From Biosignals to Affective States: a Semantic Approach

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ABSTRACT

The final goal of Affective Computing is in allowing to recognize human emotional states by means of automatic procedures. Despite scientific literature evidences the concrete usefulness of possible approaches based on biosignals analysis to detect and correctly classify emotions, existing systems and tools are generally too invasive for common subjects and in addition they are too intensive in terms of needed processing. Hence, practical application and effectiveness of such kind of solutions is really limited to laboratory-controlled contexts and this seriously compromises their porting to real scenarios. This paper aims to propose an innovative approach for the automatic interpretation of affective information. Biosignal features of subjects stimulated by emotions are extracted and annotated automatically adopting a semantically rich and non-ambiguous language. Logic-based matchmaking, leveraging non-standard inference algorithms, allows to detect the most probable emotional state of the subject. The proposed approach has been validated through the implementation and the experimental evaluation of a prototypical system.

CCS Concepts

• Theory of computation~Semantics and reasoning • Computing methodologies~Description logics • Computing methodologies~Cognitive science • Information systems~Mobile information processing systems • Hardware~Digital signal processing • Hardware~Biology-related information processing

Keywords

Affective Computing; Knowledge Representation; Semantic-based Matchmaking; Ubiquitous Computing; Biosignal Processing.

1. INTRODUCTION

Emotions are physiological and cognitive responses the organism provides given some external stimulus. The emotional component of the human personality has a fundamental role in decisional processes: "the reason allows to analyse clearly a situation, but only the emotional motivation allows to make a choice". This is what emerged in 1997 in the first publication by Rosalind Picard [1], which opened the way to a novel branch of Artificial Intelligence applications named Affective Computing. The final goal of Affective Computing is in allowing to recognize human emotional states by means of automatic procedures. Possible scenarios range from enhancing human-machine interaction to biofeedback generation devoted to the improvement of a cognitive state and the wellbeing of a generic subject. In the same way, it is warmly welcome to adopt techniques and tools to reduce potential risks the subjects are exposed to.

Starting from the above work, several studies have been pursued devoted to build automated and scalable systems able to integrate "emotionally intelligent technology" and then able to adapt their behaviour according to the detected emotions. A similar approach could allow to overcome one of the most relevant limits to an effective development of automated and interactive software agents (human-machine interfaces with social abilities, talking heads [2], avatars [3], etc.). The great enhancement of sensor technologies has allowed to progressively extend the application of such a methodology. Anyway, the intrinsic intangibility of biological data makes the above approaches even more difficult to understand and adopt.

In the first phases of studies and research in the field of Affective Computing, possible solutions have been mostly based on methodologies leveraging Natural Language Processing. More recently, studies about facial look, speech recognition and processing, motion analysis and biosignal mining have evidenced that physical expressions measurable objectively still exist for each specific emotion. In particular, biosignal processing is a promising research area as it is characterized by some not negligible strong elements in terms of:

- intrinsic affordability: there are no social masks and there are several measurement technologies exploiting non-invasive sensors which make them suitable for a wide range of applications;
- methodological advantages: the outcomes are rich and dynamic, and this is more interesting and suitable with respect to traditional approaches related to the phycology of emotions. They were based on interviews, questionnaires and experts' opinion as a mean to detect subjective sensations which are more largely influenceable and not measurable in real-time.

On the contrary, it should be considered that biosignal analysis also has some critical aspect as:

- the presence of measure artefacts deriving from different types of detection systems adopted in the signal extraction;
- invasiveness of some devices in applications on human subjects with a subsequent difficult applicability and a restricted exploitation;
- temporal variability in evidencing physiological changes;
- possible not negligible individual differences due to the physiological nature and to the context of the subject.

Possible research fields (philosophic, neurological and anthropological) face the problem in different ways and researchers have developed different theories to support the interpretation of emotions, which can be reported to three main types:

- the categorial approach [4], *i.e.* a model commonly adopted in the automated detection of emotions. It classifies each emotional experience to one of the six universal basic emotions (happiness, sadness, astonishment, fear, anger and disgust);

- the dimensional approach [5], which classifies the emotions following two different directions: valence (that is the quality of the emotion or the feeling of badness/goodness it gives) and arousal (expressing the level of activation of the emotional state or the intensity of it). The variation of valence and arousal produces the evolution from an emotion to another one;

- appraisal theory [6]: it is based on the theoretical evaluation of the cognitive situation of a subject. The appraisal can be described as a phenomenon following the perception which refers to an automatic evaluation about the presence/absence of a given object/event and about its positiveness/badness.

Despite scientific literature evidences the concrete usefulness of possible approaches based on biosignals analysis to detect and correctly classify emotions, existing systems and tools are generally too invasive for common subjects and in addition they are too intensive in terms of needed processing. Basically, they refer to common architectures supporting the processing of conventional biological data, extracted through complex sensing interfaces. This processing activity reveals distinguishing elements (also named *features*) of physiological signals by applying data mining and machine learning techniques for emotion classification. That procedures have a not negligible impact on computational resources. Hence, practical application and effectiveness of such kind of solutions is really limited to laboratory-controlled contexts and this seriously compromises their porting in real scenarios.

Starting from such state of the art, this paper describes a novel wearable cyber-physical system based on a Wireless Body Area Network (WBAN) for emotion detection and classification. It is based on the application of automated reasoning techniques grounded on the knowledge representation theory and oriented to automatically recognize emotional states by means of the continuous monitoring of physiological signals in a non-obtrusive fashion. In greater detail, it is composed by:

1. A multi-sensing architecture able to measure most relevant bio-signals for emotion identification and dynamic tracking during given intervals.
2. A processing sub-system hosting a multi-agent software able to annotate physical signals in a high-level formalism for knowledge representation based on Description Logics and executing semantic-based inferences devoted to recognize emotions effectively.

These peculiarities allow for making autonomous and independent such system from physical characteristics of the operating environment where it operates to reach a minimum invasiveness goal, so making the system itself suitable for a daily life adoption. The proposed system is also able to attempt an improvement of the emotional status of a user by identifying a feedback signal (physical stimulus), useful in orienting his/her physical and psychic wellbeing in an automatic fashion.

Feasibility of the proposed approach has been evaluated by means of tests carried out on a reference synthetic dataset: effectiveness of emotion detection has been evaluated along with the needed computational complexity in sigh of a possible implementation on a fully mobile testbed.

The paper is organized as reported hereafter. Next section presents a general survey about most relevant state-of-the-art research useful to frame and understand the proposed approach. Furthermore, it will be described the framework we propose along with devised methodology for the emotion detection. Finally, a case study will be presented in order to better evidence the experiences we have carried out with the implemented prototype before conclusion and description of future research directions.

2. STATE OF THE ART

Biosignal-based identification of a subject's affective state has recently spread by virtue of the development and availability of low-cost pervasive yet non-obtrusive sensors, capable of reliable performance and continuous measurement [7]. The most significant analyzed biosignals are as follows.

- *Brain electrical activity:* it is measured trough electroencephalography (EEG). It allows discriminating stimuli with positive or negative emotional valence as well as different levels of arousal.

- *Heart electrical activity:* by means of electrocardiography (ECG) the heart electrical activity in the cardiac cycle can be recorded. A low value of heart rate variability (HRV) can indicate a relaxed state, while an increased HRV can indicate a state of frustration or distress.

- *Face muscle electrical activity:* electromyography (EMG) detects the electrical activity of muscles involved in the expression of affective states, such as zygomatic and frontal muscles. For example, zygomatic muscle is in high tension when a distress or frustration state occurs [8].

- *Electrodermal activity:* also known as galvanic skin response (GSR), electrodermal activity (EDA) indicates variations in electric conductance of the skin caused by the action of sweat glands. Many studies have highlighted that the measured variation intensity of conductance has a mostly linear relationship with emotion arousal [9].

- *Skin temperature:* it depends on the underlying blood flow and is regulated by the sympathetic nervous system, which reduces blood flow when muscular fibers are activated. Ekman and Levenson [10] have shown that a mean temperature increase between 0.1°C and 0.2°C during the expression of anger-like emotions and a decrease between 0.01°C and 0.08°C when a feeling of fear occurs.

- *Respiration:* it is measured as the number of respiratory acts per minute, by means of an expansion sensor wrapped around the chest, providing the respiratory sinus frequency. It usually decreases with relaxation, while unexpected events or states of anxiety can determine a temporary suspension of breath, and negative emotion cause irregular respiration.

A crucial aspect for Affective Computing research is the availability of good-quality data sets. Unfortunately, existing data corpuses are few and their quality is not always adequate. In particular, for the goal of this work – the analysis of affective states starting from physiological signals – three publicly available data sets have been assessed: MANHOB-HCI [11], DEAP [12] e DECAF [13]. A detailed analysis has elicited several problems concerning the incongruence within data (due to inaccurate compilation of emotional self-assessment questionnaires) and the lack of characterization information (due to the low numbers of recorded subjects).

For the classification and detection of emotions through the analysis of physiological signals, three main kinds of approaches have been found in the literature: the mostly adopted one is based on statistical and machine learning techniques; the other relevant ones are rule-based systems and deductive inference [14] [15]. This work adopts this latter approach, as an alternative to the prevalent machine learning proposals: as demonstrated in contexts such as semantic-based product annotation and discovery [16], it allows a more effective modeling of the information describing the complex phenomenon of emotion and affective states, going beyond the simplistic classification provided by machine learning systems, which produce opaque labels and often miss the implicit relationships between biosignals, sensor observation and their context.

3. USING ARTIFICIAL INTELLIGENCE FOR EMOTION RECOGNITION

The initiative known as Semantic Web [17] has allowed to transform the World Wide Web from a collection of human-readable documents to a collection of machine-understandable data, providing a framework to describe resources, properties and relationships in a standardized way. Resource annotation is grounded on logical formalisms defined in Knowledge Representation, the branch of Artificial Intelligence which studies models and languages to formalize knowledge about the world into machine-computable structures and to apply automated inference procedures. Inference refers to the capability of deduction of implicit knowledge starting from a set of explicit assertions composing a *Knowledge Base* (KB). Every KB is grounded on an *ontology*, a formal and explicit conceptualization of the structure of the knowledge pertaining a certain domain. This knowledge can thus be used by software agents and intelligent systems.

This work refers specifically to Description Logics (DLs), a family of logic formalisms for Knowledge Representation. Basic syntax elements are:

- *concept* (a.k.a. *class*) names, representing sets of objects;
- *role* (a.k.a. *object property*) names, linking pairs of objects in different concepts;
- *individuals* (a.k.a. *instances*), used for special named elements belonging to concepts.

They can be combined using *constructors* to form *concept and role expressions*. Each DL has a different set of constructors. A constructor used in every DL is the conjunction of concepts, usually denoted as $\sqcap$; some DLs include also disjunction $\sqcup$ and complement $\neg$. Roles can be combined with concepts using existential $\exists$ or universal $\forall$ role quantification. Other constructs may involve counting, as number restrictions. Concept expressions can be used in *inclusion* assertions and *definitions*, which impose restrictions on possible interpretations according to the knowledge elicited for a given domain. In simple DLs, only a concept name can appear on the left-hand side of an inclusion: this work adopts the Attributive Language with unqualified Number restrictions ($\mathcal{ALN}$) DL, having polynomial complexity for both standard and non-standard inference procedures.

In order to build an advanced framework for emotion recognition from biosignals, this work exploits in a peculiar way some non-standard inference procedures originally defined for *semantic matchmaking.* This is the search process for discovering the resources best satisfying a given request, where both resources and request are described in a logical language and are satisfiable with respect to a common ontology.

DL reasoners provide at least two basic standard inference services [18]: *Concept Subsumption* and *Concept Satisfiability*. Given a request R and a resource S, both satisfiable w.r.t. a common ontology $\mathcal{T}$, logic-based approaches to matchmaking in literature [7] use classification and consistency to grade match results in five categories: (i) *exact* - every feature requested in R is exactly the same provided by S and vice versa; (ii) *full-subsumption* - every feature requested in R is contained in S; (iii) *plug-in* - every feature offered in S is contained in R; (iv) *potential-intersection* - there is an intersection and no conflicts between the features offered in S and the ones requested in R; (v) *partial-disjoint* - some features requested in R are conflicting with some offered in S.

Exact and full matches are the best ones, but they are infrequent in practical scenarios. *Concept Abduction* and *Concept Contraction* non-standard inference services for DLs [18] allow computing a logic-based ranking of potential and partial matches best approximating the request. Furthermore, they provide explanation of matchmaking outcomes, which is highly desirable to justify results, so increasing user confidence in the system. Given an $\mathcal{ALN}$ ontology $\mathcal{T}$ and two concepts R and S both satisfiable in T, Abduction(R, S, $\mathcal{T}$) computes a *Hypothesis H* representing what is requested in R but not specified in S. If some requirements in the request R are in conflict with the resource S, *i.e.* their conjunction is not satisfiable w.r.t. $\mathcal{T}$, Contraction(R, S, $\mathcal{T}$) returns a pair of concepts (G, K) where G (for Give up) represents the part of R in conflict with S and K (for Keep) the remaining part of the request which is compatible. *Penalty functions* are associated to both Concept Abduction and Contraction, quantifying the semantic distance between R and S and enabling a logic-based ranking of a set of resources w.r.t. a request.

The goal of the proposed approach is to devise a framework capable of monitoring a set of physiological parameters of a subject, annotating biosignals automatically w.r.t. a domain ontology modeled for the purpose and classifying emotions of the subject through semantic matchmaking with respect a model of affective states built from the analysis of a reference data set. Figure 1 illustrates the overall framework architecture, showing individual components. Biosignals produced in response to emotional stimuli are gathered by a Wireless Body Area Network (WBAN, a communication micro-network enabling short-range wireless connection of implantable and/or wearable sensors) and used as system input.

In the proposed approach, the subject is equipped with a smartphone acting as WBAN coordinator to gather all data acquired by non-invasive wearable sensors. All subsequent computations are executed on board in full mobility. Raw data streams are processed in a preliminary mining step, in order to extract the significant *features* for each signal type to feed the emotion recognition model.

The *semantic-based annotator* component assigns a meaning to data streams by building concept annotations which join the

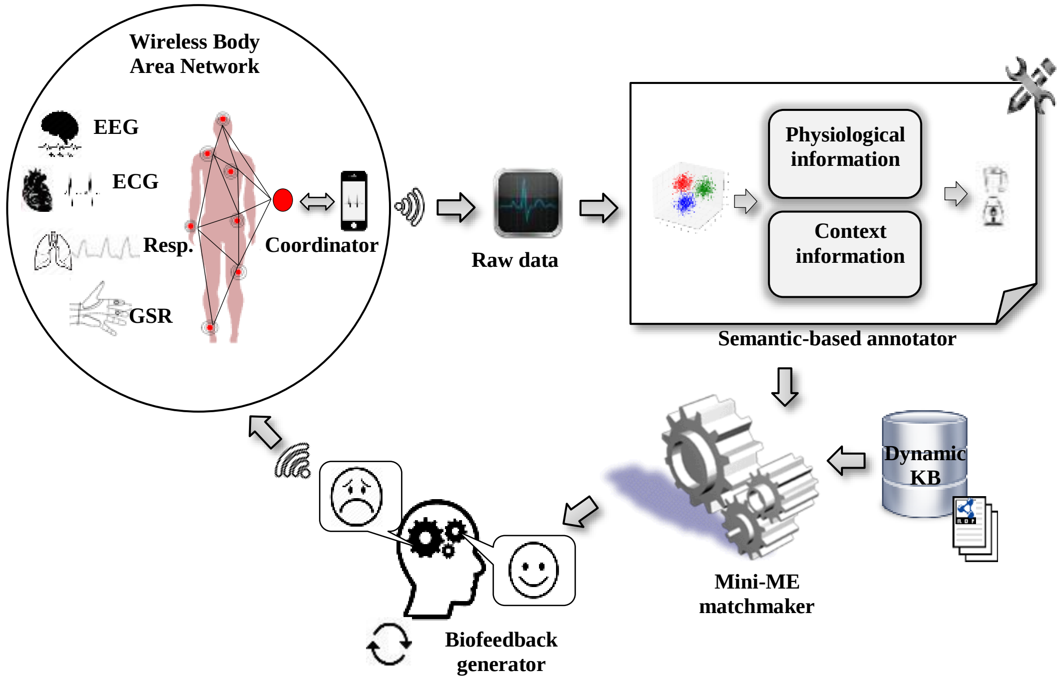

Fig. 1. Framework architecture

extracted physiological features with available context information on the subject and the environment. The above non-standard inference procedures allow matchmaking of the obtained annotation with a Knowledge Base of semantically annotated descriptions of reference emotions, modeled as an extension of the classical categorial approach. The output of the *Mini-ME* matchmaker [18] classifies the emotion as the closest one to the subject's state measured through biosignals. Finally, the system enables the best action to improve the user's affective state through an electrical feedback pulse, in order to direct responses in a fully automatic fashion.

4. CASE STUDY

The case study illustrated hereafter highlights the innovation of the proposal, centered on the affective state recognition through information endowed with rich and non-ambiguous semantics. In order to validate the proposed approach, the framework has been implemented in a prototypical system on personal computer. Collected physiological signals are EEG, ECG, skin temperature, EDA, respiration and facial EMG. Biosignals have been pre-processed with resampling and artefact removing, filtering only useful information content from signals. Before feature extraction, pre- and post-trial baselines (signals measured "at rest", respectively before and after the administration of emotional stimuli) have been removed by means of a low-pass filter with 50 Hz cutoff frequency. Furthermore, ECG signal measured on three channels has been pre-processed using Einthoven's law [19], so as to obtain the full cardiac trace. The subsequent feature extraction step exploited MATLAB (The MathWorks, Inc., version R2009a) and the open source libraries BioSig (http://biosig.sourceforge.net/) and EEGLAB (https://sccn.ucsd.edu/eeglab/). The selection of the most significant features to be extracted was obtained from a metanalysis of 134 experimental studies on the activity of the autonomous nervous system in the affective area [20]. Starting from extracted features, biosignals have been annotated automatically as individuals in a Knowledge Base. The construction of KB instances and the inference services have been executed with respect to an Affective Computing ontology, specifically modeled within this research to represent the domain. The KB construction has been performed in two distinct steps: the ontology has been modeled considering, for each emotion, the set of significant features and their intensity changes; the set of emotion instances has been built automatically by annotating extracted features of observed subjects in the data set. The three main phases for building the semantic-based description of a KB instance are:

- feature extraction from the signal waveform;
- association of semantics to the numerical values by creating a logical conjunct;
- composition of the full semantic annotation as ⊓ of conjuncts.

The first phase includes the sequential reading of each field from the time series of a subject and the association with a label corresponding to the extracted feature. The following example will clarify the process. Let us consider the Heart Rate (HR) feature related to the ECG signal. If it takes a value lower than 60 beats per minute (bpm), the associated label is "Bradycardia"; if its value is between 60 and 100 bpm the associated label is "Normal_HR", otherwise "Tachycardia". A subset of the modeled features and the corresponding labels are reported in Table 1. It is important to notice that ranges are not disjoint, therefore labels are not mutually exclusive: for example, a respiration rate of 9 respiration cycles per minute is labelled both as "Low_RR" and "Normal_RR".

Feature	Range	Label
Heart Rate (HR)	<60 bmp	Bradycardia
	60-100 bmp	Normal_HR
	>100 bpm	Tachicardia
Finger Temperature (FT)	18-23	Low_FT
	23-29	Normal_FT

	26-32	High_FT
Respiration Rate (RR)	5-10	Low_RR
	7-23	Normal_RR
	15-24	High_RR

Tab. 1 – Examples feature ranges and labels

Every conjunct is generated by evaluating the value of each feature. Table 2 shows an excerpt of the semantic annotation describing a subject, together with her feature values. From the semantic-based representation it can be observed that the subject has a high blood volume pumped by her heart, low skin temperature, high heart rate, etc.

Feature	Value	Semantic Annotation
HR	150	∀hasHR.Tachycardia
RR	15	∀hasRespiration_Rate.Normal_Respiration_Rate
FT	15	∀hasFT.Low_FT
EMG_frown	6μV	∀hasEMGfrown.EMG_frown_High
EMG_smile	0.6μV	∀hasEMGSmile.EMG_Smile_Low

Tab. 2 – Input and output of the semantic annotation phase

The subsequent classification step of a subject is performed by means of semantic matchmaking. It is based on the Concept Abduction and Concept Contraction non-standard inference services, described in Section 3. They are implemented in the Mini-ME reasoning and matchmaking engine, which is designed for efficient computation even on mobile and embedded devices [18]. The prototypical system is able to recognize the following 12 emotions: Fun, Anger, Anxiety, Disgust, Contentment, Embarrassment, Fear, Happiness, Joy, Pride, Relief, Sadness.

In the illustrative example taken from our case study, a subject is administered with a video clip which typically elicits a Fear emotion. In the matchmaking process, requests are represented by the 12 different annotations of the reference emotions, while the resource to be compared is the description of the physiological profile of the subject. Actions executed by the matchmaker to evaluate the degree of match of the subject's affective state with the ones in the KB are:

- selection of the first emotion (request) from the KB;
- semantic compatibility check between request and resource;
- in case of compatibility, execution of the Concept Abduction inference service; otherwise, execution of Concept Contraction followed by Concept Abduction on the returned *K* concept;
- calculation of the semantic distance values between requests and resource.

In the proposed example, the semantic distance values (normalized in a percentage scale) are as follows: Fear 57, Sadness 58, Joy 58, Embarrassment 59, Pride 60, Anxiety 60, Fun 61, Happiness 61, Anger 63, Disgust 64, Relief 65, Contentment 69. The lowest distance is the one for the Fear emotion, which is, in fact, characterized by an increased heart rate, a decrease in skin temperature and a gasping irregular breath. The emotion denoted as Anger is quite farther, as the increase in heart rate is associated with an increase in skin temperature and regular fast breath. Furthermore, the subject has a high value for the EMG_frown feature, because when one feels fear typically opens her eyebrows and eyes, while for the Contentment emotion the EMG_smile feature is high because in that case the sides of the mouth are curled up and eyes are straight open without differences from a neutral situation; finally, in the case of Anger one tends to frown and keep lips tight closed.

5. CONCLUSION

The proposed approach aims to extract and annotate information starting from biosignals for detecting emotions through a semantic-based automated matchmaking. The novelty of such a method and framework is in identifying the emotional state by means of knowledge representation techniques and non-standard reasoning algorithms. Biosignals analysis criteria have been studied and applied to extract the most relevant features for each class of physiological signal and there have been selected proper methods for an automatic annotation. In addition, both the Knowledge Base and the inference services refer to a shared ontology just devised for the domain conceptualization. The above framework has been further validated in a prototype. Experiments and reached outcomes show matchmaking techniques and technologies applied to the Affective Computing allow to detect the emotional state of a given subject in a proper fashion.

Now it is ongoing the implementation of the overall WBAN infrastructure and particularly we are working on the optimization of matchmaking algorithms to run them on mobile and embedded systems. A relevant future work will aim to define, design and implement adaptive running capabilities for the system: the final goal is to have a framework able to provide corrective factors –if any- as feedback stimuli and to orient system replies in a fully automated way to finally improve the cognitive status and the wellness of a subject.

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