Vision-Based Classification of Developmental Disorders Using Eye-Movements

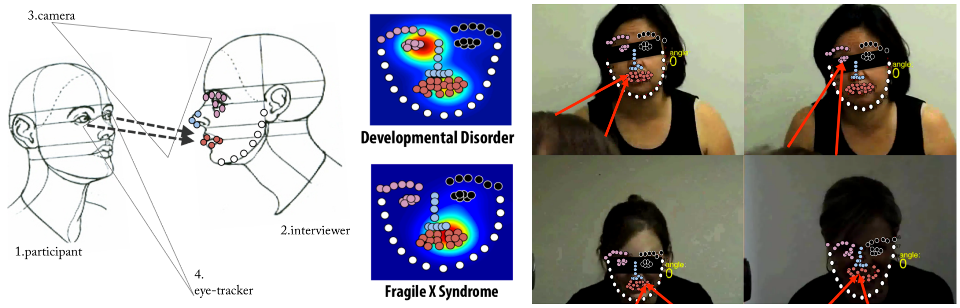
Submission: 1

Abstract. This paper proposes a system for fine-grained classification of developmental disorders via measurements of individuals' eye-movements using multi-modal visual data. While the system is engineered to solve a psychiatric problem, we believe the underlying principles and general methodology will be of interest not only to psychiatrists but to researchers and engineers in medical machine vision. The idea is to build features from different visual sources that capture information not contained in either modality. Using an eye-tracker and a camera in a setup involving two individuals speaking, we build temporal attention features that describe the semantic location that one person is focused on relative to the other person's face. In our clinical setup, the temporal attention features refer to a patient's gaze on finely discretized regions of an interviewing clinician's face, and are used to classify their particular developmental disorder.

1 Introduction

Autism Spectrum Disorder (ASD), is an important developmental disorder to account for and understand in our society today. Significant efforts are spent in early diagnosis, which is critical for proper treatment. Today, identification of ASD requires a set of cognitive tests and hours of clinical evaluations this involve extensively testing the participant and observing their behavioral patterns (i.e. their social engagement with others). In this work, we focus on Fragile-X-Syndrome (FXS). FXS is the most common known genetic cause of autism [7], affecting approximately 100,000 people in the United States. With the advent of computers and machine learning techniques, people are beginning to look for computer-assisted technology to identify ASD. Previous studies [13] suggest that gaze fluctuations play an important role in the characterization of individuals in the autism spectrum. In this work, we are going to study the underlying patters of visual fixations during dyadic interactions. In particular we will use those patterns to characterize different developmental disorders. We address to two problems. The first challenge is to build new features to characterize fine behaviors of participants with developmental disorders. We do this by exploiting computer vision and multi-modal data to capture detailed visual fixations during dyadic interactions. The second challenge is to build a system capable of discerning between developmental disorders. For this, we build machine learning methods that combined with our features can discern fairly accurate between disorders.

The rest of this work is structured as follows. In section 2, we discuss prior work. In section 3, we describe the raw data: its collection and the sensors used. In section 4, we describe the built features and analyze them. In section 4, describe our classification techniques. In section 5, we describe the experiments and results. In section 8 we discuss the results and future work.



(a) (b)

Fig. 1. (a) We study social interactions between a participant with a mental impairment and an interviewer, using multi-modal data from a remote eye-tracker and camera. The goal of the system is to achieve fine-grained classification of developmental disorders using this data. (b) A frame from videos showing the participant's view (participant's head is visible in the bottom of the frame). Eye-movements were tracked with a remote eye-tracker and mapped into the coordinate space of this video.

2 Previous Work

Pioneering work by Rehg et al. [17] shows the potential of using eye-tracking information to measure relevant behavior in children with ASD. However, it did not address the issue of fine-grained classification between ASD/FXS and other disorders in an automated way. Our work extends this to develop a means for FXS classification via multi-modal data.Individuals with FXS exhibit a set of developmental and cognitive deficits including impairments in executive functioning, visual memory and perception, social avoidance, communication impairments and repetitive behaviors [21]. In particular $[conflict]$ shows that eye-gaze avoidance during social interactions with others is a salient behavioral feature of individuals with FXS. Maintaining appropriate social gaze is critical for language development, emotion recognition, social engagement, and general learning through shared attention [4]. Previous efforts in the classification of developmental disorders such as epilepsy and schizophrenia have relied on using electroencephalogram (EEG) [14]. These methods are accurate, but they suffer from long recording times and the use of EEG probes positioned all over a participants scalp and face. Meanwhile, eye-tracking has long been used to study autism [1,10], but an automated system for inter disorder assessment as ours has yet to be proposed.

3 Dataset

Our raw data are 70 videos of an experimenter interviewing a participant, overlaid with the participant's point of gaze (as measure by a remote eye-tracker).

Participants. The participants were diagnosed with either an idiopathic developmental disorder or Fragile-X-Syndrome (FXS). There are known gender-related behavioral differences between FXS participants, so we further subdivided this group by gender into males (FXS-M) and females (FXS-F). There were no gender-related behavioral differences in the DD group, and genetic testing confirmed that DD participants did not have FXS. The participants were between 12 and 28 years old, with 51 FXS participants (32 male, 19 female) and 19 DD participants. The two groups were well-matched on chronological and developmental age, and had similar mean scores on the Vineland Adaptive Behavior Scales (VABS), a well-established measure of developmental functioning. The average score was 58.5 (SD = 23.47) for individuals with FXS and 57.7 (std = 16.78) for controls, indicating that the level of cognitive functioning in both groups was 2 – 3 SDs below the typical mean.

Data Collection. Participants were each interviewed by a clinically-trained experimenter. In our setup the camera was placed behind the patient and facing the interviewer. Figure 1 depicts the configuration of the interview, and of the physical environment. Eye-movements were recorded using a Tobii X120 remote corneal reflection eye-tracker, with time-synchronized input from the scene camera. The eye-tracker was spatially calibrated to the remote camera via the patient looking at a known set of locations prior to the interview.

4 Features of Visual Fixation

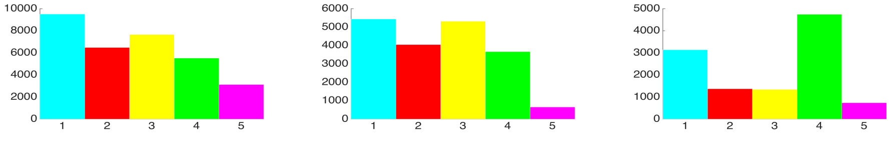
A goal of our work is to design a feature that simultaneously provide insight into these disorders and allow for accurate classification between them. These features are the building blocks of our system, and the key challenge is engineering them to properly distill the most meaningful parts out of the raw eye-tracker and video footage.
At each time step, we capture the participant's point of gaze fixating into precise areas of the interviewer's face, 5 times per second during the whole interview. There are 6 relevant areas: *nose, left eye, right eye, mouth, jaw, not looking at the face*. The precise detection of this fine grained feature enable us to study, at scale, the micro changes in the participant's gaze scanning. This behavior play substantially different social roles for individuals on the autism spectrum [13].

Implementation. For each video frame, we detect a set of 69 landmarks on the interviewer's face using a part based model [24]. Figure 1 shows real examples of landmark detections. In total, we processed 14,414,790 landmarks over 96 hours. We computed 59K, 56K and 156K frames for DD, FXS-Female, and FXS-Male groups respectively. We evaluated a sample of 1K randomly selected frames, out of which only a single frame was incorrectly annotated. We mapped the eye-tracking coordinates to the facial landmark coordinates with a linear transformation. Our features take the label of the cluster (e.g. jaw) holding the closest landmark to the participant point of gaze.

4.1 Descriptive Analyses

We next present a number of descriptive analyses of the dataset that explore the complexity of this rich data.

Feature Granularity. Participants—especially those with FXS—spent the majority of the interview looking away from the interviewer, and only a fraction of the time at the interviewer's face (Figure 2). Yet clinicians often express the opinion that the *distribution* of fixations, not just the sheer lack of face fixations—seem related to the

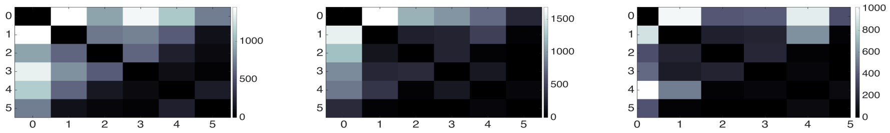


(a) DD (b) FXS-F (c) FXS-M

Fig. 2. Histograms of visual fixation for the various disorders. X-axis represents fixations, from left to right: nose (1), eye-left (2), eye-right (3), mouth (4), and jaw (5). (a)-(c) feature histograms for all participants of each class, with non-face removed.

general autism phenotype [13,11]. This opinion is supported by the distributions in Figure 2(d)-(f): DD and FXS-F are quite similar, whereas FXS-M is distinct. FXS-M focuses primarily on mouth (4) and nose (1) areas.

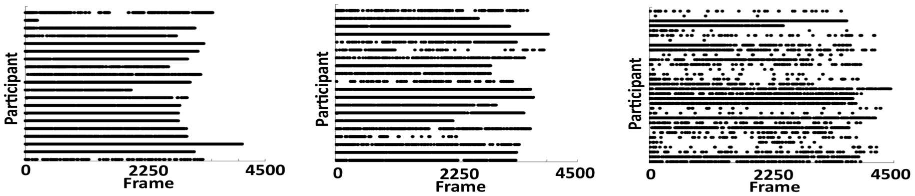
Attentional transitions. In addition to the distribution of fixations, clinicians also believe that the *sequence* of fixations describe underlying behavior. In particular, FXS participants often glance to the face quickly and then look away, or scan between non-eye regions. Figure 3 shows region-to-region transitions in a heatmap. There is a marked difference between the different disorders: Individuals with DD make more transitions, while those with FXS exhibit significantly less—congruent with the clinical intuition. The transitions between facial regions better identify the three groups than the transitions from non-face to face regions. FXS-M participants tend to swap their gaze quite frequently between mouth and nose, while the other two do not. DD participants exhibit much more movement between facial regions, without any clear preference. FXS-F patterns resemble DD, though the pattern is less pronounced.



(a) DD (b) FXS-F (c) FXS-M

Fig. 3. Matrix of attentional transitions for each disorder. Each square $[ij]$ represents the aggregated number of times participants of each group transitioned attention from state i to state j. The axes represent the different states: non-face (0), nose (1), eye-left (2), eye-right (3), mouth (4), and jaw (5).

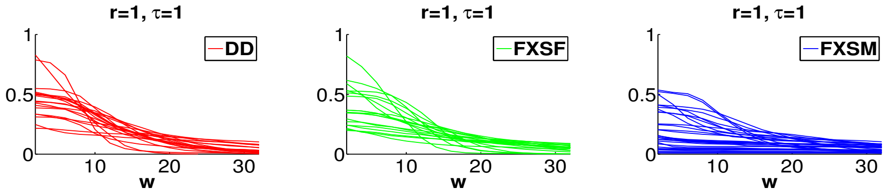
There is significant variance among individuals in the same group, making it challenging to classify between them. For example, Figure 4 shows time-series data of when individuals are glancing at the face of their interviewer or away from it. Note the varying sparsity of FXS males—some individuals glance at the face very frequently, whereas others may spend several minutes without looking at it. FXS females can easily be confused with the other two groups. DD participants, on the other hand, tend to have a much higher frequency of glancing at the face, though a few participants also spend noticeable amounts of time looking away from it.



(a) DD (b) FXS-F (c) FXS-M

Fig. 4. Temporal analysis of attention to face. X axis represents time in frames (in increments of 0.2 seconds). Y axis represents each participant. Black dot represent time points when the participant was looking at the interviewer's face. White space signifies that they were not.

Approximate Entropy. We next estimate Approximate Entropy (*ApEn*) analysis to provide a measure of how predictable a sequence is [18,3] . A lower entropy value indicates a higher degree of regularity in the signal. For each group (DD, FXS-Female, FXS-Male), we selected 10 random participants sequences. We compute *ApEn* by varying *w* (sliding window length). Figure 5 depicts this analysis. We can see that there is great variance amongst individuals of each population, many sharing similar entropy with participants of other groups.



(a) DD (b) FXS-F (c) FXS-M

Fig. 5. (a) - (c) Analysis of the *ApEn* of the data per individual varying the window length parameter *w*. Y-axis is *ApEn* and X-axis varies *w*. Each line represents one participant's data. We observe great variance among individuals.

5 Classifiers

The goal of this work is to create an end-to-end system for classification of developmental disorders from raw visual information. So far we have introduced features that capture social attentional information and analyzed their temporal structure. We next need to construct methods capable of utilizing these features to predict the specific disorder of the patient.

Model (RNN). The Recurrent Neural Network (RNN) is a generalization of feed-forward neural networks to sequences. Our model is an adaptation of the attention-enhanced RNN architecture proposed by Hinton et al. [23] (LSTM+A). The model has produced impressive results in other domains such as language modeling and speech processing. Our feature sequences fit this data profile. In addition, an encoder-decoder RNN architecture allows us to experiment with sequences of varying lengths in a cost-effective manner. Our actual models differ from LSTM+A in two ways. First, we have replaced the LSTM cells with GRU cells [2], which are are memory-efficient and could provide a better fit to our data [12]. Second, our decoder produces a single output value (i.e. class). The decoder is a single-unit multi-layered RNN (without unfolding) and with a soft-max output layer. Conceptually it could be seen as a many-to-one RNN, but we present it as a configuration of [23] given its proximity and our adoption of the attention mechanism.

For our experiments, we used 3 RNN configurations: 1_RNN: 3 layers of 128 hidden units; 2_RNN: 3 layers of 256 hidden units; 3_RNN: 2 layers of 512 hidden units.
We trained our models for a total of 1000 epochs. We used batches of sequences, the batches size varied per configuration. 1_RNN: 250, 1_RNN: 250, 1_RNN: 128. We use SGD with momentum and max gradient normalization (0.5).

Other Classifiers We also trained shallow baseline classifiers. **CNN,** we engineer a convolutional neural network approach that can exploit the local-temporal relationship of our data. It is composed of one hidden layer of 6 convolutional units followed by point-wise sigmoidal nonlinearities. The feature vectors computed across the units are concatenated and fed to an output layer composed of an affinity transformation followed by another sigmoid function. We also trained support vector machines (**SVMs**), Naive Bayes (**NB**) classifiers, and Hidden Markov Models (**HMMs**).

6 Experiments and Results

By varying the classification methods described in Section 5 we perform a quantitative evaluation of the overall system. We assume the gender of the patient is known, and select the clinically-relevant pair-wise classification experiments DD vs FXS-F and DD vs FXS-M. For the experiments we use 32 FXS-male, 19 FXS-female and 19 DD participants. To maintain equal data distribution in training and testing we build S_{train} and and S_{test} randomly shuffling participants of each class ensuring a 50%/50% distribution of the two participant classes over the sets. At each new training/testing fold the process is repeated so that the average classification results will represent the entire set of participants. We classify the developmental disorder of the participants, given their individual time-series feature data p, to evaluate the precision of our system. For N total participants, we create an 80%/20% training/testing dataset such that no participant's data is shared between the two datasets. For each experiment, we performed 10-fold cross validation where each fold was defined by a new random 80/20 split of the participants –about 80 participant's were tested per experiment.

Metric. We consider the pairwise classification of an unknown participant as having DD or FXS. We adopt a voting strategy where, given a patient's data $p = [f_1, f_2, ...f_T]$, we classify all sub-sequences s of p of fixed length w using a sliding-window approach. In our experiments, w correspond to 3, 10, and 50 seconds of video footage. To predict the participant's disorder, we employ a max-voting scheme over each class. The predicted class C of the participant is given by:

$$C = \operatorname*{argmax}_{c\in\{C_1,C_2\}} \sum_{\text{sub-seq. } s} \mathbf{1}(\text{Class}(s) = c) \tag{1}$$

Where $C_1, C_2 \in \{\text{DD}, \text{FXS-F}, \text{FXS-M}\}$, $\text{Class}(s)$ is the output of a classifier given input s. We use 10 cross validation folds to compute the average classification precision.

Results. The results are reported in Table 1. We find that the highest average precision is attained using the CNN model with a 10 second time window. It classifies DD versus FXS-F with 0.68 precision and DD versus FXS-M with 0.90 precision, a remarkably high pair of accuracies given the challenges of working with such a noisy dataset.

	window length	DD vs FXS-female (precision)	DD vs FXS-male (precision)
SVM	3	0.65	0.83
	10	0.65	0.80
	50	0.55	0.85
N.B	3	0.60	0.85
	10	0.60	0.87
	50	0.60	0.75
HMM	3	0.67	0.81
	10	0.66	0.82
	50	0.68	0.74
CNN	3	0.68	0.82
	10	0.68	0.90
	50	0.55	0.77
1_RNN	3	0.69	0.79
2_RNN	10	0.79	PROCESSING
3_RNN	50	**0.86**	0.91

Table 1. Comparison of precision of our system against other classifiers. Columns denote pairwise classification precision of participants for DD vs FXS-female and DD vs FXS-male binary classification. Classifiers are run on 3,10, and 50 seconds time windows. We compare the system classifier, RNN to CNN SVM, NB, and HMM algorithms.

We hereby demonstrate the use of computer vision and machine learning techniques in a cost-effective system for assistive diagnosis of developmental disorders that exhibit visual phenotypic expression in social interactions. Data of experimenters interviewing participants with developmental disorders was collected using video and a remote eye-tracker. We built visual features corresponding to fine grained attentional fixations, and developed classification models using these features to discern between FXS and idiopathic developmental disorder, achieving accuracies of up to 91%. Despite finding a high degree of variance and noise in the signals used, our high accuracies imply the existence of temporal structures in the data. The notorious results produced by the RNN could be related to the capacity of the model, and capability of representing complex temporal structures.

7 Conclusion

This work serves as a proof of concept of the power of modern computer vision systems in assistive development disorder diagnosis. We are able to provide, within minutes, a high-probability prediction of the individual being afflicted with one disorder or another. This system, along with similar ones, could be leveraged for remarkably faster screening of individuals. Future work will consider extending this capability to a greater range of disorders and improving the classification accuracy.

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