ELECTROMYOGRAM SIGNAL ENHANCEMENT IN FMRI NOISE USING SPECTRAL SUBTRACTION

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ABSTRACT

This paper deals with noise removal in ElectroMyoGram (EMG) signals acquired in the hostile noisy environment of functional Magnetic Resonance Imaging (fMRI). The noise due to magnetic fields and radio frequencies corrupts significantly the EMG signal which render its extraction very difficult. The proposed approach operes in the frequency domain to estimate the noise spectrum to subtract it from noisy observation spectrum. The noise estimation is based on spectral minima tracking in each frequency bin without any distinction between muscle activity and muscle rest. But it looks for connected time-frequency regions of muscle activity presence to estimate a bias compensation factor. The method is tested with a simulated noisy observation in order to evaluate its performance using objective criteria. It is also validated for real noisy observations where no clean is available.

Index Terms— fMRI noise, EMG signal, denoising, spectral subtraction, noise spectrum estimation

1. INTRODUCTION

The ElectroMyoGram (EMG) signal is the electrical manifestation of a muscular activity. It is a complex signal influenced by the anatomical and the physiological properties of the muscle and also by the peripheral nervous system. To better understand the adaptation mechanisms of the motor command coming from the brain and the muscle synergies, it is interesting to acquire the EMG signal in functional Magnetic Resonance Imaging (fMRI) environment. Indeed, it provides a mean of studying neuronal circuits that control muscles. For example, the brain Blood Oxygenation Level-Dependent (BOLD) changes determined by fMRI are used to identify areas of neuronal activation associated with muscle contraction and their dynamical behavior during muscle activity.

However, the electromagnetic environment of the fMRI is particularly hostile and makes EMG acquisition difficult. The difficulty come from the big level of noise which can be classified into three categories according to its physical origin: *i)* the very high static magnetic field having an order of Tesla (decade of thousands times the Earth's magnetic field), *ii)* the radio frequency waves imposed by the image generating system which requires the emission of successive frequency pulses to excite hydrogen nuclei, and *iii)* the fast variations of magnetic field, called gradients, introduced for spatial encoding of the image or for cutting plane selection.

While denoising of EMG signal acquired in normal environment has attracted the attention of researchers since decades ([1, 2, 3],..), it is not the case for fMRI environment. This is probably due to the novelty of the application and the difficulty of denoising due to the large amount of noise and to its specificities. However, some pioneer works should be mentioned: approaches based on Comb filtering [4] and those based on wavelet thresholding [5].

In this paper, the proposed approach is quite different. It is developed in the frequency domain and it aims at estimating noise spectrum during time intervals where only noise is present. Indeed, a relatively long time interval separates contractions which is quite enough to estimate noise correctly. This amount of noise is recursively updated over time when only noise exists. It is subtracted from noisy EMG during both intervals of muscle rest and muscle activity.

It is important to mention that this idea is well developed in speech enhancement (see for example the pioneer work of Boll [6]). But the noise and the desired signal characteristics are quite opposite. In speech enhancement, the noise has not a particular structure (it is generally assumed to be additive white or low correlated Gaussian noise) and the speech has an harmonic structure for voiced segments and looks like noise for unvoiced segments. In the case of EMG acquired in fMRI environment, the muscle signal is a quasi-white noise whereas fMRI noise is well structured with an harmonic structure imposed by the periodicity of image acquisition.

The paper is organized as follows. Section 2 is devoted to noise characteristics analysis in time and frequency domains. Section 3 details the approach proposed for fMRI noise reduction and illustrates the different steps. Section 4 validates the approach by simulating an fMRI noisy EMG and evaluating the approach using objective criteria. Section 5 gives some results for real noisy EMG signals. Finally, conclusions are drawn in Section 6.

2. CHARACTERIZATION OF NOISE AND EMG SIGNALS IN FMRI ENVIRONMENT

2.1. Time domain analysis

Fig. 1 gives an illustration of an EMG signal acquired on the fMRI tunel. The subject is doing a hand grip exercise composed of 10 contractions of 4.4 seconds duration interspersed by rest intervals of 44 seconds. The first 5 ones are acquired before the functioning of the image acquisition system whereas the five others are acquired during fMRI work. One can notice the low level of noise in the first set. This latter is due to the EMG signal acquisition system (driver amplifier, electrodes, cable movement artifact, inference with power lines...) and to cross talk (other adjacent EMG signals in activity

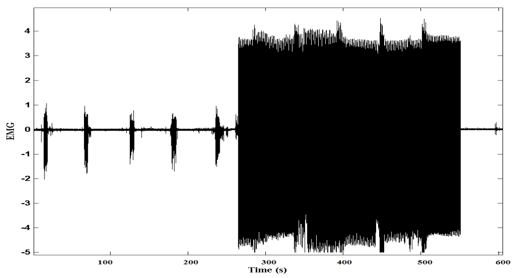

Fig. 1. Temporal evolution of EMG signal before and during image acquisition in fMRI tunel.

a)
b)

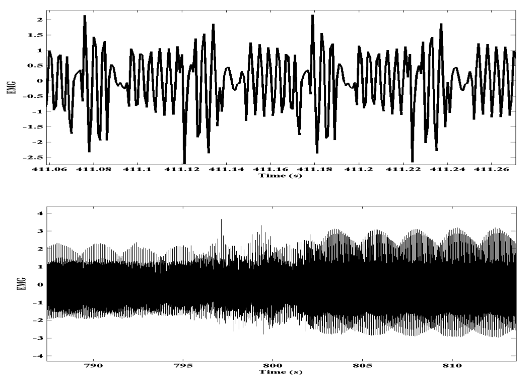

Fig. 2. A zoom on fMRI noise to show its harmonicity (a) and its variation over time (b).

acquired via skin conduction). During the second set of contractions, the fMRI noise due to the magnetic and RF sources hide completely the signal. Hence, it is impossible to locate the contractions by a simple visual inspection of the signal in the time domain as it is the case in normal acquisition conditions.

In Fig.2.a, a zoom on a noise portion of 200 ms duration is drawn. It permits to show the harmonic structure of noise. In fact, the RF pulses are applied repetitively to acquire image slices covering the whole brain volume scan. In Fig.2.b, a larger zoom of duration 20 s shows that noise amplitudes change over time. Sometimes, short abrupt changes occur due to the gradient of magnetic field. This variation is qualified as noise non stationarity.

2.2. Frequency domain analysis

Fig. 3 shows three amplitude spectrum: *i)* fMRI noise (acquired during muscle rest), *ii)* clean EMG signal (acquired in normal condition), and *iii)* noisy EMG (acquired in fMRI environment). The clean EMG signal (in the lower part of the figure) has a quasi-constant spectrum, it hence looks like a white noise. The fMRI noise appears as frequency bins situated at frequencies multiples of the slice acquisition frequency. The fundamental frequency is defined as the number of image slices N over the repetition time of image acquisition T_R. In this case, $T_R = 2215\,\text{ms}$, $N = 43$ so that the fundamental frequency is $F_0 = 19.41\,\text{Hz}$. The noisy EMG amplitude spectrum is dominated by that of noise. In fact, the level of noise is so high so that the quasi-constant spectrum of EMG appears as spectrum shifting.

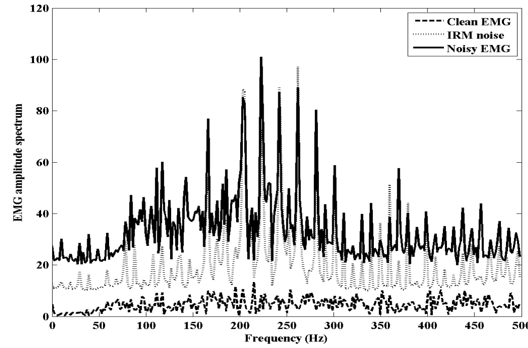

Fig. 3. Amplitude spectrum of fMRI noise, EMG signal in normal and fMRI conditions of acquisition. Spectrum are slightly shifted for the sake of clarity.

3. DENOISING TECHNIQUE

The noise estimation method developed in this work is inspired from the powerful method of Martin carried for speech enhancement [7] and extended in other works such as that of Sorensen *et al* [8]. The details are given in the following subsections.

3.1. Notations

Let $y(k) = s(k) + n(k)$ denote the noisy EMG signal, where $s(k)$ is the clean one and $n(k)$ is the fMRI noise which is assumed to be statistically independent of $s(k)$. Noisy EMG signal is transformed in the time-frequency domain by first applying a window $w(k)$ to N samples of $y(k)$ and then computing the FFT of the windowed signal. The periodogram of the noisy EMG, approximated as to the sum of periodograms of clean EMG and noise, is given by:

$$|\mathbf{Y}(m,l)|^2 = |\mathbf{S}(m,l)|^2 + |\mathbf{N}(m,l)|^2, \tag{1}$$

where l is the frequency bin and m is the frame index.
Note that in practice, the EMG signal is Hamming windowed using a 512-ms window and frames are overlapped during 256-ms. The sampling frequency is $f_s = 1000\,\text{Hz}$. The FFT has the same size as the temporal frame.

3.2. Noise estimation

Once computed, the noisy periodogram is twice smoothed: a spectral smoothing to reduce the fluctuations of the noisy EMG periodogram and a temporal process to correct important fluctuations over time. The spectral smoothing is obtained using a weighted sum of $2D+1$ frequency bins around the considered bin:

$$\mathcal{P}(m,l) = \sum_{\nu=-D}^{D} b(\nu)|\mathbf{Y}(m,(k-\nu)_K|^2, \tag{2}$$

where (m) denotes m modulus K, $\{b(\nu)\}_{\nu=-D}^{D}$ are spectral weights such as the sum of all of them is equal to one.

The temporal smoothing is performed using first order recursion:

$$\mathbf{P}(m,l) = \beta(m,l)\mathbf{P}(m-1,l) + (1-\beta(m,l))\,\mathcal{P}(m,l), \tag{3}$$

where $\beta(m,l)$ is the smoothing factor which varies over time and along frequency bins. It is optimized for tracking non stationary

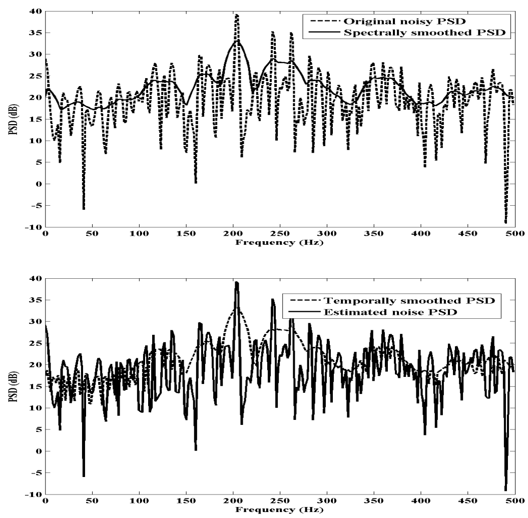

Fig. 4. Spectrums at different steps of the algorithm.

signals by minimizing a conditional mean square error criterion. It is further lower-limited to ensure a minimum degree of smoothing. The details of $\beta(m,l)$ calculus are given in [7].

During muscle rest, the EMG signal energy is close or identical to zero. Thus, the noisy observation periodogram is minimal and equals that of noise. So instead of looking for a muscle activity detection to estimate the noise, one can track for minimum periodogram. Its length is chosen wide enough to bridge the broadest peak in any muscle signal:

$$\mathbf{P}_{min}(m,l) = Min\left(\mathbf{P}(r,l) \quad m - D_{min} < r \leq m\right), \quad (4)$$

where D_{min} is chosen to bridge muscle activity presence periods (2 seconds in this case) and to follow the non stationarity of noise.

The problem with $\mathbf{P}_{min}(m,l)$ is that it is biased towards lower values. In fact, the minimum periodogram estimation is smaller than the average value. The compensation of this limitation is obtained by multiplying with a bias factor $R_{min}(m)$ which is derived from the statistics of the local minimum. The noise periodogram estimate can be written as follows:

$$|\widehat{\mathbf{N}}(m,l)|^2 = R_{min}(m,l)\mathbf{P}_{min}(m,l). \quad (5)$$

$R_{min}(m,l)$ depends on past bias factor, previous noise estimation, minimum periodogram and muscle activity presence [7].

Fig. 4 plots examples of spectra at different steps of the algorithm. The original spectrum $|\mathbf{Y}(m,l)|^2$ and the spectrally smoothed one $\mathbf{P}(m,l)$ (Eq. 2) are shown in the upper sub-figure. The temporally smoothed spectrum $\mathbf{P}(m,l)$ (Eq. 3) and the estimation of the noise spectrum $|\widehat{\mathbf{N}}(m,l)|^2$ (Eq. 5) are shown in the lower sub-figure. We can see that: *i)* the spectral smoothing allows to closely follow the peaks of original noisy spectrum and *ii)* the estimated noise recover the details of the harmonic structure of the noisy EMG. In fact, the peaks are due to the noise and not to the EMG signal.

3.3. Muscle activity detection

The muscle activity detection is an important task to refine the estimation of the bias factor $R_{min}(m)$ and then the noise spectrum. The purpose is to find a binary variable which equals one when muscle

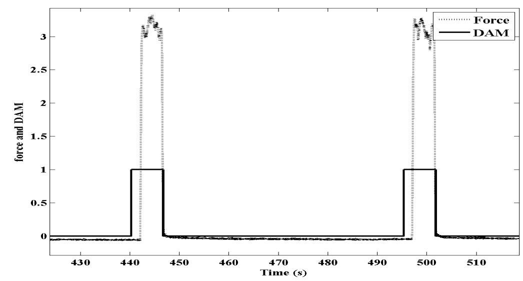

Fig. 5. Muscle activity detector superposed to the force signal.

activity takes place and zero in the opposite case. The approach used in this work is based on the hypotheses tests $H_0(m,l)$ and $H_1(m,l)$ of respective muscle rest and muscle activity:

$$\begin{array}{ll} H_0(m,l): & |\mathbf{Y}(m,l)|^2 = |\mathbf{N}(m,l)|^2 \\ H_1(m,l): & |\mathbf{Y}(m,l)|^2 = |\mathbf{S}(m,l)|^2 + |\mathbf{N}(m,l)|^2. \end{array} \quad (6)$$

The decision on which hypothesis to believe is obtained by finding connected time-frequency regions of EMG activity [8]. In fact, the individual EMG presence detection, for each frame and for each frequency separately, provides individual decisions which are not systematically coherent between them. The original idea in [8] is to identify quite-large regions which are characterized by an increase in noisy periodogram. In fact, an increase is equivalent to a beginning of muscle activity after a rest period. An approach based on the comparison between the noisy periodograms and the minimum estimated one $\mathbf{P}_{min}(m,l)$ can resolve the problem.

Fig. 5 illustrates the resulting Muscle Activity Detector (MAD) using the explained approach. It is superimposed to the force applied during the muscle activity (handgrip exercice). One can note that the muscle activity is completely detected. Moreover, the pre-motor activity is also detected. It occurs during the time interval when the exercise has not yet started but the brain prepared it and sent the command to the muscle.

3.4. Noise reduction

The restoration of the muscle spectrum $|\widehat{\mathbf{S}}(m,l)|^2$ is obtained through the subtraction of the estimated noise spectrum from the noisy signal spectrum:

$$|\widehat{\mathbf{S}}(m,l)|^2 = \begin{cases} |\mathbf{Y}(m,l)|^2 - |\widehat{\mathbf{N}}(m,l)|^2 & \\ \qquad\qquad \text{if } |\mathbf{Y}(m,l)|^2 \geq |\widehat{\mathbf{N}}(m,l)|^2 \\ \lambda|\widehat{\mathbf{N}}(m,l)|^2 \qquad \text{otherwise} \end{cases} \quad (7)$$

The parameter λ controls the amount of background noise to be kept when the noise estimation exceeds the observation.

The restored EMG signal is obtained by inverse Fourier transform (IFFT) of the enhanced magnitude spectrum combined with the phase of the original noisy amplitude spectrum. In fact, the clean EMG phase is unknown, that is why it is approximated by the available one.
The samples of the each denoised EMG frame can be expressed as:

$$\hat{s}(m,n) = IFFT\left[|\hat{\mathbf{S}}(m,l)|.e^{j\arg(\mathbf{Y}(m,l))}\right]. \quad (8)$$

4. DENOISING RESULTS

4.1. Dataset

The EMG data under fMRI were recorded from four forearm muscles which are the common extensor muscle, the brachioradialis, the flexor superficialis and the flexor profundus. The EMG measurements were performed using the BIOPAC MP150WSW MRI compatible system with a sampling frequency of 1000 Hz. Volunteers performed three successive runs. In each run, five contractions of 4.4 seconds duration are preceded by a preparation time interval of 6.6 seconds and followed by a relax interval of 44 seconds. The three runs differ by the instruction given to activate muscle:
• Verbal instruction: an external voice signal is emitted to launch the beginning of the contraction and is followed by verbal encouragement.
• A triggered instruction: a voice signal is used to activate the muscle but it is not followed by encouragement.
• Self-controlled instruction: the beginning and the ending of the contraction is initiated by the subject himself.

4.2. Simulation tests

In order to check the validity and the precision of the proposed denoising approach, both clean and fMRI noisy EMG signals are acquired separately. The first noise is acquired in normal conditions while the second one is acquired under fMRI but no muscle activity task is done. The two observations are added together according to the model of Eq.1. The denoising approach is applied and two temporal criteria are used for evaluation. The first one is the overall Signal to Noise Ratio SNR calculated for the whole signals including muscle activity and rest intervals. The second one is the segmental Signal to Noise Ratio $SSNR$ calculated exclusiveley during muscle activity:

$$SNR = 10\log_{10}\left(\frac{\sum_{k=1}^{L} s(k)^2}{\sum_{k=1}^{L} e(k)^2}\right), \tag{9}$$

$$SSNR = \frac{1}{M}\sum_{m=1}^{M} 10\log 10\left(\frac{\sum_{i=1}^{N} s(m,i)^2}{\sum_{i=1}^{N} e(m,i)^2}\right), \tag{10}$$

where L is the total number of samples, M is the total number of effective muscle activity frames, m is the frame index of size N. k (resp. i) is the temporal index of the whole signal (resp. frame). The signal denoted e is the perturbation. Before denoising, e is the noise during acquisition. After denoising, it is the difference between the clean EMG and the denoised one.

Fig. 6 gives the SNR and the SNR before (SNR_{in} and $SSNR_{in}$) and after (SNR_{out} and $SSNR_{out}$) denoising for one EMG signal. The rate of added noise is weighted by a factor α so that the amount of noise can vary from the real level ($\alpha = 1$) to a reduced one ($\alpha = 0.1$). From Fig. 6, one can notice the significant improvement of both SNR and $SSNR$. The rate of improvement varies from 5 dB for low level of noise ($\alpha = 0.1$) to 16 dB for high realistic level of noise ($\alpha = 1$). This conclusion validates the proposed denoising approach.

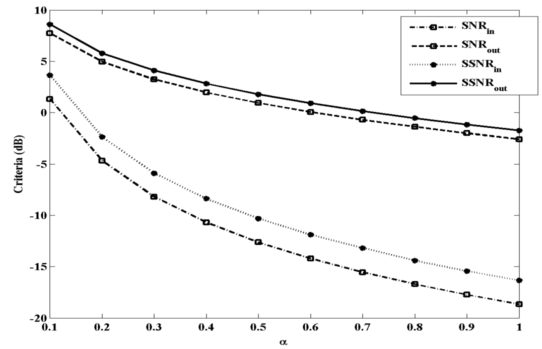

Fig. 6. Performance criteria before and after denoising in simulated conditions.

4.3. Denoising technique validation

To evaluate the ability of the denoising algorithm to enhance the EMG signal, the same handgrip exercice is carried out in the ambient environment (outside the fMRI tunnel). The objective is to have a reference EMG signal for comparison. The case of the common extensor muscle is illustrated in the following figures.

Fig. 7 shows the temporal evolution of the noisy EMG, the denoised one and the reference signal. One can notice that:
• the noise is well reduced and the enhanced signal has the same look than the reference one.
• At the begining of each run, the noise level changes brutally and the algorithm of noise estimation needs few seconds to estimate the right quantity.
• At the end of the third contraction, there is a noise pulse which is not removed because there is a abrupt change in noise level that the algorithm is not able to detect.

Fig. 8 shows the spectrograms of the noisy EMG, the denoised one and the reference signal. We can easily see the harmonic structure of noise (horizontal lines) and the noise-like structure of EMG signal (vertical regions with homogenous contents. With the proposed algorithm, the harmonic noise is well removed in low frequency regions. But, it persists in intermediate frequency regions (reduced but not totally removed). In the EMG signal acquired outside fMRI, one can notice the existence of an harmonic at 50 Hz which is the interference with power lines.

One other method used to produce waveforms that are more easily analyzable than the direct EMG signal is the Root Mean Square (RMS). It is a technique for rectifying the raw signal and converting it to an amplitude envelope which is very useful to estimate force and muscle activation degree. The RMS is defined as follows:

$$RMS(m) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} s(m,i)^2}. \tag{11}$$

Fig. 9 shows the evolution of the enhanced RMS and the reference one for four contractions of same type. It indicates that they have the same duration. In terms of waveforms, big similarities exist, they are mainly due to muscle size, its position in the forearm and the same handgrip exercise. Some differences exist and are due to the electrodes placement, the modification in the way to do the exercise, the environmental and residual noise,...

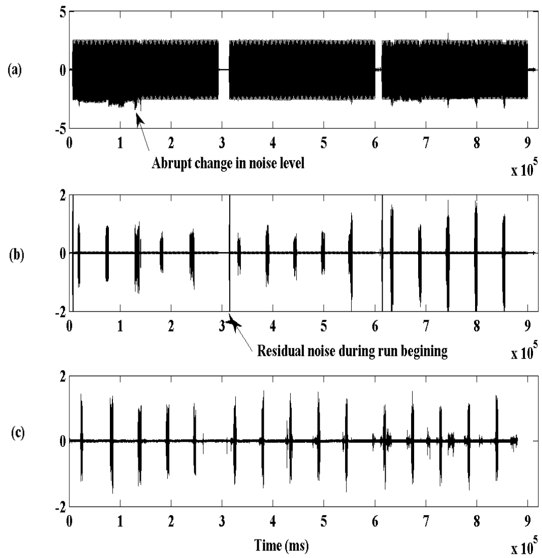

Fig. 7. Temporal EMG signals. (a): noisy, (b): enhanced, (c): reference

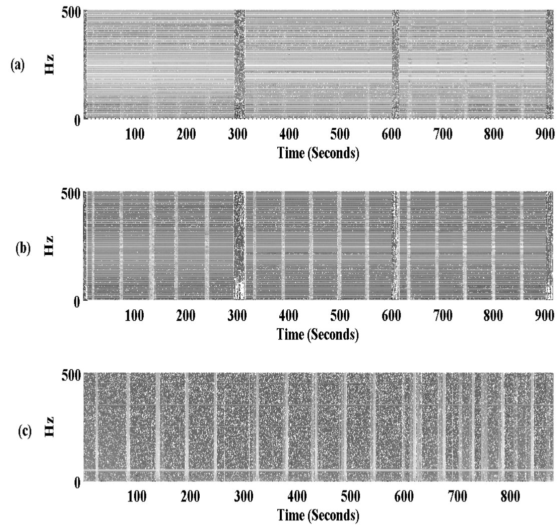

Fig. 8. Spectrograms of EMG signals. (a): noisy, (b): enhanced, (c): reference

5. CONCLUSION

In this work, we have presented a technique for denoising an EMG signal completely embedded in fMRI noise. The approach is based on the estimation of the noise spectrum using time and spectral smoothing and minimum statistics. The technique is tested with artificial noisy EMG data and validated for real data. EMG of four muscles of the forearm are considered and are shown to be clearly enhanced thanks to the proposed approach. In the future, the enhanced EMG signal will be faced to the brain Blood Oxygenation Level-Dependent (BOLD) extracted from fMRI images in order to study the co-activation mechanism of brain and muscle during the preparation of muscle task.

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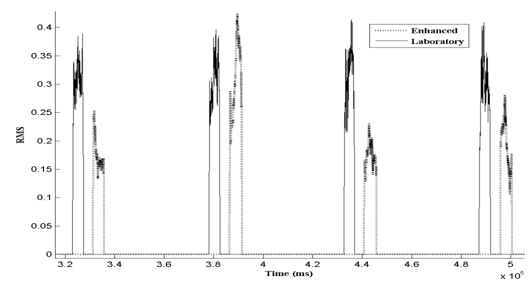

Fig. 9. RMS waveforms of enhanced and reference EMG signals.

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