Foundations of Human Computing: Facial Expression and Emotion

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ABSTRACT

Many people believe that emotions and subjective feelings are one and the same and that a goal of human-centered computing is emotion recognition. The first belief is outdated; the second mistaken. For human-centered computing to succeed, a different way of thinking is needed.

Emotions are species-typical patterns that evolved because of their value in addressing fundamental life tasks[19]. Emotions consist of multiple components that may include intentions, action tendencies, appraisals, other cognitions, central and peripheral changes in physiology, and subjective feelings. Emotions are not directly observable, but are inferred from expressive behavior, self-report, physiological indicators, and context. I focus on expressive behavior because of its coherence with other indicators and the depth of research on the facial expression of emotion in behavioral and computer science. In this paper, among the topics I include are approaches to measurement, timing or dynamics, individual differences, dyadic interaction, and inference. I propose that design and implementation of perceptual user interfaces may be better informed by considering the complexity of emotion, its various indicators, measurement, individual differences, dyadic interaction, and problems of inference.

Categories and Subject Descriptors

J.4 **[Social and Behavioral Sciences]:** psychology

I.2.1.0 **[Vision and Scene Understanding]:** video analysis, motion, modeling and recovery of physical attributes

General Terms

Measurement, Design, Reliability, Human Factors.

Keywords

Emotion, facial expression, automatic facial image analysis, human-computer interaction, temporal dynamics.

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1. INTRODUCTION

How can computers recognize human emotions? Is this even the correct question? By emotion, people often think of subjective feelings, but emotions are more than that and subjective feeling is in no sense essential. There is no *sin qua non* for emotion. Emotions are species-typical patterns consisting of multiple components that may include intentions, action tendencies, appraisals, other cognitions, neuromuscular and physiological changes, expressive behavior, and subjective feelings. None of these is necessary or sufficient. In human-human interaction, intentions and action tendencies often are more important than what an individual may be feeling. People may or may not be aware of what they're feeling, and feelings often come about some time late in the temporal unfolding of an emotion.

A goal of human-centered computing is computer systems that can unobtrusively perceive and understand human behavior in unstructured environments and respond appropriately. Much work has strived to recognize human emotions. This effort is informed by the importance of emotion to people's goals, strivings, adaptation, and quality of life [21, 37] at multiple levels of organization, from intra-personal to societal [35]. Efforts at emotion recognition, however, are inherently flawed unless one recognizes that emotion – intentions, action tendencies, appraisals and other cognitions, physiological and neuromuscular changes, and feelings – is not an observable. Emotion can only be inferred from context, self-report, physiological indicators, and expressive behavior (see Figure 1).

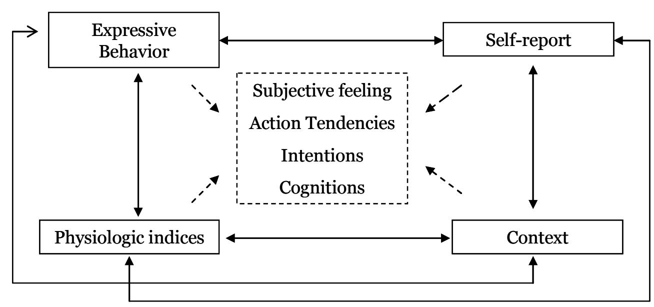

Figure 1. Components and indicators of emotion. Solid boxes represent observables, dashed boxes latent variables. Solid arrows indicate observable correlations among indicators. Large correlations among multiple indicators indicate greater coherence among indicators. Dashed arrows represent inferential paths. Paths between emotion components are omitted.

The focus of the current paper is on expressive behavior, in particular facial expression, and approaches to measurement, feature selection, individual differences, interpersonal regulation, and inference.

Facial expression is a useful place to begin when thinking about foundations of human computing. Facial expression has been a subject of keen study in behavioral science for more than a hundred years[14, 25], and within the past 10 years considerable progress has been made in automatic analysis of facial expression from digital video input [45, 46, 51].

Facial expression correlates moderately with self-reported emotion [25] and emotion-related central and peripheral physiology [15, 38]. Facial expression and self-reported emotion have similar underlying dimensions (e.g., positive and negative affect) [53] and serves interpersonal functions by conveying communicative intent, signaling affective information in social referencing, and contributing to the regulation of social interaction [7, 50]. Cultural differences in how and when to express emotion emerge in infancy [40, 43]. As a measure of trait affect and socialization, stability in facial expression emerges early in life [5]. By adulthood, stability is moderately strong, comparable to that for self-reported emotion [11]. Expressive changes in the face are a rich source of cues about intra- and interpersonal indicators and functions of emotion [29, 35].

Here, I present key issues to consider in designing interfaces that approach the naturalness of face-to-face interaction. These include approaches to measurement, types of features, individual differences, dyadic interaction, and inference.

2. APPROACHES TO MEASUREMENT

Two major approaches are sign- and message judgment [4]. In message judgment, the observer's task is to make *inferences* about something underlying the facial behavior, such as emotion or personality. In measuring sign vehicles, the task is to *describe* the surface of behavior, such as when the face moves a certain way. As an example, upon seeing a smiling face, an observer with a judgment-based approach would make judgments such as "happy," whereas an observer with a sign-based approach would code the face as having an upward, oblique movement of the lip corners. Message judgment implicitly assumes that the face is an emotion "read out." Sign-based measurement is agnostic and leaves inference to higher-order decision making.

2.1 Message Judgment

Message judgment approaches define facial expressions in terms of inferred emotion. Of the various descriptors, those of Ekman have been especially influential. Ekman [20] proposed six "basic emotions." They are joy, surprise, sadness, disgust, fear, and anger. Each was hypothesized to have universally recognized and displayed signals, universal elicitors, specific patterns of physiology, rapid, unbidden onset, and brief duration, among other attributes. Since then, some additional emotions, such as embarrassment and contempt, have been added. Examples of facial expressions for the initial six basic emotions are shown in Figure 2. Most research in automatic recognition of facial expression [47, 48] and much emotion research in psychology [34] has concentrated on one or more of these six emotions. This list, however, was never intended as exhaustive of human emotion. Rather, it was proposed in terms of conformity with the criteria noted.

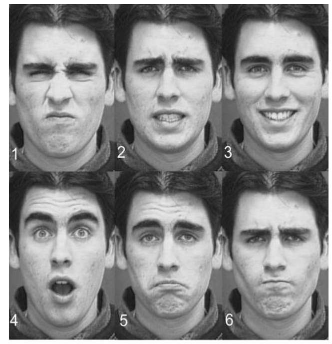

Figure 2. Emotion-specified expressions: disgust, fear, joy, surprise, sadness, and anger.

An especially important class of expressions is those that include traces of contradictory emotion expression. Masking smiles[24], in which smiling is used to cover up or hide an underlying emotion are the best known. An example is shown in Figure 3. Signs of contempt (AU 14) and sadness (AU 15) can be seen along with the smile (AU 12). Negative emotion is believed to "leak" through the dominant positive expression.

2.2 Sign Measurement

Cohn & Ekman [6] review manual methods for labeling facial actions. Of the various methods, the Facial Action Coding System (FACS) [22, 23] is the most comprehensive, psychometrically rigorous, and widely used [6, 49]. Using FACS and viewing video-recorded facial behavior at frame rate and slow motion, coders can manually code nearly all possible facial expressions, which are decomposed into action units (AUs). Action units, with some qualifications, are the smallest visually discriminable facial movements. By comparison, other systems are less thorough [39], fail to differentiate between some anatomically distinct movements [44], consider as separable movements that are not anatomically distinct [44], and often assume a one-to-one mapping between facial expression and emotion [4, 6].

Figure 3. Example of masking smile (AU 12+14+15).

The most recent version of FACS specifies 9 action units in the upper face, 18 in the lower face, 11 for head position and movement, nine for eye position and movement, and additional descriptors for miscellaneous actions, gross body movement, and supplementary codes.

Action units may occur singly or in combinations. Action unit combinations may be additive or non-additive. In additive combinations, the appearance of each action unit is independent; whereas in non-additive combinations they modify each other's appearance. Non-additive combinations are analogous to co-articulation effects in speech, in which one phoneme modifies the sound of ones with which it is contiguous. An example of an additive combination in FACS is AU 1+2, which often occurs in surprise (along with eye widening, AU 5) and in the brow-flash greeting [18]. The combination of these two action units raises the inner (AU 1) and outer (AU 2) corners of the eyebrows and causes horizontal wrinkles to appear across the forehead. The appearance changes associated with AU 1+2 are the product of their joint actions.

An example of a non-additive combination is AU 1+4, which often occurs in sadness [14] (see Figure 4). When AU 1 occurs alone, the inner eyebrows are pulled upward. When AU 4 occurs alone, they are pulled together and downward. When AU 1 and AU 4 occur together, the downward action of AU 4 is modified. An example is shown in Figure 4. The result is that the inner eyebrows are raised and pulled together. This action typically gives an oblique shape to the brows and causes horizontal wrinkles to appear in the center of the forehead, as well as other changes in appearance. Automatic recognition of non-additive combinations presents similar complexity to that of co-articulation effects in speech. Failure to account for non-additive combination in automatic recognition exploits the

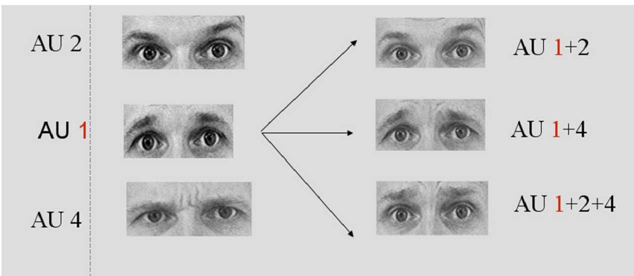

Figure 4. Examples of individual action units and action unit combinations. AU 1+2 is an additive combination. AU 1+4 and AU 1+2+4 are non-additive, comparable to co-articulation effects in speech.

correlation among AUs and can lead to inflated estimates of algorithm performance.

2.3 Reliability

The reliability of manually labeled images is a critical concern for machine learning algorithms. If ground truth is contaminated by 20-30% error, which is not uncommon, that is a significant drag on algorithm performance. For both message judgment and sign-based approaches, similar concerns arise. Using AUs as an example, at least four types of reliability (i.e., agreement between observers) are relevant to the interpretation of substantive findings. These are reliability for occurrence/non-occurrence of individual AUs, temporal precision, intensity, and aggregates. Most research in automatic facial expression analysis has focused on occurrence/non-occurrence [46, 51].

Temporal precision refers to how closely observers agree on the timing of action units, such as when they begin or end. This level of reliability becomes important when examining features such as response latency and turn taking (see Section 5). Action unit intensity becomes important for questions such as whether facial expression is influenced by audience effects [28]. Several groups have found, for instance, that people tend to smile more intensely in social contexts than when they are alone [10, 28]. A related question is whether two measurement systems have concurrent validity for continuous measures of intensity. Our research group recently examined inter-system precision for intensity by comparing Automatic Facial Image Analysis (AFA v.4) with continuous ratings of affective intensity by human observers. Lip-corner displacement in spontaneous smiles was measured by AFA at 30 frames/second. Human observers made continuous ratings of affective intensity using a joy-stick like device. We found high concurrent validity between the two methods (see Figure 5 for an example) [30, 41].

Aggregates refer to combinations of action units, which as noted may be additive or non-additive. By assessing the reliability of aggregates directly, one can more accurately estimate both their reliability and the reliability of component action units that occur in isolation.

For each of these types of reliability, a number of metrics appear in the literature. Percentage agreement is least informative because it fails to correct for agreement by chance. Chance-corrected statistics, such as Cohen's kappa and intra-class correlation are more informative [26]. In addition to average agreement or reliability across descriptors, it is informative to know the results for specific labels. Some behaviors are relatively easy to identify, others not. For reasons given above, more attention to reliability would contribute to the success of machine learning work in automatic facial expression analysis and recognition.

3. DYNAMICS

Both the configuration of facial features and the timing of facial actions are important in emotion expression and recognition. The configuration of facial actions (whether emotion-specified expressions or individual action units) in relation to emotion, communicative intent, and action tendencies has been a major research topic. Less is known about the timing of facial actions, in part because manual measurement of timing is coarse and labor intensive. We know, however, that people are highly sensitive to the timing of facial actions [17] in social settings. Slower facial actions, for instance, appear more genuine [36], as do those that are more synchronous in their movement [27]. Especially subtle facial expressions become visible only when motion information is available to the perceiver [1]. Rapid responses to perception of facial expression can be detected within 0.5 seconds using facial EMG [16]. Recently, automatic facial image analysis has shown strong concurrent validity with facial EMG [8], which suggests that it has similar capability.

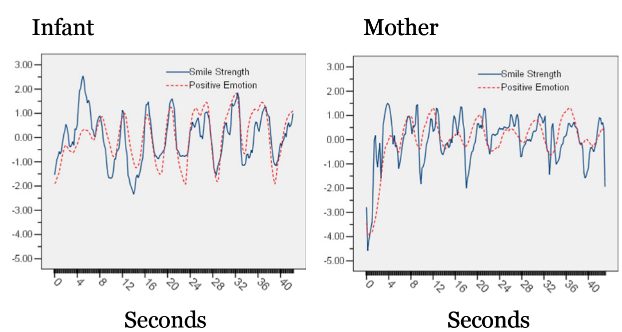

Figure 5. Time series for AFA-measured lip-corner displacement and human-observer based ratings of positive affect in a mother-infant dyad. Data series for human observers are shifted by about ½ second to adjust for human reaction time.

Dynamics is especially important to inferences about communicative intention. Using automatic facial image analysis to quantify the timing of facial actions, research by the CMU/Pitt group found that dynamic features discriminated between deliberate and spontaneous smiles with 89% accuracy [10]. Adding duration and amplitude to the classifier increased accuracy to 93%. Comparable findings were recently reported by [52]. Using similar features, amusement, embarrassment, and polite smiles were discriminated with 83% accuracy [32], which is comparable to that of human judges.

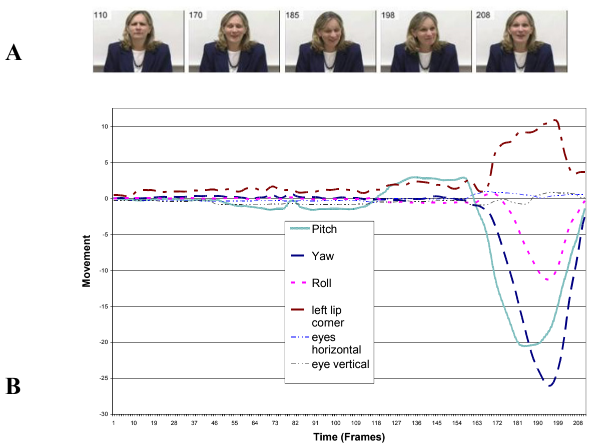

Figure 6. Multimodal coordination of head motion, lip-corner displacement, and gaze in smiles of embarrassment. A: Selected frames from image sequence depicting embarrassment. B: Corresponding time series. Reprinted with permission from [9]. (©2004 IEEE)

Recent work suggests that multimodal coordination of facial expression, head motion, and gesture is a defining feature of embarrassment [33]. An example is illustrated in Figure 6. Note that head pitch is closely coordinated with smile intensity. As the head pitches down, smile intensity increases, decreasing again only as the head comes back to frontal. For human-computer interaction, dynamic features are important to empirically based inferences about the meaning of otherwise similar facial actions, such as lip corner raise in smiling.

4. INDIVIDUAL DIFFERENCES

As noted above, stable individual differences in facial expression emerge early in development and by adulthood represent 25% or more of the variation in emotion expression [11, 42]. Individual differences include reaction range for positive and negative affect and probability of conforming to display rules. Display rules are culturally specific prescriptions for when and how to show emotion in various contexts. In some cultures, for instance, children learn not to express anger; whereas in others, anger is considered important to self expression. Display rules include intensifying, minimizing, and masking specific emotions. Sources of individual differences in emotion expression include temperament, personality, socialization, and cultural background (e.g., [43]). Our group [11] found that individual differences are strong enough to serve as a basis for person recognition. Most important, inferences about emotion become more reliable when individual differences are taken into account.

5. DYADIC INTERACTION

Synchrony or coherence refers to the extent to which individuals are moving together in time with respect to one or more continuous output measures, such as affective valence or level of arousal. Reciprocity refers to the extent to which behavior of one individual is contingent on that of the other. Both synchrony and reciprocity have proven informative in studies of marital interaction, social development, and social psychology. Figure 7 shows an example from mother-infant interaction [30, 41]. Facial features and head motion were tracked automatically by the CMU/Pitt automated facial image analysis system version 4 [8]. The time series plot shows displacement of mother and infant lip-corners during smiles. Note that while partners tend to cycle together, there is a pattern of non-stationarity in which mother and infant take turns in leading the dyad into shared smiling, which is indicated by mother and infant time series increasing together. An important advantage of measures derived from interaction analysis is that they are largely outside of people's awareness and are difficult to manipulate intentionally.

Coordinated interpersonal timing (CIT) is the extent to which participants in a social interaction match the duration of interpersonal pauses or floor switches [31]. Floor switches are pauses that occur between the time when one person stops speaking and another begins. Coordination of floor switches follows an inverted U-shaped function in relation to affective intensity and change with development. CIT has been studied most often with respect to vocal timing, but applies equally to facial expression and other modalities. In depression, CIT become longer and less predictable [54].

In behavioral science literature, time- and frequency domain analyses have emphasized issues of quasi-periodicity in the timing of expressive behavior and bidirectional influence with

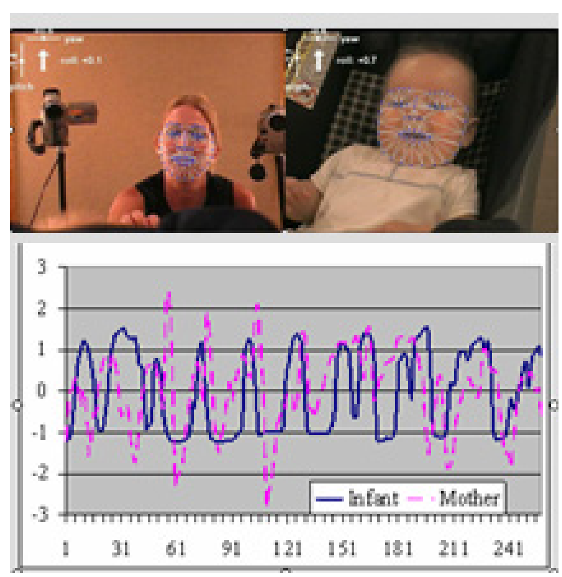

Figure 7. Example of interaction analysis. Synchrony and reciprocity of smiling between mother and infant. Source: [30, 41].

respect to amplitude (see, for instance, [12]). Lag-sequential and related hidden Markov modeling have been informative with respect to the dynamics of discrete actions and individual and dyadic states [13]. Recent work with dampened oscillator models considers regulation of changes in velocity and acceleration [3]. Most approaches assume that time series are stationary. This assumption may not always hold for behavioral data. Boker [2] identified "symmetry breaks," in which the pattern of lead-lag relationships between partners abruptly shifts. Failure to model these breaks may seriously compromise estimates of mutual influence.

6. CONCLUSION

Emotions are species-typical patterns that evolved because of their value in addressing fundamental life tasks [20]. They are central to human experience, yet largely beyond the comprehension of contemporary computer interfaces. Human-centered computing seeks to enable computers to unobtrusively perceive, understand, and respond appropriately to human emotion, to do so implicitly, without the need for deliberate human input. To achieve this goal, it is argued t[50]hat we forgo the notion of "emotion recognition" and adopt an iterative approach found in human-human interaction. In our daily interactions, we continually make inferences about other people's emotions – their intentions, action tendencies, appraisals, other cognitions, and subjective feelings – from their expressive behavior, speech, and context. The success of human-centered computing depends in part on its ability to adopt an iterative approach to inference. Computing systems are needed that can automatically detect and dynamically model a wide range of multimodal behavior from multiple persons, assess context, develop representations of individual differences, and formulate and test tentative hypotheses though the exchange of communicative signals. Part of the challenge is that the computer becomes an active agent, in turn influencing the very process it seeks to understand. Human emotions are moving targets.

7. ACKNOWLEDGMENTS

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