Original Paper

Psychopathology 1996;29:54–63

Psychopathology

Recognition of Hallucinations: A New Multidimensional Model and Methodology

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Abstract

Both from the clinical and mathematical perspectives, symptom recognition has received less attention than disease recognition. To redress this balance, it is imperative that multidimensional models are constructed for each and all mental symptoms. This paper offers one such model for 'hallucinations', and a set of prototypical data comparing the performance of pattern recognition techniques (cluster and discriminant analyses) and neural networks (Kohonen and backpropagation). It is concluded that multidimensional models are less wasteful of information than (current) categorial ones. Because of this and of the fact that symptom structure is likely to be 'isomorphic' with the brain region where the corresponding signal is generated, it is recommended that multidimensional models are preferentially used in neurobiological research.

In spite of important advances in the nosology and neurobiology of psychiatric disorders, *symptom recognition* remains under-researched. This partially results from the fact that little is known about the nature and structure of individual symptoms [1] and the cognitive rules governing their identification [2]. It is also the case that computerized (diagnostic) algorithmic approaches have been applied less to symptoms than to diseases. This preferential treatment has been encouraged by diagnostic systems such as DSM-IV [3] and ICD-10 [4] which assume that symptom recognition is unproblematic, transparent and *independent* of disease recognition. However, important evidence has been recently offered that this assumption is unwarranted [5].

Because the term 'mental symptom' names a collection of heterogeneous clinical phenomena (each showing different conceptual, semantic and dimensional structure) [2], it is likely that clinicians use a variety of recognition strategies. This task is compounded further by the fact that many symptoms show *ambiguous* presentation (i.e. descriptions by patients do not include *all definitional criteria*) [2]. This state of symptom 'incompleteness' often goes unnoticed because clinicians disambiguate symptom presentation by means of strategies such as educated guessing and the deft use of 'constancy effects' [6]. This 'rounding-off' activity may be acceptable for everyday clinical practice, but is a serious problem for neurobiological research as it threatens the reliability and validity of nosological diagnosis.

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The earliest stage in the study of symptom recognition is the creation of models that may reliably ascertain structural differences between mental symptoms. Dimensional information thus collected can then be analysed in a number of ways. For example, 'pattern recognition' statistics (e.g. cluster [7] and principal-component analysis [8]) detect regularities and structures in data sets and classify observations according to dimensions or theoretical coefficients. These techniques, however, are unable to learn and improve their recognition rate. Neural networks, on the other hand, offer an alternative inspired in the organisation of neural tissues and include models based on parallel processing (and handle data in a manner analogous to biological systems) [9, 10].

This paper describes an 11-dimensional model for 'auditory hallucinations' (here defined as utterances reporting auditory images [11]) and compares the performance of the methodologies listed above. To circumvent the problem of symptom 'incompleteness', prototypical data were generated with which to test the model and calibrate the methodology. It is concluded that both model and methodology are now ready for use with empirical data; indeed, such work is now ongoing in our group.

Methods and Data

Data were generated thus:

(a) A visual-analogue (observer-rated) scale was used including 11 putative dimensions of the symptom 'hallucination': insight, vividness, complexity, localization, intensity, control, constancy, bizarreness, situation specificity, attribution, and relationship to delusions. These *phenomenological dimensions* (definitions are included in the *appendix*) enshrine features and characteristics of the symptom hallucination that clinicians may collect by interview (the scale was constructed by the present researchers to collect information from patients with hallucinations; data are to be reported elsewhere).

(b) One of the authors (GEB, specialized in the descriptive psychopathology of hallucinations) proceeded to generate *prototypical data* for 49 *ideal patients* belonging to seven clinical categories: schizophrenia, delirium, drug intoxication, obsessive disorder (it is recognized in Europe that obsessive-compulsive disorder may include 'hallucinatory' experiences *similar* to those present in other conditions), major depression, mania, and dissociative disorder. To secure adequate variance and reduce halo effects and intra-group similarities, the *ratings were made at random and on successive days*. The clinical features to create the prototypes for each clinical category were obtained from careful reading of the empirical literature and personal experience. For example, for *schizophrenia*, a combination was used of the descriptions provided by DSM-IV [3, p. 275] and ICD-10 [4, p. 87].

Analysis

Pattern Recognition

Analysis was carried out by means of the Statistical Package for the Social Sciences, PC-V3. Cluster analysis and discriminant analysis were used to identify segregation patterns.

Neural Networks

Neural network processing was carried out by means of two models: Kohonen self-organizing feature map [12, 13], which is an unsupervised system to classify data into natural groupings according to similarities, and a backpropagation network which operates on pre-set diagnostic categories and learns by 'error propagation' (that is, 'learns' from examples to match 'feature profiles' (inputs) with diagnoses (outputs) through a process whereby, as the network confronts each new example, the strength of connections between inputs and outputs is gradually altered [9].

Kohonen Self-Organizing Feature Map. The Kohonen network was implemented as specified in Eberhart and Dobbins [14]. This network includes two layers in which each unit of the input layer is connected with all the units of the output layer. Units in the output layer are, in turn, connected to one another. Connections to neighbouring units are *excitatory*, whereas connections to units further away are *inhibitory*. This arrangement is similar to neurons having an 'on-centre/off-surround' receptive field. Connection weights between input and output layers are initially *random*. Learning takes place by presenting the input layer with activation values proportional to a vector corresponding to the input data. Activation values, multiplied by the connection weights will then affect the output layer. Because of the 'lateral inhibition connections', one of the units in the output layer becomes increasingly activated and others suppressed. Such a unit is identified as the *winning* unit. Connection weights between the winning unit and the input layer are thus modified: each connection currently active (i.e. receiving a positive input) is enhanced, and inactive connections are weakened. This procedure was repeated for the entire data set. The input data exciting the same output unit are 'categorized' as one group by the network.

Backpropagation Network. The backpropagation network was implemented with the software *Brainmaker* [15]. A three-layered network was used. Learning took place when the input layer was presented with a data vector and the output layer with a target response. The activation in the input layer was multiplied by the (initially random) connection weights to provide input to a middle, *hidden layer*. The activation of the hidden layer, in turn, was multiplied by a further set of connection weights to compute an output. The activation pattern in the output layer was then compared with a desired output pattern. Differences between the two were transformed into an error signal which was 'backpropagated' to the weights of the input and hidden layers. Modification in the weights took place so that outputs ever closer to the desired pattern were produced.

Results

Cluster Analysis

Hierarchical cluster analyses for 5 and 9 (9 was chosen to attempt replication of the groups generated by the self-organizing network – see below) clusters were implemented. For the 5-cluster solution, obsessive-compulsive disorder cases were segregated into one cluster; schizophrenia, depression and manic cases formed another cluster; organic (delirium and drug-induced psychosis) cases formed another cluster, and most cases of 'dissociation' were grouped into a fourth cluster (a fifth cluster included only one member) (fig. 1).

In the 9-cluster solution, obsessive-compulsive disorders segregated into one cluster; most of the organic cases (delirium and drug-induced psychoses) formed a second cluster; a third cluster consisted of schizophrenia and depression; cases of dissociation constituted a fourth cluster; the fifth included most of the manic cases, but also had examples from other diagnoses; the other four clusters consisted of only one or two members (fig. 2).

Discriminant Analysis

Discriminant analysis was performed 7 times on a rotational basis (each taking 42 cases and leaving out 7 for testing) (fig. 3). The discriminant functions misclassified as follows: schizophrenia (2), delirium (4), drug-induced psychoses (3), depression (0), mania (2), obsessive disorder (1), and dissociation (0).

Kohonen Self-Organizing Feature Map

The data set (without indication of diagnosis) was presented to a Kohonen network, and two resolutions (9 and 25 output units) were specified. The 9-unit network generated four main clusters: one included 'delirium' and 'drug-induced psychosis', a

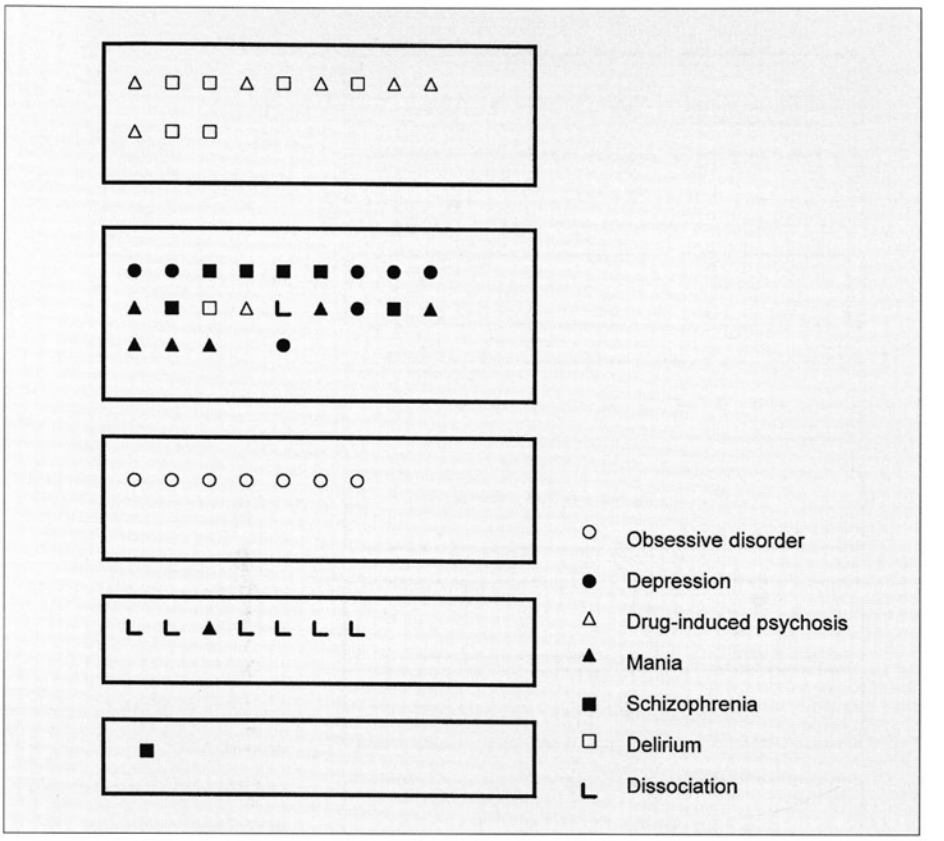

Fig. 1. Cluster analysis (5 clusters) classification of cases.

second 'obsessive and dissociative disorder', a third 'mania', and a fourth cases of 'schizophrenia' and 'depression' (fig. 4). These clusters intuitively corresponded to organic, neurotic, manic, and schizophrenia depression patterns, respectively.

The 25-unit network generated five main clusters: one with organic cases ('delirium' and 'drug-induced psychosis'), the second schizophrenia and depression, the third mania, the fourth dissociations, and the fifth obsessive disorder (fig. 5). It can be concluded that the Kohonen network offers a good classification (with some overlap) of data into organic, 'schizophrenia-depression', mania, 'dissociation', and 'obsessive disorder'.

Backpropagation

It was possible to achieve 100% accurate classification after about 15,000 training trials. Seven rotational training trials were also conducted using 6 of the 7 sets of observations (the non-included set of observations was used to test the network). Results are summarized in figure 6. Obsessive disorder cases were classified 100%. Misclassified cases were as follows: dissociation (1), mania (2), depression (4), drug-induced psychosis (3), delirium (4), and schizophrenia (2). Schizophrenia and mania cases overlapped as did delirium and drug-induced psychosis.

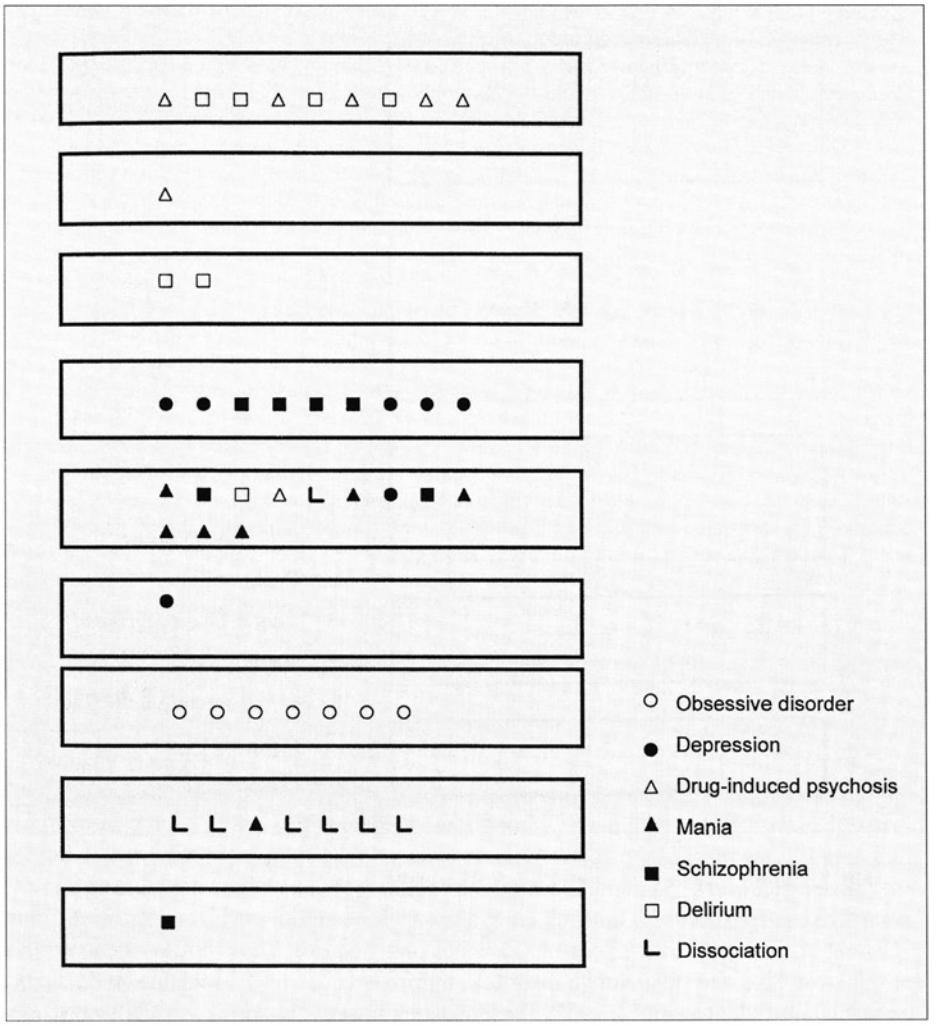

Fig. 2. Cluster analysis (9 clusters) classification of cases.

Discussion

Results show that different methods of analysis generated similar patterns. This suggests that the number and type of dimensions chosen to characterize the symptom (auditory hallucinations) might have been about right. These patterns were obsessive disorder, dissociation, manic, organic, and schizophrenia depression groups.

Comparison between Cluster Analysis and Kohonen Approach

One purpose of data analysis is to discover patterns and categories in data sets and use these to classify new observations. Both Kohonen network and cluster analysis explore inherent regularities in data sets without using information about diagnostic

Discriminant Function Classification							
Actual diagnosis	Schizophr	Delirium	Drug	Depress	Mania	Ocd	Dissoc
Schizophr	❑❑❑❑❑					❑❑	
Delirium		❑❑❑	❑❑❑❑				
Drug		❑❑	❑❑❑❑		❑		
Depress				❑❑❑❑ ❑❑❑			
Mania	❑			❑	❑❑❑❑ ❑		
Ocd	❑					❑❑❑❑ ❑❑	
Dissoc							❑❑❑❑ ❑❑❑

Fig. 3. Classification of cases by discriminant function analysis. Schizophr = schizophrenia; Drug = drug-induced psychosis; Depress = depression, Ocd = obsessive-compulsive disorder; Dissoc = dissociation.

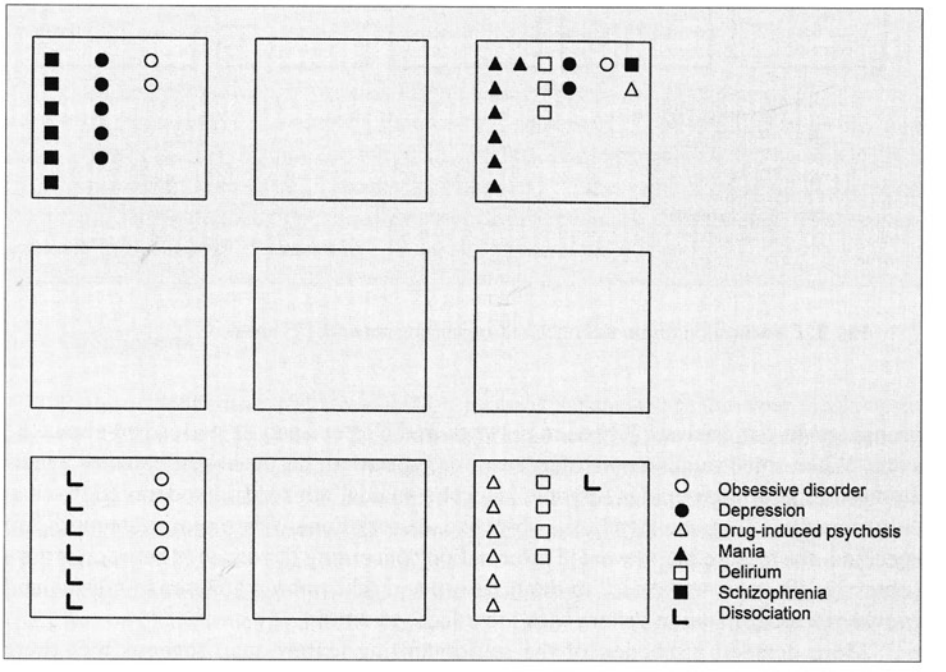

Fig. 4. Classification by Kohonen self-organizing network (9 units).

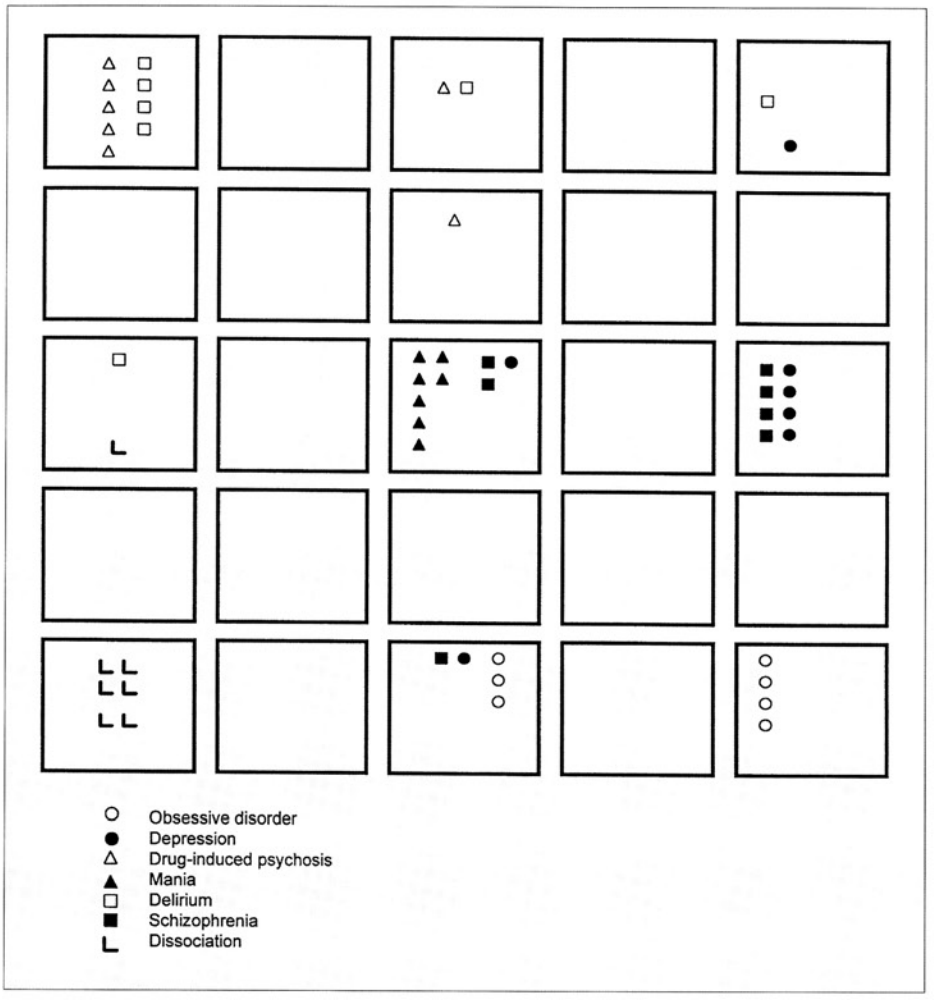

Fig. 5. Classification result: Kohonen self-organizing network (25 units).

groupings. In our analysis, Kohonen network and cluster analysis performed about the same. When small numbers of categories were specified, the Kohonen network generated more natural groupings (organic, neurotic, mania, schizophrenia depression) than cluster analysis (organic, psychotic, obsessive, dissociation). When more categories are specified, the feature map revealed information concerning the distance between groups (obsessive disorder was closer to dissociation, and schizophrenia closer to mania) and provided a categorisation system with some face validity.

More detailed inspection of the self-organizing feature map suggests that there may be a hierarchical organization of groupings: along the vertical dimension, the network produced three levels corresponding to organic, psychotic and neurotic conditions (fig. 5). Along the horizontal dimension (within each level), further groups can be noticed: dissociation and obsession disorder (neurotic level), mania and schizophrenia-de-

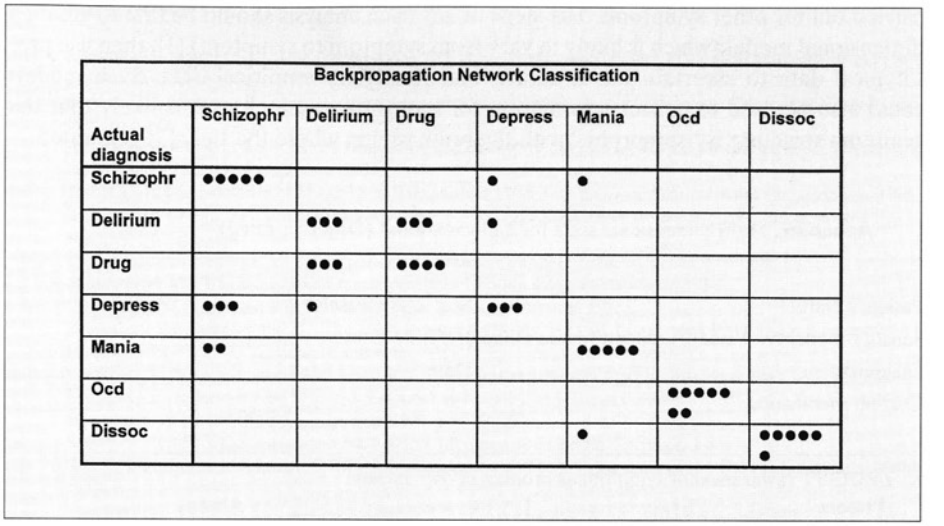

Fig. 6. Classification of cases by a backpropagation network. Abbreviations as in figure 3.

pression (psychotic level), and at the top level organic states, cannot be segregated. This extra representational capability may be related to the two-dimensional nature of the feature map, as compared with the one-dimensional nature of cluster analysis.

Comparison between Discriminant Function Analysis and Backpropagation

Backpropagation and discriminant analysis seek to discover classification rules and behaved in a similar fashion in our analysis. For example, both failed to distinguish between delirium and drug-induced psychosis and at the same time achieved a good classification for dissociation and obsession disorder. Lastly, discriminant analysis was superior in the case of depression.

Conclusions

Pattern recognition and classification tools of various types are now available to explore multidimensional data. Beyond traditional multivariate statistics, neural networks provide tools which may be closer to human cognitive processes. This paper shows how such techniques can be applied to a set of prototypical data for auditory hallucinations collected on the basis of a dimensional model. Multi-feature analysis uncovered patterns which are clinically plausible and may have diagnostic significance. Such techniques may also be used to explore the mental representation of psychiatric symptoms by clinicians, which could have crucial importance in the process of symptom formation [2].

It can be concluded that comparison between multivariate methods and neural networks validates the latter. The results reported in this paper also validate the use of dimensional structures for symptoms (e.g. auditory hallucinations) some of which may be analogous to those used by clinicians. It is suggested here that similar analysis must be

carried out for other symptoms. The steps of any such analysis should be first to create a dimensional model (which is likely to vary from symptom to symptom) [1], then use prototypical data to ascertain the structure, and finally try empirical data. Such models could also be used to collect information for biological research as it is likely that the symptom structure is 'isomorphic' with the brain region where the signal is generated.

Appendix. Multi-dimensional scale for hallucinations* (Observer-rated)

Patient's Name: _____ Sex: male/female _____ Age: _____

Sensory-modality: Visual/Auditory/Tactile/Olfactory/Taste/Other: _____

Diagnosis: _____ Date: _____

Current medication: _____

1. *INSIGHT* (awareness of symptom as product of own mind)
   Present ├----------┼----------┤ Absent
2. *VIVIDNESS* (sharpness and fullness of detail with which the hallucination is perceived)
   Vague ├----------┼----------┤ Vivid
3. *COMPLEXITY* (richness in number of detail and 'component parts' of hallucination)
   Simple ├----------┼----------┤ Formed
4. LOCALIZATION (attribution of spatial origin)
   Internal ├----------┼----------┤ External
5. *INTENSITY* (perceived 'severity' of symptom)
   Low ├----------┼----------┤ High
6. *CONTROL* (extent under voluntary control)
   Full ├----------┼----------┤ Nil
7. *CONSTANCY* (variability in content from time to time)
   Shifting ├----------┼----------┤ Fixed
8. *BIZARRENESS* (similarity to normal perception)
   Nonbizarre ├----------┼----------┤ Bizarre
9. *SITUATION* (restriction to specific places)
   Specific ├----------┼----------┤ Non-specific
10. *ATTRIBUTION* (whether patient attributes hallucination to specific cause or event)
    Focused ├----------┼----------┤ Non-specific
11. *RELATIONSHIP TO DELUSIONS* (extent of integration with any concomitant delusion)
    Direct link ├----------┼----------┤ No link

* If multiple, complete one form per hallucination. Enter your answer as short vertical line on each visual analogue scale.

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