A NEW IMPROVED FLEXIBLE SEGMENTATION ALGORITHM USING LOCAL COSINE TRANSFORM

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ABSTRACT

To the problem of no overall optimal merger for one-way merger in the segmentation algorithm proposed by Wang Yongzhong, et al., in this paper, we propose a method of overall optimal search and merger. At the same time, to the unreasonable problem of merging a segment which has non-value (value-segment) and a segment which values are zeros entirely (zeros-segment) to a large segment in Wang's method, we also propose a corresponding method to solve the problem. The main techniques are incarnated in local cosine transform (LCT) algorithm for a single small segment, rather than folding processing using its original neighboring data, instead of making zero-extension, and then fold the each zero-extension segment. A great deal of numerical simulations validate that this new improved technique solves several problems of the binary-based segment algorithm and Wang's segment algorithm, it not only obtains adapted effective segmentation result, but also there are not much more redundancy segmentations.

1. INTRODUCTION

Local cosine bases constructed by Coifman and Meyer (1991)[1] (also see Auscher, et al. 1992)[2] consist of cosines multiplied by smooth, compactly supported bell functions. These localized cosine functions remain orthogonal and have small Heisenberg products. However, the binary-based segmentation algorithm via best-basis selection[3] in the applications of adapted local cosine transform (LCT) has several inherent limitations. First, the binary-based segmentation has not only no flexibility for 1-D signal at all, but also has much more redundant segmentations. Secondly, the binary-based segmentation is very sensitive to the time-shift of the original signal, such that the resulted best-basis will change a great deal if the signal is shifted by some samples. Due to the above mentioned problems of the binary-based segmentation algorithm, a new flexible segmentation method was presented by Wang Yongzhong in the literature[4], although the new method basically solved the problems, but there are also a few questions to be solved. On the basis of Wang's method, this paper presents a corresponding improved method to solve the problem. At the same time, we also propose a method of overall optimal search and merger to overcome the problem that the one-way merger by left-to-right in the literature[4] will not be an overall optimal search merger. The improved segmentation algorithm has more flexible than the binary-based segmentation algorithm and Wang's segmentation algorithm, and it is suitable for the research of effective segmentation and speech compression, etc.

2. ADAPTED LOCAL COSINE TRANSFORM

2. 1. Brief description of local cosine transform

We recall briefly the local cosine transform[5][6]. Let us consider a partition of the line $R=\bigcup_{j\in Z} I_j$, with $I_j=[a_j,a_{j+1})$, such that the width of the intervals is never less than a fixed positive number: $a_{j+1}-a_j\ge\varepsilon>0$ for all $j\in Z$. We define the following cutoff functions

$$b_j(t)=\begin{cases}\beta\left(\frac{t-a_j}{r}\right) & t\in[a_j-r,a_j+r)\\ 1 & t\in[a_j+r,a_{j+1}-r)\\ \beta\left(\frac{a_{j+1}-t}{r}\right) & t\in[a_{j+1}-r,a_{j+1}+r)\\ 0 & t\in(-\infty,a_j-r]\cup[a_{j+1}+r,\infty)\end{cases}$$

with $\beta(t)=\sin[(\pi/4)(1+\sin(\pi/2)t)]$ and $0<r\le\varepsilon$. The set of functions

$$\psi_k^j(t)=b_j(t)\frac{\sqrt{2}}{\sqrt{|I_j|}}\cos\frac{\pi}{|I_j|}\left(k+\frac{1}{2}\right)(t-a_j)$$

with $j\in Z$ and $k\in N$ is an orthogonal basis for $L^2(R)$. Consequently, each signal $S(t)\in L^2(R)$ can be written in terms of the functions ψ_k^j

$$S(t)=\sum_{\substack{j\in Z\\ k\in N}}c_k^j\psi_k^j(t)$$

with

$$c_k^j=\left\langle S(t),\psi_k^j(t)\right\rangle=\frac{\sqrt{2}}{\sqrt{|I_j|}}\int S(t)b_j(t)\cdot\cos\frac{\pi}{|I_j|}\left(k+\frac{1}{2}\right)(t-a_j)dt \qquad (1)$$

A superposition of these functions may be depicted by a sequence of adjacent envelopes or windows, with vertical lines drawn between the nominal window boundaries. This is done in Fig.1.

It is possible to compute several local cosine transforms all at once, recursively subdividing the intervals into halves. The basis functions on each subinterval are the orthogonal direct sum of the basis functions on its left and right halves, and this orthogonality propagates up through the multiple levels of the binary "family tree" in Fig.2.

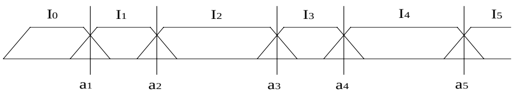

Fig.1. Lapped orthogonal basis functions on adjacent intervals

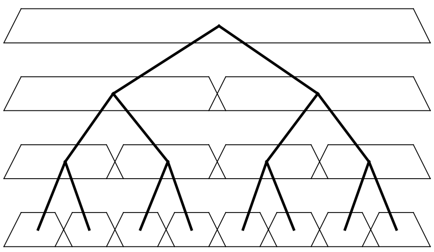

Fig.2. Several lapped orthogonal transforms computed all at once

The inner products in (1) can be computed using a standard fast discrete cosine transform, after a preliminary "folding" step described in the literature[6]. This "folding" splits $S(t)$ into a set of local finite energy signals $S_j(t)\in L^2(I_j)$, $j\in Z$, such that applying a standard discrete cosine transform to the coefficients in $S_j(t)$ is equivalent to computing all inner products with the functions ψ_k^j.

2.2. Adapted binary local cosine basis

A binary-based decomposition tree consists of the bases at different levels. However, not all the bases are efficient at matching a given signal, therefore, we want to pick up the "best-basis" from all the local cosine packets in the binary-tree library based on a cost-functional. To search for local cosine best-basis, i.e., adaptive local cosine basis, aiming to achieve the best match of the signal, there are several kinds of cost-functionals appearing in the literature[7]. Here, we use the so-called Shannon entropy as the cost-functional.

In implementation, the Coifman-Wickerhauser (1992) binary-tree fast algorithm[3] is used to search for the "best-basis" based on the Shannon entropy cost-functional. In the beginning, a full binary-based decomposition tree with a preset maximum decomposition level is produced. Then, the pruning procedure starts from the leaf nodes and proceeds toward the root. At the end of this procedure, an optimal pruned tree is obtained for the given signal, i.e., an adaptive binary local cosine basis is obtained.

3. IMPROVED FLEXIBLE SEGMENTATION ALGORITHM

3.1. Wang's segmentation algorithm

To overcome the binary segmentation constraint, a flexible segmentation algorithm was presented in the literature[4]. Let L stand for the time segmentation resolution, i.e., the length of the finest segment, for a 1-D signal with length N, it is always assumed that N is a multiple of L, say, $N=KL$, where K is the total number of finest segments.

Starting with the uniform finest segmentation, a left-right merging process is adopted to optimize the segmentation that doesn't suffer from the binary tree restriction. For each possible merger, the cost of the merged entity (segment) is compared with the total cost, i.e., the sum of costs of the two separate entities (segment). If the cost of the merged segment is smaller than the total cost of two separate segments, the merge is approved, and the merged segment will be treated as one entity in the next possible merger. Otherwise, if the opposite is true, the merger will be abandoned. Many drawbacks of the binary segmentation process have been overcomes by the new algorithm.

3.2. Improved segmentation algorithm

3.2.1. LCT algorithm for a single segment

Although Wang's method basically solved the drawbacks of the binary-based segmentation, but there are a few questions to be solved. If one of two neighboring segments outside of a segment which has non-zero values (value-segment) is a segment which values are zero entirely (zero-segment), the method will merge the value-segment and zero-segment to a large segment, obviously, this is unreasonable. On the basis of Wang's method, this paper presents a corresponding method to solve the problem. The main techniques are incarnated in LCT algorithm for a single segment, rather than folding processing using its original neighboring data, instead of making zero-extension, and then fold the each zero-extension segment, all local cosine transforms for each segment can be finished simultaneously. All of local cosine transform coefficients of a zero-segment are zero, so that the zero-segment and the value-segment will not be merged.

3.2.2. Overall optimal search and merger

The merger method in the literature[4] is an one-way merger by left-to-right, this may be not overall neighboring optimal merger. To solve the problem, to achieve an optimal merger based on overall optimal search technique, the paper presents an approach as fellows. The approach is to adopt to calculate LCT coefficients using the LCT algorithm in above section, and then computes all entropy for each segment and all segments merged by two neighboring segments simultaneously. **I**n implementation, the Shannon entropy is used, if the summation of the entropy of the two neighboring segments is larger than the entropy of the entity (segment) merged by the two neighboring segments, then the two neighboring segments will be a candidate to be merged a large segment. Otherwise, they will not be merged to a large segment. At a time, only two neighboring optimal segments of all candidates will be merged, the search method of choosing optimal candidate is that the entropy of a large segment merged by the optimal candidate is smallest in the entropy of all segments merged by other candidates. And then computes the entropy between the merged segment and its neighboring segments, confirms whether they are candidates in the next possible merger. The overall search and merger will not be terminated until without candidates to be merged. The method overcomes the problem that the one-way merger in the literature [4] will not be an overall optimal merger. The procedure can be illuminated in Fig.3. Here, E(2,3) stands for the entropy of third neighboring combination by left-to-right in the second level, the combination may be candidate to be merged to a large segment. E(1,1)=N stands for the first combination by left-to-right in the first level, but it can not be a candidate to be merged to a large segment.

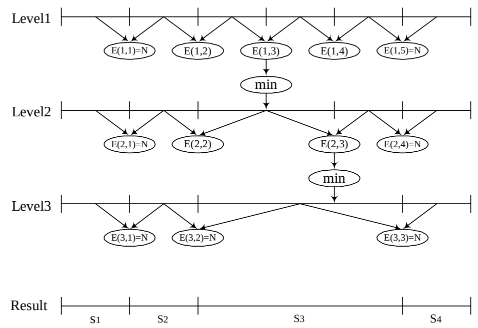

Fig.3. Sketch map of ovarall optimal search and merger

4. SIMULATION EXPERIMENTS

In all the tests on synthetic signals, we choose $N = 1024$ and the smallest time segment, $L = 32$ and thus $K = 32$, although arbitrary time resolution can be used in our improved segmentation algorithm. For the sake of comparison, in the binary tree algorithm, the maximum decomposition level is preset at 5 for synthetic signals so that the smallest time segment is also 32. The tests will be done on the following two aspects.

4.1. Without binary constraint

To highlight the binary restriction of the binary tree algorithm, and to demonstrate the advantages of the improved flexible segment algorithm, we choose as our input signal a Ricker wavelet and a blocked sinusoid(t=1~128), the support of the Ricker wavelet is 17 from t=504~520, and the peak of this wavelet just rides on the midpoint of the whole signal, a possible segmentation point for the binary tree algorithm, the algorithm in the literature [4] and the improved algorithm. Fig. 4(a) shows the best segmentation result using binary tree algorithm. We see that an intact impulse is unreasonably separated from the peak. Undoubtedly, this kind of drawback is inherent in the binary tree algorithm. By contrast, in Fig. 4(c) is the result of the improved algorithm, the Ricker wavelet can't be split into two halves from the peak. The segmentation using the improved algorithm is reasonable for the two kinds of signals, at the same time, there are no any abundant segments. Fig. 4(b) is the result using the algorithm in the literature[4], however, even though the

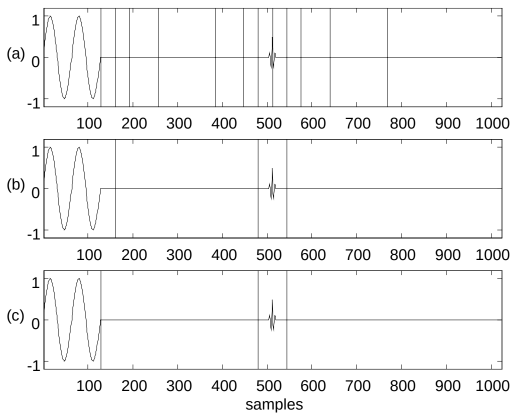

Fig.4. Comparison chart between different segmentation algorithms without time-shift

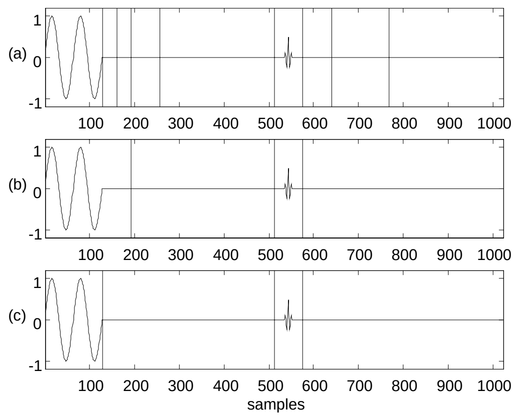

Fig.5. Comparison chart between different segmentation algorithms with time-shift

Ricker wavelet is segmented correctly, but the right segment position of the sinusoid is at t=160 instead of at t=128, this is just the reason discussed in above section, but Fig. 4(c) can commendably solve the problem.

4.2. Much reduced time-shift sensitivity

Let the signal be shifted by 32 samples, Fig. 5(a) shows us the result obtained by the binary tree algorithm, which has changed a great deal compared with Fig.4(a). This fact clearly illustrates the segmentation given by the binary tree algorithm is not time-shift invariant. However, the result in Fig.5(c) generated by the improved flexible segmentation algorithm shows it is time-shift invariant. We also see that the result in Fig. 5(b) obtained by the algorithm in the literature[4], it is also not time-shift invariant, this clearly illustrates the drawback of the algorithm in the literature[4].

5. CONCLUSIONS

To the problem of no overall optimal merger for the one-way merger in the literature[4], we propose a merger method based on overall optimal search. If one of two neighboring segments outside of a segment which has non-zero values (value-segment) is a segment which values are zero entirely (zero-segment), Wang's method will merge the value-segment and zero-segment to a large segment, it is unreasonable. In order to resolve the problem, this paper presents corresponding techniques to solve the problem.

6. REFERENCES

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