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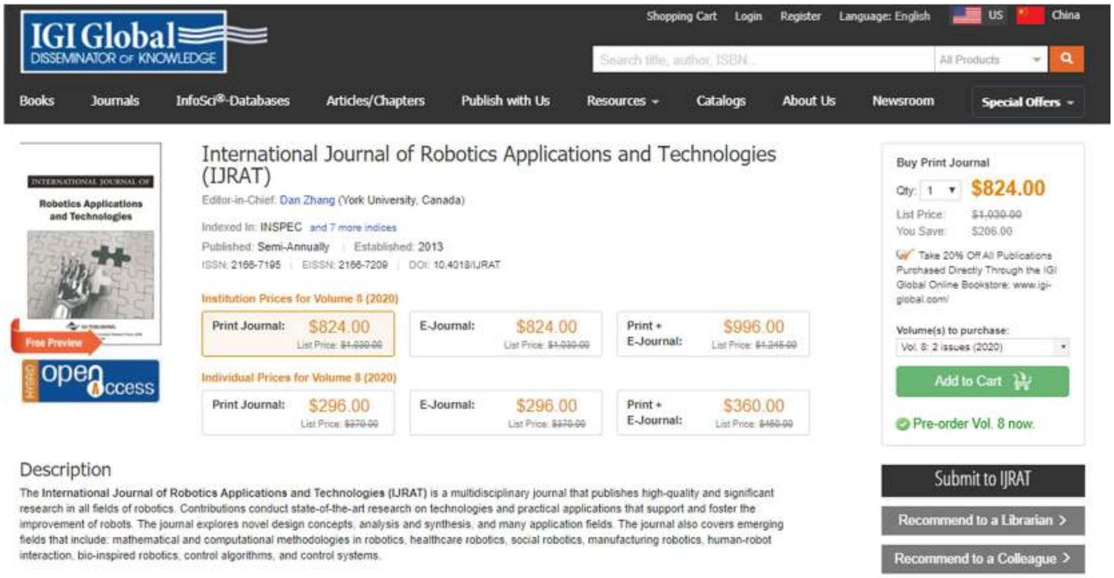

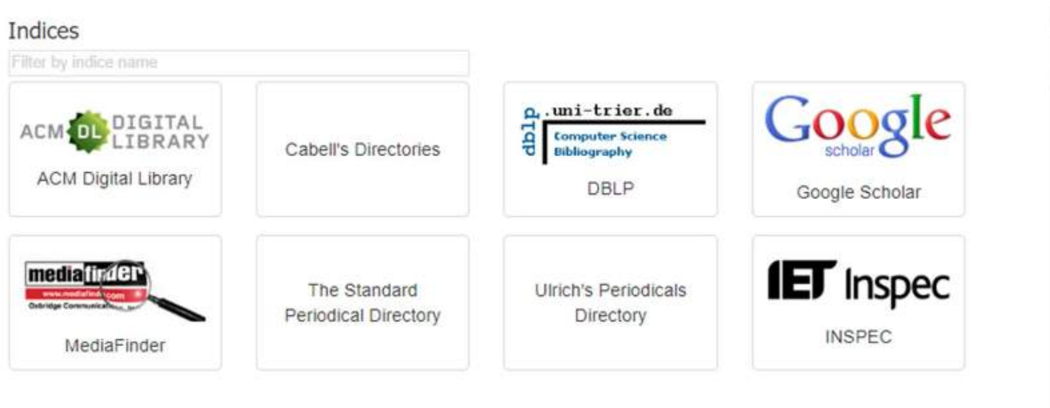

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Emotional State Recognition Using Facial Expression, Voice, and Physiological Signal

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ABSTRACT

Emotion recognition is an important aspect of affective computing, one of whose aims is the study and development of behavioral and emotional interaction between human and machine. In this context, another important point concerns acquisition devices and signal processing tools which lead to an estimation of the emotional state of the user. This article presents a survey about concepts around emotion, multimodality in recognition, physiological activities and emotional induction, methods and tools for acquisition and signal processing with a focus on processing algorithm and their degree of reliability.

KEYWORDS

Affective Computing, Emotion Recognition, Multimodal Interactions, Pattern Recognition, Physiological Signal

INTRODUCTION

For twenty years, the computer modeling of emotion is a theme increasingly recognized, particularly in the field of human-machine interaction (Picard, 1997). The term "emotion" is relatively difficult to define from a scientific point of view. Indeed, the phenomenon of emotion is based at the same time on physical, physiological, mental and behavioral considerations. Thus, many areas such as affective computing and image processing are interested in human emotional dimensions. For ten years, the emotional component has been taken into account and developed significantly in the fields of robotics, human-machine interaction, and more particularly in the context of interaction with animated conversational agent (ACA).

The growing maturity of the field of emotion recognition is creating new needs in terms of engineering. After a replication phase, during which numerous works have been proposed with recognition systems (Jaimes & Sebe, 2007), we are gradually entering an empiricism phase (Clay, Couture, & Nigay, 2009), where models for the design are developed (Jaimes et al., 2007). Most designed systems allow passive recognition of emotions. To define emotion, we base ourselves on Scherer's theory (Scherer, 2000). An emotion is characterized by a highly synchronized expression: the whole body (face, limbs, physiological reactions) reacts in unison and the human emotional expression is clearly multimodal. Indeed, a large number of studies have been carried out in order to

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define the relationship between emotion and physiological signal. These have allowed to highlight a significant correlation between this type of signal and certain emotional states.

This article is a state of the art about emotions and emotion recognition systems. We discuss some concepts about emotion, its representation and characteristics, and the multimodal approach in recognition systems. We present an analysis of physiological activity and emotional activation and review methods and tools for acquisition and processing of physiological signals, in particular classification methods. Finally, we focus on evaluation criteria and induction techniques (images, videos).

EMOTION RECOGNITION SYSTEM ARCHITECTURE

The analysis of existing emotion recognition systems reveals a decomposition into three levels, each fulfilling a specific function: Capture, analysis and interpretation levels. Figure 1 shows the emotion recognition system architecture.

At the capture level, the information is captured from the real world and in particular from the user through devices (camera, microphone, etc.). This information is then analyzed in the analysis level, where emotionally relevant characteristics are extracted from the captured data. Finally, the extracted characteristics are interpreted to obtain an emotion. This division into three level - capture, analysis and interpretation - is classic in emotions recognition and form a functional motif on which we rely to develop a model.

This architecture model offers five component types (Figure 2). Each component subscribes and issue one or more data stream. The capture unit has the role of interfacing with a physical device for capturing data. The feature extractor analyzes input data in order to extract one or more emotionally relevant characteristics. An interpreter receives the values of several characteristics. Its role is to interpret emotion. This interpretation is subject to the emotion model considered (discrete model, continuous, or componential) as well as the computer algorithm used (e.g., neural network, hidden Markov model, etc.).

The model also has two types of components unrelated to an "emotion recognition" logic. The role of the adapter is to modify a data flow. It can be a simple modification of format as a heavy processing unrelated to the recognition (3D tracking by camera for example). The purpose of the hub is to amalgamate several data stream according to an ad hoc strategy.

Figure 1. Emotion recognition system architecture

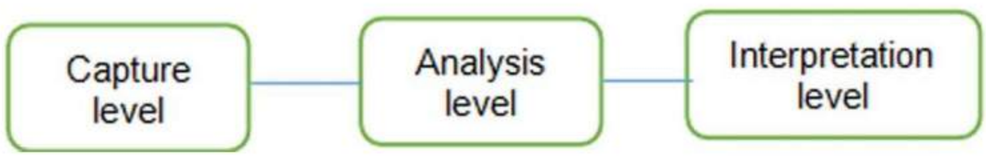
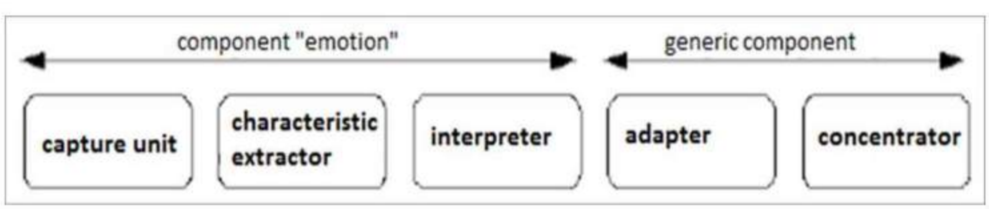


Figure 2. The five components of recognition architecture



Emotion Concept

Emotion is a vague notion and it is difficult to define. As a result, there are several definitions of the word "emotion". Etymologically, the word "emotion" comes from the Latin "emovere, emotum" (remove, shake) and "movere" (move) meaning outward movement. According to the etymology, emotion produces psychic or behavioral changes, which provokes internal subjective states. These internal states can be pleasant, positive, like joy or negative, unpleasant, like anger.

Several definitions and roles have been given to emotion. These definitions differ according to the different approaches proposed. Already in 1872, Charles Darwin, founder of evolution theory, defines it as an innate quality, universal and communicative, linked to the past of our specie evolution.

Ekman (1982), Izard (1971), Plutchik (1980) and Tomkins (1980) developed the theory of basic or fundamental emotion, but only 5 basic emotions are common to the various authors (sadness, anger, joy, disgust, fear).

In this sense Ekman and Davidson (1993) define emotion as an acute and transitory reaction, provoked by a specific stimulus and characterized by a coherent set of cognitive, physiological and behavioral responses (Petropoulou et al., 2006).

According to James, there is no limit to the number of different emotions that may exist, and that is why the emotions of different individuals may vary indefinitely both in their constitution and in the objects which engender them, because there is nothing fixed from eternity in reflex action (Hamdi, 2014). This point of view is found in many contemporary emotion specialists (Frijda, 1986).

In terms of definition, emotion concept appears to be polysemic. It is indeed difficult to give a clear and unequivocal definition of emotion. However, despite these differences, the majority of contemporary authors retain a consensual definition of emotional state. They describe emotion as a system of complex response, which integrates three aspect: (1) physiological / biological aspect that covers the physiological reactions (heart rate, respiratory rate,...), (2) behavioral aspect that covers behavioral and expressive reactions, highly influenced by the subject's personality (facial and vocal expressions) and (3) cognitive aspect that covers cognitive and experiential reactions (Luminet, 2002) (internal state / feeling).

It is generally defined as "a process of an organism reaction to a significant event" (Scherer, 2000).

Emotion Components

Emotion usually comes with the following components:

- A feeling corresponding to the subjective emotion experience often conscious and verbalizable with words;
- A neurophysiological reaction in the nervous system;
- A facial, speech, voice and gesture expressions;
- A tendency to action, also called adaptive behavior, allowing an individual to cope with his emotion;
- A cognitive evaluation of an event at origin of emotion triggering.

Dealing with the emotion components, it is important to evoke mood and personality. In psychology, we distinguish emotion from mood. The latter is an emotional state, which, contrary to emotion:

- Are diffuse origin (i.e. it is not triggered by particular event);
- Is of longer duration;
- Is of lower intensity.

Personality (or temperament) is what determines one's individuality. It is related to emotion in the sense that it can determine the disposition of an individual to feel and express emotion (Ochs, 2007). For example, an angry person will tend to feel anger more easily. An introverted individual will express little emotion (Ochs, 2007).

Emotion Expressions

Emotion can be expressed through different modalities. In interpersonal relationships, emotion is often communicated through facial expression. A facial expression is a change in the face, visually perceptible following activation (voluntary or involuntary) of the face muscles (Ekman, Levenson, & Friensen, 1983). Some gestures and postures also characterize an emotion. Emotions are also expressed through the voice. Some characteristics of the voice (intonation, articulation, intensity, tone ...) express an emotion. Finally, emotion can be expressed by linguistic statement (such as "I'm happy") (Kerbrat-Orecchioni, 2000) or physiological signal (reaction of internal organs).

Emotional Intelligence

Research has shown that emotion and component that accompany it are useful or indispensable mechanisms, both for adaptation of an individual to his environment and for the proper functioning of his cognitive processes or the regulation of his social interactions (Scherer, 2000). In interpersonal relationship, the interlocutor's emotion expressions are primarily an information vector about one's mental state (Ochs, 2007). The ability to recognize emotion of an individual can thus allow his better understanding (Hamdi, 2014). Moreover, depending on the type and intensity of emotions, cognitive abilities of an individual are different. For example, given emotion influence on reasoning, some tasks are more suited to negative emotion, others to positive emotion. While some emotions impair cognitive abilities, others improve them (Isen, 2000). Finally, understanding emotion, their origin, their influence, their consequence and knowing how to control them is intelligence form, called emotional intelligence (Salovey, Bedell, Detweiler, & Mayer, 2000). This intelligence would allow an individual to better integrate into society and to achieve his goals more quickly in both his professional and personal life (Ochs, 2007).

The researchers were interested in integrating a form of emotional intelligence into computer system. As Minsky points out (Minsky, 1986), "the question is not that intelligent machines can have any emotions, but that machines can be intelligent without any emotions".

In this article, it seems appropriate to identify emotion according to the classification proposed by Ekman and Friesen (1982) (joy, anger, surprise, disgust, fear, and sadness) by integrating stress and concentration. This emotion classification is widely used for the human emotional states study. In the field of emotional computing (affective computing), other emotional states are also studied: concentration, meditation, stress and commitment.

Emotion Model Types

Recent approaches that have been studied in the field of emotion modeling, two main model types are to distinguish: the hierarchical and componential models (Baudic & Duchamp, 2006). These two categories differ in that they denote how one can conceive the links that exist between emotion types. Thus, either they are hierarchically organized, or they place themselves in a complementarity relationship.

Hierarchical Model

According to the hierarchical model definition, emotion originate from earlier brain development stages whose dynamics are centered on the environment adaptation. They are therefore hierarchically organized, between primordial or primary emotional dimensions at the system base (Denton, 2006), and many so-called secondary emotion built from first. Thus, emotion such as joy or fear condition the appearance of more sophisticated emotion that themselves allow processes development such as jealousy or pride.

Processes located in the lowest level then have an important adaptive role and are directly related to sensory and visceral functions such as thirst or pain. Nevertheless, these functions may be considered differently from emotion and be separately classified as belonging to motives family (Mahboub, 2012). They can also become embedded in emotional processes as part of the emotional mechanism.

The classification of Griffiths (Griffiths, 1997) is one of the many hierarchical approaches that can be found in psychology. Griffiths describes three distinct kinds of emotions:

- Affect program responses are emotions in Charles Darwin sense. They are fast, automatic, adapted and above all universally recognized in all culture. Thus, fear, disgust, or surprise, are considered to belong to this category;
- Higher cognitive emotions take account into individual belief and desire. They are therefore more complex and varied than the previous ones and are linked intimately to cognitive processes, which give them greater adaptability to different problems such as social coordination;
- Socially sustained pretense that Griffiths also calls disclaimed action, that is, "refuted action". This emotional category concerns all the social pressure exerted on the individual such as ethics or social prohibition. It aims to take account of experience, not only from the individual personal history point, but also from that culture has been transmitted to him through the generation.

Component Models

In these models, emotion has different qualitative facets (Scherer, 2000). What we call the "triad of emotional response" consists of three main components for the emotion production: subjective experience, peripheral physiological response, and motor expression. Some theorists add cognitive and motivational components. Componential approach aims to determine the relative role of each component. Emotion is then the product of the whole process, from cognitive perception to effective response. Lazarus and Scherer (Hamdi, 2014) are generally associated with this approach, as are most models of cognitive assessment.

EMOTION REPRESENTATIONS AND CHARACTERISTICS

Automatic emotion recognition raises many issues. First, at the level of their representation: it is question to propose a formalism that is in agreement with the existing psychological results, while allowing a simple manipulation. Then, for a given event, one must be able to determine the emotional potential associated. In this context, Scherer (2014) proposes a description of the different models of emotion representation. We describe here the three emotion representation types, either (i) by discrete category represented by a verbal label, or (ii) by position, or a set of position, in a space defined by continuous dimension, and or (iii) by component-based model representation. We will present each of these three approaches in detail, and for each of them, highlight the various uses that have been proposed.

Categorical Approach (Discrete)

Discrete approaches represent emotion group as a discrete set in which each emotion type is designated by a specific label. This label is considered an episodic and universal feature of emotion. Universal nature of emotion leads to the definition of a finite and limited number of emotions (primary emotion) that can be observed in any individual. Number and identity of categories proposed are generally not defined in the same way.

According to several psychologists, an emotion is considered basic, in the case where it is "primary", and can be used to construct, in combination with other basic emotions, a large number of secondary emotions (Hamdi, 2014). The word "primary" means that basic emotion cannot be broken down into combination of other emotions. One of the main advantages of this definition is that it builds all emotion as a combination of basic emotions.

As we have seen, Ekman (1993) divided emotion into two classes: (1) the primary emotions (joy, sadness, anger, fear, disgust, and surprise) that are natural response to given stimuli and ensure specie survival, and (2) secondary emotions that are experienced by an individual by evoking a created mental image that correlate with the memory primary emotion.

Thus, secondary emotions result from a process of mental evaluation related to experience and memory. In addition, they elicit the same bodily reactions as the primary emotions, which they nuance strongly (so fear, for example, can experience a range variation, ranging from shyness to panic). Mowrer (Mowrer, 1960) proposes two additional dimensions: pain and pleasure. Ortony and al. (1988) present in a more complete list, the different dimensions proposed to characterize emotion. Table 1 presents several categories of basic emotions. In this table, the length of the list does not exceed 10 emotions, while the general list of emotional term may contain hundred categories (Whissell, 1989).

Discrete model, however, have several advantages. The main advantage being that once emotion to be treated identified clearly, they become simple to handle. The second advantage of these model is that they are particularly suitable for automatic recognition. They are therefore widely used in the field of emotional computing (Hamdi, 2014). Despite these advantage, emotion representation by label include defaults. Indeed, labels are discrete and cannot fully represent some emotional aspect (Yu, Aoki, & Woodruff, 2004). For example, an emotion can be seen as a dynamic process rather than a static state. This is why several works have focused on space continuous search to better represent emotion.

Dimensional Approach (or Continuous)

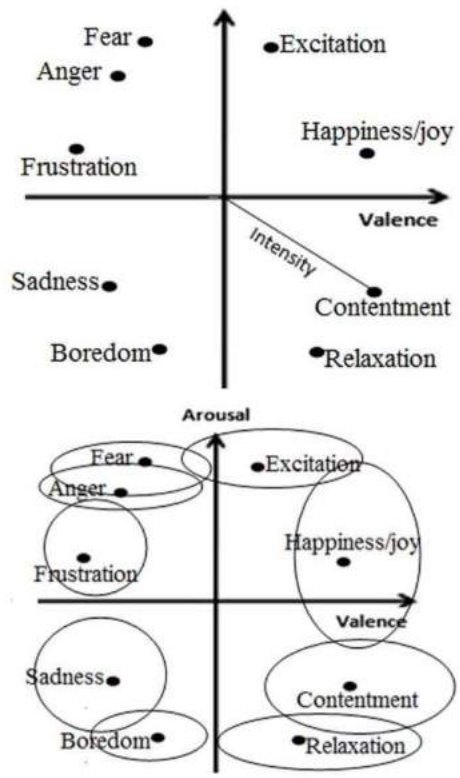
Dimensional approach is a very popular theoretical approach in psychology. Emotions are represented by a position, or a set of position defined by continuous dimension. The most commonly used dimension are bidirectional (plane) or three-dimensional (volume). Among the two-dimensional models, the best known is that of Russell (Hamdi, 2014). It represents emotion in two dimensions (Figure 3): Valencia (V) and Activation (A) (valence-arousal space). Valencia describes positive emotional character such as joy and negative emotional character such as anger. Activation is the degree of body or gestural expression that result in physiological responses (sweating, increased heart rate, etc.).

Emotions are therefore distributed in this two-dimensional space in which four quadrants can be distinguished: emotion with negative valence and weak activation (for example, sadness and boredom), emotion with negative valence and strong activation (for example, anger and fear), emotion with positive valence and weak activation (eg relaxation and contentment) and emotion with positive valence and strong activation (eg excitement and joy).

Table 1. List of basic emotions according to different authors

Author	Basic Emotion
Ekman	Anger, disgust, fear, joy, sadness, surprise
Izard	Anger, scorn, disgust, distress, fear, guilt, interest, joy, shame, surprise
Plutchik	Acceptance, anger, anticipation, disgust, fear, joy, sadness, surprise
Gray	Rage and terror, anxiety, joy.
Panksepp	Hope, fear, joy, panic
McDougall	Anger, disgust, exultation, fear, subjection, tenderness, astonishment.
Mower	Punishment, pleasure
James	Fear, sorrow, love, rage
Oatley, Johnson-Laird	Anger, disgust, anxiety, happiness, sadness

Figure 3. Two-dimensional models of valence-activation (Hamdi, 2014): (a) label with point, (b) label with zone



The two-dimensional valence-activation model has several advantages. All First, it is possible to represent emotion without used label, but using a coordinate system that include emotional meaning. As a result, any emotion can be represented by a point in this bi-dimensional space. Secondly, since this space was created from analysis of emotional expression (verbal and no), it is possible to associate some area with emotional labels (Figure 3 (b)). Figure 3 illustrates direct correspondence of verbal expression (emotion) on this two-dimensional space. As seen in Figure 3 (b), emotional labels tend to form an ellipse in a bi-dimensional space. However, it is obvious that this mapping varies from one person to another. As a result, there are no exact limit in valence-excitation space that define emotional expressions.

Despite these benefit, this approach has received some criticisms. Theorists supporting categorical approach such as Tomkins (1980), Ekman (1993) and Izard (1971) found that emotion representation in bi-dimensional or three-dimensional space implied a loss of information. In addition, some emotions may be outside bi- or three-dimensional space (e.g., surprise).

Components Based Representation Models

This more complex approach does not offer representation that is applicable to automatic emotion recognition directly. Emotions are characterized by a set of components that represent the appreciation phases of emotion themselves (for example, happiness is emotion resulting from an unexpected and pleasant event).

MULTIMODAL CONCEPT FOR EMOTION RECOGNITION

Classically in the literature, emotion recognition systems are considered "multimodal" if they allow recognition based on multiple channels of emotional communication at the same time: facial expression, voice, gestures, and physiological responses. We propose to consider emotion recognition as an interaction between human and machine.

The multimodality paradigm in human machine interaction is characterized by the use of several means of communication to communicate with a machine, as illustrated the famous example of "down here" combining word and gesture (Hamdi, 2014). We rely on modality definition given by Nigay (1996). A modality is defined by following relation:

$$modality = <d, sr> \mid <modality, sr> \tag{1}$$

with:

- d is physical device of interaction: mouse, camera, microphone, motion sensor, GPS, screen...
- sr is a representational system, i.e. a conventional structured system of sign providing a communication function.

This definition makes it possible to characterize an input interaction by taking into account and linking two abstraction levels from both human and system point of view. Human point view, the device is at a low abstraction level. Human acts on the device. The representational system is at the user cognition level: which communication channel to use (e.g. the voice), how format the information to be understood of the machine (e.g. pseudo-natural language)? From a system point of view, the couple provides information about the devices implemented and the domain and data format exchanged between man and machine.

Definition (1) is recursive. By developing this definition, we obtain that a modality consists of physical device and 1 to n representational systems a sequence. By developing definition, we obtain:

$$modality = <\ldots << d, sr1>, sr2>\ldots srn> \tag{2}$$

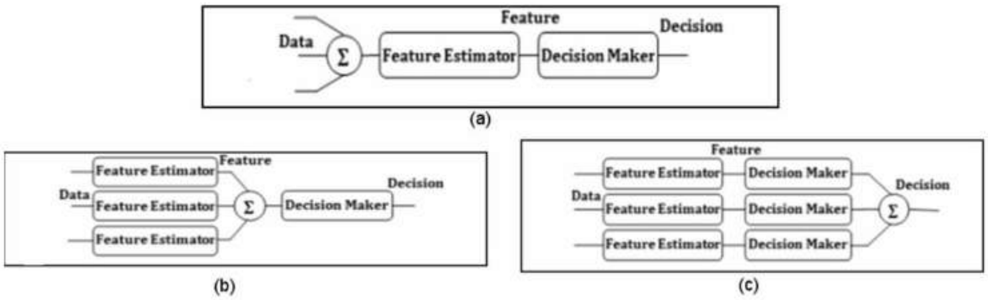
This writing explicit transfer possibility of representational system. This notion represents the fact that the same information can be translated according to several representational systems and used by other modalities before obtaining an order or a complete task. Multimodality is the multiplicity of modalities, i.e. devices and representational systems used to act on the system or to have information on this system.

Data fusion consists an essentially multimodal approach to emotion, with the aim of proposing bio-socio-emotional models, using different sensor (camera, biosensor, microphone, EEG headset). This allows to collect multimodal signal associated with emotion: physiological signal (biosensor), facial expression (camera), etc. These signals are then processed with algorithms to classify them according to the emotion most likely felt.

Some studies have investigated possible multimodal fusion mechanisms that can be used for emotion recognition. Thus, the multimodal information fusion can take different forms depending on the level at which it is performed. There are three methods to merging data from different sensors (Sharma, Paylovic, & Huang, 1998).

This Figure illustrates these three possibilities for merging at different stages of recognition. It is thus possible to merge (i) data directly after signal extraction (signal level), (ii) attribute coming from the various sensors (characteristic level), or (iii) the information during decision-making phase

Figure 4. Three levels of multimodal fusion (Sharma et al., 1998): (a) Signal level; (b) Characteristic level; and (c) Decision level



(decision or conceptual level). Each data fusion technique has its advantages and limitations. Its relevance is then always dependent on the application.

Signal Level Fusion

This merger is the lowest level of multimodal fusion (a). It is made on the raw data for each signal, and can only be applied when signals are of the same natures and have the same temporal resolutions. Thus, several signals coupling and synchronization is rarely possible because the different modalities often has sensors with different signals characteristic. This technique is therefore rarely used because the signal integration difficulty and sensitivity to noise, produced by a malfunction of sensors used.

Characteristic Level Fusion

Characteristic level fusion is performed on all characteristics extracted from each signal. The objective of this approach (b) is to obtain, from feature vectors extracted from each modality involved, a multimodal vector. This fusion is the most used for emotion recognition.

Several solutions have been proposed in literature. The simplest and most widely used is to concatenate unimodal vector. Huang and al compared the result of emotion recognition using three tests (video alone, audio alone, audio and video combined). They found using nearest neighbour method (KNN), that multimodal approaches were more efficient. They have shown that it is possible to achieve a recognition rate of 97.2% against 75% for audio and 69.4% for video.

Other methods, such as principal component analysis (PCA) or linear discriminant analysis, allow the selection of most relevant characteristics, or methods used for characteristic selections (SFFS, SFBS, etc.) (Hamdi, 2014).

Decision Level Fusion

This fusion is performed at the output of each signal classifier. As a result, affective states are first categorized for each modality and then integrated to obtain an overall view of the emotional states (Sharma et al., 1998). Thus, this approach consists of merging decision taken separately for each of the modalities. This technique, as opposed to characteristic level fusion, frees itself from the nature of the low-level characteristic used for decision-making. Partial decisions are thus taken separately for each of the modalities.

Several decision-making merging strategies has been tested. They all show a clear improvement in the result compared to taking into account a single modality.

Voting Method

Voting method is the simplest method of information fusion to be implemented and well adapted to decision-making. This no-parametric method does not require learning and has the advantages of being simple and natural. In addition, it does not require any prior knowledge. More than a fusion approach, the voting principle is a combination method particularly suited to symbolic decision

(Martin, 2005). For formulation, pose Sj (x) = i, the fact that source Sj decide di. M$_o$reover, we assume that di decisions are exclusive.

Thus, at each source, is associated the indicator function:

$$M_i^j(x) = \begin{cases} 1 & if\ S_j(x) = i \\ 0 & else \end{cases}$$

Source combination is expressed by the following relation:

$$M_K^E(x) = \sum_{j=1}^{m} M_k^j(x)$$

For all k, the combining operators is associative and commutative. The rule of majority voting is to choose the decision taken by maximum of sources, that is say the maximum of M_K^E. However, this rule does not always admit solution in the set of decision d1, ... dn as in the case where the source number m is even or in the case where each source assign to x different class. In this situation, it is necessary to add class dn+1 wh$_{ich}$ represent the total uncertainty in a closed world:

dn + 1 $_{= d1}$, ... dn

The final expert decision taken by this rule is written by:

$$E(x) = \begin{cases} k & if\ max_k M_k^E(x) \\ n+1 & else \end{cases}$$

This rule is however unsatisfactory in cases where source give a maximum point for different classes. The most common rule is then the rule of absolute majority voting. It is written:

$$E(x) = \begin{cases} k & if\ max_k M_k^E(x) > \dfrac{m}{2} \\ n+1 & else \end{cases}$$

Voting method is applied when the information is expressed symbolically, in the assumption form. That's why it is more suited to decision level fusion for discovery, detection, classification, identification and recognition applications.

Empirical method is Consists of merging decisions at the end.

Physiological Activities and Emotional Induction

There are several physiological activities that can allow the determination of emotion beyond the face, voice and body gestures.

Electro-Myographic Activity (EMG)

When muscle is contracted, electrical potentials are generated by the muscle fibres involved. This electrical potential can be measured by electro-myography (EMG).

In particular, EMG makes it possible to measure electrical activity of muscle via electrodes placed on the face. Several studies have shown that EMG signal provide an objective measure for the emotion recognition (Darwin, 1872). In this context, emotional tone is defined as an involuntary, light, moderate and permanent muscles contraction, maintained by the nervous flows. It has been shown that this muscle activity increases during stress, as well as during negative-valence emotion (Hamdi, 2014).

Heart Rate (ECG)

It defines the number of heartbeats (heartbeats) per unit of time, usually in beats per minute (BPM). It is generally associated with activation of the autonomic nervous system (ANS) (Ekman et al., 1982) itself related to the emotion treatment (Izard, 1971). Thus, the heart rate variation can be associated with different emotions.

Skin Temperature (SKT)

The body controls the internal temperature by balancing heat production and heat loss. Heat production is achieved through muscle contraction, metabolic activity and vasoconstriction of the skin blood vessels. The activation of this indicators varies according to the emotion considered and the subjects, which induces a form of complex responses making it possible to distinguish different emotions.

Respiratory Frequency (FR)

Respiratory rate (FR) is the times number of lifted chest for one minute. In other words, it corresponds to breathing number of cycles (inspiration /expiration) per minute.

During inspiration, skeletal muscle (such as diaphragm and intercostal muscle) contracts, increasing volume of chest and lungs. Upon expiration, the muscle involved in the breathing loosen, reducing chest and lungs volume.

Respiration affects many organs such as lung, respiratory tract and respiratory muscle. It is quantified by variable such as lungs volume, amount air displaced during inspiration and expiration, pressure, airflow. Respiration rate can be influenced by resistive properties and organs contraction involved (Isen, 2000). Breathing is exploited by SNA and SNS because it is usually involuntary and induce cue emotional, but it can be controlled for short periods of time.

Central Nervous System

The central nervous system (CNS) is composed of brain, cerebellum, brain stem and spinal cord. The brain activity of CNS is a prominent role in emotion recognition. Several studies on emotion recognition via analysis respiratory rate have been carried out (Pfaltz, Wilhelm, & Grossman, 2006). The result agree on a few points. Indeed, a relaxation and rest state is characterized by a slow and light breathing. This state corresponds to calm and relaxation states; while if the breathing is slow and shallow, it is rather a withdrawal state, as for depression. In contrast, rapid and deep breathing is generated by emotional excitement and significant physical activity. It is associated with stronger emotion such as anger or fear (Naqvi, Rainville, Bechara, & Damasio, 2006).

ACQUISITION AND PROCESSING OF PHYSIOLOGICAL SIGNALS

The physiological activity is characterized by the calculation of several characteristics from the recorded signals. Once the acquisition of physiological signals is done, it is important to define a methodology that allows the acquired signals to be translated into a specific emotion.

Several works in the emotion recognition has been carried out using these methods based on statistical values as well as the construction of relevant indicators vector (Darwin, 1872).

Each physiological signal (EEG, ECG, etc.) is designated by the discrete variable X. X_n represents the value of the nth sample of the raw signal, where:

n = 1. . . N

and N is the total number of samples corresponding to T seconds of signal recording.

Assuming that each measured signal is generated by a Gaussian process, with independent samples and identically distributed. The two physiological functions that can be used to characterize a raw physiological signal are the mean and the standard deviation (Equation 1 and Equation 2):

$$\mu_x = \frac{1}{T} \sum X(t) = \bar{X}(t) \tag{1}$$

$$\sigma_x = \sqrt{\frac{1}{T} \sum_{t=1}^{T} \left(X(t) - \mu_x \right)^2} \tag{2}$$

In order to evaluate the trend of an X-signal on a test, the derived average (Equation 3), the normalized first derivative (Equation 4), the second derivative (Equation 5) and the normalized second derivative of the signal (Equation 6) can also be calculated:

$$\delta_x = \frac{1}{T-1} \sum_{t=1}^{T-1} \left| X(t+1) - X(t) \right| \tag{3}$$

$$\bar{\delta}_x = \frac{1}{T-1} \sum_{t=1}^{T-1} \left| \bar{X}(t+1) - \bar{X}(t) \right| = \frac{\delta_x}{\sigma_x} \tag{4}$$

$$\gamma_x = \frac{1}{T-2} \sum_{t=1}^{T-2} \left| X(t+2) - X(t) \right| \tag{5}$$

$$\bar{\gamma}_x = \frac{1}{T-2} \sum_{t=1}^{T-2} \left| \bar{X}(t+2) - \bar{X}(t) \right| = \frac{\gamma_x}{\sigma_x} \tag{6}$$

Finally, the maximum (Equation 7) and minimum (Equation 8) of a signal can also provide relevant information:

$$\min_x = \min_x x(n) \tag{7}$$

$$\max_x = \max_x x(n) \tag{8}$$

These characteristics are very general and can be applied to a wide range of physiological signals (EEG, EMG, ECG, RED, etc.). Using these characteristics, we obtain a characteristic vector Y of 8 values for each sample. This vector can cover and expand a statistical series typically measured in the literature (Darwin, 1872):

$$X = \left[\mu_x \sigma_x \delta_x \bar{\delta}_x \gamma_x \bar{\gamma}_x \min_x \max_x\right]$$

Classification Methods

After extraction of desired characteristic, it is necessary to identify the corresponding emotion. This treatment is usually done by a classifier. A classifier is a system that group similar data into a single class. He is able to make the correspondence between calculated parameters and emotion. There are several classification methods. These include: Support Vector Machine (SVM), Bayesian Naïve Classification, Logistic Regression. Here we present some these of method.

Support Vector Machine (SVM)

Support vector machine or wide margin separator are among the best-known method. They are inspired by Vapnik's statistical theory of learning (Vapnik, 1999) and consist of a linear classification by supervised learning. The principle is to separate the data into two classes, by building hyperplane between the points of different classes. The point of data closest to the separation plane are called support vectors. This process is illustrated in the following figure.

Given the couples:

$$\left(x_1, c_1\right), \left(x_2, c_2\right), \ldots, \left(x_n, c_n\right) x_j \in R^n, c_j \in \left\{+1, -1\right\}$$

where xi is the point that has just been classified. c_i represent membership class. The first class correspond to a positive answer ($c_j = +1$), the second to a negative answer ($c_j = -1$).

The SVM method separate the positive-class vector from the negative-class vector by a hyper plane defined by the following equation:

$$w \cdot x - b = 0 \quad w \in R^n, b \in R$$

Vector of points w is perpendicular to the separation hyperplane and b represent an offset constant with respect to hyperplane. If the two classes are linearly separable, parameter w and b can be chosen so that:

$$c_i = \operatorname{sign}\left(w \cdot x - b\right)$$

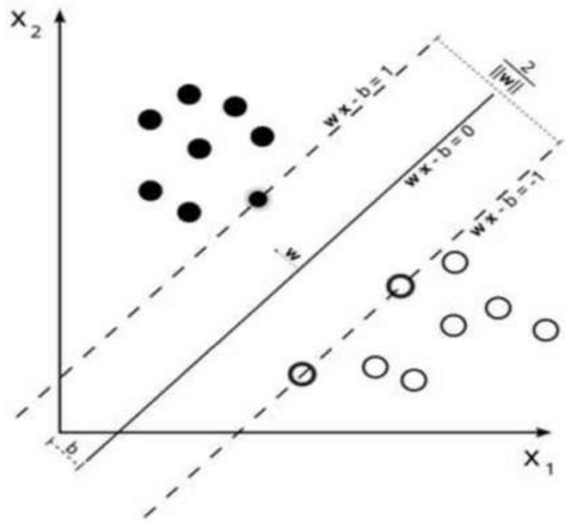
For all samples, the SVM method finds optimal hyperplane by maximizing margin (distance between positive and negative labelled vector):

$$w \cdot x_i - b = 1$$

$$w \cdot x_i - b = -1$$

With this standardization that is canonically shaped, the margin is worth $\frac{1}{|w|}$ search for the optimal hyperplane therefore amounts to maximizing the margin between separation hyperplane and

Figure 5. Illustration of SVM classifier: circles and crosses respectively represent positive and negative response; the lines represent decision surface



the two classes. Thus, this search amounts to minimizing |w|, or to solving following problem which concern parameters w and b:

$$w \cdot x_i - b > 1 \ \ for \ \ c_i = 1 \ \ et$$
$$w \cdot x_i - b < -1 \ \ for \ c_i = -1$$

We can rewrite the problem as:

$$\begin{cases} minimize & \frac{1}{2}\left\|w\right\|^2 \\ under\ \ the\ \ constraints & l_k\left(w^T x_k + w_0\right) \geq 1 \end{cases}$$

This problem writing, called primal formulation concerns the parameters w and b. To solve this problem one can use conventional minimization algorithm.

Bayesian Naïve Classification

The naive Bayesian classification is a type of probabilistic classification, based on Bayes' theorems, with a strong (so-called naive) independence of hypothesis. It belongs to the family of linear classifier. The probabilistic model for a Bayesian classifier is a conditional model based on the Bayes rule, which reads as follows:

$$p\left(A / B_1, B_2, \ldots, B_n\right)$$

where A is a dependent class variable whose instances or classes are few numerous, and conditioned by several characteristics variable B1, B2, …, Bn.

When characteristic number n is large, or when these characteristics can take a large number of values, to base this model on probabilities table becomes impossible. Therefore, we derive it so that it is more easily soluble in following way:

$$p\left(A / B_1, B_2, \ldots, B_n\right) = \frac{p\left(B_1, B_2, \ldots, B_n\right) * p\left(A\right)}{p\left(B_1, B_2, \ldots, B_n\right)}$$

These probabilities can also be calculated by Bayes rule, adaptively with the arrival of information from a new source:

$$p\left(A / B_1, B_2, \ldots, B_n\right) = \frac{p\left(B_1 / A\right) * p\left(B_2 / B_1, A\right) \ldots p\left(B_1 / A\right) * p\left(B_n / B_1, B_2, .., B_{n-1}, A\right)}{p\left(B_1\right) p\left(B_1 / B_2\right) \ldots p\left(B_n / B_1, \ldots, B_{n-1}\right)}$$

These two ways of probabilities calculating are equivalent, but the second one makes it possible to integrate the available information successively whereas the first one needs to have source information simultaneously.

In fact, the difficulty of estimating the different probabilities in the preceding equation (because it requires a large number of learning data) pushes to make a hypothesis of statistical independence of conditional source on decision.

We obtain as follows:

$$p\left(A / B_1, B_2, \ldots, B_n\right) = \frac{\prod_{j=1}^{n} p\left(B_j / A\right) p\left(A\right)}{\prod_{j=1}^{n} p\left(B_j\right)}$$

This equation show that combination type expressed as a product, so it is a conjunctive combination. Under independence hypothesis, it becomes commutative and associative, whereas it is not commutative in the version given in previous Equation. When the independence hypothesis is made, the Bayesian approach is called naive. Recent studies have shown that there are theoretical reason for classifier quality (Zhang, 2004).

Logistic Regression

Logistic regression is a statistical technique based on a binomial model (Berkson, 1944). This technique is a special case of the generalized linear model. It allows to study the relation between dependent variable and several explanatory variables. When the dependent variable has two categories, we said binary logistic regression (dichotomous logistic model). It is possible to perform a logistic regression to predict the values of a categorical variable with K (K>2) modalities. In this case, we speak of polytomic logistic regression (multi-classes logistic model). In this section, we present the dichotomous logistic model (k = 2), applicable to polytomous logistic regression (k> 2).

In what follows, we will write Y variable to predict (variable explained) with two possible modalities $\{1, 0\}$ and $X = (x_1, x_2, \ldots, x_n)$ which represent the predictor variable (explanatory variable). Objective of this method is to model the membership probability of a predictive variable to modality k (0 or 1). The following equation is used to calculate the probability of belonging:

$$\Pi\left(x\right) = p\left(Y = 1 / X = x\right) and\ 1 - \Pi\left(x\right) = p\left(Y = 0 / X = x\right)$$

Even if Π is not binary, it is always bounded in interval [0; 1]. Logistic regression thus consists of modelling some transformations of Π, called logit transformation, by a linear function of explanatory variable:

$$\operatorname{logit}\left(\Pi\left(x\right)\right) = \ln\left(\frac{\Pi\left(x\right)}{1-\Pi\left(x\right)}\right) = \beta_0$$

This model is also written:

$$\operatorname{logit}\left(\Pi\left(x\right)\right) = \frac{exp\left(\beta_0 + \sum_{j=1}^{p}\beta_j x_j\right)}{1 + exp\left(\beta_0 + \sum_{j=1}^{p}\beta_j x_j\right)}$$

Where β_0 and $\beta = (\beta_1, ..., \beta_p)$ are real coefficient to be determined from the learning game. Their estimation is usually done using the maximum likelihood method on the learning game. Since the likelihood equation do not have an analytical solution, it is necessary to use a Newton-Raphson type numerical method (Hamdi, 2014). Once the β is estimated, it is possible to apply the MAP (maximum a posteriori) rule as a decision rule.

The classification rule then amounts to assigning new observation x to the class:

C_1 if $\beta_0 + \beta'_x > \log(\Pi 2 / \Pi 1)$

and assign it to C_2 otherwise. The main advantages of logistic regression is that it is very general because it does not make assumptions about class distribution. Moreover, it allows estimation with a small parameters number (Saporta, 1990).

Logistic regression is considered one of the most successful modelling method that can be controlled by several statistical indicators. Moreover, his results are very explicit.

Evaluation Measure of a Classifier Performances

We propose several measures to give an overall evaluation of classifier performance namely: the rate of good classification, the Matrix of confusion and Precision.

Rate of Good Classification

The first measure we will be interested is the good classification rate (tbc). This is the most natural and obvious indicator for evaluating the performance of a classification systems. This value, simple to calculate, correspond to the number of elements correctly identified by system. The definition of good classification rate without taking into rejection is:

$$\text{tbc} = \frac{\text{Number of items correctly identified}}{\text{total Number elements}}$$

This criterion is therefore not sufficient for the relevant assessment of performance (Provost & Fawcett, 1998) remedy this, we will incorporate a factor that will weigh the score by taking class distribution and the costs associated with decision.

Confusion Matrix

A more precise analysis of the behaviour of the classifier can be obtained by a matrix of confusion. This matrix is a quantitative representation of overall performances of each classifier in recognition and rejection, for each class. Table 2 groups the different classification situations that allow the differentiation of errors according to each class, in order to evaluate classifier.

The confusion matrix is a double-entry array (Caloz, Bonn, Collet, & Rochon, 2001). Online, express the result in relation to the different classes defined. The columns express the result in relation to the reference emotion. The crossover cell therefore indicate the emotion number belonging to the class i, and assigned to the class j. The cells corresponding to i = j express the emotion number correctly affected.

Precision

The third measure most commonly used to compare two classifiers is the precision measurement obtained on a validation set. Precision is the proportion of true positives among the positive label. This concept is often used because it reflects the user's point of view: if the precision is low, the user will be dissatisfied because he will have to read information that does not interest him.

Precision is defined by:

$$precision = \frac{TP}{TPos} = \frac{TP}{TP + FP}$$

Standardized Induction Techniques

One of the major topic in the study of emotion is how different emotions can be induced in a standardized way. In this context, many techniques and methods have been proposed. Emotion induction is an objective to create emotional stimuli to study and characterize the emotion felt. These are based on the construction of visual or auditory data base of standardized stimuli (images, sounds, videos). They have been widely used for emotion recognition from physiological signals (Hamdi, 2014; Ochs, 2007).

Table 2. Confusion Matrix

	positive decision	Negative decision	
Positive label	True positive, TP	False Negative, FN	Pos^a
Negative label	False positive, FP	True Negative, TN	Neg^b
	$PPos^c$	$Pneg^d$	N

[a]number of labelled positive elements in the base;
[b]Number of labelled negative elements in the base.
[c]Number of positive elements;
[d]Number of negatively classified elements.

CONCLUSION

According to the different studies and theories of emotions, the definition of what is an emotion, their exact nature, or the process responsible for our emotional reactions, does not make consensus. However, it is possible to recognize and measure different emotional manifestations. This recognition is imperfect and not totally exclusive, so some theories comes from several approaches, because of the one hand, the variability between individual, and on the other hand, the complexity of the signal.

After seeing, from a psychological point of view what an emotion is, how it is generated, and how it can be represented, several studies have been interested in collecting data in order to improve model of recognition. We have studied the different aspects of emotion recognition systems. We presented the levels of analysis via different emotional communications channels, and the characteristic observed for each of these channels.

We have seen that multimodality is a widely used concept for data analysis in general. We presented a survey regarding the three methods of affective data fusion. We have indicated the advantages and limitations of each method and highlighted the fact that they are not of the same quality.

We also discussed the analysis levels, by physiological signals, and the characteristics observed for each of the proposed signal (EEG, EMG, ECG, VR). Then we presented methods and tools for acquisition and processing of physiological signals. Finally, we discussed the evaluation criteria and induction techniques of emotion.

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