An Introduction to Recent Mobile Affective Inferring Techniques: Methods, Applications and Their Challenges

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Abstract— Affective Computing has been considered as one of the most important aspects in massive human-computer interaction related projects. This paper provides a broad introduction to the recent advances in affective computing for emotion inferring based on mobile techniques. We expand the emotion inferring principles for different mobile commodity sensors, user interfaces and their possible combinations in the recent researches. Then we compare the recent popular machine learning methods and models for these sensor, and highlight the most useful methods and models with their performance. Our comparisons are not limited to traditional machine learning algorithm, they are also includes the representation learning models. In the end, we discussed few novel applications based on mobile affective computing techniques, such as how adaptive user interface and usability testing works in an emotion-aware system, as well as current limitations and open challenges of this research area.

Index Terms—Affective Computing, Emotion Inferring, Machine Learning, User Experience, Human Computer Interaction

1 Introduction

With the long-term research on emotion theory from psychology and neuroscience[20, 46], emotion has been confirmed to be a significant effect [21] on human communication, decision making, perception and so on.

Affective computing is an emerging interdisciplinary research field ranging from computer vision, machine learning, nature language understanding and human computer interaction (HCI), as well as cognitive and social sciences.

On the perspective of human computer interaction, Picard [36] pointed out that affective computing involved projects can be used for *reducing user frustration enabling comfortable communication of user emotion*, *developing infrastructure and applications to handle affective information*, as well as *building tools that help develop social-emotional skills*.

Figure 1 shows the hierarchically-structured taxonomy of this paper. In the following sections, we first how recent researches involve different mobile commodity sensors to inferring user emotions in Section 2.

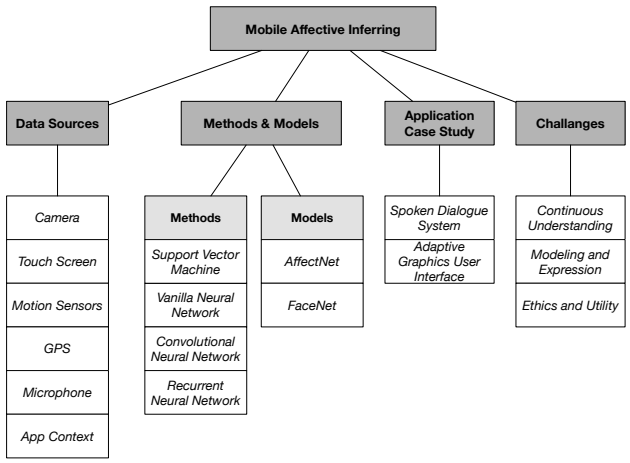

Figure 1. Hierarchically-structured taxonomy of this paper.

2 Data Sources

- [43] gives image for different information and different related sensing. - [39] gives multimodal considerations image. 90% literature consider visual, audio and text information as multimodal affect analysis

2.1 Camera

We emphasis vision sensors in the first place since face and facial expressions are undoubtedly one of the most important nonverbal channels used by the human being to convey internal emotion. This part mainly discusses vision sensors, which includes RGB camera and depth camera, and illustrates how vision sensor can be used for affective emotion inferring.

Pure RGB cameras has been widely used in commercial smartphone as image sensor. For the camera with depth informations on mobile (recently introduced TrueDepth Camera in iPhone X [1]) combines infrared camera, flood illuminator, proximity sensor, ambient light sensor, front facing camera and dot projector to provide depth images of facial information of a user.

[]

[1] https://www.apple.com/iphone-x/#truedepth-camera

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2.2 Touch Screen

Capacitive touch screen provides touch position, touch pressure, touch angle through time within a specific application context [17, 14, 41, 2] This part mainly discusses touch sensors, which includes capacitive touch screen and 3D touch screen. And also explain why touch sensor can be used for affective computing (they are applicable because of specific application context), mainly cite these papers: ...

2.3 Motion Sensors

Motion sensors typically combines gyroscope and accelerometer, with this combination they can also provide device attitude This part illustrate [40, 32, 1]

- [32]: studied the implications of human affect on general purpose touch-based mobile interaction and showed that it is possible to detect mobile users positive and neutral affective states.

Motion sensors become important because it could tells us what is user's body language.

2.4 Microphone

Audio sensor usually refers to built-in microphones, it collects voice information from current environments, which can infers user emotions based on their speech contents

Audio sensors mainly infers to input and output microphones. This leans two part of affective computing:

First is inferring emotions from user speech. This task can also split as two part of inferring task, and one is directly infer from voice; another is recognize speech text from user, then understanding or inferring from text.

Second is output a emotional speech from machines.

2.5 GPS

GPS sensors provides geographical information of a user. With Location Based Services, user emotion can be inferred by their location

2.6 Application Context

3 Methods & Models

In this section, we present technical method and models in different data type aspects.

3.1 Vision Aspect

The normal RGB camera brings us focusing on how conduct emotion recognition with RGB images. Through depth camera was recently introduced on commercial mobile phone, its principle basically as same as Microsoft Kinect. Considering these two different sensor aspects, we dive into two different research area on vision sensors.

[31]

3.2 Voice Aspect

Voice Aspect as we discussed in the previous section, emotion inferring from user speech is basically processing user speech.

There is another method, which is inferring users' emotions for human-mobile voice dialogue applications.

3.3 Touch Aspect

- linear model:
- feature engineer: [14] application specific, application context, the recognition rates are very robust even in naturalistic settings in the context of smartphone-based computer games.
- [41] hand crafted features, for three classes (happy, unhappy, neutral);
- [2] 7 proposed features, for four classes (Excited, Relaxed, Frustrated, Bored)
- [45]: Four discriminative models, namely the Nave Bayes, K-Nearest Neighbor (KNN), Decision Tree and Support Vector Machine (SVM) were explored, with SVM giving the highest accuracy of 96.75%.

3.4 Other Aspect

- Vision method: pre-trained ModelNet;
- Touch method: artificial feature engineering with support vector machine;
- Motion method: artificial feature engineering with support vector machine;
- Audio method: Speech to Text with Nature Language Processing, sequence to sequence model;

3.5 Sensors Fusion

This section should present a table for the combination of previous sensors.

4 Applications Case Study

This section put forward to the most popular applications of emotion-sensitive HCI system.

[36]

4.1 Case 1: Spoken Dialogue System

[6, 19]

4.2 Case 2: Adaptive Graphics User Interfaces

[8, 13, 22]

5 Challenges and Limitations

The primary limitation of traditional AC research refers to as impermeable emotions.

[35]

5.1 State Understanding

Continuous emotion state understanding is much more challenge since its not related to external emotion but also related to internal emotions, various emotions can be expressed as follows map *(see figure 2)*.

Figure 2. A map of human emotions [42].

6 Conclusions

In this paper, we investigated the recent papers among mobile affective computing related to human computer interaction projects.

Section 2 addresses different data sources in various mobile commodity sensors for emotion inferring in previous studies. These includes: camera, touch screen, motion sensors, microphone, GPS and application context.

Next, in the Section 3, we first considered the combinations of these types of data. According to our investigation, the following combinations has been applied in mobile affective computing: **XXX and XXX**; However, **XXX and XXX are unmined open topics**. Then, we carried out the review of emotion inferring methods based on different type of data from different sensors, and compared the tested methods and inferring models from previous researches. In these comparison, we first reviewed various models for user emotion inferring, researchers usually transfers emotion inferring problem into a classification problem or a regression problem. As a classification problem, most researchers consider user emotions can be inferred to three different state (Happy, Unhappy, Neutral, XXXX); Whereas as a regression problem, they define and calculate a continuous variable then try to learn a regression function for emotion inferring based on machine learning method. In each subsection, we highlighted the most useful methods for different type of emotion inferring that concluded by the most recent research papers, they are: XXX and XXX.

In Section 4, this paper surveys few novel applications in human-computer interaction related projects driven by emotion inferring. XXX considers user emotion as XXX and introduced XXX for XXX. XXXXXXXX

Though we researched the technic scientific approaches of emotion inferring or affective computing in human computer interaction related topics, Section 5 pointed out the current challenges and limitations of this research area. The main challenges of this area are XXXX and XXX. Moreover, the generalisability of affective computing applications are subject to certain limitations. For instance, XXX and XXX.

Today, new technologies and technic methods provide us new opportunities of affect computing in an unobtrusive mobile devices. Since the complexity of the interpretation of human behavior at a very deep level is tremendous and requires a highly interdisciplinary collaboration, we believe the true break-throughs application in this field can be established by precisely modeling and new sensing technologies in the future.

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