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

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Abstract— Affective Computing has been considered as one of the essential aspects of 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, application context and their possible combinations in the recent researches. Then we compare the recent popular machine learning methods and models for these sensors, and highlight the most useful techniques and models for their performance. Our comparisons are not limited to traditional machine learning algorithm; they also include 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—Mobile Emotion Inferring, Convolutional Networks, Recurrent Networks, Support Vector Machine, Dialogue System, Adaptive User Interfaces

1 Introduction

Affective computing is an emerging interdisciplinary research field ranging from cognitive and social sciences to human-computer interaction (HCI) researchers with techniques like computer vision, machine learning, natural language understanding, etc. With the long-term research on emotion theory from psychology and neuroscience[37, 88], emotion has been confirmed to be a significant effect [38] on human communication, decision making and perception.

On the perspective of human-computer interaction, Picard [66] 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 formulate social-emotional skills*.

Recently, the ubiquitous computing[90] and wearable computing[80], which are strictly related to affective computing, have achieved the pervasive attention of scientists. Ubiquitous computing and wearable computing are the necessary products of the combination of mobile computing technology and computer individualization.

Hence, it creates new research opportunities for affective computing to inferring user emotions with the combination of smart mobile wearable devices. We simply call it *Mobile Affective Inferring*. Such devices have been widely used over the world. The key feature of smart devices is the abundant sensors that enable various affect-related signals unobtrusive monitoring. Exploring the possibility of using smart mobile devices for affective computing will benefit at least three perspectives by the potential of long-term unobtrusive monitoring users affective states: First, it influences the affect-related research literature by the wild, natural and unobtrusive study; Second, it establishes the spontaneous affect databases efficiently to evaluate new effective methods, models, systems more accurately; and third, it enhances the user-centered HCI design for the future ubiquitous computing environments.

In this paper, we present an introduction to the mobile affective computing techniques, our next section discusses the exists data source from mobile devices, and Section 3 illustrate the recent advances for each different type of data and present the state-of-the-art model and method. Next, Section 4 based on the previous information, we reasonably assume we have finished user emotion inferring stage, then gives two typical HCI applications in this field. At last, Section 5 and 6 discusses the current challenges of mobile affective inferring and our conclusion of this introduction. Figure 1 shows the hierarchically-structured taxonomy of this paper.

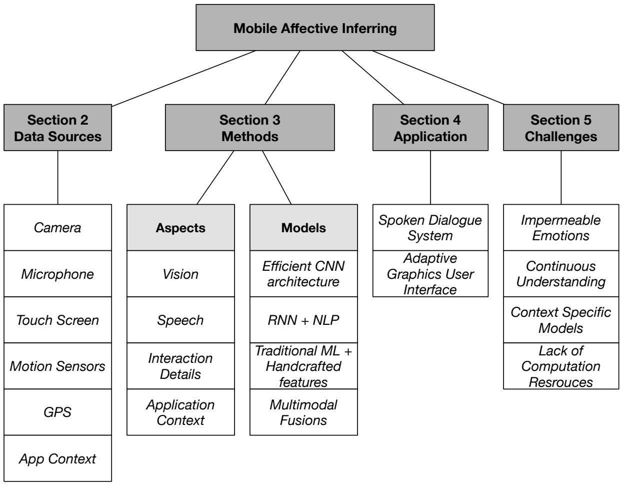

Figure 1. Hierarchically-structured taxonomy of this paper.

2 Data Sources

Previous surveys such as [1, 93, 70, 23] put forward that different data sources should be applied to various modeling methods in multimodal affective computing. [70] also give the argument that 90% literature consider visual, audio and text information as multimodal affect analysis instead of other dimensions by their extensive literature review.

In this section, we discuss the commonly existing data sources in a typical smartphone and prepare for the modelling method in the next section. Figure 2 illustrates the data flow from sensors to user emotion state.

2.1 Camera

We emphasis vision sensors in the first place since face and facial expressions are undoubtedly one of the most critical nonverbal channels used by the human being to convey internal emotion [38, 70]. This part mainly discusses vision sensors, which includes RGB cameras

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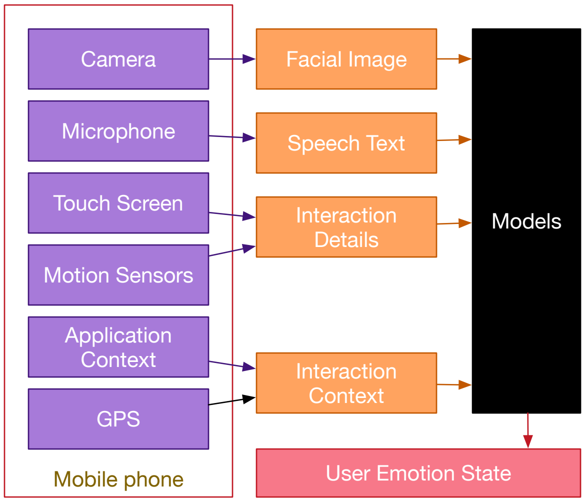

Figure 2. Data sources can be used in emotion inferring which provided by the most of commercial mobile phone devices.

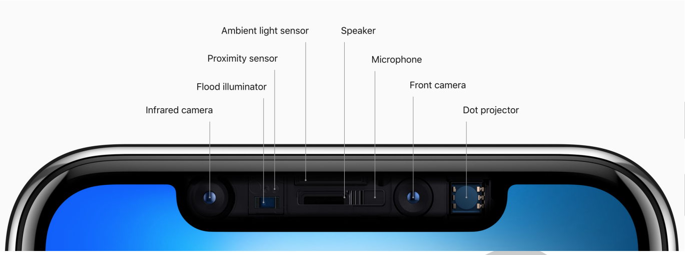

Figure 3. TrueDepth Camera in iPhone X

and depth cameras, and illustrates how vision sensor can be used for affective emotion inferring.

Pure RGB cameras have been widely used in a commercial smartphone as an image sensor. For the camera with depth information on mobile (recently introduced TrueDepth Camera in iPhone X, see Figure 2.1[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.

2.2 Microphone

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

Before recognizing user speech, a system usually should take care and preprocess the environmental noise and detect acoustic fingerprint (i.e., voiceprint) [6] for the current user, isolate their speech from mixed audio information.

Inferring emotions from user speech can split as two part of inferring task. The first part is recognizing the speech text from the user[56, 89], then understanding or inferring from the text, namely sentiment analysis [72].

2.3 Touch Screen

Human emotions can be expressed in different ways, emotional communication has focused predominantly on the facial and vocal channels but has ignored the tactile channel[31], which investigated the possible expressions of user emotion in detail while they are using mobile devices with touch screen.

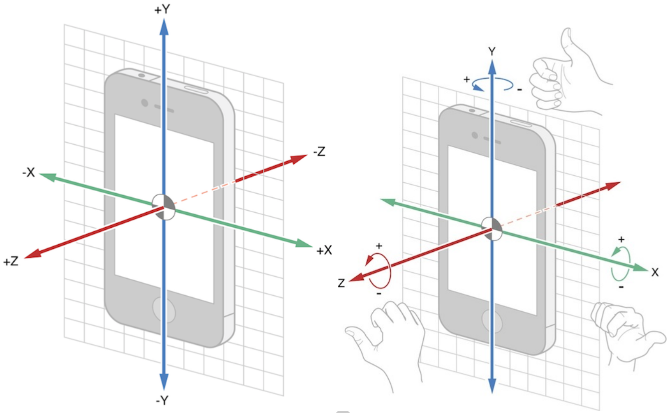

Figure 4. Coordinates information of Accelerometer (left) and gyroscope (right) as motion sensors in iOS CoreMotion framework.

A capacitive touch screen provides touch position, touch pressure, touch angle through time. Among the subsequent researches[22, 77, 60, 3], researchers explored yield results that human emotions can be inferred by capacitive touch channel in a specific application context based on these features, whose are the existed typical research on emotion inferring only with touch screen interface.

Interestingly, 3D touch screen was introduced in commercial devices a few years ago, some of the researches investigated the possibility of haptic based application [17]. [52, 48] shows a system with haptic touch response essentially can express and influence user emotions. and [4] concludes that haptic-based affect detection remains an understudied topic.

2.4 Motion Sensors

Motion sensors typically combine gyroscope and accelerometer, which are yet another interaction detail information[93]. An accelerometer measures proper acceleration (acceleration it experiences relative to free fall), felt by people or objects. Most smartphone accelerometers trade large value range for high precision. The gyroscope can be a handy tool because it moves in peculiar ways and defies gravity. Gyroscopes have been around for a century, and they are now used everywhere from airplanes, toy helicopters to smartphones. A gyroscope allows a smartphone to measure and maintain orientation. Gyroscopic sensors can monitor and control device positions, orientation, direction, angular motion, and rotation. Figure 4 shows the coordinates information of accelerometer and gyroscope sensors.

With these motion sensors, interaction details information such as device holding posture, device moving trajectory can be inferred from these sensor data [60, 70].

2.5 GPS

GPS sensors provide geographical information of a user, and it detects the location of the smartphone using 1) GPS[85]; 2) Laceration/Triangulation of cell towers or wifi networks (with a database of known locations for towers and networks)[73]; 3) Location of an associated cell tower or WiFi networks[69].

However, GPS will not work indoors and can quickly kill the battery. Smartphones can try to automatically select best-suited alternative location provider (GPS, cell towers, WiFi), mostly based on desired precision. With the location, we can study the relationship between life patterns and affective states. For example, most people in playground feel happy while most feel sad in a cemetery.

The location provides additional information to verify the subjective report from participants of affective studies. It may also help to build a confidence mechanism [85] for subjective reports. Attaching the location to the subjective report would produce confident weights

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

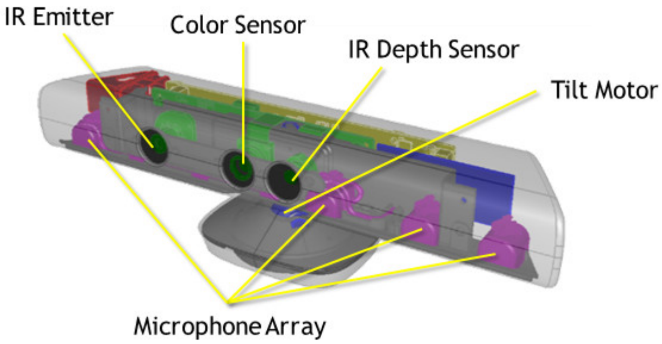

Figure 5. Principle of Microsoft Kinect.

to measure the significance of collected subjective reports. For example, a participant reported that he was happy in a cemetery. But, in common sense, people in the cemetery would be sad. Thus, we could set a low weight as a confidence value to the report.

2.6 Application Context

As we slightly mentioned in the previous section, most of the mobile affective inferring techniques based on a touch screen and motion sensors[22, 77, 60, 3] are based on specific application context, for example, application user interface. It can be another confidence mechanism for inferring system. Vice versa, the inferring systems are only modeling for a specific context. However, this could be a drawback of multimodal emotion inferring since a complete system will integrate more models.

3 Methods

Emotion inferring problems are mostly considered as a classification problem, which classifies three states of user emotion: Happy, Unhappy, Neutral. The reason for this consideration is argued by in technical constraints: more type of emotion we need to classify with more data we need to prepare. In this section, we will see the most accurate specialized method, models and their datasets in different data type aspects mainly all based on machine learning methods.

3.1 Vision Aspect

The standard RGB camera brings us focusing on how conduct emotion recognition with RGB images. Through depth camera was recently introduced on a commercial mobile phone, its principle is as same as Microsoft Kinect (see Figure 5). Considering these two different sensor aspects, we dive into two distinct research area on vision sensors.

3.1.1 Plain recognition

Recently, convolutional neural networks (CNN) method has successfully make break-through contributions to computer vision as well as its application to emotion inferring. AlexNet [46] popularized deep convolutional neural networks by winning the ImageNet Challenge (A large-scale image classification challenge). Subsequently, other powerful CNN architecture was proposed such as VGG[78], Inception series[83, 84, 82], ResNet[30], DenseNet[35] and CapsNet[75]. However, the most accurate CNN's usually have hundreds of layers and thousands of channels whereas it is entirely not possible to deploy them to the mobile system. The increasing of mobile emotion inferring needs of running high quality deep neural networks on embedded devices encourage the study on efficient model designs[29].

SqueezeNet [36] is the first model that reduces parameters and computation significantly while maintaining accuracy. MobileNet [34], ShuffleNet [94] and Xception [10] utilizes the depthwise separable convolutions among lightweight models. Table 1 shows the complexity comparation of these CNNs.

Table 1. Complexity comparison of CNN models, smaller number refers good performance

Model	Cls. Error (%)	Complexity (MFLOPs)
AlexNet[46]	42.8	720
VGG-16[78]	28.5	15300
SqueezeNet[36]	42.5	833
MobileNet[34]	31.6	325
ShuffleNet[94]	31.0	292
Xception[10]	21.0	486

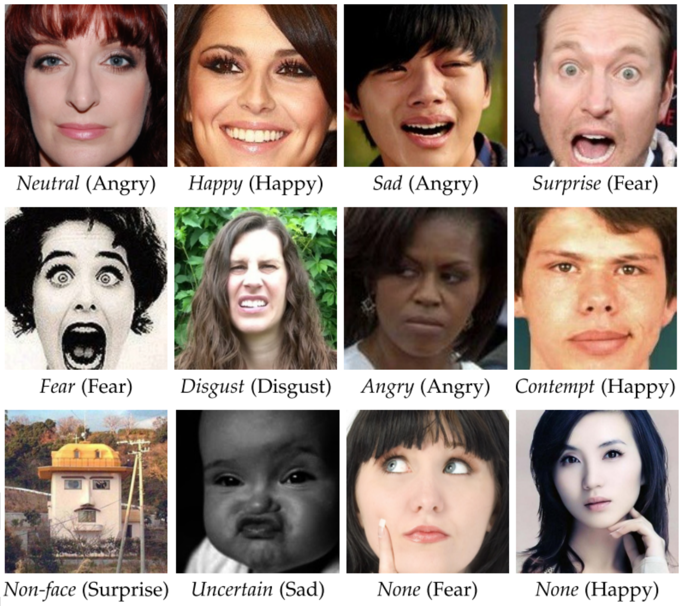
Neutral (Angry) *Happy* (Happy) *Sad* (Angry) *Surprise* (Fear)
Fear (Fear) *Disgust* (Disgust) *Angry* (Angry) *Contempt* (Happy)
Non-face (Surprise) *Uncertain* (Sad) *None* (Fear) *None* (Happy)

Figure 6. Samples of AffectNet database and classification results. The emotion expression labels is written in parentheses.

The classification of RGB images is just the final step of feedforward propagation. To determine the facial information inside an image essentially become more difficult than only a classification, then the problem refers to Landmark detection. The recent break-through contributions in this area are the Region-based CNN (R-CNN) approach [25] that to bounding-box object detection is to attend to a manageable number of candidate object regions. The state-of-the-art contribution is Mask-R-CNN [28], which serve a conceptually simple, flexible, and general framework for object instance segmentation.

With all these computer vision methods, the ICML 2013 Challenges in Representation Learning introduced the Facial Expression Recognition 2013 (FER-2013) database [26]. Fortunately, human actors/subjects databases portray the basic emotions of external human emotion has been created, which solves the problem of training data.

Benitez-Quiroz et al. [19] proposed EmotioNet database that extracts features by using Gabor filters. Their database is subject-independent and cross-database experiments. [58] uses FER-Wild database, and trained them on AlexNet with noise estimation methods and archived 82.12% accuracy on FER-Wild. AffectNet [57] is the state-of-the-art database that proposed gives the most extensive database of facial expression, valence, and arousal in the wild (see Figure 6). In their paper, various evaluation metrics shows that their deep neural network gives the state-of-the-art performance in facial emotion recognition.

3.1.2 Depth recognition

As we discussed in the previous section, depth camera principle is as same as Microsoft Kinect, the main difference between depth camera and an RGB camera is it provides 3D facial information, which leads the model difference in this field. Unlike Kinect, depth camera in most cases can only offer facial reconstruction model information instead of body gesture. Thus, depth recognition mainly focuses on modeling 3D facial points.

Paper [9] was the recent research that considering 3D modelling. They propose a real-time 3D model-based method that continuously recognizes dimensional emotions from facial expressions in natural communications. The most challenge parts of their research cover the 3D facial information reconstructed from 2D images. Zhang et al. [95] proposed their exploration on 3D facial points modeling of emotion recognition that directly gets depth information from Kinect. However, their recognition only gives three different state recognition.

Despite the already existing depth cameras in mobile phones, researchers in this area are rare and not in popular demand. We believe that primary reason is 3D modeling requires extensive computation which is not possible from mobile devices at the moment. We will discuss this issue detailly in the section of challenges.

3.2 Voice Aspect

Voice aspect as we discussed in the previous section, emotion inferring from user speech is primarily processing user speech. The first part is to deducing user speech text from their voice, and the second part of recognition is calculated sentiment from these documents.

3.2.1 Speech recognition

Speech recognition is a board research area, and there exist broad approaches to archive this goal. Previous years commercial systems modeling speech recognition by using Hiden Markov model which archived good performance, however with the raising of deep learning methods, recurrent neural network [56], Long-short term memory cell [33] and attention mechanism [89]. It is laborious to say which is the state-of-the-art model since speech recognition is much more complicated than a typical vision task. Consider there exists very successful commercial system such as Google Speech API [2]can performs stream speech recognition with returning the speech text information. We don't consider this area in detail for the primary goal of mobile affective computing.

3.2.2 Sentiment Analysis

Sentiment analysis requires text understanding, and it is not an easy problem to solve. Some machine learning techniques, including various supervised and unsupervised algorithms, are being utilized. Some algorithms rank the importance of sentences within the text and then construct a summary out of essential sentences, others are end-to-end generative models. After we have the speech text from the user, sentiment analysis can be performed to evaluate user emotions for each speech sentence or a chunk of speech contents during a period.

[72] provides board and comprehensively survey on sentiment analysis. We conclude here for the general steps of sentiment analysis:

The approach to extract sentiment from speech text is as follows:

- Tokenize each word via a public sentiment calculation dataset;
- For each word, compare it with positive sentiments and negative sentiments word in the dictionary. Then increment positive count or negative count.
- Finally, based on the positive count and negative count, once can get result percentage of sentiment to decide the polarity.

Sentiment calculation for text essentially clear defined engineering, and the final re sentiment value suits of user speech can be a training feature to different modalities.

3.3 Touch Aspect

Touch interaction modality in previous research all considered using a handcrafted feature for touch behavior and using kernel SVM to train linear models for classification. [22] is the first application specific in game, which the recognition rates are very robust even in naturalistic settings in the context of smartphone-based computer games. [77] proposed a reasonable handcrafted features, for three classes (happy, unhappy, neutral); The recent studies in [3] has 7 proposed features, for four classes (Excited, Relaxed, Frustrated, Bored) classification; and [87] compares 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%. Table 2 shows a feature set of touch interaction information and Table 3 shows the performance comparison for different classifiers. However readers should be aware that these provide solution doesn't provide any stability analysis of their classification model, it is possible can be counted as overfitting if readers cannot recur the accuracy.

Table 2. Comparison of classifiers.

Feature	Unit (%)	
Deviation in number of strikes		
Deviation in number of taps		
Mode of strike length	Millimeter	
Average strike length	Millimeter	
Mode of strike speed	Meter/second	
Average strike speed	Meter/second Mode of delay	Millisecond
Average delay	Millisecond	
Total delay	Second	
Turnaround time	Second	

Table 3. Comparison of classifiers.

Classifier	Accuracy (%)
Nave Bayes	86.13%
kNN	92.82%
SVM	96.75%

Touch interaction is typical interaction information on mobile which outputs from users. One can conclude here is SVM as the most accurate model for a handcrafted model in this research direction.

3.4 Sensors Fusion

Multimodal fusions of previous sensors is necessarily a complex challenge. Much many research has focused on this analysis, in particular, [92] gave bimodal affective recognition via facial emotion recognition and combined audio with visual modalities so that the final affect recognition accuracy is greatly improved to almost 90%. [61] proposed a multimodal system with real-time feedback for public speaking. The system has been developed within the paradigm of positive computing which focuses on designing for user wellbeing.

As multimodal sentiment analysis and emotion recognition research continue to gain popularity among the AI and NLP research communities, there needs for a timely, thorough literature review to define future directions, which can, in particular, further the progress of early-stage researchers interested in this multidisciplinary field (see Figure 2).

The recent surveys of multimodal affect analysis on mobile [16, 71, 70], focuses mainly on state of the art in collecting sample data, and reports performance comparison of selected multimodal and unimodal systems, as opposed to comprehensively reviewing key individual systems and approaches, from the growing literature in the field.

Table 4 from [16] shows the most commonly used experiments result of fusion modalities.

On the same training and test sets, the classification experiment using SVM, NN (Neural network) and ELM (Extreme learning machine). ELM outperformed NN by 12% in terms of accuracy (see Table 5). Regarding training time, the ELM outperformed SVM and NN by a considerable margin (Table 7). A real-time multimodal sentiment

[2] https://cloud.google.com/speech/

Table 4. Results of feature-level fusion

Combination of modalities	Precision
Accuracy of the experiment carried out on Textual Modality	0.619
Accuracy of the experiment carried out on Audio Modality	0.652
Accuracy of the experiment carried out on Vision Modality	0.681
Experiment using only visual and text-based features	0.7245
Result obtained using visual and audio-based features	0.7321
Result obtained using audio and text-based features	0.7115
Accuracy of feature-level fusion of three modalities	0.782

Table 5. Comparison of classifiers.

Classifier	Recall (%)	Training time
SVM	77.03	2.7 min
ELM	77.10	25 s
NN	57.81	2.9 min

analysis engine, the NN as a classifier which provided the best performance regarding both accuracy.

In conclusion, we discussed the technique method in a different method. We conclude here in this section for each type of data:

- *Vision data*: CNN models perform the state-of-the-art performance of facial analysis;
- *Speech data*: RNN models performs the state-of-the-art performance of speech recognition and sentiment analysis;
- *Interaction data*: handcrafted features are the most commonly used feature and neural networks for this kind of unstructured data are unminded;
- *Context data*: application context and geographic location are normally used as a validation dimension for emotion inferring, researchers don't consider them how to use as a training feature properly.

4 Applications Case Study

Assuming that user emotions has inferred by models or systems, [11] address a variety of issues related to the development of affective loop as well as synthesis of the appropriate affective expressions. In subsequent researches emotional systems was sugussted in [13] since emotional-sensitive system make our interactions with machines like human to human communications[66]. expressions. In this section, we illustrate the most popular applications of emotion-sensitive HCI system in the mobile affective research area.

4.1 Case 1: Spoken Dialogue Systems

A voice interaction system capable of sending the users emotional messages is able to improving the intelligence and interaction experience of a voice user interface [81].

In the early research stage, [45] proposed a personalized voice-emotion user interface in desktop system regardless of speaker's age, sex or language is presented. They experimented with participants and the results showed that voice emotion sensitive agents are feasible.

The most recent papers in emotion-sensitive voice user interface considers emotional voice tones to caring users [8], as well as the voice control system in an in-vehicle infotainment system [42].

Due to the insivible property of voice interaction system, it is almost endless of how we integrate user emotions to a spoken dialogue system, [54] addressed emotional spoken system by a markup language, which means developers can easily integrate user emotion state to adjust the system voice.

With the raising of voice assistent, there already exists successful commercial voice system such as Apple Siri[3], Google Assistant[4], Amazon Alexa[5] and Microsoft Cortana[6]. Voice user interfaces design become on board of user experience design. Even thgough they provides this kind of markup language, there still a huge unmined research to an open problem of how to evaluate this kind of emotional voice system.

4.2 Case 2: Adaptive Graphics User Interfaces

Adaptive user interfaces has been researched for years [76, 47] and addressed in many ways. User emotion is one of the aspect of adaptive user interface.

Dalvand et al.[14] introduced an adaptive user interface, the colors of user interface change according to the emotional states and mood state of users. Emotional states of a user are specified according to his/her interactions with the keyboard. After detection of emotions, the user mood reflects appropriate colors, and [39] as another example of this adaption. However they didn't have a good evaluation of such kind of system. A recent paper [20] also addresses UI adaptation by user emotions (positive, negative and neutral) at run-time. Their prototype was tested successfully of how it reacts to emotions (negative).

In conclusion, the adaptive graphics user interfaces system suguessts covered components with inferring engine (integratable with techniques we discussed in previous section), the adaptation engine (with typical personalized system rules) and the interactive system (for normal graphics user interfaces). It also evidenced that GUI changes denotes emotion changes in run-time, which was particularly beneficial for most users.

5 Challenges

Politou et al. [69] discussed most of the challenges in smartphone affective research which covers *privacy*, *data misuse*, *trust and engagement*, *multimodal fusion*, *resource constraints*, *affect modelling and representation*, *cultural differences* and *system building costs*. From the technique prespective in this paper mainly focused, challenges and limitations can be shrink to the following sections.

5.1 Impermeable Emotions

The primary limitation of traditional affective computing research refers to as impermeable emotions[65]. Impermeable emotions is broad, with many of these modalities being inaccessible (e.g., blood chemistry, brain activity, neurotransmitters), and many others being too non-differentiated. This makes it unlikely that collecting the necessary data will be possible or feasible in the near.

There is a time to express emotion, and a time to forbear; a time to sense what others are feeling and a time to ignore feelings. In every time, human need a balance when they express their emotions, and this balance is missing in computing. Figure 7 illustrates a map of human emotions.

In most cases, researches feel positive and argue that impermeable emotions can be expressed explicitly in other expressed Emotions[63] and implicity emotions are trivial and not important for most of the case of affective computing application when we need a emotion state [93]. However, impermeable emotions still a open problem and challenges in affective computing research area.

5.2 Continious Understanding

Emotions are instantaneous. 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 a map *(see Figure 7)*.

Most of the researches we introduced in privous section are trated emotion inferring problem as a classification problem, whereas the

[3] https://www.apple.com/ios/siri/
[4] https://assistant.google.com/
[5] https://developer.amazon.com/alexa
[6] https://www.microsoft.com/en-us/windows/cortana

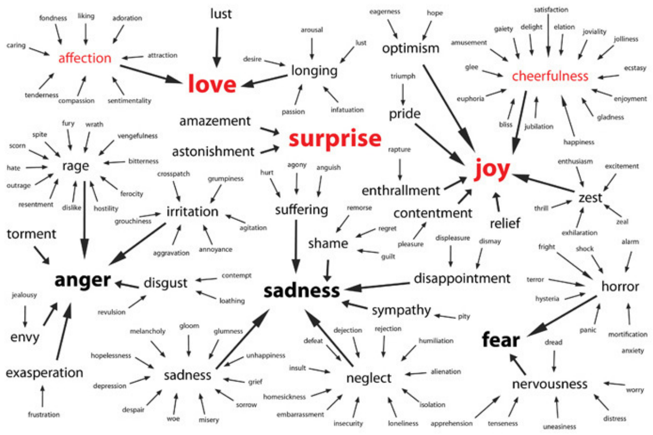

Figure 7. A map of human emotions. Image from[79].

human emotions are always passive and instantaneous. People's expression of emotion is so idiosyncratic and variable, that there is little hope of accurately recognizing an individuals emotional state from the available data sometime.

5.3 Context Specific Models

A potential ethical limitation in research studies comes from the fact that perceptions of emotions and personality are not universal but they are highly dependent on the mobile application context [22, 77, 3, 87] as well as the cultural differences between humans [55, 51, 24]. According to these perspectives, a reasonable challenge is how an affective recognition model should be designed and built in a application and cultural transparent way.

5.4 Lack of Computation Resources

Affective information, like emotions and personality traits, can be inferred from various communication channels such as facial and body expressions, speech, text and embedded smartphone sensors or biosensors. However, a challenging issue that impacts the effectiveness of affective technology is the fusion of these modalities for building competent multimodal affective recognition systems. A multimodal affective recognition system is a system that, via multiple inputs, retrieves affective information from various types of sources and associates input data with a finite set of affective states[21].

The problems in regard to the implementation of an effective system with multimodal fusion are plenty and they mainly concern the great variations of data in terms of structure and content, the varied velocity of data reception, the different sampling rate and quality of received data and the continuous growing of data size. Existing complex technical solutions should be implemented in an energy and power saving approach by keeping in mind that mobile phones have limited operation time and processing power.

Additionally, mobile affective applications should be implemented with a higher portability to address interoperability issues, since mobile devices may not only be equipped with different mobile platforms and operation environments [41], but with different sensor capabilities as well. Consequently, given the diversity of mobile devices in availability and capabilities, modelling and predicting the energy and processing requirements to accomplish even a particular emotion inferring task remains a complex issue.

6 Conclusions

In this paper, we investigated the recent advances in mobile affective computing related to human-computer interaction projects and inferring techniques.

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

Next, in the Section 3, we first carried out the review of emotion inferring methods based on different type of data source, and compared the tested methods and inferring models from previous researchers. In these comparisons, we first reviewed various models for user emotion inferring, researchers usually transfers emotion inferring problem into a classification problem. As a classification problem, most researchers consider user emotions can be inferred to three different states (Happy, Unhappy, Neutral). In each subsection, we highlighted the most useful methods for different type of emotion inferring that concluded by the most recent research papers, such as CNN as the best way of vision type, RNN as the best way of auditory type, and handcrafted feature with SVM as the best way of interaction details. At the end of this section, we considered the combinations of these types of data. According to our investigation, the most commonly used data type are suggested to *vision and audio* data in mobile affective computing; However, the combination of *vision, audio, interaction details, and context four aspects fusion are unmined open topics*.

In Section 4, we survey two novel applications in human-computer interaction related projects driven by emotion inferring. Voice user interfaces consider user emotion as inputs and suggest to please users by adjusting system voice tone; Adaptive graphics user interfaces then considers emotion state as the context of UI theme.

Despite we researched the scientific approaches of mobile emotion inferring in human-computer interaction related topics, there still apparent challenges in this area. Section 5 pointed out the current problems of this research area. The main challenges of this area are *impermeable emotions* and *continuous understanding*. Moreover, the generalisability of mobile affective computing applications are subject to certain limitations. For instance, most of *inferring models are context specific* and multimodal inferring then *requires large computation resources*.

Nowadays, new technologies and methods provide us new opportunities of affect emotion inferring in an unobtrusive mobile device. 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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