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REVIEWS

The Problem of Segmental Description of Human Electroencephalogram

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Abstract—A critical review of the principal strategies of the EEG description as a piecewise stationary process is given. Achievements, problems, and prospects of parametric and nonparametric strategies of the EEG segment structure assessment are discussed on the basis of the literature and the author's data. Among them, attention is directed to the adequacy of the EEG segmentation based on the autoregression models or on the previous fragmentation of EEG realization in pieces of fixed duration, to the relative value of EEG segmentation on different time scales, and to the spatiotemporal integration of local segmental EEG descriptions. A possibility of the hierarchical segmental EEG descriptions on different time scales and frequency ranges is discussed. It is concluded that the set of modern strategies of the segmental EEG descriptions is, on the whole, sufficient for comprehensive exploration of the EEG process in terms of its piecewise stationary organization.

A quarter of a century after Hans Berger had demonstrated the first recordings of electrical activity of the human brain, the rigorous qualitative estimation of the EEG signal raised the legitimate question of its statistical nature. Norbert Wiener proposed to consider the EEG as a stochastic signal by analogy with the output characteristics of any complex system [1]. It was thought that the principal regularities of the dynamics of the total EEG signal could be studied on the basis of its probability-statistical estimations irrespective of the real biophysical origin of cortical electrical processes [2]. Thus, a considerable body of work appeared concerning the stochastic properties of the EEG signal (for a review see [3]). The main conclusion is that the EEG may actually be approximated by the basic normal, ergodic, Gaussian, *etc.*, stochastic criteria only at rather short realizations, usually not longer than 10-20 s. This is explained by the finding that the EEG turned out to be an extremely nonstationary process. The variability of power of the main spectral EEG components, e.g., for successive short-term (5-10 s) segments, reached 50-100% [4].

Obviously, the routine statistical characteristics (including the spectral-correlational ones) are applicable to the EEG signal only after its prior segmentation into relatively stationary intervals. This, in turn, necessitated development the detection techniques of the so-called quasi-stationary segments of the EEG signal. The first positive findings in this line not only pointed the way for more correct estimation of the EEG signal statistical properties but, more importantly, approached the principally novel understanding of the EEG organization as a piecewise stationary process [5].

The conceptual problems of the structural approach to the EEG analysis were reviewed by us earlier [3]. In the present paper, we discuss the achievements, problems, and prospects of EEG signal segmentation in itself.

1. EEG AS A NONSTATIONARY STOCHASTIC PROCESS

The EEG nonstationarity is usually expressed as the short-term paroxysms (spikes, spike-waves, and K-complexes) or successively alternating longer shifts in the EEG parameters [6]. As a rule, phasic paroxysmal EEG phenomena are visually identified by researchers without question, while the detection of tonically stabilized EEG segments demands some theoretical justification.

In the limiting case, when the number of samplings and the number of realizations of each sampling tend to infinity, the procedure of signal segmentation into stationary fragments should produce an unambiguous solution. It is sufficient to compare the distributions and variances in an ensemble of each successive sampling. The presence of significant difference between the statistics at a certain comparison step would be indicative of the break of stationarity in a given point in the narrow sense of this term [7]. Successive comparisons may produce the maximally precise estimation of sizes and time positions of quasi-stationary fragments in the tested EEG recording.

Taking into account that, universally, only one realization of a random process is practically available, one can estimate its statistics only at the set of successive samplings on the assumption admissible for the EEG signal that it is ergodic [8, 9]. In this case, the stationarity of the process may be taken only in a wide sense of this term [7]. However, the estimation of the EEG statistical properties is possible only on a finite time interval. This interval may be shortened by increasing the number of samplings per unit of time due to higher digitalization frequency of a continuous process only to a certain limit, i.e., up to the moment when the neighboring counts become strongly correlated. It is this condition that limits the extrapolation of the theoretical definition of stationarity to the real processes in a wide sense. The notion of quasi-stationarity, which should be solely used in description of real physical processes, was introduced in order to stress the understanding of the confined assessments of stationarity. In terms of quasi-stationarity, the results of the EEG signal segmentation depend on some merely experimental conditions: the duration of the assessed EEG recording, size of the minimally acceptable EEG fragment tested for station arity, as well as on the choice of the EEG estimation parameters and the threshold criteria. It is apparent that, for the finite small-sized samples, all these conditions can be defined empirically and depend on subjective choice of researchers.

For the routine EEG traditionally recorded in the frequency range of 1-30 Hz the lower and upper limits of the quantization rate are 60 and 200 **Hz,** respectively. Accordingly, at the sampling rate of 100 counts per sec ond, which is necessary for a reasonable statistical esti mation of the EEG signal, the discreteness of the quasi-stationary description of a single-channel EEG cannot be more than 1-2 s. It seems appropriate that, in the pioneer work of McEwen [8] devoted to the analysis of EEG stationarity, practically all the EEG fragments of 2-4 s in duration turned to be stationary. In further EEG fragmentation, the statistical estimation of such short segments would clearly fail and the question of their stationarity would be senseless.

2. FIXED-INTERVAL SEGMENTATION OF THE EEG

In principle, if the duration of the minimal stationary interval is not less than 2 s [8], the procedure of the EEG signal segmentation into quasi-stationary fragments would consist of four steps. At the first stage, the EEG recording is predivided into equal elementary segments 2 s in size. Then, each segment is provided with a statistical description consisting of a certain set of characteristics, e.g., spectral estimations. At the third stage, the elementary EEG segments are classified and named according to their characteristics by one of the multivariate statistical procedures. Finally, the bound arises between the like segments are erased. Thus, the EEG recording transforms into a series of segments within which the EEG parameters remain relatively constant. Each such quasi-stationary segment would be distinguished by its specific duration and typological characteristics. If the number of segment classes in the real EEG is not very high, the idea of piecewise station ary organization of the EEG will offer clear-cut advantages over the alternative primary concept of the EEG as a continuous process.

This exact approach, with the previously fixed-interval EEG segmentation, was used in the first works concerned with EEG segmentation [10-13]. The number of typical EEG segments really turned out to be restricted, not more than 15-35 for different EEGs [11-
13], and the duration of the majority of segments did not exceed 4 s, which clearly testified to the piecewise EEG organization. However, the fixed-interval EEG segmentation had a material disadvantage in that a part of the segments should necessary fall on joints between the stationary EEG segments. This led to the appearance of the whole cluster of EEG fragments, which contained transition processes and, hence, were not strictly stationary segments. Moreover, interfaces between stationary segments were defined by this means rather roughly within the accuracy of no less than the duration of the fixed interval.

To avoid such errors in search for quasi-stationary EEG fragments, it was necessary to develop such a segmentation procedure which would include the successive exhaustion of possible arrangements of interseg-mental boundaries with the choice of the optimal variant. Just this technique, called adaptive segmentation, is applied in one or another form in the majority of modern methods of the automatic detection of quasi-stationary segments in the EEG [10]. Let us consider the main approaches to the adaptive segmentation of the EEG signal.

3. PARAMETRIC SEGMENTATION OF THE EEG

Generally, the procedure of adaptive segmentation would be based on the estimation of the extent of simi larity of the initial EEG fixed interval with the EEG fragment of the same duration viewed through the time window running along the EEG recording. Apparently, the monitored similarity will sharply decrease when this window runs over the boundary. This is a formal indication of the transition to the following segment.

The techniques which predict the next EEG counts by the results of estimation of a series of prior counts appear to be most adequate. The moment of discor dance between predicted and real current EEG counts would be a very sufficient indication of a local nonsta-tionarity.

3.1. Parametric EEG Segmentation Based on Autoregressive Models

The methods of predicting a time series are based on an assumption that their stochastic character is largely confined by certain dynamic regularities.

In this case, if it is possible to find the mathematical models fitting these regularities, a number of further successive EEG counts will be really predicted with a certain accuracy. Beyond the stationary segment with matched model parameters, the prediction error will sharply increase, thus signaling the termination of the foregoing segment and beginning of the next one. For the initial portion of this next segment, new model parameters may be calculated, and then search for the boundary with the next segment may be continued. Thus, the parameters of the EEG mathematical model become the key element in search for segment-to-segment transitions. Therefore, a correct choice of the EEG model is very important.

Initially, in the framework of this idea, the coefficients of Kalman filter were used for the model EEG description [14]. The remarkable feature of this specific procedure was that behavior of each of ten filtering coefficients was taken into account to identify the moment of discordance between the real EEG and the model, rather than a certain weighted mean index. A sharp change in only one of these coefficients gave sufficient reason to make a decision about the intersegmental boundary [14] which substantially increased the sensitivity of the method to detect segment-to-segment transitions. It was necessary to introduce a measure of synchronous changes in the filtering coefficients to obtain the principally novel description of the EEG signal in terms of its inherent frequency consistency. How ever, 20 years or more had to pass before the experi mental realization of this aspect of the structural EEG organization [3, 15].

The most advanced method of EEG simulation is linear extrapolation, developed by N. Wiener as early as 1942 as a supplement for autoregression analysis (see [5]) and put forward for the first time for EEG testing in the late 1960s (for a review see [16]). In the frame work of the autoregression model, the next EEG count can be calculated with a certain error as a sum of several previous counts taken with definite coefficients. The principle procedures of the EEG adaptive segmentation based on the autoregressive models of a rather low order were primarily developed by Bodenstein and Praetorius [5] and then in various modifications were successfully used by other authors [10, 17-20].

The set of the type segments revealed in the quoted papers was even more restricted than after the fixed-interval segmentation. According to these authors, the duration of a quasi-stationary segment varied, mainly, from 1-2 to 20 s, and the estimated number of segment types was from 6 to 50 [21, 22]. Application of multiple regression analysis to the EEG with a calculation of the contribution of each of the several model parameters made the segmentation procedure more correct [23]. Using this technique, the authors could detect the EEG segments associated with certain cognitive operations. It was also shown in this paper that the duration of the majority of quasi-stationary EEG segments was 2-10 s [23]. Despite the careful algorithmic working up, the methods of EEG segmentation based on the regression analysis ultimately operate with the empirically chosen threshold criteria. This condition substantially restricts the abilities of scientists not only in comparison of interindividual data but in segmentation of EEGs from different derivations in the same subject.

In addition to the inevitable empirical predetermination, the threshold criterion for EEG segmentation in the techniques under consideration has a more serious disadvantage, i.e., the absence of adaptability to changing parameters of the EEG process. In this connection, for the mathematical EEG description, it would be possible to apply the autoregressive model with the time-varying parameters tested in speech recognition [24]. Such attempts have also been made relative to EEG [25, 26]. However, the absence of a priori determined low of variations of parameters with time demanded a construction of an additional model, which in the general case should result in accumulation of greater errors.

3.2. Time Scaling in EEG Segmentation

The listed methods of EEG adaptive segmentation on the basis of autoregressive modeling used the same technique of running comparison of the EEG parameters on the referent and tested segments, which made it possible to view the EEG structure only through a fixed time window. This determined a single mode of time scaling of EEG heterogeneities and, thus, prevented the total insight into the EEG structure, because only relative sizes of neighbouring peaks can be seen in the view-finder of a camera, while the character of the mountain chain relief, as a whole, remains beyond the visual field. However, it is quite possible that the larger EEG transformations superpose on the local segmentation of the EEG process and such transformations make up a segment description of a signal on a larger time scale.

The regressive EEG modeling was also used in the work [27]. The authors studied the EEG a component on the assumption that the dynamics of a activity on a quasi-stationary segment can be approximated by a simple linear time regression of $y = at + b$ type, where y is the a rhythm power counted at the moment t from the beginning of the tested EEG interval. In this case, the problem of finding a boundary between two quasi-stationary segments was reduced to a developed statistical procedure of comparison between coefficients a and b for two linear regressions at both sides of the pre summed intersegmental boundary. The method was sufficient enough for EEG determination of the moment of the beginning of action of the neurotropic drugs and was developed just for this purpose [27].

However, in our opinion, the point of this study was that the authors approached the solution of the problem of the EEG entire structural description. Actually, the regressive models yere constructed to the left and to the right of the presumable interface between EEG segments. Since the position of this interface is not known in advance, two regressions were compared repeatedly for the left and right halves of the EEG recording relative to each successive EEG count. The moment of the maximal statistically significant difference between two regressions indicated the interface between the largest EEG segments from the viewpoint of macrode-scription of this signal. If a similar procedure was then carried out for each of the two detected segments separately, the segments corresponding to more detailed EEG analysis would be obtained. Further repetitions of such a procedure should lead to the EEG segment microdescription. Thus, there were prospects for presentation of the structural EEG organization as a hierarchy of segmental descriptions on different time scales. The authors themselves had not seen these prospects, and therefore their method turned out to be useful for revealing only one most pronounced intersegmental boundary in the whole EEG recording [27].

The last limitation was eliminated, to a certain extent, in the work [28] where the tested EEG counts were taken into consideration in searching for intersegmental boundaries. On the basis of Bayesovian approach, the authors calculated the most probable arrangement of the moments of multiple interfaces between segments over the whole length of the EEG recording. Combining this technique with autoregressive modeling, the authors gained a rather accurate EEG fragmentation into quasi-stationary segments [28]. By changing one of the segmentation algorithm parameters, it was possible to restrict the number of calculated segment-to segment interfaces in the EEG recording, which properly enabled segmentation to be carried out with more or less time resolution testing the hierarchy of subsegment relations on different time scales. However, the authors did not appraise this aspect of the EEG segmentation technique. Moreover, the complexity of calculations mentioned by the authors themselves makes this approach acceptable only for analysis of very short (not longer than several seconds) EEG fragments [28].

On the whole, the discussed set of methods of the parametric adaptive EEG segmentation, in principle, makes it possible to adequately describe the piecewise stationary structure of the EEG signal. However, all these methods, primarily directed to a search for quasi-stationary fragments, by definition, may be applied only for stationary processes. Actually, the so-called parametric methods are based on the previous construc tion of a mathematical model (e.g., the autoregressive one) in the referent window on the initial EEG segment. Apparently, sufficiently accurate simulation of the pro cess can be obtained only on the stationary interval. The longer the interval, the finer characteristics of the process can be reflected in the model. However, the longer the analyzed fragment of the real EEG, the more probable the incidence of heterogeneities within this fragment [8 *et al.]*. If the model is constructed on a very short segment, it will be very rough and it cannot be expected that segmentation on the basis of the parameters of this model would be of high quality.

Thus, the parametric methods of search for quasi-stationary EEG segments carry a rather strong contra diction: segmentation into stationary fragments is impossible without construction of an adequate mathematical model, however, such a model cannot be con structed without previous segmentation.

Moreover, since the summary EEG is a highly composite and substantially nonlinear process [29, 30], the development of a rigorous mathematical model, which
would adequately reflect the EEG intrinsic nature, is hardly probable [16]. This is why the parameters of even the well-fitted EEG models [16, 31], not reflecting the essence of the

processes underlying the EEG [2, 19], make the EEG signal segmentation procedure substantially rough in any case.
Consequently, the development of nonparametric EEG segmentation methods is undoubtedly of interest. Application of such methods do not require previous testing for stationarity, since they are not associated with construction of mathematical models of the process under study but are based on its real statistical characteristics.

4. NONPARAMETRIC APPROACHES TO DESCRIPTION OF PIECEWISE STATIONARY EEG STRUCTURE

Study [32] is an example of one of the first nonparametric approaches to EEG segmentation. The authors also used the technique of the running window, but for comparison of the referent and tested EEG fragments, they applied specific estimations of the autocorrelation functions rather than the parameters of the autoregressive model. The integral index of the relative amplitude and shape discrepancy between the autocorrelation functions of the referent and tested EEG fragments served as a nonparametric test of difference between the fragments [32].
The later modification of these technique, which used the calculation of the normalized sum of the squares of differences of five autocorrelation coefficients as a measure for spectral dissimilarity between the referent and tested EEG fragments, successfully passed the clinical evaluation test [22].
Indices of spectral expansion also belong to the non parametric estimations of time series. The possibility of application of the Fast Fourier Transform (FFT) as a nonparametric procedure of segmentation with the previously fixed-interval EEG fragmentation was discussed above. The main disadvantage of this technique, i.e., the lack of adaptability to intersegmental bound aries, was also mentioned. It would be natural to apply the FFT in a running time window with subsequent comparison of the obtained spectral estimations with similar characteristics of the referent window, like in the adaptive segmentation procedure by means of autoregressive modeling. However, the 100% variance of the single spectral estimations [33] in the absence of adequate correction algorithms for these estimations usually prevents such attempts. Nevertheless, the only work in this direction [34] did demonstrate the prospects for such an approach. In this study, the author used the maximal ratio between the narrow-band spectral estimations as a measure of EEG spectral difference in two jointly running windows [34], which made the method sufficiently sensitive to the EEG transition processes. However, the lack of the analytical justification of the threshold conditions, characteristic also of the other techniques of adaptive segmentation, still remained a problem for detection of intersegmental boundaries. In study [35], the assessment of inhomogeneity of spectral estimations of two EEG segments was carried out on the basis of the specially developed test with distribution parameters determined from statistic modeling. This allowed the author to justify the choice of the thresholds for detection of spectral differences between the tested EEG segments. However, this work was not developed in the direction of EEG segmentation.

Despite the first successful attempts at the nonparametric approach to EEG segmentation, its further advance was restricted by the apparent condition that, in each specific case, a statistical EEG characteristic most efficient for the EEG segment structure determination (expected value, variance, other statistical moments *etc.)* was unknown beforehand. Moreover, the development of a specific technique of quasi-stationary segmentation was necessary for each of these statistics;
therefore, the task of nonparametric EEG segmentation would consist in exhaustion of a rather large number of possible solutions.

The original technology of the nonparametric EEG segmentation was developed on the basis of the theory of the so-called analysis of sharp changes or heterogeneities in time series with a clear-cut piecewise stationary structure [36]. Heterogeneities determined in such a way are, in fact, the markers of the boundaries between quasi-stationary fragments. The theoretical development of this approach showed that the problem of detection of changes in any probability characteristic of a given stochastic process may be reduced to the same algorithm of detection of the expectation changes applied to different modifications of the initial time series. Each modification or diagnostic sequence can emphasize certain statistical features of the initial process. For example, the correlation transformation of the initial time series will display dynamic inconstancy of this process variance.

A special statistical procedure for heterogeneity detection was developed during adaptation of this methodology to the problem of EEG segmentation on the basis of the generalized variant of Kholmogorov-Smimov statistics [37-39]. In different forms, these statistics had been already applied for EEG estimation [8,40]. Using these tests in the EEG segmentation technique, with regard for their probability distributions obtained in a numerical experiment in the EEG-like curves made it possible for the first time to not only detect the intersegmental boundaries but estimate the confidence intervals of their positions within the tested EEG fragment [37-39]. During adaptation of techniques of heterogeneity detection for EEG segmentation, it was shown that it is expedient to use the normalized EEG autocorrelation function as a diagnostic sequence [38,39].

The specific algorithm of search for EEG heteroge neities was also intended for estimation of the whole hierarchy of the EEG segment descriptions on the different time scales. First, the window-free comparison system of EEG estimations was taken, which made it possible to account for the whole recording in search for heterogeneities: expectation estimations of the sig nal or its diagnostic sequence were compared between two portions of the EEG recording to the left and to the right of the dividing point mnning along the curve, as was done in the study [27]. Second, for more accurate calculation of the threshold criterion, heterogeneity fix ation was carried out stepwise: the most powerful het erogeneity, which marked the boundary between the two largest segments, was detected first. Afterwards, the procedure was repeated, however, only for more homogeneous parts of the recording on both sides of the first heterogeneity. More homogeneous segments were formed on the sides of heterogeneities of the second level, which, in turn, were subjected to point-to-point scanning and so on, up to the moment when the number of counts of the current EEG segment reached the threshold of statistically stable expectancy estimation. This algorithm of nonparametric EEG segmentation is described in more detail in special papers [38, 39,41].

Since in any technique of search for the moments of phasic EEG changes its results can be obtained in probability estimations, the substantial advantage of the novel approach [36, 38, 39] is a possibility to explicitly specify the probability of a false alarm (detection of the absent signal) and false tranquility (omission of the present signal) in detecting the segment boundaries. In addition to the possibility of flexible optimization of the task of detection of segment boundaries from the exper imenter's viewpoint, this allows him to tune the proce dure for the operation on different time scales. For instance, increasing the threshold level of false alarms makes it possible to tune for detection of the most pro nounced segment-to-segment transitions and estimate only the macroscopic EEG segmental structure. Decreasing the threshold of "false alarms" leads to a more detailed microscopic pattern of the EEG segmen tal organization.

Thus, a scientist has the possibility of repeated scanning of the EEG segment signal under different thresh old conditions, which finally allows him to reconstruct the whole hierarchy of the EEG segmental descriptions on different time scales. Application of the novel technique of nonparametric EEG segmentation in the practice of neurophysiological investigation demonstrated its sufficiently high sensitivity for estimating the dynamics of the EEG structural changes associated with cognitive processes [41-43]. With the help of this technique, it was shown that spontaneous EEG consists of quasi-stationary segments, the duration of the majority of which is less than 5-6 s [43, 44], but the specific proportions of stationary EEG segments of different duration strongly vary between different cortical areas [42]. The definite difference in the number of heteroge neities per unit of time was also demonstrated by this technique for different sleep stages [44].

5. PROBLEMS OF MEANINGFUL INTERPRETATION OF EEG SEGMENTAL DESCRIPTIONS

The above piecewise stationary structure of the EEG signal demonstrated by many authors turned out to be dependent on the recording area and was modified at changes in the brain functional state. In total, these data testify to indubitable functional significance of the segmental EEG architectonics. In our recent paper [3], we discussed the possible ontological grounds of such structural organization of the cortical bioelectrical field. We note here that, even before the pioneer works on segmentation, the idea about the piecewise organization of the EEG existed, and some researchers even thought that the EEG signal consisted of a limited number of type segments, i.e., a certain ABC of the EEG code [45]. This idea turned to be so attractive that after the appearance of the first evidence concerning the real EEG structure, a number of authoritative scientists came to the conclusion that a syntactic metaphor was the most adequate for the segmental description of the EEG activity [2, 11, 28, 46]. Even some attempts were made to interpret the segment code of the linear EEG by the methods of estimation of matrices of transition probabilities usually used for studying the regularities of Markov's processes [5, 20, 47]. For instance, it was possible to demonstrate for the sets of three segment types that the probabilities of mutual alternation of these segments during the preseizure period substantially differ from the normal state, although such differ ence is practically indiscernible for traditional methods of EEG analysis [47].

The analogous results suggest that the quasi-station ary segments reflect the definite operational acts of ner vous activity. However, the use of segmentation proce dures to the common EEG not always can reveal this correlation due to the composite polyphonic character of the EEG signal. In particular, each frequency EEG component has its own segmental structure [15], which seems to be indicative of the discrete operation of dif ferent morphofunctional brain systems. In this case, it is possible to gain the highest sensitivity of the EEG segmentation techniques to functional changes only by operating with the individual EEG rhythms, e.g., with a activity [43]. The segment flows for each of the EEG frequency components are more or less correlated, depending on the character of the informational brain activity [15], which emphasizes once more the functional significance of the segmental EEG descriptions and their association with the integral mechanisms of brain activity.

The polycorrelational character of the morphofunctional organization of the brain neuronal networks dis covers one more, the spatial, aspect of correlation

between EEG segmental processes. It was reasonable to suggest that segment sequences in different derivations should, to a certain extent, synchronized, forming the stable topological combinations of local segmental EEG descriptions in total [48]. This suggestion was fully justified: the segment-to-segment interfaces in EEG recordings from different derivations turned really to be strongly correlated, which suggested the existence of a specific type of cooperative activity of cortical for mations i.e., operational synchronism [3, 41-43]. Meanwhile, it had already been known long before these studies that the maps of momentary distribution of cortical biopotentials were piecewise stationary themselves [49]. Supposedly, it is just the spatiotemporal coordination between local segmental descriptions, or operational synchronization of the brain structures [41], that forms grounds for the dynamic stabilization of the cortical biopotential field demonstrated by Lehmann [50, 51, *et al.]*.

The interchannel correlation of segmental descriptions, in particular, synchronization of segment-to-segment interfaces, can also be an additional criterion for the adequacy of the applied technique of EEG segmentation. From this viewpoint, it is justified to use even the fixed-interval technique for EEG segmentation with calculation of single spectral estimations of the elementary EEG segments for their subsequent classification [52].

Thus, the whole set of available data suggests that the main operational elements of behavioral and mental activity are originated in the periods of short-term metastable states of the whole brain and its individual subsystems, when the numbers of degrees of freedom of the neuronal networks are maximally decreased [3]. This is why segmental EEG descriptions give certain unique possibility to gain a penetrating insight into the operational dynamics of the nervous activity and to register trajectories of the proper "atoms of thought" [51].

CONCLUSION

The logic of phenomenological description of the EEG signal, on the one hand, and the necessity of its correct statistical estimation, on the other, led researches to the completely novel understanding of the structural EEG organization as a piecewise stationary signal. The potential astronomic multivariativity of the neuronal networks appeared to be far from continuous in time but confined by the dynamics of the short-term local and global metastable brain states. It is possible that just in these short periods of stabilization of activity of the neuronal networks, when the main part of insignificant dynamic parameters are fixed, brain formations interact with each other most precisely on the conditions for the formation of final decisions of functional systems.

Hence, further progress in the meaningful interpretation of EEG phenomena may be apparently associated with the structural analytical approach to studying EEG as a piecewise stationary process. In any case, at present, a set of segmental EEG description is avail able, which is quite sufficient for revealing its piece-wise structure, in addition to traditional characteristics of this process.

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