Unveiling Affective Signals

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ABSTRACT

The ability to process and, subsequently, understand affective signals is the core of emotional intelligence and empathy. However, more than a decade of research in affective computing has shown that it is hard to develop computational models of this process. We pose that the solution for this problem lays in a better understanding of how to process these affective signals. This article introduces a symposium that brought together various approaches towards unveiling affective signals. As such, it is envisioned to be a springboard for affective computing.

Author Keywords

emotion, affect, affective computing, methods, signal processing, pattern recognition.

ACM Classification Keywords

G.3. Probability and statistics; H.1.2. User/Machine systems, I.5.2. Pattern Recognition: Design methodology, I.5.4 Pattern Recognition: Applications.

INTRODUCTION

The ability to process and, subsequently, understand affective signals of other people is the core of emotional intelligence and empathy. This capability continuously interacts with our behavior, in our everyday lives. Although a vast amount of work has been done on processing affective signals, progress is still limited. In particular, in ambulatory settings, automated processing of such signals is beyond science's current research [3]. We pose that substantial progress could be made when gaining on our understanding of affective signal processing.

PATTERN RECOGNITION BY MAN AND MACHINE

Recognition of affect, either by man or machine, is essentially a pattern recognition problem. The processing pipeline of pattern recognition (see also Figure 1) is as follows [1]:1) a signal that is captured and, subsequently, 2) processed byi) a physical system (e.g., the eye or a CCD sensor).This system provides us with a ii) measurement space on which iii) feature selection and/or preprocessing is applied. This results in iv) a pattern space on which again v) feature selection is applied. This provides, vi) a reduced pattern space, which is used for 3) the pattern classification process. This classification process can either be the development of the classifying system or its execution on a new set of data. In the former case, the decision rule for the classifier is developed; in the latter case, the classification process provides a label for the signal that was captured. The classification process can be supervised or unsupervised. In the case a priori knowledge on the signal is available, 4) a classification error can be determined and 5) the classification process can be adapted. Without a priori knowledge these last two steps cannot be applied and unsupervised classification is applied. Please also see Figure 1, which provides a visualization of this pattern recognition processing pipeline.

Human's pattern recognition is only known in general lines. This makes it hard, not to say impossible, to define it as a computational model. Moreover, experimentation with parameters that are of possible importance in the pattern recognition process is hard with humans. In contrast, artificial pattern recognition systems can be defined up to the highest detail, manipulation of their parameters is easy, and obtaining results from them only requires some patience, as it can take some time.

Although the differences between human and artificial systems are overwhelming, they also have things in common. Both human and artificial pattern recognition systems often try to solve the same problems; e.g., playing chess, recognizing objects, or making decisions. If such a problem is solved, it is stated that the artificial pattern recognition system has been successful. Alternatively, human's pattern recognition system itself is sometimes taken as an example for artificial pattern recognition systems. Then, not only the results of the system are of interest but also to what extent the artificial system mimics its human counterpart. In the long run, the latter approach is also expected to bring significant progress in pattern recognition results by machines.

MB'10 August 24-27, 2010, Eindhoven, Netherlands
©ACM 2010 ISBN: 978-1-60558-926-8/10/08…$10.00

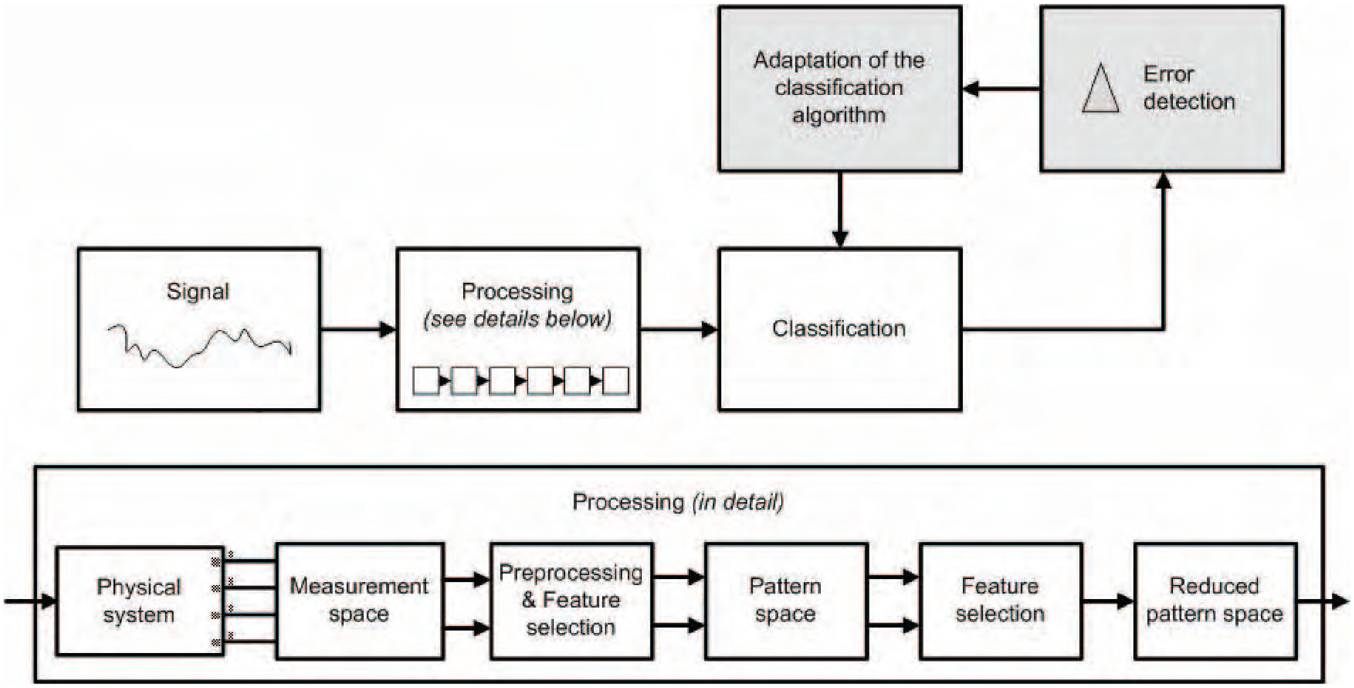

Figure 1. The pattern recognition processing pipeline, inspired by the work of Meissel[1]. The gray boxes denote the stages that only apply to supervised learning strategies. With unsupervised learning strategies the decision algorithm is fixed, as no a priori knowledge is available on which the error detection can be based.

LEARNING FROM EXAMPLES

The ease with which humans learn is deceiving, as it is a refined process and evolutes over human one's life. Artificial pattern recognition aims to mimic human learning through applying adaptive algorithms, founded on decision rules. Throughout half a century, a broad range of adaptive algorithms have been proposed. In the continuous rat race to keep improving, these algorithms became more and more complex throughout the years.

To enable learning, the decision rule has to be able to adapt.For this, first, the error in the classification has to be identified; see also Figure 1. Second, a function has to be present that receives the error as input and enables the modification of the decision rule. Third, the decision rule has to be modified. Again, this is easier said than done. For example, in what stage of the pattern recognition pipeline, the modifying function has to hook into?

The type of examples on which the learning is based, is also of importance. For each class to identify, both positive and negative samples can be employed. Further, the level of deviation of the sample compared to the system's known set is of importance. With real world problems, the level of deviation can be expressed in both the number of dimensions in which the deviation is presentand the distance in each of these dimensions.

Humans seem to have little problem with samples that urge them to adapt their pattern recognition process. However, this is possibly misleading. In either way, how humans adapt their pattern recognition processes is largely unknown. In general, machines try to adapt their pattern recognition pipeline through altering the following aspects: normalization, distance measures, dimensionality, and complexity of sample distributions.

STATE OF THE ART

Although significant differences exist between people's empathic abilities, most people sense affective signals automatically up to a level, machines are unable to reach. Withthe rise of the field affective computing, as coined by Picard [2], interest in machines that can sense people's emotions increased enormously. Now, more than a decade later, what is the status of affective computing and how was the development of this new subfield in science?

Affective computing has been mainly employed using three modalities: vision/image, speech, and biosignals. These three signals can be used to analyze facial expressions, speech utterances, movements and gestures, and physiological processes. However, it should be noted that the combination of biosignal processing with image and speech processing is rare. Most often, either image and/or speech processing of biosignal processing is applied.

Each of the three modalities applied in affective computing has its pros and cons. For example, computer vision/image processing techniques heavily rely on light sources, occlusion, and stereotype expressions. Speech processing is, in practice, heavily disturbed by environmental noise (e.g., from a radio) and is influenced by acoustic features of environments. Nowadays, biosignals can be recorded with small sensors connected to tiny, light weight devices. However, biosignal recording is still experienced as rather obtrusive, when not integrated in other tools (e.g., a helmet or joystick) or clothes. Moreover, biosignals are sensitive to movement artifacts, signal loss (e.g., sensors that fall off), and humidity, to mention a few.

The mapping of human emotions on the three signal modalities is complex. Moreover, environmental influences can have a significant impact on both signal recording and the emotions people experience. Consequently, affective computing, although aimed to be used in our daily lives, is hardly applied outside well controlled lab environments.

IT STARTS WITH THE SIGNALS

Although the pattern recognition processes of man and machine are hard to compare, when going into more detail, they have things in common. One of these things is that both rely on the input for the pattern recognition process: the signal.

The quality of the signal is of the utmost importance for the pattern recognition process. Low signal quality can cause an ill defined measurement space. This is the foundation of the feature selection processes and everything follows from that. So, signal processing should be conducted with the utmost care.

Possibly even more important than the quality of the signal is our understanding of it. How is it originated and processed and how is it or should it be interpreted? A range of issues play a role in this; e.g., ethnic background, personality type, gender, and age. Nevertheless, some characteristics seem to be general; e.g., as has been shown with FACS for cultural diversity. However, also such generally accepted knowledge is a topic of debate.

SYMPOSIUM OVERVIEW

The symposium aims to initiate a multi-disciplinary knowledge exchange on all possible aspects that are of importance for affective signalprocessing. The session will discuss conceptual issues (e.g., ground truth) but also more applied issues of filtering and machine learning. Its rationale is to gather the available, but scattered, knowledge and to bring it from controlled lab settings to noisy real world applications.

Signals that will be discussed include social signals, biosignals, facial expression recognition, and nonverbal communication (e.g., movements). Differences between lab and real world studies will be discussed and, consequently, limitations of technology and challenges for science and technology will be identified [3]. Moreover, differences between special groups (e.g., as known in psychiatry) and generic applications will be assessed.Taken together, the session will bring together a group ofdistinguished scientists, from a range of disciplines. All willhave their viewpoints and methods to unveil affective signals.Bringing them together can possibly bring us a step further inthe quest towards unveiling affective signals.

The symposium will be opened by the opening keynote speaker, Beatrice de Gelder[4] will discuss recent evidence on human's "relative affective blindsight for fearful bodily expressions".Nonconscious perception of emotions has repeatedly been shown for facial expressions. In contrast, thisis not the case for bodily expressions, although being highly salient and known to influence our behavior towards others [4]. Using a parametric masking design, the unconscious perception of bodily expressions was measured with people. Participants had to detect in distinct experiments fearful, angry, and happy bodily expressions, among neutral bodily actions that served as distracters.Subsequently, the participants had to indicate their confidence. Results revealed a phenomenon that is coined relative affective blindsight, defined as two stimulus onset asynchronousconditions showing similar values, while the confidence ratings differed. In fact, this was only found for fearful bodily expressions, not for angry and happy bodily expressions.

In line with the presentation of De Gelder, MariëlleStel will explain how mimicry can be used "as a tool for understanding the emotions of others". She will address the question: How do people understand what others are emotionally experiencing? She argues that mimicking nonverbal expressions of other people (i.e., copying others' behavior) can facilitate the understanding of emotions they are experiencing. When people mimic nonverbally expressed emotions, this affects their own emotions, correspondingto an afferent feedback mechanism. As a consequence of this mechanism, the mimicker perceives the emotions of others more strongly, which facilitates emotion understanding.The first two presentations involve research on participants, who are considered to be a representative sample of the community of healthy adult people. However, as is known from various scientific disciplines (e.g., medicine and psychology), research on special cases and people suffering from disorders as well as on the development of people should be of the utmost interest.

Floor Scheepers and Jan Buitelaarwill give an overview of the studies that investigated motor, emotional, and cognitive empathy in juveniles with autism or conduct disorder (CD). Studies that measured response to emotional faces with use of facial EMG, ECG, skin conductance, or eye-tracking are discussed [2]. In autism, facial mimicry, emotion recognition, and attention to the eyes seems to be reduced. In CD, facial mimicry and recognition of fear and sad facial expressions are impaired.Although further research is needed to investigate autonomic emotional empathic responses to emotional faces in both patient groups, major differences between autism and CDare hypothesized.

As indicated above, various biosignals are recorded and, subsequently, analyzed with the aim to unveil people's emotional state. One of these biosignals concerns the facial EMG. Facial EMG is a generally accepted tool for inferring affective states, as will be outlined by Anton van Boxtel.Van Boxtel will give a concise overview of methodological aspects of recording facial EMG signals as an index of affective states, which are known to be of the utmost importance. In addition, both strengths and weaknesses of the application of facial EMG in clinical and other applied settings will be emphasized; cf. [3].

Where Van Boxtel already outlines concerns when bringing affective signal processing to practice, HaticeGunes and MajaPanticwill provide a brief overview of the current state-of-the-art in automatic measurement of affect signals. In classifying emotions, they distinguish dimensional and continuous spaces and, consequently,seek answers to the following questions: i) *why* has the field shiftedtowards dimensional and continuous interpretations of affective displays recorded in real-world settings? ii) *what* are the affect dimensions used, and the affect signals measured? and iii) *how* has the current automatic measurement technology been developed, and *how* can we advance the field?

As already indicated by Gunes and Pantic, not only biosignals are of interest also other (social) signals can show to be a rich source of information.KhietTruongwill discuss how and what type of measurements of vocal interactional behavior can be used to recognize both affective and social signals [2,5]. Three studies will be presented that deal with i) the collection and recognition of spontaneous vocal and facial expressions, ii) the detection of laughter, and iii) the meaning of overlapping speech (i.e., interruptions) in conversations. Following the results of these studies, both the pros and cons of affective speech processing will be evaluated. In addition, fundamental issues such as 'ground truth labeling' and collection of spontaneous data will be discussed.

The second key-note speaker, Alessandro Vinciarelli, will close the symposium. In line with the presentation of Truong, he will introduce the recently emerged field of social signal processing (SSP); i.e.,understanding nonverbal communication in social interactions [5]. In a clinical context, this issue was already briefly touched by Scheepers and Buitelaar. SSP is founded on the idea that nonverbal communication is physical and, thus, provides machine detectable evidence of mutualrelational attitudes (social signals). Subsequently, SSP aims to automatically analyze, model, and synthesize nonverbal behavior in human-human (and human-machine) interactions.

Thus throughout the symposium, a plethora of affective signals are brought to attention. Both methodological and signal processing issues have been discussed. Various settings in which affective signals are recorded were touched upon; e.g., from psychiatry to gaming. Moreover, not only the technical aspects but also social aspects (e.g., people’s mimicry) have been brought to attention.

CONCLUSION

A wider scope is needed for affective computing as progress is limited and the techniques employed are still too fragile to bring from lab to life. We pose that not the pattern analysis and machine learning component of affective computing constitute is the bottle neck but instead this is formed by the affective signals that are the input for the classification processes.

Understanding affect and its signals requires an interdisciplinary approach, as is adopted for this symposium. Engineering, neuroscience, psychological, biological, and clinical approaches are explored. Through their integration, we envision a significant leap in unveiling affective signals.

The range of disciplines the speakers originate from enables a true interdisciplinary discussion and knowledge exchange. We hope that, in time, this symposium will show to be a small but significant step forward in unveiling affective signals. In this way, step by step, affective computing will find its scientific foundation and the path to true progress can be finally paved.

ACKNOWLEDGMENTS

This work has been supported in part by the European Community’s Seventh Framework (FP7/2007-2013) under grant agreement no. 231287 (SSPNet) and grant agreement no. 211486 (SEMAINE). The authors gratefully acknowledge the support of the BrainGain Smart Mix Programme of the Netherlands Ministry of Economic Affairs and the Netherlands Ministry of Education, Culture and Science. Further, would the organizers of the symposium like to thank the members of their program committee, Gert-Jan de Vries and Henriette C. van Vugt (Philips Research) andFrans van der Sluis (University of Twente), for making this session possible.

REFERENCES

1. Meisel, W.S.*Computer-oriented approaches to pattern recognition*. Series of Mathematics in Science and Engineering, vol. 83. New York, NY, USA: Academic Press, Inc., 1972.
2. Picard, R.W.*Affective Computing*.Boston, MA, USA: MIT Press, 1997.
3. Broek, E.L. van den &Westerink, J.H.D.M. Considerations for emotion-aware consumer products.*Applied Ergonomics 40*, 5 (2009), 1055-1064.
4. de Gelder, B.Whybodies? Twelve reasons for including bodily expressions in affective neurosciences. *Philosophical Transactions of the Royal Society B: Biological Sciences364*, 1535 (2009), 3475-3484.
5. Vinciarelli, A., Pantic, M. and Bourlard, H.Social signal processing: Survey of an emerging domain. *Image and Vision Computing27*, 12 (2009), 1743-1759.