Facial Action Units and Head Dynamics in Longitudinal Interviews Reveal OCD and Depression severity and DBS Energy

Ali Darzi[1], Nicole R. Provenza[2], László A. Jeni[3], David A. Borton[2], Sameer A. Sheth[4],
Wayne K. Goodman[5], and Jeffrey F. Cohn[1]

[1] Department of Psychology, University of Pittsburgh, Pittsburgh, PA, USA

[2] Brown University School of Engineering, Providence, RI, United States

[3] Robotics Institute, Carnegie Mellon University, Pittsburgh, PA, USA

[4] Department of Neurosurgery, Baylor College of Medicine, Houston, TX, United States

[5] Menninger Department of Psychiatry and Behavioral Sciences, Baylor College of Medicine,
Houston, TX, United States

Abstract— Neuromodulation therapy, specifically Deep Brain Stimulation (DBS) of the ventral capsule/ventral striatum (VC/VS), is promising treatment for severe and intractable obsessive-compulsive disorder (OCD). To assess treatment response to DBS, reliable biomarkers are needed. We explored the hypothesis that facial action units and head dynamics in an interview context reveal severity of OCD, related depression, and DBS energy in participants undergoing DBS treatment. Participants were 5 patients (3 females, 2 males) with implanted DBS to VC/VS. They were recorded during brief open-ended interviews by a clinician at pre- and post-surgery baselines and then at 3-month intervals following activation of the DBS electrodes. Facial action units and head dynamics were assessed using AFAR (Automatic Facial Affect Recognition). OCD severity was assessed using clinical interview (YBOCS-II) and depression symptoms were assessed using participant self-report (BDI). After testing for multicollinearity and dropping highly-correlated features, a linear mixed-effects model using chi-square feature selection predicted 61% of the variation in YBOCS-II; 59% of the variation in BDI; and 37% of the variation in delivered energy by DBS to VC/VS. These findings suggest that automatically detected facial action units and head dynamics are potential biomarkers of OCD, depression severity, and DBS energy.

I. INTRODUCTION

Obsessive-compulsive disorder (OCD) is characterized by obsessions and related compulsions. Obsessions are repetitive, intrusive, and distressing thoughts. Compulsions are recurrent, ritualistic behaviors that an individual feels driven to perform. Obsessive thoughts typically are briefly relieved by compulsive behavior (e.g., repetitive hand washing or checking window and door locks) and then resume. Obsessive-compulsive behavior can occur multiple hours per day and significantly impact adaptive functioning. While cognitive-behavioral therapy (CBT) and medication often are successful in providing relief, they are unsuccessful in about 25% of cases [30], [27]. Severe OCD that is unresponsive to treatment is referred to alternatively as treatment-resistant, refractory, or intractable. In patients with intractable OCD, deep brain stimulation (DBS) of the ventral striatum (VS) is effective in 52% of patients. An additional 17% respond partially [17].
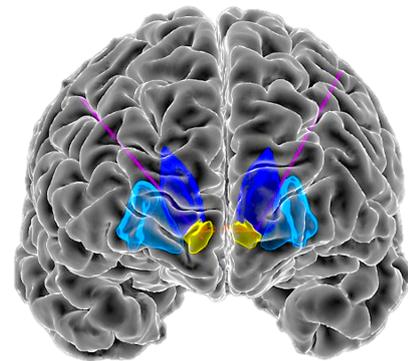
Fig. 1. Frontal view of an OCD patient's brain. The ventral striatum (target area) is in yellow. The straight lines (purple) are wire leads, each bearing a single electrode topped with an electrical contact. These leads connect to a pacemaker-like device implanted in the chest (not shown) that delivers electrical impulses that ease the patient's distressing thoughts and unwanted behaviors. For 3D view and fuller description, see https://directorsblog.nih.gov/2021/08/05/the-amazing-brain-deep-brain-stimulation-for-ocd/

In DBS, electrodes are implanted deep in the brain, in an area known as the ventral capsule/ventral striatum (VC/VS). Leads from the electrodes are connected to a pacemaker-like device (known as an internal pulse generator, or IPG) that is powered by a battery implanted in the chest. Figure 1 shows an image of the brain of a study participant with the VC/VS highlighted.

Because the VC/VS is a part of the reward circuit, stimulation affects appetitive behavior and emotion processes [28]. Over-stimulation of VC/VS may eventuate in hypomania or mania, which can have deleterious consequences and result in hospitalization, selecting the most suitable stimulation level is critical to optimizing treatment. Currently, DBS programming (i.e., adjustments) for OCD is made largely on the basis of subjective report during office visits with a psychiatrist or neurologist (open-loop paradigm) [32]. While useful, subjective judgments are idiosyncratic and difficult to standardize. Additional factors such as failed targeting and patient heterogeneity add to the complexity of the problem and reduce the efficacy of treatment [29], [32].

A potential solution would be to implement a DBS paradigm in which stimulation level adaptively changes in response to concurrent severity of OCD in a closed-loop paradigm. To achieve closed-loop modulation of DBS in response to continuous changes in OCD threat, objective, quantifiable, repeatable, and efficient biomarkers of OCD symptom severity are essential. A closed-loop system using objective biomarkers could maximize treatment efficacy while minimizing potential side effects.

Facial action units (AUs) and head movements [9] have been found to be markers of psychological states [4], [3], [7], [18]. For this reason, they are promising behavioral biomarkers of OCD symptom severity. Examples of AUs include AU 6 (orbicularis oculi, which raises the cheeks in smiles and in pain), AU 12 (zygomatic major, which pulls the lip corners obliquely in smiling), AU 14 (buccinator, which tightens the lip corners in contempt and in smile controls), AU 17 (mentalis, which raises the chin boss in negative emotion and smile controls), and AU 45 (levator palpebrae, blinking). Head dynamics (referred to in FACS as action descriptors) include head pitch and yaw. Automatic detection of AUs and head movements [10], [26], [2] have distinguished between positive and negative emotion [18] occurrence and severity of depression [7], and autism spectrum disorder [23]. They could provide reliable and efficient biomarkers essential for a closed loop DBS in social contexts, such as unstructured interviews.

Automatic detection of facial AUs and head dynamics has been used to detect disorders that include bipolar [33], dysmorphic [13], depression [7] and anxiety [15]. In the DBS context, the ultimate goal is to predict symptom severity. Facial actions and head dynamics have shown promise in detecting depression [25], [19], but have yet to be investigated for OCD occurrence and severity. Two preliminary studies suggest that DBS of VC/VS in OCD patients is related to facial AUs [5] and may differentiate between different stimulation levels [8].

To our knowledge, the present paper presents the first use of facial AUs and head dynamics in unstructured interviews in relation to OCD severity, depression severity, and level of DBS stimulation. AUs and head dynamics were measured automatically [12]. OCD severity was measured via structured interviews; depression severity was assessed by participant self-report; and AUs and head dynamics were measured automatically [12]. DBS stimulation as measured from contact sensors or Bluetooth and quantified as delivered energy, as defined below. We investigated synchronized variation between visual expressions, OCD and depression symptom severity, and DBS stimulation.

The clinical trial of 18 months duration was structured as a single-subjects with replications study with each participant serving as their own control. Given the substantial costs and subject-intensive effort of DBS studies, a between-subjects design with many participants was not feasible. Participants are a highly select group, the intervention entails implanting a device deep in the brain with a connected battery pack in the chest cavity. A multidisciplinary team of psychiatrists, neurosurgeons, clinical psychologists, neuro-scientists from multiple universities and from Medtronics, bio-engineers, and nursing and research staff are actively involved in all phases of the study. Given the nature of the research, program officials from NIH and FDA are closely involved as well.

The research questions were:

RQ1- Are facial AUs and head dynamics good predictors of OCD symptom severity?

RQ2- Are facial AUs and head dynamics good predictors of depression symptom severity, which often co-occur with OCD?

RQ3- Are facial AUs and head dynamics related to total electrical energy delivered by the DBS device?

II. METHODOLOGY

A. Study Setup and Protocol

This study is from an ongoing clinical trial in which DBS of VC/VS is used as a remedy for treatment-refractory OCD. To date, 5 patients (3 females, 2 males) have enrolled. Four of them have completed at least 15 months of the study (Table I) and are the focus of this report. Two models of DBS, both from Medtronic (Minneapolis, MN, United States), are used in the clinical trial: Percept PC+S for the first two patients and Activa PC+S for the later three. A brief description of the study protocol is as follows.

Inclusion criteria for the clinical trial were: 1) Have failed to respond to multiple evidence-based treatments (cognitive behavioral therapy and medication); 2) Severe OCD as measured by a severity score greater than 27 on the Yale-Brown Obsession Compulsion Scale-I (YBOCS-I)) (scale of 0-40).

Participants went through a pre-operation evaluation of about a month duration. They then had bilateral DBS electrodes implanted in their VC/VS. Following recovery from neurosurgery, the DBS was turned on. Afterward, the patient would either have in-person or virtual visits monthly. Each visit started with an unstructured interview in which a clinician asked a set of open-ended questions. The interviews were 3 to 8 minutes in duration and were followed by assessment of symptom severity using the YBOCS-II [31].

A GoPro camera and high-resolution microphone were positioned about 10 to 15 degrees to a frontal view and recorded the participant's face and torso. A second GoPro and separate camera recorded the interviewer. Later in the day or day following, the DBS stimulation parameters were titrated as needed in a DBS programming session. Six months into the study, the patient received CBT (cognitive behavior therapy) for two months. Among all available interview sessions (typically 18-22), 7-8 interview sessions at regular intervals were selected and analyzed: baseline 1 (before implantation), baseline 2 (after surgery but before the DBS was activated), and then every 3 months. The availability of the selected interview sessions for each patient is shown in Table I. To analyze the within-session differences, each session was divided into two halves and analyzed separately. Therefore, the dataset was consisted of 66 samples rather than 33 (total number of sessions).

In the DBS context, the delivered electrical energy is controlled via parameters that include voltage or current amplitude, pulse width, and frequency. Measurement of these parameters was influenced by variability in battery performance, failure to output an ideal-shape pulse, and changes in resistance of the brain region . Thus, the actual delivered energy might slightly differ from the one calculated. The total electrical energy delivered (TEED) per second (i.e., power) was calculated as shown in [24]:

$$TEED(W * 1s) = I(A)^2.PW(sec).f(Hz).R(\Omega), \quad (1)$$

where the units for power, current, pulse width, frequency, and resistance are Watt, Ampere, second, Hertz, and Ohm, respectively. Throughout the clinical trial, the frequency of the stimulation pulses was kept constant and equal to 150.6 Hz. Due to the nature of this study which is predicting the variation in TEED, the constant term was dropped.

B. Calculated Visual Expressions

Faces in the video were tracked and normalized using a real-time face alignment software that accomplishes dense 3D registration from 2D videos and images without requiring person-specific training [21].

Automatics Facial Affect Recognition (AFAR) centers, scales, and normalized faces to an interocular distance of 80 pixels and standardized face size. The version of AFAR, used in this study, was trained on the EB+ dataset (an expanded version of BP4D+ [34]), in which participants interact with an experimenter in a variety of emotion related tasks. Reliability of AFAR in EB+ was tested using k-fold cross validation. Average free-margin kappa was 0.75 and AUC 0.73 [11]. Cross-domain generalization was assessed by testing AFAR in Sayette GFT. Average free-margin kappa was 0.49 and AUC 0.66, which represent moderate cross-domain generalizability. Because test results in GFT were likely attenuated by the larger head motion and lower video resolution in GFT, these comparisons provide a conservative

TABLE I

THE ANALYZED INTERVIEW SESSIONS. BASELINE 1: BEFORE IMPLANTATION. BASELINE 2: AFTER IMPLANTATION BUT BEFORE DBS ACTIVATION. P1-P5: PATIENTS 1 TO 5.

Session	P1	P2	P3	P4	P5
Baseline 1	✓	✓	✓	✓	✓
Baseline 2	✓	✓	✓	✓	✓
3rd month	✓	✓	✓	✓	✓
6th month	✓	✓	✓	✓	✓
9th month	✓	✓	✓	✓	Pending
12th month	✓	✓	✓	✓	Pending
15th month	✓	✓	✓	✓	Pending
18th month	NC	✓	Pending	Pending	Pending

estimate of the cross-domain generalizability in the current study. EB+ and the clinical trial were more alike than EB+ and GFT. EB+ and the clinical trial both used higher resolution video and were more similar in their more limited head motion.

AFAR is used to assess head dynamics and the intensity of 7 facial AUs: AU1 (inner brow raiser), AU6 (cheek raiser), AU10 (upper lip raiser), AU12 (lip corner puller), AU14 (dimpler), AU17 (chin raiser), and AU45 (blinking). Another predictor, positive affect, is defined as the combination of AU6 and AU12. Overall 10 facial AUs and head dynamics time series were produced. Then, for each facial AU, the percentage of frames with the intensity of B-level and higher (2 in range of 0-5) was calculated. In a word, the feature showed the percentage of time that the AU was activated during an interview. For head dynamics, root mean square (RMS) value was calculated as the feature.

C. Machine Learning Techniques

Because the ten predictors were correlated, it was important to control for multicollinearity. Thus, on the first step, predictors with more than 0.7 correlation were found, and the one with higher correlation to the dependant variable (e.g., YBOCS-II) retained in the model. The chi-square feature selection method then was used to select the best subset of predictors [20]. The chi-square method ranked all predictors based on their significance level (p-value) in the prediction of the dependent variable. To avoid any possible over-fitting and keep the number of predictors limited, only the best 5 predictors were retained. Doing so, the number of predictors was kept at less than 8% of sample size.

Due to the nature of study design, which is a longitudinal single-subject study with repetition, implementation of a single linear regression model for all samples (and all subjects) would neglect subject-level differences. Assessments are nested within subjects. To take into account both inter- and intra-subject variation, we used a mixed effect model [14]. A mixed-effects model consists of two sets of variables: fixed (to capture intra-subject variability), and random (to capture inter-subject variability). Formula 2 shows the mixed-effects model with 'subject' as the random variable and five other predictors nested inside the 'subject' variable.

$$Output \sim 1 + pred_1 + ... + pred_5 + (1|subject) + \epsilon \quad (2)$$

III. RESULTS

AU6, AU12, and the positive affect composite (AU 6+12) were highly correlated to each other (r≈0.97). To avoid multicollinearity, AU 6 and the positive affect composite were omitted as predictors. Additional predictors were inter-correlated below the threshold of 0.70.

A. Prediction of OCD Symptom Severity

The chi-square ranked all features to predict OCD symptom severity (YBOCS-II). Table II shows the top 5 predictors, their coefficients, and their significance levels. All were statistically significantly (p-value <0.05) in the prediction of

YBOCS-II. The first row of Table V shows the goodness (R-squared) of models in prediction of OCD symptom severity for each patient individually as well as for all patients. Figure 2 demonstrates the RMS of head displacement vs. YBOCS-II score while each subject is denoted by a distinct color. Moreover, the trend of change in each patient's data is shown with a consistent-color dash line using linear regression.

B. Prediction of Depression Symptom Severity

The chi-square ranked all features to predict depression symptom severity (BDI). Table III shows the top 5 predictors, their coefficients, and their significance levels. Patient ID, head displacement, and AU17 are statistically significant (p-value <0.05) in the prediction of BDI, and adding or dropping the other leaves model prediction unchanged. The second row of Table V shows variance accounted for (R-squared) of models in prediction of depression symptom severity for each patient separately and for all patients. Figure 3 demonstrates the percentage of time that AU 12 was activated vs. BDI score while each subject is denoted by a distinct color. Moreover, the trend of change in each patient's data is shown with a consistent-color dash line using linear regression.

C. Prediction of Delivered Energy

The chi-square ranked all features to predict TEED. Table IV shows the top 5 predictors, their coefficients, and their significance level. Patient ID, head displacement, and AU17 are significant at p-value <0.05). The third row of Table V shows the variance accounted for (R-squared) of models in prediction of TEED to VC/VS for each patient separately as well as for all patients.

IV. DISCUSSION

Facial AUs and head dynamics performed well in the prediction of OCD symptom severity. They predicted 63% of variation in YBOCS-II scores (Table V, first row). The R-squares varied across subjects, which suggests individual differences. The high overall R-square could be interpreted as the ability of the mixed-effects model to predict the between-subject differences.

Treatment-refractory OCD is commonly associated with depression. We found that OCD symptom severity (YBOCS-II) and depression severity (BDI) were highly correlated (r=0.68). In light of that, facial AUs and head dynamics were expected to perform well in the prediction of depression severity. Nearly the same set of predictors (Table III) explained 59% of variation in BDI scores. Hence, facial AUs and head dynamics provided reliable and efficient biomarkers of OCD and depression severity. A next step would be to evaluate their contribution in a closed-loop system for regulating DBS in relation to continuous variation in OCD.

While the developed models for YBOCS-II and TEED explain good percentages of variability in the dependant variables, the obtained R-square for patient 5 was an exception. A reason may be that patient 5 completed only 4 of 8 assessments. Lack of data may have attenuated their findings. Once all assessments are completed, they may well conform to the experience of the other patients.

In addition to OCD and depression, the facial AUs and head dynamics were used to predict the TEED to VC/VS. Together they explained 37% of the variation. The relationship between behavior and DBS energy was consistent with the hypothesis that AUs and head dynamics provide a behavioral biomarker of OCD and brain activity.

All three developed mixed-effects models shared three significantly important predictors: Patients' ID, head displacement, and AU17.

Patient's ID was a nominal variable that enabled the mixed-effects model to compensate for the subject-level differences. As the most important predictor in all three cases was the patient's ID, it could be concluded that the subject-level differences were significant across the 5 patients. A significant difference in facial AUs and head dynamics response across patients was expected. This finding was in line with the interviewer's observations that patients differed in expressivity.

TABLE II

BEST PREDICTORS OF YBOCS-II, THE COEFFICIENTS, AND THEIR SIGNIFICANCE LEVEL*. SIGNIFICANT EFFECT (<0.05)

Selected Predictor	Coeff	p-value
Patient ID	N/A	<0.001*
Head Displacement	-3.2	<0.001*
AU17	-23.8	0.02*
AU10	-15.5	0.03*
AU14	-18.4	0.04*

TABLE III

BEST PREDICTORS OF BDI, THE COEFFICIENTS, AND THEIR SIGNIFICANCE LEVEL. *. SIGNIFICANT EFFECT (<0.05)

Selected Predictor	Coeff	p-value
Patient ID	N/A	<0.001*
Head Displacement	-2.4	0.001*
AU17	-36.3	0.03*
Blinking Rate	-12.6	0.2
AU1	5.5	0.3

TABLE IV

BEST PREDICTORS OF DELIVERED ENERGY, THE COEFFICIENTS, AND THEIR SIGNIFICANCE LEVEL *. SIGNIFICANT EFFECT (<0.05)

Selected Predictor	Coeff	p-value
Patient ID	N/A	<0.001*
Head Displacement	0.21	<0.001*
AU17	2.42	0.04*
AU14	14.9	0.1
AU12	5.8	0.2

TABLE V

R-SQUARED VALUE IN PREDICTION OF YBOCS-II, BDI AND DELIVERED ENERGY TO VC/VS.

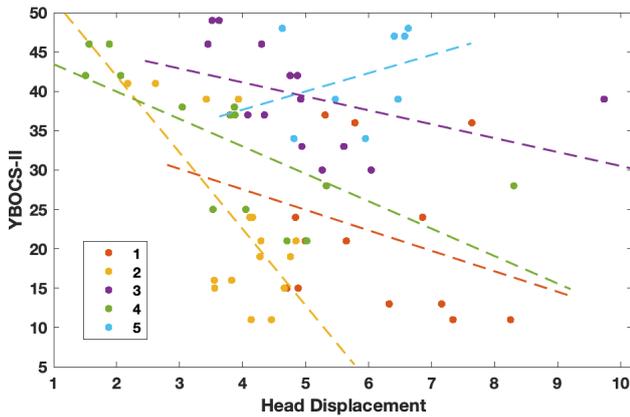|	P1	P2	P3	P4	P5	All
YBOCS-II	40%	44%	43%	42%	3%	63%
BDI	50%	9%	37%	15%	30%	59%
Energy	42%	56%	31%	56%	2%	37%

Fig. 2. RMS of Head displacement vs. YBOCS-II score. Each patient is denoted by a distinct color. Each point represents half a session.

Fig. 3. Percentage of AU12 Activation vs. BDI score. Each patient is denoted by a distinct color. Each point represents half a session.

While subject-level differences are often ignored, Figure 3 demonstrates their importance. If the subject-level differences were ignored, there would be a spurious positive correlation between AU 12, BDI and YBOCS-II, which means more smiling during severe depression. When individual differences are taken into account, however, the correlation between AU 12 and depression is found to be negative, which is consistent with previous research [16].

Head displacement had a negative correlation with both YBOCS-II (Figure. 2) and BDI, which suggests that patients became more active and animated as their symptom severity decreased. Several head motions were shown to be associated with arousal [22], thus higher head displacement levels could be interpreted as higher arousal or expressiveness.

AU17 was negatively correlated (both on the subject level and overall) to YBOCS-II and BDI. Because AU17 is usually present in negative states such as sadness or distress, the negative correlation with OCD and depression severity was counter intuitive. Given the high correlation among many predictors, it is difficult to interpret findings for any one. Further research will be needed to disambiguate specific signals.

As a next step, additional types of predictors, such as whole body movement and audio features could be considered. Audio features such as loudness and pitch have shown to be effective in detecting depression [6]. Including them in predictive models could provide additional insights and more robust set of potential behavioral biomarkers.

V. CONCLUSIONS

To our knowledge, this paper presents the first use of facial AUs and head dynamics to predict OCD symptom severity and total energy (TEED) from DBS to the VC/VS. Five participants treated with implanted DBS were video-recorded in unstructured interviews regularly for a period of up to 18 months. Thirty three interview sessions in all were analyzed. Eight facial AUs and two measures of head dynamics were tested to find reliable and efficient biomarkers of OCD symptom severity and total energy. A subset of facial AUs and head dynamics explained 61% of the variation in
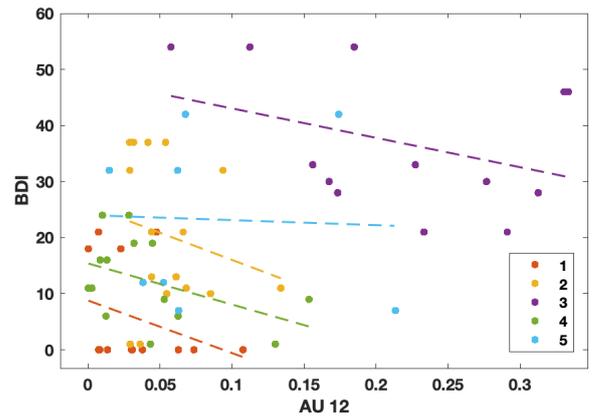
the OCD symptom severity, 59% of depression symptom severity, and 37% of variation in total energy (TEED) to the VC/VS. Of the biomarkers, head displacement was the strongest. Participants become increasingly expressive as their symptom levels decreased, which is consistent with previous research in depression [1], [7]. While the obtained results are promising, testing additional predictors such as auditory features and social interaction effects could further increase prediction of symptom severity and total energy. The findings suggest that behavioral biomarkers could be important imputs to a closed-loop system for DBS treatment of OCD. A closed-loop system informed by behavioral and physiological signals would enable continuous modulation of DBS in response to level of OCD threat for optimal symptom reduction.

VI. ACKNOWLEDGMENTS

REFERENCES

[1] K. Anis, H. Zakia, D. Mohamed, and C. Jeffrey. Detecting Depression Severity by Interpretable Representations of Motion Dynamics. In *2018 13th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2018)*, pages 739–745. IEEE, 5 2018.

[2] T. Baltrusaitis, P. Robinson, and L.-P. Morency. OpenFace: An open source facial behavior analysis toolkit. In *2016 IEEE Winter Conference on Applications of Computer Vision (WACV)*, pages 1–10. IEEE, 3 2016.

[3] J. T. Cacioppo, J. S. Martzke, R. E. Petty, and L. G. Tassinary. Specific forms of facial EMG response index emotions during an interview: From Darwin to the continuous flow hypothesis of affect-laden information processing. *Journal of Personality and Social Psychology*, 54(4):592–604, 1988.

[4] K. Campbell, K. L. Carpenter, J. Hashemi, S. Espinosa, S. Marsan, J. S. Borg, Z. Chang, Q. Qiu, S. Vermeer, E. Adler, M. Tepper, H. L. Egger, J. P. Baker, G. Sapiro, and G. Dawson. Computer vision analysis captures atypical attention in toddlers with autism. *Autism*, 23(3):619–628, 2019.

[5] J. F. Cohn, L. A. Jeni, I. Onal Ertugrul, D. Malone, M. S. Okun, D. Borton, and W. K. Goodman. Automated Affect Detection in Deep Brain Stimulation for Obsessive-Compulsive Disorder. In *Proceedings of the 2018 on International Conference on Multimodal Interaction - ICMI '18*, pages 40–44, New York, New York, USA, 2018. ACM Press.

[6] N. Cummins, S. Scherer, J. Krajewski, S. Schnieder, J. Epps, and T. F. Quatieri. A review of depression and suicide risk assessment using speech analysis. *Speech Communication*, 71:10–49, 7 2015.

[7] H. Dibeklioglu, Z. Hammal, and J. F. Cohn. Dynamic Multimodal Measurement of Depression Severity Using Deep Autoencoding. *IEEE Journal of Biomedical and Health Informatics*, 22(2):525–536, 2018.

[8] Y. Ding, I. Onal Ertugrul, A. Darzi, N. Provenza, L. A. Jeni, D. Borton, W. Goodman, and J. Cohn. Automated Detection of Optimal DBS Device Settings. In *Companion Publication of the 2020 International Conference on Multimodal Interaction*, pages 354–356, New York, NY, USA, 10 2020. ACM.

[9] P. Ekman, W. V. Friesen, and J. C. Hager. Facial action coding system: Research Nexus. In *Network Research Information, Salt Lake City, UT.*, 2002.

[10] I. O. Ertugrul, J. F. Cohn, L. A. Jeni, Z. Zhang, L. Yin, and Q. Ji. Cross-domain AU Detection: Domains, Learning Approaches, and Measures. In *2019 14th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2019)*, pages 1–8. IEEE, 5 2019.

[11] I. O. Ertugrul, J. F. Cohn, L. A. Jeni, Z. Zhang, L. Yin, and Q. Ji. Crossing Domains for AU Coding: Perspectives, Approaches, and Measures. *IEEE Transactions on Biometrics, Behavior, and Identity Science*, 2020.

[12] I. O. Ertugrul, L. A. Jeni, W. Ding, and J. F. Cohn. AFAR: A Deep Learning Based Tool for Automated Facial Affect Recognition. In *2019 14th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2019)*, pages 1–1. IEEE, 5 2019.

[13] J. D. Feusner, J. Townsend, A. Bystritsky, and S. Bookheimer. Visual Information Processing of Faces in Body Dysmorphic Disorder. *Archives of General Psychiatry*, 64(12):1417, 12 2007.

[14] G. M. Fitzmaurice and C. Ravichandran. A primer in longitudinal data analysis, 2008.

[15] M. Gavrilescu and N. Vizireanu. Predicting Depression, Anxiety, and Stress Levels from Videos Using the Facial Action Coding System. *Sensors*, 19(17):3693, 8 2019.

[16] J. M. Girard, J. F. Cohn, M. H. Mahoor, S. M. Mavadati, Z. Hammal, and D. P. Rosenwald. Nonverbal social withdrawal in depression: Evidence from manual and automatic analyses. *Image and Vision Computing*, 32(10):641–647, 10 2014.

[17] W. K. Goodman, E. A. Storch, J. F. Cohn, and S. A. Sheth. Deep Brain Stimulation for Intractable Obsessive-Compulsive Disorder: Progress and Opportunities. *American Journal of Psychiatry*, 177(3):200–203, 3 2020.

[18] Z. Hammal, J. F. Cohn, C. Heike, and M. L. Speltz. Automatic Measurement of Head and Facial Movement for Analysis and Detection of Infants' Positive and Negative Affect. *Frontiers in ICT*, 2, 12 2015.

[19] S. Harati, A. Crowell, Y. Huang, H. Mayberg, and S. Nemati. mc. *IEEE Journal of Biomedical and Health Informatics*, 24(3):815–824, 3 2020.

[20] I. Iguyon and A. Elisseeff. An introduction to variable and feature selection, 2003.

[21] L. A. Jeni, J. F. Cohn, and T. Kanade. Dense 3D face alignment from 2D video for real-time use. *Image and Vision Computing*, 2017.

[22] B. J. Li, J. N. Bailenson, A. Pines, W. J. Greenleaf, and L. M. Williams. A Public Database of Immersive VR Videos with Corresponding Ratings of Arousal, Valence, and Correlations between Head Movements and Self Report Measures. *Frontiers in Psychology*, 8, 12 2017.

[23] K. B. Martin, Z. Hammal, G. Ren, J. F. Cohn, J. Cassell, M. Ogihara, J. C. Britton, A. Gutierrez, and D. S. Messinger. Objective measurement of head movement differences in children with and without autism spectrum disorder. *Molecular Autism*, 9(1):14, 12 2018.

[24] M. D. McAuley. Incorrect calculation of total electrical energy delivered by a deep brain stimulator. *Brain Stimulation*, 13(5):1414–1415, 9 2020.

[25] M. V. McCall, P. Riva-Posse, S. J. Garlow, H. S. Mayberg, and A. L. Crowell. Analyzing non-verbal behavior throughout recovery in a sample of depressed patients receiving deep brain stimulation. *Neurology Psychiatry and Brain Research*, 37:33–40, 2020.

[26] K. Niinuma, H. Han, and A. K. Jain. Automatic multi-view face recognition via 3D model based pose regularization. In *2013 IEEE Sixth International Conference on Biometrics: Theory, Applications and Systems (BTAS)*, pages 1–8. IEEE, 9 2013.

[27] L.-G. Öst, A. Havnen, B. Hansen, and G. Kvale. Cognitive behavioral treatments of obsessive–compulsive disorder. A systematic review and meta-analysis of studies published 1993–2014. *Clinical Psychology Review*, 40:156–169, 8 2015.

[28] N. R. Provenza, E. R. Matteson, A. B. Allawala, A. Barrios-Anderson, S. A. Sheth, A. Viswanathan, E. McIngvale, E. A. Storch, M. J. Frank, N. C. R. McLaughlin, J. F. Cohn, W. K. Goodman, and D. A. Borton. The Case for Adaptive Neuromodulation to Treat Severe Intractable Mental Disorders. *Frontiers in Neuroscience*, 13(152), 2 2019.

[29] S. A. Rasmussen, G. Noren, B. D. Greenberg, R. Marsland, N. C. McLaughlin, P. J. Malloy, S. P. Salloway, D. R. Strong, J. L. Eisen, M. A. Jenike, S. L. Rauch, L. Baer, and C. Lindquist. Gamma Ventral Capsulotomy in Intractable Obsessive-Compulsive Disorder. *Biological Psychiatry*, 84(5):355–364, 9 2018.

[30] R. J. Romanelli, F. M. Wu, R. Gamba, R. Mojtabai, and J. B. Segal. Behavioral Therapy and Serotonin Reu Behavioral therapy and serotonin reuptake inhibitor pharmacotherapy in the treatment of obsessive-compulsive disorder: a systematic review and meta-analysis of head-to-head randomized controlled trials. *Depression and Anxiety*, 31(8):641–652, 8 2014.

[31] E. A. Storch, S. A. Rasmussen, L. H. Price, M. J. Larson, T. K. Murphy, and W. K. Goodman. Development and psychometric evaluation of the Yale–Brown Obsessive-Compulsive Scale—Second Edition. *Psychological Assessment*, 22(2):223–232, 2010.

[32] A. S. Widge, S. Zorowitz, I. Basu, A. C. Paulk, S. S. Cash, E. N. Eskandar, T. Deckersbach, E. K. Miller, and D. D. Dougherty. Deep brain stimulation of the internal capsule enhances human cognitive control and prefrontal cortex function. *Nature Communications*, 10(1536), 2019.

[33] T.-H. Yang, C.-H. Wu, M.-H. Su, and C.-C. Chang. Detection of mood disorder using modulation spectrum of facial action unit profiles. In *2016 International Conference on Orange Technologies (ICOT)*, pages 5–8. IEEE, 12 2016.

[34] Z. Zhang, J. M. Girard, Y. Wu, X. Zhang, P. Liu, U. Ciftci, S. Canavan, M. Reale, A. Horowitz, H. Yang, J. F. Cohn, Q. Ji, and L. Yin. Multimodal Spontaneous Emotion Corpus for Human Behavior Analysis. In *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2016.