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METHOD OF ICTAL AND ICTAL FREE DETECTION OF EEG RECORD

Mrs. Pratibha Singh, Gaurav Kapoor
Professor Dept. Of Electronic & Instrumentation Engineering
Institute of Engineering & Technology
DAVV, Indore, Madhya Pradesh, India

Abstract - In recent survey it is found that 1 % of world's population is suffering from neurological anarchy like tumour, stroke, brain injury etc. For this purpose EEG records are used to obtain information from brain and help in examine different mental tasks. This paper compares different earmark extraction methods such as time frequency distribution, Empirical mode decomposition and multivariate empirical mode decomposition which gives different property and measurement obtained from section of different methodology pattern. It should be carefully examine that extracted earmarks should not lose the information it contained. The review on these methods mainly focuses on earmark extraction techniques used in EEG record analysis.

Keywords – *EEG, EMD, IMF*

I. INTRODUCTION

The encephalography has undergone massive progress during 100's of year. The existence of electrical currents in the brain was discovered in 1875 by an English physician Richard Catton. In 1924 Hans Berger, a German neurologist, used ordinary radio equipment to amplify the brain's electrical activity measured on the human scalp. It is a neurological disorder which affects about 1% of world's population [33]. An electroencephalogram (**EEG**) is a medical test to examine the electrical activity of your brain [1]. In this test special sensor i.e. electrodes are attached to your head and to a computer that measures and records the electrical activity of your brain. The computer records your brain's electrical activity on the screen or on paper as wavy lines. It is commonly non-meddling, with the electrodes placed along the scalp, although meddling electrodes are sometimes used in specific purpose. EEG measures voltage variations coming from ionic current within the neurons of the brain. In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a period of time, as recorded from multiple electrodes placed on the scalp. Diagnostic applications generally focus on the spectral content of EEG, that is, the type of neural oscillations popularly called "brain waves" that can be observed in EEG records.

Epileptic seizures [1] are episodes that can vary from precise and nearly undetectable to large period of no. of spikes [2]. In epilepsy, seizures tend to recur, and have no immediate underlying cause while seizures that occur due to a specific cause are not deemed to represent epilepsy. Epilepticictal is a collection of anarchy as the result of brain-injury, stroke, brain tumour and substance use anarchy. Genetic mutations are linked to a small proportion of the disease. These are characterized by recurrent discharge from the cerebral cortex that results in random disturbance of brain working. Epilepsy can often be assured with an electroencephalogram (EEG) but a normal check-up does not rule out the actual situation. As EEG record is very complicated and carries lots of information about brain working. However analysis of these waves for the detection of neurological anarchy and functioning of brains by visual scanning is momentary and imprecise but not actual.

Therefore various parameters are used to diagnose neurological anarchy such parameters are time domain analysis of EEG record, frequency domain analysis [3] and many more. As later on studies shows that the EEG record is a non-stationary process as frequency component of EEG record changes over time. Therefore various time-frequency domain [4], based methods have been introduced to detect seizure epileptic from EEG record. Several time frequency domain methods that are used include the multiwavelet transform [5], the wavelet transform [6], [7], the short time Fourier transform [4] and Wigner-Ville distribution [4]. Now the researchers are focused on the application of empirical mode decomposition to analyse EEG records for the detection of seizure and ictal EEG recordings. The parameters included in this paper is short time Fourier transform, multiwavelet transform, wavelet transform, Wigner–Ville distribution and Empirical mode decomposition and multivariate empirical mode decomposition.

II. METHODOLOGY

The several earmark extraction techniques used for EEG records are generally time frequency domain analysis methods and empirical mode decomposition method. The data sets used in this paper are publically available named as Z, N, O, S and F. which is represent as in fig 1. The different methodologies for EEG record analysis are as follows:

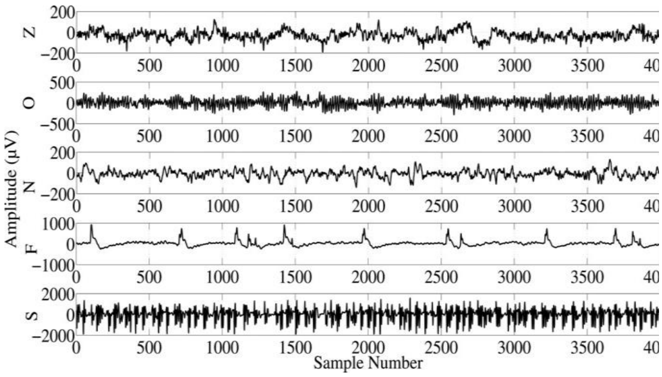

Fig 1. Data set Z, O, N, F and S which are publically available

1.) Time frequency Distribution based methods [4]

In Short Time Fourier Transform(STFT) method[4], the signal 'x(t)' over a time period 't' and the FT is measured for each time 't', where h(t) is a short time window. The difficulty that stft experience is a pact between its window length and frequency verdict. The power spectral density of the signal is appraised by using STFT which represents the energy distribution of the signal over the t- f plane.

$$\text{STFT (t, f)} = \int_{-\infty}^{\infty} x(\tau)h(\tau - t)e^{-if\tau}\, d\tau$$

Unlike STFT, t-f representation of Cohen's class distribution is quadratic in nature, which can be represent as

$$\rho(t,f) = \iiint e^{i2\pi v(u-t)} g(v,r) x^*\left(u - \frac{1}{2}\tau\right) \times x\left(u + \frac{1}{2}\tau\right) e^{-i2\pi f\tau} dv du d\tau$$

In which, t is the time, f is the frequency, x (t) is the signal $x^*(\tau)$ is its complex conjugate and g (v,τ) is arbitrary function called kernel Cross term interference.

After analysis of PSDs of EEG record, it is used to obtain various earmarks. A framework is used as a separation both in time domain which is having some similar sized windows and in frequency domain, where the employed separation divided the frequency in several sub bands that are, on the basis of medical knowledge are 0–2.5 Hz, 2.5–5.5, 5.5–10.5, 10.5– 21.5, and 21.5–43.5 Hz, where specific earmark are expected to be recognized The size of the time windows was defined and it is within the range of windows selected in related works[8]. Every earmark is obtains as –

$$\text{f(i,j)} = \int_{ti}\int_{wj} PSDx(t,w)\,dw dt$$

where PSDx is the psd of x signal appraised from the above mentioned methods and ti is the ith time widow and wj is the jth in frequency window. In this analysis, the previously described dataset [10] (Z,O,N,F,S,) to create several different categorization problems to evaluate our method.

1) In the first problem, two classes are examined: ictal and non-ictal. The undiseased class includes only the Z-type EEG segments while the diseased class includes the S type. Thus, the dataset used for the first categorization problem consists of 200 EEG segments.
2) The next in the line of categorization problem includes three classes: normal, ictal-free, and ictal. The normal class includes the Z-type EEG segments; the ictal-free segments includes the F-type EEG segments and the seizure class includes the S type. In the dataset of the second categorization problem, 300 EEG segments are included.
3) In the third problem, all five segments are used, including all EEG segments from the already described dataset (thus 500 EEG segments).

Now all the TFDs are used to evaluate above problems on the basis of the parameter of selectivity and sensitivity. Thus, for each case, using the data for practicing and the rest for testing, matrices were discovered. The matrix length is defined on the categorization problem: 2 × 2 for the initial allocation problem, 3 × 3 for the second, and 5 × 5 for the third. For each of them, results for each class *i* are presented in terms of sensitivity (SEN_i) & selectivity (SEL). This can be appraised as follows –

$$\text{SEN} = \frac{\#\ of\ patterns\ of\ class\ i\ classified\ in\ class\ i}{total\ \#\ patterns\ in\ class\ i}$$

$$\text{SEL} = \frac{\#of\ patterns\ of\ class\ i\ classified\ in\ class\ i}{total\ \#\ patterns\ classified\ in\ class\ i}$$

The results obtained for each categorization problem by each t-f analysis methods in terms of sensitivity and selectivity are measured as the mean value of the result which involves the categorization of STFT (short time fourier transform), WV (Wigner Ville), SPWV (Smoothed pseudo wigner ville) and BUT (Butterworth) and other tfds methods is obtained in [4]

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2.) Empirical Mode Decomposition

The empirical mode decomposition method is highly preferred as it is a flexible and data dominated process and it does not need any requirements like linearity and signal's stationarity. As the result of this method, the non-linear and non-stationary signal x(t) is decompose into the sum of intrinsic mode function. There are several earmark extraction method are proposed using EMD[18][20], in all these methods firstly the EMD of each signal is classified along with IMF (Intrinsic Mode Function) of each signal then various methodology is used to further classify these signal and to make categorization easy.
EMD algorithm [21] for signal x(t) is given as-

1.) Classify the maxima and minima of the given set of EEG records
2.) By connecting maxima and minima separately, generate upper and lower envelopes.
3.) Appraise sectional average as –

$$a(t) = \frac{[e_m(t)+e_l(t)]}{2}$$

4.) Extract IMF $h_1(t)$ = x(t) – a(t).

Now we applied Hilbert transform on all the IMF obtained by repeating above algorithm. The analytic signal z(t) of any real IMF is defined as -

$$z(t)= A(t)e^{-j\emptyset(t)} \quad (1)$$

Where,
A(t) = signal amplitude

2.1.) by analysis of Amplitude Modulation and Frequency Modulation bandwidth [23]

The EEG record is decomposed by using Empirical mode decomposition and its IMF is obtained by using above algorithm. Then the bandwidth of the signal is an estimate of the expansion in frequency for the time period of records use, this spread in frequency is due to aberration from the average frequency or due to differences in amplitude and blend of the one and the other. To appraise amplitude modulation bandwidth and frequency modulation bandwidth [23], first we appraise the centre frequency of IMF as follows –

$$w = \frac{1}{E}\int \frac{d\emptyset(t)}{dt} A^2(t)dt \quad (2)$$

Where
W = centre frequency
E = energy signal

The band width of analytical imf is defined as-

$$B^2 = \frac{1}{E}\int (w-(w))^2 |Z(w)|^2\, dw \quad (3)$$

It can be further expressed as –

$$B^2 = \frac{1}{E}\int \left(\frac{dA(t)}{dt}\right) dt + \frac{1}{E}\int \left(\frac{d\emptyset(t)}{dt} - \langle w\rangle\right)^2 A^2(t)$$

It shows that the signal's bandwidth has some terms, depending on extent and phase respectively. Therefore bandwidth by virtue of amplitude modulation and by virtue of frequency modulation are defined as –

$$B_{AM}^2 = \frac{1}{E}\int \left(\frac{dA(t)}{dt}\right)^2 \mathrm{dt} \quad (4)$$

$$B_{FM}^2 = \frac{1}{E}\int \left(\frac{d\emptyset(t)}{dt} - \langle w\rangle\right)^2 A^2(t)dt$$

Therefore the total bandwidth is given as –

$$B = \sqrt{B_{AM}^2 + B_{FM}^2} \quad (5)$$

Later on, LSSVM (least square support vector machine)[22] is used to evaluate the effectiveness of the bandwidth parameters to detect ictal and ictal free EEG records. The Support vector machine (SVM) use to determine a separating hyperplane to identify different classes of data to maximize the margin and minimize the categorization error. By this methodology we determine the ictal and ictal free signal, as in non-seizure signals, it is observed that the changing rate of amplitude envelops of IMFs is large in number and the amplitude modulation bandwidth is larger with respect to the IMFs of seizure EEG record. Whereas the changing rate of frequency modulation components of IMF are less in number in seizure EEG records and the value of frequency modulation bandwidth is lower with respect to the IMFs of non-seizure signals. Therefore we can conclude that the total bandwidth of the IMFs of ictal EEG record is smaller as compares to the IMFs of the non-ictal EEG records.

2.2) Phase Space Representation of IMF [23]

The EEG record is firstly decompose using Empirical mode decomposition and then for obtained IMFs; phase space has been reconstructed [23]. Two dimensional (2D) and three dimensional (3D) phase space representation have been used to detect elliptical ictal and ictal free EEG records. In this extraction method, two measures have been defined to detect ictal and ictal free EEG records i.e. For 2D PSR, 95% confidence ellipse area and for 3D PSR, interquartile range (IQR) of the Euclidian distances of IMFs of EEG records. The earmark set for the categorization of epileptic seizure EEG records are form by utilizing the blend of these measured parameter of different IMFs and then LSSVM is employed and its performance has been evaluated using different kernels.
Any dynamic system consist of two parts, one is state that refers to the essential information of the system at a time instance and the other is dynamic which mention to the rule that explains judgment of state with time. Time

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series vector representation of EEG record can be represent as –

V = $\{v_1, v_2, v_3, \dots\dots\dots\dots\dots\dots\dots v_k$

Where k is total no. of data points

For PSR, time delay process is frequently used in which phase space is reformed by its trajectories and can be given as –

$Y_k = \left(V_k, V_{k+\tau}, \dots\dots\dots\dots\dots . V_{k+(d-1)\tau}\right)$

Where, k = 1, 2, 3…………..K-(d-1)τ,

T is a time lag and d is the embedding dimension.

The 95 % ellipse area of 2D PSR can be appraised as follows:-

It is a plot between two vectors V_k and V_{k+1}, mean value can be obtained as,

$$M_x = \sqrt{\frac{1}{k-1}\sum_{k=1}^{k-1} V_K^2} \quad \dots\dots\dots(6)$$

$$M_y = \sqrt{\frac{1}{k-1}\sum_{k=1}^{k-1} V_{k+1}^2} \quad \dots\dots\dots (7)$$

$$M_{xy} = \frac{1}{K-1}\sum_k^k V_k V_{k+1} \quad \dots\dots\dots(8)$$

Computation of parameter L by using equation 6, 7 and 8 can be taken as –

$$L = \sqrt{\left(M_x^2 + M_y^2\right) - 4\left(M_x^2 M_y^2 - M_{xy}\right)} \quad (9)$$

$$a = 1.7321\sqrt{\left(M_x^2 + M_y^2 + L\right)} \quad (10)$$

$$b = 1.7321\sqrt{\left(M_x^2 + M_y^2 - L\right)} \quad (11)$$

Now the area for 2D PSR, can be appraised by using equation 10, 11 as below –

Area $((A_e)$ = πab

Inter quartile range (IQR) of Euclidian distance computed from 3D PSR is the plot of three delayed vectors V_k , V_{k+1} and V_{k+2} to envision the dynamics of the system. Euclidian distance is the distance of the point from basis in 3D PSR, which can be defined as –

$$E_k = \sqrt{v_k^2 + v_{k+1}^2 + v_{k+2}^2}$$

Variability of data is measured with the help of IQR, based on distributing the set of record into quartiles. It is defined as the variation between the 25^{th} percentile and 75^{th} percentile i.e. first and the third quartile. Analysis of seizure and seizure-free EEG record is based on 95% elliptical area which is vary with high range around 0-16 whereas in IQR varies in smaller range around 0-6 in which range of seizure is higher than seizure free signal.

2.3) 2^{nd} order differential plot and Computation of ellipse area [30]

Valuable diagnostic earmark for categorization of EEG records can be obtained from second order difference plot (SDOP) of intrinsic mode decomposition (IMF) [30]. SDOP of a signal may be acquire by plotting X(n) with respect to Y(n) [24]

X (n) = x(n+1) – x(n) (14)

Y (n) = x(n+2) – x(n+1) (15)

It is the graphical representation of successive rates with respect to both and gives change of variability of data. As an earmark we have used ellipse area of 95% confidence from the SODP of IMFs for analysis. SODP of IMFs have elliptical pattern which makes it easy to appraise ellipse area. Procedure is given as [26][27] –

Appraise mean values of X(n) and Y(n) as –

$$S_x = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1} X(n)^2}$$

$$S_y = \sqrt{\frac{1}{N}\sum_{n=0}^{N-1} Y(n)^2}$$

$$S_{xy} = \frac{1}{N}\sum_{n=0}^{N-1} X(n)Y(n)$$

Now by using equation 9, 10 and 11 , appraise the ellipse area as –

$$A_{ellipse} = \pi ab$$

Statistical parameters that are commonly used to analyse the performance of the categorization method [28][29] are sensitivity, specificity and accuracy which can be given as –

$$\text{SENS} = \frac{TPP}{TPP+FNP} \times 100$$

$$\text{SPEC} = \frac{TNP}{TN + FPP} \times 100$$

$$\text{ACC} = \frac{TPP+TNP}{TPP+TNP+FPP+FNP} \times 100$$

In which,

TPP = total no. of true positive pattern

TNP = Total no. of true negative pattern

FPP = Total no. of erroneously positive pattern

FNP = Total no. of erroneously negative pattern

These positive and negative patterns represent the detected seizure and seizure free EEG records. Therefore SODP forms the graph is elliptical in nature. Thus we can appraise the 95% confidence elliptical area and then using the parameters we can easily classify seizure and seizure-free EEG record as range of seizure free is lower than the range of seizure EEG records.

2.4) Hilbert transform

Analysis of EEG records is hinge on the Hilbert-Huang transformer (HHT). Before evaluating HT of piece by piece IMF, the HHT extraction of IMF is done using EMG. The measurement of area of trace of analytic

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form of IMF's has been used as an earmark to segregate epileptic seizure EEG records from normal EEG records. The HT of aboriginal signal x(t) is given as:

$$y(t) = x(t) * \frac{1}{\pi t}$$
$$= \frac{1}{\pi} p.v. \int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau}\, d\tau$$

With Fourier transform, we have

$$X(\omega) = -jsgn(\omega)Z(\omega)$$

Where p.v. indicates Cauchy principle value $Z(\omega)$ is FT of signal z(t).

The analytic signal of z(t) is given as:

$$x(t) = z(t) + jx(t)$$

Further can be expressed as:-

$$a(t) = A(t)e^{i\phi(t)}$$

Where,

$A(t)=\sqrt{z^2(t)+x^2(t)}$ (modulus of a(t))

$\phi(t) = arc\tan\frac{x(t)}{z(t)}$ (Instantaneous phase)

$\omega(t) = \frac{d\phi(t)}{dt}$ (Instantaneous frequency)

$$= \frac{x(t)y(t)-x(t)y(t)}{A^2(t)}$$

$\omega(t)$ Measures the rate of rotation in the complex plane of the corresponding analytic signal. Hilbert transform should be applied on all IMF's obtained by EMD method [23]. Analytic signal representation for each IMF is given by:

$$D_m(t) = A_m(t)\cos(\phi_m(t))$$
$$Z_m(t)=A_m(t)e^{i\phi_m(t)}$$

The central tendency measure [31] has been used to evaluate the radius of the circle of the analytic signal presentation of IMF in complex plane. The imaginary part of the signal z[n] (i.e. $A[n]\sin(\phi[n])$) is drawn opposite to the real part of z[n] (i.e. $A[n]\cos(\phi[n])$), in analytic signal representation of z[n]. The intrinsic function satisfies following two conditions:

1.) The plot has direction of rotation.
2.) The rotation in plane has unique centre.

The analytic signal representation which satisfies above conditions which makes possible to appraised surface area in complex plane. The CTM is appraised by selecting a circular region of radius r, around the origin counting the points that falls within the radius and dividing by total number of points. Consider N be the total number of points and r be the radius of the central are. Then,

$$CTM = \frac{\sum_{n=1}^{N}\delta(d_n)}{N}$$

$$\delta(d_n) = \begin{cases} 1\ if\ ([\Re\{z[n]\}]^2 + [\Im\{z[n]\}]^2)^{.5} < r \\ 0\ otherwise \end{cases}$$

CTM gives fraction of the total number of point lies with radius r. Hilbert transform is used in this method, before calculating the use of EMD which detected differences in surface area between normal and epileptic seizure EEG records. Here we estimated area as a earmark in distinguishing epileptic seizure EEG records from the normal EEG records. The value of appraised area is small in normal EEG than that of seizure EEG record due to greater amplitude of EEG record. The work of EMD to deteriorate EEG into IMF's is an encouraging method, which gives set of proper rotations which makes possible to accurately identify the centre and estimating surface areas in complex plane. The area parameters has been appraised for both the classes using IMF and various window lengths (i.e. N=2000 and 4000) is used as the area covered by seizure signal is more than the area covered by normal signal.

3.) Multivariate EMD [8,9]:-

As inl EMD, the computation of sectional average is carried by taking an average of upward envelopes and downward envelopes, which in turn, are acquired by intercalated between the sectional maxima and minima, which is not possible in case of multivariate signal i.e. to define local maxima and minima directly is not easy. Therefore, the perception of 'oscillatory manner' exemplify an obtained IMF is more perplexing for multivariate (MV) signals. To overcome these issues, multivariate EMD (MEMD) was proposed by N.Rehman and D.P. Mendic in which generates multiple n-dimensional envelopes by taking signal projections along different directions in n-dimensional spaces; these projections are then averaged to obtain the Local mean. The quasi-Monte Carlo-based low-disparity progressions are used to sample n-sphere to prepare modified sample set. Once the average signal is defined, the rest of the proceeding is utterly akin to the definitive EMD epitomize in EMD algorithm. Therefore, the algorithm for MEMD is given as-

1.) First of all select a appropriate point set for sampling on an (n-1)- sphere;
2.) reckon a projection, given by $p\theta k\ (t)\ t$ =1, of the applied signal $\{\mathbf{v}(t)\}Tt$ =1 along the direction vector $\mathbf{x}\theta k$, for all k (the whole set of direction vectors), giving $p\theta k\ (t)\}Kk$=1 as the set of projections.
3.) discover the time instants $\{t\theta ki\}$ comparable to the maxima of the set of projected signals $p\theta k\ (t)\}Kk$ =1;
4.) Insinuate $[t\theta k\ i$, $\mathbf{v}(t\theta k\ i)]$ to reap MV envelope curves $\mathbf{e}\theta k\ (t)\}Kk$ =1;
5.) For a set of K direction vectors, the mean $\mathbf{m}(t)$ of the envelope curves is reckon as:
$\mathbf{M}\ (t) = 1\ K\Sigma K\ k$=1 $\mathbf{e}\theta k\ (t)$
6.) Excerpt the "detail" (t) using $(t) = (t) - (t)$. If the "detail" (t) fulfils the stoppage criterion for a MV IMF, imply, the given procedings to $(t) - (t)$, otherwise apply it to (t).

In this algorithm MEMD and HHT of multivariate signal is use to retrieve average frequency of signal, which is used to detect ictal and non-ictal EEG record. The use of MEMD assist the progress of the decomposition of multichannel EEG records in narrow frequency bands via matched multivariate intrinsic mode functions (IMF). Further application of the Hilbert-Huang transform (HHT) on these IMFs helps to accurately define the instantaneous frequencies. We have used a consolidation of MEMD and HHT to appraise the average frequency, as a spectral earmark, in order to diagnose the ictal condition in EEG patterns.

III. CONCLUSION

In this paper three different methods are discussed for EEG record analysis. Introduction of new method and technology could make the analysis of EEG record more swift and easy and allow doctor to take immediate step instead of wasting lot of time in analysis of the signal. The comparative analysis of all the methods used is given as -

Table 1. Comparative analysis of EEG detection methods

Method name	Analysis method	Advantages	Suitability
Empirical mode decomposition [19, 21, 22, 24]	Amplitude and frequency modulation	Better categorization accuracy	Bandwidth of signals
Time frequency distribution [3, 4, 11]	Both time and frequency domain	feasible of examining great continuous segments	Stationary signal
MEMD [8, 9]	Mean frequency calculation	Better categorization accuracy	Multichannel EED signal

Each method is having some advantages and limitations. Frequency domain methods do not provide high-quality performance for some EEG records whereas a time-frequency method does not provide detailed information about EEG data as much as frequency domain methods. Time frequency method is feasible to examining great continuous segment whereas EMD and MEMD provide better categorization accuracy. EMD signal is suitable for both stationary and non-stationary signal whereas time frequency is only for stationary signals and MEMD is suitable for multichannel EED signals. Hence according to different mental task related applications accurate method should to be chosen for better results.

IV. PROPOSED WORK

Trying to generate new analysis technique by blend of other techniques. I am working on the technique which could make the analysis more precise and accurate and also going to use other extracting earmarks like EMD also going to apply others method on EMD extracted signals like AM and FM method in which I am going to apply a method to obtain its maxima and minima and try to classify seizure and non-ictal signal by analysing maxima & minima of the EEG spikes.

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