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Fast Codeword Search Algorithm for Split-dimension Vector Quantization Based on the Sequence of Characteristic Value

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ABSTRACT

*A Fast Codeword Search Algorithm for Split-dimension Vector Quantization based on the Sequence of Characteristic Value is proposed. Firstly, an improved PSO (*Particle Swarm Optimization)*method is adopted to design split-dimension vector codebook in LCT (Local Cosine Transform) domain. Before coding, for each splitted vector(a vector splitted into a few sub-vectors), the characteristic value of each codeword is calculated and ranked. During coding, the search sequence is decided by the characteristic value of each input vector. In the meantime, the search range is confined and an efficient elimination criteria is used in order to accelerate the coding process significantly. A great deal of experimental results shows that this algorithm can achieve a similar performance to full search algorithm while the coding time is only 1.7%~5.0% of full search process.*

1. INTRODUCTION

Since the LBG (Linde Y., Buzo A., Gray R. M.) algorithm[1] for Vector Quantization was proposed in 1980, Vector Quantization has been widely applied in image compression and speech coding.

The Full Search (FS) algorithm requires finding the smallest distortion from all distortion calculation between input vectors and codewords. It will cause great complexity if the size of the codebooks and the dimension of the vectors are big. So it is very necessary for a fast codeword search to solve the problem.

The three indispensable factors for a fast codeword search are: (1) good initial matching codewords; (2) reasonable codeword search sequence; (3) efficient elimination criteria. At present, all fast codeword search algorithms applied in speech coding are classified into three categories, i.e., inequation criteria; adaptive search range and search sequence; transform domain.

The Partial Distortion Search (PDS) [2] is an easy and efficient fast codeword search algorithm based on inequation criteria. Even though it doesn't require additional storage space, it has limited efficiency. So Equal-average Nearest Neighbor Search (ENNS)[3], Equal-average Equal-variance Nearest Neighbor Search (EENNS)[4] were proposed respectively and among them, a Modified EENNS (MEENNS)[5-6] is the most efficient one. However, the algorithm adopts three elimination criteria, the sum and variance of sub-vectors require additional calculation and space.

Search algorithms based on inequation usually focus only on eliminating unmatched codewords by adopting various criteria, which inevitably neglect the search range and sequence. To solve the problem, an Adaptive Search Range and Search Sequence (ASRSS)[7-10] algorithm is proposed. However, the small search quantity will reduce the coding quality and the excessive search will affect the coding efficiency.

In order to save a great deal of offline calculation and storage space for satisfaction of the coding quality, and meanwhile reduce online calculation, a new improved algorithm based on Adaptive Search Range and Search Sequence (ASRSS)[7-9] is proposed to accelerate codeword search.

Many fast codeword search algorithms adopt inequation elimination criteria in space (time) domain. However, some orthogonal transforms such as KLT, DCT and DWT can concentrate energy within a few transform domain coefficients while the energy remains unchanged. Since the square variance between vectors in transform domain tends to concentrate within low frequency transform coefficients. The PDS algorithm is proved to be very efficient in this situation.

So an improved Adaptive Search Range and Search Sequence algorithm with PDS inequation criteria in Local Cosine Transform domain[11-12] is proposed in this paper. An improved PSO codebook design[13-14] is adopted in split-dimension vector quantization codebook design.

2. CODEBOOK DESIGN OF SPLIT DIMENSION VECTOR

An Improved PSO codebook design[13-14] is adopted in split-dimension vector quantization codebook design in

Local Cosine Transform domain[11-12]. The global extremum updating condition in basic particle swarm optimization algorithm is modified by adopting random probability condition to enhance the search ability in the global optimum area, and avoid the premature phenomena of the particles.

In general, the first four formants of adult speech signal lie at 500Hz, 1500Hz, 2500Hz and 3500Hz. They divide the speech signal into four important areas which require different coding processing. In split-dimension vector quantization, the numbers of transform coefficients of each vector dimension are 40, 40, 40, 20 respectively from low frequency to high frequency. Remaining the frequency spectrum below 3500Hz will be enough for 8k Hz sampling to restore satisfying speech signal. 20 coefficients are adopted in 4th vector dimension to reduce calculation complexity. In the inverse LCT transform, the 20 coefficients of the highest frequency part are set 0[15].

3. FAST CODEWORD SEARCH ALGORITHM FOR SPLIT-DIMENSION VECTOR QUANTIZATION BASED ON THE SEQUENCE OF CHARACTERISTIC VALUE

After split-dimension codebook design, a fast codeword search algorithm for Split-dimension Vector Quantization based on the Sequence of Characteristic Value (SVQSCV) is proposed.

In codeword search, each codeword and input vector are of k dimensions. So the characteristic value is defined as $E(V)=\sum_{l=1}^{k} l \times v_l^2$ in this paper, among which $V=\{v_1,v_2,...,v_k\}$ is any vector of k dimensions.

The characteristic value of a vector is defined as $E(V)=\sum_{l=1}^{k} v_l^2$ in literatures[7-8] and defined as $E(V)=\prod_{l=1}^{k} v_l$ in literature[9]. Two additional characteristic values $E(V)=\sum_{l=1}^{k} v_l$ and $E(V)=\sum_{l=1}^{k}(k-l+1)v_l^2$ are defined in literature[10].

Actually, the sequence of components of k-dimension vector V can not be reflected by the characteristic values defined in literatures[7-9]. The reason is that if the sequences of components of two k-dimension vectors V_1 and V_2 are just opposite, they will have the same characteristic value. In fact, the two vectors have distinct differences. So a lot of unnecessary codeword search is not avoided. However, the two characteristic values defined in literature[10] is well described in the characteristic value proposed in this paper. It's clear to see from the distortion formula $d(X,Y_i)=\sum_{l=1}^{k}(x_l-y_{il})^2$ that the quadratic polynomial is more reasonable to express the characteristic value. Though several characteristic values are defined in literature[10] to express each codeword and each input vector in an all-round way, they actually require an additional quantity of offline calculation and storage space, especially require more online calculation for each input vector.

To solve the problems mentioned above, a single characteristic value is adopted to define each vector in this paper. This can save a great deal of offline calculation and storage space while ensuring the coding quality, and especially can reduce online calculation in order to accelerate codeword search.

Obviously, if the characteristic value of a certain codeword $Y_i=\{y_{i1},y_{i2},...,y_{ik}\}$ is very close to that of a certain input vector $X=\{x_1,x_2,...,x_k\}$, then the codeword is probably the most matching codeword of the input vector and needs further comparison. On the other hand, the objectively most matching codeword $Y_j=\{y_{j1},y_{j2},...,y_{jk}\}$ of a certain input vector must have very close characteristic value to its own. So if the training codebook is satisfying enough, the most matching codeword is not likely to be omitted. This is the reason that why the coding quality of the algorithm proposed in this paper is quite close to that of full search algorithm.

So all the codewords are ranked according to characteristic value and registered. As to a certain input vector $X=\{x_1,x_2,...,x_k\}$, select the codeword with the closest characteristic value to its own as its initial matching codeword. In this way, factor (1) in fast codeword search mentioned above is considered. Then the codewords with close characteristic values to the input vector are searched so that factor (2) is considered.

During the search, the efficient PDS algorithm is adopted for further elimination of codewords so that factor (3) is considered. In the meantime, the search range confined within a certain area near the most matching codeword will further promote search efficiency.

4. IMPLEMENTATION STEPS OF THE PROPOSED ALGORITHM

Step 1, an improved PSO algorithm in literatures[13-14] is adopted to design split-dimension vector codebook of speech signal in Local Cosine Transform domain. The numbers of transform domain coefficients of the four vector dimensions are set 40, 40, 40, 20 respectively from low frequency to high frequency. After codebook design, suppose the size of the codebook is N, calculate the characteristic value of each codeword offline, rank them according to value and store them in a space with the size of N, register their original indexes in the codebook.

Step 2, for each input vector, calculate its characteristic value online, select the codeword with the closest characteristic value to it as its initial matching codeword, set the index of the codeword $index$, calculate the distortion and set it $d_{\min}$.

Step 3, select q codewords from both former and latter of the most matching codeword which situated at index p as the search targets, that are $begin = p - q$, $end = p + q$. If $p - q < 1$, then $begin = 1$. If $p + q > N$, then $end = N$. q is determined by the size of the codebook , the codebook capability and the demand for coding quality here. Generally, the coding will be quite satisfying when the search range($2 \times q + 1$) is about 2% ~ 8% of the size of the codebook.

Step 4, the PDS algorithm is adopted to eliminate codewords selected in step 3. If the final distortion between a certain codeword and the input vector is less than $d_{\min}$, then update $d_{\min}$ and $index$.

Step 5, repeat step 2 to step 4 to deal with the next input vector.

Step 6, after codeword search, the transform coefficients of four Split-dimension vectors are combined and dealt by inverse LCT to restore the speech signal.

5. EXPERIMENTAL RESULTS

The speech data in standard speech test database of UT Dallas University are adopted in the experiment. The 1st and 2nd dimensions of the codebook vectors are of the same size, that are 256, 512, 1024 in turn. The 3rd and 4th are 1/4 of the 1st and 2nd. Peak Signal Noise Ratio(PSNR) calculated on the quantizer output is used to define the coding quality in dB.

Table 1 is the comparison of the algorithm proposed in this paper (SVQSCV) with Full Search (FS), Partial Distortion Search (PDS), Adaptive Search Range and Search Sequence (ASRSS) and modified EENNS (MEENNS) algorithm. The average search percent means the ratio between average search quantity of each input vector and full search quantity. 256, 512, 1024 in Table 1 stand for the codebook sizes of the 1st and 2nd vector dimension.

6. CONCLUSIONS

A new fast codeword algorithm for Split-dimension Vector Quantization based on the Sequence of Characteristic Value (SVQSCV) is proposed. The new algorithm modifies the codeword search algorithm based on adaptive search range and search sequence proposed in literatures[7-10]. So the algorithm can save a great deal of offline calculation and storage space while ensuring the coding quality, and especially can reduce online calculation in order to accelerate codeword search.

A great deal of experimental results show that this algorithm can achieve a similar performance to full search algorithm while the average search percent is only 0.8% ~2.8% and the coding time is only 1.7%~5.0% of full search process. The coding speed is significantly accelerated compared with efficient algorithms such as ASRSS and MEENNS. Also, coding time and coding quality are more satisfying when the size of the codebook is bigger.

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Table 1. Comparison of SVQSCV with other algorithms

Algorithms			Coding time (s)			Average Search Percent(%)			Coding Quality (dB)		
			256	512	1024	256	512	1024	256	512	1024
F S			3.79	7.64	15.64	100	100	100	17.64	18.06	18.66
PDS			0.73	1.45	2.85	20.09	19.67	19.04	17.64	18.06	18.66
ASRSS			0.28	0.57	1.10	4.52	4.36	4.18	16.83	17.10	17.70
MEENNS			0.27	0.55	1.06	5.71	5.44	5.32	17.64	18.06	18.66
SVQSCV	Search Range of Characteristic Value	2%	0.10	0.16	0.27	1.10	0.96	0.83	15.27	15.62	16.25
		8%	0.19	0.31	0.59	2.86	2.65	2.33	16.68	17.05	17.64

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