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Fuzzy Sets and Systems in Building Closed-Loop Affective Computing Systems for Human-Computer Interaction: Advances and New Research Directions

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***Abstract*—Affective computing is computing that relates to, arises from, or deliberately influences emotions. It has lots of applications in the next generation of human-computer interfaces. We have proposed a closed-loop affective computing system, which includes affect recognition, affect modeling, and affect control. Because emotions include both intra-personal uncertainty, which is the uncertainty a person has about an emotion, and inter-personal uncertainty, which results from the fact that different people have different perceptions and expressions of the same emotion, it is promising to use fuzzy sets and systems, especially type-2 fuzzy sets and systems, to handle these uncertainties in an affective computing system. This paper introduces four applications of affective computing, reviews some recent advances on the application of fuzzy sets and systems to affect recognition, modeling, and control, and points out some new research directions. It will be very useful to both the fuzzy logic research community and the affective computing research community, especially to researchers working at the intersection of these two areas.**

***Index Terms*—Affective computing, affective medicine, affect recognition, affect modeling, affect control, affective engineering, Kansei engineering, fuzzy logic**

I. Introduction

Affective computing (AC) [46] is "*computing that relates to, arises from, or deliberately influences emotions.*" It has been gaining popularity rapidly in the last decade because it has great potential in the next generation of human-computer interfaces. An important goal [52] of AC is to design a computer system that responds in a rational and strategic fashion to real-time changes in user affect, cognition, and motivation, as represented by speech, facial expressions, physiological signals, neurocognitive performance, multimodal combination, etc.

Wu et al. [62] proposed a closed-loop AC system, shown in Fig. 1. It consists of three essential building blocks:

1) *Affect recognition*, which is to recognize a user's affect from various body signals, e.g., speech, facial expressions, physiological signals, etc.
2) *Affect modeling*, which is to model the relationship between the environment surrounding the user and the change of the user's affect.
3) *Affect control*, in which a controller outputs appropriate control signal to change the environment and hence to move the user's affect towards a desired state.

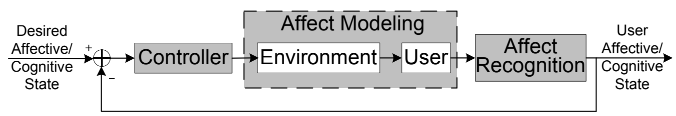

Fig. 1. Diagram of a closed-loop AC system [62].

The closed-loop AC system raises many challenges for pattern recognition, model building, and control theory, which are corresponding to the three building blocks in Fig. 1, respectively. As fuzzy sets (FSs) and fuzzy logic systems (FLSs) have been successfully applied in all these areas, they are ideal candidate in building the closed-loop AC system. In this paper we review some recent advances on the application of FSs and FLSs to these three building blocks and point out some new research directions.

The rest of this paper is organized as follows: Section II describes in detail four applications of AC. Section III briefly introduces background knowledge on FSs and FLSs. Section IV presents advances and new research directions for using FSs and FLSs in building closed-loop AC systems, including affect recognition, affect modeling, and affect control. Finally, Section V draws conclusions.

II. Applications of AC

AC has many applications. Four of them are described in detail in this section. Some of them, e.g., personalized learning and affective gaming, are closed-loop AC systems; however, some may only use affect recognition and/or affect modeling. Note that another very important application of AC in product design is Kansei/affective engineering [41], [42], which translate a consumer's feeling and image for a product into design elements to evoke desirable emotional responses.

A. Affective Robot Companions

Affective robot companions are robots which interact with people using emotional intelligence. Affective robot companion has become a very strategic and active research area around the world. In 2011 US President Obama announced that the US is launching a National Robotics Initiative to accelerate the development and use of robots in the US that work beside, or cooperatively with, people. The NSF said that methods for the establishment and infusion of robotics in educational curricula and research to gain a better understanding of the long term social, behavioral and economic implications of co-robots across all areas of human activity are important parts of this initiative.

The European Union has been particularly supportive to affective robot companion research. The HUMAINE (HUman-MAchine Interaction Network on Emotions) Network of Excellence was established in 2004, which now has 33 partners from 11 countries. It established the bi-annual International Conference on Affective Computing and Intelligent Interaction, and the IEEE/ACM Transactions on Affective Computing. The COGNIRON (Cognitive Robot Companion) project (2004-2008) involved 10 European partners and aimed at developing robots able to serve humans as assistants or companions, and able to learn new skills and tasks in an open-ended way and to grow their capacities in constant interaction with human. The COMPANIONS project (2006-2010) involved 14 partners across the Europe and the US to develop virtual companions for conversation to change the way people think about the relationships of people to computers and the Internet. The CompanionAble project (2008-2011) aims to develop integrated cognitive assistive and domotic companion robotic systems for ability and security. The LIREC (Living with Robots and Interactive Companions, 2008-2012) project is a collaboration of 10 European partners to create a new generation of interactive, emotionally intelligent companions that is capable of long-term relationships with humans. The SERA (Social Engagement with Robots and Agents) project (2009-2010) aims to advance science in the field of social acceptability of verbally interactive robots and agents, with a view to their applications especially in assistive technologies (companions, virtual butlers). The KSERA (Knowledgeable Service Robots for Aging) project (2010-2013) aims to develop a socially assistive robot that helps elderly people with their daily activities, care needs and self-management of their disease. The RoboCom (Robot Companions for Citizens) project is one of the six candidates for the two €1billion 10-year (2013-2022) Future and Emerging Technologies Flagships. RoboCom is an ecology of sentient machines that will help and assist humans in the broadest possible sense to support and sustain our welfare. It will have soft bodies based on the novel integration of solid articulated structures with flexible properties and display soft behavior based on new levels of perceptual, cognitive and emotive capabilities.

B. Personalized Learning

Personalized learning is selected by the US National Academy of Engineering as one of its 14 Grand Challenges [1]. The idea is that "*instruction can be individualized based on learning styles, speeds, and interests to make learning more reliable. ... Personal learning approaches range from modules that students can master at their own pace to computer programs designed to match the way it presents content with a learner's personality.*" We believe that a learner's affective/cognitive state is also an important consideration in personalized learning.

Research on affect [50] has shown that affect can be represented as points in a multi-dimensional space. One of the most frequently used affect spaces consists of three dimensions [11]:

- *Valence*, which ranges from *negative* to *positive*.
- *Arousal*, which ranges from *low* to *high*.
- *Dominance*, which ranges from *weak* to *strong*.

Among them, arousal is closely related to a subject's performance in mental tasks. According to the well-known Yerkes-Dodson Law [72], performance is a non-monotonic function of arousal, as shown in Fig. 2. Performance increases with arousal when the arousal level is low, then reaches its peak at the optimal arousal level, and then decreases as arousal continues to increase. So, in a personalized learning system, it is very important to be able to identify the learner's optimal arousal level and to recognize whether or not the learner's actual arousal level is close to that optimal level.

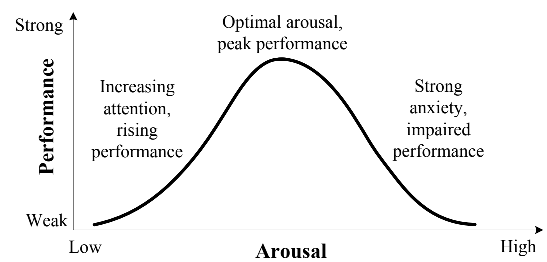

Fig. 2. The Yerkes-Dodson Law.

The above idea has been used in the MIT Media Lab Affective Learning Companion project, in which a computerized learning companion was built to facilitate the student's own efforts at learning, by occasionally prompting with questions or feedback, and by watching and responding to the affective state of the student, e.g., watching for signs of frustration and boredom that may precede quitting, for signs of curiosity or interest that tend to indicate active exploration, and for signs of enjoyment and mastery which may indicate a successful learning experience.

C. Affective Gaming

Affective gaming, which is referred to by Gilleade et al. [17] as "*where the player's current emotional state is used to manipulate gameplay,*" is gaining popularity rapidly recently. Most affective games use physiological signals, including electroencephalography (EEG), electrocardiography (ECG), electromyography (EMG), electrodermal activity (EDA), respiration, temperature, etc, to recognize the player's current emotional state [27], [43]. Pope and Palsson [48] argued that "*entertaining games that incorporate biofeedback in the background may offer a palatable and effective way to systematically guide the cerebral rewiring occurring during prolonged video game playing towards fostering creativity,* *concentration skills, precision motor skills, and other valuable abilities.*"

Gilleade et al. [17] distinguished between two types of feedbacks in affective gaming using physiological signals: biofeedback, where "*the player explicitly participates in controlling their physiological responses in order to control the game world,*" and affective feedback, where "*the physiological changes in the loop are uncontrolled. ... the players may not even be aware that their physiological state is being sensed during play of an affective videogame as the intension is to capture their normal affective reactions.*" They proposed three high level design heuristics for affective gaming: *assist me, challenge me*, and *emote me* (ACE). In *assist me* gameplay, the player's emotional state (e.g., frustration) can be used to adjust the game accordingly to assist the player (e.g., to reduce frustration). In *challenge me* gameplay, "*the player's engagement as measured through their arousal level can be used to dynamically alter the challenge the game provides, thus suiting the individual player better.*" This design heuristics can also be used in personalized learning software design. In *emote me* gameplay, the game can modify its content to provoke the intended emotions according to the user's actual emotional state, e.g., to make the user happy or relaxed.

Nacke et al. [40] distinguished between direct and indirect physiological controlled games, which are corresponding to Gilleade et al.'s definition of biofeedback and affective feedback, respectively. Their experiments suggested that "*direct physiological sensors should be mapped intuitively to reflect an action in the virtual world,*" and "*indirect physiological input is best used as a dramatic device in games to influence features altering the game world.*"

D. Affective Medicine

People have known for a long time that emotion can affect human health [7]. For example, it was found that negative emotions like stress or depression weaken the human immune system [18], and positive emotions like laughter improve the functions of the immune system [5]. So, the integration of AC with medical informatics is a natural move.

The term "affective medicine" was first introduced by Picard in 2002 [47] to denote the integration of AC with medical informatics. According to Smith and Frawley [53], there are two scenarios for affective medicine: 1) emotional user interfaces in virtual environments for healthcare professionals and patients; and, 2) emotions in computer as support for psychiatry. Numerous research and applications have been made in both scenarios [33].

One popular application of affective medicine is Autism treatment [24]. According to the NIH, Autism is a developmental disorder that appears in the first three years of life, and affects the brain's normal development of social and communication skills. Autistic children prefer a predictable and structured environment, and to be in control of the interaction. As a result, affective robots and affective human-computer interaction are promising approaches for Autism treatment [12], [39]. AC researchers have been designing novel sensors (e.g., the Zeo personal sleep coach, which allows people to track their sleep cycles over time; the Q-sensor, which measures skin conductance; and the Basis, which detects heart rate from the wrist and tracks movement, skin and ambient temperature, and skin conductance) and machine learning algorithms to infer a person's affective or cognitive state from various body signals, and developing machines that respond affectively and adaptively to these states.

MIT Technology Review recently had a section on *The Measured Life* [2], which explores new tools and trends in self-tracking, a growing movement in which people monitor various personal metrics in order to make more informed choices about living a healthier and more productive life. These tools can be used in tele-home healthcare [31], another area that has received great attention from the AC community. Healthcare services can benefit from knowing a client's cognitive and emotional states in real-time. The physiological signals recorded in everyday life contain very valuable health information and are complementary to clinic data.

III. Fuzzy Sets and Fuzzy Logic Systems

FSs and FLSs have been successfully applied in many areas. In this section we briefly introduce some background knowledge on type-1 (T1) and type-2 (T2) FSs and FLSs.

A. Type-1 Fuzzy Sets (T1 FSs)

T1 FS theory was first introduced by Zadeh [73] in 1965. An example of a T1 FS, X, is shown in Fig. 3(a). When only integer numbers are considered in the x domain, the T1 FS can be represented as $\{0/2, 0.5/3, 1/4, 1/5, 0.67/6, 0.33/7, 0/8\}$, where $0/2$ means that number 2 has a *membership degree* of 0 in the T1 FS X, $0.5/3$ means number 3 has a membership degree of 0.5 in the T1 FS X, etc. In contrast, for a crisp set, the membership degree of each element in it can be either 0 or 1; there is no value (e.g., 0.5) in between.

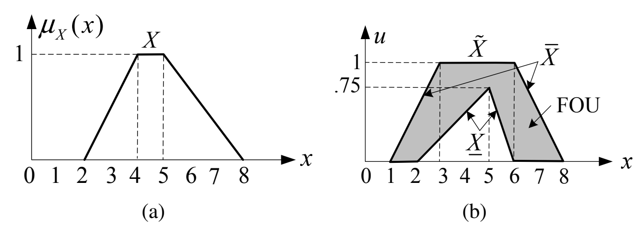

Fig. 3. Examples of a T1 FS (a) and an IT2 FS (b).

The *membership function*, $\mu_X(x)$, of a T1 FS can either be chosen based on the user's opinion (hence, the membership functions from two individuals could be quite different depending upon their experiences, perspectives, cultures, etc.), or, it can be designed using optimization procedures [59].

B. Type-1 Fuzzy Logic Systems (T1 FLSs)

Fig. 4 shows the schematic diagram of a T1 FLS. Knowledge is embedded within the rulebase in the form of rules whose antecedent and consequent are T1 FSs that partition the input and output domains. The crisp inputs are fuzzified into

T1 FSs, which are converted to a new T1 FS by the inference engine. The defuzzifier transforms this new T1 FS into a crisp output. In summary, though FS operations are used in a T1 FLS, it still maps crisp inputs into a crisp output.

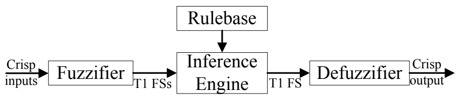

Fig. 4. A T1 FLS.

C. Type-2 Fuzzy Sets (T2 FSs)

Despite having a name which carries the connotation of uncertainty, research has shown that there are limitations in the ability of T1 FSs to model and minimize the effect of uncertainties [61]. This is because a T1 FS is certain in the sense that its membership grades are crisp values. Recently, T2 FSs [74], characterized by membership functions that are themselves fuzzy, have been attracting interests. Interval type-2 (IT2) FSs [37], a special case of T2 FSs, are currently the most widely used for their reduced computational cost.

An example of an IT2 FS, $\tilde{X}$, is shown in Fig. 3(b). Observe that unlike a T1 FS, whose membership for each x is a number, the membership of an IT2 FS is an interval. For example, the membership of number 3 is [0.25, 1], and the membership of number 5 is $[0.75, 1]$. Observe also that an IT2 FS is bounded from the above and below by two T1 FSs, $\overline{X}$ and $\underline{X}$, which are called *upper membership function* and *lower membership function*, respectively. The area between $\overline{X}$ and $\underline{X}$ is the *footprint of uncertainty* (FOU).

T2 FSs are particularly useful when it is difficult to determine the exact membership function, or in modeling the diverse opinions from different individuals. They are very popular in computing with words [38], where it is argued that they can model both intra-personal uncertainty (the uncertainty a person has about a word) and inter-personal uncertainty (the uncertainty that a group of people have about the word, because words mean different things to different people). As emotions also have both intra-personal uncertainty (the uncertainty a person has about an emotion) and inter-personal uncertainty (which results from the fact that different people have different perceptions and expressions of the same emotion), T2 FSs should also find wide applications in AC, as elaborated in the next section.

D. Interval Type-2 Fuzzy Logic Systems (IT2 FLSs)

Fig. 5 shows the schematic diagram of an IT2 FLS. It is similar to its T1 counterpart, the major difference being that at least one of the FSs in the rulebase is an IT2 FS. Hence, the outputs of the inference engine are IT2 FSs, and a type-reducer is needed to convert them into a T1 FS before defuzzification can be carried out [37].

Fuzzy logic control has been one of the most successful application areas of IT2 FLSs. Many experiments have shown that IT2 fuzzy logic controllers (FLCs) are better able to cope with noises, disturbances, and modeling uncertainties than

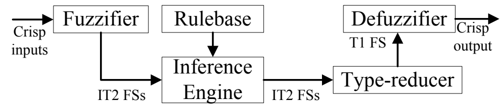

Fig. 5. An IT2 FLS.

their T1 counterparts [20], [68], [69]. Wu [61] has pointed out several reasons:

1) An IT2 FS can better model intra-personal uncertainty and inter-personal uncertainty, which are intrinsic to natural language, because the membership grade of an IT2 FS is an interval instead of a crisp number in a T1 FS.
2) Using IT2 FSs to represent the FLC inputs and outputs will result in the reduction of the rulebase when compared to using T1 FSs, as the ability of the footprint of uncertainty to represent more uncertainties enables one to cover the input/output domains with fewer FSs. This makes it easier to construct the rulebase using expert knowledge and also increases robustness.
3) An IT2 FLC can give a smoother control surface than its T1 counterpart, especially in the region around the steady state (for a Proportional-Integral controller this means both the error and the change of error approach 0). This will help reduce oscillations.
4) IT2 FLCs are more adaptive and they can realize more complex input-output relationships which cannot be achieved by T1 FLCs.
5) IT2 FLCs have a novelty that does not exist in traditional T1 FLCs: in an IT2 FLC *different* membership grades from the same IT2 FS can be used in different rules, whereas for traditional T1 FLC the *same* membership grade from the same T1 FS is always used in different rules. This again implies that an IT2 FLC is more complex than a T1 FLC and it cannot be implemented by a T1 FLC using the same rulebase.

IV. FSs and FLSs in Building Closed-Loop AC Systems

In this section we review some recent advances on the application of FSs and FLSs in building closed-loop AC systems and point out some new research directions. We consider affect recognition, affect modeling, and affect control, separately.

A. Affect Recognition

Affect recognition in this paper means to recognize affects from body signals. Ellison and Massaro [14] had performed experiments to verify that the fuzzy logical model of perception (FLMP) [36] fit the human judgments significantly better than an additive model, and they questioned previous claims of categorical and holistic perception of affect. They argued that [14] "*because analyses under the FLMP allow participants to respond to stimuli with a continuum of responses rather than an arbitrarily forced categorization, the model should allow a* *more precise exploration of the question of the processing of a continuum of facial affect changes.*" Heide et al. [58] also argued that "*fuzzy logic is the perfect tool for its (computational model of affect and emotion) implementation, for the modeling of core affect dynamics, the linguistic description of emotions, the description of a cognitive rule base, as well as the mapping between the core affect level and the cognitive level.*"

In fact, FSs and FLSs have been extensively used in affect recognition from various body signals, e.g., speech [19], [29], facial expressions [6], [56], and physiological signals [35], [49]. Lee and Narayanan [29] used a FLS to classify emotions into two classes (negative and non-negative) from speech signals. Grimm et al. [19] used a FLS to estimate the continuous values of emotions in the 3D space of Valence, Activation, and Dominance, from speech signals. Tsapatsoulis et al. [56] used a FLS to recognize six basic emotions from facial expressions represented by the MPEG-4 Facial Definition Parameter Set. Balomenos [6] employed FSs in facial expression analysis, and then combined the results with Hidden Markov Models based gesture analysis, for emotion classification. Rani et al. [49] studied affect recognition from physiological signals using FLS and compared it with a regression tree approach. Mandryk et al. [35] used EDA, EMG and heartrate to estimate arousal and valence levels in an interactive game play environment. Khushaba et al. [26] developed an efficient fuzzy mutual information based wavelet packet transform feature extraction method for classifying the driver drowsiness state into one of predefined drowsiness levels from physiological signals.

Many of the above fuzzy logic approaches have achieved outstanding performance. However, all of them used T1 FSs. As research has shown T2 FSs are better able to handle both intra-personal uncertainty and inter-personal uncertainty, it is natural to extend these approaches to T2 FSs and FLSs. There has been only limited research in this direction. Konar, Chakraborty and their co-authors [21], [34] used T2 FSs to recognize emotions from facial expressions and achieved 96.67% accuracy in their experiment, outperforming many other approaches including multi-layer perceptron, radial basis function network, support vector machine, Bayesian classifier, principal component analysis, T1 FS approach and an IT2 FS approach. It is very interesting to extend many previous approaches on T1 FSs and FLSs to T2 and see whether there are performance improvements. This will benefit both the fuzzy logic community and the AC community.

Additionally, there are several new machine learning approaches that can be combined with the fuzzy logic approach for more efficient and reliable affect recognition, particularly, preference learning [16], [71] and transfer learning [45].

Rating and pairwise preference are two popular self-reporting schemes in user studies. Yannakakis [71] proposed a *comparative affect analysis* experimental protocol for efficiently capturing human response of preference. For each pair of different experimental settings A and B, subjects report their emotional preference using a 4-alternative forced choice (4-AFC) protocol:

1) A (B) felt more E than B (A)
2) Both felt equally E, or
3) Neither of the two felt E

where E is the emotional state under investigation, e.g., boring, exciting, etc. Then preference learning is used to build a model to infer the preference relationship for new experimental setting from the subject's body signals. Fuzzy logic can be used to enhance the 4-AFC design, e.g., a statement like "A felt *much (slightly)* more exciting that B" is more informative than "A felt more exciting that B." The terms like "slightly more" and "much more" can be modeled by FSs. Also, fuzzy logic techniques can be used in building the preference learning model, which has never been investigated before.

A major assumption in many classification and prediction algorithms is that the training and test data are in the same feature space and have the same distribution [45]. However, it does not hold in many real-world applications. For example, in our previous experiment [62] on arousal classification from physiological signals a subject's physiological responses at a certain arousal level are generally quite different from another's. In such cases, knowledge transfer, if done successfully, would greatly improve the learning performance by eliminating much training example acquisition efforts. Transfer learning [45] is a framework for addressing this problem. Particularly, in AC transfer learning can be viewed as a promising approach for handling individual differences, or the inter-personal uncertainty. We have introduced an inductive transfer learning approach for arousal classification from physiological signals [67] and achieved good results. A k-nearest neighbors classifier was used; however, it handles only the inter-personal uncertainty explicitly through transfer learning. It seems promising to develop a fuzzy logic based transfer learning approach, in which FSs can be used to handle the intra-personal uncertainty. Moreover, a T2 FS based transfer learning approach may also enhance the transfer learning's ability to handle the inter-personal uncertainty.

B. Affect Modeling

It is well-known in the psychology literature that many environment factors [22], [28], [44] and social interactions [4], [54] can affect people's affects. Laukka's study [28] on 500 community living older adults in Sweden showed that "*listening to music is a common leisure activity encountered in many everyday situations, and that listening to music is a frequent source of positive emotions for older adults.*" Averett and Heise [4] believed that there is a formal mathematical model that predicts what emotion a person will experience after participating in a social interaction. Affect modeling in this paper means to model the relationship between the environment (music, color, weather, waiting time in traffic, difficulty level of a game, pace of a learning module, etc) surrounding the user and the affect of the user, or the relationship between the change of the environment settings and the user's affect. Once a model is available, we can use a controller to set the appropriate environment or to change the environment dynamically to move the user's affect towards a desired state.

Clearly, affect modeling is very subjective, and it also includes both intra-personal uncertainty (a person may display different affects in the same environment at different times, and an environment setting may elicit several different affects that are hard to distinguish) and inter-personal uncertainty (different people may display different affects in the same environment). Fuzzy logic, especially T2 fuzzy logic, is very promising in handling these uncertainties. Another reason for using fuzzy logic in affect modeling is pointed out by Heide et al. [58] as "*the large majority of computational systems on affect and emotion use rules to express cognitive functions such as appraisal and coping processes. These processes work on the fuzzy emotion concepts. Fuzzy concepts together with cognition which is expressed in the form of rules suggest the use of a fuzzy logic rule base system for the modeling of cognition.*"

In fact there has been considerable research on affect modeling using fuzzy logic. A relatively simple affect modeling task is to recognize the affects/emotions conveyed by different environment settings (instead of body signals in the previous subsection). Many different environment settings have been considered so far. Friberg [15] used a FLS to map cue values extracted from tone parameters such as tempo, sound level and articulation from music into three emotion classes (happiness, sadness, and anger). Yang et al. [70] used two FLS approaches to classify the emotions expressed by music into four classes (negative/positive $\times$ Valence/Arousal). Jun et al. [23] used a FLS to estimate the continuous valence and arousal values from music signals. Um et al. [57] used a FLS and a neural network to evaluate the emotions expressed by color patterns. Subasic and Huettner [55] proposed a method to integrate fuzzy logic with natural language processing for analyzing the affect content in free text. Li and Wang [30] modeled the relationship between traffic conditions at intersections (waiting time and road alignments) and driver emotions using a FLS. Achiche and Ahmed [3] used a FLS to describe the relationship between geometric information of a 3D object and the intended emotion.

A more advanced affect modeling task involves modeling the dynamic change of affects under environment change and social interactions. El-Nasr and Yen [13] proposed a Fuzzy Logic Adaptive Model of Emotions (FLAME) to produce emotions and to simulate the emotional intelligence process. In a related work, El-Nasr and Skubic [51] used FLSs to estimate the intensities (e.g., low, medium, or high) of three emotions (anger, pain, and fear) individually from physical damage, sound, brightness, anxiety, etc, and then another FLS to determine the behavior of a robot according to the emotional intensity and the surrounding environment.

As pointed out by Heide et al. [58], rules are very important in affect modeling. There are several challenges associated with the rules:

1) Rules are usually expressed linguistically; so the first questions is how to model these linguistic terms. As we have mentioned, to incorporate both intra-personal and inter-personal uncertainties, it is best to model them by T2 FSs. There have been some systematic approach to obtain IT2 FS word models from survey data [32], [66], which should be very useful here. Liu and Mendel's Interval Approach [32] has been used by Kazemzadeh et al. [25] to encode emotional words by IT2 FSs. Then, by considering the similarity among these words [63] they can reduce a large vocabulary to a small one or to translate between these words.
2) Sometimes we have numerical data, which need to be mapped into rules so that they can be used by the FLS. There can be different approaches for generating rules from data [60], [65], given the linguistic terms have been defined. Particularly, the linguistic summarization approach [65] can be applied to both T1 and IT2 FSs.
3) How to make use of the rules? Perceptual reasoning [38], [64] is to infer the output for a new scenario based on rules. Its output is an IT2 FS, which can be mapped into a linguistic recommendation for the ease in understanding. It is very suitable for social decision-making where rules and natural language are preferred, e.g., in affective modeling.

We plan to apply the above new techniques, which were originally developed for computing with words [38], to affect modeling in our future research.

C. Affect Control

Affect control is to generate appropriate control signal to change the environment and hence to move the user's affect towards a desired state. As we have seen in Section II-C, affect control (feedback) using physiological signals have been widely used in affective gaming. However, to the best knowledge of the author, Chakraborty, Konar and their co-authors [8]–[10] are the only ones working on affect control applications other than gaming. Interestingly enough, they used fuzzy logic based approaches.

Chakraborty et al. [10] provided a scheme for human emotion recognition from facial images, and its control, using fuzzy logic. They assigned numerical indices to four emotions (4 to happy, 3 to anxious, 2 to sad, and 1 to disgusted) so that the difference (error) between the desired emotion and the user's actual emotion can be computed. They then generated fuzzy rules like "If error is Small and error is Positive, Then apply positive influence of small strength." The membership functions were determined by trail-and-error. After defuzzification the FLC output a crisp value indicating the strength of the audiovisual movie that should be presented to the user for affect control. Experimental results showed that the proposed control scheme had good accuracy and repeatability.

However, because the above FLC requires many parameters of emotional dynamics, which are very difficult to extract, Chakraborty et al. [8] also proposed a fuzzy automata based approach. First, they obtained the state transition memberships for all possible stimuli (audiovisual movies), and then marked specific state transitions corresponding to the highest memberships due to occurrence of a given input stimulus in a predefined state. They then identified all alternative sequence of transitions between a predefined staring and goal state and determined the most reliable sequence. The input stimulus corresponding to this sequence was then presented in order. Their experiment included 100 undergraduate students and 50 audio-visual stimuli and showed 86% accuracy in obtaining the goal emotional state from a starting state. Their method has many interesting applications, e.g., psycho-therapy to control the emotional state of the subject to relaxed/happy state from fear/anger/anxiety state.

Clearly, more advanced fuzzy logic techniques can be used to design the affect controllers. As we have seen from the previous two subsections, both affect recognition and affect modeling involve lots of uncertainties, and hence the controller must be able to cope with them effectively. Research [61] has demonstrated that IT2 FLCs are very robust to noises, disturbances, and modeling uncertainties, which makes IT2 FLCs an ideal candidate for affect control. However, real-world experiments are needed to verify this proposal.

Another challenge with FLCs in affect control is how to tune the parameters of the membership functions and the rules. Chakraborty et al. [8] did that manually by trial-and-error, which is very difficult and time-consuming. As optimization algorithms like the Genetic Algorithms have been widely used in FLC design for traditional control applications [68], [69], it is meaningful to examine how evolutionary algorithms can be used in affect control. However, an important requirement for using an optimization algorithms is that we need to be able to define an objective (cost) function so that the fitness of a design candidate can be evaluated. The 3D representation of emotions is preferred here because it is easier to compute the difference between different emotions, and sometimes we may be only interested in controlling one dimension of the emotion, e.g., valance in affective robot companion, arousal in personalized learning software, etc.

V. Conclusions

Affective computing has lots of applications in the next generation of human-computer interfaces. Because emotions include both intra-personal uncertainty, which is the uncertainty a person has about an emotion, and inter-personal uncertainty, which results from the fact that different people have different perceptions and expressions of the same emotion, it is promising to use FSs and FLSs, especially T2 FSs and FLSs, in affective computing. In this paper we have introduced four applications of affective computing, reviewed some recent advances on the application of FSs and FLSs to affect recognition, modeling and control, and pointed out some new research directions. This paper will be very useful to both the fuzzy logic research community and the affective computing research community, especially to researchers working at the intersection of these two areas.

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