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Study of Wavelet Transform based Technique in Document Images

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Abstract-
This paper deals with the documentation for the extraction of textual areas of a document image using globally matched wavelet filters. Document Image Segmentation, Feature Extraction and Image components classification form a fundamental problem in many applications of multi-dimensional signal processing. We discussed the Wavelet Techniques like Continuous Wavelet Transform (CWT), Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT) and calculating the performance metrics implementing with text images.

Keyword: Document Image Segmentation (DIS), Gabor Filter, Wavelet Transform, CWT, DCT, DWT.

1. INTRODUCTION

Document Image Segmentation (DIS) procedures partition an image into its constituent parts or objects. In general, segmentation is one of the most difficult tasks in digital image processing. A rugged segmentation procedure brings the process a long way toward successful solution of imaging problems that require objects to be identified individually. On the other hand, weak or erratic segmentation algorithms almost always guarantee eventual failure. The more accurate the segmentation, the more likely recognition is to succeed. The wavelet transform provides a compact description of document images and it is very helpful in description of edges and lines that are highly localized. 2-D wavelet decomposition is used for document images. The process of texture segmentation using Gabor filters involves proper design of a filter bank tuned to different spatial-frequencies and orientations to cover the spatial-frequency space; decomposing the document image into a number of filtered document images; extraction of features from the filtered document images; and the clustering of pixels in the feature space to produce the segmented document image. This paper deals with segmentation of document image based on wavelet transform method. The experimental results are obtained for wavelet transform using Discrete Cosine Transform coefficients & DWT, Inverse DWT and creating Gabor filter for document images [1].

The wavelet transform plays an extremely crucial role in image compression. For image compression applications, wavelet transform is a more suitable technique compared to the Fourier transform. Fourier transform is not practical for computing spectral information because it requires all previous and future information about the signal over the entire time domain and it cannot observe frequencies varying with time because the resulting function after Fourier transform is a function independent of time. Wavelet transforms are based on wavelets which are varying frequency, and the improvements that can be made to enhance the performance of the wavelet transforms [4]. Background information such as time-frequency analysis and multiresolution analysis. The mid-portion of the paper focuses on the wavelet transforms and their derivations for both one dimensional and two dimensional cases. Improved algorithms for the wavelet transforms including the fast wavelet transform, lifting scheme, and reversible integer wavelet transform. Lifting-based discrete wavelet transform has many advantages over the convolution-based transform and it can be combined with the concept of integer-to-integer transform in order to enhance the performance of lossless image compression.

The discrete wavelet transform (DWT) is a linear transformation that operates on a data vector whose length is an integer power of two, transforming it into a numerically different vector of the same length. It is a tool that separates data into different frequency components, and then studies each component with resolution matched to its scale. DWT is computed with a cascade of filtering followed by a factor 2 sub sampling (Fig.1).

Discrete Wavelet transform (DWT) is a mathematical tool for hierarchically decomposing an image. This transform is based on wavelets which are of varying frequency. The transform of a signal is just another way of representing the signal; it does not change the information content present in the signal. The Discrete wavelet transform provides a time-frequency representation of the signal. DWT is the popular technique which is used for image watermarking and image compression applications with excellent visual quality of the processed image.

The basic idea of discrete wavelet transform in image processing is to decompose the image into sub-image of different spatial domain and independent frequency sub-bands. After the cover image has been DWT transformed, it is decomposed into four frequency parts (LL, LH, HL, and HH) as shown in Fig. 1. LL is the low frequency sub-band which contains the approximation of the original image. HL represents the high frequency sub-band which contains the horizontal details of the image. LH represents the high frequency sub-band which contains the vertical details of the image. HH represents the high frequency sub band of the diagonal image [4].

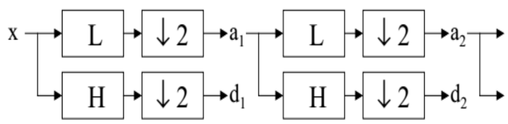


Fig 1. DWT tree

H and *L* denotes high and low-pass filters respectively, ↓2 denotes subsampling. Outputs of this filters are given by equations (1) and (2).

$$a_{j+1}[p] = \sum_{n=-\infty}^{+\infty} l[n-2p]\, a_j[n]$$

$$d_{j+1}[p] = \sum_{n=-\infty}^{+\infty} h[n-2p]\, a_j[n]$$

Elements a_j are used for next step (scale) of the transform and elements dj, called wavelet coefficients, determine output of the transform. *l[n]* and *h[n]* are coefficients of low and high-pas filters respectively One can assume that on scale $j+1$ there is only half from number of a and d elements on scale j. This causes that DWT can be done until only two a_j elements remain in the analyzed signal. These elements are called scaling function coefficients.

The wavelet transform has similar properties to Fourier transform as a mathematical technique for document image analysis, the basic difference between both is that wavelets are localized in both time and frequency, whereas the standard Fourier transform is only localized in frequency. When digital document images are viewed or processed at multiple resolutions, the discrete wavelet transform (DWT) is the mathematical tool of choice. In addition to being an efficient, highly intuitive framework for the representation and storage of multiresolution document images, the DWT provides powerful insight into a document image spatial and frequency characteristics. The wavelet transform is important to provide a compact description of document images that are limited in time and it is very helpful in description of edge and line that are highly localized. 2-D wavelet decomposition is use for document images. This 2-D wavelet transform requires two wavelets such as ψ1(x, y) and ψ2(x, y). At a particular scale s we have,

$$\psi_s^i(x,y) = \frac{1}{s2}\ \psi i\left(\frac{x}{s},\frac{y}{s}\right) \quad i = 1, 2 \ldots$$

By applying each one f(x, y), at a scale s=2j we will have a component

$$W_{2^j}^i f(x,y) = \left(f * W_{2^j}^i\right)(x,y) \quad i = 1, 2 \ldots$$

Then the original signal f(x, y) can be represented by the 2-D wavelet transform in terms of the two dual wavelets §1(x, y) and §2(x, y) [2].

$$f(x,y) = \sum\left(\left(W_{2^j}^1 f * \xi_{2^j}^1\right)(x,y) + \left(W_{2^j}^2 * \xi_{2^j}^2\right)(x,y)\right).$$

And it is required a scaling function φ(x, y) for build a multistage representation, corresponding component at a scale 2j is:

$$S_{2^j} f(x,y) = (f * \varphi_{2j})(x,y)$$

These wavelet measure function variations along different directions. We may interpret the component $S_{2^j}f(x,y)$ as a smoothed version of f(x, y) and the components for j = 1…J, as the document image details lost by smoothing going from $S_{2^0}f(x,y)$ to $S_{2^j}f(x,y)$ [3-4].

1.1 Image compression

Even though the wavelet transforms have been widely used in image coding since the late 80s, they only gained their notoriety in the field by the adoption of the first wavelet-based compression standard scheme, known as the FBI fingerprint compression standard Bradley, et al., 1993). Recently, what did Sweldens state in (Sweldens, 1996) as a need of standardizing a wavelet-based compression scheme under the header "problems not sufficiently explored with wavelets", has seen the day, by the adoption of the JPEG2000 new compression standard (Ebrahimi et al., 2002). The block diagram of the JPEG2000 standard does not really differ from the JPEG standard one. The discrete wavelet transform, which replaces the DCT, is applied first to the source image. The transformed coefficients are then quantized. Finally, the output coefficients from the quantizer are encoded (using either Huffman coding or arithmetic coding techniques) to generate the compressed image (Smith, 2003; Do & Vetterli, 2005; Hankerson et al., 2005; Xiong & Ramchandran, 2005; Chappelier & Guillemot, 2006; Nai-Xiang et al., 2006; Raviraj & Sanavullah, 2007; Mallat, 2009; Oppenheim & Schafer, 2010). To recover the original image the inverse process is applied. Figure 21 shows the basic JPEG2000 Encoding Scheme (Ebrahimi et al., 2002) [5].

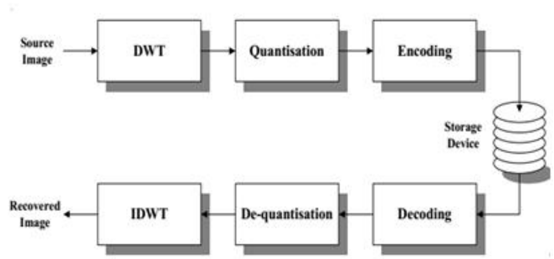


Fig 2. Wavelet-based encoding scheme

1.2 Image denoising

Image manipulation, includes a wide range of operations like digitizing, copying, transmitting, displaying etc. Unfortunately, such manipulations generally degrade the image quality by spanning many types of noise. Hence, to recover the original structure of the image, the undesired added noise needs to be localized and then removed [6]. Traditionally, image denoising or image enhancement is performed using either linear filtering or non-linear filtering. Linear filtering is achieved either by using spatial techniques, as low pass filtering, or frequency techniques, as the Fast Fourier Transform (FFT). On the other hand, statistical and morphological filters are typical examples of non-linear filtering. However, the filtering techniques lead in some cases to baneful effects when applied indiscriminately to an image. In fact, if it is not the whole image that is blurred, some of its important features (e.g. edges) are baneful effects when applied indiscriminately to an image. In fact, if it is not the whole image that is blurred, some of its important features (e.g. edges) are, a solution to overcome this problem has been introduced by Denoho and Johnstone (1994). Instead of exploiting either linear or non-linear filtering, their technique consists of using the DWT followed by a thresholding operation. This method exploits the energy compaction ability of the wavelet transform to separate the image from the added noise. The role of the threshold is to eliminate the noise present in the image. Finally, the enhanced "denoised" image is recovered by applying the inverse DWT [7]. This method is also known as the wavelet shrinkage denoising, and is classified as a nonlinear processing technique due to the thresholding operation involved in the process as illustrated in Fig. 3.

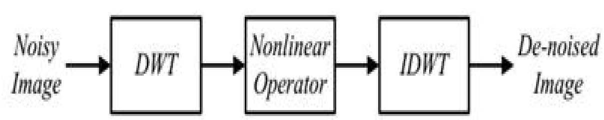


Fig. 3 Wavelet-based denoising system

Another method, which achieves better performances when compared to the previous one, consists of using an undecimated version of the DWT (Donoho & Johnstone, 1995). This choice is motivated by the fact that originally, the DWT is not a shift-invariant transform, and as such, visual artifacts can be spanned by the transform. This like-noise is more apparent around discontinuities in the image. However, in this particular case the inverse transform is not unique. As a solution, it is appropriate to take the average of the possible reconstruction. The computational complexity of this approach is O(nlog(n)) [8].

1.3 Continuous Wavelet Transform

Continuous Wavelet Transform (CWT) is an implementation of the wavelet transform using arbitrary scales and almost arbitrary wavelets. The wavelets used are not orthogonal and the data obtained by this transform are highly correlated. For the discrete time series we can use this transform as well, with the limitation that the smallest wavelet translations must be equal to the data sampling. This is sometimes called Discrete Time Continuous Wavelet Transform (DT-CWT) and it is the most used way of computing CWT in real applications

In principle the continuous wavelet transform works by using directly the definition of the wavelet transform, i.e. we are computing a convolution of the signal with the scaled wavelet. For each scale we obtain by this way an array of the same length N as the signal has. By using M arbitrarily chosen scales we obtain a field N×M that represents the time-frequency plane directly. The algorithm used for this computation can be based on a direct convolution or on a convolution by means of multiplication in Fourier space (this is sometimes called Fast Wavelet Transform).

Different ways to introduce the wavelet transform can be envisaged (Starck et. al., 1998). However, the traditional method to achieve this goal remains the use of the Fourier theory (more precisely, STFT). The Fourier theory uses sine and cosine as basic functions to analyses a particular signal. Due to the infinite expansion of the basic functions, the FT is more appropriate for signals of the same nature, which generally are assumed to be periodic. Hence, the Fourier theory is purely a frequency domain approach, which means that a particular signal f(t) can be represented by the frequency spectrum F(w), as follows:

$$F(\omega) = \int_{-\infty}^{+\infty} f(t)e^{-j\omega t}dt$$

The original signal can be recovered, under certain conditions, by the inverse Fourier Transform as follows:

$$f(t) = \frac{1}{2\pi}\int_{-\infty}^{+\infty} F(\omega)e^{j\omega t}d\omega$$

Obviously, discrete-time versions of both direct and inverse forms of the Fourier transform are possible

1.4 Discrete Cosine Transform

A discrete cosine transform (DCT) expresses a finite sequence of data points in terms of a sum of cosine functions oscillating at different frequencies. DCTs are important to numerous applications in science and engineering, from lossy compression of audio (e.g. MP3) and images (e.g. JPEG) (where small high-frequency components can be discarded), to spectral methods for the numerical solution of partial differential equations. The use of cosine rather than sine functions is critical for compression, since it turns out (as described below) that fewer cosine functions are needed to approximate a typical signal, whereas for differential equations the cosines express a particular choice of boundary conditions.

In particular, a DCT is a Fourier-related transform similar to the discrete Fourier transform (DFT), but using only real numbers. The DCT are generally related to Fourier series coefficients of a periodically and symmetrically extended sequence whereas DFT are related to Fourier series coefficients of a periodically extended sequence. DCT are equivalent to DFTs of roughly twice the length, operating on real data with even symmetry (since the Fourier transform of a real and even function is real and even), whereas in some variants the input and/or output data are shifted by half a sample. There are eight standard DCT variants, of which four are common.

The most common variant of discrete cosine transform is the type-II DCT, which is often called simply "the DCT its inverse, the type-III DCT, is correspondingly often called simply the inverse DCT or the IDCT Two related transforms are the discrete sine transform (DST), which is equivalent to a DFT of real and odd functions, and the modified discrete cosine transform (MDCT), which is based on a DCT of overlapping data. Multidimensional DCTs (MD DCTs) are developed to extend the concept of DCT on MD Signals. There are several algorithms to compute MD DCT. A new variety of fast algorithms are also developed to reduce the computational complexity of implementing DCT.

JPEG stands for the Joint Photographic Experts Group, a standards committee that had its origins within the International Standard Organization (ISO).JPEG provides a compression method that is capable of compressing continuous-tone image data with a pixel depth of 6 to 24 bits JPEG is primarily a lossy method of compression [9]. JPEG was designed specifically to discard information that the human eye cannot easily see. Slight changes in color are not perceived well by the human eye, while slight changes in intensity (light and dark) are. Therefore JPEG's lossy encoding tends to be more frugal with the grayscale part of an image and to be more frivolous with the color.DCT separates images into parts of different frequencies where less important frequencies are discarded through quantization and important frequencies are used to retrieve the image during decompression. Compared to other input dependent transforms, DCT has many advantages: (1) It has been implemented in single integrated circuit; (2) It has the ability to pack most information in fewest coefficients; (3) It minimizes the block like appearance called blocking artifact that results when boundaries between sub-images become visible. The forward 2D_DCT transformation is given by (1): C(u,v)=D(u)D(v)

$$\sum_{x=0}^{N-1} \sum_{y=0}^{N-1}$$

f(x,y)cos[(2x+1)uπ/2N]cos[(2y+1)vπ/2N])

Where u, v=0, 1, 2, 3,---N-1 The inverse 2D-DCT transformation is given by the following equation

$$\sum_{u=0}^{N-1} \sum_{v=0}^{N-1} D(u)D(v)$$

f(x,y)= f(x,y)

cos[(2x+1)uπ/2N]cos[(2y+1)vπ/2N]

where, D(u)=(1/N) ^1/2 for u=0
D(v)=2(/N)^1/2 for u=1,2,3…….,(N-1) [10-11].

1.5 Discrete Wavelet Transform

In this section, we specify the framework in which the algorithms will be derived. We also briefly motivate the need for further reduction of complexity in a DWT. We assume real data and filters (of finite length), but the results extend easily to the complex-valued case. It can be shown that the FFT-based algorithms described next require about twice as many multiplications in the complex case than in the real case, a property shared by FFT algorithms [SI, .However, a straightforward filter bank implementation of the DWT or the "short-length" algorithms described in Section 111-E require about three times as many multiplications in the complex case, assuming that a complex multiplication is carried out with three real multiplications and additions.

In our derivations, we do not take advantage of possible constraints (such as orthogonality), even though these can be used to further reduce the complexity. The resulting algorithms therefore apply in general. The derivation of fast algorithms is primarily based on the reduction of computational complexity. Here, "complexity" means the number of real multiplications and real additions required by the algorithm, per input point. In the DWT case, this is also the complexity per output point since the DWT is critically sampled of course, complexity is not the only relevant criterion. For example, regular computational structures (i.e., repeated application of identical computational cells) are also important for implementation issues.

However, since most algorithms considered in this paper have regular structures, a criterion based on complexity is fairly instructive for comparing the various DWT algorithms. We have chosen the total number of operations (multiplications+ additions) as the criterion. With today's technology, this criterion is generally more useful than the sole number of multiplications at least for general purpose computers (another choice would have been to count the number of multiplication-accumulations). Due to the lack of space, we shall not derive algorithms explicitly for the inverse DWT. However, a IDWT algorithm is easily deduced from a DWT algorithm as follows: If the wavelets form an orthogonal basis, the exact inverse algorithm is obtained by taking the Hermitian transpose of the DWT flow graph. Otherwise, only the structure of the inverse algorithm is found that way, the filter coefficients g[n] ,h[n] have to be replaced by g[n], h[n], respectively. In both cases, any DWT algorithm, once transposed, can be used to implement an IDWT. It can be shown that this implies that the DWT and IDWT require exactly the same number of operations (multiplications and additions) per point. The filters involved in the computation of the DWT (cf usually have equal length L. This is true in the orthogonal case, while in the biorthogonal case the filter lengths may differ by a few samples only.

Although an implementation of "Morlet-type" wavelets used in uses a short low-pass filter g [n]and a long high-pass filter h [n], we restrict in this section to the case of equal filter lengths for simplicity. If lengths differ, one can pad the filter coefficients with zeros. Section 111-G discusses the case when filters are of very different lengths. It is important to note that the standard DWT algorithm, implemented directly as a filter bank, is already "fast." This fact was mentioned by Ramstad and Saramaki in the context of octave-band filter banks. What makes the DWT "fast" is the decomposition of the computation into elementary cells and the subsampling operations (called decimations) which occur at each stage. More precisely, the operations required by one elementary cell at the j^{th} octave are counted as follows. There are two filters of equal length L involved. The "wavelet filtering" by h [n]directly provides the wavelet coefficients at the considered octave, while filtering by g[n] and decimating is used to enter the next cell. A direct implementation of the filters g [n]and h[n] followed by decimation requires 2 L multiplications and 2(L- 1) additions for every set of two inputs. That is, the complexity per input point for each elementary cell is L mults/point/cell and L - 1 adds/point/cell. Since the cell at the j^{th} octave has input subsampled by 2J-', the total complexity required by a filter bank implementation of the DWT on J octaves is (1 + 1/2 + ¼ + ... + 1/2"-') = 2(1 - 2-") times the complexity, that is

2 L (1 - 2-") mults/point and

2 (L - 1) (1 - 2-") adds/point.

The DWT is therefore roughly equivalent, in terms of complexity, to one filter of length 2 L. A remarkable fact is that the complexity remains bounded as the number of octaves, J, increases. We remark, in passing, that a naive computation of the DWT would implement exactly as written, with precomputed discrete wavelets hj[n] .This does not take advantage of the dilation property of wavelets (9), and therefore is not effective. Since the length of h j [n]is (L - 1)(2' - 1) f 1 , one would have, at the j^{th} octave, (L- 1)(2' - 1) + 1 real multiplications and (L - 1)(2' - 1) real additions for each set of 2 j inputs. For a computation on J octaves (j = 1 ; . . . , J),this gives J (L - 1) + 1 mults/point and J (L - 1) adds/point.

This complexity increases linearly with J, while that of the "filter bank" DWT algorithm is bounded as J increases. The use of the filter bank structure in the DWT computation thus reduces the complexity from JL to L. This is a hug gain; the DWT already deserves the term "fast" [12].

EXPERIMENTAL RESULTS

In this paper we calculate the metrics are as follows.

2.1 Bit Per Pixel (BPP)

The number of bits of information stored per pixel of an image or displayed by a graphics adapter. The more bits there are, the more colors can be represented, but the more memory is required to store or display the image

2.2 Compression Ratio (CR)

Compression ratio indicates the efficiency of compression technique, more the compression ratio, less memory space required. The compression ratio is equal to the size of the original image divided by the size of the compressed image. The compression ratio achieved usually point out the picture quality. Generally, the higher the compression ratio, the poorer the quality of the resulting image.

2.3 PSNR(Peak Signal Noise Ratio)

PSNR value is used to measure the difference between a reconstructed image and original image. In general, the larger PSNR value, the better is image quality, so there is an inverse relationship of MSE and PSNR. There is an inverse relationship between MSE and PSNR. Hence, the larger PSNR value gives the better image quality.

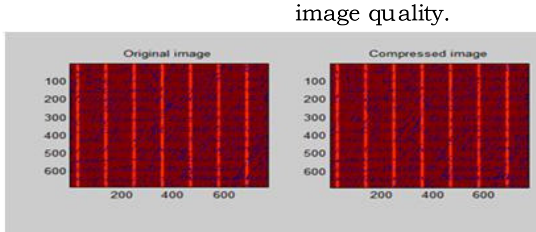


Fig. 4 Original Document Image Original & Compressed

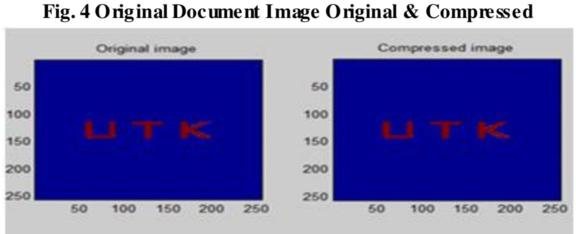
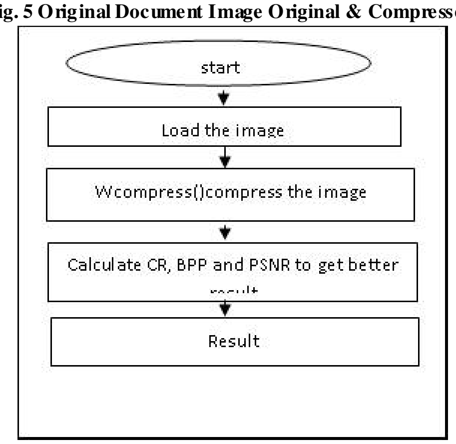
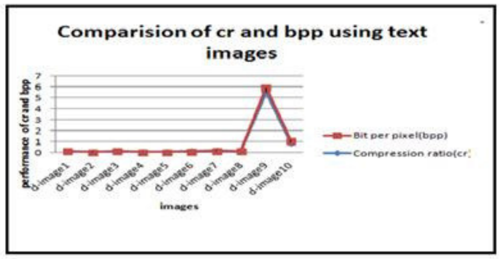


Fig. 5 Original Document Image Original & Compressed





Graph 1: Comparison of Compression (cr) and Bit-Per-Pixel (bpp) using text images

The above graph bit per pixel (bpp) ratio are constant at point zero and some little more increase at point d image 9 increase at point 0.5 .compress ratio of text images are increased at point d-image 8 at level 5.5.so that it's a high resolution image.

Images	Compression Ratio(cr)	Bit Per Pxel (bpp)
d-image1	0.1370	0.0110
d-image2	0.0216	0.0052
d-image3	0.1370	0.0110
d-image4	0.0399	0.0032
d-image5	0.0342	0.0027
d-image6	0.0933	0.0075
d-image7	0.1534	0.0123
d-image8	0.1133	0.0091
d-image9	5.4794	0.4384
d-image10	0.8985	0.2156

2. CONCLUSION

In this paper, we have described document images performed by using wavelet transforms. To solve this problem, wavelet transforms are used for increasing accuracy. Resolution reduction by wavelet is dependent on amount of noise in the document image and also the desired target size.

In the paper, image compression techniques using DCT and DWT were implemented. DCT is used for transformation in JPEG standard. DCT performs efficiently at medium bit rates. DWT provides high quality compression at low bit rates. The use of DWT basis functions or wavelet filters produces blurring near edges in images. DWT performs better than DCT in the context that it avoids blocking artifacts which degrade reconstructed images. However DWT provides lower quality than JPEG at low compression rates.

DWT requires longer compression time. A new image compression scheme based on discrete wavelet transform is proposed in this research which provides sufficient high compression ratios with no appreciable degradation of image quality. The effectiveness and robustness of this approach has been justified using a set of real images. Wavelets are better suited to time-limited data and wavelet based compression technique maintains better image quality by reducing errors.

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