Can an Unobtrusive AI-based System Based on Open-Ended Interviews Effectively Guide DBS Programming for OCD?

Jeffrey F. Cohn [1,2] , Saurabh Hinduja[1], Ali Darzi[1], Itir Onal Ertugrul[3], Nicole Provenza[4], Marc Aafjes[2], Ron Gadot[4], Sameer Sheth[4], & Wayne Goodman[4]

[1] University of Pittsburgh, [2] Deliberate AI, [3] Utrecht University, [4] Baylor College of Medicine

Research Question

In participants treated with deep brain stimulation (DBS) for intractable obsessive-compulsive disorder, can an unobtrusive, multimodal AI-based system effectively infer total electrical energy delivered and severity of symptoms?

Introduction

Deep brain stimulation (DBS) in the region of the ventral capsule/ventral striatum (VC/VS) (Figure 1) is a promising treatment for severe and intractable obsessive-compulsive disorder (OCD). To assess treatment response to DBS, reliable, valid, and easily obtainable biomarkers are needed. Previous work by the investigators suggests that unobtrusive multimodal AI-based can meet this need.

We explored the hypothesis that an unobtrusive AI-based multimodal system can reveal both total electrical energy delivered (TEED) to the VC/VS and clinically-reported outcomes (ClinROs) in patients with a history of intractable (treatment-resistant) OCD.

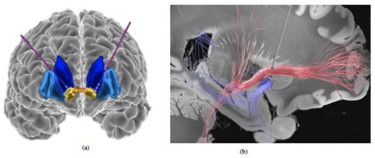


Figure 1. (a). Frontal view of an OCD's patient's brain. Implanted leads and their electrodes are shown in purple lines and white circles, respectively. (b) Lateral view of electrodes in relation to the cortico-striatal-thalamus circuit.

Methods

Participants and observational methods

Six patients (3 women, 3 men) with treatment-resistant OCD were treated with DBS in the region of the VC/VS. Audio/video recordings were obtained during open-ended clinical interviews conducted in-person or via Zoom at baselines prior to activation of the DBS and then every three months through 12 to 18 months post-implantation. Audio was recorded at 48 kHz in-person and 32 kHz Zoom. Video was sampled at 25 Hz for both settings.

Total electrical energy delivered (TEED) from the DBS device was computed from amplitude, pulse width, and frequency. Outcomes were assessed via structured interviews (YBOCS-II for OCD) and self-report (BDI-II for depression).

Modalities and feature selection

Automatically measured features from audio and video included occurrence and intensity of facial action units (AUs); dynamics of head pitch, yaw, and roll; dynamics of facial landmarks; acoustics and timing of speech; and linguistic variables (Figure 2).

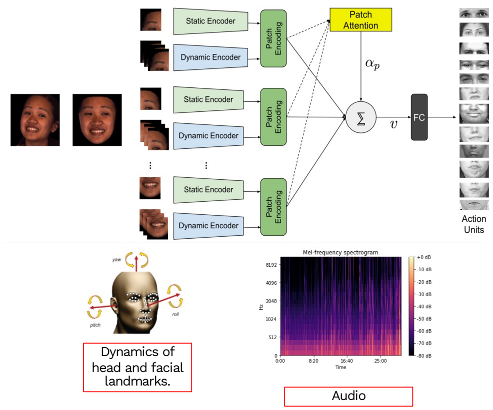


Figure 2. Automatically measured multimodal features.

Multimodal feature reduction

A mixed-effects random forest regressor was used to infer intensity. To reduce the potentially large number of features and avoid overfitting, we used multi-level modeling with Shapley (SHAP) feature reduction.

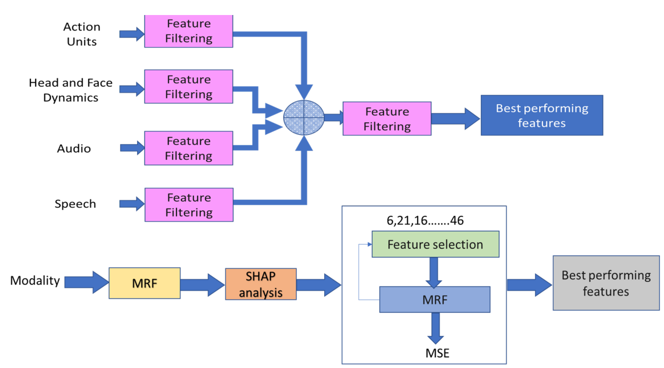
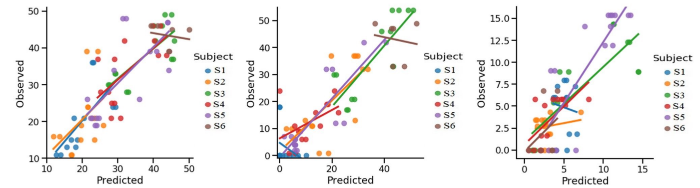


Figure 3. Multimodal feature reduction for estimating total energy delivered (TEED) and symptom severity.

Results



(a) YBOCS-II

ICC = 0.83

R^2 = 0.70

(b) BDI-II

ICC = 0.87

R^2 = 0.76

(c) TEED

ICC = 0.81

R^2 = 0.69

Figure 4. Multi-level random forest regression of best performing features for symptom severity (YBOCS-II and BDI-II) and TEED. ICC is calculated for consistency. R^2 is the coefficient of determination.

Modality	Feature	YBOCS-II	BDI-II	TEED
Acoustic	MCEP 4	1	4	2
	Loudness	2	-	-
	HMPDM 13	3	1	-
	MCEP 6	5	8	-
	MCEP 8	6	3	-
	MCEP 18	-	2	1
	HMPDM 8	-	6	-
	MCEP 24	-	7	5
	MCEP 13	-	11	-
	NAQ	-	-	16
	HMPDM 10	-	-	4
Linguistic	Words with greater than six letters	-	-	6
	Work	-	-	8
	Tentative	-	-	11
	Auxiliary verbs	-	-	15
Head and Face	Yaw spkt Welch density	-	-	9
	Mouth apx entropy	-	-	10
	Eyes spkt Welch density	-	-	12
	Eyes permutation entropy	-	5	-
	Eye change in quantile of mean	-	10	-
	Eye velocity of change in opening	-	9	-
	Mouth longest strike below mean	-	-	3
	Yaw partial auto correlation	-	-	13
	Yaw permutation entropy	-	-	7
Action Unit	AU1 Benford correlation	4	-	-
	AU1 augmented dickey fuller	-	-	14

Figure 5. Relative importance of predictors to symptom severity and TEED. The color indicates the sign of the correlation: Red for positive, blue for negative. The number denotes the feature's rank by SHAP analysis.

Conclusions

An objective, unobtrusive, open-ended AI-based system strongly predicted symptom severity and total electrical energy delivered. Audio was the most influential modality; all modalities were necessary to optimize prediction. These findings support the feasibility of this approach for DBS programming and objective measurement of distress disorders more broadly.

Acknowledgments

Supported in part by NIH award UH3NS100549 to Baylor College of Medicine.

deliberate.ai Utrecht University Baylor College of Medicine