Band Correlation Histogram to Improve Classification of Acute Encephalopathy in Infants

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***Abstract*—We propose a method to determine whether the early onset of acute encephalopathy causes severe sequela by analyzing the frequency of electroencephalogram waves. Even though sequela can severely damage the brains of infants, no prevalent method can automatically diagnose acute encephalopathy in them. We solve this problem by designing a discriminative feature that delivers impressive classification performance. Based on knowledge of the diagnosis, our method applies a bandpass filter, randomly selects pairs of waves over a short period, and computes a band correlation histogram from a distribution of their correlation coefficients. The results of experiments show that the band correlation histogram is superior to the prevalent method in the classification of a dataset of patients with acute encephalopathy.**

***Index Terms*—EEG waves, acute encephalopathy, band correlation histogram**

I. Introduction

Impaired consciousness and convulsions are typical symptoms of acute encephalopathy in infant patients. Acute encephalopathy is caused by a viral infection that induces high fever, such as in people afflicted with the influenza virus. Severe sequela frequently persists if acute encephalopathy has progressed [1]. Thus, a system is needed to support the diagnosis of acute encephalopathy at early onset to avoid severe sequela.

To diagnose acute encephalopathy, doctors generally employ diagnostic imaging through magnetic resonance imaging (MRI) or electroencephalography using EEG. However, MRI scans cannot be used for the diagnosis of the early onset of acute encephalopathy because the relevant abnormalities are not apparent [2]. On the contrary, EEG can help discover abnormalities relating to acute encephalopathy in case of early onset [3]. The doctor can then administer appropriate treatment to prevent severe sequela.

There are two representative cases of status epilepticus: acute encephalopathy with biphasic seizures and late reduced diffusion (AESD), and prolonged febrile seizure (FS). Although FS is easily curable, AESD in patients has a high probability of progressing to severe sequela. Distinguishing AESD from FS using EEG is a challenging task because AESD waves are visually similar those representing FS. Doctors thus need adequate training and experience to correctly distinguish the AESD waves from those of FS. An experienced doctor can manually read EEG waves and detect abnormalities when slow waves of long wavelengths ($0.5 - 8$ Hz) appear repeatedly [4]. However, abnormal findings such as waves of this kind frequently appear in representations of both AESD and FS. An inexperienced doctor can thus make an erroneous diagnosis. In this paper, we propose a method to automatically determine whether a given case of acute encephalopathy can be classified as AESD using EEG waves. In particular, our method splits frequency bands used by experienced doctors for diagnosis. Note that we consider waves that have previously been manually selected by a doctor such that they contain no artifacts.

Several methods have been proposed to classify cases of encephalopathy other than AESD [5]–[10]. For example, Chandaka et al. [5] exploited a feature vector using cross-correlation among EEG waves to diagnose epilepsy in patients. However, the waves of AESD exhibit different characteristics in terms of frequency distribution from those of epilepsy. In a preliminary experiment, we were unable to obtain high classification performance in the diagnosis of AESD using the prevalent method [5] (the likelihood of correct diagnosis was close to chance).

In light of the above, we propose a method to determine whether cases of acute encephalopathy are those of AESD, using the feature vector of a band correlation histogram extracted from EEG waves. We design our feature vector based on knowledge of the diagnosis, where the doctor identifies temporal differences among waves over a short period. Our method extracts the feature by applying a bandpass filter, computing the coefficients of correlation among waves over a short period, and generating a correlation histogram based on their distribution.

II. Related work

The relevant methods extract features from EEG waves to classify various types of encephalopathy. Bajaj and Pachori [6] proposed a method that uses the bandwidth of the amplitude and phase of EEG waves to identify cases of epilepsy. Kumar and Dutt [7] proposed a method that employs graph structures between channels of EEG to determine schizophrenia in patients. Temko et al. [8] proposed a method using EEG waves and the heart rate to identify cases of hypoxic-ischemic encephalopathy, and Ahmed et al. [9] proposed a method that uses a Gaussian mixtures' model to estimate the level of sequela in patients of the same illness. Furthermore, Ahmed et al. [10] proposed a method that uses features of speech

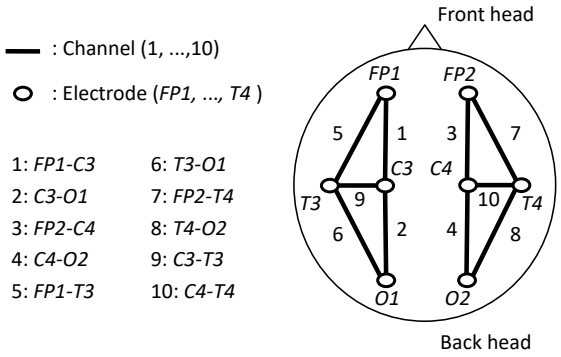

Fig. 1. Setup of channels for measuring EEG waves.

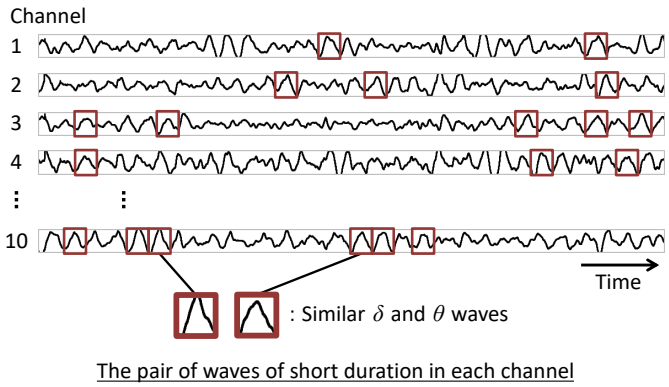

Fig. 2. Overview of knowledge of the diagnosis of acute encephalopathy.

recognition to estimate the level of brain injury. These methods were designed to extract a feature for each classification of encephalopathy. On the contrary, our method extracts a discriminative feature for AESD using a correlation histogram computed from EEG readings of infant patients.

III. Band Correlation Histogram for Feature Extraction

A. Overview

We design a feature vector to identify AESD based on knowledge of the diagnosis by a doctor in a clinical setting. To measure EEG waves from an infant patient, the doctor sets electrodes on the patient's head as shown in Figure 1. The doctor then records the potential difference at each channel by subtracting the potentials between electrodes. As described in [11], [12], he/she diagnoses encephalopathy by observing a pair of EEG waves over a short period. For instance, as illustrated in Figure 2, the doctor checks whether similar δ and θ waves ($0.5-8$ Hz) appear temporally. Five types of brain waves are of most interest in neuroscience ($\delta(0.5-4$ Hz), $\theta(4-8$ Hz), $\alpha(8-13$ Hz), $\beta(13-30$ Hz), γ (above 30 Hz)) from low to high frequencies, respectively. We use δ and θ waves based on the doctor's knowledge of the diagnosis. To extract the feature to identify AESD using knowledge of the diagnosis, our method computes a correlation coefficient from

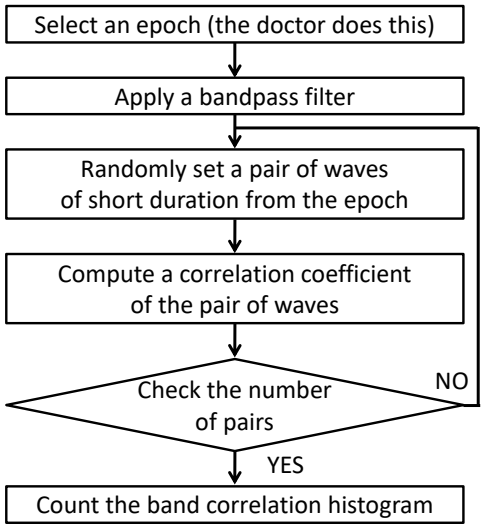

Fig. 3. Flow to generate the band correlation histogram.

a pair of waves over a short period randomly sampled from EEG waves. It then generates a band correlation histogram using the distribution of the correlation coefficients as shown in Figure 3. The details of our method are described below.

B. Algorithm to generate the band correlation histogram

The doctor measures the EEG waves of an infant patient and selects ones with no artifacts, but with the abnormalities that feature in both AESD and FS. We call a selected wave an epoch. To extract δ and θ waves used for diagnosis by a doctor, we simply apply a bandpass filter to an epoch to extract the components of these waves. We define an epoch $\boldsymbol{x}_{b,i}(i \in \{1,\cdots,N\}$ and, a band $b \in \{\delta,\theta,\alpha,\beta\})$ containing N channels as

$$\boldsymbol{x}_{b,i} = [x^1_{b,i}, x^2_{b,i}, \cdots, x^{T_1}_{b,i}]^{\mathrm{T}} \ , \tag{1}$$

where $x^t_{b,i}$ is the potential difference acquired by the i-th channel at time t and T_1 is the length of the epoch used for feature extraction.

To compare waves over short periods in epoch $\boldsymbol{x}_{b,i}$, we set the pair of waves acquired in period T_2. Our method selects S pairs by randomly repeating the below procedure. We denote the start time (m_k, n_k) of the k-th pair by

$$m_k \sim \mathrm{U}(0, T_1 - T_2) \ , \tag{2}$$

$$n_k \sim \mathrm{U}(0, T_1 - T_2) \ , \tag{3}$$

where $k \in \{1,\cdots,S\}$, and U() represents the discrete uniform distribution that randomly returns the duration from zero to $T_1 - T_2$.

However, when returning the margin part by Hamming window, we randomly return the duration again. We define the pair of waves of short period $\boldsymbol{x}^m_{b,i}, \boldsymbol{x}^n_{b,j} (j \in \{1,\cdots,N\})$ using the start time (m, n) as

$$\boldsymbol{x}^m_{b,i} = [x^{m+1}_{b,i}, x^{m+2}_{b,i}, \cdots, x^{m+T_2}_{b,i}]^{\mathrm{T}} \tag{4}$$

$$\boldsymbol{x}^n_{b,j} = [x^{n+1}_{b,j}, x^{n+2}_{b,j}, \cdots, x^{n+T_2}_{b,j}]^{\mathrm{T}} \tag{5}$$

Having randomly selected S pairs of waves, we compute a correlation coefficient for each. We define the correlation coefficient $r_{b,i,j}^{m,n}$ relating the waves of short period $\boldsymbol{x}_{b,i}^{m}$ and $\boldsymbol{x}_{b,j}^{n}$ as

$$r_{b,i,j}^{m,n} = \frac{\mathrm{cov}(\boldsymbol{x}_{b,i}^{m}, \boldsymbol{x}_{b,j}^{n})}{\sqrt{\mathrm{cov}(\boldsymbol{x}_{b,i}^{m}, \boldsymbol{x}_{b,i}^{m})\mathrm{cov}(\boldsymbol{x}_{b,j}^{n}, \boldsymbol{x}_{b,j}^{n})}} \tag{6}$$

where cov() represents the covariance computed among these waves of short periods. The correlation coefficient uses the range of values $-1 \leq r_{i,j}^{m,n} \leq 1$.

To generate the feature vector for classification, we compute the distribution of the correlation coefficients. We define a feature vector: the band correlation histogram within the channel $\boldsymbol{h}_b$. We compute $\boldsymbol{h}_b$ to temporally compare the waves at the same channel as

$$\boldsymbol{h}_b = \sum_{i=1}^{N} [h_b^1, h_b^2, \cdots, h_b^D]^{\mathrm{T}} \tag{7}$$

where D is the number of bins in the histogram and h_b^l is the frequency of the l-th bin. We count frequency h_b^l using $r_{b,i,j}^{m,n}$ as

$$h_b^l = \mathrm{card}\{r_{b,i,j}^{m,n} | a_l \leq r_{b,i,j}^{m,n} < a_{l+1}\} \tag{8}$$

where card is an operator representing the number of elements in a set consisting of $r_{b,i,j}^{m,n}$ under $a_l \leq r_{b,i,j}^{m,n} < a_{l+1}$. Note that $a_l = -1 + 2(l-1)/D$. When $r_{b,i,j}^{m,n} = 1$, we count it in h_b^D. The total number of pairs of waves of short period is NS. We apply L1-norm normalization for $||\boldsymbol{h}_b|| = 1$.

IV. Experiments

A. Dataset of EEG waves of AESD and FS

To evaluate the classification performance of our method, we collected EEG data from 34 infant patients (22 males, 12 females; average age 1.7 ± 1.4 years). Seventeen patients had AESD and the other half had FS. When measuring EEG waves, the patients were comatose or in deep sleep. The setup of the channels and electrodes for the EEG readings is shown in Figure 1. The number of channels was $N = 10$. The doctor selected 10 epochs for each patient. The length of an epoch was $T_1 = 15$ s and the sampling interval was 10 ms.

B. Parameters of the band correlation histogram

We used 17-fold cross-validation. Data for two patients were used as test samples and those for the remaining 32 as training samples. We used the liner support vector machine [13], and compared classification performance in terms of the methods determining whether patients were suffering from AESD or FS using the band correlation histogram. We conducted our evaluations with frequency bands for $b = \delta, \theta, \alpha$, and β waves, and number of bins $D = 5, 10$, and 20, and waves of periods $T_2 = 0.5, 1, 2$, and 3.5. We randomly sampled $S = 1,000$ pairs of waves of short period.

Figure 4 shows the classification performance of the band correlation histogram while changing the frequency band.

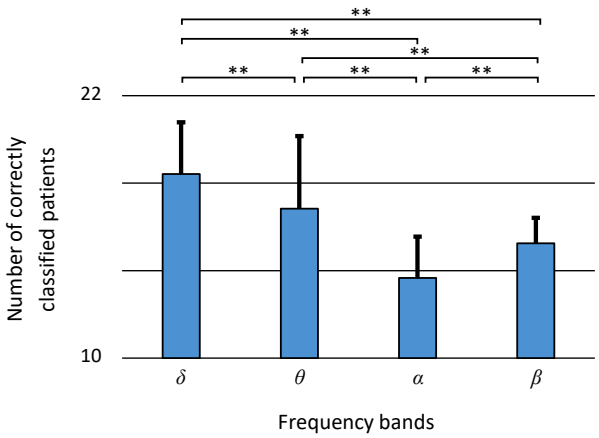

Fig. 4. Classification performance of band correlation histogram while changing the frequency bands.

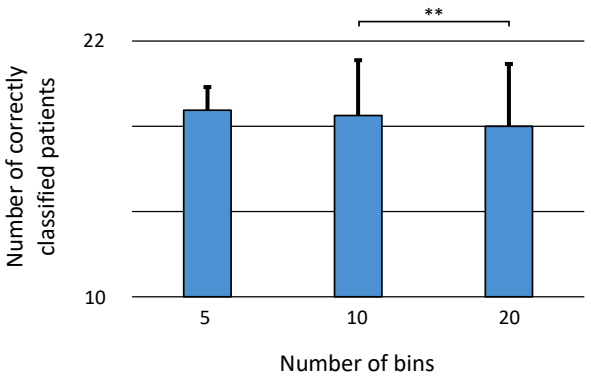

Fig. 5. Classification performance of band correlation histograms using δ waves while changing the number of bins D.

We calculated the average and the standard deviation of the number of patients correctly classified by fixing a certain parameter and changing the others. We used Bonferroni's method for multiple tests. We also used the Wilcoxon signed-rank test ($p < 0.01 : **$). We can see that δ waves yielded better performance than θ,α and β waves. Figure 5 shows the classification performance of the methods using the band correlation histogram using δ waves while changing the number of bins D and Figure 6 shows classification performance using δ waves while changing the duration of waves. We can see that $D = 10$ yielded better performance than $D = 20$, and $T_2 = 1$ yielded better performance than $T_2 = 0.5, 2$, and 3.5. We obtained the best performance (21 patients were correctly classified) using the correlation histogram of θ waves with $D = 10$ and $T_2 = 2$, or $D = 20$ and $T_2 = 3.5$.

C. Comparison with methods that spatially compute the correlation coefficient

We compared the proposed method with an inter-channel method that spatially compares waves at the same time, and a random method that spatially compares them at different times. The proposed method used feature vector $\boldsymbol{h}_\delta$ with $D = 10$ and

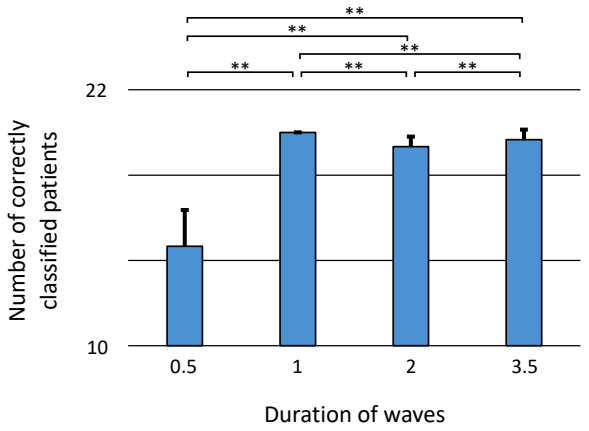

Fig. 6. Classification performance of band correlation histograms using δ waves while changing the duration of waves.

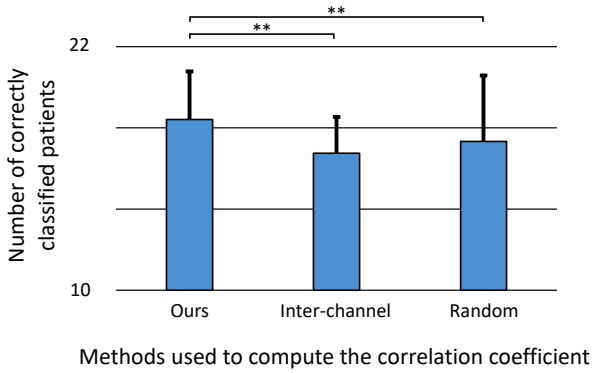

Fig. 7. Classification performance of the band correlation histogram using the three methods on δ waves. The inter-channel method spatially compares waves at the same time. The random method spatially compares them at different times.

$T_2 = 1$. All three methods used the linear SVM classifier. We used the same dataset as described in Section IV-B. Figure 7 shows the classification performance of band correlation histograms using the three methods on δ waves. We see that the proposed method yielded better performance than the inter-channel method and the random method. As described in Section III-A, an expert doctor checked to whether similar δ waves ($0.5-4$ Hz) appear temporally. We think that the feature vector of the proposed method generated by comparing waves of short periods benefited from knowledge of the diagnosis of AESD.

D. Comparison with prevalent method

We compared the proposed method with a method prevalent in practice [5] using the five elements of the cross-correlation (peak value, instant at which peak occurs, centroid, equivalent width, mean square abscissa) computed from the EEG waves between channels. The prevalent method used a feature vector of $5 \times 45 = 225$ dimensions by computing the five elements between ${}_{10}\mathrm{C}_2 = 45$ combinations of channels. Our method used the feature vector described in Section IV-C. Both methods used a linear SVM classifier. We used the same dataset as described in Section IV-B. Our method correctly classified 20 patients whereas the prevalent method classified only 18 correctly. Thus, our method improved classification performance compared with the prevalent method. We thus think that it can help correctly diagnose AESD. The prevalent method directly applied cross-correlation to the EEG waves. On the contrary, our method applied correlation to waves of short period selected from the EEG waves. An expert doctor cannot observe the EEG waves all at once. We think that the band correlation histogram generated by waves of short period benefited from knowledge of the diagnosis of AESD.

E. Visualization

We investigated the bins of the band correlation histogram that contributed to enhancing the classification performance of AESD. We used the parameters of the feature described in Section IV-C. Figures 8 (a), (b), and (c) show the band correlation histograms using δ waves for AESD and (d), (e), and (f) show those for FS. As shown in Figure 8, the frequencies of the bins for AESD representing the correlation coefficients -1 or 1 were higher than those for zero in the δ waves. Figures 9 (a) and (b) show the weights using the normal vector to the hyperplane of the linear SVM classifier. The positive weights were discriminative in classifying AESD and the negative weights in classifying FS. We see that the weights -1 and 1 took large positive values in δ waves. We think that the pairs of waves taking -1 or 1 as coefficients contained discriminative features in δ waves.

F. Evaluation using a control group

We evaluated classification performance on a control group of healthy infants and another consisting of those suffering from encephalopathy. The former consisted of patients who had been cured of FS and shuddering attacks, or were originally healthy. The other group contained infants suffering from epilepsy (ES). We added 18 healthy infants (10 males, eight females; average age, 8.4 ± 2.3 years), 11 cured infants (six males, five females; average age, 3.3 ± 2.9 years), and six other encephalopathy patients (three males, three females; average age, 2.8 ± 2.0 years) to the dataset described in IV-A. The doctor measured the EEG waves using the same setup as in Figure 1. The EEG waves of the added infants did not yield abnormal findings. The doctor selected an epoch containing normal, slow waves of sleep. We used data for 52 patients in total: data for 34 patients (17 AESD patients, nine healthy patients, six cured infants, and two ES patients) as the training sample and those for 18 (nine healthy patients, five cured infants, and four ES patients) as test sample. We generated feature vectors and a classifier in the manner described in Section IV-C. We calculated the average and standard deviation of the number of patients correctly classified by changing the epochs selected. Iterated 10 times, our method correctly classified 14.0 ± 0.0 test patients. We thus think that our feature

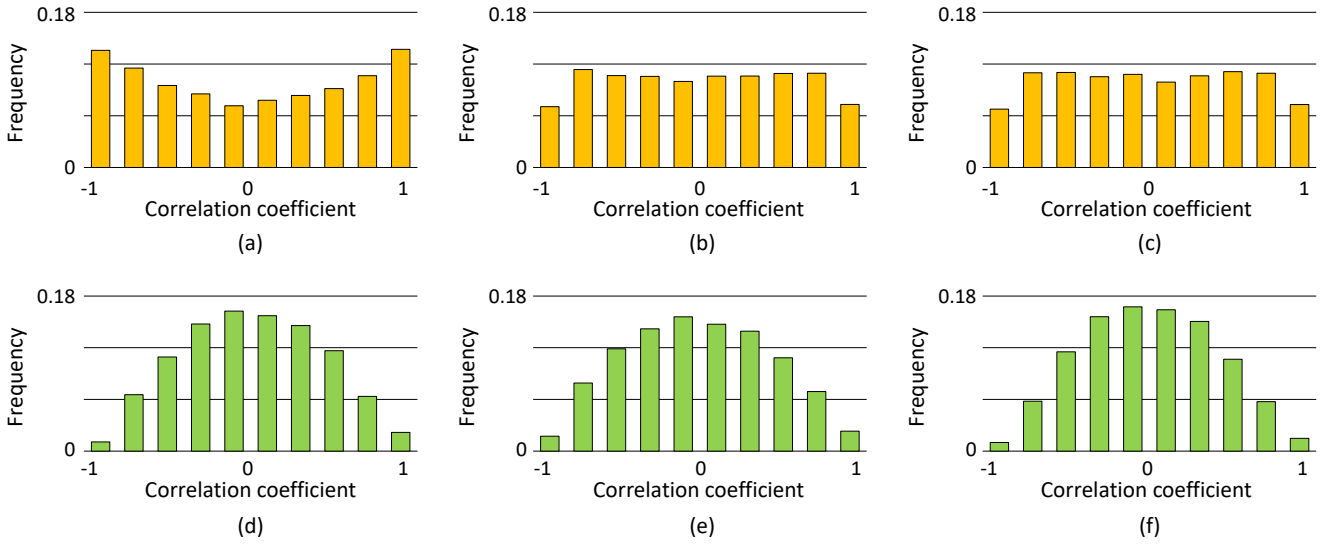

Fig. 8. Examples of correlation histograms of δ waves of AESD in (a), (b), (c) and FS in (d), (e), (f).

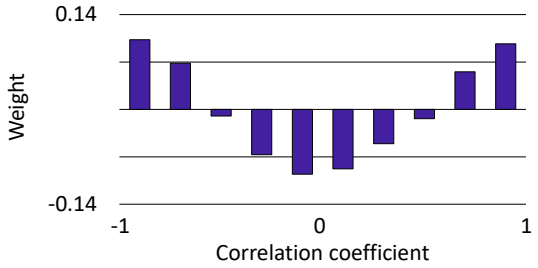

Fig. 9. SVM weights contributing to classifying AESD and FS using δ waves.

can help identify patients with AESD with the likelihood of progressing to severe sequela.

V. Conclusion

In this study, we proposed a method for identifying AESD among infants suffering from acute encephalopathy using a band correlation histogram. Our method computes the distribution of the correlation coefficients of EEG waves taken over a short period in frequency bands based on the doctor's knowledge of the diagnosis. We also showed that our method can improve classification performance compared with a prevalent method by conducting evaluations on a dataset of infant patients with acute encephalopathy.

In future work, we intend to evaluate classification performance with a greater number of the patients and conduct a user study involving doctors who are not experienced in treating AESD.

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