# An Affective Agent for Studying Composite Emotions (Demonstration)

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## **ABSTRACT**

Using an affective agent to estimate humans' composite emotions is important for creating believable interactions in human-agent collectives. However, there is a lack of suitable platforms for building large scale datasets on this topic to help researchers improve the accuracy of estimations. In this paper, we design and implement an affective agent architecture, which uses explicit emotion appraisals and a historical group emotion dataset to estimate a user's hidden emotion compositions. The historical group emotion data are based on web users' self-reported emotion labels of their feelings when reading news articles on sina.com.cn between 1 January to 30 June, 2013. Experiment results show that the artificially generated composite emotions of the agent are highly similar to real users' composite emotions.

# **Categories and Subject Descriptors**

I.2.11 [Artificial Intelligence]: Distributed Artificial Intelligence - Intelligent Agents

#### Keywords

Affective agent; composite emotion; human-agent interaction; human-agent collectives

#### 1. INTRODUCTION

In social interactions, peoples' actions are more driven by emotions (e.g., trust for someone [9, 13, 18, 19, 21, 22]) than by logic. Hence, emotion is an important factor in human-agent interaction that needs to be closely studied [7]. Modelling human emotions in artificial agents is an interdisciplinary field spanning computer science, psychology, and cognitive science [1]. As computing devices become ubiquitous, artificial companions are becoming a viable emerging mode of human computer interaction [17, 23]. This has spawned a new paradigm of interactive environments called human-agent collectives [5]. Endowing artificial companions with affective analysis and estimation capabilities has now become increasingly useful in many application domains [2, 4, 6, 8, 12, 16, 20, 24, 25].

In this paper, we describe a demonstration of an Affective Agent (AA), its architecture, and its test-bed platform. Our

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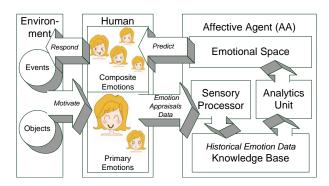


Figure 1: The affective agent architecture.

work first focuses on the group emotion data collection and analysis. Then, the AA estimates a user's current composite emotion as a result of reading a given online article based on a combination of self-report emotions, qualitative appraisals of the events in the article, and historic emotion data.

## 2. THE AA ARCHITECTURE

The AA Architecture consists of four major components, including: 1) the Knowledge Base (KB), which stores historical emotional data; 2) the Sensory Processor (SP), which accepts the input of explicit emotion appraisals reported by users; 3) the Analytics Unit (AU), which executes the emotion estimation logic; and 4) the Emotional Space (ES), which presents the estimated composite emotion to user.

These components work together in a complex network of information gathering, processing, and decision-making. As shown in Figure 1, external events (e.g., reading a news articles) may cause composite emotions in a user. The agent implemented using the AA architecture receives those emotion triggers. It compares them with the internal historical emotion data in the KB and derives possible composite emotions the user is currently experiencing. The SP and the ES integrate the same types of emotion data into the agent's KB. Sensory inputs received by the SP activate AA's predefined goals and are processed by the AU to estimate the user's composite emotions. The appropriateness of the suggested composite emotions are then verified by the user.

#### 3. THE DEMONSTRATION

An interactive platform has been developed to act as a gamified system for motivating users to provide labelled data

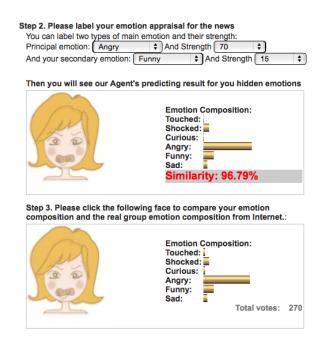


Figure 2: The estimated composite emotions by the AA and the average of the past emotion responses.

on composite emotions triggered by news reports in order to facilitate affective computing research. We collected Sina society news articles from 1 Jan. 2013 to 30 Jun. 2013 as our data source<sup>1</sup>. Sina society news allows a reader to cast his/her vote for one of six basic emotion labels after reading. These six choices describe the feelings of Touched, Shocked, Curious, Angry, Funny, and Sad. Based on the OCC emotional model [11] and emotional space theory [3, 15], we define a six dimensional emotional space, consists of above six basic emotions.

For each news article, the strength of each emotion can be reflected by the percentage of votes it received among all six basic emotions. According to [10], these online emotion labels are a true reflection of human experiences. Based on this, we store the emotion votes for each news article as a composite emotion vector into the Agent's KB.

The online test-bed platform<sup>2</sup> for demonstration and evaluation of the AA is shown in Figure 2. In the platform, a user first reads a society news article. Then, he/she can report the strengths of his/her principal emotion and another secondary emotion (optional). The emotion appraisal(s) will be used by AA to retrieve a number of N most similar news articles from the KB, according to the historical mood labels data, and then AA will calculate their average levels of the six basic emotions to estimate user's current composite emotion. The method of calculation is as follows:

1. We have collected the readers' feedback data on their emotional responses to news reports on the http:// news.sina.com.cn/society/ website from 01/01/2013 to 30/06/2013. There are 1,954 news reports attracted over 100 responses each. These records are used to form the KB of the AA. Each record consists of an

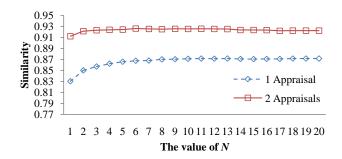


Figure 3: The similarity curve (with  $1 \le N \le 20$ ).

ID of the news, the URL to the news report, and the percentage of responses for the six basic emotions.

- 2. Based on the current user's reported primary emotion(s) and the strength of the primary emotion(s), N records from the KB which have similar strength value(s) of the reported primary emotion(s) are selected based on the Euclidean distance-based similarity measure [14]. Here, N is an adjustable parameter.
- 3. With the N most similar previous emotion response records obtained, the AA then uses the average values for the six basic emotions among these N records to produce an estimation of the current user's composite emotion.

At the end of the interaction, the user can rate the correctness of the estimated composite emotion by clicking on the "Like" or "Dislike" button on the interface. In this way, the AA platform can produce a unique dataset of labelled data over time to help advance the research in generating composite emotions for human-like agents.

# 4. PRELIMINARY RESULTS

The AA uses Euclidean Distance-based Similarity to calculate the similarity between the estimated composite emotions and the group emotion components from the dataset. We randomly selected 100 Sina society news articles as the test dataset. Figure 3 shows the similarity curve when N ranges from 1 to 20. The 1 Appraisal curve reflects the changes of user who has only reported the strength of the principle emotion that is same to real voting data. The 2 Appraisals curve reflects the changes of user who has reported the strength of both the principal emotion and the secondary emotion that are same to real voting data. From the curves, it can be observed that when N>8, the similarity measure can reach 87% for 1 appraisal and 92% for 2 appraisals. When  $N\geq 13$ , both inputs reached highest similarity.

## 5. SUMMARY

Predicting user's composite emotions are important to designing believable artificial companions. In this demonstration, we showcase an Affective Agent, including its architecture and an online test-bed platform for this purpose. Compared with real emotion voting data collected from Sina society news website shows our AA can achieve high estimation accuracy.

http://news.sina.com.cn/society/

<sup>2</sup>http://www.linjun.net.cn/affectiveagent/

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## **REFERENCES**

- [1] Affective computing. http://affect.media.mit.edu/.
- [2] Y. Cai, Z. Shen, S. Liu, H. Yu, X. Han, J. Ji, M. J. McKeown, C. Leung, and C. Miao. An agent-based game for the predictive diagnosis of parkinson's disease. In *Proceedings of the 13th International Conference on Autonomous Agents and Multi-agent Systems (AAMAS'14)*, pages 1663–1664, 2014.
- [3] I. Hidenori and T. Fukuda. Individuality of agent with emotional algorithm. In Proceedings of the 2001 IEEE/RSJ International Conference on Intelligent Robots and Systems, pages 1195–1200, 2001.
- [4] M. J. Jacobson, B. Kim, C. Miao, Z. Shen, and M. Chavez. Design perspectives for learning in virtual worlds. In M. J. Jacobson and P. Reimann, editors, Designs for Learning Environments of the Future, pages 111–141. Springer US, 2010.
- [5] N. R. Jennings, L. Moreau, D. Nicholson, S. Ramchurn, S. Roberts, T. Rodden, and A. Rogers. Human-agent collectives. *Communicates of the ACM*, 57(12):80–88, 2014.
- [6] B. Li, H. Yu, Z. Shen, and C. Miao. Evolutionary organizational search. In Proceedings of The 8th International Conference on Autonomous Agents and Multiagent Systems (AAMAS'09), pages 1329–1330, 2009.
- [7] J. Lin, Ailiya, C. Miao, and Z. Shen. A FCM based approach for emotion prediction in educational game. In Proceedings of the 3rd IEEE International Conference on Computer and Communication Technology (ICCCT'12), pages 980–986, 2012.
- [8] J. Lin, H. Yu, Z. Shen, and C. Miao. Studying task allocation decisions of novice agile teams with data from agile project management tools. In Proceedings of the 29th ACM/IEEE International Conference on Automated Software Engineering (ASE'14), pages 689–694, 2014.
- [9] S. Liu, H. Yu, C. Miao, and A. C. Kot. A fuzzy logic based reputation model against unfair ratings. In Proceedings of the 12th International Conference on Autonomous Agents and Multi-Agent Systems (AAMAS'13), pages 821–828, 2013.
- [10] Y. Ning, A. Li, and T. Zhu. Are online mood labels a true reflection of our experiences? In *Proceedings of* the 3rd Symposium on Web Society (SWS'11), pages 21–26, 2011.
- [11] A. Ortony, G. L. Clore, and A. Collins. The Cognitive Structure of Emotions. Cambridge University Press, Cambridge, UK, 1988.
- [12] L. Pan, X. Luo, X. Meng, C. Miao, and M. He. A two-stage win-win multiattribute negotiation model: Optimization and then concession. *Computational Intelligence*, 29(4):577–626, 2012.
- [13] L. Pan, X. Meng, Z. Shen, and H. Yu. A reputation pattern for service oriented computing. In *Proceedings*

- of the 7th International Conference on Information, Communications and Signal Processing (ICICS'09), 2009
- [14] A. Strehl, J. Ghosh, and R. Mooney. Impact of similarity measures on web-page clustering. Technical Report WS-00-01, AAAI Technical Report, 2000.
- [15] Z. Wei, Z. Cui, and J. Zeng. Social emotional optimisation algorithm with emotional model. International Journal of Computer Science and Engineering, 7(2):125–132, 2012.
- [16] Q. Wu, X. Han, H. Yu, Z. Shen, and C. Miao. The innovative application of learning companions in virtual singapura. In Proceedings of the 12th International Conference on Autonomous Agents and Multi-agent Systems (AAMAS'13), pages 1171–1172, 2013
- [17] H. Yu, Y. Cai, Z. Shen, X. Tao, and C. Miao. Agents as intelligent user interfaces for the net generation. In Proceedings of the 15th International Conference on Intelligent User Interfaces (IUI'10), pages 429–430, 2010.
- [18] H. Yu, C. Miao, B. An, Z. Shen, and C. Leung. Reputation-aware task allocation for human trustees. In Proceedings of the 13th International Conference on Autonomous Agents and Multi-agent Systems (AAMAS'14), pages 357–364, 2014.
- [19] H. Yu, Z. Shen, C. Leung, C. Miao, and V. R. Lesser. A survey of multi-agent trust management systems. *IEEE Access*, 1(1):35–50, 2013.
- [20] H. Yu, Z. Shen, and C. Miao. Intelligent software agent design tool using goal net methodology. In Proceedings of the 2007 IEEE/WIC/ACM International Conference on Intelligent Agent Technology (IAT'07), pages 43–46, 2007.
- [21] H. Yu, Z. Shen, C. Miao, and B. An. A reputation-aware decision-making approach for improving the efficiency of crowdsourcing systems. In Proceedings of the 12th International Conference on Autonomous Agents and Multi-Agent Systems (AAMAS'13), pages 1315–1316, 2013.
- [22] H. Yu, Z. Shen, C. Miao, C. Leung, and D. Niyato. A survey of trust and reputation management systems in wireless communications. *Proceedings of the IEEE*, 98(10):1755–1772, 2010.
- [23] H. Yu, Z. Shen, C. Miao, and A.-H. Tan. A simple curious agent to help people be curious. In *Proceedings* of the 10th International Conference on Autonomous Agents and Multiagent Systems (AAMAS'11), pages 1159–1160, 2011.
- [24] H. Yu, X. Yu, S. F. Lim, J. Lin, Z. Shen, and C. Miao. A multi-agent game for studying human decision-making. In Proceedings of the 13th International Conference on Autonomous Agents and Multi-agent Systems (AAMAS'14), pages 1661–1662, 2014.
- [25] H. L. Zhang, Z. Shen, X. Tao, C. Miao, B. Li, Ailiya, and Y. Cai. Emotional agent in serious game (DINO). In Proceedings of The 8th International Conference on Autonomous Agents and Multiagent Systems (AAMAS'09), pages 1385–1386, 2009.