Technical University of Sofia
Faculty of Computer Systems and Technologies

PROCEEDINGS

NINTH INTERNATIONAL SCIENTIFIC CONFERENCE

COMPUTER SCIENCE' 2020

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ISBN: 978-619-167-433-6

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Contents

Weight based model for emotion recognition in a multimodal agent based architecture

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Abstract: *Expressing and perceiving emotions is a vital part of communication between people and an important advance in improving the human-machine interface. Efficient and robust recognition is based on input data from different modalities thus imposing the usage of multimodal recognition architecture and multimodal recognition frameworks. The paper presents a multimodal agent-based architecture for emotion recognition and suggests a weight based model for the influence of the input multimodal data on the output results and also defines the impact of several factors such as gender, age, ethic group and personality. The suggested weight based model considers the emotion detection as a complex non-linear system and can be used in a multimodal agent based architecture for empirical evaluation of the weight, errors and the unknown parameters.*

Keywords: *emotion recognition, multimodal architecture, weight based model.*

1. INTRODUCTION

Emotion is a mental experience, feeling or sensation caused by external influences. Due to their subjective nature, individuals as well as different ethnic groups have a specific and different way of expressing emotions. Expressing emotions refers to how a person communicates emotional experience through verbal and non-verbal behavior. According to Ray Birdwhistell in [1], the final message of a statement is affected only 35% by actual words and 65% by non-verbal cues. Emotions are best treated as a multifaceted phenomenon consisting of:

- behavioral reactions (body and gesture),
- expressive reactions (voice and face),
- psychological reactions (EGG, electro dermal activity, body temperature) and
- subjective feelings (semantic voice channel, text).

A recognition system based on multimodal architecture has to explore every one of this emotion faceted. Schematic representation of a multimodal system is given on fig. 1.

The paper presents a multimodal architecture for emotion recognition and suggests a composition of the output signal. A weight based model that presents the influence of the input multimodal data on the output results is suggested. The model also defines the impact of several factors such as gender, age, ethic group and personality. The suggested weight based model considers the emotion detection as a complex nonlinear system and can be used in a multimodal agent based architecture for empirical evaluation of the weight, errors and the unknown parameters.

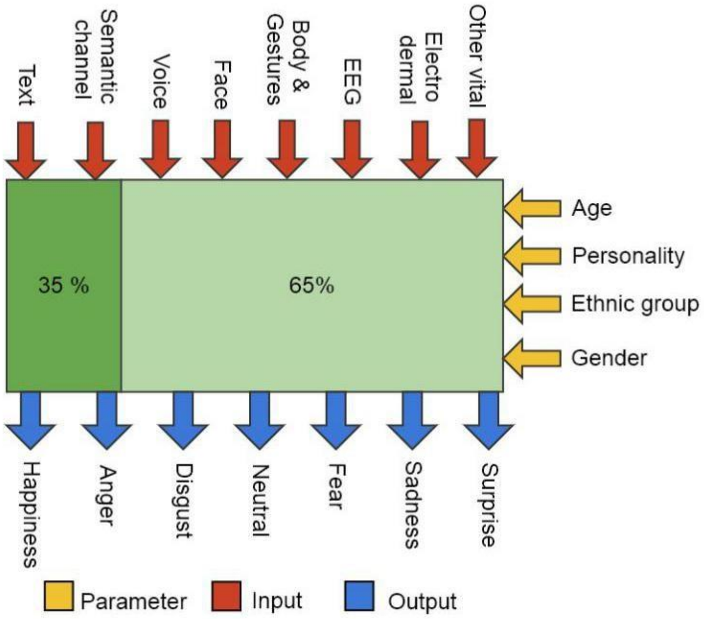

Fig. 1: Schematic representation of a multimodal system for emotion recognition

2. EMOTION MODELS

To better conceptualize human emotions different emotion models are constructed. The theories presented throughout the first years of research in the field of human psychology have been unanimous in the minimalist idea of reducing the great range of emotions in a small group of mental states by calling them basic or fundamental. This presentation is known as discrete emotion model. A discrete emotion model is representation of emotions with categories. The Swedish anatomist Carl-Hermann Hjortsjö proposed one of the first discrete models, categorizing emotions based on the idea that there is a limited set of human emotions [2]. Later the idea was extended by the FACS system (Facial Action Coding System) developed by a group of scientists under the direction of Paul Ekman [3], where seven main categories are defined: happiness, sadness, surprise, fear, anger, disgust and contempt.

Human emotions can generate data that can be recorded and quantified. The idea to represent these quantitative measurements in a multidimensional space are the basis of the dimensional emotion model. A dimensional emotion model is representation of emotions in a multidimensional space. Wundt [4], proposed the first dimensional model by decomposing the emotion space along three axes, namely: valence (positive– negative), arousal (calm–excited), and tension (tense–relaxed). The physiological model of the emotional state PAD [5] uses three dimensions to represent emotions: Pleasure– Arousal–Dominance. Instead of three dimensions Russell uses independent bipolar dimensions of emotion such as pleasure–displeasure and few years later present circumflex model (fig. 2) of affect where emotions are located in a two dimensional circular space containing arousal and valence [6].

A hybrid model of Plutchik uses psycho-evolutionary classification. According to Plutchik, there are four basic problems in life: identity, hierarchy, territory and transience. Environmental stimuli are given a positive or negative valence, which triggers behavioral reactions that vary according to the evaluation and re-evaluation of the stimulus.

Therefore, for every basic problem in life, there are two opposing primary emotions. Identity - the primary opposing emotions associated with identity are the functions of acceptance (admiration) and rejection (loathing). Hierarchy - related to the first access to food, sex, shelter and comfort. The primary antithetical emotions of the hierarchy have the functions of protection (terror) and destruction (rage). Territoriality - each animal must establish a territory. Thus the binary opposition exploration (vigilance) and orientation (amazement). Transience - the finite life span of all creatures ensures that the processes of life and death pose a problem for each animal species. Primary opposing emotions here are reproduction (ecstasy) and reintegration (grief). In Plutchik's multidimensional model of emotions the vertical dimension is the intensity with which each primary emotion is experienced.[7] The non-basic emotions are obtained from the mixture of the basic ones. This psycho-evolutionary classification is presented in fig. 3 [8].

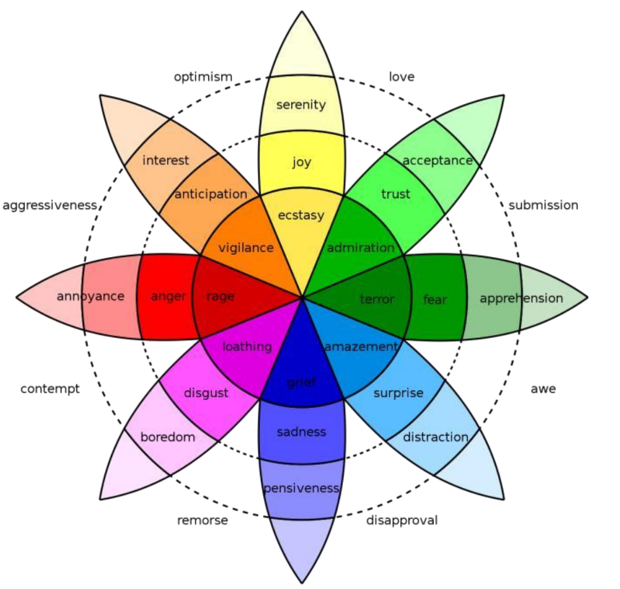

Fig. 3: Plutchik hybrid model

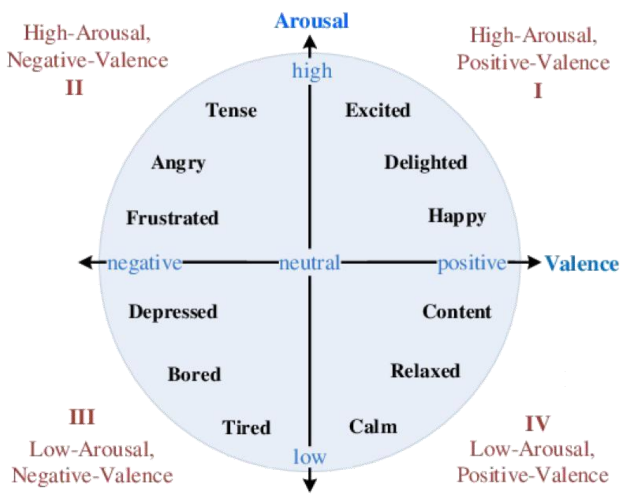

Fig. 2: Circumflex model

3. MULTIMODAL AGENT BASED ARCHITECTURE FOR EMOTION RECOGNITION

Multimodal and multiagent systems that process and use signals from various sensors are used to improve the accuracy and efficiency of emotion recognition results. The classification characteristics and the recognition of emotions derived from the use of verbal, visual and psychological signals.

This type of system includes all stages of recovery and processing of the various aspects of human emotional state detection. The detectors correspond to the input sources: sensors, files, etc. that provide the input data for the agent-based system. The general framework of the multiagent system architecture is shown in fig. 4.

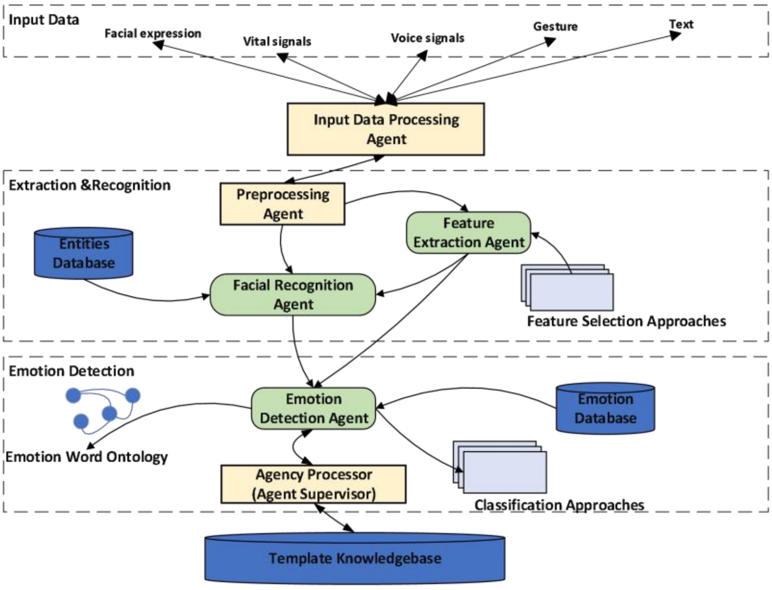

Fig. 4 General multi-agent system framework for multimodal human emotional state recognition

The aim of AgencyProcessor (Agent Supervisor) is to combine the results of different emotion detection agents. It also combines the results with weights based on specific parameters such as gender, age, ethnic group, temperament.

4. WEIGHT BASED MODEL FOR EMOTION DETECTION

According to the detection sensors used the emotion detection technologies can be classified into the following groups: verbal, visual or physiological. Each of them has a different influence on the output signal.

In a multimodal emotion recognition system the output function, i.e. the emotion (E_t), depends on the input components (i) that can be attributed different weights (w). The components with the highest weight are the meaning components which represent one third of the result.

(1) $$i(input) = \frac{1}{3}(meaning) + \frac{1}{3}(non\ verbal\ \ signals)$$

The rest of the inputs influence the final result in different ways. The voice, face and body signals are related to the arousal, this means that for input emotions such as fear or happiness the weight of this inputs will be greater. Face and body input signal will be more representative than others input signals including voice. Thus the face and body weight will be greater. The EEG and other physiological signals are related to the valence, in this case the weight of this input will increase if the input emotions are related to the valence.

A multimodal emotion recognition system is not completely determinant. The state of the moment can never be measured with certainty and therefore the input signals will always carry integrated errors (ε) which will affect the output signal that determines the emotion itself:

(2) $$E_t = F[(i_0 w_0 + \varepsilon_0)...(i_n w_n + \varepsilon_n)]$$

where i_k, $k = 0 \div n$, is input signal equal to the output signal from a simple modal, w_k denotes the weight and ε_k is an error.

Several studies states that women report more negative affect than men but equal happiness as men, and revel that gender accounted for less than 1% of the variance in happiness but over 13% in affect intensity [9, 10, 11].

Some studies have suggested that the intensity of subjective reactions to emotionarousing stimuli remains stable, whereas the magnitude of autonomic reactions declines with age. The authors in [11, 12] reported than greater self-reported sadness was found in older than in younger adults. When older people are exposed to stimuli featuring themes that are relevant to their age group, they show greater subjective and physiological reactions.

Different researches has shown that cultures and ethnic affiliation exert considerable influence over emotion expression and perception [13, 14].

A wealth of cognitive and behavioral research has demonstrated that individual differences in people's personality can affect the manner in which they process emotional stimuli [15].

Consequently the factors such as gender, age, ethic group and personality need to be taken into consideration while studying emotions too:

(3) $$E_t = F[(i_0 w_0 + \varepsilon_0)...(i_n w_n + \varepsilon_n)] * \mathrm{P}$$

where parameters P are defined by individual characteristics like gender, age, ethic group and personality.

5. CONCLUSION

If the sensitivity of the input conditions is taken into account in determining the attributes that influence the emotion detected, we can observe that the mathematical definition is extremely complex, to the point that it compares to the difficulty in analyzing the accuracy of non-linear systems of weather forecasting and natural phenomena, considered one of the most complex systems.

The incorporation of the initial errors and those arising during the process, together with the fact that it is a non-linear system, means that the system becomes much more complex, including unknown parameters that must be found empirically.

Each detection module will obtain at the output a list of the emotions detected with their respective errors and percentage of correspondence. These outputs are the inputs for the Supervising Agent, whose task is to combine them.

The suggested weight based model can be used in a multimodal agent based architecture for empirical evaluation of the weight, errors and the unknown parameters.

6.ACKNOWLEDGMENT

The work presented in the paper is supported by research grant 192ПД0002-09 financed by the Research and Development Centre of the Technical University of Sofia, Bulgaria.

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