

Emotion Recognition for Self-aid in Addiction Treatment, Psychotherapy, and Nonviolent Communication

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Abstract. This position paper aims to highlight possible future directions of applications for Affective Computing (AC) and Emotion Recognition (ER) for self-aid applications, as they emerge from the experience of the ACER-EMORE Workshops Series. ER in Artificial Intelligence offers a growing number of problem-solving multidisciplinary opportunities. Most current AC and ER applications are focused on a somewhat controversial enterprise-centered approach, i.e., recognizing user emotions to enable a third-party to achieve its own goals, in areas such as e-commerce, cybersecurity, behavior profiling, user experience. In this work we propose to explore a human-centered research direction, aiming at using AC/ER to enhance user consciousness of emotional states, ultimately supporting the development of self-aid applications. The use of facial ER and text ER to help forms of assistive technologies in the fields of Psychotherapy and Communication is an example of such a human-centered approach.

A general framework for ER in Self-aid is depicted, and some relevant application domains are suggested and discussed: dependencies treatment (DT) (e.g., workaholism, sexaholism); non-violent communication (NVC) for people in leading roles using e-mail or chat communication; empathy learning for parents and teachers in the circle-of-security (COS) caring environment.

Far from being complete and comprehensive, the purpose of this work is to trigger discussions and ideas for feasible studies and applications of ER in self-aid, which we hope to see published in the future editions of our workshops, believing that it may be one of the drops needed in the ocean of a better world.

Keywords: Workaholics · Sexaholics · Non-violent communication · Circle of security · Assistive technologies · NVC · COS

1 Introduction

Among the most studied and efficient technologies for Emotion Recognition (ER) in Affective Computing (AC) and Artificial Intelligence are facial recognition [1] and text analysis. Several models and algorithms have been developed with promising results to

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exploit ER in these areas [2–4]. Starting with simple sentiment analysis [5–8] to emotion recognition in texts, [5, 9, 10] following with more sophisticated models of emotion and affect extraction, [11, 12] to future application for intelligent interactive systems [13–15] for daily life support [16–24] or medical assistance, [25–31] emotions and emotional intelligence [32–34] play a crucial role [35]. Crucial is also the application of existent technologies and models, as it is evident from the well-recognized resources cited above, because emotions and affect perception can vary based on culture and other parameters. Crucial is the meaning that we may give to emotions, depending on ethical values and opinions, often vague and not linkable to science decisions.

Finally, emotions analysis can easily be misused for unethical purposes, such as controlling people's emotions to influence their commercial or political choices.

In our vision the research in the ER and AC should be informed by three basic principles:

I. ***Ethical goals.*** Emotion Recognition deeply involves the user intimate believes and states, sometimes even unknown to the same user which can be unaware of his/her emotional state. Researchers entering in such domains should consider and reflect on their own research goals, in order to avoid creating methods with unclear or no application, or which can easily be misused for different, unethical goals.
II. ***Sound and Incremental approach***. New commoners to AC are very easy to contribute to the proliferation of new models, i.e., *reinventing the wheel*: the risk is to create a lot of models and algorithms that reach the same goal starting from the same primary resources, with similar precision, instead of advancing the already existent methods and algorithms. The relevant research contributions from psychology and physiology of human emotions cannot be ignored, and they should represent the starting point and a reference background to understand the difference among affect, moods, emotions, and sentiments [36–38]. One of the aims of this paper is to provide an excellent bibliography to start working in this domain.
III. ***Practical and Helping applications***. The third guideline, in our opinion, should be to find practical **applications** to help human beings to live better. This aim is approachable for instance improving management and consciousness of emotions in order to choose the appropriate behavior. E.g., with applications to help who has short availability of funds (i.e. cheap applications, usable from the mass; or applications to help who has ideas but not resources), to invent aids for the weakest (e.g. elders, people with disabilities, people with physical or psychological pathologies), to support helping to diminish pain and providing support for who suffers.

In one sentence, we strongly support a vision of emotion *recognition for self-aid* as an ethical approach to a field of research which is deeply involved with the intimate mental privacy of individuals, which can quickly become controversial or misused. The idea is that applications aiming at self-aid ultimately preserve the individual emotional privacy since the application is playing a prosthetic role for emotional behavior rather than trying to modify or influence it.

Our vision is global and biased: every researcher can find where EM and AC problem-solving need is required in their own culture, state of life, sensibility to the needs of people around them in specific cases.

In Sect. 2 we will depict the general architecture of ER and AC for Self-aid. Sections 3, 4 and 5 three real-life problems are discussed that, in our view, may gain a consistent benefit from application involving Automated Emotion Recognition. In Sects. 6 and 7, two ER techniques for text ER and face ER will be presented as possible tools to support ER based self-aid application. Conclusions will be finally drawn.

2 An Architecture for Emotion Recognition for Self-aid

The scheme we propose shows a general system architecture encompassing a whole class of potential applications focusing on emotion recognition for self-aid. The *user* plays a central role since it is the primary source and object of the system. The role of the system is to support the user without substituting it in decisions which are ultimately under the user's responsibility and choice. The most relevant component is undoubtedly the *ER module* which uses information acquired by sensors for recognizing user emotions and emotions generated by, or embedded, in other human subjects in the application context. Different sources acquire users sensors' information, e.g., text, messages, speech, tone of voice, biometric parameters (e.g., blood pressure, heart pulse rate, myoelectric activity), body tracking and face-tracking videos generated by the user or documenting the user activity. The *AC Reasoning & Modeling* module has the purpose of interpreting the detected emotional input within the *Affective Computing* framework and goals characterizing the application scenario and taking into account the of the particular current context in which the application is used.

Typical goals of this module are:

- *classifying* emotions from sensors data;
- *ranking* the relevance of the detected emotions concerning the application goal and the current context;
- *projecting* the consequence of emotions concerning a specific AC model;
- eventually *triggering* a user emotional feedback in order to call for a *self-aid* action, if the detected emotion appears to affect the application goals.

The *Emotional Status* feedback module is in charge of generating the appropriate emotional affordances [12] to draw the user attention on his/her messages, speech behaviors, gestures or acts which can potentially represent a danger for her/himself or the relationship with a single or many communication partners.

The *contextual info* can vary depending on the application domain. It can represent simple contextual information, like a generic scenario in which the user's emotional behavior takes place or can involve cultural information and may require to analyze the emotional behavior of other human actors, which can be extracted by documents, messages or videos.

In general, because of different reasons, either psychological and perceptive, the user can be unaware of the emotional consequences or their inner status which leaks

through their emotions. The idea is that although their emotions are deeply analyzed, users' are not substituted but supported in their decisions. The system has only the role of highlighting the emotional content and consequences of user behavior either respect to themselves or others. In a typical self-aid application, the user feedbacks can range from simple hints, e.g., a danger sign or a meme, to casual explanations, e.g., for instance, a graphic chain of the emotional interaction with other subjects (Fig. 1).

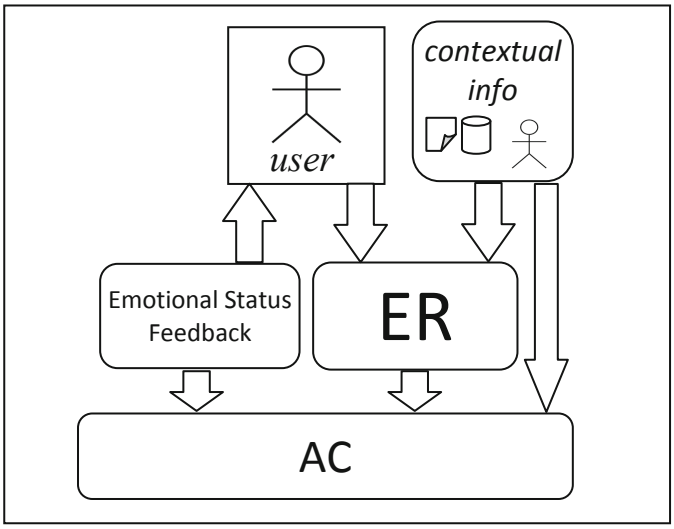

Fig. 1. ER for Self-aid Architecture

3 Self-aid Using ER for Three Real-Life Problems

Considering the ER for self-aid architecture and the three guidelines proposed in the introductory section, we identified three instances of paradigmatic problems which may gain significant added value from the integration of automatic emotion recognition with self-aid components:

A. Self-evaluation in addiction treatment (e.g., *workaholism*, *sexaholism*), where emotional self-evaluation is proved to help to gain and keep sobriety (emotional sobriety helps sobriety) [39–44].
B. Self-support for empathy learning for parents and teachers in a *circle-of-security* (COS) [45–47] caring environment, when they are undergoing therapy to understand their child's emotions better.
C. Self-assessment in *non-violent communication* (NVC) [48–50] for people in leading roles using e-mail or chat communication (e.g., group leaders, professors, managers), often prone to be unconsciously aggressive to their staff.

Problem A represents a class of ER-based self-aid applications, which we can call ***one-to-self***, where the ER component supports the user in getting control of his/her own emotions for the betterment of his/her behavior.

Problem B represents the class of ***one-to-one*** *(or one-to-few)* ER-based applications, where the individual is supported in recognizing and improving the emotional interactions he/she undergoes, with another single individual, or a small community.

Problem C is the class of ***one-to-many*** *(or one-to-few)* ER-based self-aid applications, where the individual is helped to become aware of the emotional interactions with communication with many other individuals.

In the following sections, we will briefly present the problems and, then, our proposed solutions using text ER and face ER.

4 Addiction Treatment

Many people suffer from dependencies, e.g., *sexaholism* (i.e., the addiction to sex in dependency relationships, or pornographic fantasy), [39] *workaholism* (i.e., the addiction to work and productivity) [41, 42]. Such dependencies have several common traits, and also the treatment can benefit from the same process [44]. Associations exist in these cases to help the addicted with self-evaluation and group help, usually aided with a *12-steps program*, [40] useful not only to exit the dependency, but to keep staying out of it, because in most cases the addiction raises from problems related to the patient history, which cannot be changed, thus the danger to re-fall in the addiction can still be present in all the rest of the life of the ex-addicted.

The 12-steps program was initially created by the association of alcoholics anonymous and then adopted by associations for different dependencies. The process aims to support the personal choice of treatment and recovery, through a progressive mental, spiritual and physical awakening and healing, and includes the following phases:

1. **Admission** of the addiction
2. **Submission** to a Higher Authority (e.g., God)
3. **Restitution**, making amend to any person harmed
4. **Spreading** the message of the 12 steps to help other addicted people

The effectiveness of the program has been proved mainly by experience in all the association helping addicted people who, initially feeling inadequate, driven inward and out of reality, disconnected from others and themselves, and afraid, become confident, autonomous and caring, even if always conscious of needing to be cautious and avoid certain situations in order to stay sober.

During the rest of their life, the recovered addicted should **self-evaluate emotions**, considered the manifestation of future dangerous states which can help to prevent following again in the addiction. Such a method is followed because the addict may fall in situations, especially about relations, [43] which may stir up confusing emotional states leading to be weaker against the temptation of addiction. E.g., any emotional state which leads to self-punishment is dangerous.

Being conscious of emotions helps to react to such states and avoid weakness adequately: *emotional sobriety helps sobriety*. Tools using facial ER to regularly check our facial expression can help in this process, to connect again with ourselves, with others and with the real world.

5 Circle of Security (COS)

The Circle of Security Parenting program (COS-P) is a parent education and psychotherapy intervention developed by Glen Cooper, Kent Hoffman, Robert Marvin, and Bert Powell [48] to shift problematic patterns of attachment-caregiving interactions to a more appropriate developmental pathway.

The COS paradigm [51] describes the aim of the therapy as to:

1. Increase the caregivers **sensitivity** and appropriate responsiveness to the child's signals moving away to explore, and moving back for comfort and soothing.
2. Increase the caregiver's ability to reflect on their own and the child's behavior, **thoughts,** and **feelings** regarding attachment-caregiving interactions.
3. Reflect on experiences in their histories that affect their current **caregiving patterns**. This latter point aims to address the eventually defensive strategies of the caregiver.

The COS-P program is based on filming the interactions within the caregiver/child dyad in a particular situation called *strange situation*, and let the caregiver see the video and reflect on it with the help of a professional psychotherapist, eventually in groups with other caregivers. Professionals classify the dyads based on the interactions as secure, insecure or disorganized, where each class can have further classifications and thus should be treated with the proper therapy.

Such program broadly implies the ability of the caregiver to sense and recognize the child's emotions through the video, supported by the psychotherapist. In this environment, a tool for face-based ER can be useful to support the caregivers in recognizing the child's emotions and their own emotions filmed in the videos of the *strange situation*.

6 Non-violent Communication (NVC)

People in leading roles, e.g., group leaders, professors, managers, often have communication problems when they communicate through emails and chats because such written communication naturally lacks expressivity about emotions. When the staff, employer or student has no sufficient information to understand the tone or mood behind the text, may be due to a wrong interpretation of underlying emotions and see the leader as aggressive. Some words are more emotionally meaningful than others, therefore using synonyms or alternative expressions may help to avoid unconscious aggressivity and the consequent reaction.

Moreover, it is established that a patient relationship with colleagues and superiors leads to a better work environment and higher productivity. Self-assessment about the emotional value of our communication through text can improve people management.

Non-Violent Communication (NVC), developed by the clinical psychologist Marshall Rosenberg in last century, [47] and used in different domains, e.g., work environment and marital relationships, [45, 46] is a specific method for communicating emphatically to avoid any verbal violence. NVC theory supposes all human behavior stems from attempts to meet universal human needs, which are never in conflict. NVC proposes that people identify mutually shared needs, revealed by the words expressing thoughts and by the emotional feelings surrounding such needs, and collaborate to develop strategies and make requests to meet each other's needs, aiming to an interpersonal harmony and social cooperation.

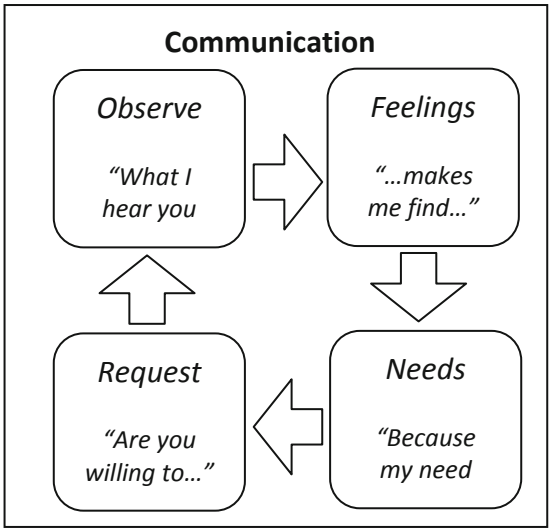

Fig. 2. The NVC Model

The model includes four components (also depicted in Fig. 2):

1. The concrete actions we **observe** that affect our well-being
2. How we **feel about** what we observe
3. The **needs**, values, desires that create our feelings
4. The concrete **actions** we request in order to enrich our lives

NVC is useful not only to choose better words to make requests but also enhance meeting efficiency, bolster teamwork, resolve conflict resolution, because it helps to meet the needs both of the sender and the receiver, in a win-win negotiation approach.

The method, to apply the model in understanding others, better includes questions building for understanding the thought and emotional feelings of the people with whom we are communicating, using particular emotional words to express the understatement. Such questions ask for feedback: if the feedback is positive, the thoughts and

feelings are considered well understood; otherwise the questions are repeated with corrections until understatement.

Text ER can help especially for understanding the emotional value of the NVC feedback.

7 Text ER Using the Semantic Emotions Model (SEMO)

The Semantic Emotions Model (SEMO) [38, 52, 53] is based on semantic similarity relations that can be extracted from an emotional ontology, taxonomy or a simple web-based search engine. The main idea is that words with similar meaning often appear together in documents on the Web: Web-based semantic similarity is computable searching for the number of results for each term of a pair, and then the number of results of the search for the pair. These three numbers combined in appropriate formulas (e.g., Normalized Google Distance, [54, 55] Pointwise Mutual Information, [56] PMING distance [57]) give a proximity evaluation between 0 (different) and 1 (equal), in decimal scale. Calculating the semantic proximity between a term/expression and each word [58] expressing the emotions of a model (e.g., Ekman, Plutchick), [11] it is possible to calculate which emotions are carried by the term/expression semantics.

More formally, let the emotion model

$$E_M = \{e_1, \ldots, e_n\} \tag{1}$$

and the Vector Space Model

$$\pi_p(w, E_M) = \big(\pi_p(w, e_1), \ldots, \pi_p(w, e_n)\big) \tag{2}$$

for term w, emotion model E_M and proximity measure p, where each component $\pi_p(w, e_i)$ of the vector represents the proximity between term w and emotion e_i. Then, for sentence s,

$$\pi_p(s, E_M) = \big(\pi_p(s, e_1), \ldots, \pi_p(s, e_n)\big) \tag{3}$$

will be the vector containing the overall emotional content depending on the whole sentence. Each component $\pi_p(s, e_i)$ is calculated considering the single $\pi_p(w, e_i)$ values.

Formally,

$$\pi_p(s, e_i) = AGGR\big(\pi_p(w_1, e_i), \ldots, \pi_p(w_k, e_i)\big) \tag{4}$$

where *AGGR* can be an aggregation function, e.g., *Max, Average* [56]. In the first case, the *Max* aggregation, the components of the *emotional sentence* vector are obtained by choosing the maximal value for each emotion in words composing the phrase; i.e., it tends to amplify all the emotions. The *Average* aggregation function points out the average emotional content of the phrase.

As a starting phase of the process, the sentence to be analyzed is parsed and preprocessed using NLP techniques; [38] each sentence is decomposed in a set of tokens, from which non-relevant words are removed, including stop-words, ordinal numbers, cardinal numbers and short words, such as articles and prepositions not carrying any emotional value. The set of stop-words is taken from the all-corpora package of the widely used NLTK Python library, [59] while numbers are detected using regular expressions. At the end of this preprocessing phase, each sentence is reduced to an array of potentially emotionally costly words.

The final output of the process is the primary emotion associated with each term of the sentence, which can also be visualized in a radar graph as in Fig. 3.

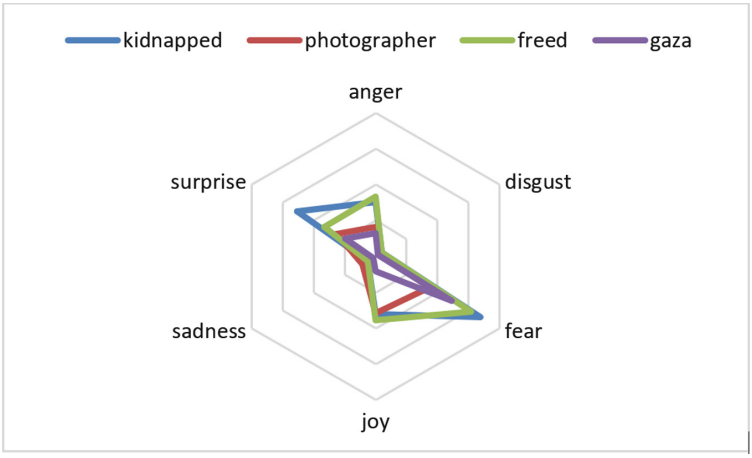

Fig. 3. Visualization in a radar graph of the Ekman emotions associated with the sentence "Kidnapped photographer freed in Gaza"

8 Face ER Using Convolutional Neural Networks (CNN)

The proposed method takes insights from literature about lip reading, [60] and the GUI-based *EmEx* [61] and *EmEx2* [1] software, implemented to recognize in real time emotions of the users whose face is in the camera streaming, but personalized software is easy to develop using the open-source *Caffe* framework [62] for classification, and *OpenCV* libraries [63] for image processing. The classes of recognized emotions are the underlying emotions of the *Ekman* model [37].

After an initial phase of Artificial Intelligence training, feeding the system with a high number of images of the user's facial expressions, each tested image is then processed by the *Convolutional Neural Network* (CNN) [64]. The personal features associated to the emotion expressions of the face of the user are identified, in order to recognize and label the corresponding emotion, giving real-time feedback (visual, with a tag or an emoticon, and sounds).

The two phases of training and test are structured in a similar way, where the training phase is customized on the user's face characteristics (e.g., wrinkles, moles, shapes, [65] imperfections), implying a more complex communication scheme among the layers of the CNN.

The neural network consists of several layers connected. The main level is for the appropriate dataset and tags. A second layer is a *convoluted layer*, where the convolution operations are performed on the image, extracting the specific information of the face. Then, a *pooling layer* reduces the magnitude of the parameters, thus the time needed for computation, and the process continues with convolutional layers.

The layer sequence is crucial to obtain good classification scores: convolutional layers are alternated to normalization layers or pooling layers when it is necessary to improve the quality of the input data making transformations without altering the quality of the image. The *normalization layer* is used to make a linear transformation of the image to improve the readability; the pooling layer is needed to reduce the size of the input data, to speed up the computation. Finally, *inner product layers,* i.e. fully connected layers, alternated with a rectified linear unit layer, quickly train the CNN, ended with the output layer.

During the training phase, the output is represented by the accuracy of the process and the lost information; during the test phase, the output will be the emotion classification.

9 Conclusions

In this position paper, we introduced and motivated, the *ER for Self-aid* paradigm as a theme for emotion recognition research, which can reach, at the same time, the ethical goal of respecting individual emotional privacy and focusing on application improving quality of life. At the basis of a significant number of psychological or interpersonal communications difficulties, there is a correct perception and consciousness of emotions, in either communication directions displaying or reading.

Rather than using emotion analysis for reaching some other goals such as influencing people behavior, we maintain that the focus should be on the prosthetic role of ER.

We have presented a general architecture for ER for Self-aid, and we have identified three classes of applications, *one-to-self*, *one-to-one* and *one-to-many*, for which we have exemplified useful practical applications respectively in the area of *addiction treatment*, *circle-of-security,* and *nonviolent communication*. State of the art techniques for ER, like the ones sampled in the last sections without claiming to be complete, show that the goal of developing ER for Self-aid applications is suitable and realistic and we strongly advocate for a research effort in this direction.

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