PREDICTING PROXIMAL AGGRESSION ONSET IN MINIMALLY-VERBAL YOUTH WITH AUTISM SPECTRUM DISORDER USING PRECEDING PHYSIOLOGICAL SIGNALS

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ABSTRACT

We test the hypothesis that changes in preceding physiological arousal can be used to predict aggression proximally before it occurs in youth with autism spectrum disorder (ASD) who are minimally verbal (MV-ASD). We evaluate this hypothesis through statistical analyses performed on physiological biosensor data wirelessly recorded from 20 MV-ASD youth over 69 independent naturalistic observations in a hospital inpatient unit. Using ridge-regularized logistic regression, results demonstrate that, on average, our models are able to predict the onset of aggression 1 minute before it occurs using 3 minutes of prior data with a 0.71 AUC for global, and a 0.84 mean AUC for person-dependent models.

Index Terms— autism, minimally verbal, aggression, physiological arousal, naturalistic observation

1. INTRODUCTION

A substantial number of youth with autism spectrum disorder (ASD) show unpredictable and potentially dangerous aggressive behavior [1–3]. Aggression is particularly impairing in youth with ASD who are minimally verbal (MV-ASD). Due to their inability to adequately self-report increasing distress, aggression in MV-ASD is often unpredictable, which makes it dangerous, difficult to manage, and constitutes a barrier to accessing the community. In typically developing youth, greater ability to regulate physiological arousal is associated with fewer behavior problems [4], and prior research suggests an association between physiological arousal and problem behavior to alleviate distress in ASD [5–7]. Thus, our current study evaluates whether proximal physiological biomarkers of arousal [8, 9] can predict aggression before it occurs.

A growing number of researchers have approached this goal using various observational designs; however they all rely on artificial experimental settings and tasks [10–13]. In the present study, we utilize a novel data set in which physiological biosignals were collected wirelessly from behaviorally unstable MV-ASD youth during unstructured inpatient hospital observations. We use regularized linear classifiers with time-series features of cardiovascular, electrodermal and motor movement activity as physiological biomarkers of imminent aggression. Using both global as well as person-dependent models, we predict aggressive behavior onset in an upcoming time interval with high accuracy.

2. MATERIALS AND METHODS

2.1. Participants and Data Acquisition

Physiological and physical activity data collected from 20 ADOS-2 confirmed behaviorally unstable MV-ASD youth recorded over 69 unstructured observational sessions in the Developmental Disorders Unit at Spring Harbor Hospital, Portland, ME, United States, were used in this Institutional Review Board approved study. Data were collected during naturalistic observational sessions at this specialized ASD psychiatric inpatient unit using a wrist-worn E4 biosensor (Empatica Inc., United States) as well as time-synchronized observational coding of aggression by inpatient research staff with at least 80% inter-rater reliability. All MV-ASD youth in our sample tolerated the sensor after desensitization, usable data were obtained in all cases, and total resulting observation time of approximately 87 hours was achieved with an average of 4.35 ± 4.8 hours across participants. Aggressive episodes were observed 27.4 ± 33.8 times with average durations of 28 ± 32.2 seconds across participants.

To capture measures of physiological arousal, the following autonomic nervous system indices were recorded by the wrist-worn E4 biosensor: (1) heart rate and heart rate variability, which is a measure of the variation in beat-to-beat interval, both derived from blood volume pulse (BVP) and inter-beat interval (IBI) via photoplethysmography [14] at 64 Hz; and (2) electrodermal activity (EDA) sampled at 4 Hz, which reflects autonomic innervation of sweat glands and provides a sensitive measure of alterations in physiological arousal. To quantify changes in physical activity, the E4 records movement acceleration (ACC) using an embedded 3-axis accelerometer at 32 Hz sampling rate.
2.2. Time-Series Feature Extraction

Statistical analyses on physiological and physical activity signals were performed through extracted time-series features offline. For each one of the 6 signal sources (i.e., BVP, IB1, EDA, ACCX, ACCY, ACCZ) the following features were calculated in bins of 15 seconds: first, last, maximum, minimum, mean and median value, amount of unique values, and the sum, standard deviation and variance of values falling in a bin. To exploit temporal information of aggression episodes, we extracted two more features using time-synchronized binary aggression labels offline; time since past aggression (TPA), which indicates the amount of time elapsed since the last observation of an aggression episode; and a binary aggression observation flag (AOF) feature, indicating whether an aggression episode has so far occurred within that recording session. The standard deviation of each calculated feature across time-series bins was included in all models.

2.3. Logistic Regression Classifier Model

The predictability of aggressive behavior onset using extracted features was investigated through a ridge-regularized logistic regression for binary decision making in time. In particular, at every time point \( t \), using features extracted in a previous time range \([t - \tau_p, t]\), a classifier was used to predict a binary dependent variable \( l \), estimating whether aggression will be observed or not in an upcoming time range \([t, t + \tau_f]\).

We adopted a 5-fold cross-validation protocol to generate training and testing data splits, and repeated five times to produce confidence intervals. At each fold, the classifier was constructed with the training split through maximum likelihood estimation for optimal ridge-regularized regression weights \( \hat{\beta} = [\beta_0, \beta_1, \ldots, \beta_d]^T \), where \( d \) is the number of features. To predict, the classifier generates probabilities for two classes \( l = +1 \) (i.e., aggression) and \( l = -1 \) (i.e., non-aggression) in the form:

\[
P(l = +1|x; \hat{\beta}) = \frac{1}{1 + e^{-\hat{\beta}^T x}},
\]

where \( x = [1, x_1, \ldots, x_d]^T \) corresponds to the concatenated feature vector from \([t - \tau_p, t]\). Receiver Operator Characteristic (ROC) curves and corresponding Area Under the Curve (AUC) values were calculated depending on the decision thresholds over these probabilities.

Among all extracted features described in Section 2.2, five different feature subsets were used as predictor variables (\( x \)) in our further analyses: (1) only temporal information (TPA, AOF); (2) only physical activity (ACC); (3) only physiological activity (BVP, IB1, EDA); (4) physical and physiological activity features combined (BVP, IB1, EDA, ACC); and (5) all extracted features combined (BVP, IB1, EDA, ACC, TPA, AOF).

3. RESULTS

Classification analyses for particular values of \( \tau_p \) and \( \tau_f \) were performed through both global prediction and person-dependent models. In the former, time-series data across all sessions and all participants were concatenated, whereas in the latter data were pooled across sessions within each person. Data was processed for decision making every 15 seconds, which resulted in 20, 863 samples in global models.

3.1. Global Prediction Models

Global prediction models of aggression in the upcoming one minute using all extracted features from the past \( \tau_p = 180 \) seconds, which was the highest value the shortest individual session data permitted, resulted in the blue solid ROC curve presented in Figure 1 with a corresponding AUC value of 0.71. Figure 2(a) depicts increases in AUC when E4 biosensor data is included, compared to using temporal information on aggression episodes alone. Similar analyses for \( \tau_p = 60 \) seconds are presented in Figure 2(b).

Regarding the relationship between past time range (\( \tau_p \)) and future time range used to make aggression onset predictions (\( \tau_f \)), Figure 2(c) depicts stationary performance in global prediction models using all features from various past \( \tau_p \) durations. However, when using only physiological biosensor data from the past (c.f. red curve), we observe relative AUC increases compared to temporal data of

**Fig. 1.** ROC curves with 90% confidence intervals to predict onset of aggression in the upcoming minute, using all features from the past three minutes. Blue solid line represents the global prediction model, and each curve with dashed lines represents one of the person-dependent models.
In the present study we demonstrate that naturalistically observed aggressive behavior in MV-ASD youth in a hospital in-patient setting can be predicted with relatively high accuracy using proximal physiological and physical activity biosensor data and temporal information on recently observed aggressive episodes. We implemented a linear classifier model with regularization over relevant time-series features during training. Our results demonstrate proof-of-concept, feasibility, and incipient validity predicting proximal aggression in this population and setting using both global and person-dependent models.

4. DISCUSSION

Regarding future work currently underway, we will test whether hybrid models improve prediction performance, wherein person-dependent models are iteratively modified to include the most significant physiological biomarker features from global models. We are also exploring ways to...
create more robust global prediction models, wherein we will test whether aggression onsets can be modeled as a nonhomogeneous Poisson process. In that regard, we will evaluate whether regressing hazard rates from past observations can be performed through maximum likelihood estimation, comprising an iterative solution of several weighted linear regressions [15], lead to improved predictive performance across upcoming time ranges.

Finally, we should note that our proposed detection task is less tolerant to false negatives (i.e., missing detection of an aggression episode) than false positives (i.e., predicting an aggression onset is coming and it does not). However, as communicated to us by inpatient clinical staff, the potential benefit of avoiding or reducing a dangerous aggressive event is likely to outweigh the potential harm associated with a false positive in clinical practice. Hence, a high true positive rate is more desirable. Nevertheless, predicting aggression onset during naturalistic observation in the upcoming 1 minute with at least 80% sensitivity is of high clinical value and could create new opportunities for preventing or mitigating aggression emergence, occurrence, and impact in MV-ASD.

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6. REFERENCES


