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Emotion Intensification in 6-Month-Old Infants: The Role of Eye Constriction

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EMOTION INTENSIFICATION IN 6-MONTH-OLD INFANTS: THE ROLE OF EYE CONSTRICTION

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Previous inquiry suggests that the constriction of the muscle around the eye serves to intensify smiling expressions. This study investigated whether eye constriction not only leads smiling expressions to be more positive but also leads negative (cry-face) expressions to be more negative. Twelve parents and their 6-month old infants interacted within a protocol designed to elicit positive and negative emotion (the Face-to-Face Still-Face). Facial actions were measured frame-by-frame from video using automated methods (computer vision and pattern recognition). Non-experts rated positive and negative affect. Eye constriction intensity (*obicularis oculi pars orbitalis*) was associated with both smiling (*zygomatic major*) and lateral lip-stretching (action of the *risorius*, a component of the cry-face expression) intensity. Eye constriction intensity predicted both positive and negative emotion ratings, beyond the effects of smiling and lateral lip-stretching intensity, respectively. These finding suggest that eye constriction serves an intensifying role in both positive and negative infant expression.

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Chapter 1

Introduction

Infants communicate recognizable positive and negative emotions through facial expression (Galati & Lavelli, 1997; Johnson, Emde, Pannabecker, Stenberg, & Davis, 1982; Oster, Hegley & Nagel, 1992). Smiles with constriction of the *obicularis oculi pars orbitalis* muscle (eye constriction) occur more often in positive contexts and are perceived as more positive than smiles without eye constriction (Fox & Davidson, 1988; Messinger, Fogel, Dickson, 2001; Messinger, Cassel, Acosta, Ambadar & Cohn, 2001; Messinger, Mahoor, Chow, & Cohn, 2009). I investigated whether eye constriction plays a similar role in both negative and positive expressions. This issue was addressed using automated facial measurement and non-expert ratings of affect.

Facial Actions and Emotion

Constriction of the *obicularis oculi pars orbitalis* muscle around the eye (hereafter eye constriction) paired with oblique action of *zygomatic major* muscle (hereafter smiling) has been consistently linked with positive emotion in adults (Frank, Ekman, & Friesen, 1993) and infants (Messinger et al., 2008; Fox & Davidson, 1988). Infant expressions thought to reflect distress, anger, pain, and sadness in adults tend to be classified by observers as undifferentiated negative affect more frequently than these more specific categorizations (Camras et al., 2007, Camras, Sullivan & Michel, 1993; Oster, Hegley & Nagel, 1992). The cry-face expression is linked to this overarching category of negative affect, encompassing distress and anger (Camras et al., 2007; Oster, Hegley & Nagel, 1992). Cry-face expressions involve knitting of the brows, constriction around the outer edge eyes with raising of the cheeks, lateral tightening of the eyelids, opening of the mouth and a key component: lateral stretching of the *risorius* muscle (hereafter lateral-lip stretching). Cry face expressions involve constriction of the *orbicularis oculi pars lateralis* muscle which tightens the eyelid laterally and narrows the eye aperture, a facial action separate from eye constriction (involving constriction of the outer edge of the eyes and raising of the cheeks in *orbicularis oculi pars orbitalis*). Discrete emotion theory includes eye constriction in its formulations for not only expressions of joy (positive affect), but also physical distress, sadness and anger (negative affect) (Izard, 1983). It is worth noting that, unlike smiles, cry-face expressions involve some degree of eye-constriction as a component of the expression (Oster, 2009). Overall, these findings suggest that eye constriction plays a role in infant positive emotion expression and potentially during the generalized negative emotion seen in infants.

Recent studies have laid the groundwork for the hypothesis that eye constriction indexes more intense emotion during infant positive and negative expression. Evidence for this relationship is found in non-expert's ratings of smiles and cry-face expressions. Ratings of smiles were more positive when accompanied by eye constriction and mouth opening than smiles without these features (Messinger, 2002). Ratings of cry-faces, within these same ratings studies, were more negative when accompanied by eye constriction and mouth opening than cry-faces without these features. This suggests a certain parity in the role of eye constriction in both of these emotional expressions.

Dinehart and colleagues (2005) had non-expert raters view still photographs of infants. Each photograph had been edited to show different degrees of smiling, lateral lip-stretching, mouth opening, and eye constriction. Higher intensity of smiling was associated with higher ratings of positive affect. Higher intensity of lateral lip-stretching was associated with higher ratings of negative affect. Higher intensity eye constriction was also associated with higher ratings of both positive and negative affect. However, this study used still pictures of infant expressions, rather than video. Using these snapshots of behavior might have failed to capture the intricacies of the interaction between eye constriction, smiling, lateral lip-stretching, and positive and negative affect.

Messinger and colleagues (2008) used brief video stimuli to investigate the relationship between smiles and eye-constriction. The strength of eye constriction in infants was associated with higher positive affect ratings; the strength of infant smiles was also associated with higher positive affect ratings (Messinger, Cassel, Acosta, Ambadar, & Cohn, 2008). They did not assess the unique predictive relationship of eye constriction beyond its association with smiling, or include negative emotion as part of their investigation. I employed similar non-expert ratings to validate automated measurements. It expands on previous investigation of eye constriction by exploring its relation to positive and negative ratings and by using longer video samples.

Messinger and colleagues (2009) measured eye constriction, mouth opening, and smile intensity using automated methods, Automated facial measurements revealed that the intensity of eye constriction was strongly correlated with the intensity of smiling; the intensity of eye constriction with the intensity of mouth opening and the intensity of mouth opening with the intensity of smiling were also moderately correlated. Further, eye constriction, mouth opening, and smiles were also moderately correlated with ratings of positive emotion. However, this study was limited to data from two dyads. I employed automated methods in the current study to code a larger sample of video data and to provide additional evidence of the feasibility of automated measurement, not only for smiles but also for lateral lip-stretching.

Measuring Facial Actions

The Facial Action Coding System (FACS; Ekman & Friesen, 1978) is a widely-used tool for measuring facial expression. FACS is composed of individual action units (AUs) that are the minimally separable units that are both anatomically and visually distinct (Ekman, Davidson, & Friesen, 1990). When combined, these action units describe a facial expression. FACS has been found to be reliable in frame-by-frame video coding (Sayette, Cohn, Wertz, Perrot, & Parrott, 2001). The current study employed coders certified in FACS and trained in BabyFACS (Oster, 2009) to measure facial actions. The current study concentrated on facial actions thought to convey positive emotion (smiling) and negative emotion (cry-faces, here indexed by lateral lip-stretching) in infants.

Automated Approaches

A supplementary aim of the study was to expand and replicate the recent use of automated measurement of facial actions (Cohn & Sayette, in press; Cohn, Zlochower, Lien, & Kanade, 1999; Messinger, Mahoor, Chow, & Cohn, 2009). In particular, recent research (Cohn & Sayette, in press) suggests that an automated approach can yield comparable automatic action unit detection throughout naturalistic interactions in adults. An automated measurement approach provides an objective method of coding a large amount of video data based on a small amount of training. Additional work is needed to implement a fully automated approach to facial measurement and the current study was designed to further this goal. A central concern of automated measurement is reliability with manual coding, which has been specifically addressed in our hypotheses.

Chapter 2

Hypotheses

I employed automated measurement of three facial actions (smiles, lateral lip-stretching, and eye constriction) in infants across an emotion eliciting interaction. The first hypothesis considered the consistency of automated and manual FACS ratings of these actions.

B) Automated coding exhibits associations with expert manual coding comparable to the associations between manual coders.

The following three hypotheses addressed the relationship of facial actions and their relationship with non-expert ratings:

2. The intensity of eye constriction (FACS Action Unit 6) rises and falls with the intensity of smiles (FACS Action Unit 12) and with the intensity of lateral lip-stretching (FACS Action Unit 20):

    A) Greater intensity of smiling (FACS Action Unit 12) is associated with greater intensity of eye constriction.

    B) Greater intensity of lateral lip-stretching (FACS Action Unit 20) is associated with greater intensity of eye constriction.

    C) Greater intensity of smiling will is not associated with greater intensity of lateral lip-stretching.

3. Smiles and lateral lip-stretching accompany positive and negative emotion ratings, respectively:

    A) Greater intensity of smiling (FACS Action Unit 12) is associated with greater non-expert positive ratings.

B) Greater intensity of lateral lip-stretching (FACS Action Unit 20) is associated with greater non-expert negative ratings.

4. Eye constriction is uniquely predictive of positive and negative emotion ratings beyond the respective effects of smiles and lateral lip-stretching:

A) Eye constriction intensity predicts unique variance of non-expert ratings of positive emotion beyond the effects of smile intensity.

B) Eye constriction intensity predicts unique variance of non-expert ratings of negative emotion beyond the effects of lateral lip-stretching intensity.

Chapter 3

Method

Participants

To measure early infant expressions and perceived emotional intensity, a total of 12 infants and their mothers were recruited though the University of Miami and Nova Southeastern University Center for Autism and Related Disabilities (UM-NSU CARD) South Florida registry, the Autism Spectrum Assessment Clinic, and the University of Miami Psychological Services Center. Additionally, subjects were also recruited via Miami-Dade County birth records and through flyers and brochures distributed to the public. Autism risk status was not considered as a part of the study. All infant were of approximately six months of age (M = 6.20, SD = .43). The infants were African American (16.7%), Asian (16.7%), Hispanic (33.3%), and White (33.3%). In this sample 66.7% of infants were male. Mothers were compensated monetarily ($30) for completion of this protocol and for other measures unrelated to the current study.

To obtain measures of perceived emotions, a total of 78 non-expert raters were recruited from an undergraduate population attending a major university. The mean age of raters was 19.59 years (SD = 1.55). These raters were African American (6.4%), Asian (2.6%), Hispanic (32.1%), White (51.3%), and Bi-racial/Other (7.7%). The non-expert raters were 47.4% male. For their time and participation, raters were provided with either additional credit in an introductory psychology course or monetary ($20) compensation.

Procedure

Mother-infant interactions were conducted in a sound-attenuated chamber designed to minimize outside distractions. Infants were placed in a car seat facing their mother at eye level. Mothers were asked to engage in a face-to-face still-face paradigm (Cohn & Tronick, 1983) with the infant. Mothers were asked to spend three minutes engaging their child's attention. This was followed by two minutes of disengagement and flat affect, and then three minutes in which the mother attempted to re-engage the infant. Throughout this protocol the infant was video-recorded. From these recordings, video clips were generated for each portion of the face-to-face still-face paradigm. Non-expert raters were asked to rate either the infant's positive (joy, happiness, and pleasure) or negative affect (anger, sadness, and distress) continuously throughout each video clip. These ratings were then compared to automated measures of infant facial actions.

Chapter 4

Measurements

Automated Measurement

Automated measurements were gathered through a three-stage process (see figure 1 for a summary). Active Appearance Models (AAM) were used to track infant's faces. An AAM consists of a series of connected points on the face which serves to separate rigid movement, both translational (up and down, left and right on the same plane) and rotational (pitch, turning up and down; yaw, turning left and right; and roll, tilting clockwise or counter-clockwise) from non-rigid movement, deformation within the face (Cootes, Taylor, & Edwards, 2001; Messinger et al. 2009). This model employs both an appearance and shape component. From the raw video of the mother-infant interaction, individual gray-scale values were extracted from the image (the appearance component). A series of X and Y coordinates on the facial image were selected to represent the position of facial features on the infant's face (the shape component). A subset of video frames (2.75%) was manually adjusted in order to inform the AAM's fit of the infant face. Based on these initial coordinates and the surrounding grayscale values, the AAM learned to place these same positions in the remaining video frames. If visualized as interconnected points, a mesh would be formed which describes the overall shape of the face (see figure 1B). The AAM was then used to extract data both on the shape and appearance of the infant face.

Non-linear data reduction techniques were then applied to this data to decrease its dimensionality (a Laplacian eigenmap; Belkin and Niyogi, 2003). With the shape and appearance information streamlined, separate Support Vector Machines (SVM) for each facial action were then used to obtain data about the intensity levels of facial actions. Each SVM was composed of six binary classifiers which distinguished each intensity level from all other intensities (one-versus-all approach) for each facial action. SVM uses a machine learning method which takes existing classification information and generates rules for the classification of new information. It does this by fitting a linear plane in dimensional space between data points as a criterion for classification; this criterion maximizes the accuracy of classification while minimizing the overall distance between data points and the classification plane. In this instance, a radial basis function kernel was applied to account for the non-linear nature of the data, allowing for the fit of a linear classifier. A manual master coding of three facial actions (smiles, lateral lip-stretching, and eye constriction) were used by the SVM to generate classification rules. These rules were based on patterns in the relative shape and appearance of the infant face. The rules for the classification of each level of intensity were based on training conducted with 20% of the manually coded video frames in which face tracking could be established, omitting frames from the video to be rated. Based on these rules the SVM classified the intensity of facial actions in each video. This technique provided the intensity of facial actions from 0 (absent) to 1 (trace) to 5 (maximum) by orthogonally distinguishing each level, producing coding corresponding to FACS intensities A to E.

For each subject, the automated application was trained using a leave-one-subject-out approach. This entailed the automated application generating a coding for each subject based on 20% of the manual coding of the other subjects in the sample. This ensured that classification of facial actions was being generalized across subjects, rather than being based on the coding of each individual.

In order to determine the validity of the automated coding, reliability was assessed with manual coding. Additionally, 25% of the video sample was also coded by a second manual reliability coder. This served primarily as a comparison to the reliability of the automated coding to manual coding. This also served to ensure the reliability of the master manual coding.

Non-expert Raters

Non-expert raters were instructed to move a joystick apparatus (see figure 1G) either forward or backward depending on whether they feel the infant is showing more or less emotion (e.g., “More positive emotion” or “No positive emotion” for those rating positive emotions). Order of video presentation was randomized from within the application (the Continuous Measurement System) to control for ordering effects. As raters move the joystick, each change was recorded at the same rate as the video (30 frames per second). The degree to which the joystick was moved forward or backward was translated into a continuous measurement (ranging from -500 to +500) via the presentation software.

Chapter 5

Data Preparation

Automated Measurement

Due to factors such as occlusion of the infant face and extreme variations in pose, the AAM was prevented from modeling 40.6% of the overall video data. Individual data exclusion is summarized by subject in figure 2. The modeled image data forms the sample discussed below.

Co-occurrence of Primary Facial Actions

There were periods when smiles and lateral lip-stretching co-occurred (see table 1 for a summary). For the correlational analyses in Hypothesis 1, when smiling and lateral lip-stretching co-occur they mask the relationship between eye constriction and each primary action. To minimize this effect, periods where smiling and lateral lip-stretching occur at the same time were excluded from these analyses. Overall, 5.7% of the image data was excluded from correlational analyses due to the co-occurrence of smiles and lateral lip-stretching. Excluding these data points did not impact whether correlational results were significant or non-significant.

Non-expert Ratings

As in previous studies, analyses of ratings data were conducted using mean ratings, (Dinehart et al., 2005; Messinger et al., 2008). This is based on the expectation that ratings based on a mean of several raters tend to be more accurate and less variable than the ratings of individuals (Ariely et al., 2000). Additionally, this specific rating method has demonstrated utility in several similar contexts to the current study (Baker et al., 2010; Messinger et al., 2009) as well as similar methods across more disparate contexts such as comparing self-ratings of affect to physiological response, alcohol consumption to anxiety levels, and empathy (Ruef & Levenson, 2007).

Examination of cross-correlations showed a lag of approximately one second between non-expert ratings and automated measurement. This discrepancy was likely due to non-experts taking longer to consider changes than the automated method, Non-expert ratings were lagged to compensate for this difference between non-expert ratings and automated measures. This approach is consistent with previous methods (Messinger et al., 2009), although the exact lag value differed in the current study. Messinger et al. (2009) employed a lag of 18 frames within their sample of 9,090 frames of video. Within our larger sample of 96,974 frames of video, a lag of 30 frames was selected. Lags in ratings between 0 and 60 frames produced similar correlations and significance levels as subsequent analyses.

Correlations of ratings of mean positive affect and mean negative affect were examined to explore the relationship between these measures. These correlations revealed that negative affect ratings were effectively the inverse of positive affect ratings (mean $r = -.87$). Non-expert raters appeared to conflate higher positive affect with lower negative affect and lower positive affect with higher negative affect. This is likely due to non-experts operating under a working model in which positive and negative affect are two poles of the same axis. Accordingly, ratings were combined to form a single axis, the mean rating of positive affect and inverted negative affect. This composite axis ranged from -500 (most negative affect) to 0 (neutral) to +500 (most positive affect).

Multi-level Analyses

Smiling (AU12) and lateral lip-stretching (AU20) were combined to form a single axis from -5 (most intense lateral lip-stretching) to 0 (neutral) to 5 (most intense smile) to match the hypothesized relationship between these facial actions and ratings. Based on this change, the directionality of eye constriction was adjusted based on whether AU12 (positive) or AU20 (negative) was greater within a given video frame. Within our sample there were also periods of time in which values of AU12 and AU20 were equal. We had no hypothesis about the role of AU6 when smiling and lateral lip-stretching were present at the same intensity. Consequently, eye constriction was excluded from multi-level analyses when both AU12 and AU20 were equivalent (42.7% of image data).

Chapter 6

Results

Hypothesis 1

Automated coding exhibits associations with expert manual coding comparable to the associations between manual coders. To address the first hypothesis, reliability was first compared between the primary manual coder and a secondary manual coder to get an index of expected reliability. For each subject, absolute Intra-Class Correlations (ICC) were calculated for eye constriction, smiles and lateral lip-stretching. Reliability was assessed over 25% of the video data, and was acceptable for AU6 (mean $ICC = .78$), AU12 (mean $ICC = .84$), and AU20 (mean $ICC = .75$).

The concurrent validity of automated and manual measurement was then assessed using an absolute intra-class correlation coefficient (ICC) for each subject. Agreement between manual coding and automated coding was below acceptable levels. Mean ICC values were higher in AU6 (mean $ICC = .76$) and AU12 (mean $ICC = .74$) than in AU20 (mean $ICC = .59$). It is worth noting that reliability of manual to automated coding was assessed using 100% of the image data, while manual reliability was only assessed over 25% of the image data, however this change is unlikely to account for these differences. To further explore patterns in these lower reliability values, follow-up analyses of these comparisons were conducted. Bivariate correlations were run between absolute ICC values by subject and average intensity of behavior. Correlations were low for AU6 ($r = .15$), but relatively high for AU12 ($r = .70$) and AU20 ($r = .69$). This pattern of results suggests that at low intensities of AU12 and AU20 the accuracy of automated measurement is more strongly impacted than at low intensities of AU6. When absolute ICCs were run over the entire dataset, they yielded relatively high concordance between measuring methods, AU6 *ICC* = .82, AU12 *ICC* = .83, AU20 *ICC* = .87 (see table 2 for a summary of these analyses).

To follow up these comparisons, the following analyses were run within each infant, assessing associations and predictive relationships at the level of subject. These subsequent hypotheses were tested for consistency across subjects through t-tests of mean associations. We used an *r* to *z* transformation on these associations to address extreme values of *r*. For ease of interpretation mean associations are reported in their untransformed state. For a summary of the key results please see figure 3.

Hypothesis 2

The intensity of eye constriction rises and falls with the intensity of smiles and with the intensity of lateral lip-stretching. To investigate the second hypothesis, the association between the intensity of eye constriction and the intensity of smiling in the absence of lateral lip stretching were assessed through bivariate correlations. The association between the intensity of eye constriction and the intensity of lateral lip-stretching in the absence of smiling were also assessed through bivariate correlations. These correlations revealed a consistent pattern of association, eye constriction was correlated with both the intensity of smiles (mean r = .55) and with the intensity of lateral lip-stretching (mean r = .48). One-sample t-tests of r-to-z transformed values showed these sets of correlations were significantly greater than 0 for both smiles, $t(11) = 6.42$, $p < .001$, and lateral lip-stretching, $t(11) = 4.24$, $p = .001$.

Hypothesis 3

Smiles and lateral lip-stretching accompany positive and negative emotion ratings, respectively. To address the third hypothesis, both the degree to which smiling is associated with composite positive and negative emotion ratings and the degree to which lateral lip-stretching is associated with composite positive and negative emotion ratings was assessed through the construction of a hierarchical linear model. This approach had the benefit of accounting for variability in the relationship of interest between each subject. The model was specified as follows, with the smile/lateral lip-stretching (AU12 AU20) composite allowed to randomly vary and no predictors of level 2 variance:

Level 1

$$Affect\ Ratings = \pi_{0i} + \pi_{1i}(AU12\ AU20\ Composite) + e_{ti}$$

Level 2

$$\pi_{0i} = \beta_{00} + r_{0i}$$

$$\pi_{1i} = \beta_{10} + r_{1i}$$

Where:

π_{0i} represents the expected non-expert ratings of affect given an smile/lateral lip-stretching composite intensity of 0 for the i-th individual;

π_{1i} represents the expected change in non-expert ratings given a one unit increase in the smile/lateral lip-stretching composite intensity for the i-th individual;

e_{ti} represents the residual non-expert ratings of affect at the t-th frame of the i-th subject;

β_{00} represents the average non-expert ratings of affect given a smile/lateral lip-stretching composite intensity of 0 over the entire sample;

r_{0i} represents the residual of the average non-expert ratings of affect given a smile/lateral lip-stretching composite intensity of 0 for the i-th individual;

β_{10} represents the average change in non-expert ratings given a one unit increase in smile/lateral lip-stretching composite intensity over the entire sample;

r_{1i} represents the residual of the average change in non-expert ratings given a one unit increase in smile/lateral lip-stretching composite intensity for the i-th individual.

Building from an unconditional model, the smile/lateral lip-stretching composite intensity was added as a predictor. The specified predictor significantly improved model fit both over the unconditional model of growth, χ^2 (3, J = 12) = 941,326.14, $p < .001$. The smile/lateral lip-stretching composite intensity was a significant predictor of affect ratings, $t(11) = 6.87$, $p < .001$. See table 3 for a summary of all fixed effects in this and subsequent models.

Hypothesis 4

Eye constriction is uniquely predictive of positive and negative emotion ratings beyond the respective effects of smiles and lateral lip-stretching. To address the fourth hypothesis, the predictive effect of eye constriction on ratings of emotional valence was assessed through the addition of eye constriction as predictor to the previous hierarchical linear model in Hypothesis 3. The intended model was specified as follows, with all predictors were allowed to randomly vary and no predictors of level 2 variance:

Level 1

$$Affect\ Ratings = \pi_{0i} + \pi_{1i}(AU12\ AU20\ Composite)$$

$$+\pi_{2i}(Eye\ Constriction) + e_{ti}$$

Level 2

$$\pi_{0i} = \beta_{00} + r_{0i}$$

$$\pi_{1i} = \beta_{10} + r_{1i}$$

$$\pi_{2i} = \beta_{20} + r_{2i}$$

Where:

π_{0i} represents the expected non-expert ratings of affect given an smile/lateral lip-stretching composite intensity of 0 and valence-adjusted eye constriction intensity of 0 for the i-th individual;

π_{1i} represents the expected change in non-expert ratings given a one unit increase in the smile/lateral lip-stretching composite intensity when valence-adjusted eye constriction intensity is 0 for the i-th individual;

π_{2i} represents the expected change in non-expert ratings given a one unit increase in valence-adjusted eye constriction intensity controlling for smile/lateral lip-stretching composite intensity for the i-th individual;

e_{ti} represents the residual non-expert ratings of affect at the t-th frame of the i-th subject;

β_{00} represents the average non-expert ratings of affect given a smile/lateral lip-stretching composite intensity of 0 and a valence-adjusted eye constriction intensity of 0 over the entire sample;

r_{0i} represents the residual of the average non-expert ratings of affect given a smile/lateral lip-stretching composite intensity of 0 and a valence-adjusted eye constriction intensity of 0 for the i-th individual;

β_{10} represents the average change in non-expert ratings given a one unit increase in smile/lateral lip-stretching composite intensity controlling for valence-adjusted eye constriction intensity over the entire sample;

r_{1i} represents the residual of the average change in non-expert ratings given a one unit increase in smile/lateral lip-stretching composite intensity controlling for valence-adjusted eye constriction intensity for the i-th individual;

B_{20} represents the average change in non-expert ratings given a one unit increase in valence-adjusted eye constriction intensity controlling for the smile/lateral lip-stretching composite intensity over the entire sample;

r_{2i} represents the residual of the average change in non-expert ratings given a one unit increase in valence-adjusted eye constriction intensity controlling for the smile/lateral lip-stretching composite intensity for the i-th individual.

Building from an unconditional model, predictors were added sequentially to determine significant model improvement. The specified predictors significantly improved model fit both over the unconditional model of growth, χ^2 (7, J = 12) = 946,318.66, p < .001, and the previous model in which eye constriction was not specified as a predictor of affect ratings, χ^2 (4, J = 12) = 4, 992.52, p < .001. Within the specified model, eye constriction intensity was a significant positive predictor of affect ratings after controlling for the effect of the smile/lateral lip-stretching composite intensity, t(11) = 4.50, p = .001.

Chapter 7

Discussion

The current study assessed facial behavior continuously across time using an automated measurement approach. Eye constriction was observed to rise and fall with the intensity of both smiling and lateral-lip stretching. Eye constriction also indexed perceived emotional valence in both positive and negative affective contexts. These findings point toward the possibility that other facial actions might exhibit common roles across contexts. Further, the findings support conceptualizing expression as a dynamic interplay between facial actions over time. These findings in relation to each hypothesis are discussed in the following sections.

Hypothesis 1

The first hypothesis indicated that automated coding would exhibit associations with expert manual coding comparable to the associations between manual coders. Results with respect to the first hypothesis were not conclusive. Automated coding had varying levels of reliability when compared to expert manual coding. Reliability of automated ratings was strong when assessed over the entirety of the sample but was lower when assessed subject by subject and represented as a mean. When reliability was assessed on a subject-by-subject basis, ICC values were lowest for smaller mean intensity values of AU12 and AU20, but not for AU6. This pattern suggests that for AU12 and AU20 the automated coding is most reliable during stonger intensities of AU12 and AU20. Given the higher reliability when assessing across the entire sample, the results from subsequent analyses may be less generalizable for infants that show relativity low intensities of smiles and lateral lip-stretching. Improving measurement at these lower intensity levels is a viable area for further refinement of these automated techniques.

One limitation to this automated approach within the current study was the amount of video data that could not be modeled and measured. Although this was a substantial amount of exclusion, to the author's current knowledge this is the largest percentage of valid data gathered about facial action units through automated measurement, let alone intensity in an infant sample. Previous implementations have had success both using automated approaches to detect a variety of action units (Cohn et al., 1999) and in employing an automated approach in naturalistic conditions (Cohn & Sayette, in press). The current study, however, gathered automated measurements of facial actions over longer periods of naturalistic interaction than in previous research.

Hypothesis 2

The second hypothesis indicated that the intensity of eye constriction rises and falls with the intensity of smiles and with the intensity of lateral lip-stretching. Given strong correlations between eye constriction intensity and smile intensity as well as comparable correlations between eye constriction intensity and lateral lip-stretching intensity, the current findings support this relationship. This current findings contrasts with theories conceiving of eye constriction as a qualitative, static differentiator of joy vs. non-joy expressions in adults (Frank, Ekman, & Friesen, 1993; Ekman, Davidson, & Friesen, 1990). The current findings extend initial exploration of intensity scoring (Messinger et al., 2009) by measuring the intensity of eye constriction, smiles, and lateral lip-stretching over time rather than just the presence of these actions. Eye constriction appears instead to continuously increase and decrease in intensity alongside the intensity of smiles.

Hypothesis 3

The third hypothesis asked whether smiles and lateral lip-stretching accompany positive and negative emotion ratings, respectively. Through the use of multi-level modeling we found that, controlling for inter-individual variation, the intensity of a smile/lateral lip-stretching composite indexes non-expert ratings of affect. This serves to confirm our basic assumptions about smiling and lateral lip-stretching as indices of perceptions of emotional valence. Further, this reinforces the utility of non-expert raters to measure affect in infancy, replicating past findings (Baker et al., 2010; Dinehart et al., 2005; Messinger et al., 2008; Messinger at al. 2009).

Hypothesis 4

The fourth hypothesis asked whether eye constriction is uniquely predictive of positive and negative emotion ratings beyond the respective effects of smiles and lateral lip-stretching. The current findings indicate that eye constriction not only varies alongside smiles and lateral lip-stretching but also appears to uniquely predict perceptions of emotional valence. In one form or another, nearly all formulations of joy and happiness include eye constriction as an element of their definition (Oster, 2009; Izard, 1983; Ekman & Friesen, 1978). The current findings support a similar role of eye constriction during periods of negative affect observed in infants (Oster, Hegley, & Nagel, 1993).

The proposition that eye constriction intensity serves as an index of positive and negative affect tends to diverge from theoretical perspectives that draw strongly on discrete theories of emotion (Izard, 1983). Within this framework, facial expressions follow particular prototypic programs, which result in particular facial movements. Although there is some criticism of the accuracy of MAX-specified formulations (Camras, Sullivan, & Michel, 1993; Camras et al., 1997, Matias & Cohn, 1993), there is a degree of implicit indication of variation in expressive intensity in Izard's Maximally Discriminative Facial Movement Coding System (MAX). Within MAX descriptions of emotion formulas, lower intensity expressions are acknowledged in that "formulas showing coded movement in only one region of the face may be considered as identifying an affect of low intensity when the other 2 regions show no codeable movements." Within the context of the current findings this description suggests that smiles with eye constriction (Duchenne smiles) are more intense than smiles without eye constriction, and that cry-faces with eye constriction are more intense than cry-faces without eye constriction have been noted within another theoretical orientation. I seek less to refute these past lines of research with the current study, but rather to extend these theories to a more continuous treatment of expression over time. Further, through making the first attempt to measure the intensity of eye constriction, smiles, and lateral lip-stretching over time, the current findings help to tease apart dynamic interplay of particular facial actions.

This continuous treatment is supported in a growing line of research which emphasizes the dynamic interplay of the fine-grained intensity of facial actions across time (Messinger, et al., 2008; Messinger & Fogel, 2007; Messinger, et al., 2009). The current findings expand upon this line of research by providing larger sequences of video over a greater number of subjects and affective contexts, as well as expanding analytical techniques to better model the interaction of facial actions with one another and perceptions of affective valence.

There is a growing trend within the research toward considering the intensity of eye constriction in studies of facial expression. Within the infant literature there is evidence of smiling being more intense during periods where eye constriction was present than not present (Fogel, Nelson-Goens, Hsu & Shapiro, 2000). Further, non-expert ratings of affect in still images have been strongly correlated with higher intensities of the facial actions (which include eye constriction) involved in smiles and cry-faces (Oster, 2003). The combination of higher intensities of both eye constriction and smiles during brief periods of time has also been used as an indicator of outcomes such as temperament and family affect in school-age children(Oveis, Gruber, Keltner, Stamper, & Boyce, 2009) and lifetime satisfaction through adulthood (Harker & Keltner, 2001). In this light of these contexts, mapping the intensity of eye constriction over time early in development becomes crucial. Current findings in combination with the literature reviewed suggest that eye constriction is serving as an intensifier of affect expression in infants.

Of ultimate interest is understanding eye constriction's function in infant expression. The current findings continue the process of illustrating the role eye constriction plays in multiple contexts. Scaffolded by previous inquiry, we have gained additional descriptive data supporting eye constriction as an intensifier of facial expression across two affective contexts. This lays the groundwork for exploring other contexts, both its role in other infant expressions and across other interactions. It also gives us a basis for expanding exploration of dynamic expressions as they develop through early childhood. The role of particular salient facial actions in infancy is an area ripe for continued exploration, new methods of measuring behavior can help improve future research. Through precise, quantitative measurement of facial actions across time, we gain a unique perspective as to how expression in early infancy evolves into its highly differentiated state in adulthood. Fully realized, an automated methodological approach can help us to gain more complete information on the interaction of facial actions essential to improving our understanding of the intricacies of infant expression. Automated measurement holds promise for providing this window into eye constriction's role in infant positive and negative expression, and has general promise for precise measurement of infant emotional expression. More broadly, replicating the current findings utilizing the same measurement approach in adults, with appropriate expressive analogues, could help inform understanding of eye constriction's overall role in emotion. The current findings provide encouraging steps toward further unraveling the complex relationships between facial actions within the human face.

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Figures

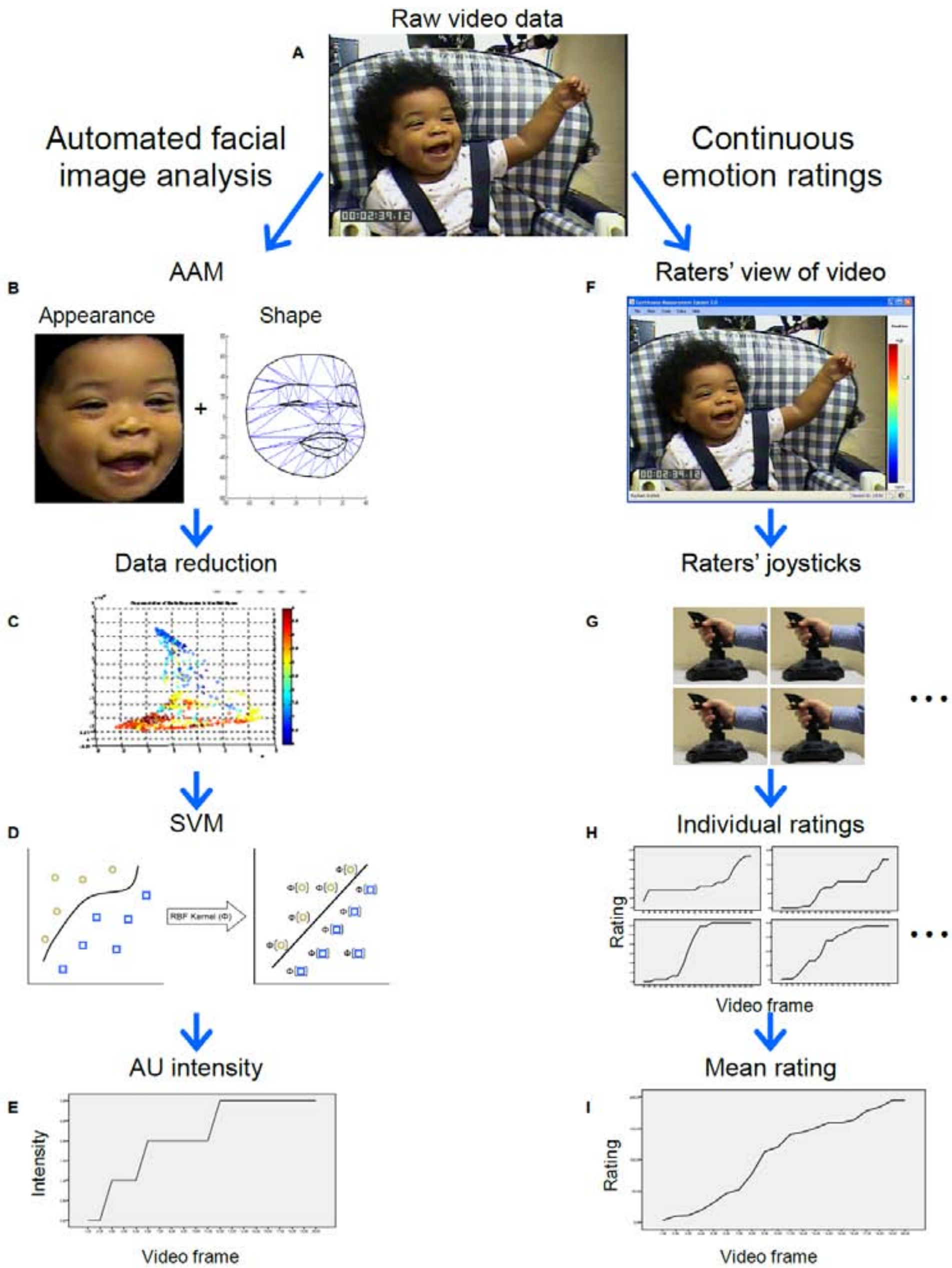

Figure 1. The measurement approach. (A) Raw video. (B) Appearance and shape features of the face. (C) Laplacian Eigenmaps reduce dimensionality. (D) Employing a radial basis function kernel, a SVM classifies the occurrence and intensity of each FACS AU. (E) AU intensity by video frame. (F) Raters' view of video. (G) Joysticks used to rate. (H) Individual ratings. (I) Mean ratings by video frame.

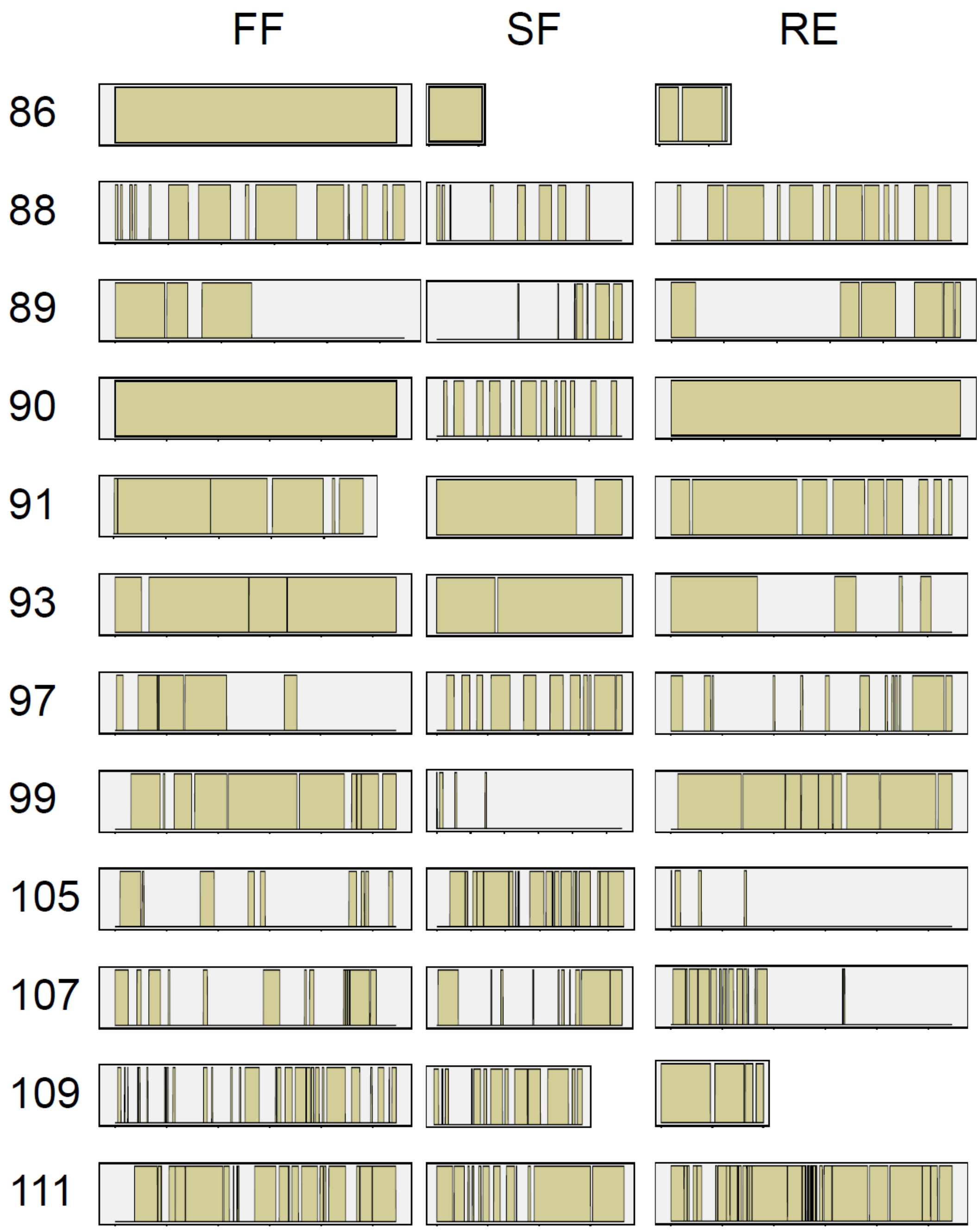

Figure 2. Visual Summary of Valid Data by Subject and Episode of the FFSF. Note: filled sections represent trackable data and unfilled sections represent unmodelable data. Length of each graph is proportional to the amount of available video data.

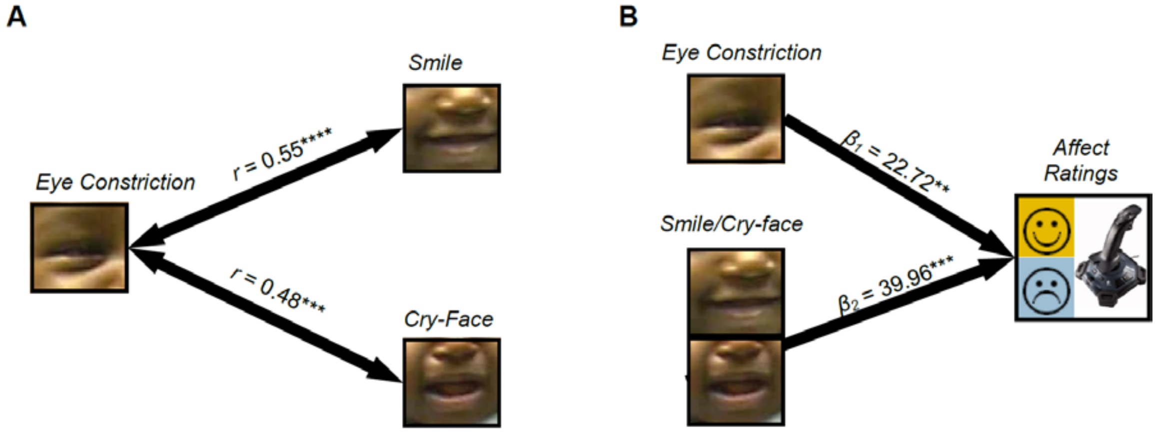

Figure 3. (A) Overall correlation (*r*) between the intensity of smiles and eye constriction; and between the intensity of cry-faces and eye constriction. Correlations were calculated separately for smiles (when cry-faces were absent), and for cry-faces (when smiles were absent). These correlations represent mean values across infants. (B) Estimated fixed effects (β) for the composite of smiles and cry-faces and eye constriction. Significance values reflect *t*-tests of those values: * - $p < .025$, ** - $p <$ 01, *** - $p < .001$, **** - $p < .0001$.

Tables

Table 1. *Crosstabulation of Percentages of Smile (AU 12) and Lateral Lip-stretching (AU20) Intensities*

	AU 12 Intensity					
AU 20 Intensity	0	A	B	C	D	E
0	41.3	0.7	1.8	13.3	10.1	7.4
A	6.0	0.0	0.4	1.4	0.2	0.6
B	3.7	0.0	0.1	0.6	0.1	0.1
C	7.4	0.1	0.2	1.2	0.2	0.1
D	2.1	0.0	0.1	0.1	0.0	0.1
E	41.3	0.7	1.8	13.3	10.1	7.4

Table 2. *Average AU Intensity and Intra Class Correlations (ICCs) by SN, Overall ICCs*

Subject Number	Average AU Intensity			Intra Class Correlation		
	AU6	AU12	AU20	AU6	AU12	AU20
86	2.18	0.59	2.36	0.78	0.88	0.84
88	1.04	1.14	0.04	0.78	0.87	0.23
89	1.46	0.77	0.58	0.72	0.83	0.78
90	2.60	0.04	3.22	0.70	0.02	0.75
91	2.32	0.67	2.04	0.71	0.86	0.79
93	0.31	0.23	0.39	0.68	0.72	0.06
97	1.88	0.47	1.00	0.82	0.79	0.71
99	1.05	0.85	0.02	0.76	0.80	0.26
105	1.66	0.73	1.06	0.79	0.92	0.88
107	1.12	1.13	0.03	0.82	0.85	0.27
109	2.91	0.48	2.47	0.80	0.72	0.65
111	1.83	0.54	1.93	0.81	0.59	0.89
Overall	35.4	15.1	23.2	0.82	0.83	0.87
Mean	37.2	15.4	25.1	0.76	0.74	0.59

Note. Average behavioral Intensity is quantified as the mean intensity of a given AU for each subject’s valid data. Overall ICCs represent the absolute ICC without separating data by subject. Mean ICCs represent the mean of the absolute ICCs when separating by subject.

Table 3. Estimated Fixed Effects of AU6 Intensity, and a Composite of Smile/Lateral Lip-stretching Intensities on Ratings of Affect.

Fixed Effect	*Coefficient*	*(SE)*	*t*	*p*
Model with Smile/Lateral Lip-stretching Composite Alone				
β_0 (Intercept)	5.48	37.98	0.14	.888
β_1 (AU12 AU20 Composite)	58.06	8.46	6.87	< .001
Model with Smile/Lateral Lip-stretching Composite and Eye Constriction				
β_0 (Intercept)	6.84	37.60	0.18	.859
β_1 (AU12 AU20 Composite)	39.96	6.69	5.98	< .001
β_2 (Eye Constriction)	22.72	5.04	4.51	.001