Engineering Applications of Artificial Intelligence 91 (2020) 103562

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Interpretation and modeling of emotions in the management of autonomous robots using a control paradigm based on a scheduling variable ☆

Zdzisław Kowalczuk *, Michał Czubenko, Tomasz Merta

Department of Decision Systems and Robotics, Faculty of Electronics, Telecommunications and Informatics, Gdańsk University of Technology, Narutowicza 11/12 Gdańsk, Poland

ARTICLE INFO

Keywords:
Emotions
Decision-making systems
Cognitive modeling
Human mind
Computational models
Fuzzy approach
Intelligent systems
Autonomous agents

ABSTRACT

The paper presents a technical introduction to psychological theories of emotions. It highlights a usable idea implemented in a number of recently developed computational systems of emotions, and the hypothesis that emotion can play the role of a scheduling variable in controlling autonomous robots. In the main part of this study, we outline our own computational system of emotion – xEmotion – designed as a key structural element in the developed target device, being an Intelligent System of Decision-making (ISD) for autonomous and robotic units.

The ISD system has a cognitive architecture based on the principles of human psychology. The main purpose of building such a system is to prepare a framework for autonomous units used in system engineering (Kowalczuk and Czubenko, 2011; Czubenko et al., 2015). In particular, ISD is based on the concepts of *cognitive psychology* (in information processing) and *motivation theory*, which includes the system of *needs* (for decision-making). The xEmotion subsystem, however, focuses on modeling an alternative approach based on emotion. The xEmotion implementation covers aspects of somatic, appraisal and evolutionary theories of emotions using fuzzy sets.

In this article, we also illustrate the core emotional behavior of the ISD system using simulation. The first application is a user interface for identifying emotions and predicting human behavior. The second is an eSailor simulation, which illustrates the possible behavior of the xEmotion subsystem. The last is an xDriver simulation experiment, which is to prove the validity of the concept of using emotion-based systems, according to the SVC principle. In summary, we also discuss other possible applications of the xEmotion system.

1. Introduction

Designing human-like creatures has long been a dream of humanity, starting with the golem (from Jewish legends), through the da Vinci knight and mechanical Turks (chess machines), and ending with advanced robots, such as SHAFT, Valkyrie, and FLASH (Kowalczuk and Czubenko, 2015). However, the physical construction of humanoid robots does not conclude the task.

To practically implement this idea, the most important thing is to realize (mechanical) action resulting from a thinking process, based on artificial intelligence (AI). Over the years, various types of AI systems have been tested to see if the resulting robot or agent is smart enough.

Among the tests of machine intelligence, the most important and famous is the Turing test for the Imitation Game (Turing, 1950). Theoretically, it was met by a chatterbot Eugene Goostman, who pretended to be a 13-year-old boy from Ukraine (where English is not the mother tongue). A *smart* agent was Tay Twitterbot from Microsoft Corporation, who quickly learned to behave like a frivolous teenager (Suárez-Gonzalo et al., 2019). What is more, Google's assistant recently showed that it can imitate human speech almost perfectly. Further machine intelligence tests include a coffee maker test (how to use a coffee maker without any external directions) and a student test (how to successfully pass one semester in college and avoid problems with the dean's office). At this point, we should also mention the Lovelace test, which concerns a machine that, among other things, can create an element incomprehensible to its programmer (Bringsjord et al., 2001; Elamrani and Yampolskiy, 2019).

Recently, a new proposal based on the concept of emotions and called the Frampton test was formulated, which can be described by the title of the song 'Do You Feel Like We Do?' (Lovell, 2015). To be more precise, the test poses the question of: whether the machine has its own awareness, whether it is aware of its emotions, and whether it

☆ No author associated with this paper has disclosed any potential or pertinent conflicts which may be perceived to have impending conflict with this work. For full disclosure statements refer to https://doi.org/10.1016/j.engappai.2020.103562.

* Corresponding author.
E-mail addresses: kova@pg.edu.pl (Z. Kowalczuk), micczube@pg.edu.pl (M. Czubenko), tomasz.merta@pg.edu.pl (T. Merta).

https://doi.org/10.1016/j.engappai.2020.103562
Received 16 August 2019; Received in revised form 22 December 2019; Accepted 10 February 2020
Available online 11 March 2020

is able to recognize them. This, in turn, raises further questions about: what the emotion is, how it arises and evolves, and whether and how the robot can utilize it. All these questions lead directly to the new branch of Artificial Intelligence called *Affective Computing*.

As part of Affective Computing, two branches can be distinguished. The first path (introduced above) is related to the emotions of a robot or virtual agent. The respective systems can be called computational systems of emotions (Kowalczuk and Czubenko, 2016). The second path concerns the issue of recognizing people's emotions, in which the latest solutions are able to identify and classify emotions based on images from a video camera (Morsy, 2016) or a thermal camera (Nummenmaa et al., 2014). Currently, sentence sentiment is also recognized — i.e. its positive or negative emotional value, and even more. There are classifiers that correctly recognize the emotions associated with sound or text (Perikos and Hatzilygeroudis, 2016). What is more, recently, emotions can even be derived from the video (Hu et al., 2019).

1.1. Purpose and structure of this article

The paper presents the hypothesis that emotions can play the role of a scheduling variable in the control of autonomous robots. Clearly, this is another revelation of Affective Computing. As mentioned above, more and more systems and robots are being humanized, have their own personality and model and express their emotions. The main goal of this article is to show a complex mechanism of creating emotions in a system based on human psychology. It can be used to express emotions by a robot or, after appropriate supplementation, to predict human emotions.

The main purpose of this study is to present a working concept of a computational emotion system called xEmotion. It combines the somatic and appraisal theories with a usage of fuzzy logic. A short review of basic psychological theories can be found in Section 2, moreover a long review and detailed description of computational emotions systems can be found in Kowalczuk and Czubenko (2016). In the main part of the paper (Section 3), we outline our own computational system of emotion – xEmotion – designed as a key building block in the Intelligent System of Decision-making projected for autonomous and robotic units. The simulation scenarios, which illustrate the core emotional behavior of the ISD, can be found in Sections 5, 6. The first one describes the evolution of emotion according to our system, whereas the second one is a simple case of usage. Another case of use with an external estimator can be found in Section 2.5.

The main purpose of this study is to present the developed system of computational emotions called xEmotion, which combines somatic and appraisal theories with the use of fuzzy logic. In the Intelligent System of Decision-making (ISD), the emotional system plays a role similar as in human — it changes the point of view in the decision-making process. The xEmotion system is thus a kind of Schedule Variable Controller (SVC) in the case of autonomous units.

The basic motivation behind xEmotion is the lack of a coherent system of computational emotions (from a psychological point of view) that would combine both somatic and appraisal theories of emotion. Using fuzzy logic, such a system can effectively model emotions for robotic purposes, because fuzzy sets and language variables perfectly represent the human standard in the field of emotions. Consequently, using correctly estimated parameters based on environmental data, the xEmotion system can effectively predict human emotions. There is no similar system in the literature, and the innovative side of our concept is the use of emotion as a scheduling variable in controlling intelligent robots and agents — which can be considered another consequence of the cybernetic approach that involves the practical use of emotions by people. What is more, the presented system mimics people both in the context of creating and using emotions.

2. Emotion

There are several branches of science, studies, and particular theories, which study emotions. There are different trends in psychology. Therefore, different definitions of emotions are given and various processes of creating and triggering emotions are distinguished. What is more, emotion can have a different meaning depending on the duration, intensity of the emotion, or the color of the emotion. There are also many implementations of computational emotion models developed for various applications. Importantly, from a technical point of view, emotions can be treated as an indirect controller of behavior or a higher level (attendant) controller.

2.1. Emotion in psychology

Although in the field of psychology there are many overlapping definitions of emotions that can be quoted, we will only list some of them here:

- "Emotions are a primary idiom for defining and negotiating social relations of the self in a moral order" (Lutz and White, 1986)
- "Emotions are organized psychophysiological reactions to news about ongoing relationships with the environment" (Lazarus and Lazarus, 1994)
- "Emotions (...) are, first and foremost, modes of relating to the environment: states of readiness for engaging, or not engaging, in interaction with that environment" (Frijda, 1994)
- "Emotion is a complex chain of loosely connected events that begins with a stimulus and includes feelings psychological changes, impulses to action and specific, goal-directed behavior" (Plutchik, 2001).

Basically, emotions are designed to improve social contact, e.g., through facial expressions or body language (which are just controlled by emotions) (Martinez et al., 2016), and to better adapt to the changing environment (Lazarus and Lazarus, 1994; Frijda, 1994; Plutchik, 2001) of the individual. From the cybernetic paradigm's point of view, however, the most important is the way in which emotions arise and their impact on human behavior and action. Foundations of emotion theory can be found in Wundt (1874), Schlosberg (1954) and Osgood et al. (1975).

There are two views on the creation or triggering of emotions, referring to the postulate that emotions arise before recognizing an object or after:

- According to the theory of cognitive appraisal (Lazarus, 1991), phenomena (objects or events) are evaluated first for the emotional sign — yielding the so-called stressor ratio (primary assessment stage). Then (in the secondary assessment stage) the phenomenon is analyzed in terms of its convergence with the goals of the agent and the possibilities of dealing with (negative) effects of the phenomenon (so-called copying).
- Somatic theory suggests that emotions are primary to cognitive processes (Zajonc et al., 1989). This means that (at the biological level) there are processes that emit emotions even before the (more accurate) recognition of this phenomenon.

It is noteworthy that most computational emotion models use only the appraisal theory of emotion. However, in our opinion, both theories can be used to model emotions. In this way, the model will be more complete and better suited to the task of imitating human psychology.

2.2. Psychological models and types of emotions

There are several psychological models of emotions, which are often placed in multidimensional spaces. For example, the pure Russell model (Russell, 1980) has two dimensions — arousal and valence. Although this system distinguishes only 8 patterns of emotions, its extended version showed an effective implementation of another 28 emotions (in the same 2D space). A similar model proposed by Thayer (1989) uses coordinates referred to as calm-tension and fatigue-energy. A slightly more complex model of biological origin is the cube of Lövheim (2012). Its axes represent the intensity of three neurotransmitters: serotonin, dopamine and noradrenaline. Each of the extreme points of the cube portrays one full emotion. Another well-developed model, the Plutchik paraboloid (Plutchik, 2001), based on eight primordial emotions, is presented in more detail in the next section, because it lays the foundation for the xEmotion system discussed here. Emotions in the Plutchik model are color-coded and have intensity, which means that each emotion can be perceived (noticeable) to varying degrees. A mix of neighboring (basic) emotions can also create a derivative emotion (for example, joy and acceptance give rise to love).

From a psychological point of view, there are at least seven different dimensional models of emotion (*circumplex*, Thayer's, Plutchnik's, Lóvheim's, and others such as PANA, PAD, PNAS Plus, etc.) and different models of emotion placed in one dimension (Ekman, OCC and many others).

Various emotion models based on a dimensionless approach can be found in Kołakowska et al. (2015). The Ekman and OCC emotional systems are the most used and worth mentioning. Paul Ekman divides emotions into six separate states: anger, disgust, fear, happiness, sadness and surprise (Ekman, 1992), based on facial expression research. This model is widely used in applications that recognize emotions. The OCC model created by Ortony, Clore and Collins is also a popular solution for the computer modeling of emotions. It introduces 22 emotions in six families and is based on a detailed description of all states. The innovation in this model relates to the exact cause pattern (presented in conditional steps). For example, if the consequences of an event (the first step) concern other agents (the second step), and the consequences are undesirable (the third step), then this agent may feel the negative emotions *loathing* or *pity*.

In selected cases, you can show methods of transition between emotion models (Landowska, 2018). There are also many implementations of computational emotion models, as described, for example, in Kowalczuk and Czubenko (2016).

A different part of the psychological knowledge about emotions can be expressed through the distinction of four types of emotions, taking into account duration (Biddle et al., 2000; Oatley et al., 2012):

- autonomous/physical sensations — very short, spontaneous and related to the somatic theory of emotion
- expressions — as short as autonomous, assigned to certain objects and related to the theory of emotion assessment
- *classic* emotions that last for a longer period of time, can be verbalized (named) and consciously observed, and are associated with both of the theories of emotion
- mood is a prolonged emotion, lasting up to a month, less intense than the classic emotion and changing very slowly.

On the other hand, impressions and *classical* emotions are characterized by intensity and color. A list of such emotions based on the work of Plutchik (2001) is given in Table 1.

Table 1
List of emotions based by color and intensity.

		intensity		
		low	medium	high
color	■ (light blue)	distraction	surprise	amazement
	■ (dark green)	apprehension	fear	terror
	■ (light green)	acceptance	trust	admiration
	■ (yellow)	serenity	joy	ecstasy
	■ (orange)	interest	anticipation	vigilance
	■ (red)	annoyance	anger	rage
	■ (purple)	boredom	disgust	loathing
	■ (blue)	pensiveness	sadness	grief

2.3. Computational models of emotion

From the AI and control theory viewpoints, different computational models of emotion can lead to various hypotheses, such as the one discussed in this paper and concerning the (SVC) role of emotions in autonomous systems. Moreover, adapting the idea of emotional systems to complex control applications may lead to more intelligent, flexible and capable systems. Emotions can be the basis for a procedure to interrupt the agent's normal behavior to consider competitive goals (selected and profitable for the current state) with the intention of generating more effective reactive behavior. The recognition of emotions (connected with facial expressions), such as anger or guilt, can minimize the effects of conflicts between (virtual) members of multi-agent systems. The computational models of emotions are not new in AI, but they are still underestimated, and most researchers focus their attention rather on the bottom-up models of human thinking, such as deep learning/neural networks, data mining, etc. Note that, a bottom-up approach claims that a system composed of a combination of many primary elements (such as a single neuron) can lead to complex system behavior, while a top-down approach uses symbolism to break a problem down into simple tasks (Shapiro, 1992).

An important role of computational models of emotions is shaping the human–robot-system interaction. From the systemic point of view, the robot may better understand humans' behavior by modeling their emotions. Such systems are nowadays widely used in computer and network applications (for example, a Flash robot with an emotional head called EMYS). The robot (or virtual/internet interlocutor) can also provide additional information for the interaction, cooperating or uncooperating person, directly, using indicators or indirectly, through actual emotional behavior. This means that concepts such as beliefs, desires, intentions, etc. are also suitable for the design of robots.[1] The direct method takes into account the use of emotions as a show (for example to make a more friendly impression), and thus avoiding the "uncanny valley" characteristic of human perception of humanoid robots.

Most of the known architectures of computational systems of emotions principally rely on appraisal theories of emotion only (Marsella et al., 2010; Ong et al., 2019). They do not take into account the possibility of creating emotions based on impressions (simple stimuli, pre-observations), which can be recognized and associated to earlier memories or pre-programmed objects.

In the literature, one can find many works concerning the issue of modeling human emotions: CBI (Marsella, 2003), ACRES (Swagerman, 1987), Will (Moffat and Frijda, 1994), EMILE (Gratch, 2000), TABASCO (Staller and Petta, 2001), ActAffAct (Rank and Petta, 2007), EM (Reilly, 1996), Flame (El-Nasr et al., 2000), EMA (Gratch and Marsella, 2004), ParleE (Bui et al., 2002), FearNot! (Dias, 2005), Thespian (Mei et al., 2006), Peactidm (Marinier et al., 2009), Wasabi (Becker-Asano, 2008), AR (Elliott, 1992), CyberCafe (Rousseau, 1996), Silas (Blumberg, 1996), Cathexis (Velásquez and Maes, 1997), OZ (Reilly and Bates, 1992), MAMID (Hudlicka, 2005), and Affect and Emotions (Schneider and Adamy, 2014). A short description and selective comparative study of them can be found in Kowalczuk and Czubenko (2016) and Marsella et al. (2010).

2.4. The paradigm of the scheduling variable

The scheduling variable, or gain-scheduling control is one of the most popular approaches to the design of adaptive and nonlinear

[1] Beliefs, Desires, Intentions (BDI) is an architecture commonly used in robotics agents (Lincoln and Veres, 2013; Cranefield and Dignum, 2019).

systems. The strategy of Scheduling Variable Control (SVC) itself leads to nonlinear control. SVC can be based on different principles, for instance, on series expansion linearization of a controlled nonlinear system (Leithead, 1999), or on Jacobian linearization for a family of equilibrium points of such a system (Rugh and Shamma, 2000). In short, there are many methods of using such a universal approach to the design of nonlinear control systems. For illustrative purposes, we mention here only a few of them:

- classic SVC (Kaminer et al., 1995),
- quasi-LPV scheduling (Rugh and Shamma, 2000),
- fuzzy gain-scheduling (Krzaczek and Kowalczuk, 2012; Rojo-Rodriguez et al., 2019),
- neural/fuzzy gain-scheduling (Tan et al., 1997),
- Lyapunov-based LPV approach (Leithead, 1999).

Basically, the SVC strategy is a method of switching between controllers and models due to recognized operating points of the control system. First, this design strategy leads to simplification of the control issue for non-linear systems. Second, this method can be used even in the absence of an analytic model of the controlled object. Nevertheless, the most important advantage of SVC is the possibility of immediate adaptation of the controller to the changes of the system's operation point. Now, this brings to mind the practical and perspective effects of emotions.

We assume that using an emotion-based approach, the agent can immediately, without a 'second thought' (e.g. without a complex decision-making process), respond to specific cases (clear and extreme situations regarding the external or internal environment) (Kowalczuk and Czubenko, 2017).

In particular, in the case of causing strong emotions, recognized as anger, disgust or anxiety, a quick response can be crucial to the survival of an agent. The principle of operation is practically identical to the original SVC strategy, being in common use for many years. For instance, in the case of changing the operating point (which causes the emotional state of the agent to change), the controller can be easily redesigned (i.e. change the agent's behavior), enabling efficient operation of the agent's system in various conditions, and survival in dangerous circumstances, for example.

The presented earlier cases lead us to the idea of an evolutionary theory of emotion. The concept of using emotion as a scheduling variable is our innovation announced in Kowalczuk and Czubenko (2017). Note that the desired change in the agent behavior based on the occurrence of emotions strongly resembles the concept of SVC, for instance, in the context of an agent's pre-selected (optimized) reaction set. The adopted control scheme (SVC) with gain scheduling and the fuzzy set approach (TSK) are widely known and practically applied.

There are a large number of projects that implement a certain computational model of emotions. Most of them, however, do not take into account any autonomous mechanism of adaptation associated with emotions. Moreover, they rely mainly on the appraisal theory of emotion, which in the overall assessment is not complete.

2.5. *Human interface application — possible application*

The xEmotion system presented later in this article can be used in autonomous and robotic units, but also in various haptic applications and human–system interfaces (HSI), wherever emotions and reactions similar to people are considered. Such applications require sensors that provide data related to human emotions, e.g. a camera, IR camera, EEG, skin conductance sensor (Liu et al., 2010; Maaoui et al., 2008). In this way, equipped with a suitable sensor, the xEmotion system, implementing a chatterbot or a humanoid robot, can perform designed tasks matching its emotional state. As a result, such a system should be able to present a given content in a manner adequate to the state of human emotions. Quite a straightforward approach can be based on a simple camera and image processing algorithm that detects facial expressions.

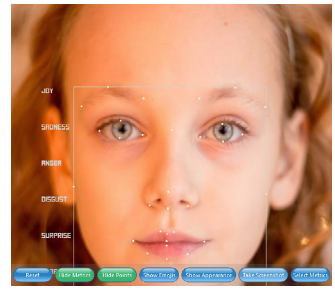

Fig. 1. Exemplary detection of facial expression in Affectiva (license CC0).

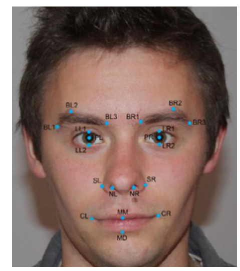

Fig. 2. Identification using auxiliary face identifiers.

The latest image processing solutions are able to recognize basic facial expressions such as smile, lip shape, eyebrow rise or furrow. An example of such a system is Affectiva (Fig. 1), which provides not only 20 facial expressions, but also their interpretation (Morsy, 2016). Based on consecutive video frames, Affectiva supplies the actual state of basic emotions: anger, contempt, disgust, fear, joy, sadness and surprise. Moreover, this solution recognizes two additional parameters: arousal and valence. The first represents the level of human expressiveness that is associated with the value of the emotional state. The second parameter is a measure of the positive or negative nature of each emotion. Despite the fact that emotions in Affectiva are not fully compatible with our system, it is still possible to transfer the output variables from Affectiva to our system in terms of anger, disgust, fear, joy, sadness and surprise.

It is noteworthy that many systems recognize facial expressions by encoding them in Action Units (AU) known from the famous FACS system (*Facial Action Coding System*).

Certain preliminary results regarding the identification of human emotions are shown in Kowalczuk and Chudziak (2018), where another image-based Emotion system was proposed for the detection and recognition of facial expressions/emotions using a webcam video in real time. The Emotion system detects 9 emotional states (anger, disgust, joy, sadness, fear, surprise, contempt, wonder/delight, and neutrality), describing the appearance of the face, represented by combined Extended Action Units (EAU), based on the Cohn–Kanade database (Kanade et al., 2000), which allows us to distinguish features characteristic for both sides of the face, and also combine two basic AUs as one synthetic unit. The effective average quality of face feature points tracking was obtained by using auxiliary identifiers for each characteristic point (an example is shown in Fig. 2), where the tests consisted of performing specific facial movements, each of which was a characteristic gesture for a concrete feature.

Such stand-alone applications (as opposed to the developed xEmotion system) are of course purely reactive. Nevertheless, they are extremely useful not only in typical HSI applications, but also in social robots, including, for example, humanoid robots for autistic children. To practically test our concepts in systems with a simple camera or video sensor and in stable and reproducible conditions, we constructed an appropriate video station. This station was thus built primarily to enable (in the near future) the direct evaluation of various sensors and detection algorithms, as well as their effective comparison.

3. xEmotion system

There are no theories which completely model the human brain for the purpose of engineering applications. Nevertheless, we still believe that intelligent control can be based on self-regulation using an appropriate model of the human mind, which can be derived from available psychological knowledge. One of the main reasons for developing such a project is also the lack of top-down approaches resulting from the known research on autonomous robotics.

In view of the above, the leading idea of the Intelligent Decision-making System (ISD) is to embody 'intelligence', based on the many psychological theories (which unfortunately are often conflicting), and to prepare a framework for autonomous units used in systems engineering (Kowalczuk and Czubenko, 2010a,b, 2011; Czubenko et al., 2015; Kowalczuk and Czubenko, 2018a). The ISD system has been coherently designed using selected elements from *cognitive psychology* (in the aspect of the information path), *motivation theory* (needs and emotions as the primary motivation/drives used for stimulating the system), and other detailed theories which concern *memory*, *categorization*, *perception*, and *decision-making*. An outline of the design considerations regarding the ISD agent's memory construction can be found in Kowalczuk et al. (2016).

Due to the continuous development of ISD, we do not yet have low-level processing procedures or large experimental data. However, our partial experiments and proof of concept (Kowalczuk and Czubenko, 2011) show that robots controlled by ISD can take care of themselves (our results are similar to that of the *Yuppy* robot controlled by the Cathexis system of computational emotion (Velásquez and Maes, 1997)). Moreover, in a predetermined virtual world, the ISD system can easily act as an independent agent, and adapt to the changing environment.

The ISD concept allows the agent to create its individual artificial emotions in a sub-system referred to as xEmotion (eXtended Emotion), in response to observations and interactions, as in the case of a dictobot, i.e. an interactive avatar (Kowalczuk and Czubenko, 2010a, 2013), or an autonomous driver (Czubenko et al., 2015; Kowalczuk and Czubenko, 2017).

xEmotion, as a sub-system of ISD, covers the psychological theories on emotions, including the appraisal, evolutionary and somatic theories of emotion. The system considers a certain time division of emotions, and in particular, takes into account both short-term emotions (e.g. autonomous changes or expressions) and long-term changes (e.g. emotional disorder or personality changes). A pivotal tool for the compiling and interpreting of emotions in ISD are (common/real and private/imaginary/individual) wheels/circles of emotion, which will also be referred to as the 'rainbows' of emotions.

3.1. General description

The general scheme of the xEmotion system is shown in Fig. 3. First, the agent's pre-emotions arise when recognizing sensations related to impressions. Similarly, the recognition of objects (discoveries) can generate some sub-emotions (or sub-equalia), but only if they have been previously assigned to these objects and remembered (in the agent's memory). Then the center of sub-emotions is calculated on the basis of all currently cognized (experienced) sub-emotions and the averaged value of (experienced) pre-emotions.

The emotional state (classical emotion) of the agent is updated taking into account the center of the sub-emotions, the effect of satisfying the needs and the effect of calming down. Its initial state is neutral and without external effects (sub-emotions and needs), does not change.

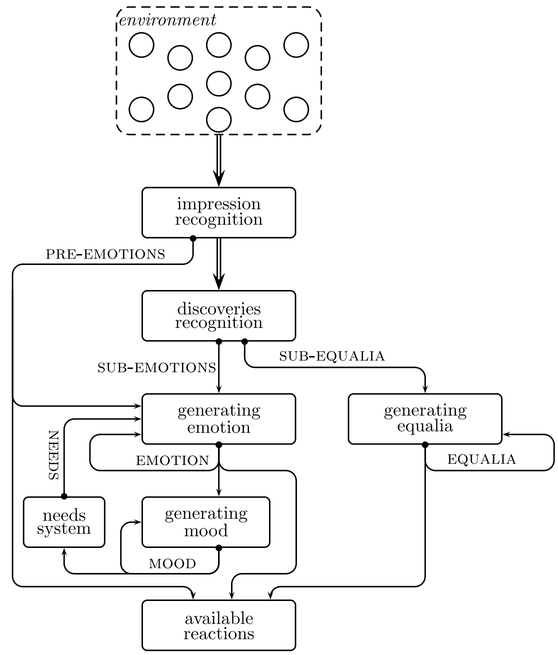

Fig. 3. Generating of emotions, and their continuous impact.

Table 2
List of symbols used in xEmotion.

κ^p	Pre-emotion
κ	Sub-emotion related to objects
κ^c	Sub-emotion (expressive)
κ^i	Sub-equale (individual)
ξ	Emotional state of the agent
ξ^c	Classical emotion
ξ^i	Equalia
$(r_{\kappa^c}, \omega_{\kappa^c})$	Polar coordinates of κ^c (intensity, color)
$r_{\kappa^c} e^{j\omega_{\kappa^c}}$	Sub-emotion as a complex value
Ξ	mood
$\Delta°$	Emotional constant 22.5°
Υ	Mental health factor
c_{pre}	Support of fuzzy κ^p
n_{pre}	Number of currently experienced κ^p
k	Sensitivity of pre-emotion
β	Gain of pre-emotion
$\mu_{pre}(\kappa^p)$	Fuzzy value of κ^p
$\zeta(\eta)$	Degree of fulfillment of the agent's needs
η_l	lth need of the agent
$\mu_s(\eta)$	Satisfaction membership function
$\mu_a(\eta)$	Alarm membership function
$\mathfrak{T}_\alpha(X, Y)$	Semi-translation of X, in direction Y, by α
α	Semi-translation parameter
δ	Calm down coefficient
$\Pi(\omega_{\xi^c})$	Non-linear color transformation function
f_Ξ	TAWS dynamics function

Equale is calculated in a similar way, and the mood is determined according to the change in classical emotion. Emotion and equale can modify the spectrum of the agent's available reactions (according to SVC, by switching its work point). Whereas mood can change the rate at which the agent's needs are met.

A detailed description of the xEmotion system is described in the following sections. In particular, we present each component of the system (Section 3.2), our model of emotion, based on the Plutchik paraboloid (Section 3.3), a simplified version of the system (Section 3.4) and our model of mood (Section 3.5). All symbols used in the xEmotion model are listed in Table 2. At the end of this chapter, the mechanism of emotion evolution is presented.

3.2. Components of xEmotion

A principal criterion for the categorization of emotions is their duration (Oatley et al., 2012). Taking similar assumptions for the designed xEmotion system, we distinguish:

- autonomous pre-emotions κ^p, which are based on a linear model of emotions and associated with stimuli and impressions,
- emotional context of objects $\kappa = (\kappa^c; \kappa^i)$, including:
  - expressive sub-emotions κ^c (common), related to perceived objects or recognized discoveries (identified on the real wheel of emotions), and
  - expressive sub-equalia κ^i, also associated with perceived objects (but located on the private/imaginary wheel of emotions),
- emotional state of the agent $\xi = (\xi^c; \xi^i)$, including:
  - classic emotion ξ^c, using the common (universal/real) rainbow of emotions,
  - equalia, or private emotion ξ^i, cast on the private (imaginary) rainbow of emotions,
- mood Ξ, generated based on a nonlinear mechanism TAWS (*Temporary Amplifier With Saturation*) (Kowalczuk and Czubenko, 2011).

Autonomous pre-emotions κ^p are similar to Oatley's (Oatley et al., 2012) autonomous changes, which are (very) short-term emotions based on a simplified model (Section 3.4) and triggered by a single stimulus or simple impression from the environment. Pre-emotions are based on the somatic theory of emotion (Zajonc, 1980). For example, the detection of sudden movement, which is out of sight, in a closed environment, evokes some simplified emotional signals of fear. This mechanism allows the agent to take quick action (e.g. escape).

Expressive sub-emotions κ^c are relative to (standard, universal) human emotional expressions and refer to already known objects, situations or events that directly evoke emotions associated with them — based on the appraisal theory of Lazarus (1991). Emotional associations are created according (conditionally or unconditionally) to the advent of objects during a state of high emotional intensity of the agent. Such sub-emotions can therefore be linked to certain events, during which there was a strong emotion (above a certain threshold). The next emergence of such objects will automatically generate a sub-emotional signal.

Thus, in general, subsequently generated sub-emotions are related to the priorly remembered experience in similar situations. Sub-emotions are modeled using classical emotion, and precisely located on the rainbow of emotions (Section 3.3). Consequently, the identification of an object that has previously been assigned to a specific emotion will generate an adequate sub-emotion signal. Sub-emotions on the wheel of emotions weaken as time passes, which corresponds to the process of *scuffing* objects in memory. For a clear optical interpretation, the rainbow of sub-emotions is represented by colors (ω_{κ^c}) and their intensity (r_{κ^c}).

According to philosophical sources[2] quale is a subjective feeling of quality for a given object (Hardin, 1987; Jackson, 1982). Therefore, equale ξ^i is defined as a subjective individual (private) emotional factor. In the xEmotion system, sub-equalia κ^i implement a direct analogy to sub-emotions, except that they are subjective and relative. Defined by similar parameters (intensity and color), sub-equalia are similarly inscribed, but in the rainbow of equalia and have no names/labels. Due to this assumption the agent can have relative, private emotions (feelings). Sub-equalia are completely subjective in contrast to the well-defined set of common emotions. The introduction of emotional qualia allows the agent to *feel* private emotions — generally difficult to describe, independent of cultural/inherited emotions, and defined by the individual and for itself. At the same time, thanks to such a mechanism, it is possible to implement a delicate path of evolutionary creation of emotions.

The classic (reasonable, verbalized) emotion described as ξ^c defines the basic (objective and universal) emotional state of the agent. It is implemented directly on the rainbow of emotion. The classic emotion is the result of the interplay between the current sub-emotions, pre-emotions, the level of meeting (satisfying, fulfilling) the needs, the previous emotional state and the effect of calming-down (dropping away). It may take different fuzzy states, related to an adaptive fuzzy membership function. Classic emotion influences the selection of a detailed agent reaction by defining a set of acceptable (sub-optimal) reactions. Some reactions are inactive without a proper emotional arousal. For example, fear unlocks the reaction of escape (and makes it more desirable).

In this work, equale ξ^i understood as a private emotion, represents a dual (private or individual) side of emotions. Similarly to the classical emotion which results from feelings at a given moment, current equale is the result of the set of previously perceived equalia, sub-equalia, and the dropping away effect.

The mood Ξ is a long-lasting emotional state based on a specific (time[3]-based) 'difference' of classical emotion. It shows whether and how (positive or negative) emotions affect the agent. The mood makes modifications in the functions responsible for the fulfillment of needs possible. In the case of positive mood, the needs can be satisfied much easier than in the case of a negative mood. The mood is modeled using the TAWS function (Kowalczuk and Czubenko, 2013), shown in Fig. 7, which describes the increase of mood (to the degree of saturation) for increasing classical emotion (positive derivative), while at the occurrence of any negative derivative of emotion the mood falls immediately (also with saturation).

Essentially, the mood is a long-lasting emotional component that can be positive or negative. However, its functional part can be derived from the current decline or growth of the agent's emotion. Then, such a trend present in the evolution of emotion can directly (though with some restrictions) represent a mood change, while a specific TAWS function is used to precisely model the mood.

3.3. The rainbow of emotion — 2d fuzzy model

The basic model of emotions, used in the xEmotion system, is a spread paraboloid of emotions proposed in Plutchik (2001) and adapted for our agent/robot control purposes (Kowalczuk and Czubenko, 2013). The changes are related essentially to three aspects:

- introduction of a common-and-explicit neutral state of stability,
- preventing the direct transition between intense, extreme emotions,
- reversal of the values of the emotion function (the model resulting from the above two assumptions).

Our contributions result from several reasons. In Plutchik's model, there is an unnatural assumption that the agent is always in a certain emotional state (there is no neutral state in the paraboloidal model). Our first modification introduces a neutral state to which the emotion converges in a certain time frame.

[2] "The sensation of color cannot be accounted for by the physicist's objective picture of light-waves. Could the physiologist account for it, if he had fuller knowledge than he has of the processes in the retina and the nervous processes set up by them in the optical nerve bundles and in the brain? I do not think so". Schrödinger (2001).

[3] This article does not take into account the immediate impact of time. The indirect effects of time result from the dynamics of the decision-making process.

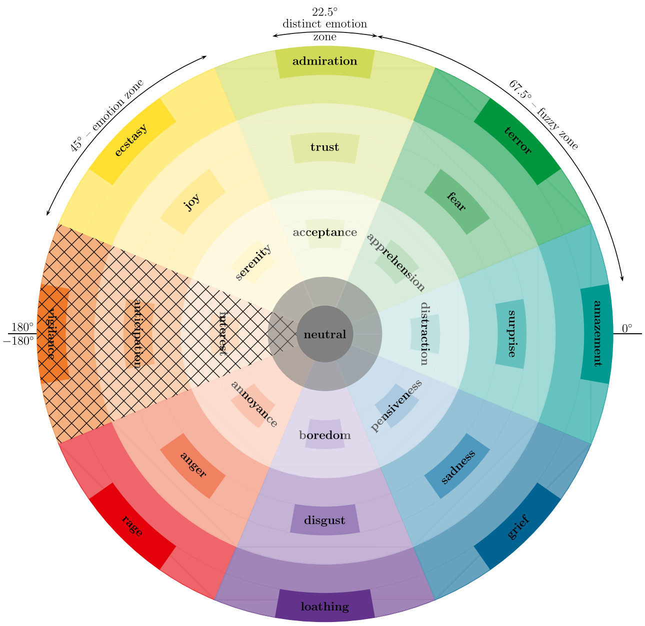

Fig. 4. Rainbow of emotion; full (intense) color means the maximum value of the function of membership to a specific emotional state (the angle width of each islet-shaped intense-color area/zone takes $\Delta°$, and the full width of any colored zone takes $3\Delta°$ Kowalczuk and Czubenko, 2017).

An issue that raises doubts is the possibility of a direct transition between extremely high and conflicting emotions. The possible passage through the center of the paraboloid implies an undesirable (rapid) change in the emotional state (allows the agent to change admiration into sorrow or disgust, or even transit from ecstasy to rage). A system that allows such a transition is clearly vulnerable to instability and is therefore not practical (a person exhibiting such behavior can be considered to be emotionally unstable or mentally ill). Now, the proposed amendment allows for a smooth (blurred) transition between these states (at the crossing of emotions, one of them loses its intensity, and the other begins to gain).

The third innovation – reversing the level of emotions – means a natural increase of intensity along with the distance from the center of the coordinate system representing the neutral state (whereas in the paraboloidal model, the weakest emotions are in most extreme positions). Obtained through such adaptation, the adopted rainbow of emotions is shown in Fig. 4.

Each emotional state is modeled with the use of 2D trapezoid fuzzy membership functions, which allows us to easily adopt two neighboring (fuzzy) variables (one of the variables takes a value less than one, and the other equals the completion of the first value). This effect (in the one-dimensional case corresponding to the diameter cross-section) is shown in Fig. 5, where the horizontal axis represents a crisp (real) emotional intensity value and the vertical axis shows the values of the respective fuzzy membership functions. In turn, a circular section with a constant radius is shown in Fig. 6.

Due to such fuzzy modeling, it is possible to tell apart:

- fuzzy emotion (colored) zone — based on the support of each membership function,
- dominant emotion (one color) zone — resulting from the maximum of (two or three) different membership functions (the so-called α-section, for $\alpha = 0.5$), and
- isolated emotion (islet-shaped intense-color) zone — based on the core/max of each membership function.

Modeling the agent's emotional state and sub-emotions (object-related emotions) is based on fuzzy set theory using membership functions,

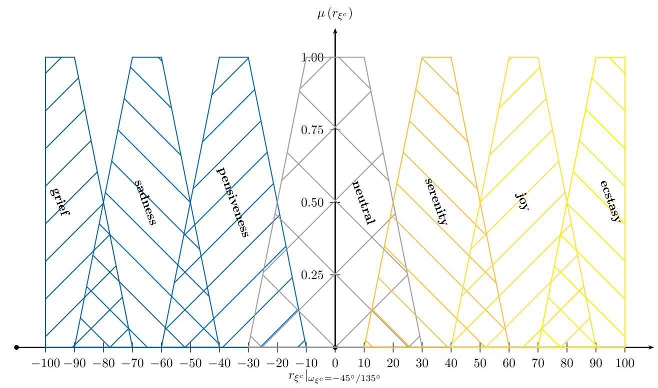

Fig. 5. The cross-section through the emotions along the grief-ecstasy line, passing through the center of the coordinate system.

which have many advantages. This allows easy interpretation by a human (e.g. 'more or less negative emotion') and use in other applications requiring scaling (e.g. assigning an emotional color of appropriate intensity to the objects perceived). What is more, a smooth transition between individual emotions can be maintained and the agent may be in several (two or four) different emotional states simultaneously, which in turn increases the possibility of matching an adequate set of reactions (according to SVC). Finally, the adopted solution in the simplified (linguistic) version allows direct reference to other emotion systems.

In the proposed system, two-dimensional emotional features are easily expressed using polar coordinates on a circle of emotions. The angle represents the color/valence of emotions, whereas the radius expresses the agent's arousal (so neutral emotion is near zero). This circular concept also makes it easy to relate our model to other popular dimensional emotion models (Russell, 1980).

The mechanism of the rainbow model is supplemented with a mental health factor Υ, which does not allow a healthy individual to go beyond vigilance (i.e. to transit from ecstasy to rage) due to an excessive positive stimulation (expressed by an absolute increase of classical/linear emotion). This introduces a useful non-linearity to our model. The resulting linear (angular) range of classical emotion is $(-180° + \Delta°; 180° - \Delta°)$, and the non-linear one is $(-180°; -180° + \Delta°) \cup (180° - \Delta°; 180°)$.

3.4. Linear emotion — simplified model

A simplified linear emotion model is useful in inducing rapid reactions. In the simplest case, such a mechanism can be built on the basic emotions formulated by Plutchik (1980). Then linear emotions can be caused by single impressions perceived (such as a special taste, pain, or specific movement, etc.). Such a simple model of emotions allows the decision-making system to unlock (make available) certain most appropriate reactions (at the present moment), for example:

- joy → find new positive stimuli,
- trust → share resources, cooperate,
- surprise → stop the currently executed reactions,
- sadness → search for compassion,
- anticipation → prepare itself,
- disgust → stay away from the subject,
- fear → escape/run,
- anger → fight.

using the following scheme: the color of the emotion → the exemplary reaction to be unblocked. This kind of inference and decision-making mechanism achieves a high level of priority in the ISD system developed. A special, safety role is assigned to negative emotions (located

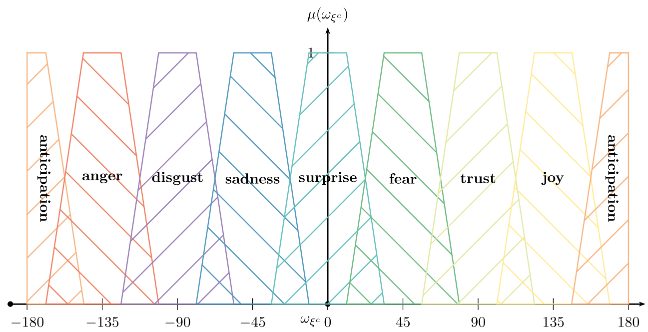

Fig. 6. Simplified linear model of emotions (the middle ring, or medium intensity on the rainbow of emotions of Fig. 4).

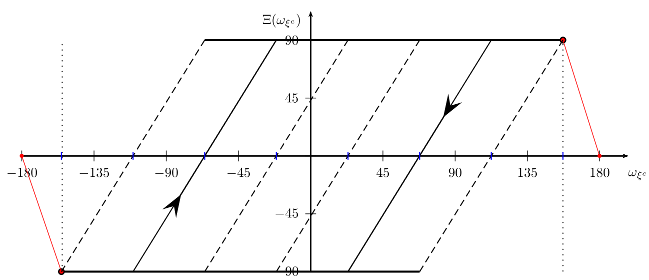

Fig. 7. TAWS, mood transition function, describing the mechanism of mood change according to the evolution of emotions (Kowalczuk and Czubenko, 2013).

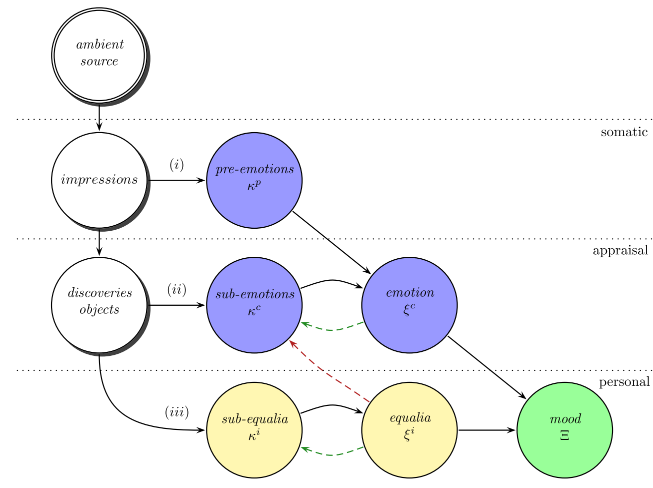

Fig. 8. Emotional components and their basic relationships (Kowalczuk and Czubenko, 2018b). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

on the negative part of the real axis). In practice, they enable the agent/individual to protect or defend itself against an unknown threat or known objects that pose a threat.

Linear models of emotion are also shaped using fuzzy membership. In the adopted standard approach (also applied in 3-dimensional modeling of the rainbow of emotions shown in Fig. 4), the neighboring membership functions overlap linearly. The rainbow of emotions is depicted in Fig. 4 from the top view. Whereas, the linear model of emotion of Fig. 6 is the result of cutting the rainbow of emotions along a half-diameter circle (medium-intensity emotions).

The linear model of emotion is based both on the appraisal theory of emotion and the somatic theory of emotion. Impressions received by the agent can be easily evaluated in terms of the type of the emotion (the phase on the wheel of emotions) and its intensity (the radius on the circle), and, in consequence, allow us to design an intelligent decision-making system taking into account component emotions and impressions.

3.5. *The mood model — taws*

The proposed model of mood (Ξ) is described by the TAWS function, which has properties similar to the dynamic hysteresis loop (Fig. 7). In particular, at any moment, regardless of the current point on the saturation characteristic, the change of the accretion mark (derivative) of the linear emotion variable (X axis) causes an immediate linear change (decrease or increase) of the mood (of course, the dynamics of saturation requires memory). Thus, the mood acts as a dynamic Temporal operational Amplifier With Saturation (TAWS).

Considering the non-linear part of the mechanisms of classical emotion, when the mental health factor is 1 (normal), a transition between the maximum value of the angle (180°) and the minimum (−180°) is impossible. The non-linear mechanism of emotion also has a definite effect on the mood.

Mood calculations, which also have non-linear features, follow the differences in the angle of classical emotion. A positive change in this angle (towards the 'joy' emotion) causes an increase in mood (up to a point). Similarly, reducing the angle of emotion lowers the mood. While in the corresponding non-linear *modus operandi* the mood changes to the opposite with some restrictions. In this way, the saturation level is not maintained, and a further increase in emotion causes the loss of (positive) mood. The whole process is precisely described in the next section.

4. From stimulus to emotion — a use case

As has been mentioned before, the emotional system has six components. Figure 8 shows the relationships between them. Emotion results from the emotional context of impressions (pre-emotions) and the emotional context of objects (sub-emotion). Whereas private emotion (equalia) results only from personal, emotional context of objects (sub-equalia). Both classic (shared) and private (individual) emotions affect the mood.

The concept of the xEmotion (sub)system assumes embedding in the native system ISD, which provides a list of currently perceived impressions (features of objects) and a list of previously perceived discoveries (objects appropriately modeled in the agent's memory). Of course, both lists are created during the process of agent perception. The emotional system, in accordance with its basic task, returns the emotional state of the agent (including classical emotion, equalia and mood).

4.1. *Somatic emotions*

According to the results of somatic theory, perception of impressions can lead to the formation of a certain emotion (to be precise, a pre-emotion). Similarly, and based on appraisal theory, the perception of phenomena or objects having an emotional context evokes sub-emotions. Considering all these emotional factors, the agent's emotional state (classical emotion) is calculated as follows: the average of pre-emotions is treated as one sub-emotion, and the centroid of all sub-emotions is the sought emotional goal. Personal emotion (equale) evolves in a similar way. In a state of high emotional arousal, the agent can attribute the current emotion and/or equale to current discoveries (as sub-emotion and sub-equale — see the green dashed lines in Fig. 8), whereas sub-equale can morph to sub-emotion (red dashed line) under certain conditions. A more detailed description of emotional qualia can be found in Kowalczuk and Czubenko (2019).

An important factor of influence on the xEmotion system are pre-emotions. They appear after the detection of relevant impressions — features of the objects recognized in the environment. Those impressions also contribute to the emotions of the agent as follows:

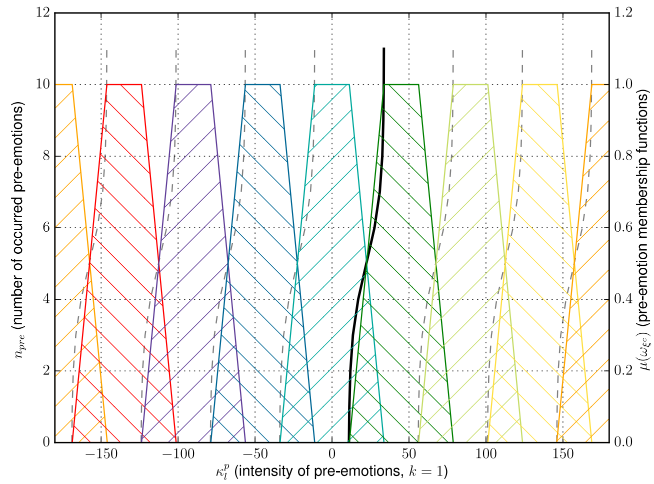

Fig. 9. Transformation of (1) to the color of pre-emotion in the linear model of Fig. 6.

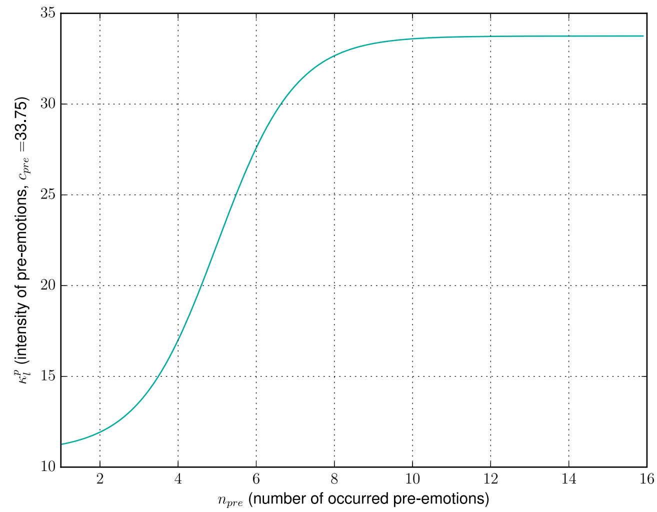

Fig. 10. Intensity of pre-emotion (1) for $k = 1$, $\beta = 1$, $c_{pre} = 33.75$.

- a smile → joy,
- slow gestures or immobility → trust,
- sudden gestures, unexpected movements (in good light) → surprise,
- tears → sadness,
- focus on the detection of stimuli → anticipation,
- certain odors or flavors → disgust,
- sudden movement behind the agent's back, unexpected movement in the dark → fear,
- attack → anger.

Each of the perceived impressions is mapped into an appropriate fuzzy (lth color) pre-emotion. This is done primarily in line with the linear emotion model (Fig. 6). All pre-emotions gain the same intensity calculated according to their number (a larger number of emotional impressions generates a lower intensity). Fig. 9 shows an exemplary black line along which the intensity changes. In particular, the intensity (κ_l^p) of pre-emotion is due to the number of currently perceived emotional impressions and the lth color[4] in the following non-linear way:

$$\kappa_l^p = c_{pre}[l] - \Delta^\circ \cdot \frac{1 + e^{\beta-(k+3)}}{1 + e^{\beta \cdot n_{pre} - (k+4)}} \tag{1}$$

where c_{pre} is a parameter representing the right end of the support of the trapezoidal membership function of the (lth) color of the considered pre-emotion, n_{pre} is the number of all currently experienced pre-emotions, β and k are the sensitivity and gain of the curves of particular emotional colors (see the example in black in Fig. 9, and other views shown in Figs. 10, 11, and 12). $\Delta^\circ = \frac{360^\circ}{8*2} = 22.5^\circ$ is an emotional constant based on the number of distinct emotions (dominated zones or colors) arranged on the rainbow of emotions depicted in Fig. 4.

For the common spectrum of emotions of Fig. 6, c_{pre} takes its values from the following set:

$\{-146.25, -101.25, -56.25, -11.25, 33.75, 78.75, 123.75, 168.75\}$

as illustrated in Fig. 9, where the calculated value of κ_l^p (abscissa) directs us to the fuzzy set of a particular emotion (color) with its properly positioned membership function (right ordinate). This graph also explains the effect of n_{pre} (left ordinate) on κ_l^p (the thick curve refers to the case $l = 0$). Fig. 10 shows the value of pre-emotions (1), where n_{pre} is the number of currently perceived impressions having a pre-emotional context. Parameter k confines the sensitivity of the system to the number of stimuli.

[4] Which is preserved for a given pre-emotion.

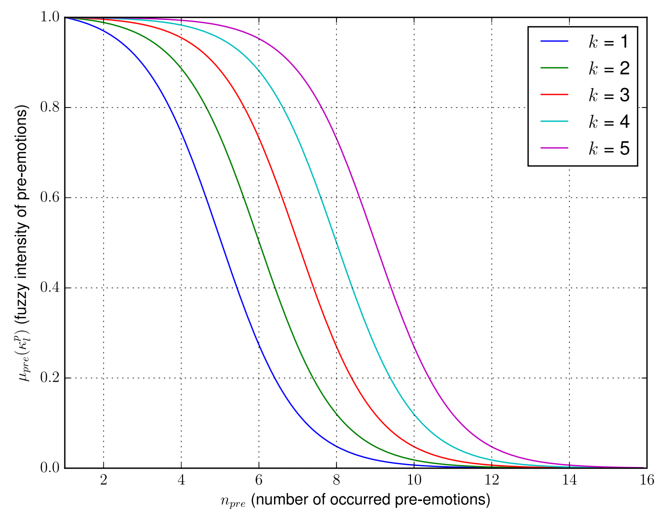

Fig. 11. Effect of k shifting the inflection point (at $\beta = 1$).

The default value is $k = 3$, which means that at one moment only three pre-emotions of maximal intensity are considered (Fig. 11). Constants (4,3) in formula (1) modifying the effect of parameter k allow for the desired shift of the curve.

The β parameter affects the desired dynamics of pre-emotion changes, as shown in Fig. 12.

Detected pre-emotions are averaged and normalized:

$$\kappa_0^c = \frac{1}{\Sigma_{l=0}^{l=n_{pre}} \mu_{pre}(\kappa_l^p)} \cdot \Sigma_{l=0}^{l=n_{pre}} \mu_{pre}(\kappa_l^p) \cdot \kappa_l^p \tag{2}$$

where $\mu_{pre}(\kappa_l^p)$ is the value of the appropriate emotion membership function shown in Fig. 9. Thus, the value (κ_0^c) of pre-emotion is the averaged value of all pre-emotions associated with perceived impressions, and represents the prime (i) component of the classical emotion, as shown in Fig. 8. In particular, pre-emotion is mapped onto the wheel of emotions at a point corresponding to the fixed radius $r = 65$ (the third ring) and the phase of the averaged/aggregate pre-emotion κ_0^c. In systemic categories (xEmotion), the current color (linguistic value) of pre-emotion determines the emotionally preferred, quick, unconscious reactions.

The classic emotion ξ^c arises on the basis of perceived and recognized external objects. Each recognized object exerts a similar effect as

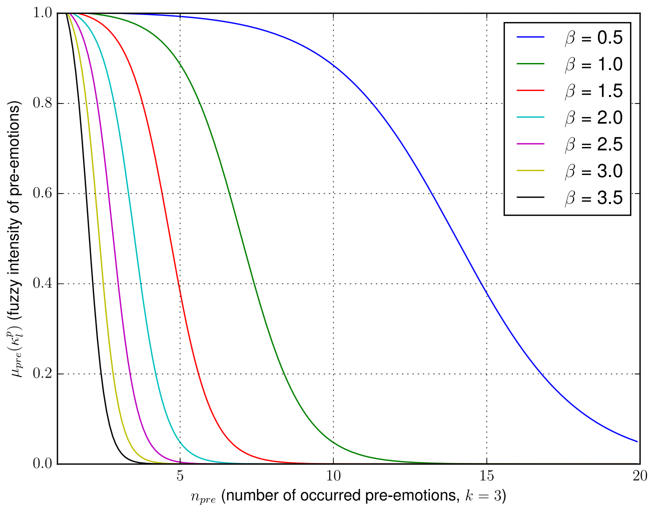

Fig. 12. Effect of changing the gain parameter β.

the aggregate pre-emotion (κ_0^c). We assume that objects in the xEmotion system (including those which are imaginary) can have an emotional context. They appear right at the time of recognition. This context is referred to as sub-emotion κ^c.

4.2. Appraisal of emotion

Taking into account the secondary (*ii*) or sub-emotional components shown in Fig. 8, the system evaluates a 'gravity' center of sub-emotions (weighted, fuzzy average of all sub-emotions, including pre-emotion κ_0^c) on the emotional circle of Fig. 4, where the weights of sub-emotions are selected from the respective (maximally four[5]) membership functions. The center of sub-emotions (in the classic emotional context) is thus defined as follows:

$$\varepsilon^c = \frac{1}{n}\Sigma_{l=0}^{l=n}\kappa_l^c \cdot max\left\{\mu_1\left(\kappa_l^c\right), \mu_2\left(\kappa_l^c\right), \mu_3\left(\kappa_l^c\right), \mu_4\left(\kappa_l^c\right)\right\} \tag{3}$$

where κ_l^c is the lth sub-emotion, while various μ describe the corresponding membership functions applied. This center of sub-emotion can be further spread into polar coordinates $\kappa^c = (r_{\kappa^c}; \omega_{\kappa^c})$, which makes it easier to perform 'rotation' on the classical emotion.

Another factor that contributes to the classical emotion system is a function specifying the degree of fulfillment of the agent's needs. Such a function affects the rotation of the classical emotion by a certain angle. The domination of unfulfillment moves the classical emotion towards negative emotions (clockwise), while the domination of satisfaction — moves it in the positive direction (anticlockwise):

$$\zeta(\eta) = 2 \cdot \Delta^\circ \cdot \begin{cases} \frac{1}{n_s}\Sigma_{l=0}^{l=n_s}\mu_s\left(\eta_l\right) & \text{if} \quad n_s \geq n_a \\ -\frac{1}{n_a}\Sigma_{l=0}^{l=n_a}\mu_a\left(\eta_l\right) & \text{if} \quad n_s < n_a \end{cases} \tag{4}$$

The above ζ describes the degree of fulfillment of all needs, where n_s denotes the number of satisfied needs, and n_a is the number of alarmed needs (*i.e.* the needs in the fuzzy state of 'alarm') and μ_s is the membership function of the satisfaction state, while μ_a denotes the membership function describing the state of alarm.

The last element that affects the classic emotion is referred to as the *calm-down* mechanism (effect). After a certain, relatively short, period of time, the classic emotion tends to a neutral state. Let δ be a parameter describing the effect of calming down, with its default value set to 0.8. Note that the calming effect 'draws' the emotion to the center of the coordinate system, and thus it affects only the radius of classical emotion.

The evolution of emotion in time can easily be mathematically described as a set of operations:

$$\xi^c := \mathfrak{T}_\alpha\left(\delta \cdot |\xi^c| \cdot e^{j(\omega+\zeta(\eta))}, \varepsilon^c\right) \tag{5}$$

where $\mathfrak{T}(X,Y)$ is a semi-translation of X, in direction Y, by α, a parameter of translation. The semi-translation function is described as follows:

$$\mathfrak{T}_\alpha(r_0 \cdot e^{j\omega_0}, r_1 \cdot e^{j\omega_1}) = (\alpha \cdot r_0 + (1-\alpha) \cdot r_1) \cdot e^{(\alpha \cdot \omega_0 + (1-\alpha) \cdot \omega_1)} \tag{6}$$

The above operations are graphically presented in Fig. 13. The agent perceives one pre-emotion (e.g. a certain odor) and recognizes three objects related to sub-emotions. The sub-emotion center is located in the serenity emotion. Its initial emotional state was 'terror' (with intensity $\sim$ 1). Due to the negative effect of meeting the needs, the emotional state turns into 'terror' (with intensity ~ 0.5). Then the state calms down towards neutral emotion and is pulled towards the center of sub-emotion. The final state of emotion is 'fear' of intensity ~ 0.6.

In summary, changes in classic emotions in the polar coordinate system can be independently described as:

$$\begin{cases} \omega_{\xi^c} = \alpha(\omega_{\xi^c} + \zeta(\eta)) + (1-\alpha) \cdot arg(\varepsilon) \\ r_{\xi^c} = \alpha \cdot \delta \cdot |\xi^c| + (1-\alpha) \cdot |\varepsilon| \end{cases} \tag{7}$$

It should be noted that there is some defect in the circular model of emotions. From a systemic point of view, it seems unnatural and even harmful that the transition between the emotions of (positive) joy, including ecstasy and serenity/peace (through anticipation, with vigilance/alertness and interest) and (negative) anger, with rage and annoyance/irritation, is possible. To show and model this effect, a third dimension is introduced into the emotion system, leading to a spatial (spiral) model of emotions. This means that changes in the angle of classic emotion are parallel to changes in altitude (in the 3rd dimension). This allows us to introduce and develop a necessary nonlinear mechanism. Depending on the distance (angle) from the maximum value of anticipation (180°/ – 180°), a 'resistance' to moving the emotional point varies. In other words, each step that increases the angle, is replaced with a smaller step described by the formula:

$$\omega_{\xi^c} := \begin{cases} \omega_{\xi^c} & \text{if} \quad \omega_{\xi^c} \in (-180 - \Delta^\circ; 180 - \Delta^\circ) \\ 180 - \Pi(\omega_{\xi^c}) & \text{if} \quad \omega_{\xi^c} \geq 180 - \Delta^\circ \wedge \Delta\omega_{\xi^c} > 0 \\ \omega_{\xi^c} & \text{if} \quad \omega_{\xi^c} \geq 180 - \Delta^\circ \wedge \Delta\omega_{\xi^c} < 0 \\ -180 + \Pi(\omega_{\xi^c}) & \text{if} \quad \omega_{\xi^c} \leq -180 + \Delta^\circ \wedge \Delta\omega_{\xi^c} < 0 \\ \omega_{\xi^c} & \text{if} \quad \omega_{\xi^c} \leq -180 + \Delta^\circ \wedge \Delta\omega_{\xi^c} > 0 \end{cases} \tag{8}$$

where $\Pi(\omega_{\xi^c})$:

$$\Pi(\omega_{\xi^c}) = \Delta^\circ \cdot (2 - \Upsilon) \cdot e^{-\frac{\omega_{\xi^c} - 180 - \Delta^\circ}{\Delta^\circ}} \tag{9}$$

and the parameter $\Upsilon \in (0,1)$ describes 'mental health'. In the case of a technical agent (robot), this parameter is set to $\Upsilon = 1$, which means that the transition between joy and anger is not possible. Certainly, you can consider here a variety of non-linear functions implementing the transformation $\Pi(\omega_{\xi^c})$. Fig. 14 illustrates the applied mechanism of the nonlinear function.

4.3. Personal emotions

In a similar manner, in the dual (private, individual) part of emotion, the equalia ξ^i is determined (being the tertiary (*iii*) component of emotion marked in Fig. 8), based on all the current sub-equalia κ^i. It should be emphasized that equalia do not take predetermined linguistic values and originally have only a relative individual-agent meaning. We assume that the agent creates its individual (dual) emotional states in the context of personal experiences, represented on the rainbow (wheel) of equalia.

[5] Remember that there are regions on the emotional wheel in which we have even four membership functions, e.g. a cross-section of fear, terror, amazement and surprise.

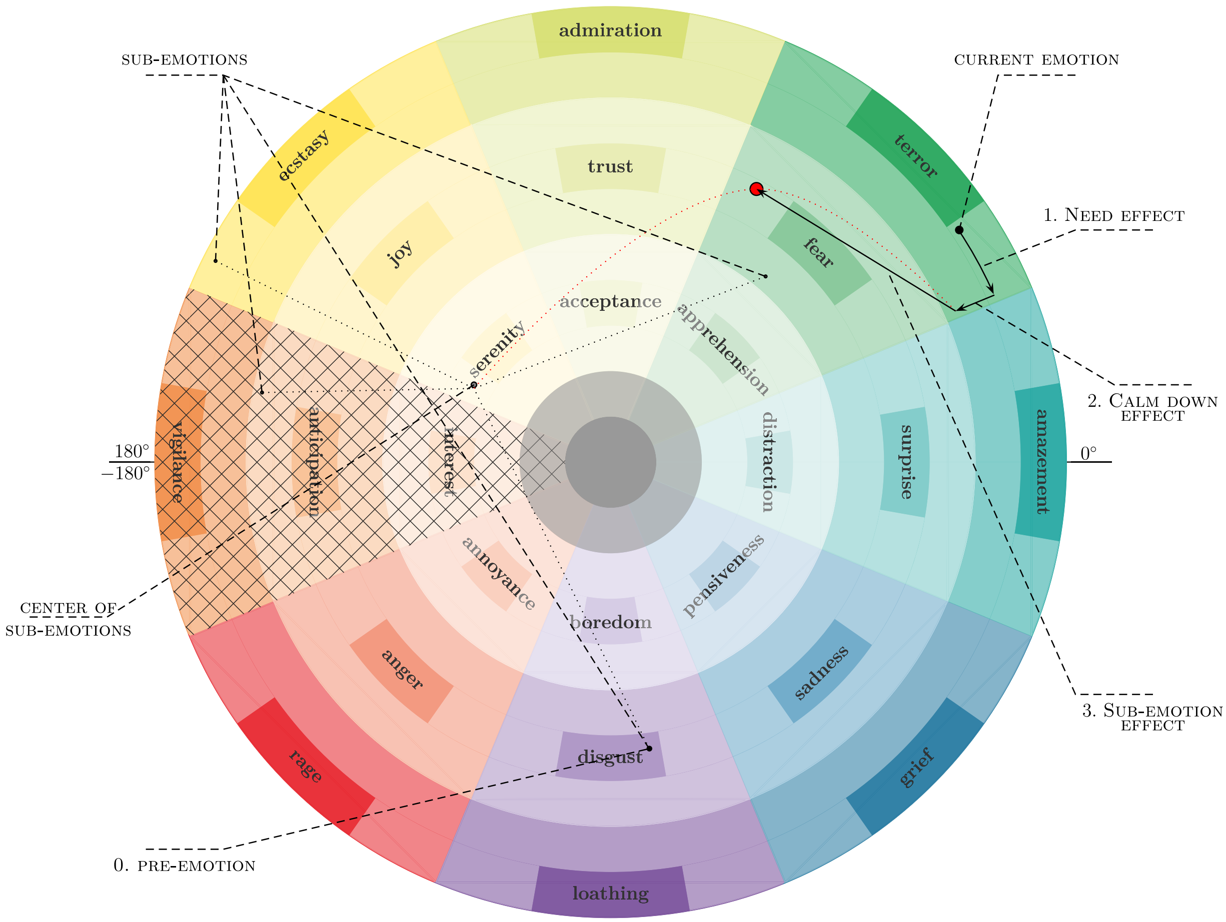

Fig. 13. Exemplary evolution of emotions (Kowalczuk and Czubenko, 2017) in response to pre-emotion and sub-emotions, and the effects of calming down and needs.

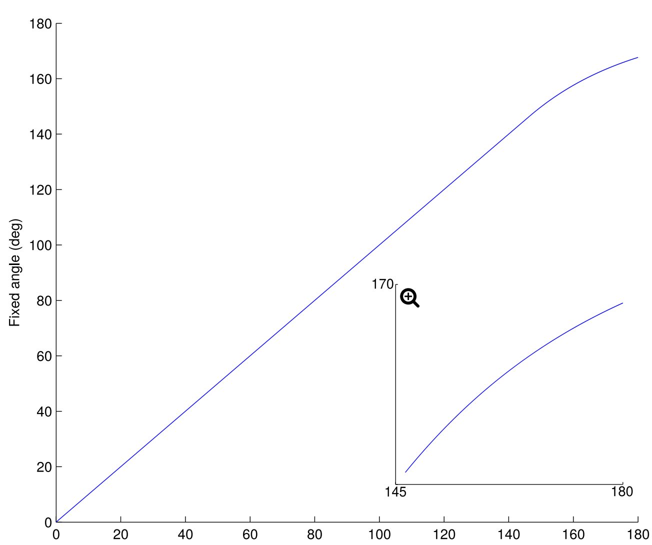

Fig. 14. The third 'dimension' of classic emotions that allows you to scale the increase of the target angle (axis X is the primary target angle ω_{ξ^c}, and axis Y shows the fixed angle, as the effect of the nonlinear warping).

Initial sub-equalia (*i.e.* equalia assigned to objects using some internal equalia trigger or a somatic/bio-systemic factor) are created during a persistent experience (perhaps with different strong stimuli), leading to an intense classical emotion (see the highest ring on the rainbow of emotions: ecstasy, admiration, terror, amazement, ...) and to its isolated emotion zone (intense color). It is this emotion (ξ^c) that is assigned to every currently perceived object as its sub-equale.

Considering the perceived objects already known and having sub-equalia, they contribute to the state of equalia in the same way as on the classic rainbow of emotion (see Fig. 13).

In the process of creating the agent's emotion (see Fig. 8), a new pre-emotion is remembered when a strong emotion occurs while perceiving an impression more than n times, where n is a large number. Similarly, a sub-emotion is associated to new discoveries when the agent has a highly non-neutral emotion. On the same basis, a new sub-equale is memorized only if the agent's emotional state is in one of the isolated emotional zones. On the other hand, using a deep (intermediate, inner) affective approach in the xEmotion system, intense and stable equalia can create a sub-emotion based on the linear/common emotion model and portray this fact within the system models of currently perceived objects.

Taking into account that the rainbow of equalia is organized with the use of the same fuzzy (spacial) structure as the rainbow of emotions (with maximally four overlapping membership functions), the center of current sub-equalia κ^i is calculated as follows:

$$\varepsilon^i = \frac{1}{n}\Sigma_{l=0}^{l=n}\kappa_l^i \cdot max\left(\mu_1^i\left(\kappa_l^i\right), \mu_2^i\left(\kappa_l^i\right), \mu_3^i\left(\kappa_l^i\right), \mu_4^i\left(\kappa_l^i\right)\right) \tag{10}$$

where μ_k^i is the kth (fixed) fuzzy membership function of equalia, while κ_l^i is the lth point of a new/considered sub-equale. Based on the computed center and the previous equalia state, the system determines the current state of equalia (on the rainbow of equalia):

$$\xi^i := (\varepsilon^i + \xi^i)/2 \tag{11}$$

4.4. The mood

The last principal issue discussed here is the impact of the classic emotion (ξ^c) on the mood (Fig. 3). The mood changes the kernel of the membership functions of all needs, resulting in a new interpretation of the levels of fulfillment of needs (their faster or slower satisfaction). The mood is generated using the TAWS transformation (Fig. 7), which always increases and decreases according to the increase or decrease of the linear emotion state (the medium ring of the wheel of emotion), but for the saturation positive and negative levels. Due to the (priorly modified) angle of the current classical emotion ($\omega_{\xi c}$), the mood is determined according to the following formula:

$$\Xi = \begin{cases} \frac{90}{\Delta^\circ}(180-\omega_{\xi c}) & \text{if} \quad \omega_{\xi c} \geq 180-\Delta^\circ \\ \frac{90}{\Delta^\circ}(-180-\omega_{\xi c}) & \text{if} \quad \omega_{\xi c} \leq -180+\Delta^\circ \\ f_{\Xi}(\omega_{\xi c}, \omega'_{\xi c}, \Xi') & \text{else} \end{cases} \tag{12}$$

where Ξ is the TAWS output, and f_{Ξ} describes the behavior of the dynamic TAWS element in its active (linear in the principal part) range, namely:

$$f_{\Xi}(\Xi', \omega'_{\xi c}, \omega_{\xi c}) = min\left(90,\ max\left(-90,\ \Xi' + 2\left(\omega_{\xi c} - \omega'_{\xi c}\right)\right)\right) \tag{13}$$

while Ξ' means the previous mood, and $\omega'_{\xi c}$ stands for the previous angle of classical emotion (such previous knowledge requires memory). The TAWS parameters have been determined adequately to the range and limits of saturation (see also the red line shown in Fig. 7). Note that the first two conditions relate to the emotion of anticipation and vigilance, which corresponds to (8) and the red line in the TAWS mechanism from Fig. 7. The full idea of mood dynamics is described in (13).

The linear part of the mood function is fixed (it could, for instance, be related to the intensity of the classical emotion), and its inclination is adjusted based on the assumption that the maximum mood change, by 180 degrees, results from a 90 degree advance in the color/phase of emotion (along the intermediate circle).

Taking into account the actual state of mood (Kowalczuk and Czubenko, 2011), a specific derivative parameter is calculated, which defines and adapts the kernel of the membership functions of needs (satisfied, pre-alarmed, alarmed). By this means, the xEmotion system controls the speed of achieving the fulfillment states of the needs (faster — in a positive mood, or slower — in a negative mood). It should be noted that through the operation of the needs system, the mood also has an indirect impact on the emotional state and, consequently, also on the newly stored discoveries (objects).

5. Simulation

Simulation of the xEmotion system was carried out for procedural and quantitative purposes and to prove the concept of the system. The presented simulation material is equivalent to the results of a laboratory test in which various environmental objects are shown to the agent for a specified period of time. In this case, the agent is transparent in the sense that we can observe its internal emotional states. It should be noted that in the presented case of object perception, the agent did not interact with the environment.

The time of the simulation was limited to 20 steps. During the simulation, the agent experienced the perception of objects associated with emotions (having emotional context expressed by the object's sub-emotions). In this experiment, pre-emotions (associated with impressions) were omitted.[6] Moreover, it was assumed that currently the agent was fully satisfied with its needs, which means that the motivational sub-system had a positive impact on the emotional sub-system according to the model (4), in particular, the increment (the need impact) $\zeta(\eta) = 2 \cdot \Delta^\circ$. The translation parameter was set to $\alpha = 0.6$, which means that the classic emotion of the agent was strongly adapted.

[6] Note that according to the principle of creating emotions described earlier, they come down to one sub-emotion.

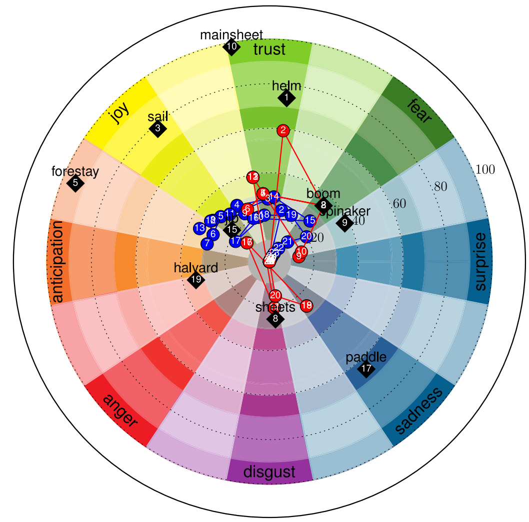

Fig. 15. Evolution of sub-emotions (black diamonds), their center (red line) and classic emotion (blue line) in time (numbered cycles). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

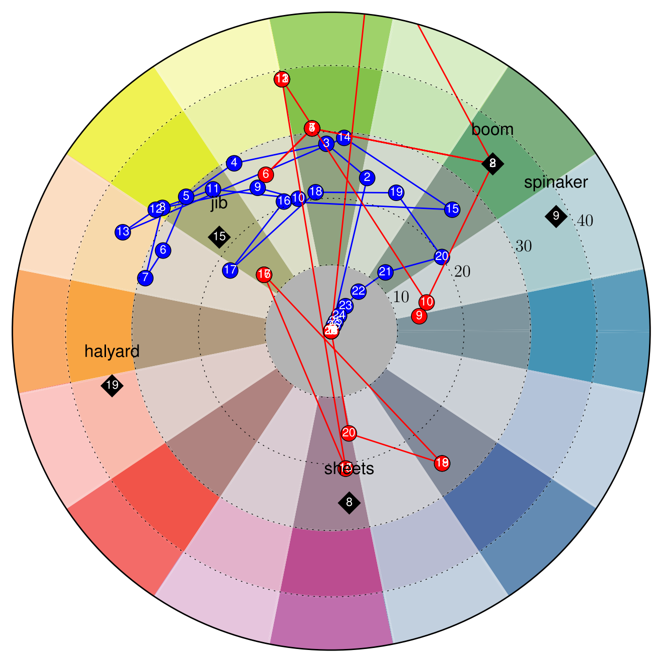

Fig. 16. Details of the evolution of the emotional variables: sub-emotions (black diamonds), their center (red line), and classic emotion (blue line). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

As is known from the literature (Section 2.1), sub-emotions (psychological expressions) last only a short time from the first moment of exposition. Therefore, normally the full exposure time of objects does not really matter, since a particular sub-emotion affects the agent if, and only if, such an object has the attention of the agent.

Nevertheless, in order to simplify our experiment and to obtain expressive emotions in continuous development, we also assumed that each of the objects during the whole time of their perception by the agent, generated sub-emotions (that is, the agent simply paid attention to the objects within the whole time of the object's exposition).

Table 3
Scenario of objects with different sub-emotions and exposition time.

Object name	Sub-emotion	ω_{ξ^c}	r_{ξ^c}	$\mu(\xi^c)$	Exposition time [steps]
Boom	Apprehension	46°	35	1	2–10
Tiller (helm)	Trust	84°	74	0.8	1–2
Sail	Joy	130°	78	0.6	3–7
Forestay	Vigilance	158°	94	0.27	5–6
Sheets	Boredom	−84°	26	0.8	8–15
Spinnaker	Apprehension	27°	38	0.49	9–10
Mainsheet	Admiration	100°	98	1	10–13
Jib	Serenity	140°	22	0.6	15–20
Paddle	Surprise	−48°	65	1	17–20
Halyard	Interest	−166°	34	0.77	19–20

In the experiment, the agent experienced the perception of 10 different objects (and their associated sub-emotions), whose 'original' emotional contributions are denoted by black diamonds in Fig. 15, and designated by the number of the computation cycle in which they first appeared. More detailed trajectories of the emotional variables are shown in an augmented version in Fig. 16. The particular exposition time of these objects is directly illustrated in Fig. 17 in its first sub-graph. The linguistic value (label) of sub-emotions (different for different objects, for simplicity) and the value of its (3D) membership function can be read from the legend and Table 3, where we provide the exposition time, which determined how long the object and the emotions associated with it affected the agent (namely, such an exposure resulted in a corresponding shift of the agent's current emotional state towards the sub-emotion associated with the perceived object). The simulated evolution of the center of all sub-emotions (as described in (3)) is marked as a red line in Figs. 15, 17, where the blue line represents the effective trajectory of the classic emotion of the agent.

After the initial phase of simulation (step 0), at first only one object was exposed to the agent (in step 1) which had a positive sub-emotion $\omega_{\xi^c} > 0$. Due to the low value of its membership function (and the weighted average implemented), the effective sub-emotion center (red line in step 2) and the intensity of classical emotion (blue line in step 2) were suitably suppressed (with respect to the only sub-emotion, and the center, respectively). It is interesting to see that, in both steps 0 and 2 (for instance), in spite of a non-supportive effect of emotions, and due to the positive impact ($\zeta(\eta) > 0$) of the motivational sub-system, the classic emotion (blue) got higher (w.r.t. its angle), etc. …

Next, in step 13, the agent lost its attention on the 'main sheet', which caused a great fall in the color (represented precisely by ω_{ξ^c}) of emotion. This, in turn, caused a rapid fall in the mood of the agent (see fourth sub-graph). Note that there is a sensitive mechanism preventing the agent from entering the kernel of anticipation (in the vicinity of 160°). One can also find an interesting point at the end of the simulation (after step no. 20), when all objects were gone from the attention of the agent. As a consequence, the classical emotion (mainly its intensity) drops to zero due to the calm-down effect. Thus, finally, the color of emotion slowly grows (the effect of fulfilled needs), and the agent's mood goes up slightly.

6. xDriver agent

Another type of simulation study is outlined in Kowalczuk and Czubenko (2017) and applied in a control system (Czubenko et al., 2015), which was intended to simulate the behavior of an intelligent driver (xDriver) in a virtual environment with a simple road scenario, including traffic disruption in the form of a pedestrian on the road.

The decisions and emotions of the xDriver are described in Table 4, Figs. 18 and 19. As can be seen in the first stage, the xDriver system's behavior was similar to that of cruise control (CC), while in the second phase, when xDriver saw a pedestrian on the road, the xEmotion subsystem developed its emotion, which under the SVC regime changed the *modus operandi* of the xDriver system resulting in well-chosen reactions.

Table 4
Reactions of the xDriver agent (Kowalczuk and Czubenko, 2017).

Mileage [km]	xDriver reaction	Emotion
0.00	Increment speed to 90	Indifference
0.66	Brake to 50 [km/h]	Indifference
0.79	Keep current speed 0	Indifference
0.85	Increment speed to 50	Indifference
1.06	Brake to 50 [km/h]	Indifference
1.09	Keep current speed 0	Indifference
1.26	Increment speed to 90	Indifference
2.09	Keep current speed 0	Indifference
2.45	Brake to 30 [km/h]	Indifference
2.62	Keep current speed 0	Indifference
3.25	Keep current speed 0	Indifference
4.45	Increment speed to 90	Indifference
4.61	Increment speed to 90	Distraction
4.63	Emergency brake 0	Surprise
4.63	Emergency brake 0	Fear
4.65	Emergency brake 0	Terror
4.85	Keep current speed 0	Terror
4.85	Keep current speed 0	Fear
4.85	Keep current speed 0	Surprise
4.85	Keep current speed 0	Distraction
4.85	Increment speed to 90	Indifference
5.65	Keep current speed 0	Indifference

The initial part of the discrete-time simulation shows how the xDriver selected the appropriate reaction, based on its system of needs (for details see Czubenko et al., 2015; Kowalczuk and Czubenko, 2017). Every action of the agent was extended in time until the car reached the goal. For instance, xDriver implemented the decision about 90 km/h or neutral action indicated as 'keep the current speed' (note that a lack of success or changing the emotion trigger another cycle of thinking).

The overshoot shown in Fig. 18 results from the non-optimal tuning of the simple PI controller, which was triggered every time the agent's decision about its speed changed. The red dashed line shows the current speed limit in advance of 350 m. In the same way, the xDriver agent observed the pedestrian from a distance of 350 m.

The main part of the emotional simulation began at a distance of 445 m, where the agent perceived the pedestrian. A man on the road induced in the agent the sub-emotion of terror, which remained as long as the xDriver was approaching the pedestrian. In effect, the xDriver system braked, stopped, and waited until the passer-by left the road. Although the model human sub-emotions lasted only a few seconds; for our purposes, the sub-emotions were sustained until the observed object was in the agent's spotlight (*i.e.* xDriver saw the obstacle).

The evolution of the classical emotion *felt* by xDriver was the following: first, it turns to distraction, surprise, next fear, and finally to terror, as shown in Fig. 19, and as explained earlier. Under the influence of the applied single sub-emotion, the classic emotion went up, and then fell down to the neutral point (in the absence of any sub-emotions) along the same trajectory.

A change in the labeled classic emotion interrupted the currently executed action of the agent, and switched it to a new set of available reactions (the effect of SVC), and thus shaped the method of functioning the xDriver. The 'emergency brake' action is attributed to the emotions of terror and fear, while other reactions only work when the agent's emotional state is 'indifference'.

The exception is the action 'keep the current speed', which, as neutral, may be chosen at any time. The emotional states of the agent are fuzzy — they infiltrate as shown in Fig. 4, and the agent can have four fuzzy emotions at the same time. For example, at a distance of 4.61 km, the agent had two different emotions ('indifference' and 'distraction'), and could choose reactions associated with 'indifference' (most reactions), and 'distraction' (none).

When the agent chose the action labeled 'emergency brake', it was interrupted, but continued to be chosen (two times), due to the change of emotion. After the 'emergency brake', and obtaining zero speed

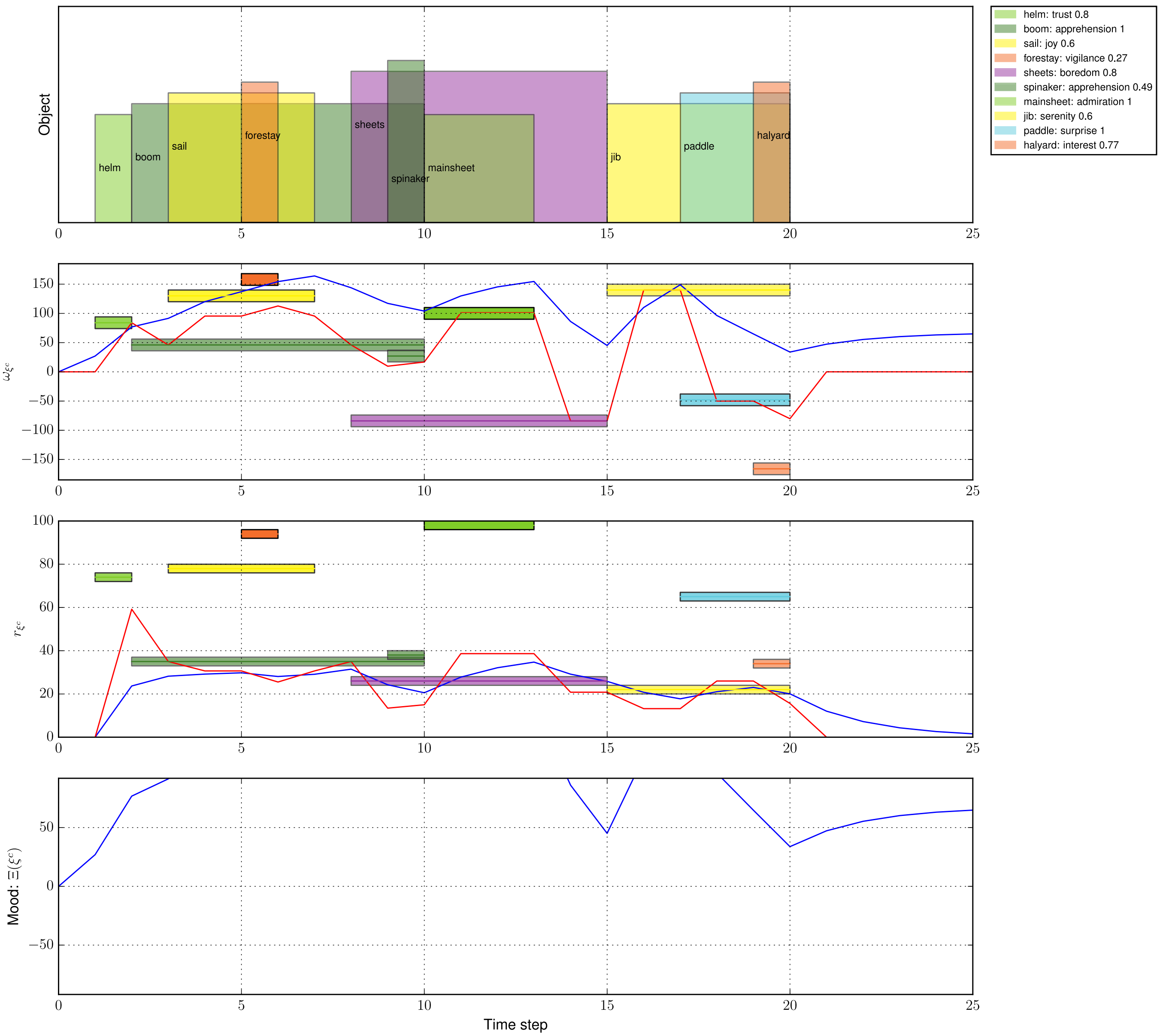

Fig. 17. Exposition window of objects with sub-emotions (first subgraph), sub-emotion names and the membership function (legend), radius and angle of sub-emotions, their center (red line), and classic emotion (blue line) in time (second and third subgraph) and changes in the mood of the agent (fourth subgraph). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(stopping), when the pedestrian went away, no new sub-emotion affected the xDriver agent. Thus the agent stuck to ‘keeping/maintaining the current speed’ (0), until its emotion relaxed to the neutral state (even if it could select other reactions, resulting from the border between ‘distraction’ and ‘indifference’). After calming down, the xDriver decided to move on, taking the standard reaction of speed increase (‘increment speed’).

7. Summary

In this article, we have described the original and working xEmotion system, based on our computational model of emotions designed to reflect a wide range of key aspects of psychological theory that were not captured by other known computational models. Adopting the cybernetic paradigm, the xEmotion system models emotions as a state of a complex process designed online to ensure agent adaptivity (e.g., through the auto-creation of emotions and other control tools) and its security and safety (e.g., by using pre-emotions automatically created or designed by the programmer for perceived environmental objects).

Sub-emotions and pre-emotions provide important information for the emotional and motivational subsystems of the agent and additional information for other ISD modules. In a natural way, emotions also allow the agent to communicate with the environment in a more advanced, or even human way (verbal and non-verbal). It is important that the system includes emotions according to *affective neuroscience* (which means that not only psychological elements are implemented in ISD):

- feelings — sub-emotions,
- affect — emotion,
- moods — mood.

Affective computation can lead to effective mechanisms in different branches of science and technology.

The proposed emotional architecture can be used to rationalize the search for the role of emotions in human cognition and behavior. From

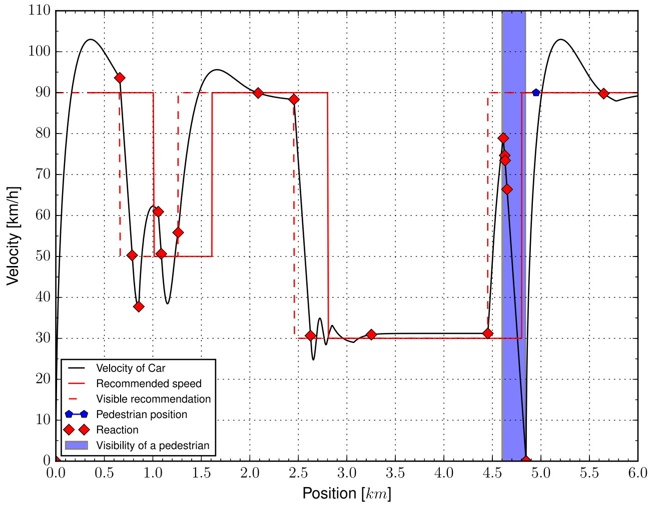

Fig. 18. Velocity (black) of the xDriver car, visible recommended speed (red dashed), decision points (red diamonds), and perception area (blue area, at 4.70 km), and real position of the passer-by (blue pentagons) (Kowalczuk and Czubenko, 2017).

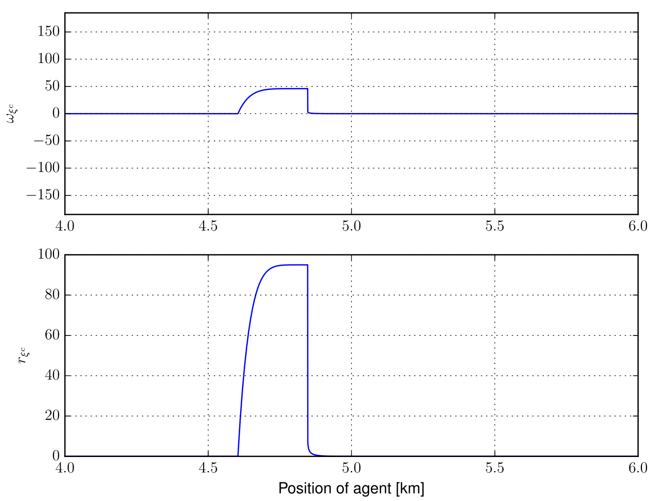

Fig. 19. Time evolution of emotions in xDriver (Kowalczuk and Czubenko, 2017).

the point of view of control theory, computational models of emotions allow us to imitate the role of SVC in autonomous systems or agents; and such emotion-based systems can lead to more flexible control of difficult non-linear systems.

The xEmotion subsystem of the ISD system has been designed to allow the selection of the most appropriate response of the agent (robotic carrier) to specific changes in the environment. An autonomous agent or robot controlled by the ISD system can operate faster and more efficiently, due to its system of emotions, which – from the control theory viewpoint – can be interpreted as an approach based on the scheduling variable strategy.

The developed xEmotion system, integrated in a coherent and possibly comprehensible way with psychological theories, allows the agent to construct individual emotions in response to observations and interactions, as it is in the case of an interactive avatar — dictobot (Kowalczuk and Czubenko, 2010a), or the autonomous driver (Czubenko et al., 2015; Kowalczuk and Czubenko, 2017; Kowalczuk et al., 2019a,b), for instance.

The processed emotions can be used both to promptly select an appropriate reaction using the proposed two-level procedure, and to present emotions understandable to the human interlocutor, which is in accordance with contemporary trends in robotics. Certainly, the effective operation and interaction of the emotional systems of such an autonomous agent strongly depends on a properly developed system memory (Kowalczuk et al., 2016).

In conclusion, emotions in the ISD xEmotion system is used not only as a scheduling variable (for making decisions and shaping reactions or a general behavior), but also as a tuning parameter (in the motivational subsystem).

In robots, agents or avatars based on the ISD xEmotion system, emotion expression can be used both as an input signal (generated by the human operator) and as an output factor (transmitted to the human operator). Furthermore, in various social and psychological applications, the xEmotion system can also model different variants of the human personality (*e.g.* a mentally stable or unstable agent).

To sum up, the concept of interpretation and use of emotions as a scheduling control variable is one of the main inventions and contributions of this work, which solves the key problem of designing autonomous systems (the comparison of different emotion calculation models can be found in publication (Kowalczuk and Czubenko, 2016)).

Because the general idea of discovering the 'functional' structure of the mind seems obvious and attractive enough, we are now focusing on the possible applications of our ISD solution and the SVC concept, which briefly expresses the following passage describing the directions for further research.

The directions of further work seem to be a really big challenge (and as such are also very attractive). These works are related to the further functional development of the ISD concept, but mainly in the context of implementations tailored to various medical and industrial applications. In the medical field, this can be, for example, evaluation and filtration of the patient's emotional (psychophysical) state after surgery and/or rehabilitation. In the field of technical applications, mainly in automation and robotics, we intend to build laboratory implementations on available devices, e.g. mobile robots (such as Husarion). It is clear that in order to design this type of autonomous devices, several problems related to robot navigation, control, sensors, SLAM procedures, real-time processing and many other issues need to be solved.

However, there is hope that in the near future we will be able to test the proposed solution on various mobile robot systems. On the other hand, providing a complete hardware platform and solving practical problems related to autonomous interaction and exploration of the environment for a specific purpose is one of the biggest challenges of modern engineering science.

CRediT authorship contribution statement

Zdzisław Kowalczuk: Conceptualization, Methodology, Formal analysis, Writing - review & editing, Project administration. **Michał Czubenko:** Software, Investigation, Validation, Resources, Visualization, Writing - original draft. **Tomasz Merta:** Software, Investigation, Validation.

References

Becker-Asano, C., 2008. WASABI: Affect Simulation for Agents With Believable Interactivity (Ph.D. dissertation). Faculty of Technology, University of Bielefeld.
Biddle, S., Fox, K.R., Boutcher, S.H., 2000. Physical Activity and Psychological Well-Being. Psychology Press, London.
Blumberg, B., 1996. Old Tricks, New Dogs: Ethology and Interactive Creatures (Ph.D. dissertation). Massachusetts Institute of Technology.
Bringsjord, S., Bello, P., Ferrucci, D., 2001. Creativity, the turing test, and the (better) lovelace test. Minds Mach. 11 (1), 3–27.
Bui, T., Heylen, D., Poel, M., Nijholt, A., 2002. ParleE: an adaptive plan based event appraisal model of emotions. In: KI 2002: Advances in Artificial Intelligence. Springer, pp. 1–9.
Cranefield, S., Dignum, F., 2019. Incorporating social practices in BDI agent systems. In: International Conference on Autonomous Agents and MultiAgent Systems. Richland, SC, pp. 1901–1903.
Czubenko, M., Ordys, A., Kowalczuk, Z., 2015. Autonomous driver based on intelligent system of decision-making. Cogn. Comput. 7 (5), 569–581.

Dias, J.A., 2005. FearNot!: Creating Emotional Autonomous Synthetic Characters for Emphatic Interactions (Ph.D. dissertation). Lisbon: Instituto Superior Técnico, Lisbon, Portugal.
Ekman, P., 1992. An argument for basic emotions. Cogn. Emot. 6 (3–4), 169–200.
El-Nasr, M.S., Yen, J., Ioerger, T.R., 2000. Flame - fuzzy logic adaptive model of emotions. Auton. Agents Multi-Agent Syst. 3 (3), 219–257.
Elamrani, A., Yampolskiy, R.V., 2019. Reviewing tests for machine consciousness. J. Conscious. Stud. 26 (5–6), 35–64.
Elliott, C.D., 1992. The Affective Reasoner: Aprocess Model of Emotions in a Multi-Agent System (Ph.D. dissertation). Northwestern University, Chicago.
Frijda, N.H., 1994. The lex talionis: on vengeance. In: van Goozen, S.H., de Poll, N.E.V., Sergeant, J.A. (Eds.), Emotions: Essays on Emotion Theory. Lawrence Erlbaum Associates, p. 352.
Gratch, J., 2000. Émile: marshalling passions in training and education. In: Proceedings 4th International Conference on Autonomous Agents. Barcelona, Spain.
Gratch, J., Marsella, S., 2004. A domain-independent framework for modeling emotion. Cogn. Syst. Res. 5 (4), 269–306.
Hardin, C.L., 1987. Qualia and materialism: closing the explanatory gap. Phil. Phenomenol. Res. 48, 281–298.
Hu, M., Wang, H., Wang, X., Yang, J., Wang, R., 2019. Video facial emotion recognition based on local enhanced motion history image and cnn-ctslstm networks. J. Vis. Commun. Image Represent. 59, 176–185.
Hudlicka, E., 2005. A computational model of emotion and personality: applications to psychotherapy research and practice. In: Proceedings of the 10th Annual Cyber Therapy Conference: A Decade of Virtual Reality. Basel, Switzerland, pp. 1–7.
Jackson, F., 1982. Epiphenomenal qualia. Phil. Q. 32 (127), 127–136.
Kaminer, I., Pascoal, A.M., Khargonekar, P.P., Coleman, E.E., 1995. A velocity algorithm for the implementation of gain-scheduled controllers. Automatica 31 (8), 1185–1191.
Kanade, T., Cohn, J., Tian, Y., 2000. Comprehensive database for facial expression analysis. In: Proceedings of the 4th IEEE International Conference on Automatic Face and Gesture Recognition. Grenoble, France, pp. 46–53.
Kołakowska, A., Landowska, A., Szwoch, M., Szwoch, W., Wróbel, M., 2015. Modeling emotions for affect-aware applications. In: Wrycza, S. (Ed.), Information Systems Development and Applications. Faculty of Management University of Gdańsk, Sopot, pp. 55–67.
Kowalczuk, Z., Chudziak, P., 2018. Identification of emotions based on human facial expressions using a color-space approach. In: Kościelny, J.M., Syfert, M., Sztyber, A. (Eds.), Advanced Solutions in Diagnostics and Fault Tolerant Control. In: Advances in Intelligent Systems and Computing, vol. 635, Springer IP AG, Cham, pp. 291–303.
Kowalczuk, Z., Czubenko, M., 2010a. DICTOBOT an autonomous agent with the ability to communicate. In: Zeszyty Naukowe WydziałU ETI Politechniki Gdańskiej. Technologie Informacyjne. pp. 87–92.
Kowalczuk, Z., Czubenko, M., 2010b. Model of human psychology for controlling autonomous robots. In: 15th International Conference on Methods and Models in Automation and Robotics. pp. 31–36.
Kowalczuk, Z., Czubenko, M., 2011. Intelligent decision-making system for autonomous robots. Int. J. Appl. Math. Comput. Sci. 21 (4), 621–635.
Kowalczuk, Z., Czubenko, M., 2013. XEmotion – obliczeniowy model emocji dedykowany dla inteligentnych systemów decyzyjnyjnych. Pomiary Autom. Robot. 2 (17), 60–65.
Kowalczuk, Z., Czubenko, M., 2015. Przegląd robotów humanoidalnych, in polish (overview of humanoid robots). Pomiary Autom. Robot. 19 (4), 67–75.
Kowalczuk, Z., Czubenko, M., 2016. Computational approaches to modeling artificial emotion–an overview of the proposed solutions. Front. Robot. AI 3 (21), 1–12.
Kowalczuk, Z., Czubenko, M., 2017. Emotions embodied in the SVC of an autonomous driver system. IFAC-PapersOnLine 50 (1), 3744—-3749. http://dx.doi.org/10.1016/j.ifacol.2017.08.573.
Kowalczuk, Z., Czubenko, M., 2018a. Embodying intelligence in autonomous and robotic systems with the use of cognitive psychology and motivation theories. In: Gawęda, A., Kacprzyk, J., Rutkowski, L., Yen, G. (Eds.), Studies in Computational Intelligence. In: Computational Intelligence, vol. 738, Springer, Cham, pp. 335–352. http://dx.doi.org/10.1007/978-3-319-67946-4_15.
Kowalczuk, Z., Czubenko, M., 2018b. An intelligent decision-making system for autonomous units based on the mind model. In: 23rd International Conference on Methods & Models in Automation & Robotics (MMAR). IEEE, Międzyzdroje, Poland, pp. 1–6.
Kowalczuk, Z., Czubenko, M., 2019, Qualia: A brief note on personal emotions representing as the temporal form of impressions – implementation hypothesis. Gdańsk University of Technology, Gdańsk.
Kowalczuk, Z., Czubenko, M., Jędruch, W., 2016. Learning processes in autonomous agents using an intelligent system of decision-making. In: Kowalczuk, Z. (Ed.), Advances in Intelligent Systems and Computing. In: Advances in Intelligent Systems and Computing, vol. 386, Springer, Berlin - Heidelberg - New York, pp. 301–315.
Kowalczuk, Z., Czubenko, M., Merta, T., 2019a. Emotion monitoring system for drivers. IFAC-PapersOnLine 52 (8), 200–205.
Kowalczuk, Z., Piechowski, O., Czubenko, M., 2019b. The impact of the temperament model on the behavior of an autonomous driver. IFAC-PapersOnLine 52 (8), 206–210.
Krzaczek, M., Kowalczuk, Z., 2012. Gain scheduling control applied to thermal barrier in systems of indirect passive heating and cooling of buildings. Control Eng. Pract. 20 (12), 1325–1336.
Landowska, A., 2018. Towards new mappings between emotion representation models. Appl. Sci. 8 (2), 274.
Lazarus, R.S., 1991. Emotion and Adaptation. Oxford University Press, USA, New York.
Lazarus, R.S., Lazarus, B.N., 1994. Passion and Reason: Making Sense of Our Emotions. Oxford University Press.
Leithead, W., 1999. Survey of gain-scheduling analysis design. Internat. J. Control 73, 1001—-1025.
Lincoln, N.K., Veres, S.M., 2013. Natural language programming of complex robotic bdi agents. J. Intell. Robot. Syst. 71 (2), 211–230.
Liu, Y., Sourina, O., Nguyen, M.K., 2010. Real-time EEG-based human emotion recognition and visualization. In: 2010 International Conference on Cyberworlds. pp. 262–269.
Lovell, D., 2015. What human emotions do we really want of artificial intelligence?. The Conversation.
Lövheim, H., 2012. A new three-dimensional model for emotions and monoamine neurotransmitters. Med. Hypotheses 78 (2), 341–348.
Lutz, C., White, G.M., 1986. Anthropology of emotions. Ann. Rev. Anthropol. 15, 405–436.
Maaoui, C., Pruski, A., Abdat, F., 2008. Emotion recognition for human-machine communication. In: 2008 IEEE/RSJ International Conference on Intelligent Robots and Systems. pp. 1210–1215.
Marinier, R., Laird, J., Lewis, R., 2009. A computational unification of cognitive behavior and emotion. Cogn. Syst. Res. 10 (1), 48–69.
Marsella, S.C., 2003. Interactive pedagogical drama: carmen's bright IDEAS assessed. In: Rist, T., Aylett, R.S., Ballin, D., Rickel, J. (Eds.), Intelligent Virtual Agents. In: Lecture Notes in Computer Science, vol. 2792, Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 1–4.
Marsella, S., Gratch, J., Petta, P., et al., 2010. Computational models of emotion. Bluepr. Affect. Comput. A 11 (1), 21–46.
Martinez, L., Falvello, V.B., Aviezer, H., Todorov, A., 2016. Contributions of facial expressions and body language to the rapid perception of dynamic emotions. Cogn. Emot. 30 (5), 939–952.
Mei, S., Marsella, S.C., Pynadath, D.V., 2006. Thespian: modeling socially normative behavior in a decision-theoretic framework. In: Proceedings of the 6th International Conference on Intelligent Virtual Agents. Marina del Rey.
Moffat, D., Frijda, N.H., 1994. Where there's a will there's an agent. In: Wooldridge, M., Jennings, N. (Eds.), Proceedings of the Workshop on Agent Theories, Architectures, and Languages on Intelligent Agents. In: Lecture Notes in Computer Science, vol. 890, Springer-Verlag New York, Inc, pp. 245–260.
Morsy, A., 2016. Emotional matters: innovative software brings emotional intelligence to our digital devices. IEEE Pulse 7 (6), 38–41.
Nummenmaa, L., Glerean, E., Hari, R., Hietanen, J.K., 2014. Bodily maps of emotions. Proc. Natl. Acad. Sci. USA 111 (2), 646–651.
Oatley, K., Keltner, D., Jenkins, J., 2012. Understanding Emotions, second ed. Blackwell Publishing.
Ong, D.C., Zaki, J., Goodman, N.D., 2019. Computational models of emotion inference in theory of mind: A review and roadmap. Top. Cogn. Sci. 11 (2), 338–357.
Osgood, C.E., May, W.H., Miron, M.S., 1975. Cross-Cultural Universals of Affective Meaning. University of Illinois Press.
Perikos, I., Hatzilygeroudis, I., 2016. Recognizing emotions in text using ensemble of classifiers. Eng. Appl. Artif. Intell. 51, 191–201.
Plutchik, R., 1980. A general psychoevolutionary theory of emotion. In: Plutchik, R., Kellerman, H. (Eds.), Emotion: Theory, Research, and Experience, Vol. 1. Academic, New York, pp. 3–33.
Plutchik, R., 2001. The nature of emotions. Am. Sci. 89, 344.
Rank, S., Petta, P., 2007. From actaffact to behbehbeh: increasing affective detail in a story-world. In: Cavazza, M., Donikian, S. (Eds.), Virtual Storytelling. using Virtual Reality Technologies for Storytelling. In: Lecture Notes in Computer Science, vol. 4871, Springer, Berlin, Heidelberg, pp. 206–209.
Reilly, W.S.N., 1996. Believable Social and Emotional Agents (Ph.D. dissertation). Carnegie Mellon University, Pittsburgh, PA.
Reilly, W., Bates, J., 1992. Building Emotional Agents. Tech. Rep., Carbegie Mellon University, Pittsburgh, PA.
Rojo-Rodriguez, E.G., Ollervides, E.J., Zambrano-Robledo, P., Garcia, O., 2019. A fuzzy gain scheduling control algorithm for formation flight of multi-UAVs. In: International Conference on Unmanned Aircraft Systems (ICUAS). pp. 712–720.
Rousseau, D., 1996. Personality in computer characters. In: AAAI Workshop on Entertainment and AI / a-Life. Portland, Oregon, pp. 38–43.
Rugh, W.J., Shamma, J.S., 2000. Research on gain scheduling. Automatica 36 (10), 1401–1425.
Russell, J.A., 1980. A circumplex model of affect. J. Personal. Soc. Psychol. 39 (6), 1161–1178.
Schlosberg, H., 1954. Three dimensions of emotion. Psychol. Rev. 61 (2), 81.
Schneider, M., Adamy, J., 2014. Towards modelling affect and emotions in autonomous agents with recurrent fuzzy systems. In: IEEE International Conference on Systems, Man and Cybernetics (SMC). San Diego, CA, 31–38.
Schrödinger, E., 2001. What Is Life? : The Physical Aspects of the Living Cell.. Cambridge University Press, Cambridge.

Shapiro, S.C., 1992. Encyclopedia of Artificial Intelligence, second ed. Wiley & Sons, Inc..
Staller, A., Petta, P., 2001. Introducing emotions into the computational study of social norms: A first evaluation. J. Artif. Soc. Soc. Simul. 4 (1), 1–11.
Suárez-Gonzalo, S., Mas-Manchón, L., Guerrero-Solé, F., 2019. Tay is you. The attribution of responsibility in the algorithmic culture. Observatorio (OBS*) 13 (2).
Swagerman, J., 1987. The Artificial Concern REalization System ACRES: A Computer Model of Emotion (Ph.D. dissertation). University of Amsterdam, Amsterdam.
Tan, S., Hang, C.-C., Chai, J.-S., 1997. Gain scheduling: from conventional to neuro-fuzzy. Automatica 33 (3), 411–419.
Thayer, R., 1989. The Biopsychology of Mood and Arousal. Oxford University Press.
Turing, A.M., 1950. Computing machine and intelligence. Mind: Q. Rev. Phil. 59 (236), 433–460.
Velásquez, J.D., Maes, P., 1997. Cathexis: a computational model of emotions. In: Proceedings of the First International Conference on Autonomous Agents. In: AGENTS '97, ACM, New York, NY, USA, pp. 518–519.
Wundt, W.M., 1874. Grundzüge de hPysiologischen Psychologie, Vol. 1. W. Engelman.
Zajonc, R.B., 1980. Compensance. In: Paulus, P.B. (Ed.), Psychology of Group Influence. Erlbaum.
Zajonc, R.B., Murphy, S.T., Inglehart, M., 1989. Feeling and facial efference: implications of the vascular theory of emotion. Psychol. Rev. 96 (3), 395–416.

Zdzisław Kowalczuk – Prof. DSc PhD MScEE (2003, 1993, 1986, 1978). Since 1978 he has been with the Faculty of Electronics, Telecommunications and Informatics at the Gdańsk University of Technology, where he is a Full Professor in automatic control and robotics, and the Chair of the Department of Robotics and Decision Systems. He held visiting appointments at University of Oulu (1985), Australian National University (1987), Technische Hochschule Darmstadt (1989), and at George Mason University (1990-1991). Main scientific interests include robotics, control theory, adaptation, system modeling, identification and estimation, diagnostics, failure detection, signal processing, artificial intelligence, control engineering and computer science. He has authored and co-authored over 20 books (incl. WNT 2002, Springer 2004–2016, PWNT 2007–2016), about 120 journal papers (45 on JCR) and over 300 conference publications and book chapters. He is the President of the Polish Consultants Society (TKP) and of the Polish Society for Measurements, Automatic Control and Robotics (POLSPAR, the NMO of IFAC), and a member of the Automation and Robotics Committee of the Polish Academy of Sciences. Since 2003 professor Kowalczuk is the founder and chief editor of the publishing house PWNT – the Pomeranian Science and Technology Publishers. He is also a recipient of 1990 and 2003 Research Excellence Awards of Polish National Education Ministry, and the 1999 Polish National Science Foundation Award in automatic control, as well as the 2014 Medal of the Association of Polish Electrical Engineers SEP named after Professor Paweł Jan Nowacki.

Michał Czubenko – PhD is a graduate of the Faculty of Electronics, Telecommunications and Computer Science at the Gdańsk University of Technology (GUT), where he defended his doctoral dissertation in 2017 in the discipline of automation and robotics with distinction. In 2015, he was the vice-chairman of the Organizing Committee at the 12th International Conference on Process and System Diagnostics. In 2012, he completed a three-month internship at the Kingston University London. Currently, he is an adjunct at the GUT in the Department of Decision and Robotics Systems. He currently works on the concept of modeling emotions for autonomous systems. His research area is in the field of artificial intelligence, robotics and psychology. He is the author of several important journal publications on JCR (Applied Mathematics and Computer Science, Cognitive Computation, and Engineering Applications of Artificial Intelligence). His citation rate in Google Scholar has exceeded 160. In private, he is interested in chess, playing the guitar, trekking in difficult conditions and sailing.

Tomasz Merta graduated from the Faculty of Electronics Telecommunications and Informatics of the Gdańsk University of Technology. In 2019, he defended his doctoral thesis "Mapping of objects of the limited environment on a three-dimensional digital map using mobile robots equipped with stereovision" and obtained a PhD degree in technical sciences. Since 2011, he has been dealing with image processing issues in the context of mobile robotics at the Department of Robotics and Decision Systems of the ETI Faculty of GUT. His scientific interests relate to signal processing, vision systems and the theory of navigation and control of robots.