**SUPPLEMENTARY METHODS**

Patient group assessments

Patients were assessed for the presence of Impulse-Compulsive Behavior (ICB) by a neurologist who is an expert in movement disorders using clinical interviews with the patient and the care-giver. Patients and care-givers were asked about the presence of one or more of the following: pathological gambling, hypersexuality, compulsive shopping, binge eating disorder, obsessive hobbying, punding, and compulsive medication use. Moreover, all patients underwent a neuropsychiatric examination as part of the screening for deep brain stimulation. The Barratt impulsiveness scale was administered to assess different aspects of impulsiveness. The dataset of ICB+ patients was composed of 16 patients with ICB diagnosed as described above, who underwent DBS implant surgery at the Careggi Hospital (Florence, Italy). We performed spike sorting on all the microelectrode recordings (MER) used to identify the optimal stimulation location during the implant (see below). Four patients were discarded as the number of identified neurons was less than ten and hence, judged not sufficient to perform robust statistics. In the remaining twelve patients [14-74], neurons were identified. Three out of the remaining twelve patients with ICB displayed more than one ICB. ICBs developed after PD diagnosis and dopaminergic therapy (including both levodopa and dopamine agonist treatment) and included pathological gambling (n = 3), hypersexuality (n = 4), compulsive shopping (n = 1), binge eating disorder (n = 1) and hobbyism (n = 7). The dataset of ICB- patients was composed of 16 patients without ICB who underwent DBS implant surgery in the same period at the same hospital. We performed spike sorting on the MER of all patients. To ensure robustness and balance of the statistics, we selected the 12 patients with the largest number of recorded neurons (range: 13-53) to form the control ICB- group. Supplementary Table 1 reports the inter-group comparisons we performed to assess the presence of confounding factors.

Supplementary Table 1: Demographic and clinical characteristics of the two groups: ICB+ and ICB-. The Barrat impulsiveness scale is in bold as it is the only scale displaying significant difference between the two groups.

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| --- | --- | --- | --- | --- |
| Measure | T-test assumptions Shapiro Wilk test (p>0.05) and Levene’s test (p>0.05)  matched | ICB- group  Mean ± std if t-test assumptions matched;  median [range] or occurrences if assumptions did not match | ICB+ group  Mean ± std if t-test assumptions matched;  median [range] if assumptions did not match | Test, significance |
| Age | Yes normality, no equal variance | 64 ± 4.3 years | 59.8 ± 7.7 years | Unequal variance T-test, p = 0.11 |
| Sex | NA [proportion data] | 9/3 M/F | 8/4 M/F | Fisher Exact test, p = 0.99 |
| Hoen Yahr off scale | yes | 3.46 ± 0.90 | 3.04 ± 0.88 | T test,  p=0.28 |
| Unified Parkinson's Disease Rating Scale III off scale (UPDRS III) | yes | 36.25 ± 11.02 | 27.42 ± 9.48 | T-test, p=0.06 |
| L-dopa–equivalent dose (LEDD) | yes | 1325 ± 417.03 mg/day | 1207.25 ± 551.09 mg/day | T test,  p=0.58 |
| Dopa agonist LEDD | no | 320 [160-1070] mg/day  (9/12 patients) | 420 [140-535] mg/day  (9/12 patients) | Mann-Whitney U test, p=0.9 |
| Clinical subtypes | NA [proportion data] | 7/12 bradykinetic-rigid, 5/12 tremor dominant | 6/12 bradykinetic-rigid, 6/12 tremor dominant | Fisher exact test p=0.9 |
| **Barrat Impulsiveness Scale (BIS)** | **yes** | **53.7±2.8** | **65.8 ±4.8** | **T-test, p=0.001** |

STN entry point identification

Microelectrodes were inserted during DBS implant surgery to identify the optimal location for DBS. When inserted microelectrodes first penetrate the STN, their activity is characterized by increased background activity and firing rate. As the electrodes are progressively lowered during surgery, we determined the STN depths according to the 80th percentile of the raw recording (PRC80) as previously described (1). For each insertion, the PRC80 values were expressed as the fraction of the highest value across the three tracks. Only the recordings which presented a PRC80 that was ≥ 50% of the highest value and deeper than -5 mm from the target point (supposedly chosen in the dorsal part of the STN) were considered as belonging to the STN and included in the following analysis (see Fig B). Only insertions with at least one track matching condition and presenting a transition from an activity below 50% to an activity above 50% were considered valid.

Neural markers computation

Microelectrode recordings acquired during DBS implant surgery were analyzed offline to find neural markers able to discriminate between the ICB+ and ICB- groups. Any recording interval that was corrupted by noise or by spike amplitude instability that could affect the analysis was visually identified and discarded, i.e., a track was considered reliable if the noise period was below 50% of the total length of the signal. Spike detection and sorting were performed using MATLAB ToolBox Wave\_Clus(2). Every isolated unit was visually inspected, and only the well-separated ones were selected for further analysis. We used the following selection criteria(3): more than 90% of the total area of the amplitude histogram had to be above the detection threshold; the mean waveform had to have a typical action potential shape, i.e., biphasic shape either with a positive or negative most prominent peak; the percentage of spikes occurring within 3 ms of each other had to be less than 1%; and the number of spikes detected had to be more than 20. We sorted single-unit activity (SUA) using MATLAB ToolBox Wave Clus, extracting 742 SUA (330 SUA in the ICB- group and 412 in the ICB+ group) from 548 tracks across all subjects. The SUA firing rate was estimated using the Gaussian Kernel bandwidth optimization method(4). The regularity of discharge patterns was assessed by fitting each Inter Spike Interval (ISI) with a gamma distribution, and determining the shape factor log(k) of the distribution associated to each pattern. Patterns were then divided according to this value into “Tonic” (log(k)>0.3), “Bursting” (log(k)<-0.3) or “Irregular” (intermediate values)(5). The bursting activity was characterized using the Rank Surprise Method(6), setting -log (.01) as the surprise threshold, and the 75th percentile of the ISI distribution pooled across neurons (48 ms) as the limit for an ISI to be considered part of a burst. We averaged the Intra-Burst Frequency (IBF), Inter-Burst Interval (IBI), and the burst duration for each SUA. The power spectral analysis of the Background Unit Activity (BUA), i.e., the raw signal once action potentials were removed(7), was computed for each of the following frequency bands: delta (1–4) Hz, theta (4–8) Hz, alpha (8–12) Hz, beta (13–30) Hz, and gamma (30–100) Hz. Oscillatory SUA was identified according to the “modulation index”(8) and corrected for the refractory period (3 ms) to avoid biases in comparing spike trains with different firing rates and recording lengths. The relationship between oscillatory SUA and BUA was assessed through spectral cross-coherence(9) and computed at the oscillation frequency of the SUA.

Uber-patient analysis

Statistical comparisons of the distribution of feature values between the two groups and mutual information analysis were carried out using the uber-patient approach, i.e., pooling all neurons/channels from all the patients in each group and comparing the distribution of each feature in the two resulting populations. This operation requires features to have similar values across patients of each group so that each patient makes a similar contribution to the pooling. To test this assumption, we performed the following procedure(10). For each feature, we computed the mean value and the standard deviation for each patient, and the median value *Fgroup* of the means of the feature across patients of the same group. A patient was considered to have a feature distribution homogeneous to the rest of the group if

For the ICB- group, the condition was matched by 12/12 patients for all inspected features. For the ICB+ group, the condition was matched by 12/12 patients for all features except cross-coherence theta, for which two outliers were present. We concluded that the feature distributions within groups were sufficiently homogeneous to allow for uber-patient analysis.

Statistical Analysis

To control for multiple comparisons, we applied the False Discovery Rate (FDR) correction with the Benjamini and Hochberg method (11) (𝛼 = 0.05) within each group of features (firing patterns, bursting activity, spectral power, spectral coherence).

Mutual information analysis

We computed the mutual information carried by single neural features about the ICB condition using the Information Breakdown Toolbox in MATLAB (12). The mutual information I(G;Fi) quantified how much information the neural feature Fi carried about the set of groups G = {ICB+, ICB-} as follows (13):

where P(g) is the probability of the occurrence of the group g, P(fi) is the probability of the i-feature to have value fi over all patients and groups, and P(fi|g) is the probability of the value fi  occurring during group g. We limited the information bias due to the small data set by grouping neural feature values in four bins and applying the Panzeri–Treves bias correction (14). We assessed information significance by defining the 95th percentile of information obtained across 500 bootstrapped datasets as *p* < 0.05 significance threshold (12).

General Linear Model

To test for a significant relationship between neural features and clinical scores and to rule out possible confounding factors such as motor severity and disease phenotypes, we performed the following analysis. We performed a general linear model (GLM) analysis using the neural features playing a critical role in the classification procedure as predictors for UPDRS OFF meds scores, BIS scores, and their sub-scales. An interaction of predictors was allowed if the full model (with interactions) was justified by the Akaike Information Criterion(15). Also, in this case, to control for multiple comparisons, we applied the False Discovery Rate (FDR) correction with the Benjamini and Hochberg method(11) (𝛼 = 0.05) within each group of features (firing patterns, bursting activity, spectral power, spectral coherence).

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