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Affective Computing as Complex Systems Science

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Abstract

Pioneered in the early '90s by Rosalind Picard, a professor and IEEE Fellow of the MIT Media Lab, Affective Computing – rooted originally in artificial intelligence – now branches into wearable computing, big data, psychology, neuroscience, and modeling in order to advance the knowledge, understanding, and development of systems for sensing, recognizing, categorizing, and reacting to human emotion. Yet, the challenges of sensing multiple modalities simultaneously, disambiguating complex emotional states non-linearly, and modeling multiple individuals' emotional states dynamically have continued to ring true, despite dramatic advances in affective computing. This paper seeks to serve two objectives. The first objective is to discuss how these three challenges are related to the three characteristics of complex systems – namely multiple components, non-linearity, and emergent behaviors. The second objective is to identify opportunities from the complex systems domain to address these challenges in novel and comprehensive ways. Recent advances in the utilization of Dynamical Systems Theory (an applied complexity science methodology) have shown that complex human interaction can be rigorously studied and modeled. Coupling the technological advances that cloud-based affective computing have brought with the emerging complex systems science-perspective may well catalyze a new era of human-machine and human-human collaboration.

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1. Introduction

Pioneered by MIT professor Rosalind Picard, affective computing aims to create "cold blooded" machines or systems that can recognize and express emotions. In her landmark book, Affective Computing[10], Picard was among the first to propose that emotion could be modeled using the nonlinear sigmod function. Since then, the affective computing community has come to realize that merely combining or fusing various verbal, non-verbal, and behavioral signals is not sufficient for inferring emotional states. Furthermore, these signals or variables do not exist in a vacuum. To infer, differentiate, and express emotional states accurately, researchers must realize that these signals are activated as they interact with each other. Through such interactions, a pattern would then emerge to indicate a particular type of emotion—e.g., fear, apprehension, satisfaction, etc. Moreover, activation of these signals is usually triggered by one or more events.

Today, one of the most popular and dominant theories modeled by affective computing researchers and computer scientists is appraisal theory. Prior to discussing more about appraisal theory, describing models based on this theory, and drawing parallels between appraisal theory and complexity science applications, we will provide an overview of the diverse field of computational modeling of emotions.

1.1. Prevalent Computational Models of Emotion

Numerous computational models exist within the affective computing community. These models provide different ways and frameworks for addressing the various applications of affective computing. However, the fact that multiple models exist also points to a lack of a single unifying theory for modeling emotions[3]. Currently, these available models can be categorized into five areas: dimensional, anatomical, rational, communication, and appraisal[5].

Dimensional models[5] (also known as constructivist models) tend to focus on high-level core affects (e.g., positive, negative, or mood) and do not categorize emotions into discrete states (e.g., happiness, fear, or anger). Instead, dimensional models identify a given emotional state as a single point along an "emotional continuum," so to speak. Models based on this theory tend to simplify the types of physical behaviors typically associated with an emotional dimension[11]. The second model type is known as anatomical; this model ties emotions to certain neural and biological centers/circuits of the brain. Unlike the dimensional models, anatomical models[5] are governed by various brain theories and focus on low level perceptual-motor tasks[2].

Rational models[5] are principally influenced by researchers in the artificial intelligence (AI) community. Models of this kind are designed to identify the functions or roles that emotional states facilitate. For example, AI-based agents could be built to experience fear, which would then lead these agents to flee. Similarly, agents who are programmed to experience anger would then attack other agents. In short, researchers who work with rational models typically use them to advance machine intelligence—for instance, by translating these functions into a series of processes in an agent's architecture. Communicative models[5] are inspired by social theories. In one sense, agents based on this kind of model would exhibit the behavior of social intelligence or facilitation by displaying or sharing emotional states. In another sense, agents built according to communication models could use emotion as a form of threat to drive other agents away or warn other agents.

The final model, appraisal theory[5], is currently the most widely used theory for modeling emotion. Ideally, appraisal models are component-based in which multiple sub-models constitute the whole model. According to appraisal theory, a given emotional state will emerge from an individual's evaluation of the surroundings, situation, or contextual cues. As these emotions and their intensity unfold, the individual will likely manifest certain physical and cognitive behaviors. These behaviors could, in turn, further alter the individual's surroundings, which would lead to a continuous evaluation of the situation – also known as re-appraisal. Over time, re-appraisal serves as a feedback loop in a recursive fashion to enable the individual to evolve into experiencing different emotional states.

2. Affective Computing and the Challenges and Properties Associated with Complexity Science

Modeling emotions is widely implemented by researchers from the affective computing, AI, and computer science communities—principally because it facilitates the construction of emotion-based agent architectures. Typically, building such an architecture requires some or all of the following components.

2.1. Multimodal Sensory Agents

Human beings employ different modalities to sense, recognize, and categorize their world. These internal modalities work together with external contextual factors to enable the individuals to appraise or assess a given situation. Hence, based on one's assessment of that situation and the individual's capabilities to manage that situation, the individual will experience the emergence of certain emotional states.

Just like human beings, systems capable of recognizing and expressing emotional states need to have similar modalities available. These modalities could also be thought of as various independent agents that work together to accomplish the goal of perceiving the physical world through various sensors. These sensory agents could include a "recognizer" and classifier for facial expressions, gestures, postures, physiological states (i.e., heart rate, galvanic skin response, blood volume pulse, and respiration rate), autonomic nervous system signals, voice (i.e., volume, pitch, and tone), and speech. Particularly, these various agents then interact and communicate to form different patterns. When these patterns align with contextual signals—also gathered by other agents—a properly-configured system could then infer emotional states from these patterns.

Traditionally, research directed at how modalities infer emotional states tend to focus on either a single modality (e.g., facial expressions only) or on a single individual. However, such approaches are too limiting from the standpoint of inference accuracy, emotion differentiation (different emotions could share same intensity of modalities), and multiple individuals. For example, in today's educational domain, researchers have been looking into using affective computing-based systems to help educators identify students who might be distracted, losing attention, frustrated, or bored by the learning materials. Such a goal means that scalability is a challenge because a system capable of accomplishing this task needs to infer and disambiguate multiple individuals' emotional states by sensing and collecting multiple modalities using a large number of interacting agents.

2.2. Nonlinear Nature of Emotions

Meuleman & Scherer[7] discussed that traditional approaches of modeling emotion using appraisal theory has been dominated by linear analysis. As Afraimovich et al.[1] pointed out, however, emotion is not static and can change over time (sometimes within minutes or seconds); moreover, emotion-motivated cognitive activity can be transient over a lengthy period of time until the cognitive activity has been completed.

Furthermore, because of the feedback or double backing property of emotion during appraisal, the concept of *hysteresis* in chaos theory could help explain why emotion is nonlinear. Particularly, Scherer[12] illustrated how a nonlinear one-dimensional function could lead from varying degrees of frustration to varying degrees of anger. By extending this concept to a higher dimension known as a control space, different types and degrees of emotion can be modeled.

2.3. Emergent Process Property

Referring back to appraisal modeling, it must be stressed that modeling emotion is a continuous, adaptive, and recursive process. One of the misconceptions in the theory of emotion is that individuals are constantly switching from one state of emotion to another. In other words, different sub-systems of appraisal are in a constant state of oscillation and synchronization to reflect the self-regulation and feedback properties of emotion. Hence, different starting points of appraisal may lead to different sets of "push" and "pull" in order to lead to a stable state. However, as individuals re-appraise emerging situations, they might be drawn back into a chaotic state. Nesse[8] referred to these recursive pull and push actions as attractor and repeller in complexity science. This process further suggests that emotions are unlikely to correlate in a direct, linear fashion. Instead, covariation, nonlinearity, and differential damping are just some of the properties that can arise when modeling such a complex synchronization[12].

3. Promises of Dynamical Systems Theory

Dynamical systems theory is a branch of nonlinear mathematics that seeks to model systems by proposing the existence of certain elements across complex systems: attractor, repeller and saddle nodes being the most prominent. Dynamical systems exist on a varied landscape in which the initial conditions (i.e., where on the landscape a system may begin) play a large role in determining the path along which a system evolves. Along with the possibility of settling at an equilibrium state, dynamical systems can find themselves in never ending cycles or never settling in a single state. One of the main representational mechanisms involves ordinary differential equations (ODEs). This means that dynamical systems models require a computational treatment that involves integrating the equations from many different initial conditions to uncover the underlying phase space. These mathematical expressions can have embedded conditional statements (e.g., an 'if-else' statement) that offer a way to capture the fundamental nonlinearities hypothesized to be at work.

It has been shown that nonlinear emotional dynamics between two people can be modeled mathematically using Dynamical Systems Theory[6]. This theoretical approach was validated experimentally[9] by utilizing John Gottman's Specific Affect Coding System (SPAFF)[4] to quantify the emotional dynamics of an interaction.

The problem with wide-spread employment of such a technique is its lack of scalability due to the human-in-the-loop nature of SPAFF. The introduction of cloud-based affect detection technologies has opened up the possibility for the human to be removed from the analysis loop. This is of vital importance if predictions about how to vary emotional state are to be made. The most important aspect of such an approach is that it recognizes the ecological nature of relationships; how a person is influenced by another varies from relationship to relationship. There is no one-size-fits-all training data set for all of the possible relationship dynamics that may emerge from an agent coming together with another, so the classical approach of training a machine learning system that is static and free of context is not sufficient. This is a problem space that is best addressed from a complexity science viewpoint; attempts to reduce relationships to any specific component of an individual participating end up missing the fact that these components derive their properties based on the context (i.e., the dynamic affect of the person with whom they are interacting) as much as they do from intrinsic properties of the complex system (i.e., human) of which they are an aspect.

Imagine replacing one of the humans that constitute the relationship with an automaton that is able to recognize affect. This automaton could reference an internal dynamical systems model of the interaction in which it is participating and make predictions about how to best influence the human with whom it is interacting by altering the parameters of this internal model it is referencing, changing its behavior accordingly, then iteratively refining its internal model based on the results of future interactions (an implementation of re-appraisal). The proposed methodology has potential applications that span many areas including clinical psychology (diagnosis and treatment of disease), sales/marketing (targeted advertising) and military/intelligence, just to name a few (see Fig. 1).

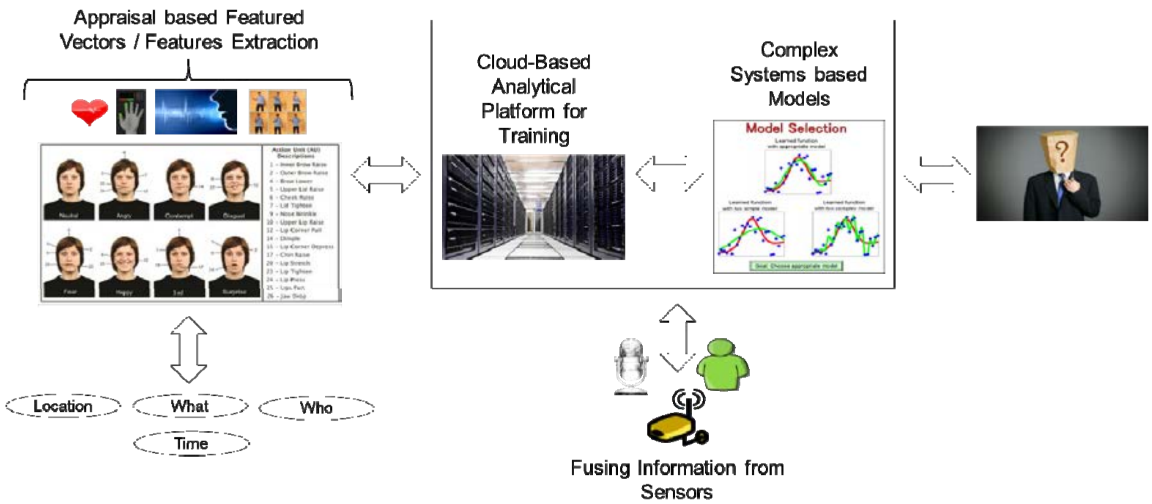

Fig. 1: Visual description of proposed methodology: integrating complex systems based modelling with appraisal

The other major dimension of scalability that needs to be addressed is for a single point of measurement to be able to disambiguate among multiple people who are dynamically interacting with the affective computing system. This is especially important for military/intelligence applications where sensor placement can be less than ideal.

4. Concluding Remarks

We have presented herein the current and ongoing challenges of affective computing—with an emphasis on the available architecting computational models for understanding human emotion and advancing human-agent interactions. The study of affective computing is vast and continues to gain importance among a diverse group of researchers across a number of areas. Despite a sizable body of scholarship, the "grand challenge" of creating a machine that understands human emotion is currently out of reach. As this paper suggests, we believe that by studying affective computing within a systems thinking perspective (and especially one targeting complex systems), the affective computing, AI and systems engineering communities will all benefit from such an approach.

Below, we chart three future directions whereby a "complex science" approach could be applicable for advancing our understanding of affective computing and its potential for modeling emotions.

- With no less than 150 theories proposed in the psychological literature to explain how and why humans experience emotion, it is clear that it will be challenging to create reliable computational models to reflect human emotion. However, developing and utilizing complex science-based models—and coupling them with applicable components of various emotional theories—could serve as the building blocks for constructing a systematic process for better understanding human emotion.
- Currently, there are no known objective standards to measure the performance and validate the accuracy of today's affect detection systems. Similarly, the available data pertaining to training affect detection systems tend to be context-free. Hence, complex science can be used to create models for measuring and validating such systems and associated data.
- Finally, building affective agents or affective agent architectures remains a challenge. General cognitive architectures, such as Soar or ACT-R, have been supplemented with emotional modules. And while specific affective agent architectures do exist, they are rare. Furthermore, applying or integrating these architectures

with other applications (e.g., Virtual Human Toolkit) is also no easy task. Hence, an increased understanding of affective computing, and in particular complex systems based affective architectures, could facilitate the construction of emotion-based computational agent architectures.

References

1. Afraimovich, V., Young, T., Muezzinoglu, M., & Rabinovich, M. (2011). Nonlinear dynamics of emotion-cognition interaction: when emotion does not destroy cognition? *Bulletin of mathematical biology*, 73(2), p.266-284.
2. Armony, J. L., Servan-Schreiber, D., Cohen, J. D. & Ledoux, J. E. (1997). Computational modeling of emotion: explorations through the anatomy and physiology of fear conditioning. *Trends in Cognitive Science*, 1, p. 28-34.
3. Calvo, R. (2010). Affect detection: an interdisciplinary review of models, methods, and their applications. *IEEE Transactions on Affective Computing*, 1(1), pp. 18-37.
4. Gottman, J. M. (2002). The mathematics of marriage: dynamic nonlinear models. MIT Press.
5. Gratch, J. & Marsella, S. (2015). Appraisal models. In *The Oxford Handbook of Affective Computing*, Oxford University Press.
6. Liebovitch, L. S., Peluso, P. R., Norman, M. D., Su, J., & Gottman, J. M. (2011). Mathematical model of the dynamics of psychotherapy. *Cognitive Neurodynamics*, *5*(3), p. 265-275.
7. Meuleman, B. & Scherer, R. (2013). Nonlinear appraisal modeling: an application of machine learning to the study of emotion production. *IEEE Transactions on Affective Computing*, 4(4), p. 398-411.
8. Nesse, R. (2009). Evolution of emotion. In *Oxford Companion to Emotion and The Affective Sciences*, Oxford University Press.
9. Norman, M.D. (2012) Mathematical model of the dynamics of psychotherapy (Doctoral dissertation). Retrieved from ProQuest Dissertations and Theses. (Accession Order No. AAT 3536489)
10. Picard, R. (1997). Affective Computing. MIT Press.
11. Scherer, R. & Ellgring, H. (2007). Are facial expressions of emotion produced by categorical affect programs or dynamically driven by appraisal? *Emotion*, 7(1), p. 113-130.
12. Scherer, R. (2009). Emotions are emergent processes: they require a dynamic computational architecture. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 364, p. 3459-3474.