CHAPTER

39

Affective Computing, Emotional Development, and Autism

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Abstract

Affective computing can illuminate early emotional dynamics and provide tools for intervention in disordered emotional functioning. This chapter reviews affective computing approaches to understanding emotional communication in typically developing children and children with an autism spectrum disorder (ASD). It covers the application of automated measurement of the dynamics of emotional expression and discusses advances in the modeling of infant and parent interactions based on insights from time-series analysis, machine learning, and recurrence ~~theory,~~ The authors discuss progress in the automated measurement of vocalization in infants and children and new methods for the efficient measurement of sympathetic activation and its application in children with ASD. They conclude by presenting translational applications of affective computing to children with ASD, including the use of embodied conversational agents (ECAs) to understand and influence the affective dynamics of learning, and the use of robots to improve the social and emotional functioning of children with ASD.

Key Words: children, automated measurement, infant–parent interaction, autism spectrum disorder, high-risk siblings, modeling, embodied conversational agent, robotics

Introduction

Affective Computing and Child Development

Children's development is a fertile application of affective computing. The nonverbal emotional communication of children and infants may be less impacted by social display rules than the communication of older individuals, thus offering a rich environment for the automated detection and modeling of emotion. Substantively, early dyadic interaction between infants and parents offers a model for understanding the underpinnings of nonverbal communication throughout the lifespan. These interactions, for example, may lay the basis for the development of turn-taking and mutual smiling that are fundamental to later nonverbal communication (Messinger, Ruvolo, Ekas, & Fogel, 2010). At the same time, the child's development affects the adult he or she will become. Interventions based in affective computing that help children develop optimally have the potential to benefit society in the long term. Throughout, whenever appropriate, we discuss how the reviewed studies of detection and modeling of emotions have contributed to our understanding of emotional development in children with ASD.

Affective Computing and the Development of Autism Spectrum Disorders

Disordered development can provide insights into typical development. This chapter discusses the detection and modeling of emotion—and the application of interventions grounded in affective computing—in children with autism spectrum disorders (ASDs) and their high-risk siblings. Autism spectrum disorders are pervasive disorders of social communication and impact a broad range of nonverbal (as well as verbal) interactive skills (American Psychiatric Association, 2000). Because the symptoms of these developmental disorders emerge before 3 years of age, ASDs provide a window into early disturbances of nonverbal social interaction. In addition, the younger siblings of children with an ASD—high-risk siblings—can offer a prospective view of the development of ASDs and related symptoms. Approximately one-fifth of these ASD siblings will develop an ASD and another fifth will exhibit ASD-related symptoms by 3 years of age that are below the threshold for a clinical diagnosis (Boelte & Poustka, 2003; Bolton, Pickles, Murphy, & Rutter, 1998; Constantino et al., 2006; Messinger et al., 2013; Murphy et al., 2000; Ozonoff et al., 2011; Szatmari et al., 2000; Wassink, Brzustowicz, Bartlett, & Szatmari., 2004). Automated measurement and modeling often focuses on high-risk siblings to provide objective data on the development of ASD-related symptoms.

Chapter Overview

In a developmental context, affective computing involves the use of computer software to detect behavioral signs of emotions and model emotional functioning and communication and the construction of software and hardware agents that interact with children. The chapter begins with a review of automated measurement of facial action and the application of those measures to better understand early emotion expression. Emotional communication is complex, and the chapter then reviews time-series and machine-learning approaches to modeling emotional communication in early interaction, which includes comparisons between typically developing children and children with ASDs. Next, we review automated approaches to emotion detection—and to the identification of ASDs—from children's vocalizations, and we discuss efforts to model the vocal signal using graph-based and time-series approaches. The final measurement section reviews new approaches to the collection of electrophysiological data (electrodermal activation [EDA]), focusing on efforts in children with ASD. Finally, we review translational applications of affective computing in two areas that have shown promise in helping children with ASD develop skills in the areas of emotional development and social communication: embodied conversational agents (ECAs) and robotics. The chapter ends with a critical discussion of accomplishments and opportunities for advancement in affective computing efforts with children.

Automated Measurement of Emotional Behavior

Automated Facial Measurement

The face is central to the communication of emotion from infancy through old age. However, manual measurement of facial expression is laborious and resource-intensive (Cohn & Kanade, 2007). As a consequence, much more is known about the perception of facial expressions than of the production of facial expressions. Software-based automated measurement offers the possibility of efficient, objective portraits of facial expression and emotion communication. Here, we describe a methodological framework for the automated measurement of facial expression in infants and their parents during early interaction.

A growing body of research on infant–parent interaction uses automated measurement based on the facial action coding system (FACS) (Ekman & Friesen, 1992; Ekman, Friesen, & Hager, 2002) and its application to infants (BabyFACS) (Oster, 2006). FACS is a comprehensive manual system for recording anatomically based appearance changes in the form of facial action units (AUs; Lucey, Ashraf, & Cohn, 2007). To better understand the dynamics of expression and emotional communication, the strength of key AUs is measured using an intensity metric that specifies whether a facial action its present and, if present, its strength from minimal to maximal using FACS criteria (Mahoor et al., 2008). Objective measurement of facial expression intensity allows for time-series modeling of interactive influence.

A commonly used automated measurement pipeline combines active appearance and shape models (AASMs) and support vector machines (SVMs) (Messinger et al., 2012). Active appearance and shape models are used to detect and track facial movement (see Figure 39.1). The shape component of the AASM unites the two-dimensional representations of the movement of 66 vertices (Baker, Matthews, & Schneider, 2004; Cohn & Kanade, 2007). Mouth opening can be measured as the vertical distance between the upper and lower lips in the shape component of the AASM. The appearance component of the AASM contains the grayscale values for each pixel contained in the modeled face. Appearance is the grayscale texture within the region defined by the mesh. In the research reported here, nonlinear manifold learning (Belkin & Niyogi, 2003) was used to reduce the dimensionality of the appearance and shape data to produce a set of variables that are used to train SVMs. Support vector machines are machine learning classifiers that were used to determine whether the AU in question was present and, if present, its intensity level. To make this assignment, a one-against-one classification strategy was used (each intensity level was pitted against each of the others) (Chang & Lin, 2001; Mahoor et al., 2008).

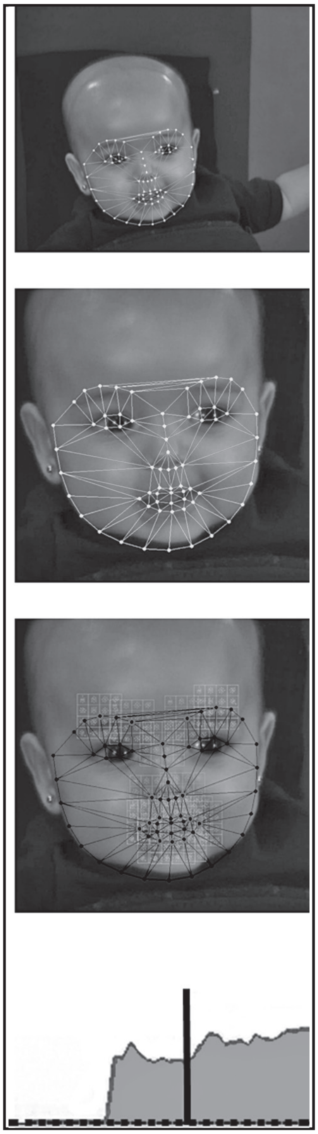

Fig. 39.1 Facial measurement. From top to bottom: Input video with overlaid shape model, affine warp to control for orientation and size, extracted features, and action unit (AU) detection with respect to support vector machine threshold and ground truth (manual facial action coding system [FACS] coding).

Emotion Measurement via Continuous Ratings

Here, we describe a method for collecting continuous ratings of emotion constructs in time that can be modeled in their own right and used to validate automated measurements of emotional behavior. In the automated facial expression measurement, expert manual measurement of facial actions' levels of cross-system (automated vs. manual) reliability are typically comparable to standard interobserver (manual vs. manual) reliability. However, intersystem agreement speaks to the validity of the automated measurements but not to the emotional meaning of the underlying behaviors. One approach to validating automated measurements of the face as indices of emotion intensity are continuous ratings made by third-party observers (http://measurement.psy.miami.edu/).

Continuous emotion measurement is similar to the affect rating dial in which participants in an emotional experience can provide a continuous report on their *own* affective state (Gottman & Levenson, 1985; Levenson & Gottman, 1983; Ruef & Levenson, 2007). In the research described here, however, continuous ratings were made by observes who moved a joystick to indicate the affective valence they perceived in an interacting infant or parent. The ratings of multiple independent observers were united into a mean index of perceived emotional valence (Waldinger, Schulz, Hauser, Allen, & Crowell, 2004). Continuous nonexpert ratings have strong face validity because they reflect a precise, easily interpretable description of a construct such as positive ("joy, happiness, and pleasure") or negative emotion ("anger, sadness, and distress").

Applying Automated and Other Measurement to Early Emotion Expression

THE CASE OF SMILING

Automated measurement of the intensity of smiling has yielded insights into early positive emotion. Although infant smiles occur frequently in social interactions and appear to index positive emotion, adult smiles occur in a range of contexts, not all of which are associated with positive emotion. This has led some investigators to propose that a particular type of smiling, Duchenne smiling, is uniquely associated with the expression of positive emotion whereas other smiles do not reflect positive emotion (Ekman & Friesen, 1982). In Duchenne smiling, the smiling action around the mouth—produced by zygomaticus major (AU12)—is complemented by eye constriction produced by the muscles around the eyes, the orbicularis oculi and pars orbitalis (AU6). Anatomically, however, smiling and eye constriction are not yes/no occurrences but reflect a continuum of muscular activation (Williams, Warick, Dyson, & Bannister et al., 1989). Automated measurement of the intensity of these two actions could indicate whether there is a continuum of Duchenne smiling.

A CONTINUUM OF DUCHENNE SMILING

Automated measurement of the intensity of smiling and eye constriction indicated that smiling was a continuous signal (Messinger, Mahoor, Chow, & Cohn, 2009; Messinger, Mattson, Mahoor, & Cohn, 2012). Infant smile strength and eye constriction intensities were highly correlated and were moderately associated with degree of mouth opening. Mouth opening is another continuous signal that frequently occurs with smiling, where it may index states of high positive arousal such as laughing. Mothers exhibited similar associations between smiling and eye constriction intensity, whereas links to mouth opening were less strong. In essence, there did not seem to be different "types" of smiling—for example, Duchenne and non-Duchenne—during infant–mother interactions (Messinger, Cassel, Acosta, Ambadar, & Cohn, 2008). Rather, associations between smiling and eye constrictions revealed by automated measurement made it more appropriate to ask a quantitative question: "How much Duchenne smiling is being displayed?" or, even more simply, "How much smiling is present?"

A GRAMMAR OF EARLY FACIAL EXPRESSION

Automated measurements of facial expressions and continuous ratings of affect have yielded insights into similarities between early positive and negative emotion. Infants exhibit a tremendous range of affective expression, from intense smiles to intense cry-face expressions. The cry-face expression—and not expressions of discrete negative emotion such as sadness and anger—is the preeminent index of negative emotion in the infant.

Since Darwin and Duchenne de Boulogne, investigators have asked how individual facial actions combine to convey emotional meaning (Darwin, 1872/1998; Duchenne, 1990/1862; Frank, Ekman, & Friesen, 1993). Darwin, in particular, suggested that a given facial action—to wit, eye constriction—might be associated not only with intense positive affect but with intense negative affect as well. Ratings of still photographs suggested that eye constriction and mouth opening index the intensity of both positive and negative infant facial expressions (Bolzani-Dinehart et al., 2005). However, automated measurements—complemented by continuous ratings of emotion—were required to determine whether this association was present in dynamically unfolding, real-time behavior.

Messinger et al. (2012) used automated measurements of infants and parents in the face-to-face/still-face (FFSF) procedure to examine these associations. When infants smiled—as noted earlier—the intensity of the smile, the intensity of eye constriction, and the degree of mouth opening were all associated. In parallel fashion, when infants engaged in cry-face expressions, the intensity of eye constriction and the degree of mouth opening were also associated (see Figure 39.2A). That is, automated measurement revealed similar signatures of facial intensity in both positive and negative expressions. In both smile and cry-face expressions, degree of eye constriction intensity and mouth opening predicted the absolute intensity of continuously rated emotional valence (see Figure 39.2B). That is, pairing automated measurement and continuous ratings indicated a parsimony in the expression of early negative and positive emotion that was first suggested by Darwin. Automated measurement and continuous emotional ratings can be used to understand not only emotional expression but—through modeling of interaction—emotional communication.

Modeling Emotional Communication

Here, we review windowed cross-correlations, advances in time-series modeling, and machine learning approaches to modeling dyadic emotional communication. Fundamental questions in infant–parent communication concern the influence of each partner on the other. Previous research indicates that the degree to which parents match the affective states of their infants predicts subsequent self-control, internalization of social norms, and cognitive performance (Feldman & Greenbaum, 1997; Feldman, Greenbaum, & Yirmiya, 1999; Feldman, Greenbaum, Yirmiya, & Mayes, 1996; Kochanska, 2002; Kochanska, Forman, & Coy, 1999; Kochanska & Murray, 2000). Yet it is not clear that the degree to which one partner responds to the other—or the degree to which both partners are synchronous with one another—is stable over the course of several minutes. Both automated measurement and continuous emotion rating have been used to ascertain the temporal stability of measures of interactive responsivity.

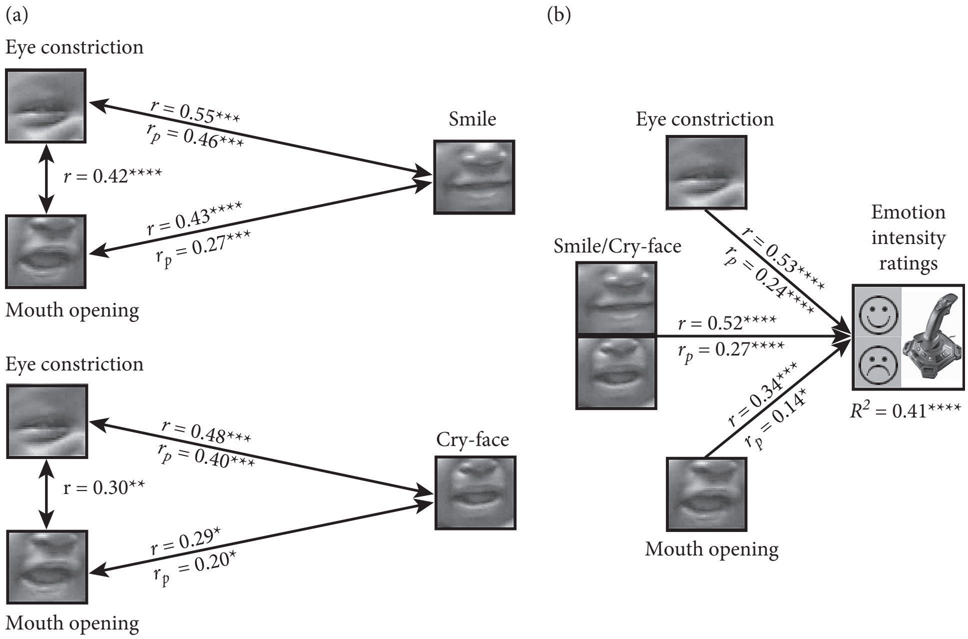

Fig. 39.2 (A) The intensity of eye constriction and mouth opening are associated with the intensity of both infant smiles and cry-face expressions. Overall (*r*) and partial correlations (*r*p) between the intensity of smiles, eye constriction, and mouth opening and between the intensity of cry-faces, eye constriction, and mouth opening. Frames of video in which neither smiles nor cry-faces occurred (zero values) were randomly divided between the smile and cry-face correlation sets to maintain independence. (B) Eye constriction and mouth opening intensity predict affective valence (emotion intensity) ratings during both smile and cry-face expressions. *R*2, *r*, and *r*p from regressing affective valence ratings on the intensity of smile/cry-faces, eye constriction, and mouth opening. All statistics represent mean values across infants. *p* values reflect two-tailed, one-sample *t* tests of those values: * $p < .05$. ** $p < .01$. *** $p < .001$. **** $p < .0001$.

WINDOWED CROSS-CORRELATIONS AND TIME-VARYING CHANGES IN INTERACTION

Automated measurement of Duchenne smiling intensity illustrated apparent variability in interactive synchrony in two infant–mother dyads engaged in face-to-face play (Messinger et al., 2009). Differences in interaction existed between the two dyads and in the microstructure of interaction within these segments (see Figure 39.3). At the dyad level, there were differences in tempo, with one dyad's interactions being faster paced than the other's. Within dyads, the microstructure of coordination was examined using windowed cross-correlations of sliding 3-second epochs of interaction (Boker, Rotondo, Xu, & King, 2002). The midline of the rectangular plot in Figure 39.3 indicates the changing levels of zero-order correlation of Duchenne smiling intensity over time. The varying associations produced by windowed cross-correlations of automated measurement indicate continuous changes in the degree of dyadic synchrony over the course of interaction. This changing pattern suggests that disruptions and repairs of emotional synchrony—a potential predictor of social resiliency—are a common feature of infant–mother interactions (Schore, 1994; Tronick & Cohn, 1989).

TIME-SERIES MODELS CHARACTERIZING DYNAMIC CHANGES IN THE STRENGTH OF INTERACTION

Descriptions of temporal changes in synchrony are not a statistical demonstration of time-varying changes in interaction dynamics. To address this issue, statistical modeling of time-varying changes in interactive influence was carried out using nonexpert ratings of affective valence (Chow, Haltigan, & Messinger, 2010). Infants and parents were observed in the FFSF procedure in order to present infants with the stressor of parental nonresponsivity. In the FFSF, a naturalistic face-to-face interaction is disrupted by the still-face, in which the parent is asked not to initiate or respond to the infant, and ends with a 3-minute reunion in which the parent re-engages with the infant (Adamson & Frick, 2003; Bendersky & Lewis, 1998; Cohn, Campbell, & Ross, 1991; Delgado, Messinger, & Yale., 2002; Matias & Cohn, 1993; Tronick,

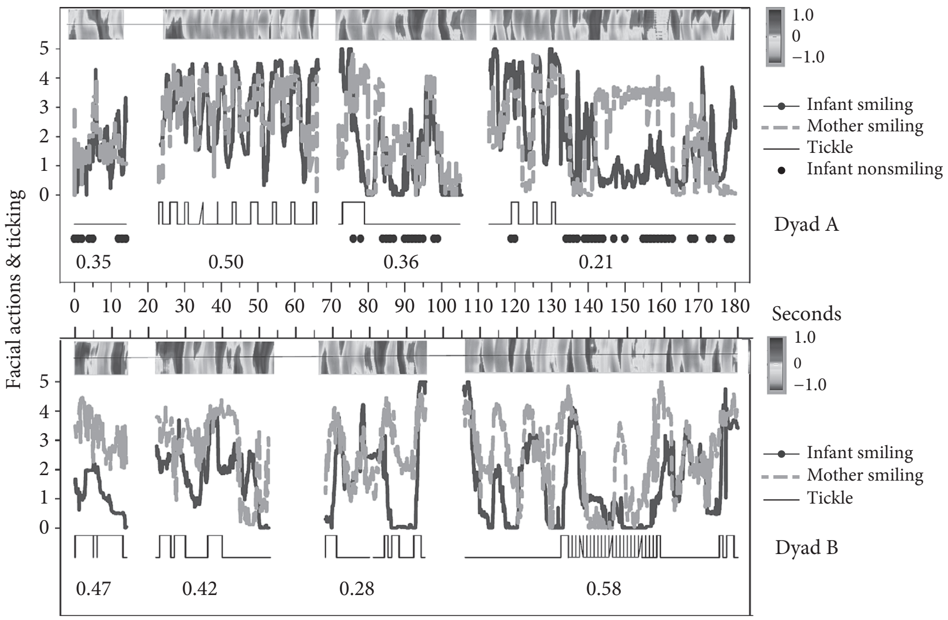

Fig. 39.3 Automated measurements of the intensity of infant and mother smiling activity plotted over successive seconds of interaction. This is Duchenne smiling activity, the mean of smile strength and eye constriction intensity. Correlations between infant and mother smiling activity are displayed below each segment of interaction. Above each segment of interaction is a plot of the windowed cross-correlations between infant and mother smiling activity. ~~As seen in the color bar to the right of the plots, high positive correlations are deep red, null correlations are pale green, and high negative correlations are deep blue.~~ The horizontal midline of these plots indicates the zero-order correlation between infant and mother smiling activity. The correlations are calculated for successive 3-second segments of interaction. The plots also indicate the associations of one partner's current smiling activity with the subsequent activity of the other partner. Area above the midline indicates the correlation of current infant activity with subsequent mother smiling activity. Area beneath the midline indicates the reverse. Reprinted from *Infancy*.

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Als, Adamson, Wise, & Brazelton, 1978; Yale, Messinger, & Cobo-Lewis, 2003).

A stochastic regression approach applied in the context of a time-series analysis allowed the investigators to test whether interactive influence itself changed dynamically over time. These analyses address the longstanding problem of nonstationarity in time-series by modeling changes in interactive influence (Boker et al., 2002; Newtson, 1993). During face-to-face interaction, and particularly during the reunion episode following the still-face perturbation, the strength of interactive influence varied with time. The finding of changes in the dynamics of interaction suggests new avenues of research in statistical modeling of dyadic interaction. Applications include not only infant–parent interaction, but dyadic interchanges involving children, adults, and, potentially, software agents and robots.

Modeling Dynamics among ASD Siblings

Bivariate time-series models with random effects have been used to document ASD-related differences in temporal processes (Chow et al., 2010). These time-series models incorporated siblings at high risk for an ASD in order to address potential deficits in emotional expressivity and reciprocal social interaction among these ASD siblings (Baker, Haltigan, Brewster, Jaccard, & Messinger, 2010; Cassel et al., 2007; Constantino et al., 2003; Yirmiya et al., 2006). No risk-related differences in interactive influence were apparent, but differences in self-regulation emerged (Chow et al., 2010). Infant siblings of children with ASDs (ASD-sibs) exhibited higher levels of self-regulation—indexed by lower values of autoregression variance parameters—than comparison infants. This tendency of ASD-sibs to exhibit less variability in their self-regulatory dynamics than comparable control siblings (COMP-sibs) was evident during the still-face and reunion, suggesting that ASD-sibs were less emotionally perturbed by the still-face than were other infants (Chow et al., 2010).

Machine Learning Approaches to Modeling Dyadic Interaction

Machine learning approaches can be used not only to measure emotional signals but to model emotional communication and social interaction more broadly. Machine learning draws on algorithms and theory from a wide range of disciplines including Bayesian statistics, approximation algorithms, numerical optimization, and stochastic optimal control, providing a rich toolbox applicable to the study of interaction and development. At its core, machine learning is concerned with developing computational algorithms to learn from data. Of particular relevance is discovering underlying structural relationships in interaction and making predictions about the development of these patterns. Using entropy as a dependent measure, for example, researchers found that infant behavior was most predictable (most self-similar over time) during the still-face episode of the FFSF but least predictable in the reunion episode, during which infants may exhibit high levels of both positive and negative affect (Montirosso, Riccardi, Molteni, Borgatti, & Reni, 2010).

Researchers have used machine learning methods to characterize the development of interactive behavior between mothers and infants both at the level of weekly sessions and at the level of specific interactive contexts in a longitudinal dataset covering the first 6 months of life (Messinger et al., 2010). The researchers first asked whether weekly sessions of infant–mother face-to-face interaction become more similar to each other—and so more predictable to each partner—over developmental time (Messinger et al., 2010). Sessions were characterized with respect to infant, mother, and dyadic smiling states (e.g., mutual smiling). Similarity metrics explored included not only the mean and variance of these parameters but the entire distribution of values. A similarity metric (the Bhattacharyya coefficient) was computed over a dyad's consecutive interactive sessions. Over a range of measures, there were increases with age in the similarity of models describing consecutive interactions sessions. This suggests that the consistency—and thus predictability—of interaction patterns increases with development. These findings suggest the potential of machine learning for describing how repeated interactions between infant and parent produce stable dyadic differences that contribute to personality development.

The researchers next focused on those factors that influenced the predictability of infant smiling within specific interactive contexts and asked how that predictability changed with development (see Figure 39.4). That is, they predicted the timing of the infant's next social action based on the current state of the interaction. To do so, they built a model predicting when the infant would initiate or terminate a smile given the current state of the dyad (whether the infant and the mother were each currently smiling and which of the partners had smiled

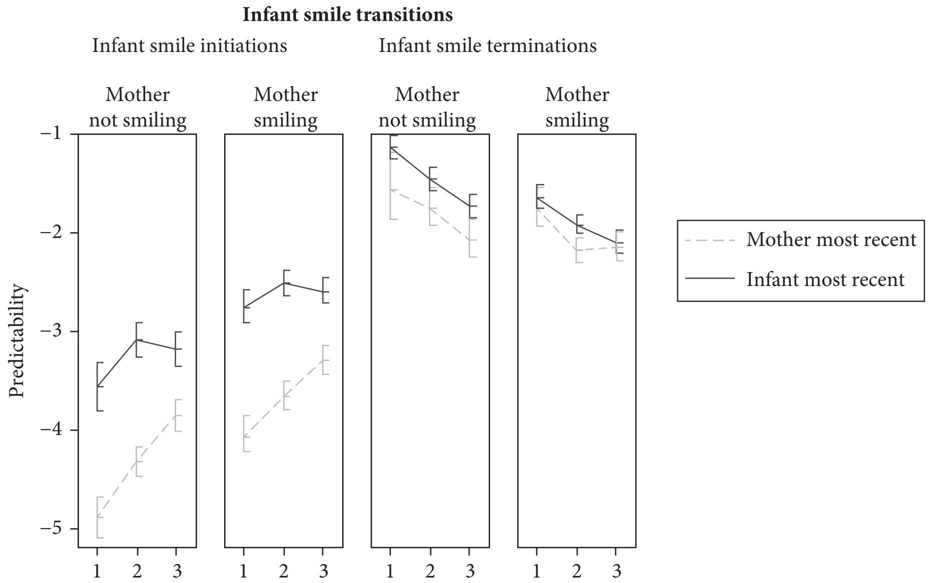

Fig. 39.4 Predictability (reverse-signed entropy) of infant smiling actions in multiple contexts. Each panel describes the predictability of a given infant action in a given context (e.g., infant smile initiation while mother is not smiling in the hand panel of the top ~~left~~ graph) both when the infant acted most recently (infant last) and when the mother acted most recently (mother last). Predictability is described with respect to infant age categories: 4–10 weeks (1–2.5 months), 11–17 weeks (2.5–4 months), and 18–24 weeks (4.5–6 months). Figure component reprinted from *Neural Networks*.

or stopped smiling most recently) and the infant's age. The researchers assessed predictability by measuring the entropy of the probability distribution of the time until the infant's next action. Entropy is the inverse of predictability, such that more entropic distributions are more difficult to predict.

Infant smile initiations become more predictable (less entropic) with development, whereas infant smile terminations become less predictable with age. That is, infant smiling became a more stable state with development. Both infant smile initiations and terminations were more predictable if the infant—rather than the mother—had last changed his or her smiling state. Overall, then, infants were most predictable when their last action had created the dyadic conditions in which they were acting. Thus, parents who smile to elicit an infant smile may, paradoxically, lessen the predictability of that smile occurring. The results point to the potential of machine learning approaches to produce insights into real-time emotional communication and development, a theme that we next explore with respect to infant vocalizations.

Automated Measurement of Emotion in Vocalizations

The majority of work on the automated detection of infant emotion from vocalizations has focused on infant cries, whereas the detection of other emotional characteristics of child vocalizations is less frequent. Infant crying is a ubiquitous signal of distress that develops into a more variegated expression of negative emotion in the first year of life (Gustafson & Green, 1991). Researchers have distinguished among the communicative functions of infant cries and other vocalizations (Fuller, 1991; Petroni, Malowany, Johnston, & Stevens, 1995). Petroni et al. classified cries as ~~pain/distress cries or other~~ using a neural network approach, whereas Fuller (1991) classified cries as pain-induced, hunger-related, or fussy using discriminant function analysis. A robotics group used low-level auditory features to achieve both cry detection (Ruvolo & Movellan, 2008) and the classification of both crying and playing/singing from ambient sound in a preschool environment (Ruvolo, Fasel, & Movellan, 2008). More generally, researchers have used partial least squares regression to classify child sounds according to child mood and energy level (Yuditskaya, 2010) and achieved some success using a least squares minimum distance classifier to distinguish between infant vocalizations that mothers' interpreted as more emotional and more communicative (Papaeliou, Minadakis, & Cavouras, 2002). Overall, automated identification and characterization of cries is a more mature area of research than is classification of other features of child emotional vocalizations.

AUTOMATED MEASUREMENT OF VOCALIZATIONS AND ASD

There is evidence for differences between the vocalization of children with ASD, their high-risk siblings, and the vocalizations of low-risk, typically developing infants (Paul, Fuerst, Ramsay, Chawarska, & Klin, 2011; Sheinkopf, Iverson, Rinaldi, & Lester, 2012; Sheinkopf, Mundy, Oller, & Steffens, 2000). The cries of infant high-risk ASD siblings tend to have ~~a~~ higher fundamental frequency than those of other children, and it appears that siblings who will go on to an ASD diagnosis have among the highest pitched cries. Although automated vocalization research typically uses samples of relatively short duration, the LENA system identifies child and adult speech characteristics during day-long naturalistic audio recordings. Oller et al. (2010) used LENA to distinguish among typically developing children, children with an ASD, and children with a non-ASD developmental delay based on acoustic features of their vocalizations ~~(Oller, Yale, & Delgado, 1997)~~. The LENA system includes a cry and a laugh detector, although only the reliability of detection of speech-related child vocalizations versus non–speech-related vocalizations (including cries, laughter, and vegetative sounds) has been established (Xu, Yapanel, & Gray, 2009). It remains to be seen whether automated detection of emotional features of vocalization—or more general acoustic features of vocalizations—could be used for the prospective classification of ASD. As in facial measurement, audio measurements have also led to new advances in the modeling of emotional signals in the audio domain.

DEVELOPMENTAL PREDICTIONS FROM MODELED VOCALIZATION

In a seminal longitudinal study, researchers Jaffe, Beebe, Feldstein, Crown, and Jasnow (2001) implemented automated measurement of the timing of infant and adult vocalizations during infant–parent and infant–stranger interactions at 4 months of age (Feldstein et al., 1993). Time-series analyses of interactive patterns indicated that the quantity of infant vocal interruptions was predicted by the immediately previous quantity of ~~previous~~ mother interruptions, a demonstration of what the researchers term *coordinated interpersonal timing*. Overall, higher levels of coordinated interpersonal timing at 4 months were associated with a predilection toward disorganized attachment at 12 months, whereas secure attachment was associated with mid-range pattern levels of interactive influence timing. The results point to curvilinear patterns in development, which suggests the importance of nonlinear modeling in understanding vocal interaction.

Modeling Vocal Interactions with Cross-Recurrence Quantification Analysis

Cross-recurrence quantification analysis (CRQA) and recurrence quantification analysis (RQA) are promising visual approaches to the analysis of interactions. The analyses document patterns within time-series data that either recur within a single time series (RQA) or are coordinated across two separate time series (CRQA). Recurrence quantification analysis is a recurrence plot in which a single time-series is represented in a 2-D plot, with time increasing along both the x-axis and y-axis. In most approaches, a pixel is filled in when the value of the time-series at the x-axis time point matches (or comes within some threshold of similarity to) the value of the time-series at the y-axis time point. Other pixels are not filled in. Diagonal lines in the recurrence plot indicate recurring sequences of values in the time-series (Webber & Zbilut, 2005). Cross-recurrence quantification analysis begins with a cross-recurrence plot that compares the values of two time-series—such as those produced by two conversation partners—with one time-series being represented along the x-axis and one time-series being represented along the y-axis. The cross-recurrence allows for the creation of a diagonal cross-recurrence profile, which shows the degree of coordination between the two time-series at each of a range of lags (Dale, Warlaumont, & Richardson, 2011).

Although researchers have used RQA and CRQA to analyze heart rate coordination among groups of individuals (Konvalinka et al., 2011), these approaches are typically applied to the analysis of dyadic communication—often in the vocal modality—and have been used to characterize the interactions of children with an ASD. Focusing on mother and infant gaze data during a reunion episode of a still-face procedure, researchers derived a "trapping time" metric from the lengths of vertical lines in an RQA plot that indexed the flexibility of gaze interactions between child and mother (de Graag, Cox, Hasselman, Jansen, & de Weerth, 2012). Cross-recurrence quantification analysis can also be applied to mother–infant acoustic coordination, such as pitch coordination (Buder, Warlaumont, Oller, & Chorna, 2010). Warlaumont, Oller, Dale, Richards, Gilkerson, and Xu (2010) found that there was less vocal interaction between children with ASD and adults (reflected in the height of the diagonal cross recurrence profile) and that, in cross-recurrence plots across a variety of lags ~~(Warlaumont et al., 2010)~~, the ratio of child leading to adult following was smaller in dyads including a child with ASD. Taken together, this literature suggests that RQA and CRQA can be usefully applied to the study of emotional and behavioral coordination dynamics between children and caregivers and, in some cases, can reveal differences between typically developing children and children with ASD.

Electrodermal Activity, Measurement, and Applications to ASD

In addition to facial and vocal signals, physiological indices of arousal are key to understanding emotional dynamics in both typically children and children with developmental disorders such as autism. Electrodermal activity is measured by skin conductance and can serve as an index of sympathetic nervous system arousal. As such, it can provide a reasonable physiologic index of children's emotional responses and regulation, providing information on baseline arousal (tonic EDA), reactions to events (phasic EDA), and subsequent return to baseline (recovery or habituation) (Benedek & Kaernbach, 2010; Rogers & Ozonoff, 2005). In non-ASD samples, there is evidence that higher EDA may be linked to more internalizing problems in children, whereas lower EDA may convey risk for externalizing behaviors (El-Sheikh & Erath, 2011). Complicating associations between EDA and child outcomes, however, is evidence that it is involved with and predicted by interactive effects involving various biological (e.g., the long allele of the 5-HTTLPR serotonin genetic variant) and environmental factors (e.g., harsh parenting; El-Sheikh, Keiley, Erath, & Dyer, 2013; Erath, El-Sheikh, Hinnant, & Cummings, 2011; Gilissen, Bakermans-Kranenburg, Ijzendoorn, & Linting, 2008).

ELECTRODERMAL ACTIVATION IN CHILDREN WITH ASD

The measurement of EDA can provide information regarding the form and correlates of individual differences in children with ASD. Recent trends emphasize the need to understand heterogeneity in ASD from a social-cognitive perspective (Mundy, Henderson, Inge, & Coman, 2007), and the same is true for emotion and its regulation (Mazefsky, Pelphrey, & Dahl, 2012). Mazefsky and colleagues have argued cogently for the benefits of integrating traditional autism emotion research with emotion regulation frameworks more widely applied to normative populations. Such an integration would require that EDA patterns be tied to children's behavioral responses, emotional expressions, regulation "strategies," broader functioning, and/or to other internal and external correlates (Cole, Martin, & Dennis, 2004).

As an index of sympathetic nervous system arousal, EDA has been of longstanding interest to ASD researchers examining sensory dysfunction in these children. Despite the increased presence of sensory-related behaviors in ASD, the extant literature on sensory dysfunction has not supported propositions that children with ASD exhibit atypical general arousal or hyperarousal reactions, with the little evidence for group differences suggesting reduced reactivity to certain stimuli (Rogers & Ozonoff, 2005). In reaction, researchers have proposed that group differences in EDA may be obscured by the presence of distinct subgroups of children with ASD who exhibit patterns of either high or very low arousal (Hirstein, Iversen, & Ramachandran, 2001; Schoen, Miller, Brett-Green, & Hepburn, 2008).

Traditional electrodermal measurement tends to be more difficult for children than for adults due to difficulties with the application and tolerance of the sensors (Fowles & Fowles, 2007). Moreover, children with ASD may have difficulties with comprehension, high sensory discomfort, and behavioral noncompliance that represent challenges to the feasibility of traditional EDA measurement. A recent development is wireless wearable wrist sensors that approximate the size and appearance of a watch (Poh et al., 2012; Poh, Swenson, & Picard, 2010) and can be worn continuously during naturalistic laboratory tasks, thus facilitating the integration of EDA data with behavioral observations of emotion. A pilot study, for example, is currently being conducted of children with ASD in which the wrist sensors are used to track arousal across a series of naturalistic and structured parent–child and child-alone laboratory tasks (Baker, Fenning, Howland, & Murakami, 2014). In selected EDA data tasks for two early participants (see Figure 39.5), one child

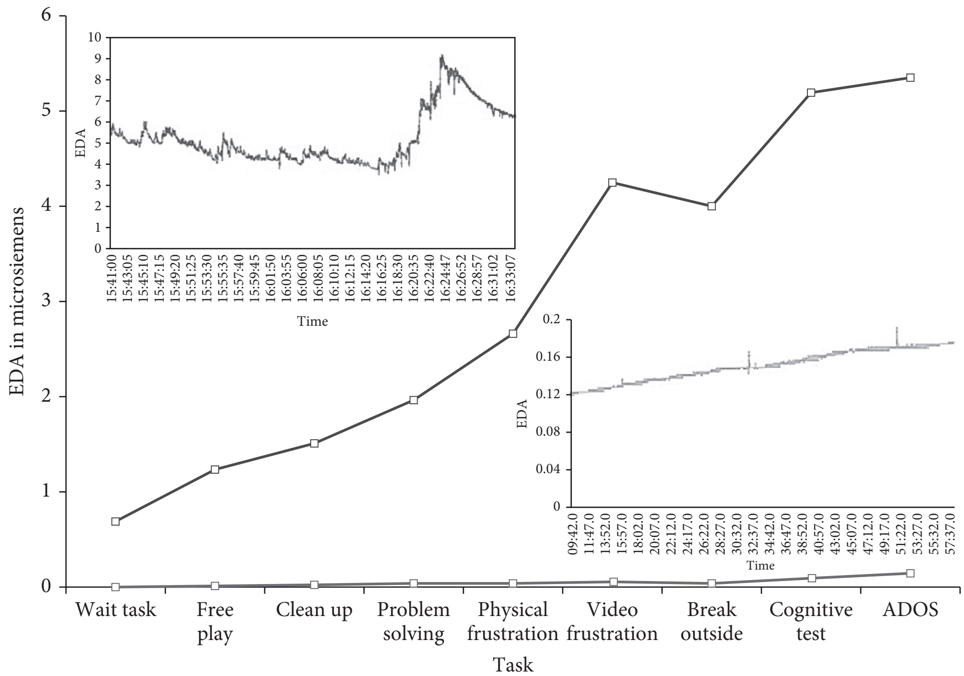

Fig. 39.5 Electrodemal activity (EDA) measurements for two children. The large plot visualizes EDA across laboratory tasks, whereas specific measurements for each child within the Autism Diagnostic Observation Schedule (ADOS) task are inset. Of note, the phasic peak in EDA for the child in the ~~blue~~ inset occurred when the examiner asked the child about uncomfortable emotions and problematic peer interactions.

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appears to be exhibiting more typical EDA levels whereas the profile of the other child appears more consistent with the underaroused group discussed in the literature (Hirstein et al., 2001). More generally, the potential for extended use of such sensors would allow for measurement of EDA in children with ASD during completely natural daily activities in the home, school, and community. Continuously collected acquisition of EDA measurements in naturalistic settings has the potential to spur new research initiatives that parallel similar initiatives in vocalization research sparked by continuous recording of vocalization data through the LENA system.

Translational Applications of Affective Computing to Children with ASD

In addition to advances in emotion recognition and modeling, affective computing approaches can also be used to model a system's "emotional response" to a user and to express emotion via embodied conversational agents or robots (Graesser & D'Mello, 2011; Picard, 1997). Children with ASD have special challenges in the areas of social communication, social interaction, and stereotyped behaviors. From an affective perspective, children with ASD often have difficulty recognizing emotions in others and sharing enjoyment, interests, or accomplishments, as well as in interpreting facial cues to decode emotion expression. Many children with ASD also display a preference for sameness and routines, indicating that the uniform, predictable interactions offered by translational applications such as embodied conversational agents and robotics may also be particularly beneficial for these children. This section reviews recent studies on translational applications to facilitate the socioemotional development of children (including children with ASD) through the use of agents and robots.

Embodied Conversational Agents

Embodied conversational agents are software-based automata with varying degrees of autonomy that can be used to assist children in emotional or other tasks. Agents are represented with a human audiovisual form whose appearance ranges from cartoon-like to photographic. Typically, developing children appear to communicate as much with an embodied conversational agent as with a human psychologist using the same script (Black, Flores, Mower, Narayanan, & Williams., 2010), make similar nonverbal gestures with both, and smile more often and fidget less when interacting with an agent than with a psychologist (Mower, Black, Flores, Williams, & Narayan, 2011). Agents have primarily been geared toward improving the academic performance of intelligent tutoring systems (ITS) within typically developing children domains (Graesser, Chipman, Haynes, & Olney, 2005; Lane, Noren, Auerbach, Birch, & Swartout, 2011) and tend to focus on cognitive aspects of learning, to the neglect of emotional dimensions of learning.

Recent decades have seen increased recognition of the interplay between emotions and learning and of the centrality of the role of emotions to learning (Cicchetti & Sroufe, 1976; Graesser & D'Mello, 2011; Kort, Reilly, & Picard, 2001). Findings from the growing literature on emotions and computing suggest that a broader array of emotions are relevant to learning than those mentioned in discrete theories of emotion, and learners often report negative emotions such as frustration, confusion, and boredom, some of which facilitate, rather than hinder, deep learning (Graesser & D'Mello, 2011). Partially as a result, many ITSs are increasingly incorporating affect-based agents (e.g., Mao & Li, 2010) in a range of tutoring systems, including more traditional academic applications (e.g., Arroyo, Woolf, Royer, & Tai, 2009). An example is Affective Auto-Tutor, arguably the first fully automated, affect-aware dialogue-based ITS for computer literacy (D'Mello & Graesser, 2013). This affective tutoring system was designed to detect students' emotions and use this information to guide response selection to help children regulate their emotions during learning (D'Mello & Graesser, 2012). The tutor led to better learning outcomes than its non–affect-aware equivalent counterpart, particularly for novice students with low domain knowledge.

Agent-based intervention systems can also directly target emotional responsiveness by eliciting empathy to help the learner practice experiencing and expressing different target emotional states. *FearNot!* (Fun with Empathic Agents to Achieve Novel Outcomes in Teaching) is a prime example of an agent-based system used to elicit emotion and teach typically developing children regulation and coping skills related to bullying prevention (Paiva et al., 2004). *FearNot!* taught different coping strategies to children using three affect-based agents: a bully, a victim, and a narrator. Children, for example, acted as an invisible friend to the victim agent. They watch the victim agent interact with the bully, have a private conversation with the victim agent about what happened—where they offer coping strategies that the agent might accept or refuse—and then watch the outcome of the agent's chosen coping strategy. *FearNot!* agents were autonomous, with a complex architecture guiding their behavioral decisions, including a model of the world representing the agent's own emotions as well as those of others (based on agent appraisals). Agents had a parameter-based personality including role-based (e.g., victim or bully) thresholds for experiencing different emotions, speed of decay for different emotions, and a function for recalculating the intensity of equivalent emotions. Agents also had an action selection module, which included unplanned action tendencies based on the agent's role and personality (e.g., in the victim role, the agent would cry if bullied, but did not know it would cry). The efficacy of these empathy-eliciting agents was examined empirically with 52 children aged 8–12 and appeared successful: 86% of children felt empathy for an agent (usually the victim), and 72% felt angry (usually with the bully). *FearNot!* offers a prime example of a future direction for using agents to target important core emotional skills for children that might also be applied to children with ASD (Paiva et al., 2004).

AGENTS AND CHILDREN WITH ASD

As with typically developing children, embodied conversational agents can facilitate academic learning among children with ASD (Bosseler & Massaro, 2003). Increased learning in systems that incorporate an embodied agent (an animated face) versus disembodied voice-based teaching, for example, have been found in children with ASD (Massaro & Bosseler, 2006). Agents also have the potential to help children with ASD learn to recognize emotions in others and in themselves. Rachel is an example of pedagogical emotional coach that collects multimodal data from children with ASD as they engage in emotion recognition and emotion storytelling tasks using a "person-in-the-loop" paradigm in which children interact with the agent and the system is guided in real time by a therapist, unbeknownst to the child (Mower et al., 2011). Support vector machine classification indicated that children's speech patterns were not distinguishable between parent and Rachel, suggesting that Rachel is able to elicit ecologically valid interactions from children with ASD in the context of emotional learning.

Despite these promising efforts, there is substantial untapped potential in the use of embodied conversational agent applications for children with ASD. To facilitate self-recognition and expression of emotion, systems might detect facial expressions and physiological signals in children with ASD and prompt them to report on their emotional experiences by matching their emotional experience to sample emotional faces. Alternately, posing facial expressions could be integrated into playing an ongoing game (see Cockburn et al., 2008). In summary, the main untapped potential in the use of agents to help children with ASD arguably rests with matching emerging technological potential to the core social deficits of children with these disorders.

Robots and Autism

An increase in the presence of social robots around children appears likely (Movellan, Eckhardt, Virnes, & Rodriguez, 2009; Tanaka, Cicourel, & Movellan, 2007), although the potential developmental effects of interactions with these robots are only beginning to receive attention in the psychological literature (Kahn, Gary, & Shen, 2013). Several research groups have studied the response of children with ASD to both humanoid robots and nonhumanoid toy-like robots in the hope that these systems will be useful for understanding affective, communicative, and social differences seen in individuals with ASD and to utilize robotic systems to develop novel interventions and enhance existing treatments for children with ASD (see Diehl, Schmitt, Villano, & Crowell, 2012).

Many individuals with ASD show a preference for robot-like characteristics over nonrobotic toys (Dautenhahn & Werry, 2004; Robins, Dautenhahn, Boekhorst, & Billard, 2005) and, in some circumstances, respond faster when cued by robotic movement than by human movement (Bird, Leighton, Press, & Heyes, 2007; Pierno, Mari, Lusher, & Castiello, 2008). Although these findings concern school-aged children and adults, the preference for very young children with ASD to orient to nonsocial contingencies rather than biological motion suggests that downward extension of this preference may be particularly promising (Annaz et al., (2012) Klin, Lin, Gorrindo, Ramsay, & Jones, 2009). Furthermore, a number of studies have indicated the advantages of robotic systems over animated computer characters for skill learning and optimal engagement, likely due to the capability of robotic systems to utilize physical motion in a manner not possible in screen technologies (Bainbridge, Hart, Kim, & Scassellati, 2011; Leyzberg, Spaulding, Toneva, & Scassellati, 2012).

Despite this hypothesized advantage, there have been relatively few systematic and adequately controlled applications of robotic technology investigating the impact of directed intervention and feedback approaches (Duquette, Michaud, & Mercier, 2008; Feil-Seifer & Matarić, 2009; Goodrich, Colton, Brinton, & Fujiki, 2011; Kim et al., 2012). Kim and colleagues (2012) demonstrated that children with ASD spoke more to an adult confederate when asked by a robot than when asked by another adult or by a computer. Duquette and colleagues (2008) found that children paired with a robot had greater increases in shared attention than did those paired with a human. Goodrich and colleagues reported (2011) that a low-dose robot-assisted ASD exposure with a humanoid robot yielded enhanced positive child–human interactions immediately afterward. Feil-Seifer and Mataric (2009) showed that when a robot acted contingently during an interaction with a child with ASD, it had a positive effect on that child's social interaction. Although these approaches have demonstrated the potential and value of robots for more directed intervention, the majority of robotic systems studied to date have been unable to perform autonomous closed-loop interaction. As such, these platforms have limited applicability to intervention settings necessitating extended and meaningful adaptive interactions.

By contrast, examples of adaptive robotic interaction with children with ASD include proximity-based closed-loop robotic interaction (Feil-Seifer & Mataric, 2011), haptic interaction (Amirabdollahian, Robins, Dautenhahn, & Ji, 2011), and adaptive game interactions based on affective cues inferred from physiological signals (Liu, Conn, Sarkar, & Stone, 2008). Although these systems are capable of adaptive interaction, the paradigms explored were focused on simple task and game performance and had little direct relevance to the core deficits of ASD. Recent work has explicitly focused on realizing co-robotic interaction architecture capable of measuring behavior and adapting performance in a way that addresses fundamental early attentional and affective impairments of ASD (i.e., joint attention skills). Mazzei et al. (2011) used a combination of hardware, wearable devices, and software algorithms to measure the affective states (e.g., eye gaze attention, facial expressions, vital signals, skin temperature, and EDA signals) of children with ASD, and these were used for controlling the robot reactions and responses. Bekele and colleagues (Bekele, et al., 2013a; Bekele et al., 2013b) studied the development and application of a humanoid robotic system capable of intelligently administering joint attention prompts and adaptively responding based on within-system measurements of gaze and attention. Preschool children with ASD directed their gaze more frequently toward the humanoid-robot administrator, were frequently capable of accurately responding to robot-administered joint attention prompts, and also looked away from target stimuli at rates comparable to typically developing peers. This suggests that robotic systems endowed with enhancements for successfully pushing toward correct orientation to target might be capable of taking advantage of baseline enhancements in nonsocial attention preference in order to meaningfully enhance skills related to coordinated attention.

For effective ASD intervention, innovative therapeutic approaches using robot systems should have the ability to perceive the environment and users' behaviors, states, and activities. Increasingly, researchers are attempting to detect and flexibly respond to individually derived, socially, and disorder-relevant behavioral cues within intelligent adaptive robotic paradigms for children with ASD. Systems capable of such adaptation may ultimately be utilized to promote meaningful change related to the complex and important social communication impairments of the disorder itself. However, questions regarding generalization of skills remain for the expanding field of robotic applications for ASD. Although many are hopeful that sophisticated clinical applications of adaptive robotic technologies may demonstrate meaningful improvements for young children with ASD, it is important to note that it is both unrealistic and unlikely that such technology will constitute a sufficient intervention paradigm addressing all areas of impairment for all individuals with the disorder. However, if systems are able to discern measurable and modifiable aspects of adaptive robotic intervention with meaningful effects on skills important to neurodevelopment, the field may realize transformative robotic technologies with pragmatic real-world application of import.

Conclusion and Discussion of Alternate Approaches

Overview

Children potentially offer a relatively simple model for the application of software-based tools for the automated measurement and modeling of emotional behaviors. At the same time, the affective computing tools implemented in software- and hardware-based nonhuman agents have the potential to help children—both with and without serious developmental and clinical conditions such as ASD—confront social and emotional problems that may impact their development. Here, we present a critical summary of key issues in the detection and modeling of emotional behaviors in and the implementation of autonomous software and hardware agents designed to help children.

Facial Expressions

The automated detection of infant and parent facial expressions—paired with continuous ratings of emotional valence—has yielded insights into the continuous flow of emotion expression during interaction and suggested parallels between infant positive and negative emotion expression (Messinger et al., 2009; Messinger et al., 2012). To date, however, this research has been conducted with relatively small sample sizes, and the efficiency promised by automated facial measurement has not been clearly realized. It is also of note that although substantial research has been conducted on the detection of emotion signals in infants younger than 1 year of age, there is relatively little research on facial expressions of emotion in older children. Developments that may begin to correct this imbalance include plans for the release of (1) a large database of annotated audio and video measurements of children between 1 and 2 years of age (Rehg et al., 2013); (2) a multilaboratory repository of audiovisual data on older children collected in multiple laboratory settings via the Databrary project (http://databrary.org/); and (3) the availability of publicly available databases containing child behavior, such as YouTube.

Vocalizations and Electrodermal Activation

The automated detection of cry-vocalizations—a key signal of infant negative emotion—is relatively robust. However, automated differentiation between cries on the basis of apparent communicative intent and the classification of emotional signals other than cries appears to be a more difficult challenge. However, the advent of systems for day-long recording of ambient audio in naturalistic settings and their automated analysis suggests the tremendous potential of affective computing to understand naturalistic behavior in context. Likewise, continuous measurement of EDA in extended and naturalistic conditions offers substantial potential for understanding the time course of arousal in response to naturalistic stressors among typically developing children and children with ASD.

Multimodal Fusion

In the research reviewed, visual and vocal (audio) signals of emotion were measured separately. Recently, however, Rehg and colleagues fused video-based (e.g., smile and gaze-at-examiner detection) and audio-based measurements (e.g., number and fundamental frequency of child speech segments) to index child engagement (Rehg et al., 2013). Although such efforts are rare, the importance of fusing multimedia measurements—including physiological as well as visual and audio sensors—cannot be underestimated. Such fusion offers the possibility of a better understanding of the emergence of emotional states from the interplay of their behavioral and physiological constituents (Calvo, 2010), as well as a better understanding of children's emotional interaction and development.

Modeling Advances

Although not commonly used in the analysis of automated measurements, there have been widespread advances in the modeling of complex communicative systems that are important to affective computing researchers. Time-series approaches can now be used to assess the communicative influence of one partner on another (e.g., parent to infant influence) across dyads (Beebe et al., 2007). Additional progress in time-series modeling has led to the quantification of time-varying changes in communicative influence and group-based differences in self-regulation (autocorrelation) (Chow et al., 2010). At the same time, innovative approaches based in recurrence quantification analysis and machine learning approaches that quantify entropy (the predictability of a given action during communication) are gaining prominence.

What Modeling Approach Is Most Appropriate?

Generally, time-series approaches are appropriate when a continuous signal such as the intensity of a facial action is being modeled. The modeling of discrete emotional signals (e.g., the presence of a smile) is well-suited to recurrence quantification analysis and entropy-based approaches. Descriptive approaches to modeling, such as windowed cross-correlations, offer an intuitive description of emotional communication dynamics whereas approaches based in time-series analyses offer the ability to conduct inferential testing of hypotheses. Despite these rules of thumb, however, there is not yet consensus on which modeling approach is most appropriate to understanding a given expressive or communicative system. Projected future growth in automated measurement (e.g., via Kinect) and the need to understand and control how software- and hardware-based agents interact suggests that modeling may become a more central aspect of affective computing initiatives with children in the future.

Modeling to Detect Interaction

In the research reviewed, behavior was measured and then modeled to detect and understand interaction. Rehg and colleagues have demonstrated an alternate approach that involves directly detecting interaction structures and defined as quasi-periodic spatiotemporal patterns (Prabhakar, Oh, Wang, Abowd, & Rehg, 2010; Prabhakar & Rehg, 2012; Rehg, 2011). Sequencing video into a string of visual words, they detected patterns in naturalistic YouTube videos and used supervised learning to identify instances of adult–child interaction directly from those videos. This approach highlights the potential importance of modeling—broadly construed—in the measurement of interaction.

Modeling to Simulate Development

The modeling approaches reviewed are concerned with characterizing communicative systems. Additional models that simulate interaction and development have been implemented by Deák and collaborators (Deák, Fasel, & Movellan, 2001; Fasel, Deák, Triesch, & Movellan, 2002; Jasso, Triesch, & ~~Gedeon~~, 2008; Lewis, ~~Gedeon~~, & Triesch, 2010; Triesch, Teuscher, Deák, & Carlson, 2006). Using a bottom-up perspective, these researchers posit a set of infant perceptual preferences, the ability to learn spatiotemporal contingencies, and a relatively structured environment that is based on the researchers' coding of observed infant–parent play with toys. By assigning variable reward values to gazes at the parent's face and toys, the researchers shed light on the basic abilities required for more complex developmental processes. Modeled processes include following a parent's gaze (responding to joint attention) and turning toward a parent's face when confronted with an unknown object and responding to the parent's positive or negative emotional expression (social referencing). This approach highlights the potential of modeling to contribute to an understanding of how development occurs in both typical and atypical (e.g., ASD) cases.

Software Agents

Initial "person-in-the-loop" systems for children with ASD have targeted emotional competencies (e.g., Rachel; Mower et al., 2011). More advanced, agent-based systems intended for typically developing children detect and respond to learner's emotions in real time in teaching an academic content area (e.g., Affective Auto-Tutor; D'Mello & Graesser, 2012). Ideally, future applications for children with and without ASD would synthesize these features. These applications could address core emotional functioning, including both the identification and the expression of emotion in dynamic (e.g., dyadic) contexts as targets, while using detection and user-modeling approaches to detect emotions such as boredom, confusion, and frustration. Such a synthetic approach could provide automated, emotion-based feedback to children with ASD—as is being done to some degree with typically developing children—during ongoing interactions.

Robots

In comparison with embodied conversational agents, relatively more research has been conducted in which hardware-based agents—robots—have been used to interact and intervene with children with ASD (Diehl et al., 2012). Children tend to respond positively to robots, and they offer potential for facilitating emotional development in children with ASD. As with conversational agents, the greatest area for future development is likely to be the development of autonomous closed-loop systems that apply to social-emotional targets of core importance to children with ASD. In addition, the extent to which social-emotional skills acquired and developed via conversational agents and robots are generalized to social interaction with other children and adults is not clear. Finally, the degree to which agent-based interventions can supplement more established clinical interventions in real-world settings has yet to be addressed.

Ethics and Outcomes in a Changing World

In addition to scientific concerns, a recent review suggests that the projected increase in autonomous agents such as robots presents complex ethical issues (Kahn et al., 2013). Children are likely to interact with technologically "smart" entities such as social robots as play partners but have ultimate control over these partners. That is, the reciprocity inherent in social relationships with another child does not exist with robots which, ultimately, can be turned off. Although children may benefit from many aspects of these interactions, there is concern that they may generalize their likely objectification of the robots to their interactions with other children (Kahn et al., 2013). Finally, parental-sensitive responsivity is a robust predictor of optimal outcomes (Belsky & Fearon, 2002; NICHD-ECCRN, 2001). It is of some concern, then, that little is known about the emotional impact of parent-, child-, and infant-held personal digital assistants on children's outcomes. If the potential of affective computing is to be used for children's benefit, the ethical, moral, and developmental impact of both academic and commercial affective computing tools require continued investigation.

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