International Conference on Automatic control, Telecommunications and Signals (ICATS15)
University BADJI Mokhtar - Annaba - Algeria - November 16-18, 2015

Single-Trial Evoked Potential Extraction Using VSS-LMS Adaptive Hermite Modelling

Mahmoud Boudiaf
Badji Mokhtar Annaba University
BP:12, Annaba, 23000, Algeria
Email: mahmoudboudiaf@hotmail.fr

Moncef Benkherrat
ECAM-EPMI
13 bd de l'Hautil, 95092,
Cergy Pontoise cedex, France
Email: m.benkherrat@ecam-epmi.fr

Khaled Mansouri
Badji Mokhtar Annaba University
BP:12, Annaba, 23000, Algeria
Email: mansouri.khaled@voila.fr

***Abstract*—This study presents a method for improving signal-to-noise ratio of single-trial event-related potentials. The method is based on adaptive linear combiner Hermite model. The choice of the Hermite basis functions is justified by their resemblance to the event-related potentials. The variable step-size least-mean square algorithm is used to estimate and to adjust the parameters of the filter. The performances of the method are evaluated with both simulated data and real event-related potential recordings, and compared with the ensemble average method.**

***Keywords*—Event-related potentials, adaptive linear combiner, Hermite basis functions, VSS-LMS algorithm.**

I. Introduction

The Event-Related Potentials (ERPs), also called Evoked Potentials (EP), are brain waves collected at the scalp under experimental conditions in which the subject has to perform simple cognitive tasks. These electrical brain activities reflect the cognitive processes involved in information processing. ERPs are useful diagnostic tools of both psychiatric and neurological disorders. Moreover, ERPs, and especially the P_{300} component, are widely used in brain computer interfacing (BCI).

It is difficult to extract the ERP signals from noise for the several reasons. First, their low amplitudes compared with the ongoing background electroencephalogram activity (EEG), second, their non-stationarity and finally the overlap between the spectrum of the ERP signal and EEG signal. The classical method usually employed to extract the signal from the noise is ensemble average (EA). Hundreds of recordings are needed to reach adequate signal to noise ratio (SNR). But the assumption that the averaged signal is representative of the individual ERPs is not necessarily true; changes of shape, amplitude or latency of the ERPs may occur. Important information about the variability between single-trials will be lost by averaging, and it will be impossible to investigate the cognitive process (e.g. the habituation or the attention of the subject).

In this regard, various methods have been proposed to denoise the individual ERP signal such as parametric method [1], the matching pursuit (MP) [2], the Wiener filtering [3], [4] and the wavelet transform [5], [6], [7], [8]. Most of these methods need prior information about the temporal and the spectral characteristics of both the signal and the noise, or take the average of the signals as template. Adaptive filtering (AF) was widely exploited in signal enhancement and noise cancellation [9], [10], [11]. It has the advantage of auto-adjusting its parameters and requires no a priori knowledge of signal features. If the SNR is not too low and if the signal does not present a large variability, the method can obtain a good estimation. However, the SNR of the ERP signal is low, so the AF will take longer to converge and may not be able to track fast changes of the signal. Orthogonal basis functions were also used to model the ERP signals [12], [13], [14], where the coefficients of the filter are estimated and adapted using the Least Mean Square algorithm (LMS) [15].

In the present work, the adaptive Hermite model filter [16], [17], [18] is used to model individual ERP signals. The morphology of the Hermite functions looks similar to the morphology of ERP signal. This similarity allows to extract the ERP features. We made use of the Variable Step-Size least Mean Square (VSS-LMS) algorithm [19] to estimate and adjust the parameters of the model. The VSS-LMS is well suitable for tracking rapid changes in non-stationary signals like ERPs. We applied the adaptive Hermite model to both simulated data and real EEG recordings, and compared it with the conventional EA method.

II. Method

A. Hermite model

ERP can be modeled, with a finite number of parameters, by the orthogonal Hermite basis functions. These functions are expressed by:

$$\phi_i(t,b) = \frac{1}{\sqrt{b.2^i.i!\sqrt{\pi}}} e^{-\frac{t^2}{2b^2}} H_i(t/b) \tag{1}$$

where $\phi_i(t,b)$ is the Hermite polynomial of order i, and b is the scale factor that determines the temporal width of the functions. The Fig. 1a shows the first nine Hermite functions for $b = 30$ ms. The ERP can be described as the linear combination of these basis functions as:

$$y(t) = \sum_{i=0}^{M-1} w_i \phi_i(t,b) \tag{2}$$

where M is the number of the adjustable weights w_i.

B. Model structure

The primary input of the filter structure is the noisy ERP signal, $d(k)$ composed of the underlying ERP signal $(s(k))$

and an additive noise ($n(k)$). The reference inputs are the Hermite functions $\phi_i(k, b)$. The output of the model, $y(k)$ the best estimate of the signal $s(k)$, is the linear combination of the weighted reference inputs. The weights vector $W(k) = [w_0 w_1 \ldots w_{M-1}]$ is updated at each iteration (Fig. 1b).

C. Model parameters

The model coefficients w_i and b parameter are estimated by a variable step-size least mean squares algorithm (VSS-LMS). The VSS-LMS algorithm minimizes the mean square error (MSE) between the noisy ERP input signal $d(k)$ and the output signal of the model ($y(k)$) by adjusting the weights vector W. The output of the model is expressed by:

$$y(k) \simeq \sum_{i=0}^{M-1} w_i(k)\phi_i(k, b) = W^T(k)\Phi(k, b) \tag{3}$$

Where:

$$\begin{aligned} W(k) &= [w_0(k)w_1(k)\ldots w_{M-1}(k)] \\ \Phi(k, b) &= [\phi_0(k, b)\phi_1(k, b)\ldots \phi_{M-1}(k, b)] \end{aligned}$$

We can express the error signal as:

$$e(k) = d(k) - y(k, b) = d(k) - W^T(k)\phi(k, b) \tag{4}$$

We express the MSE as:

$$\xi = E[e^2(k)] \tag{5}$$

The model includes two adaptation processes: the first one to estimate the coefficients and the second to estimate the optimum width parameter b. In this respect, we have considered two convergence parameters μ_1 and μ_2 for the weights vector and width parameter respectively.

The LMS algorithm used to adjust the weights vector, is implemented by the recursive expression:

$$W(k+1) = W(k) + \mu_1(k)\Phi(k, b)e(k) \tag{6}$$

$$e(k) = d(k) - \Phi^T(k)W(k) \tag{7}$$

$$\mu'_1(k+1) = \alpha\mu_1(k) + \gamma e^2(k) \tag{8}$$

$$\mu_1(k+1) = \begin{cases} \mu_{1max} & \text{if } \mu'_1(k+1) > \mu_{1max} \\ \mu_{1min} & \text{if } \mu'_1(k+1) < \mu_{1min} \\ \mu'_1(k+1) & \text{otherwise.} \end{cases} \tag{9}$$

where α and γ are positive control parameters with: $0 < \alpha < 1$ and $\gamma > 0$.

To adapt the parameter b, we use a steepest descent method [15], [16]:

$$b(k+1) = b(k) + 2\mu_2 e(k) \sum_{i=0}^{M-1} w_i \frac{\partial\phi_i(k, b(k))}{\partial b(k)} \tag{10}$$

Laguna et al. [16] have proved that:

$$\frac{\partial\phi_i(t, b)}{\partial b} = \frac{1}{2b}\times \left[-\sqrt{i(i-1)}\phi_{i-2}(t, b) + \sqrt{(i+2)(i+1)}\phi_{i+2}(t, b)\right] \tag{11}$$

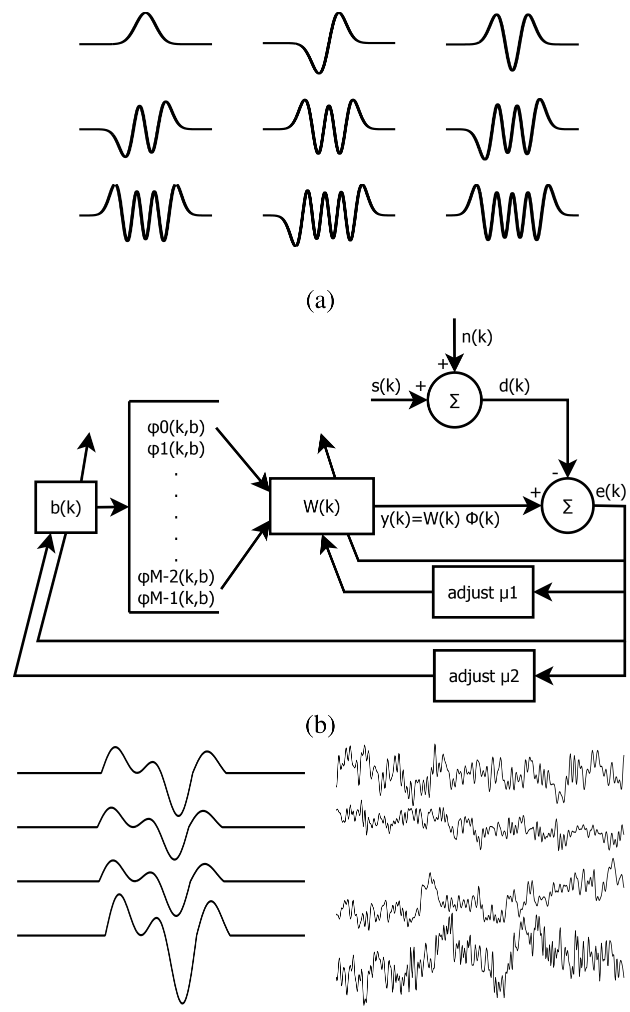


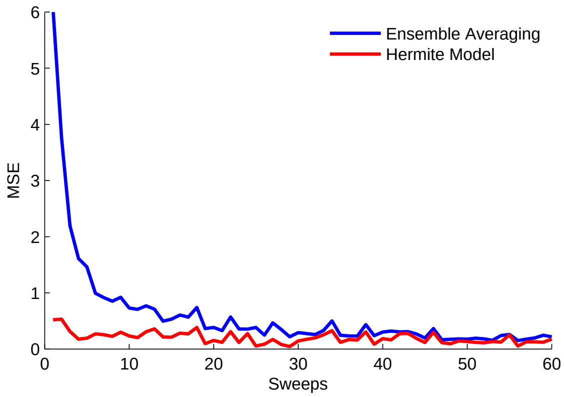
Fig. 1. (a): First nine Hermite functions used as reference inputs to the adaptive estimator for $b = 30ms$. (b): Structure of the VSS-LMS adaptive Hermite model filter, $d(k)$ = primary input signal composed of ERP signal sequence $s(k)$ plus noise $n(k)$, output signal is $y(k)$, W = the weights of the filter, b = the scale factor used to generate the Hermite basis functions. (c): Examples of noise-free signals used for the simulation. (d): Same signals with different added noises.

The convergence parameter μ_2 is controlled by the same type expressions than μ_1 (Eqs.):

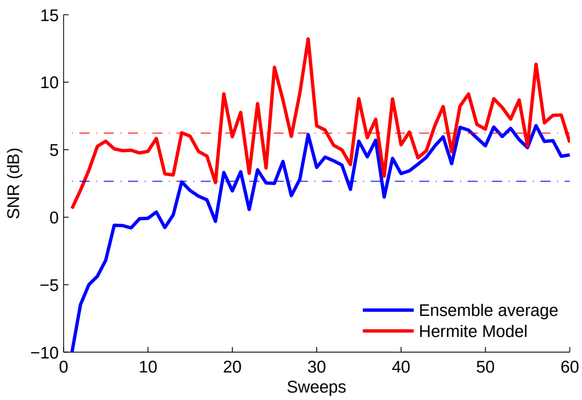
$$\mu'_2(k+1) = \alpha\mu_2(k) + \gamma e^2(k) \tag{12}$$

$$\mu_2(k+1) = \begin{cases} \mu_{2max} & \text{if } \mu'_2(k+1) > \mu_{2max} \\ \mu_{2min} & \text{if } \mu'_2(k+1) < \mu_{2min} \\ \mu'_2(k+1) & \text{otherwise.} \end{cases} \tag{13}$$

The initial step-size is usually taken to be $\mu_{\max}$. The prediction error and the two parameters α and γ control the step-size μ. The parameter α is chosen to provide exponential forgetting. The parameter γ is chosen conjointly with the parameter α to meet the misadjustement requirements [19]. The constant $\mu_{\max}$ is chosen to ensure that the mean-square error (MSE) of the algorithm remains bounded. A sufficient condition for



(a)



(b)

Fig. 2. The figure (a) compares the MSE after a successive averaging of the 60 trials with the MSE of adaptive Hermite model. The figure (b) compares the SNR after a successive averaging of the 60 trials with the SNR of adaptive Hermite model. The dashed lines represent the mean value of the SNR for each method.

$\mu_{1\,\max}$ to guarantee bounded MSE as in [19], [16] is:

$$\mu_{1\,\max} \leq \frac{2}{3tr(R)} \tag{14}$$

where R is the autocorrelation matrix of the input Φ and tr denotes the trace of the matrix. The minimum step-size $\mu_{1\,\min}$ and $\mu_{2\,\min}$ are chosen to provide a minimum level of tracking ability.

III. Simulation

For the simulation, we built sixty synthetic traces of 512 points. Each signal is composed of a set of waves (Fig. 1c). The temporal window of the primary signal is approximately 600 ms. This temporal window is extended with zero flat line 400 ms on the right and on the left of window (-0.4 s to 1 s). The latency and the amplitude of the waves are varied to match the variability of real ERP recordings. The added EEG noise is generated such that the power spectrum matches the power spectrum of a human EEG (Fig. 1d). To generate the EEG noise, we used a MATLAB programme implemented by Rafal Bogacz and Nick Yeung (Princeton University, December 2002) [20]. Indeed the SNR of the real records is very low and has a mean value of approximately -10 dB.

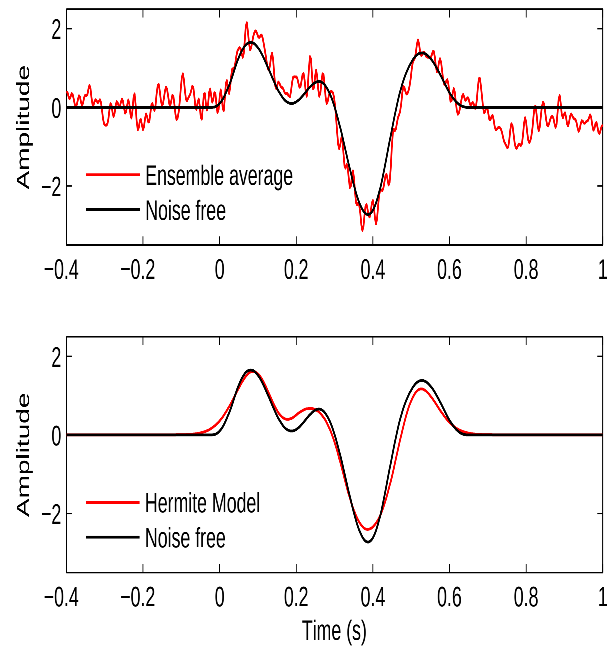


Fig. 3. Comparison between the average of sixty signals and the average of the sixty output signals denoised by the adaptive Hermite model filter.

We choose the order M so that linear combiner represents more than 95% of the signal power. This corresponds to an order $M = 9$ for the adaptive Hermite model. The values of α and γ that worked well in simulations are respectively equal to 0.97 and 0.5. For the adaptation step-sizes, the used values are: $\mu_{1min} = 10^{-8}$, $\mu_{1max} = 0.05$, $\mu_{2min} = 10^{-8}$ and $\mu_{2max} = 0.01$. The weights vector W is initialized to zero, μ_1 and μ_2 are initialized to μ_{1max} and μ_{2max} respectively and the scale factor b to 30 ms. In order to measure the efficiency of our model, the adaptive Hermite model and the EA method were compared by using noisy signals with an SNR equal to -10 dB. To quantify the results, we used the mean-square error (MSE) and the SNR enhancement calculated between the noise-free signals and the noisy signals after denoising by the VSS-LMS adaptive Hermite Model filter. The SNR is defined as:

$$SNR = \frac{\sum_{k=1}^{L_e} s^2(k)}{\sum_{k=1}^{L_e} (s(k) - y(k))^2} \tag{15}$$

where L_e is the number of samples per trial.

In Fig. 2a, we can see that the adaptive Hermite model filter converges faster than the EA. The MSE of Adaptive Hermite model filter reaches the steady state after processing about ten signals. It means that only ten recordings are necessary to estimate the average with high SNR and consequently avoid the fatigue of the subject. We can see, in Fig. 2b, that the improvement of SNR is much important for the Hermite Model than for the EA method. The mean value of the SNR improvement is about 16 dB.

The Fig. 3 shows a higher similarity between the average of the noise-free signals and the average of the individual signals

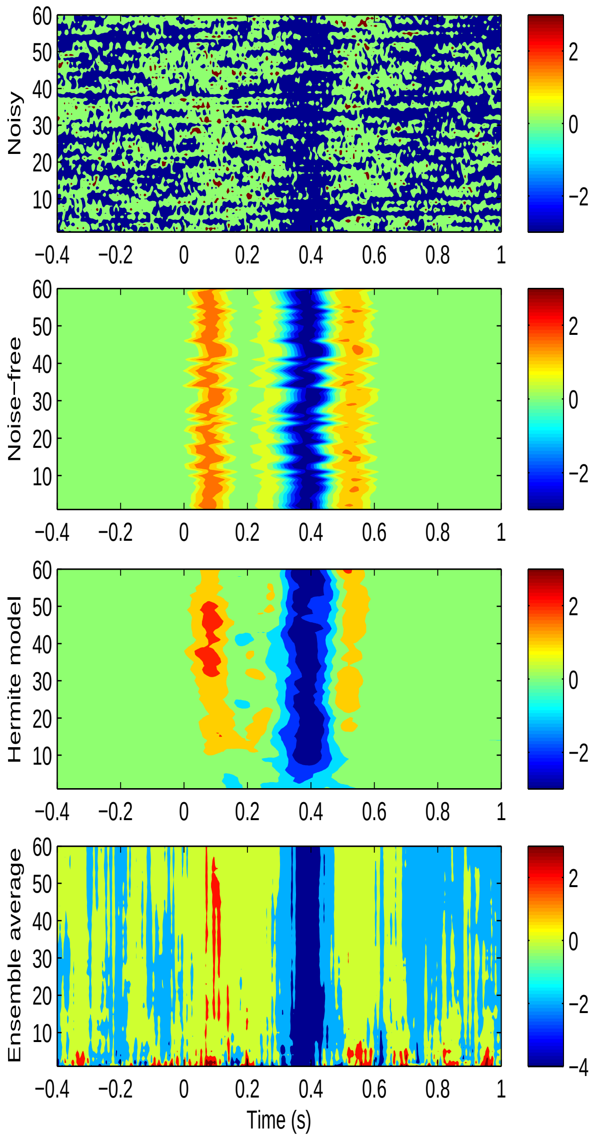


Fig. 4. Contour plot: results of the simulated data analysis.

obtained by the adaptive Hermite model than the EA method. The contour plot in the Fig.4 brings out the similarity between the noise-free signals and the filtered signals by VSS-LMS adaptive Hermite model filter and we can clearly notice that the noise before 0 s and 600 ms was removed.

IV. Recordings and preprocessing

The EEG data was recorded from 7 electrodes (F3, F4, C2, P3, P4, O1 and O2) placed conforming to the international 10-20 system, filtered between 0.1 and 70 Hz and sampled at 250 Hz. Two seconds (2 s) of data were stored on hard disc (256 samples pre-stimulus and 256 samples post-stimulus). Visual Event-Related Potentials (VERPs) were obtained, from healthy subject, using oddball paradigm (for more details on the experiment setup, see [21], [8]).

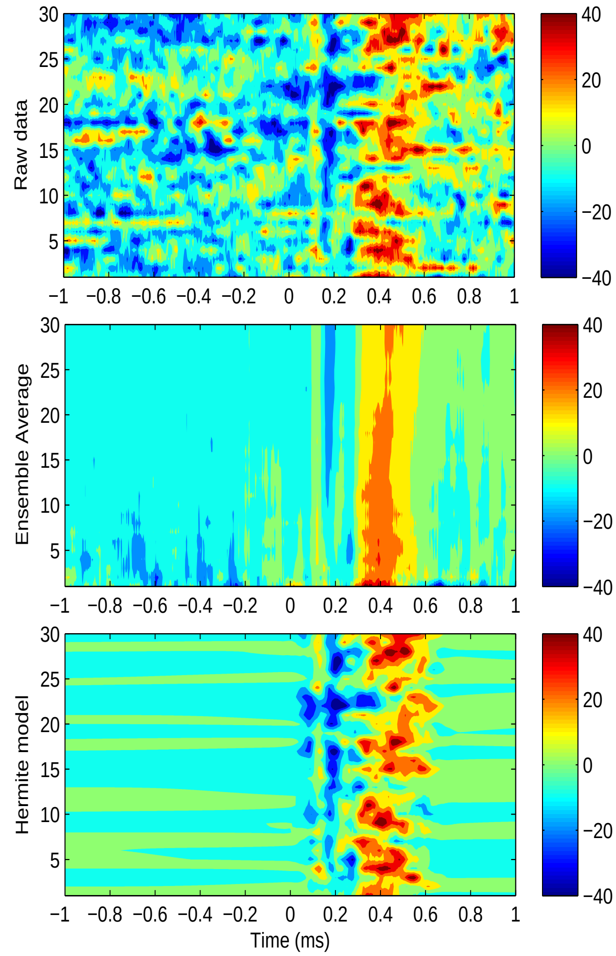


Fig. 5. Contour plot: results of the real data analysis.

V. Real data processing

The VSS-LMS adaptive Hermite filter was applied to real EEG recordings. The recording contains thirty (30) signals. Since the proposed method is for individual channel, only EEG signals from O1 electrode will be presented. The VSS-LMS algorithm is used with an order $M = 8$. For the adaptation step-sizes, we used $\mu_{1min} = 10^{-4}$, $\mu_{1max} = 2$, $\mu_{2min} = 10^{-8}$ and $\mu_{2max} = 10^{-4}$. We found $\alpha = 0.97$ and $\gamma = 0.5$ to be a good choice for real data processing. The weights vector W is initialized to zero, μ_1 and μ_2 are initialized to μ_{1max} and μ_{2max} respectively and the scale factor b to 30 ms.

There are three evoked components: the P_{100} is a positive peak at about 100 ms followed by the N_{200} a negative deflection at 200 ms and the P_{300} a large late positive peak at about 400 ms. In Fig. 5, we present the single-trial ERPs by contour plot before and after denoising using the adaptive Hermite filter and the EA method. We can observe that both methods have removed the noise before 0 s, but the P_{100}-N_{200} peaks are more recognisable on results of the Hermite filter and the P_{300} is less masked by high frequency activity. We can also see that our method keeps the variability between trials, which is clearly missed with the EA method.

VI. Discussion and conclusion

We proposed a filtering method to enhance the signal-to-noise ratio of the single-trial ERPs and we showed its application to simulated data and real ERPs. For the synthetic traces, the VSS-LMS adaptive Hermite model filter gave considerably better estimation of the individual ERPs compared with the original noisy traces and in comparison with the EA filtered data even if the SNR is low. We should mention as well that usually, for high SNRs, the difference between the original data and denoised data becomes small. In the other hand, filtering using VSS-LMS adaptive Hermite model of clean ERP signal gives roughly the same ERP, that is, it does not introduce significant artifacts in the modelling of the ERPs in contrast with Wiener filtering which, for higher SNRs, gives significant errors [8]. The adaptive Hermite model converges to a lower MSE faster than the EA method. This allows to reduce the number of recordings needed to reach a satisfactory signal quality.

Furthermore, the VSS-LMS adaptive Hermite model filter was applied to real data. The components of the single-trial ERPs were more recognisable after filtering by the adaptive Hermite filter. In VERPs, the P_{100} reflects the response of the visual cortex, and depends mainly on the physical stimulus. The P_{300} is the cognitive component of the ERP that is used to investigate cognitive functions, and is evoked in the process of decision-making. This wave depends only on the reaction of the subject to the stimulus. The P_{300} is preceded by the N_{200} wave when the target stimuli are rare among a more common non-target stimuli, which is the case in the oddball paradigm adopted for recording the real data used in this study [22], [23], [24].

The similar morphology of the Hermite functions with the morphology of ERP signals and the orthogonality of those functions justify our choice. They allow to model the ERP signals in a few non-redundant parameters. The VSS-LMS algorithm is well appropriate to non-stationary signals analysis as compared with fixed step-size LMS. The VSS-LMS is more stable because its adaptation step-size parameters are bounded. The results obtained in simulation and real data confirm that the adaptive Hermite model filter is more efficient to denoised the individual ERP signals than the ensemble average method.

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