular Formation to the nodes, but for clarity of the figure, every component of the limbic system is not included.

According to figure 4, emotional evaluation proceeds as follows: Initially, the environmental input gets evaluated within our neural network consisting of the nodes inside the Appraisal box. Based on the ERP research, we know that this initial appraisal happens within the range of 300 msec. During initial appraisal, the Circumplex form of emotional state layout is produced in the 2 dimensional space of valence and arousal. However, as indicated by Norris et.al (2010), within our complex environment, valence can be activated bi-modally. For example, a thirsty animal may evaluate the sight of a pond as positive and arousing, but this animal may also realize that predators are nearby, adding a negative and arousing evaluation for the entire situation. Norris et. al (2010) postulates that valence is a bi-variate entity, which is modeled in our network as positive valence (+VAL) and negative valence (-VAL). I claim that the initial appraisal is fast, and captures all of the circumplex, providing detailed emotional differentiation. In this evaluation, NA, AMG, Thal might have higher weights than the other nodes of our network (as indicated by bold borders). At this point the second stage starts, which inputs all the current output from the brain nodes, as well as the emotional state indicated by the outputs of the arousal (ARO) and valence nodes (±VAL). The second stage of processing consists of goal-oriented/motivational or regulatory analysis. In this stage, the inputs to the network are processed to reach a target. This target might be a better emotional state (as in regulation) or the initiation of an approach/avoid response. Needless to say, prefrontal mechanisms as represented by LPFC and ACC have a higher weight at this stage. This is why these nodes are shown bold-weighted. This type of processing is late, on the order of 3-6 seconds as we know from the ERP literature, and generates an emotional evaluation as represented by the PANA model. Going back to our example above, the ACC and LPFC interact to resolve the conflict between drinking from the pond to satisfy the animal's thirst versus escaping elsewhere to avoid the predators. Iterations between the appraisal and motivation phases occur through the recurrent connections of the outputs as indicated on the left part of figure 4. The role of the OFC might change over the iterations, becoming highly weighted in one phase versus the other. It is important to mention that, although not shown in this figure, the network nodes have lateral connections among themselves at every processing stage.

Obviously the model described herein is completely hypothetical, since such a model has not been implemented yet. However, in its current form, it supports the early (valence modulation) and late (arousal modulation) processes observed in the ERPs as well as the bi-modal activation of the valence component observed in both fMRI (Lewis et.al., 2007), and pupil dilation (Bradley et. al., 2008), along with both Circumplex and PANA data distributions. In order to test this

Figure 4. A neural network model of iterative evaluative processes in emotion



model, experiments should be designed to dissociate the appraisal and motivational processes. Needless to say, to identify which brain areas play what kind of a role, at what time, the data collection has to be made in a multi-modal fashion, preferably using simultaneous EEG and fMRI. Furthermore, in these experiments, complex stimuli rather than single words or pictures should be used, to reflect the situations in daily life representing all sorts of emotions around the circumplex. This model might also be extended by using replicas of the boxes to represent right and left hemispheres. As known in the emotion research, the right and left hemispheres assume differential roles in emotional processing and this can be incorporated into our model as well (see Harmon-Jones et. al (2010) for a recent review on emotional lateralization).

CONCLUSION

Over the last few decades, factor analyses of emotion words, as well as ANS/ERP/fMRI responses to affective stimuli, have consistently found two main factors that account for most of the emotional variance: valence and arousal. The data distributed along these axes reflect how emotions are evaluated: when the data occupies all quadrants, emotional differentiation is at is best, when the data occupies only the top two quadrants, a motivational tendency due to appetitive or aversive exposures is revealed. However, behavioral studies of attention, memory, priming, etc. return conflicting results regarding how emotion modulates cognitive processes. This is probably due to the lack of standardized attempts for manipulating the experiments across a matrix of conscious versus unconscious, appraisal versus motivation-related, and voluntary versus spontaneous behaviours. In addition, the stimuli used in the current experiments are too simplistic, using discrete events or happenings, despite the fact that humans operate in dynamically situated complex environments which reflect a larger emotional palette. Inarguably, these factors should be taken into account to deepen our knowledge regarding the effect of emotional processes in cognition. Our improved understanding in this regard will definitely enhance the applications within the newly emerging field of affective computing.

REFERENCES

Anders, S., Lotze, M., Erb, M., Grodd, W., & Birbaumer, N. (2004). Brain Activity Underlying Emotional Valence and Arousal: A Response-Related fMRI Study. *Human Brain Mapping*, *23*, 200–209.

Barrett, L. F. (2004). Feelings or Words? Understanding the Content in Self-Report Ratings of Experienced Emotion. *Journal of Personality and Social Psychology*, *87*(2), 266–281.

Bradley, M. M., Hamby, S., Low, A., & Lang, P. J. (2007). Brain potentials in perception: picture complexity and emotional arousal. *Psychophysiology*, *44*, 364–373.

Bradley, M. M., & Lang, P. J. (1999a). *Affective norms for English words (ANEW): Instruction manual and affective ratings*. Technical Report C-1. Gainesville, FL: The Center for Research in Psychophysiology, University of Florida.

Bradley, M. M., & Lang, P. J. (1999b). *International affective digitized sounds (IADS): Stimuli, instruction manual and affective ratings*. Technical Report B-2. Gainesville, FL: Center for Research in Psychophysiology, University of Florida.

Bradley, M. M., Miccoli, L., Escrig, M. A., & Lang, P. J. (2008). The pupil as a measure of emotional arousal and autonomic activation. *Psychophysiology*, *45*, 602–607.

Cuthbert, B. N., Schupp, H. T., Bradley, M. M., Birbaumer, N., & Lang, P. J. (2000). Brain potentials in affective picture processing: covariation with autonomic arousal and affective report. *Biological Psychology*, *52*, 95–111.

Damasio, A. R. (1996). The Somatic Marker Hypothesis and the Possible Functions of the prefrontal cortex. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences*, *351*, 1413–1420.

Faith, M., & Thayer, J. F. (2001). A dynamical systems interpretation of a dimensional model of emotion. *Scandinavian Journal of Psychology*, *42*, 121–133.

Fontaine, J., Scherer, K., Roesch, E., & Ellsworth, P. (2007). The world of emotions is not two-dimensional. *Psychological Science*, *18*(12), 1050–1057.

Gökçay, D., & Smith, M. A. (2008). TÜDADEN:Türkçede Duygusal ve Anlamsal Değerlendirmeli Norm Veri Tabanı. *Proceedings of Brain-Computer Workshop*, 4.

Harmon-Jones, E., Gable, P. A., & Peterson, C. K. (2010). The role of asymmetric frontal cortical activity in emotion-related phenomena: A review and update. *Biological Psychology*, *84*, 451–462.

Kreibig, S. D. (2010). Autonomic nervous system activity in emotion: A review. *Biological Psychology*, *84*, 394–421.

Lahl, O., Göritz, A. S., Pietrowsky, R., & Rosenberg, J. (2009). Using the World-Wide Web to obtain large-scale word norms: 190,212 ratings on a set of 2,654 German nouns. *Behavior Research Methods*, *41*(1), 13–19.

Lang, P. J., & Bradley, M. M. (2010). Emotion and the motivational brain. *Biological Psychology*, *84*(3), 437–450.

Lang, P. J., Bradley, M. M., & Cuthbert, B. N. (2008). *International affective picture system (IAPS): Affective ratings of pictures and instruction manual.* Technical Report A-8. Gainesville, FL: University of Florida.

Lang, P. J., Reenwald, M. K. C., Bradley, M. M., & Hamm, A. O. (1993). Looking at pictures: Affective, facial, visceral, and behavioral reactions. *Psychophysiotogy*, *30*, 261–273.

Lewis, P. A., Critchley, H. D., Rotshtein, P., & Dolan, R. J. (2007). Neural Correlates of Processing Valence and Arousal in Affective Words. *Cerebral Cortex*, *17*, 742–748.

Libkuman, T. M., Otani, H., Kern, R., Viger, S. G., & Novak, N. (2007). Multidimensional normative ratings for the International Affective Picture System. *Behavior Research Methods*, *39*, 326–334.

Mikels, J. A., Fredrickson, B. L., Larkin, G. R., Lindberg, C. M., & Reuter-Lorenz, P. A. (2005). Emotional category data on images from the International Affective Picture System. *Behavior Research Methods*, *37*(4), 626–630.

Norris, C. J., Gollan, J., Berntson, G. G., & Cacioppo, J. T. (2010). The current status of research on the structure of evaluative space. *Biological Psychology*, *84*, 422–436.

Olofsson, J. K., Nordin, S., Sequeira, H., & Polich, J. (2008). Affective picture processing: An integrative review of ERP findings. *Biological Psychology*, *77*, 247–265.

Osgood, C. E., May, W. E., & Miron, M. S. (1975). *Cross cultural univrsals of affective meaning*. University of Illinois Press.

Osgood, C. E., Suci, G. J., & Tannenbaum, P. H. (1957). *The measurement of meaning*. University of Illinois Press.

Pessoa, L. (2008). On the relationship between emotion and cognition. *Nature Reviews. Neuroscience*, *9*, 148–158.

Phelps, E. A. (2006). Emotion and Cognition: Insights from Studies of the Human Amygdala. *Annual Review of Psychology*, *57*, 27–53.

Phillips, M. L., Drevets, W. C., Rauch, S. L., & Lane, R. (2003). Neurobiology of Emotion Perception I: The Neural Basis of Normal Emotion Perception. *Biological Psychiatry*, *54*, 504–514.

Posner, J., Russell, J. A., & Peterson, B. (2005). The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology. *Development and Psychopathology*, *17*(3), 715–734.

Redondo, J., Fraga, I., Padrón, I., & Comesaña, M. (2007). The Spanish adaptation of ANEW (Affective Norms for English Words). *Behavior Research Methods*, *39*(3), 600–605.

Redondo, J., Fraga, I., Padrón, I., & Piñeiro, A. (2008). Affective ratings of sound stimuli. *Behavior Research Methods*, *40*(3), 784–790.

Rozenkrants, B., & Polich, J. (2008). Affective ERP Processing in a Visual Oddball Task: Arousal, Valence, and Gender. *Clinical Neurophysiology*, *119*(10), 2260–2265.

Rubin, D. C., & Talarico, J. M. (2009). A comparison of dimensional models of emotion: Evidence from emotions, prototypical events, autobiographical memories, and words. *Memory (Hove, England)*, *17*(8), 802–808.

Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, *39*(6), 1161–1178.

Samsonovic, A. V., & Ascoli, G. A. (2010). Principal Semantic Components of Language and the Measurement of Meaning. *PLoS ONE*, *5*(6), e10921.

Sánchez-Navarro, P. J., Martínez-Selva, J. M., Torrente, G., & Román, F. (2008). Psychophysiological, Behavioral, and Cognitive Indices of the Emotional Response: A Factor-Analytic Study. *The Spanish Journal of Psychology*, *11*(1), 16–25.

Sauter, D. A., Eisner, F., Calder, A. J., & Scott, S. K. (2006). Perceptual cues in nonverbal vocal expressions of emotion. *Quarterly Journal of Experimental Psychology*, *63*, 2251–2272.

Stephens, C. L., Christie, I. C., & Friedman, B. H. (2010). Autonomic specificity of basic emotions: Evidence from pattern classification and cluster analysis. *Biological Psychology*, *84*, 463–473.

Stevenson, R. A., & James, T. W. (2008). Affective auditory stimuli: Characterization of the International Affective Digitized Sounds (IADS) by discrete emotional categories. *Behavior Research Methods*, *40*(1), 315–321.

Terracciano, A., McCrae, R. R., Hagemann, D., & Costa, P. T. Jr. (2003). Individual Difference Variables, Affective Differentiation, and the Structures of Affect. *Journal of Personality*, *71*(5), 669–703.

Võ, M. L.-H., Conrad, M., Kuchinke, L., Urton, K., Hofmann, M. J., & Jacobs, A. M. (2009). The Berlin Affective Word List Reloaded (BAWL-R). *Behavior Research Methods*, *41*, 534–538.

Watson, D., Wiese, D., Vaidya, J., & Tellegen, A. (1999). The Two General Activation Systems of Affect: Structural Findings, Evolutionary Considerations, and Psychobiological Evidence. *Journal of Personality and Social Psychology*, *76*(5), 820–838.

KEY TERMS AND DEFINITIONS

Valence: One of the principal affective axes, which is also referred as pleasentness or evaluation

Arousal: One of the principal affective axes, which is also referred as activity

Circumplex: A model of the distribution of emotion data along the valence and arousal axes which looks like a doughnut, and fills all quadrants

PANA: A model of the distribution of emotion data along the valence and arousal axes which looks like a bumerang having arms situated at a 45 degrees angle with respect to the main axes

SCR Response: A psychophysiological measure of the autonomic nervous system, derived from sweat

Startle Eyeblink Response: A psychophysiological measure of the autonomic nervous system, derived from eyeblink magnitude in response to a white noise burst

ERP Signal: A signal obtained from eeg, by averaging all data that applies to a certain category of stimuli. The independent measure is time that starts with stimulus onset. This signal has a msec resolution in time.

fMRI Signal: A signal obtained from MR, by applying a repetitive task condition and measuring the blood oxygenation level which somewhat predicts gross neural activity. This signal has mm resolution in space and is recorded for all the voxels in the brain. In time, the resolution is on the order of 2-3 sec.