

Chapter 2

Emotions and Mood States: Modeling, Elicitation, and Classification

Common experience suggests that emotions cannot be reduced to single word definitions. Researchers exploring the subjective experience of emotions have pointed out that emotions are highly intercorrelated both within and between the subjects reporting them [61, 62]. For example, subjects rarely describe feeling a specific positive emotion without also claiming to feel other positive emotions [63]. This high variability in expression and definition of emotions implies that the development of an automatic emotion recognition system is a very challenging task.

In this chapter, three crucial issues are addressed: modeling, elicitation and classification of emotions. Moreover, the role of the Autonomic Nervous System (ANS) patterns is emphasized along with the related nonlinear dynamics.

2.1 Modeling Emotions

In the literature, several approaches for modeling emotions have been proposed. Discrete, dimensional, appraisal, and dynamical models are the most interesting, and in addition, they are not exclusive from each other.

In *discrete models*, emotions can be seen as the result of a selective adaptation that ensures survival [64]. This survival concept could be illustrated by the following relation: danger \Rightarrow fear \Rightarrow escape \Rightarrow survival. The result of this selection is a small set of basic, innate and universal emotions. For instance, Ekman proposed 6 basic emotions which are identified on the basis of facial expressions: anger, disgust, fear, joy, sadness and surprise [65, 66]. Besides, in the literature other discrete models have been proposed which include more or less basic emotions, usually from 2 to 10 ([67–69]). These emotions are called primary emotions as opposed to secondary emotions which result from a combination of the primary ones (e.g. contempt = anger + disgust). Nevertheless, this model can be insufficient to describe mixed emotions which necessarily require much more than one word to be expressed, and in addition there are some controversies in the assumption of universality of basic emotions (Darwinian hypothesis [64]). What seems true is that emotions are universally expressed (e.g. facial expressions [70]) but dependent on semantic attributions.

It shows that inter-cultural differences, e.g. difference between Asian and occidental people, are more important than intra-cultural differences, e.g. between genders, and that no significant differences between primary and secondary emotions exist. From an evolutionary point of view, basic emotions may be the first emotions infants could experience [71]. See Ortony et al. [72], for basic emotion categories defined over the years.

Unlike discrete models, *dimensional models* consider a continuous multidimensional space where each dimension stands for a fundamental property common to all emotions. This kind of model has already been used by Wilhelm Wundt [73]. Over the years, a large number of dimensions has been proposed [74–79]. Two of the most accepted dimensions were described by Russel [80]: valence (i.e. pleasure, positive versus negative affect), and arousal (low versus high level of activation). These dimensions were derived from a valence, arousal, and dominance space developed by Russell and Mehrabian [81], in which dominance represents the degree of control over the emotion.

Appraisal models are based on the evaluation of current, remembered or imagined circumstances. At the heart of appraisal theory is the idea that the particular judgments made about the environment and ourselves causes different emotions. The situational appraisals appear to be highly dependent on motives and goals. In other words, how we feel depends on what is important to us, indeed all our appraisals are connected to what we want and, therefore, to how we feel. For example, frustration results from a goal which is not achieved. This model was introduced by Arnold [82] and has been developed and refined by Frijda [83], Ortony et al. by developing the OCC model [84], Scherer with the Component Process Theory [85] and the derived one by Lisetti and Gmytrasiewicz [86]. The appraisal process can be thought of having a continuous as well as a categorical nature. Roseman's (1996) model shows that appraisal information can vary continuously but categorical boundaries determine which emotion will occur. To solve the problem between categorical and continuous appraisal order, it may be a good idea to place discrete emotional categories (i.e. happiness, sadness, etc.) while continuous models represent the varieties, styles, and levels of these already defined distinct emotions [87].

Finally, the *dynamical model* approach considers emotions as a dynamical process. This model starts from an evolutionary perspective and characterizes emotion in terms of response tendencies. In the dynamics perspective emotion is a regulable system and the capability of understanding its rules is essential. According to a process model of emotion regulation, emotion may be regulated at five points in the emotion generative process: selection of the situation, modification of the situation, deployment of attention, change of cognitions, and modulation of responses. It may be useful to take into account concepts like mood and personality (see Egges et al. for an implemented model [88]).

In all the studies presented in this book, a common dimensional model which uses multiple dimensions to categorize emotions, the Circumplex Model of Affects (CMA) [89] is adopted. This model interprets emotional mechanisms underlying affects as a continuum of highly interrelated and often ambiguous states. They are distributed on a Cartesian system of axes; each axis represents a neurophysiological

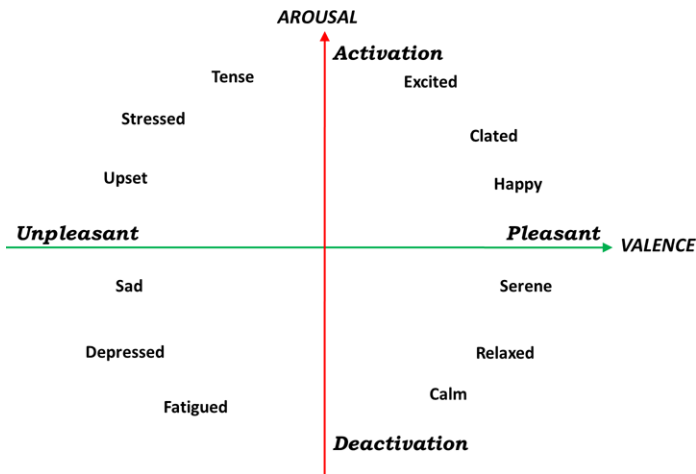


Fig. 2.1 A graphical representation of the circumplex model of affect with the *horizontal axis* representing the valence dimension and the *vertical axis* representing the arousal or activation dimension (adapted from [31])

pathway by which emotion is being processed. In many cases, by using factor analysis and multidimensional scaling of a wide set of psychometric assessments and self-reports on emotional states, it is possible to use a more simplified bi-dimensional model. In particular, in the CMA used in the reported experiments the two dimensions are conceptualized by the terms of valence and arousal, which can be intended as the two independent, predominantly subcortical systems that underlie emotions (see Fig. 2.1). Valence represents how much an emotion is felt by people as positive or negative. For example, someone feeling sad has evaluated surrounding events as very negative. On the contrary, someone feeling joy would have appraised the environment as positive for his well being. Arousal indicates how relevant the surrounding events are and therefore how strong the emotion is. In this case, someone feeling excited will have an emotion represented by a bigger arousal and someone feeling bored will experience a much less relevant emotion. Accordingly, in CMA, arousal and valence can be considered adequate parameters to identify specific emotions. This simplified model addresses most of the methodological issues raised by experimental studies on emotions and provides a reliable means for comparing outcomes.

2.2 Autonomic Nervous System Correlates of Emotions

The idea behind this book is that ANS (nonlinear) dynamics reflects measurable changes according to the emotional experience [89, 90].

Many researchers have observed that peripheral physiological responses to affective stimuli vary incrementally with subjective ratings of valence and arousal. As a matter of fact, several physiological ANS signs, e.g. Heart Rate Variability (HRV), Respiration (RSP), Electrodermal Response (EDR), pupil size and eye movement variation) correlates with subject behavior or emotional status [91–94]. Nevertheless, the correlation between emotions and physiological reactions controlled by the ANS are complex. Anger, for example, has been associated with higher heart rate than happiness, and on the other hand, has been associated with higher finger temperature than fear [95, 96].

2.2.1 Heart Rate Variability

One of the most important ANS-related marker is the HRV. It refers to the variations in the beat-to-beat intervals or correspondingly in the instantaneous heart rate (HR). HRV reflects the regulation mechanism of the cardiac activity by the ANS [97]. Over the last 20 years, several studies have demonstrated the significant relationship between ANS and HRV, especially by means of frequency domain indexes, e.g. LF/HF ratio [98]. Since the human cardiovascular system is intrinsically nonlinear, methods for studying dynamic systems have been adopted to quantify HRV and find nonlinear fluctuations in the HR, that are otherwise not apparent. Although a detailed physiological explanation behind these complex dynamics has not been completely clarified, several nonlinearity measures of HRV have been used as important quantifiers of the complexity of cardiovascular control in healthy and impaired subjects [99–101]. Some nonlinear methods used for studying the HRV include Lyapunov exponents [102], $1/f$ slope [103], approximate entropy (ApEn) [104], Detrended Fluctuation Analysis (DFA) [105], Recurrence Plot (RP) [106, 107], and entropy analysis [108]. As reported in [109], HRV of sinus rhythm is characterized by being a chaos-like determinism, with at least a positive Dominant Lyapunov Exponent (DLE) and $1/f$ -like broad-band spectrum with an exponent of approximately -1 . Moreover, HRV chaos-like determinism is modulated but not eliminated by the inhibition of the autonomic tone or by exercise.

2.2.2 The Electrodermal Response

Electrodermal Responses (EDR) has been shown to be a powerful emotion-related signal [110]. EDR represents changes in the skin electrical properties, i.e. electric impedance, due to psychologically-induced sweat gland activity [111] upon an external stimulus. More specifically, it is strictly related to the activity of the eccrine sweat glands (located in the palms of the hands and soles of the feet) and the skin pore size. In a variety of induction contexts, electrodermal reactivity consistently varies with emotional intensity, with largest responses elicited in either unpleasant and pleasant contexts with high rate of arousal. Many studies, for example, have

found that skin conductance increases when people view pictures rated as emotional, compared to neutral, regardless of whether they are rated pleasant or unpleasant [111–113]. Moreover, when listening to affective sounds [114], or music [115], skin conductance activity increases as the acoustic stimuli are highly rated in emotional arousal. Demonstrating consistent modulation by affective intensity across perceptual contexts, elevated electrodermal reactions are also found when people view film clips that are either unpleasant or pleasant [116]. The scientific community has accepted to consider the EDR as indirect indicator of the sympathetic nervous system [110]. Several approaches are used to measure this signal (e.g. [117]).

In this work, a small continuous voltage is applied to the skin and the induced current is measured through two electrodes positioned at the index and middle fingertips of the non-dominant hand. The ratio between voltage drop and induced current represents the skin electric impedance. EDR changes depend on the individual physiological state as well as on interaction with environmental events. Using a continuous voltage as source, the EDR can be referred to as Skin Conductance (SC). SC can be split into two components: tonic and phasic. Tonic component is the baseline level of skin conductance (also called skin conductance level-SCL), whose trend is different from person to person and depends on both patient physiological state and autonomic regulation. Phasic component (also called Skin Conductance Responses—SCRs), superimposed on the tonic baseline level, changes with specific external stimuli such as lights, sounds, smells, etc. or events.

This book also focus on identifying emotional cues, due to arousal elicitation, in EDR measurements by using a textile-based sensing glove. The use of a wearable textile system exhibits several advantages in terms of portability and usability for long-term monitoring, and gives minimal constraints. Therefore, this kind of system broadens scientific horizons which autonomic regulation investigation is currently based on, providing high acceptability and usability in daily activities.

2.2.3 Information Coming from the Eyes: Pupil Size Variation and Eye Tracking

Eye movements can provide an estimation of what information an individual is considering. Eye tracking is becoming an increasing popular measurement of cognitive information processing [118]. The most recent eye-tracking technology development (e.g. ease of use, improved accuracy, and enhanced sampling rate) also offers the possibility for unobtrusive monitoring in the field of emotions because no sensors need to be attached to the user. By gathering and analyzing data on where and how long eyes are looking, a lot of information about the cognitive and emotional structure could be inferred. Eye tracking allows estimating cognitive or affective states exploiting the property of the immediacy (people process information as it is seen) and the eye-mind (the eye remains fixated upon an object while the object is being processed). Concerning eye-tracking methods, two popular methods are currently used:

1. shining a light on the eye and detecting corneal reflection
2. simply taking visual images of the eye and then locating the dark pupil area.

Generally, the choice of the best method depends upon the external lighting conditions. To compute where a person is fixating, the eye-tracking apparatus can be placed on the person head along with a camera so that a visual image is captured showing what the person is currently looking at, with a point on the image indicating the object being fixated. Pupil dilations and constrictions are also governed by the ANS [119]. Previous studies have suggested that pupil size variation is related to both cognitive and affective information processing. As a matter of fact, it has been pointed how the eye tracking information plays a crucial role on emotional processing related to visual stimuli [120, 121]. Moreover, some works reported on how eye tracking information can be related to selective attention to emotional pictorial stimuli [122]. They found out that preferential attention depends on the affective valence of visual stimuli, i.e. pleasant and unpleasant pictures.

Concerning information provided by the pupil, previous studies suggested that pupil size variation is related to both cognitive and affective information processing [58, 123]. More specifically, [124] pointed out that during cognitive tasks such as recalling something from memory the pupils dilate and return to previous size within a few seconds of completing the mental work. However, previous works on affective elicitation and pupil size variation have been somewhat controversial. Dated research activity of [125] studied the effects of various sensory and psychological stimuli to pupil size variation and argued that none of them caused pupil constriction except for increased light intensity. On the contrary, [126] found out that there would be a continuum ranging from extreme dilation due to interesting or pleasing stimuli to extreme constriction due to unpleasant or distasteful content. Almost in the same years, [127] contradicted this bi-directional view arguing that there is no pupil constriction in response to negative stimuli, or it can be limited to a few individuals and a small range of stimuli. He proposed that pupil size should be linearly related to the stimulation intensity. From this point of view, pupil size variation seems to be sensitive to the valence scale, resulting largest at the negative and positive ends of the continuum and smallest at the center, that would represent neutral affect. The latest work of [123] reported a study concerning pupil size variation during and after auditory emotional stimulation. Their results showed that pupil size was significantly larger after both negative and positive than neutral stimulation. These results suggested that the autonomic nervous system is sensitive to systematically chosen highly arousing emotional stimulation. It is reasonable that the above contradictory results and theories may be due to the variety of stimuli used. Mostly, they have used limited sets of pictures varying in content, and they have suffered from methodological problems with color, luminance, and contrast [128]. Clearly, controlled stimulus set is a fundamental requirement for a systematic study of the effects of emotions on pupil size variation.

2.2.4 Cardio-Respiratory Coupling

The coupling between cardiac and respiratory patterns has been increasingly gaining interest in the scientific community. Starting from the pioneering work of Angelone et al. [129], the coupling between the respiratory system and the heart is known to be both neurological and mechanical [130, 131] as well as nonlinear [132]. However, the exact physiological mechanisms responsible for cardio-respiratory synchronization are, so far, poorly understood. In the literature, at least two levels of interaction are known.

One level is identified as the frequency modulation of the heart's primary pacemaker (sino-atrial node) through autonomic neural and hormonal control. In this level two concurrent effects take place, the efferent neural activity (the respiratory related rhythms [133]) and a mechanical coupling between the systems. In the latter, the variation of the intra-thoracic pressure causes a mechanical stretch of the sinus node, which alters the electrical properties of the sino-atrial node membrane, and therefore influences the frequency of heart excitation [134].

The second level has been found in the cardio-respiratory center of the brain stem where the respiratory rhythm is generated, [135]. At this level, the brain stem modifies the heart rhythm according to information regarding blood pressure provided by arterial baroreceptors, and, in turn, the baroreceptor reflex depends on the respiration phase [136].

Nowadays, it is well accepted that the cardiovascular system and its relationship with respiration is a truly complex system. Therefore, nonlinearities and nonlinear coupling measures should be taken into account in its modeling and analysis [137].

As a matter of fact, the current literature provides plenty of nonlinear methods that are able to distinguish between healthy subjects and patients, and sometimes can even predict the status of the latter ones (e.g. see [100, 138]).

Although it is well-known that the cardiovascular and respiratory systems do not act independently, in the biological physics community these two systems were often considered to be not synchronized. So, there is a weak coupling between respiration and cardiac rhythm, and the resulting rhythms are generally not phase locked [139]. As a matter of fact, in rest conditions, while long synchronization episodes were observed in athletes and heart transplant patients (several hundreds of seconds) [140, 141], shorter episodes were detected in normal subjects (typical duration less than one hundred seconds) [141, 142].

In other several cases the cardio-respiratory synchronization was well demonstrated ([43, 143–145]). Since Pecora and Carroll [146] presented the conception of chaotic synchronization for two identical chaotic systems with different initial conditions, many synchronization methods have been proposed [147–151]. Recently,

Schafer et al. presented a new technique for the analysis of cardio-respiratory interaction, [140, 152], making use of their recent achievements in understanding hidden synchronization effects in chaotic and noisy oscillators [39, 153]. Even though some recent works have shown that ANS and cerebral cortex are implicated in the changes of cardio-respiratory synchronization during mental tasks [154], the effect of emotional stimuli on the cardio-respiratory interaction has been poorly investigated [155]. Starting from the hypothesis that respiratory and cardiac systems adapt their rhythms as a response to an external emotional stimulation, in this book it will be demonstrated that the cardio-respiratory system tends to become synchronized when experiencing strong affective events [36].

2.3 Emotion Elicitation

How emotions can be elicited is a crucial issue still open. The difficulty associated to the elicitation is related to a complex interaction between cognition and neuro-physiological changes. Several modalities and several perceptual channels could be used for this purpose, which can be thought as affected by several “noisy” factors, including physiological process such as attention, social interaction, and body-to-biosensors connections. In the literature, a wide range of elicitation methods have been applied: introspection, movements, lights and colors [156], set of actions, images (e.g. IAPS described below) [157, 158], sounds (e.g., music and IADS described below) [12, 93, 159, 160], (fragments of) movies [161, 162], speech [163], commercials [164], games, agents/serious gaming/virtual reality [165], reliving of emotions [166], real world experiences [167, 168] along with using personalized imagery stimuli [92].

In order to induce a specific emotion, some of these methods employ stimuli belonging to international standardized databases. In this context, the International Affective Picture System (IAPS) [157] and the International Affective Digital Sounds system (IADS) [169] are two of the most frequently cited tools in the area of affective stimulation. They consist of hundreds of images and sounds, with associated standardized affective values. A commonly used approach is to have a collection of stimuli in which each is slightly varied in terms of intra-individual standard deviation of affective ratings.

In several experiments reported on this book, a set of images gathered from the IAPS is chosen [170]. Specifically, IAPS is a set of 944 images having a specific emotional rating, in terms of valence, arousal, and dominance. The emotional ratings are based on several studies previously conducted where subjects were requested to rank these images using the self assessment manikin [171]. The elicitation by IAPS is able to activate segregated neural representations of the different emotion dimensions in different prefrontal cortical regions [172, 173].

2.4 Affective Computing: From Theory to Emotion Recognition

Emotion recognition using intelligent systems is a crucial issue to be addressed for understanding human behavior, investigating mental health, interpreting social relations, etc. Recently, several engineering approaches have been used in order to guarantee acceptable emotion recognition systems having high accuracy, robustness, and adaptability to practical applications. An emotion recognition system is generally comprised of two main parts: emotion elicitation and identification of physiological correlates. Such systems are devised to map physiological patterns into well-defined emotional states for an automatic classification. The physiological signs include implicit and explicit emotional channels of human communication, such as speech, facial expression, gesture, physiological responses [7]. Recently, numerous automatic emotion recognition systems have been proposed involving, among others, patient-robot interactions [174], car drivers [175], facial expression [176], and adaptation of game difficulty [177]. Table 2.1 summarizes the most relevant results reported in the literature during the last decade about the emotion recognition through the ANS biosignal response [92–94, 165, 168, 175, 178–188]. All the acronyms used in this table are expanded in Table 2.2. Each row of Table 2.1 shows the first author along with the publication year, the set of physiological signals used for that study, the typology of stimulation pattern, the emotion classes, the type of the classifier and the results in terms of best percentage of successful recognition. Besides, the rest of the state-of-the-art of ANS-based emotion recognition is referred to a recent review written by Calvo et al. [7] which reports on the most relevant theories and detection systems using physiological and speech signals, face expression and movement analysis.

The detection and recognition of emotional information is an important topic in the field of *affective computing*, i.e., the study of human affects by technological systems and devices [91].

2.5 Emotions and Mood Disorders: The Bipolar Disorders

Mood has been defined as a long-lasting, diffuse, affective state, not associated to a specific trigger [189]. In turn, emotions are considered transient, acute and arousing responses to specific stimuli. It is well-known, however, that mood status affects the normal emotional response, and for this reason a possible assessment approach is to study the physiological variations provoked by external affective stimuli.

Table 2.1 Performance of the peripheral biosignal based emotion recognition methods reported in the literature of last decade

| Authors | Signals | Elicitation | Emotion classes | Accuracy | Best results (%) |
|--------------------------------|---------------------------------|--|---|----------|------------------|
| Picard et al. 2001 [92] | EMG, BVP, EDR, RSP | Internal feeling of each emotion | Neutral, anger, hatred, grief, platonic love, romantic love, joy, reverence | LDA | 81.0 |
| Lisetti & Nasoz 2004 [178] | ECG, EDR, ST | Film clips and difficult mathematics questions | Sadness, anger, fear, surprise, frustration, and amusement | MBA | 84 |
| Haag et al. 2004 [179] | EMG, EDR, ST, BVP, ECG, RSP | IAPS | Valence | ANN | 90 |
| Yoo et al. 2005 [181] | ECG, EDR | Video clip | Arousal | ANN | 96 |
| Choi & Woo et al. 2005 [182] | BVP, EDR | Music and image chosen by subject | Sad, calm pleasure, interesting pleasure, fear | ANN | 80 |
| Healey & Picard 2005 [168] | EMG, ECG, EDR, RSP | Driving | Joy, anger, and sadness | ANN | 74.5 |
| Li & Chen 2006 [183] | ECG, BVP, EDR, ST | Film clips | 3 stress levels | LDA | 97 |
| Rani et al. 2006 [184] | ECG, BVP, EDR, EMG | Cognitive tasks (i.e. anagrams and pong) | Fear, neutral, and joy | CCA | 93.33 |
| Rainville et al. 2006 [185] | ECG, RSP, EDR, EMG | Self induction | Engagement, anxiety, boredom, frustration and anger | SVM | 86 |
| Zhai & Barreto 2006 [186] | EDR, BVP, PD, ST | Stroop test game | Anger, fear, happiness, sadness | SDA | 49 |
| Leon et al. 2007 [165] | ECG, EDR, BVP | IAPS | 2 stress levels | SVM | 90 |
| Liu et al. 2008 [187] | ECG, ICG, BVP, HS, EDR, EMG, ST | Cognitive tasks (i.e. anagrams and pong) | Neutral, negative, positive | ANN | 71 |
| Katsis et al. 2008 [175] | EMG, ECG, RSP, EDR | Car-racing drivers | Anxiety, engagement, liking | SVM | 83 |
| Yannakakis & Hallam 2008 [188] | ECG, BVP, EDR | Interactive games | High stress, low stress, disappointment, euphoria | SVM | 79.3 |
| Kim & Andr  2008 [93] | EMG, ECG, EDR, RSP | Music listening | 2 fun levels | SVM, ANN | 70 |
| Katsis et al. 2010 [94] | BVP, ECG, EDR, RSP | IAPS | 4 musical emotion | LDA | 70/95 |
| | | | Relaxed, neutral, startled, apprehensive, very apprehensive | ANN, SVM | 84 |

Table 2.2 Peripheral biosignals and classification methods used in the literature, along with acronyms

| Peripheral biosignals | Acronym |
|-------------------------------------|---------|
| ElectroCardioGram | ECG |
| ElectroMyoGram | EMG |
| Blood Volume Pulse | BVP |
| ElectroDermal Response | EDR |
| ReSPiration Activity | RSP |
| Skin Temperature | ST |
| Pupil Diameter | PD |
| Impedance CardioGram | ICG |
| Heart Sound | HS |
| Classification methods | Acronym |
| Linear Discriminant Analysis | LDA |
| Marquardt Backpropagation Algorithm | MBA |
| Artificial Neural Network | ANN |
| Support Vector Machine | SVM |
| Canonical Correlation Analysis | CCA |
| Stepwise Discriminant Analysis | SDA |

Specifically, paradigms based on emotional reactions have been proven to be widely able to differentiate among different mood states both in normal [190] and pathological conditions [191].

As a case study on patients, the concepts and methodologies developed in this book were applied to data coming from patients with bipolar disorders. *Bipolar disorder*, formerly known as manic-depressive illness, is a psychiatric condition in which patients experience drastic mood shifts. Typically, the disorder is cyclic with patients experiencing episodes of pathological low moods (depressive episodes), pathological elevated moods (maniacal or hypomaniacal episodes) and episodes in which depressive and maniacal symptoms are present at the same time (mixed episodes). In the intervals between these episodes, patients typically experience periods of relatively good affective balance (euthymia). Patients during a depressive episode experience a sad and desperate mood presenting a lack of interest together with other several neurovegetative symptoms including loss of appetite and sleep. Other symptoms such as cognitive retardation, somatic pain or functional symptoms (headache, dyspepsia etc.) are frequent as well. Depressed patients might also experience thoughts of ruin, guilt or death including suicidal thoughts that might end in suicide attempts. On the other hand, maniac patients express an increase in activity and an acceleration of thoughts. Rather than being a positive effect, these conditions are the cause of attention loss and prevent the patient from expressing a coherent mental stream of thoughts. Hyperactivity is often not finalized and patients switching from task to task are not able to complete any activity. In the maniac phase

patients also experience a reduction of the necessity to sleep, sleeping a few hours per night without feeling tired. Finally, mania is often dominated by a feeling of an excited mood with the idea of grandiosity and hypertrophic self-esteem. Maniacs, differently from hypomaniacs, might be delusional, e.g. they often believe of being a descendent of some important historical character. In the mixed state, patients share symptoms of both mania and depression, i.e. they exhibit symptoms of both mood states. For instance, patients can be hyperactive but have insomnia, have an increased self-esteem but also thoughts of inadequacy, and so on.

According to epidemiological studies,

almost 15% of the population in the United States has suffered from at least one episode of mood alteration [192], and more than two million Americans have been diagnosed with bipolar disorder. Moreover, it has been estimated that about 27% (equals 82.7 million; 95% confidence interval: 78.5–87.1) of the adult European population, from 18 to 65 years of age, is or has been affected by at least one mental disorder [193, 194].

Despite its prevalence and the high cost of treating mood disorders, the clinical management of this condition is still ill-defined. First of all, this long-term illness may go undetected for years before it is diagnosed and treated. Secondly, bipolar patients are extremely heterogeneous with respect to the phenomenology and severity of the symptoms, the number and duration of the episodes, as well as the time interval between them. Even during euthymic periods (i.e. after remission from manic or depressive episodes), patients tend to experience sub-threshold mood alterations over time. In spite of the non-specific symptoms, currently the patient's mood is typically assessed by clinician-administered rating scales.

For clinical and research purposes, several clinical rating scales have been proposed and validated, but at present neither biological markers nor physiological signals highlighted in research studies are used for clinical purposes [195–197]. In this view, there is another fundamental issue concerning both the research and clinical domains. Relying on subjective mood evaluation alone, there is no possibility to evaluate the preclinical indicators of relapse or patient response to treatment. For instance, previous studies on sleep [198–200], circadian heart rate rhythms [201, 202] and the hormonal system [203–205] highlighted changes in these parameters according to the clinical status that may be considered predictors of clinical changes. However, none of these studies have reached an acceptable level of accuracy for clinical use in order to forecast the clinical course in single patients. A possible explanation for these negative results can be that mood disorders are more heterogeneous, in terms of psychophysiological, neuroendocrine and neurobiological correlates, than relatively simple clinical phenotypes usually adopted for clinical and also for research purposes. This might result in gathering subjects in groups that, although homogeneous in a clinical descriptive point of view, are extremely dishomogeneous in terms of endophenotypes.

2.6 Autonomic Nervous System as a Nonlinear Physiological System

Most of the methodologies developed and applied within this book are related to nonlinear dynamics and the theory of nonlinear system identification. This choice is justified by both physiological and experimental evidences.

As a matter of fact, it has been well-accepted by the scientific community that physiological models should be nonlinear in order to thoroughly describe the characteristics of such complex systems. Within the cardiovascular system,

the complex and nonstationary dynamics of heartbeat variations have been associated to nonlinear neural interactions and integrations occurring at the neuron and receptor levels, so that the sinoatrial node responds in a nonlinear way to the changing levels of efferent autonomic inputs [29].

In fact, HRV nonlinear measures have been demonstrated to be of prognostic value in aging and diseases [24, 25, 99–101, 138, 206–211].

For instance, ApEn and DLE are adopted to characterize the complexity of HRV [46]. ApEn is chosen because it can distinguish between wide variety of systems. Moreover, its estimation can be achieved with relatively few points, as reported by Pincus et al. [104]. The DLE index has been already used in the literature, e.g. [109], to characterize HRV in terms of low-dimensional chaos-like determinism.

In several previous works [30, 212–215], it has been demonstrated how it is possible to estimate heartbeat (nonlinear) dynamics in cardiovascular recordings under nonstationary conditions by means of the analysis of the probabilistic generative mechanism of the heartbeat. Concerning emotion recognition, the crucial role of nonlinear dynamics has been demonstrated in order to perform an effective arousal and valence recognition from ANS signals [22, 31, 36, 46].

Autonomic Nervous System Dynamics for Mood and
Emotional-State Recognition

Significant Advances in Data Acquisition, Signal
Processing and Classification

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2014, XIX, 162 p. 49 illus., 36 illus. in color., Hardcover

ISBN: 978-3-319-02638-1