Infant sentiment analysis in behavioral qualification

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RESNA

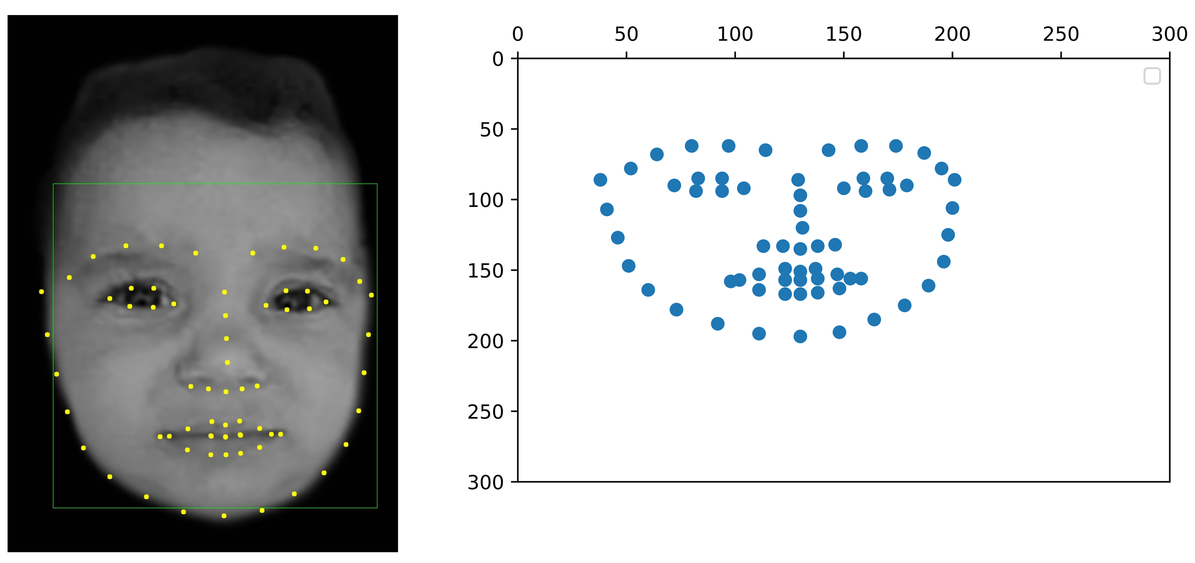
Supervised machine learning algorithms can automate infant emotion classification to aid in the assessment of neurodevelopmental delay.

Introduction

- The World Health Organization estimates that 15 million infants are born preterm every year [1]. The Play and NeuroDevelopment Assessment (PANDA) Gym is a system created to address the need for a natural and effective tool to detect neurodevelopmental delays in young infants.
- Although aspects of human emotion have been investigated, the relationship between infant emotional behavior and movement has yet to have been studied in quantitative detail [2]. Automatic sentiment analysis may show promise as a further parameter for understanding the possible dependencies of infant movement and emotion.
- In this case study we present our process to develop an automatic algorithmic method that utilizes localized and specific facial features for infant sentiment analysis. The method's purpose is to explore the relationships between infant sentiment, movement, and engagement in the context of the infant's developmental ability.

System

Figure 1.1 68 keypoint extraction performed on sample CIF image (B1PosBW)



Discussion and Conclusions

- Infant facial expression is distinguishable and reliable in infant sentiment prediction, specifically for concavity features in the Linear, Polynomial, and Gaussian Kernels (Table 1). The Linear and Polynomial Kernel performed better than the Gaussian and Sigmoid Kernels across all three classes of emotion with F1 scores equal to or greater than 0.50 (Table 2) when applied to the PANDA infant data. The F1 scores of this subset were consistently less than those of the CIF data (column 4), which was most likely due to the more naturalistic angles of the face of the infant in the PANDA video data.
- Additional classes of emotion, as well as a balanced training data set of diverse facial orientation, must be included to address the need to classify finer facial motions to more exact emotional states. Further study to date has explored if emotion and movement are interdependent and indicative of an infant's development, specifically for cerebral palsy.
- Emotional state in infants is a differentiable factor by Support Vector Machine Analysis (SVM), and the algorithms presented have the capability to be utilized as a tool to improve the kinematic analysis of infants in the context of their condition, such as for cerebral palsy. Current work investigates the dual analysis of both processes and their effects in further data by analyzing data from the full infant set (28 infants) with the infant condition and pose data (motion).

Methods

- **Data:** The 154 City Infant Faces Database (CIF) and 1 PANDA Study infant video were used [3].
- **Facial Keypoint Extraction:** A pre-trained facial key point extraction algorithm (Dlib) [3] and a face normalization algorithm were used for raw data extraction. (Figure 1.1) [4]. Grouped features of the upper and lower eyes and mouth were formed by fitting functions to these points and calculating the second derivative (Figure 1.2).
- **Principal Component Analysis (PCA):** Components indicate the most prominent variation. Plotted to view positive, negative, neutral clustering (Figure 2, 3).
- **Support Vector Machine Classification:** Linear, Polynomial, Gaussian, and Sigmoid Kernels tested. K-folds cross validation performed to prevent overfitting (% of the data was allocated for test and the rest to training [5]). Hypothesized that due to complexity of the data, Linear Kernel would be least accurate; Polynomial Kernel would be most accurate. F1 score: indicator of accuracy (Table 1).

Results

Table 2. PANDA: F1 Score Distribution Among All Data and Kernel Types

	Concavity		
	-	0	+
Linear	0.5	0.84	0.73
Polynomial	0.57	0.74	1
Gaussian	0.6	0.87	0.75
Sigmoid	0	0.79	0

From Figure 2, it is evident that images labeled as positive are separable from images labeled as neutral. As shown in Table 1, the CIF data exhibited greatest F1 scores when y key points and concavity were utilized for classification. The Polynomial Kernel performed on y keypoints from CIF data and Linear and Gaussian Kernels performed on concavity from the CIF data yielded an F1 score of 1 for all classes, and therefore were utilized when analyzing the PANDA data.

Figure 2. Neutral and Negative Y points (CIF)

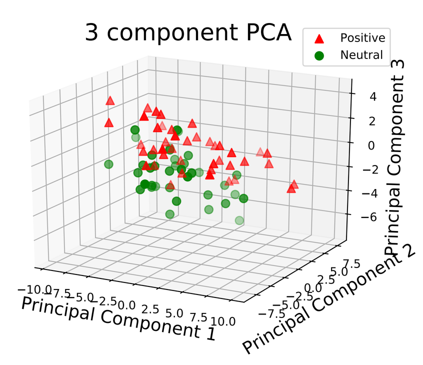


Figure 3. Negative, Neutral, Positive Concavity (PANDA)

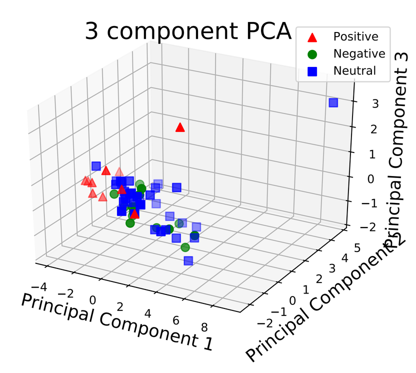


Table 1. CIF: F1 Score Distribution (+: positive, -: negative, 0: neutral)

	x keypoint			y keypoint			x and y			Concavity		
	-	0	+	-	0	+	-	0	+	-	0	+
Linear	0.93	1	0.93	0.83	0.95	0.92	0.22	0.47	0.53	1	1	1
Polynomial	0.94	0.91	1	1	1	1	0	0	0.56	0.96	0.93	1
Gaussian	0	0.44	0.59	0	0.8	0.62	0	0.08	0.48	1	1	1
Sigmoid	0	0.37	0.5	0	0.12	0.3	0.19	0	0.46	0	0	0.31

Acknowledgements

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