Psychogenic Tremor Disorders Identified Using Tree-Based Statistical Algorithms and Quantitative Tremor Analysis

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Abstract: Detecting psychogenic tremors (PsychT) is often challenging. As there are no laboratory investigations or imaging techniques that can confirm the diagnosis, PsychT is identified on a clinical basis. We present a tree-based statistical algorithm derived from quantitative computerized tremor recordings as a novel method to help in the recognition of PsychT. The goal of this study was to show that objective data from computerized tremor recordings, when processed through a tree-based statistical algorithm, can be used to determine whether a patient can be classified as having PsychT. © 2005 Movement Disorder Society

Key words: psychogenic tremor; tree-based modeling; neurophysiology; tremor analysis; Parkinson's disease; essential tremor; dystonia; movement disorders

Psychogenic neurological conditions account for 1% to 9% of admissions to a neurological unit.[1–3] They are considered manifestations of underlying psychiatric disorders such as somatoform disorders and factitious disorders, or malingering. Diagnosing psychogenic tremor (PsychT) is difficult because it can mimic tremors secondary to organic disorders or even coexist in a patient with tremors of organic origin. In the absence of laboratory investigations or imaging techniques to confirm the diagnosis, PsychT, like other psychogenic movement disorders, is diagnosed clinically. Features consistent with the diagnosis of psychogenic movement disorders include distractibility, acute onset, inconsistency over time, spontaneous remission, responsiveness to placebo, unresponsiveness to appropriate medications, an increase in movements with attention, underlying psychopathology, and remission with psychotherapy.[4] To confirm the diagnosis, symptoms must abate with psychotherapy or be absent when patient is unobserved. Such documentation, however, is often not possible.

Because of these issues, the diagnosis of psychogenicity is often made reluctantly, which may result in treatment delay. If correctly identified, however, psychogenic movement disorders are potentially curable through a regimen of medical and psychiatric care.[4] Conversely, the misdiagnosis of psychogenicity in patients with organic movement disorders may be harmful.[5]

Recent studies have indicated that PsychT has unique physiological characteristics not often found in patients with organic tremor disorders.[6–13] These include:

1. Increase in tremor amplitude with inertial loading.
2. Fluctuations in tremor frequency and amplitude during prolonged recordings.
3. Coactivation of antagonist muscles at the onset of tremor characterized by antagonist muscles tonically discharging approximately 300 msec before the onset of tremor bursts.
4. Absence of finger tremors, presumably due to the lack of clonus mechanisms in fingers.
5. Absence of independent oscillators and therefore no frequency dissociation with bilateral limb movements.

Although these physiological criteria have not been applied in a widespread manner, they can be useful in categorizing PsychT patients. Making an accurate diagnosis remains difficult even with these criteria, however, because unlike organic tremor disorders with specific physiological characteristics there are no unique frequency ranges, amplitudes, or helpful electromyographic (EMG) findings (e.g., antagonist muscle phase relationships) for PsychT. Frequency ranges for PsychT have been shown to be inconsistent between and within patients. Furthermore, an increase in tremor amplitudes with loading is not invariable in PsychT and may occur in other conditions. It is therefore neither practical nor useful to identify such tremors according to physiological characteristics like frequency or amplitude as organic tremor disorders are often classified.[10]

We introduce a tree-based statistical method that helps resolve these issues because it handles complex and highly variable data such as PsychT amplitudes and frequencies. Fully developed, this method can be used to help classify whether a patient may have PsychT simply by following the branches to the right or left according to frequency or amplitude of the tremors in specific conditions[14] once the tree has been created. The result is a statistically accurate method that is nevertheless fast and easy to utilize.

SUBJECTS AND METHODS

Subjects

In total, 92 subjects (71 tremor patients and 21 age- and gender-matched normal control subjects) were recruited consecutively over a 3-year period. The 71 patients comprised 23 with clinically established PsychT (using criteria proposed by Fahn and Williams),[15] 22 with Parkinson's disease (PD), 11 with dystonia (DT), and 15 with essential tremor (ET). All patients were diagnosed clinically after a complete work-up by movement disorders specialists in the Neurological Institute of New York at Columbia University Medical Center. Age and gender-matched normal control subjects were recruited from patients' relatives, spouses, and the local community. All subjects gave their consent and participated in the study in accordance with institutional guidelines. Exclusion criteria included subjects with tremor of unclear cause, subjects with tremor possibly secondary to medication(s), or subjects with predominant laryngeal, head, leg, or truncal tremors. PsychT patients who participated in this study had resting, postural, or kinetic tremor of one or both arms.

Materials

Computerized quantitative tremor analysis using accelerometry and EMG was used to obtain movement signals and muscle activity from the arms. Four channels were used to record forearm flexor and extensor muscles bilaterally with silver/silver chloride EMG surface electrodes. Two channels recorded accelerometry using ultralight piezoresistive miniature accelerometers ($\pm$ 25 g; weight, 1.2 gm) with linear sensitivities of approximately 4.5 mV/g in the physiological range, attached midline at the distal portion of the dorsum of each hand. Data were acquired and analyzed using semiautomatic interactive software developed in the Clinical Motor Physiology Laboratory.

Recording Techniques and Experimental Protocol

Accelerometric and surface EMG signals were digitized with a14 bit A/D system at 500 Hz and stored in multiple 4- to 10-second trials of three different clinical conditions: at rest, with both arms extended, and during finger-to-nose movements with each arm separately. Electronic artifacts were removed at the beginning and end of each recording. The measurement of the arms at rest was carried out with the subjects' elbows flexed 90 degrees and kept stationary to prevent transmitted upper arm movement into the lower forearm and hand. The arms of the chair supported the subject's forearms and the hands freely rested over the edge. In the arms-extended condition, the arms were flexed at the shoulders with the forearms, hands, and fingers held straight in a horizontal plane level with the shoulders. To distinguish mechanical reflex factors in exaggerated physiological tremors from centrally driven tremor components, inertial weighting using 500-gm loads were added to the dorsum of the wrists with the arms extended. The muscle/movement acquisition set-up allowed unhampered natural activity of the arms and hands throughout testing. By not limiting movements with mechanical restraints, tremors were measured as close to the realistic clinical state as possible. Stress factors during data acquisition were kept to a minimum by having the subjects seated comfortably and relaxed. Subjects were reassured that the test was safe, that electrical shocks and needles would not be used, and that there were no injections or medications given.

Quantitative Tremor Analysis

Tremor amplitudes were derived offline by double integration of accelerometric data after filtering out low-frequency drift (less than 2 Hz) and averaging. Tremor frequencies were calculated using a fast Fourier trans-

form algorithm to generate autocorrelation spectra. For purposes of analysis, the most dominant peaks of the spectra were used. When there was no clearly dominant peak, the center of the largest cluster of peaks was used. EMGs were full-wave rectified, integrated, and processed with the accelerometric data. Side-to-side coherence was calculated using cross-spectra analysis. Measurements of the hand with largest tremor amplitude of each subject were used to determine the predictor variables and build the tree-based statistical models. When tremors in both arms are equally severe, data from the dominant hand were analyzed. EMG and accelerometric data were then processed to develop the tree model.

Tree Modeling Analysis

S-Plus Statistics (Insightful Corporation, Seattle, WA) was used to establish and "grow" the tree model. This software was based on binary recursive partitioning, the major advantage of which was that unlike other more traditional classification or prediction methods such as linear or logistic regression, data from tremor analysis, e.g., amplitude or frequency, can be used as predictor variables once, not at all, or several times in any order and with different cut-off thresholds each time. The predictor variables were displayed at nodes and branches, and the result was an easy-to-follow interactive graphical classification scheme for specific tremor types.

Predictor variables were identified as those with the most functional relationships to clinical tremor based on the distribution and variance of the tremor analysis data. To grow the tree, the data then were recursively split and classified according to variables and cut-off values until all nodes became as homogeneous as possible, or contained five or less observations.

RESULTS

The PsychT group comprised 16 women and 7 men with mean age at the time of testing of 45.57 ± 14.23 years (age range, 26–89 years), and symptom durations ranging from 0.08 to 35 years. For the normal control group, the mean age was 48.25 ± 18.58 years (age range, 21–83 years). Clinical information for PsychT patients is detailed in Table 1. Sudden onset of tremor was reported in 19 of 23 patients. Of 12 patients who were tested for distractibility, all were found to have reduced or completely diminished tremor amplitudes when asked to perform mental tasks. Somatization, conversion, and depressive disorders were present in 9 patients with defined psychiatric disorders. Eighteen patients reported a pre-

ceding trauma or diagnosis of a disease that occurred within months before the onset of their tremor. Tremor characteristics over time were evaluated and were categorized as progressive (worsening over time), intermittent (tremor would stop and start), and changeable (tremor characteristics varied over time).

Table 2 shows physiological data from all subjects. There was a marked degree of overlap in tremor frequencies among four groups of subjects. Tremor amplitude standard deviations were highest in the PsychT group, particularly with posture and during action, indicating the greater irregularity and variability of PsychT amplitudes compared with that in organic tremors. In general, the means and standard deviations of all measurement overlapped greatly, rendering it difficult to distinguish between the four groups of patients and normal controls based on physiological values alone.

Analysis

S-Plus software utilized five predictor variables from the accelerometric and EMG physiological data acquired during the different testing conditions (Table 2): amplitude and frequency at rest (AR amp and AR freq), amplitude when the arms are extended (AE amp), and amplitude and frequency during finger-to-nose movement (F-N amp and F-N freq). These were found to have the most discriminating power to develop the tree model. The recursive partitioning algorithm worked by determining the initial and all subsequent predictor variables, splitting each at their most discriminating cut-off thresholds such that all nodes became homogeneous or contained five or fewer observations. Predictor variables were chosen in series, obviating between-variable interactions.

Example data from two conditions (Fig. 1), presented as box plots, illustrate the distribution of two variables (AR amp and F-N freq) to show the marked overlap in data ranges rendering separation between disease states virtually impossible by traditional discriminating methods. These graphs also illustrate how AR amp data ranges were somewhat more distinctive between disease states, particularly for PD, thus rendering AR amp a reasonable initial predictor variable.

The final tree model consisted of 12 nodes and 22 branches (Fig. 2). All subjects were classified. The number under each terminal node indicates the accuracy of classification for that diagnosis, calculated from the proportion of the correctly diagnosed subjects and total subjects entering that terminal node. The tree model revealed the classification of PsychT at four terminal nodes with correct classifications ranging from 60% to

TABLE 1. *Psychogenic tremor patients clinical information*

Subject no.	Age (yr), gender	Duration (yr)	Abrupt onset	Time course	Preceding trauma or disease	Distractibility	Psychiatric diagnosis
1	59, F	12.0	Yes	Progressive	None	Yes	
2	49, M	6.0	Yes	Unknown	Ingestion of plastic	Unknown	
3	30, M	0.8	Yes	Progressive	None	Yes	
4	30, M	0.4	Yes	Progressive	Depression	Yes	Conversion disorder
5	41, F	3.5	Yes	Intermittent	Diagnosed with connective tissue disease	Yes	
6	50, F	3.0	Yes	Progressive	MVA	Yes	Somatization disorder; major depression
7	55, F	1.0	Yes	Progressive	Arthroscopic surgery	Unknown	Depression
8	43, F	1.5	Yes	Intermittent	Hit by lightening	Yes	Depression
9	26, F	0.6	Yes	Intermittent	MVA	Yes	
10	42, F	1.0	Yes	Changeable	Treatment for shoulder adhesions	Yes	
11	27, F	0.3		Changeable			
12	41, F	2.0	Yes	Intermittent	Pregnancy, and then MVA		Somatization disorder, depression, PTSD
13	89, F	11.0	Yes	Intermittent	Death of sister	Yes	
14	51, F	0.8	Yes	Progressive	"Stroke" by history	Yes	Depression
15	53, F	2.0	Yes	Intermittent	Hospitalization for colitis	Unknown	Major depression
16	28, F	4.5	Yes	Progressive	Bottles fell on head and shoulder (no permanent injury)	Unknown	
17	44, M	35+	N	Progressive	Worsened after 2 accidents (struck in the head, and a fall)	Unknown	Depression
18	61, M	15.0				Unknown	
19	61, F	0.1	Yes	Progressive	Lightheadedness	Yes	
20	42, F	0.7	Yes	Progressive	None	Unknown	
21	49, M	2.0	Yes	Changeable	2 accidents (neck injury, and MVA)	Unknown	
22	39, F	2.0	No	Changeable	Diagnosis of Lyme disease	Yes	Conversion and somatization disorder
23	38, M	0.5	Yes	Intermittent	Discectomy and spinal fusion	Unknown	

MVA, motor vehicle accident.

100%, depending on the path that directs to the terminal node. Of 92 subjects including the controls, all of whom were identified as normal, 78 (85%) were classified correctly, giving an overall misclassification error rate of 15%. Excluding the normal controls, the tree algorithm classified 57 of 71 (80%) remaining subjects correctly.

There were five false positive classifications where DT (n = 3), ET (n = 1), and PD (n = 1) patients were incorrectly identified as PsychT. There were three false negative classifications where PsychT cases were classified as DT (n = 2) and ET (n = 1). The classification algorithm for PsychT thus had a sensitivity of 0.870, a specificity of 0.928, a positive predictive

TABLE 2. *Physiological data used as predictor variables to develop the tree*

Group	AR amp (mm)	AR freq (Hz)	AE amp (mm)	F-N amp (mm)	F-N freq (Hz)
PsychT (n = 23)	5.46 ± 8.78	6.55 ± 2.10	10.00 ± 28.44	11.02 ± 20.56	6.99 ± 2.50
PD (n = 22)	17.55 ± 18.58	5.38 ± 2.03	7.76 ± 14.88	8.07 ± 7.19	5.89 ± 1.77
DT (n = 11)	0.23 ± 0.20	7.98 ± 2.70	1.50 ± 2.79	5.37 ± 4.38	5.72 ± 2.31
ET (n = 15)	0.16 ± 0.25	8.59 ± 2.46	1.53 ± 1.91	4.28 ± 3.42	5.76 ± 1.09
Normal (n = 21)	0.07 ± 0.11	11.70 ± 2.08	0.14 ± 0.25	1.74 ± 2.68	9.03 ± 2.47

Values are given as mean ± SD.
AR amp, amplitude at rest; AR freq, frequency at rest; AE amp, amplitude when arms extended; F-N amp, amplitude during finger-to-nose movement; F-N freq, frequency during finger-to-nose movement; PsychT, psychogenic tremor; PD, Parkinson's disease; DT, dystonia; ET, essential tremor.
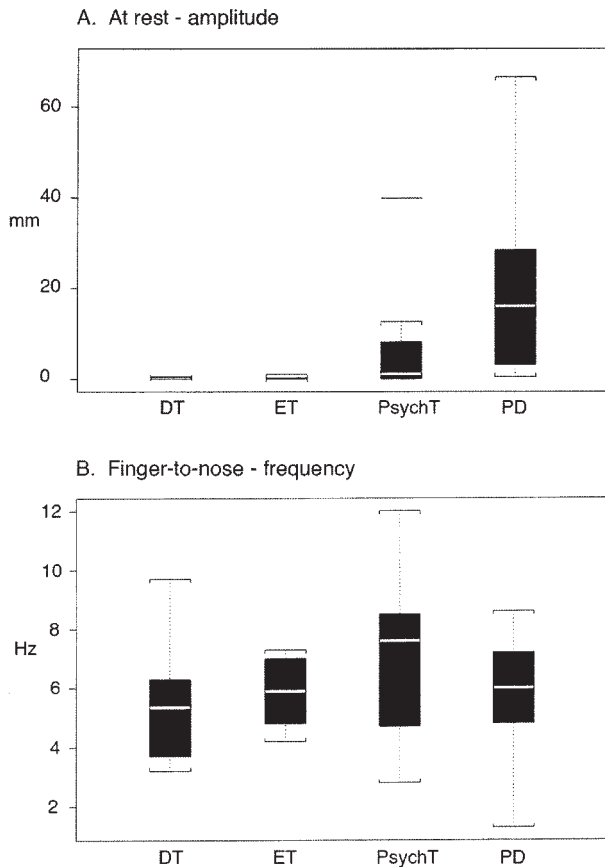
A. At rest - amplitude

B. Finger-to-nose - frequency

FIG. 1. Box plots illustrating sample distributions of rest tremor amplitudes (**A**) and kinetic tremor frequencies (**B**) in each tremor category. The white lines represent the medians. The surrounding darkened areas represents upper and lower quartiles of the data ranges and the brackets indicate the extent of the data beyond the quartiles. Single lines indicate outliers. These two graphs show that despite the marked overlap in data ranges, rest tremor amplitudes are more distinguishable than the are kinetic tremor frequency distributions. Rest tremor amplitude, with more potential to separate tremors types, is used by the tree model as the initial splitting variable.

value of 0.800, and a negative predictive value of 0.955 (Fig. 3).

DISCUSSION

A tree-based statistical algorithm is an exploratory method for uncovering structure in data.[14,16] This technique has developed interest outside of medicine although has been increasingly applied in internal medicine, oncology, nephrology, and neurology.[17–24] Tree-based models are simple and efficient when dealing with domains with many variables and marked overlap in data ranges and are an alternative to more traditional linear and logistic classifications.

Three general steps are used to develop the tree model. The first step (projection) is to identify all possible variables

functionally related to tremor. The second step (selection) is to determine the variables that are the best predictors for the tree. The last steps is to develop the tree (classification) using the appropriate variables and cut-off values. The terminology used for describing the tree models includes root (the top node of the tree), leaf (a terminal node of the tree), and split (a rule for creating new branches).[16] The tree is obtained using an algorithm that recursively partitions the given training data into smaller subsets until either the node is homogeneous or contains too few observations.[10,16] Each inner node of the tree is a logical test on a predictor variable. There are two outcomes of the test at each node to the left or right: predictor variable less than the cut-off value, and predictor variable greater than cut-off value. Each path will direct to the terminal node, which indicates the final classification. One of the more interesting aspects of the tree model is that any variable can be used more than once and at different ranges. This allows for complex statistical manipulations that may be nevertheless logical or intuitive.

We developed the tree model from the data obtained from 71 subjects with different types of clinically established tremors (PsychT, PD, DT, and ET) and 21 normal controls. Based on tremor amplitude and frequency for each of three conditions (AR, AE, and F-N), the tree model classified PsychT accurately from 60% to 100% of the time, depending on the data taken from the start to the terminal node. For example, if the patient had AR amp > 1.06 mm, the data path would be directed to the right at the first split to the second node querying the next predictor variable AE amp. If AE amp >0.71 mm, the data path is directed to the right, splitting again according to the AR amp. If AR amp ≤ 14.95 mm, the predictor pathway is directed to the left, splitting for a third time according to AR amp. If AR amp > 5.26 mm, the patient has PsychT with probability of 100% based on our original data set. In summary, if the patient had AR amp between 5.26 and 14.95 mm and AE amp > 0.71 mm, the likelihood of being classified with PsychT is 100%. This illustrates both the notable power and simplicity of the tree in identifying PsychT.

The tree algorithm classified 78 of 92 of all subjects correctly, resulting in an overall misclassification rate of 15%. There were five false positive and three false negative classifications for PsychT. Most of the errors occurred with DT, which like PsychT is often more variable and irregular than are other tremor disorders.[25] The tree model classification for PsychT thus had a sensitivity of 0.870 and a specificity of 0.928, which is notably better than what might be achieved by other classification methods using the same highly overlapping physiological tremor data.

Because there are no gold standards for diagnosing PsychT apart from clinical criteria and exclusion of organic disorders, a tree-based statistical algorithm can be
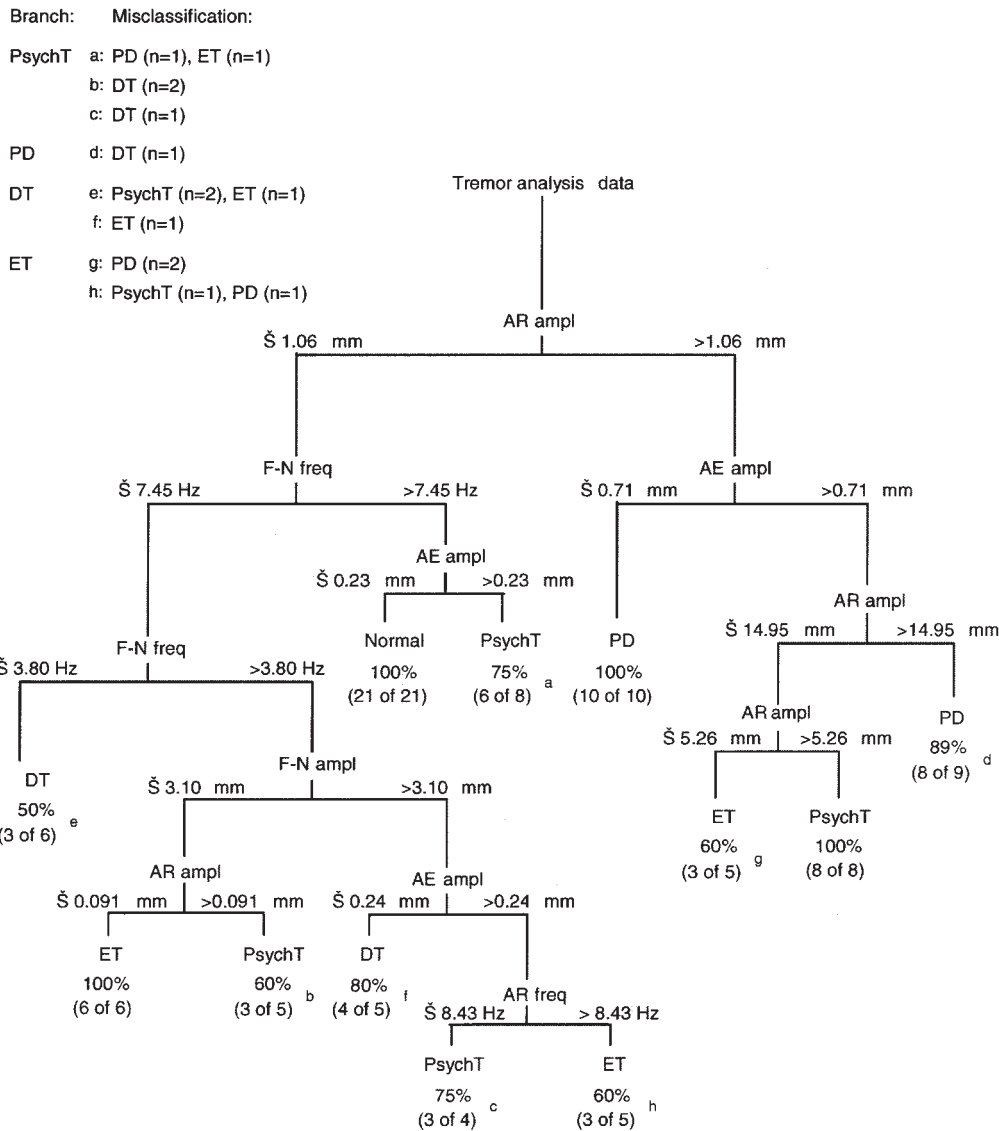
FIG. 2. Tree-based model revealing the proportion and classification of tremors. There are 11 nodes with 22 branches, 12 of which are terminal. Data are based on hand tremors from the most-affected side. Each branch is labeled by its predictor variable, with pathways to either side indicating the direction taken depending on the predicator variable's value. Beneath each terminal node, there are numbers indicating the number and proportion of subjects with that diagnostic classification. At terminal branches where the proportion is not homogeneous, i.e., not 100%, the superscripted letter refers to the listing at the bottom left revealing the actual clinical diagnosis and number of misclassified subjects. For example, where the terminal branch shows classification of psychogenic tremor at 75% (6 of 8 subjects), the two misclassified subjects are PD (n = 1) and ET (n = 1).

a useful adjunctive diagnostic tool in addition to other neurophysiological findings such as inconsistency of the tremor characteristics, increased tremor amplitudes with loading, etc. The tree model also may be used as a heuristic aide in diagnosing PsychT when objective measurements of tremor amplitude and frequency are obtainable.

It should be emphasized that the specific tree model developed in our laboratory and reported here with its branches, rules, and variable ranges would not be applicable to other clinical laboratories due to differing tremor mea-surement methods and instrumentation; however, the statis-tical tree algorithm could be applied in any laboratory with similar clinical and computerized tremor data collection. Moreover, although it is apparent that the algorithm can also identify PD, ET, and DT at terminal nodes, it was designed for detecting PsychT with its specific classifica-tion variables, branch value ranges, and splitting rules.

As with any new application, limitations and con-founding issues need to be recognized such as variable interactions and masking effects. Because the tree is

Tree classification for PsychT

		+	−		
Diagnosis of PsychT	+	20	3	0.870	Sensitivity
	−	5	64	0.928	Specificity
		0.800	0.955		
		Positive predictive value	Negative predictive value		

FIG. 3. Classification sensitivity and specificity of PsychT based on the tree algorithm.

developed vertically, predictor variables are evaluated in series and between-variable interactions during tree building do not occur. Taken in its entirety, however, the tree method utilizes multiple variables and potential interactions between sequential variables should be noted. Although not done in this study, it is also possible to purposefully hide a variable or division selected by the statistical algorithm to suppress specific variables or cut-off values, effectively masking data and altering the results. Finally, before using this tree-based method of assessment in the clinical setting, it needs to be validated with new untested PsychT, PD, ET, and DT patients and normal controls.

CONCLUSIONS

Tree-based statistical algorithms in combination with quantitative tremor analysis provide powerful yet easy-to-use guidelines for classification of PsychT. By applying tremor amplitude and frequency data from the commonly used clinical conditions for tremor assessment (rest, posture and action) to a series of binary rules, we have developed an objective and reproducible method of recognizing PsychT. This technique represents a novel application of tree-based modeling in neurology that may be useful in clinically elusive conditions such as PsychT with highly variable physiological data.

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