A Fast Search Approach for LSF Parameters Codebook

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ABSTRACT

In this paper[•], a fast-search algorithm is introduced to reduce the complexity of LSF quantization in speech coding. A new inequality between the weighted mean and the weighted Euclidean distance is derived. Using this inequality, many codewords that are impossible to be the nearest codeword are rejected directly. The proposed algorithm produces the same output as conventional full search algorithm and the experiment results confirm its effectiveness.

1. INTRODUCTION

Linear predictive coding (LPC) is widely used as short time spectral envelope estimation in various speech processing applications. LPC coefficients are converted into line spectral frequency (LSF) parameters [1] for the purpose of quantization and checking the stability of the synthesis filter.

Vector quantization (VQ) [2] is a very efficient approach for different speech processing due to its excellent rate-distortion performance. In low bit rate speech coding, most speech coders standardized after 1994 utilize some sort of VQ for the LSF parameters.

In order to find the best-matched codeword in the codebook, the ordinary VQ coding scheme employs the full search algorithm (FSA), which examines the Euclidean distances between the input vector and all codewords in the codebook. The expensive computational complexity of the FSA often limits the application of VQ to the real-time compression systems requiring good coding efficiency. To overcome this problem, many researchers have looked into a fast algorithm to speed up the VQ process [3-5].

A well-known algorithm is equal-average nearest neigh-bor search (ENNS) algorithm [2], which utilizes the mean of input vector to reject the unlikely codeword. This algorithm shows a great deal of computation time savings over conventional full search algorithm with only N additional memory.

Generally, we use the Euclidean distance as the distortion measure in ENNS algorithm. But weighted Euclidean distance is employed in the quantization of LSF parameters to improve the perceptual performance. Hence, ENNS algorithm is not suitable for this case.

In this paper, we proposed a new fast-search algorithm which is based on the ENNS algorithm but the weighted Euclidean distance was used as distortion measure. The proposed algorithm develops a new inequality between the weighted mean and the weighted Euclidean distance. Since the codeword searching complexity is reduced by this inequality, the proposed algorithm requires less computation time than the full search algorithm.

The rest of this paper is organized as follows: The detailed algorithm was given in section 2. In section 3, the practical quantizer was described. Section 4 showed the results of experiments to prove the effectiveness of this algorithm. Section 5 introduced a remained problem. A solution to this problem will speed up the search process further. Finally, we summarized our work in section 6.

2. THE PROPOSED ALGORITHM

Before describing the proposed algorithm, we will give a definition and review the ENNS algorithm firstly.

*Definition 1: L*et $\mathbf{x} = (x_1, x_2, ..., x_N)$ and $\boldsymbol{\alpha} = (\alpha_1, \alpha_2, ..., \alpha_N)$ be a vector, respectively. The mean of vector **x**, m_x is defined as:

$$m_x = \frac{1}{N}(x_1 + x_2 + ... + x_N) \qquad (1)$$

The weighted mean of vector **x**, $m_{\alpha,x}$ is defined as

$$m_{\alpha,x} = \frac{1}{N}(\alpha_1 x_1 + \alpha_2 x_2 + ... \alpha_N x_N) \qquad (2)$$

ENNS algorithm uses the vector mean to reject many unlikely codewords. The main logic of ENNS algorithm can be stated as follows.

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Theorem I [1] *(ENNS algorithm)*: Let $\mathbf{x} = (x_1, x_2, ..., x_N)$ be a vector and $\mathbf{y} = (y_1, y_2, ..., y_N)$ be a codeword. If the distortion is the Euclidean distance, then

$$d(\mathbf{x}, \mathbf{y}) \geq \sqrt{N} \, | m_x - m_y | \tag{3}$$

For any codeword $\mathbf{y}$, if

$$N(m_x - m_y)^2 \geq d_{\min}^2 \tag{4}$$

where $d_{\min}$ is a current minimum distance of $\mathbf{x}$ represented by a certain codeword, $\mathbf{y}$ can not be the nearest codeword and it is unnecessary to calculate $d(\mathbf{x}, \mathbf{y})$.

For the quantization of LSF parameters, the weighted Euclidean distance is employed instead of the Euclidean distance to improve the perceptual performance. Hence, ENNS algorithm is not suitable for this case.

In practical, the following weights are used, which is proposed by Paliwal and Atal in 1993 (for convenience, the weights are given by squared form) [6]:

$$w_i^2 = \begin{cases} [\mathrm{P}(\omega_i)^{0.15}]^2 & 1 \leq i \leq 8 \\ [0.8 \cdot \mathrm{P}(\omega_i)^{0.15}]^2 & i = 9 \\ [0.4 \cdot \mathrm{P}(\omega_i)^{0.15}]^2 & i = 10 \end{cases} \tag{5}$$

where $P(\omega_i)$ is power spectrum density (PSD) defined by the set of LSFs $\{\omega_i\}$ and a system with a prediction order equal to ten is considered. Hence, the weights $\{w_i\}$ vary with each LSF vector.

We divided the weights into two parts: IWV (invariable weighted vector) and VWV (variable weighted vector). The IWV is defined as $\boldsymbol{\alpha} = [1, 1, ..., 1, 0.8, 0.4]$. The VWV is defined as $\mathbf{s} = [P(w_1)^{0.15}, P(w_2)^{0.15}, ..., P(w_{10})^{0.15}]$ and it changes each frame.

Now it is time to describe our algorithm. Firstly, we have the following theorem:

Theorem II: Let $\mathbf{x} = (x_1, x_2, ..., x_N)$ be a vector and $\mathbf{y} = (y_1, y_2, ..., y_N)$ be a codeword. The weighted vector is $\mathbf{w} = [w_1, w_2, ..., w_N] = [\alpha_1 s_1, \alpha_2 s_2, ..., \alpha_N s_N]$, where $\boldsymbol{\alpha} = [\alpha_1, \alpha_2, ..., \alpha_N]$ is IWV and $\mathbf{s} = [s_1, s_2, ..., s_N]$ is VWV. If the distortion is weighted Euclidean distance, then

$$d_w^2(\mathbf{x}, \mathbf{y}) \geq \min_{1 \leq i \leq N}\{s_i^2\} N(m_{\alpha,x} - m_{\alpha,y})^2 \tag{6}$$

For any codeword $\mathbf{y}$, if

$$\min_{1 \leq i \leq N}\{s_i^2\} N(m_{\alpha,x} - m_{\alpha,y})^2 \geq d_{w,\min}^2 \tag{7}$$

where $d_{w,\min}$ is a current minimum weighted distance of $\mathbf{x}$ represented by a certain codeword, $\mathbf{y}$ can not be the nearest codeword and it is unnecessary to calculate $d_w(\mathbf{x}, \mathbf{y})$.

Proof:

$$\because d_w^2(\mathbf{x}, \mathbf{y}) = \sum_{i=1}^{N} [w_i (x_i - y_i)]^2 = \sum_{i=1}^{N} [\alpha_i s_i (x_i - y_i)]^2,$$

$$\begin{aligned} \therefore d_w^2(\mathbf{x}, \mathbf{y}) &= \sum_{i=1}^{N} [s_i \alpha_i (x_i - y_i)]^2 \\ &\geq \sum_{i=1}^{N} \min_{1 \leq i \leq N}\{s_i^2\} [\alpha_i (x_i - y_i)]^2 \\ &= [\min_{1 \leq i \leq N}\{s_i^2\}] \sum_{i=1}^{N} [\alpha_i (x_i - y_i)]^2 \\ &= [\min_{1 \leq i \leq N}\{s_i^2\}] d_\alpha^2(\mathbf{x}, \mathbf{y}) \end{aligned}$$

Let $x'_i = \alpha_i x_i, \; y'_i = \alpha_i y_i$, we have

$$\begin{aligned} d_\alpha^2(\mathbf{x}, \mathbf{y}) &= \sum_{i=1}^{N} [\alpha_i (x_i - y_i)]^2 \\ &= \sum_{i=1}^{N} (x'_i - y'_i)^2 = d^2(\mathbf{x'}, \mathbf{y'}) \end{aligned}$$

By theorem I, we have $d^2(\mathbf{x'}, \mathbf{y'}) \geq N(m_{x'} - m_{y'})^2$, then

$$\begin{aligned} d_w^2(\mathbf{x}, \mathbf{y}) &\geq [\min_{1 \leq i \leq N}\{s_i^2\}] \cdot d_\alpha^2(\mathbf{x}, \mathbf{y}) = [\min_{1 \leq i \leq N}\{s_i^2\}] \cdot d^2(\mathbf{x'}, \mathbf{y'}) \\ &\geq [\min_{1 \leq i \leq N}\{s_i^2\}] \cdot N(m_{x'} - m_{y'})^2 \\ &= [\min_{1 \leq i \leq N}\{s_i^2\}] \cdot N(m_{\alpha,x} - m_{\alpha,y})^2 \end{aligned}$$

With the above definitions and theorem in hand, we now turn to describe the proposed algorithm. For an input vector, the algorithm first calculates its weighted mean value. For each codeword $\mathbf{y}$, the algorithm checks whether inequality (7) is satisfied or not. If the answer is yes, codeword $\mathbf{y}$ is rejected. Otherwise, the weighted Euclidean distance is calculated between the input vector and the codeword.

Secondly, we need to explain the reason for dividing the weight vector into IWV and VWV here. In a word, it is for improving efficiency. If we don't divide it, we can get another inequality corresponding to (7) through the similar approach:

$$\min_{1 \leq i \leq N}\{w_i^2\} N(m_x - m_y)^2 \geq d_{w,\min}^2 \tag{8}$$

Since the weight $\mathrm{P}(\omega_9)^{0.15}$ and $\mathrm{P}(\omega_{10})^{0.15}$ are multiplied by 0.8 and 0.4 respectively, the coefficient $\min_{1 \leq i \leq N}\{s_i^2\}$ is larger than $\min_{1 \leq i \leq N}\{w_i^2\}$ in most cases. So there is more chance to reject a codeword through inequality (7) than (8). In section 4, the experimental results will show it.

Now, we can use our algorithm to accelerate the quantization of LSF parameters. The detail is described in section 3.

3. PRACTICAL CASE

In this section, we apply our fast algorithm on a predictive split VQ (PSVQ) structure [7, 8], which employed a (4,6) split VQ scheme and 10 bits codebook respectively.

Compared with the full search algorithm, the search complexity can be reduced largely when theorem II is used directly. In the practical case, another two technologies were used to speed up the searching process further.

3.1. Sorting the codewords by their weighted means

Similar to the ENNS algorithm, the proposed algorithm employed the sorted codebook to accelerate the search process.

For our purpose, the codewords are sorted in the ascending order by their weighted means. Thus, some codewords can be rejected directly without any computation. Suppose **x** is the input vector and $\mathbf{y}_k$ is the k-th codeword. If $\min_{1\le i\le N}\{s_i^2\}N(m_{\alpha,x}-m_{\alpha,y_k})^2$ is larger than $d_{w,\min}^2$ and $m_{\alpha,x}$ is less than m_{α,y_k}, the rest of the higher-index codewords as well as the k-th codeword can be rejected as a whole since inequality (7) is always true for these codewords. Similarly, if $\min_{1\le i\le N}\{s_i^2\}N(m_{\alpha,x}-m_{\alpha,y_k})^2$ is larger than $d_{w,\min}^2$ and $m_{\alpha,x}$ is larger than m_{α,y_k}, the rest of the lower-index codewords as well as the k-th codeword also can be rejected as a whole.

3.2. Setting flag points to aid search

In practice, we find it has less chance to reject a codeword by inequality (7) in the beginning phase of search process. The reason is $d_{w,\min}^2$ is usually not small enough and $(m_{\alpha,x}-m_{\alpha,y})^2$ is not large enough. So we use full search algorithm other than the new fast algorithm to process codewords in this phase. We set some flag points to aid search. Table.1 shows the distribution of flag points. At the beginning, for each codeword whose index is equal to the flag point, we calculate the weighted mean distance $(m_{\alpha,x}-m_{\alpha,y})^2$. Then we can find the minimum one and corresponding index: index_opt. After that, we use full search algorithm directly to deal with the codewords whose indexes are located in the range of [index_opt - M, index_opt + M], where M is equal to 49 for the first subvector and 124 for the second subvector.

Now, we can summarize the practical search process. An example of the search procedure was illustrated in Figure 1.

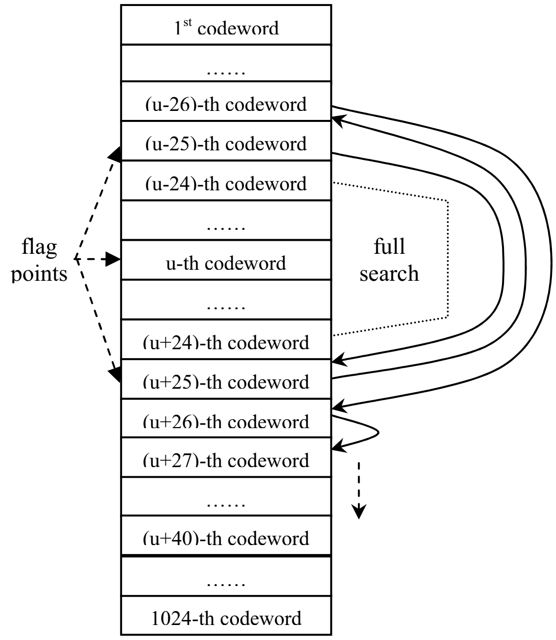

Fig. 1. An example of the proposed fast search algorithm

Table.1 Distribution of flag points

	Number of flag points	Index of first flag point	Index of last flag point	Interval of flag points
LSF 1 – 4	38	24	999	25
LSF 5--10	32	99	924	25

1) Before the search process, make sure the codebook is sorted by the weighted means.
2) For each flag point, we calculate the weighted mean distance $(m_{\alpha,x}-m_{\alpha,y})^2$ between input vector and codeword. Assume that the u-th codeword is found to have the minimum weighted mean distance.
3) Using full search algorithm to deal with codewords whose indexes are located in the range of [u-24, u+24].
4) Using proposed fast algorithm to search from the (u-25)-th codeword. Suppose inequality (7) is false at this codeword. The weighted Euclidean distance has to be calculated in succession. The same case is for the (u+25)-th codeword.
5) Suppose inequality (7) is true for the first time at the (u-26)-th codeword. Then, the rest of the lower-index codewords as well as the (u-26)-th codeword are rejected as a whole. The reason has been explained in section 3.1.
6) The search continues only for the higher-index codewords. Suppose inequality (7) is true again at the (u+40)-th codeword, which indicates the rest of

the higher-index codewords as well as the (u+40)-th codeword can be rejected as a whole.

7) The search process is now terminated.

Although PSVQ is employed here, it is worth mentioning that other VQ structures can also benefit from this algorithm.

4. EXPERIMENTAL RESULTS

To compare with the full search algorithm, we use speech test files (2426 frames all together) to evaluate the proposed algorithm. The LSF parameters quantizer uses PSVQ structure [7, 8] and the codebook is designed by the Linde-Buzo-Grey (LBG) algorithm. The (4,6) split VQ scheme and 10 bits codebook are employed respectively.

Table.2 Comparison of computation complexity

Algorithm Name	Memory consu-mption	Complexity of LSF1-- 4	Complexity of LSF 5--10
Full search	10K	100	100
Proposed by inequality (8)	12K	23	81
Proposed by inequality (7)	12K	23	43

Note: the complexity of full search is normalized to 100.

Table.2 shows the computation complexity of different algorithms. The complexity of full search is normalized to 100. It is seen from the table that the proposed algorithm offers considerable improvement over full search method. We also find that the complexities are same when we quantize the first four LSF parameters by inequality (7) or (8). The reason is that two inequalities are same under this situation since IWV for the first four LSF parameters is $[1,1,1,1]$. But for the last six LSF parameters, the situation is changed. Compared with inequality (8), using (7) can save about half complexity, which is consistent with the explanation in section 2.

5. ONE REMAINED PROBLEM

Let us review the inequality (6). We rewrite it here:

$$d_w^2(\mathbf{x},\mathbf{y}) \geq f(\mathbf{s})N(m_{\alpha,x} - m_{\alpha,y})^2 \qquad (9)$$

where f(**s**)= $\min_{1\le i\le N}\{s_i^2\}$. Let us recall how we get the factor $\min_{1\le i\le N}\{s_i^2\}$. In fact, when we deduct this inequality, we use the relation:

$$d_w^2(\mathbf{x},\mathbf{y}) = \sum_{i=1}^{N}[s_i\alpha_i(x_i - y_i)]^2 \geq \min_{1\le i\le N}\{s_i^2\}\sum_{i=1}^{N}[\alpha_i(x_i - y_i)]^2$$

Naturally, someone will ask a question: Can we find another f(**s**) which satisfies inequality (9)? To answer this question is not an easy task.

If we let **S**, **Z** be a N-dimension vector, respectively, where the i-th element of **S** is s_i^2 , and the i-th element of **Z** is $(\alpha_i(x_i - y_i))^2$, the above question can be abstracted to a math problem:

Find a function f(.) which satisfies the relation

$$<\mathbf{S},\mathbf{Z}> \ \geq f(\mathbf{S})\cdot \|\mathbf{Z}\|_1 \qquad (10)$$

where <**S**, **Z**> is inner product of **S** and **Z**, and $\|\mathbf{Z}\|_1$ is the L1-norm of **Z**.

Obviously, if we can find an f(**S**) which is larger than $\min_{1\le i\le N}\{s_i^2\}$ for any vector **S**, using (9) can reject more code-words than (7) and we can speed up the search process further.

6. CONSLUSION

In this work, an improved fast search algorithm is proposed. A new inequality between the weighted mean and the weighted Euclidean distance was derived. We apply the proposed fast-search method to a predictive split vector quantizer. The experimental result shows that the complexity can be reduced to 23% and 43% for the first 4 LSF and last 6 LSF parameters, respectively. In the end, it is worth mentioning that if we can solve a remained problem proposed in section 5, this algorithm can be speeded up further.

7. REFERENCES

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