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Positing A Growth-Centric Learning of Empathy Models in HSI

HSI における Empathy モデルの"Growth-Centric"な学習に関する考察

レガスピ ロベルト 栗原聡 福井 健一 森山 甲一 沼尾正行
Roberto Legaspi Satoshi Kurihara Ken-ichi Fukui Koichi Moriyama Masayuki Numao

大阪大学産業科学研究所知能システム科学研究部門
Division of Intelligent Systems Science, The Institute of Scientific and Industrial Research, Osaka University

Studies have emphasized that empathy is a skill that can be acquired and that this ability develops through experience by learning and practice. Applying this in the context of human-system interaction (HSI) can mean that a system can be permitted to have an initial knowledge of empathy provision that is incomplete, hence inaccurate and imperfect, but with this knowledge increasing and improving over time through its interaction experiences with the user. This paper posits a *growth-centric*, i.e., self-improving, empathy learning for user-centric systems. Because of the nature of experiential learning involved in the problem, we reckon that this problem is a machine learning application. Hence, we also highlight the need for emerging machine learning techniques that possibly can cope with the challenges of efficiently self-improving the model of empathy provision online from incomplete knowledge.

1. Introduction

It does not come as a surprise that the consideration of empathy in intelligent computerized systems is seldom dealt as a subject. We surmise that the general issues alone that surround the topic are sufficient to immediately confront and intimidate the researcher. The literature has yet to present a widely accepted unified explanation of the nature of empathy [Preston 02]. Furthermore, we have yet to have empathy models that are as expressive as the computational models of emotion [McQuiggan 07]. Lastly, how can the human emotion, the recognition of which is fundamental to empathy, with its integrated complex individual elements behaving differently according to individuals and presented stimuli be measured, and how can an artificial intelligence (AI) system at all respond with empathy adaptively?

The word *empathy* originated from the German term *einfühlung*, which refers to projecting oneself into the object being perceived (in [Preston 02]). Broadly, this notion generally involves recognizing the thought, affect (emotion or mood), intention, and/or situation of another and attempting to put oneself into the other's state, expressing an understanding of this perception, and possibly extending support and help provisions ([Stotland 78, Ickes 93, Hoffman 00, Preston 02] richly informative understanding of the concept empathy). Applying this concept into human-system interaction (HSI), for an intelligent system to demonstrate empathic ability, it should have the mechanisms to (1) infer the user's affective state from the informative cues presented by the human body (e.g., facial or vocal expressions, body gestures, gait, etc.), (2) display emotion contagion, which is the tendency to express emotions reflective of and/or influenced by another's state, (3) attribute the state to some identifiable cause, i.e., to infer the reason why the emotion surfaced, which enables the system to anticipate similar occasions, and (4) demonstrate empathic support provisions.

連絡先:レガスピ　ロベルト, 博士研究員, 大阪大学産業科学研究所, 〒567-0047 大阪府茨木市美穂ヶ丘 8-1, Tel:06-6879-8426, roberto@ai. sanken. osaka－u. ac. jp

We aim to investigate the usability of infusing empathy in the human-centric interaction design of an ambient intelligence (AmI) system. The AmI paradigm, which builds upon ubiquitous computing and human-centered intelligent user interfaces, is the integration of networked microprocessors into the surrounding everyday objects to support the activities of the user who is immersed in the system [Riva 05].

The paper structure is as follows. We first present insights to our prior work (section 2) that will help introduce the fundamentals of our proposed concept, which we elucidate in terms of its architectural and learning paradigms (section 3).

2. Affective Music Composition: A Case Study

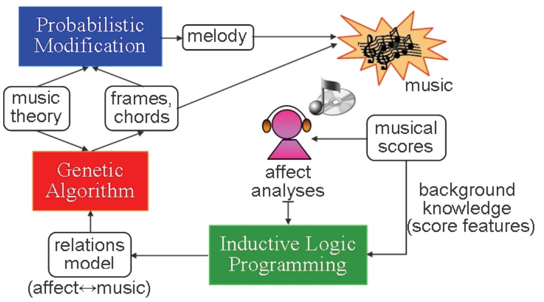

Fig.1. Learning framework of a constructive adaptive user interface for an automatic affect-based music composition.

One of our department's unique research problems is to develop an automatic music composition system that is tightly coupled with the user's impressions of music [Numao 02, Legaspi 07]. Although attempts have been made to precisely point which components of music theory (e.g., tempo, rhythm, chord function, etc.) elicit which affect, the case remains open because the solutions are either partial or uncertain [Sugimoto 08]. Furthermore, music, like empathy, is a difficult domain to model because of its complexity and broad scope. These make the task compelling. As shown in Fig.1, briefly, our approach has been to induce an affect-music relations model that describe musical events related to the listener's affective perceptions and then use the predictive knowledge of the model to automatically control the music compositional task.

What have we learned so far in this endeavor? Learning has been feasible even with the characteristic of our dataset, i.e., with only 75 musical score samples and 19 attributes representing concepts in music theory. The system was able to compose musical pieces that can convey 2-3 kinds of emotion pairs that are distinct at a significance level of α=0.01 and 4 emotion pairs at α=0.05 level when student's t-tests were performed on user evaluations of new system-composed musical pieces [Numao 02, Legaspi 07]. Furthermore, the system's 80% average accuracy in classifying the musical structure parts to the chosen affect dimensions is an indication of its ability to infer rules that are predictive of the listener's affective responses to musical events [Legaspi 07]. Though learning is feasible, the learning framework has yet to scale to online interactive learning.

The system can be considered empathic if given the objective or desire of the user, e.g., to be happy, a composed "happy" piece can be played specifically for that user. It can also be that the user is presented the various system compositions with distinct affective flavors and then pick what suits his/her goal. The system is clearly adaptive, but has yet to show that it can improve its compositions incrementally. First, the compositions should be improved continuously through subsequent user-system interactions through continuous refinement of the model of music-affect relations with the new compositions incorporated in the training data for the subsequent induction task. Though refinements can be done offline after each interaction thereby producing the desired revisions, doing these online is the most natural approach [Langley 97]. Second, the set of attributes we have used are fixed leaving no room to remove features that may have become irrelevant nor add new features that are potentially influential to distinct affect-based compositions. A dynamic scheme for feature selection will equate to a refinement, for example, of the adopted music theory. If other user features would need to be incorporated in the future, dynamic feature selection will be useful in determining which of these user features will eventually be relevant to the empathy learning task. This scheme will also prove useful in solving the problems that may emanate from high dimensionality of data (large number of attributes) that usually impedes the machine learning process or from changing contexts due to changes in the problem domain or in the physical environment.

We intend to branch out and scale our research goal and form from a sit-down human-computer interaction to that of an AmI system that is empathic and has the ability to adapt and self-learn in possibly changing contexts.

3. A New Goal and Form of Research

We are positing a *growth-centric*, i.e., self-improving, approach to empathy learning in an empathic ambient intelligent system. Studies have emphasized (refer to [Legaspi 08] for noteworthy citations) that empathy is a skill that can be acquired and that this ability develops through maturity and experience by learning and practice. Translating this into human-system relations can mean that a system is an empathy learner that can assume limited and incomplete, hence inaccurate and imperfect, initial empathy knowledge that obviously does not cover all possible events or situations and is therefore expected to improve on its ability to empathically interact adaptively with the dynamic user. In other words, this empathic learner may acquire an initial partial knowledge that is incomplete but continuously induce improved knowledge after each interaction with the user thereby, discovering, and "growing" or maturing in, its empathic ability. It is necessary for the learner to learn quickly online without sacrificing effectiveness since a system that is perceived to be ineffective or slow to adapt can easily turn away the user. This research aims to answer the following research question: How can an empathic AmI system adapt and improve its ambient responses online to help the user transition from a negative to a positive affective state? This main research problem can be broken down into several specific subproblems:

- How can a multimodal emotion detection scheme effectively achieve a robust interpretation of the user affective state?
- How can the system infer the reasons behind the emotional state in terms of user goals, ambient and situational contexts?
- How can a system adapt the ambient state and self-improve on its empathic actions over time?

3.1 The Architectural Design

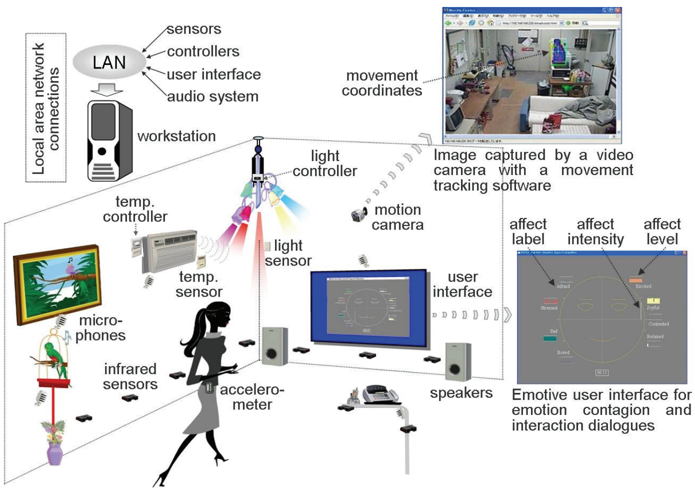

Fig.2. The architecture of the proposed ambient intelligent empathic environment.

Fig.2 illustrates our proposed ambient empathic space with the devices that will comprise it. The system interprets the affective state of the user for about every five seconds, which is the average duration of an emotion [Prendinger 02]. There have been various broad approaches in assessing emotional states (in [Legaspi 08]). What is essential to us, however, is an emotion detection scheme that can (1) capture the dynamic flow of human-system interaction, i.e., it provides immediate response to the user's current affective state which requires the affect being interpreted, and the response being modified, in real-time, (2) present a dialogue scheme that can help overcome any imprecise, ambiguous and/or partial interpretation, but at the same time does not impose upon the user a heavy cognitive load, and (3) permit mobility of the user in the known space. In this regard, we aim to infer human affect as expressed through body movement features (e.g., gait features, walking path, etc.). As its initial means to show emotional empathy, the system will mirror the user affect through an emotive graphical display. The next aspect involves a dialogue that will be initiated by the system stating its perception of its user's feeling, and with the user legitimizing the interpretation thereby avoiding any misunderstanding or inaccuracy in the interpretation. The obtained affective label will also trigger an *initial* empathic response from the system that is based on the user's current state effecting the same emotion (e.g., System: "Does my action complement how you feel?"). In the case of negative affective states, the system may respect the user's decision to stay within the predicament, or offer *continuing* support or partnership when requested upon (e.g., User: "I want to feel happy. Can you help me?"; System: "I understand. Let's see what we can do together."). The system attempts at this stage to modify its ambient empathic responses based on the changes in affective state that it senses from the user. At this conceptual stage, we have identified three means of system empathic responses, namely, changing the light's color and intensity, adjusting the room temperature, and modifying the ambient audio expressions. We have explained in detail the motivations and fundamental concepts behind the architectural framework of the empathic ambient space in [Legaspi 08].

3.2 The Learning Framework

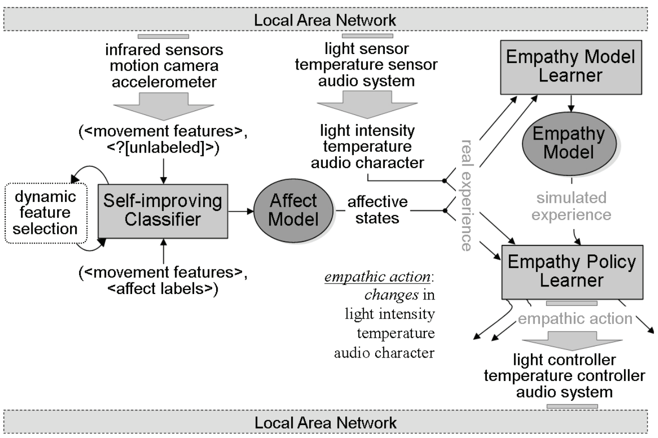

Fig.3. The learning framework of the AmI empathic space.

We posit that our empathy learner can achieve a growth-centric learning if it can (1) use unlabeled data to learn various concepts in empathy, (2) dynamically modify its set of attributes that characterizes the concepts to be modeled, and (3) learn quickly from interaction. Fig.3 roughly shows our proposed learning framework. An unlabeled data signifies an unknown, unforeseen or uncertain scenario, hence, to learn from unlabeled data equates to learning in such scenarios. Second, a dynamic attribute selection will prove critical in changing contexts. A fixed and static set of context (e.g., user affect features, interaction characteristics, etc.) attributes will leave no room to remove attributes that may have become irrelevant nor add new features that can be influential to effective empathy learning. Lastly, for the empathy learner to learn quickly has not much to do with the CPU or program's execution speed, rather, on its ability to achieve an asymptotic effective concept-learning rate as quickly as possible online. Is there sufficient grounds for us to assume that techniques in machine learning are in place or can be improved to support a self-improving empathy learning?

Several researchers have discovered that the joint use of labeled and unlabeled data can considerably improve learning accuracy. Semi-supervised [Chapelle 06, Zhu 07] and active learning [Freund 97, Angluin 04, Dasgupta 05] are important and useful techniques when labeled data are hard to obtain while there is an abundance of unlabeled data. Their combination also proved useful (e.g., [Muslea 02, Zhu 03, Zhu 07]).

To efficiently accommodate changing contexts, the empathy learner must be able to alter its attribute set when necessary. There should be mechanisms to include potentially useful features that can bring about the possibility of learning new relations, and to remove irrelevant or noisy features which is synonymous to unlearning wrong ways of relating. Several works in emotion recognition have employed dynamic feature selection (e.g., [Petrushin 00, Amershi 07, Alvarez 07], but the task is done offline. We need to achieve this online.

The advantage of online learning is that training instances are continuously processed upon arrival, consequently updating the concept theory that covers all seen instances [Oza 05]. Online variants of ML algorithms are available for decision trees, naïve Bayes models, and nearest-neighbor classifiers [Oza 05], for adversarial setting, online agnostic learning, and learning a drifting target concept [Blum 98]. There are also online algorithms for active (e.g., [Baram 04, Dasgupta 05]) and semi-supervised (e.g., [Li 06, Zheng 07]) learning and for real-time feature selection (e.g., [Last 01, Auer 02, Grabner 06]).

Another ML technique that can cope with online experiential learning is reinforcement learning that relies on experience to discover a policy for acting optimally in given situations [Sutton 98]. Reinforcement learning clearly suits unknown or changing contexts. Furthermore, a model of the system's empathic dynamics that generates simulated experiences [Sutton 98] and/or similar cases [Sharma 07] can be used for planning to supplement real-time direct learning from experience. A notable progress has been demonstrated recently by a reinforcement learning algorithm that requires only an approximate model and only a few real-life training samples to achieve a near-optimal performance in a deterministic environment [Abbeel 06].

Although these approaches have found many useful applications, these still need to be noticed in HSI.

4. Conclusion

The main goal of this paper is to lay down for consideration a growth-centric learning process when constructing AmI systems that have the capacity to be empathic. Addressing the issues when developing this process calls for (1) systems to have notions of affect recognition and provisions of affective support based on that perception (in cognitive science), (2) machine learning techniques that can support the system's self-improvement of its knowledge when interacting with the user in order to overcome the restrictions imposed by inaccurate approximated models (in machine learning in HSI), and (3) addressing the wide open problem of emotion recognition from human movements (in affective computing).

We believe that the learning process we discussed and the promise from emergent machine learning techniques that can address future issues are compelling enough to solicit future discussions and which may not be dismissed easily.

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