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# Hybrid VQ and Neural Models for ISF Quantization in Wideband Speech Coding

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**Abstract:** Wideband speech coding has become an important research area in the speech processing field. Algebraic code exited linear prediction (ACELP) algorithm has been adapted for narrowband and wideband speech coders such as adaptive multi-rate wideband (AMR-WB). In AMR-WB, immittance spectral frequency (ISF) parameters are sent to decoder, instead of linear prediction coding (LPC) coefficients. To reduce the bit rate in AMR-WB, vector quantization (VQ) technique is used. On the other hand, artificial neural networks (ANNs) can be used for VQ. In this paper, three hybrid models are presented for quantization of ISF parameters in AMR-WB speech coders. These models are "hybrid of switched split vector quantizer (S-SVQ) and split multistage vector quantizer (S-MSVQ)", "hybrid of self organizing map (SOM) neural network and S-MSVQ" and "hybrid of growing hierarchical SOM (GHSOM) neural network and S-MSVQ". Experimental results show that the hybrid model of GHSOM and S-MSVQ performs better than traditional S-SVQ and S-MSVQ models. The performance of GHSOM and S-MSVQ hybrid model is also better than two other hybrid models in computational complexity reduction. The number of bits per frame is also reduced in this hybrid model, without significant degradation in spectral distortion.

**Key words:** Wideband speech coding · Vector quantization · Neural network

## INTRODUCTION

In recent years, wideband speech coding has received attention from many researchers. The range of frequency in narrowband and wideband speech is considered as 300-3400 Hz and 50-7000 Hz, respectively. Algebraic code exited linear prediction (ACELP) algorithm [1] has been adapted for narrowband and wideband speech coders such as adaptive multi-rate wideband (AMR-WB) [2, 3] and adaptive multi-rate narrowband (AMR-NB) [4], respectively. Although, narrowband speech coding does not offer high quality, which is due to a lack of naturalness and speaker 'presence' (as experienced in face-to-face speech communication) and also difficulty of distinguishing fricative sounds [5].

In AMR-NB, the $10^{th}$ order LPC is used for representation of spectral envelope which has captured two formants of speech below 4 kHz. However, three formants which belong to higher than 4 kHz are not detected [6]. In AMR-WB, which is standardized by $3^{rd}$ Generation Partnership Project (3GPP) for global system for mobile communications (GSM) and third generation/wideband code division multiple access (WCDMA 3G) system [7], $16^{th}$ order linear prediction coding (LPC) is used to achieve higher quality. Thus, high frequency formants are captured by increasing the order. LPC coefficients are not directly sent to decoder in most of speech coding algorithms. In this way, some conversions are preformed on it, e.g. LPC to line spectral pair (LSP) and LSP to immittance spectral frequency (ISF) conversions [8, 9]. To send ISF parameters to decoder, many bits are needed. Thus the bit rate of coding is increased. So, vector quantization (VQ) technique is used to reduce the bit rate. In this way, only the index of corresponding vector is sent to the decoder, instead of ISF parameters.

The aim of VQ is to represent a set of vectors $x \in X \subset R^n$ by a set of codevectors $v=\{v_1, v_2 ... v_c\} \subset R^n$ which generate a codebook. Design of codebook can be performed by clustering algorithms such as C-means and fuzzy C-means algorithms [10]. Several methods, such as switched split vector quantizer (S-SVQ) [11, 12] and split multistage vector quantizer (S-MSVQ) [13], are used to reduce the complexity and bit rate of the coders. All of the quantization techniques need a codebook generation algorithm e.g. generalized Lloyd algorithm (GLA) which was also known as LBG [14].

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Artificial neural networks (ANNs) can also be used for VQ. For example, an efficient way of exploiting self organizing maps (SOMs) for a fast search quantization procedure is presented in [15] that reduces the complexity of spectral envelope VQ, significantly. A modified Hopfield neural net is also used to search in the codebook of a CELP coder [16]. A codebook design algorithm for LD-CELP, based on a modified self-organizing feature map (SOFM) neural network, is introduced in [17]. A neural network-based vector quantizer for low bit-rate coders is also proposed in [18]. Complexity reduction of LD-CELP speech coding in prediction of gain using Elman, multi-layer perceptron (MLP) and fuzzy ARTMAP neural networks is reported in [19]. Multi-SOM structure is used in [20] for codebook search in LD-CELP. Also, fuzzy ARTMAP neural network is used to reduce the codebook search time in G.728 speech coder [21].

In this paper, we apply some changes to S-SVQ and S-MSVQ techniques to develop new schemes for quantization of ISF parameters. In this way, we use SOM [22, 23] and growing hierarchical SOM (GHSOM) [24, 25]. It is noted that GHSOM is a dynamically growing hierarchical structure of SOMs according to the input data.

The rest of paper is organized as follows. Section 2 gives a brief overview of the AMR-WB ISF quantization scheme. The hybrid model of S-SVQ and S-MSVQ is introduced in Section 3. Hybrid-models of "SOM+S-MSVQ" and "GHSOM+S-MSVQ" are introduced in Section 4 and 5, respectively. Empirical results are reported in Section 6. Finally, conclusions are provided in Section 7.

**AMR-WB ISF Quantization Scheme:** The AMR-WB speech codec is standardized by 3rd Generation Partnership Project (3GPP) for GSM and WCDMA 3G systems. This codec is multi-rate with nine different modes. According to the functional block diagram of this codec, after decimating input speech from 16 kHz to 12.8 kHz, the decimated signal is preprocessed and then linear prediction (LP) parameters of synthesis filter are extracted based on the CELP model [3]. These parameters should be converted to LSPs for more stability [26]. Also, LSPs are converted to ISFs and then quantized. The ISF representation is as follows:

$$f_i = \frac{f_s}{2\pi} arccos(q_i); \quad i=1,2, ..., 14$$
$$f_i = \frac{f_s}{4\pi} arccos(q_i); \quad i=15 \tag{1}$$

**Where:**

$f_i$ is ISF in the range of [0,6400] Hz and sampling frequency ($f_s$) is equal to 12800 Hz and $q_i$ is LSP in the cosine domain. This paper is focused on ISF quantization scheme modifications. In AMR-WB, a 1st-order moving average (MA) prediction is applied to ISF vector. The prediction residual vector, $r(n)$, is given by:

$$r(n) = z(n) - p(n) \tag{2}$$

**Where:**

$p(n) = \frac{1}{3}\hat{r}(n-1)$. $\hat{r}(n-1)$ is the quantized residual vector in pervious frame. $z(n)$ denotes the mean-removed ISF vector at $n^{th}$ frame [3].

In the hybrid scheme of split vector quantization (SVQ) and multi-stage vector quantization (M-SVQ), which is called S-MSVQ, the residual LSP vector is quantized. Fig. 1 shows the quantization scheme in AMR-WB [2, 3]. As shown in Fig. 1, $r(n)$ is split to $r_1(n)$ and $r_2(n)$ of dimensions 9 and 7, respectively. Then, these two vectors are quantized separately with two codebooks (with the size of 256×9 and 256×7). Then, quantization errors are calculated ($Error_i\_Quant$; $I=1,2$) and split (into 3 subvectors of dimensions 3, 3 and 3 for $r_1(n)$ and into 2 subvectors of dimensions 3 and 4 for $r_2(n)$). Then quantization is performed according to five codebooks with the size of 64×3, 128×3, 128×3, 32×3 and 32×4, respectively (Fig. 1). Table 1 shows the bit allocation in ISF quantization scheme [3].

**Hybrid of S-SVQ and S-MSVQ:** The switched split vector quantization (S-SVQ) is a hybrid scheme of switched vector quantization and split vector quantization, which was introduced by So and Paliwal [11]. In this scheme, the vector space is classified into $m$ clusters in the following steps:

- LBG algorithm is applied to all of the vectors to produce $m$ centroids ($C_i$; $i=1:m$)
- The index of row which minimizes the Euclidean distortion between input vector and centroids ($C_i$) is found using (3) [6]:

$$Cluster_j = argmin_i \ d(input, C_i) \tag{3}$$

These $m$ centroids are the best in Voronoi region. A group of vectors is assigned to each of these $m$ centroids and a distinct SVQ is used for each of them. After codebook training phase, all of the designed codebooks are located in the corresponding part.

Table 1: Bit allocation for ISF quantization scheme in AMR-WB [3]

| Vector | $r_1(n)$ | $r_2(n)$ | $Error_1\_Quant_1$ | $Error_1\_Quant_2$ | $Error_1\_Quant_3$ | $Error_2\_Quant_1$ | $Error_2\_Quant_2$ |
|---|---|---|---|---|---|---|---|
| Number of bits | 8 | 8 | 6 | 7 | 7 | 5 | 5 |

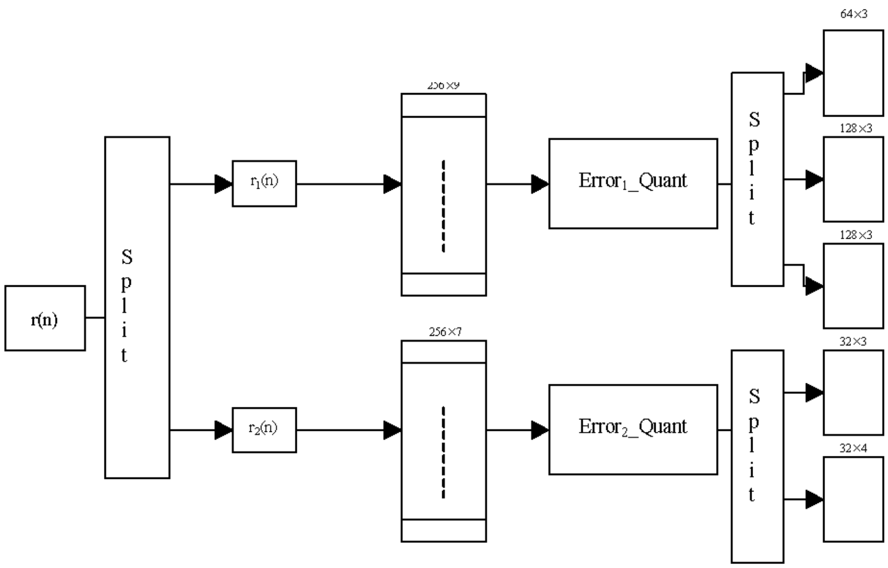


Fig. 1: ISF quantization scheme in AMR-WB

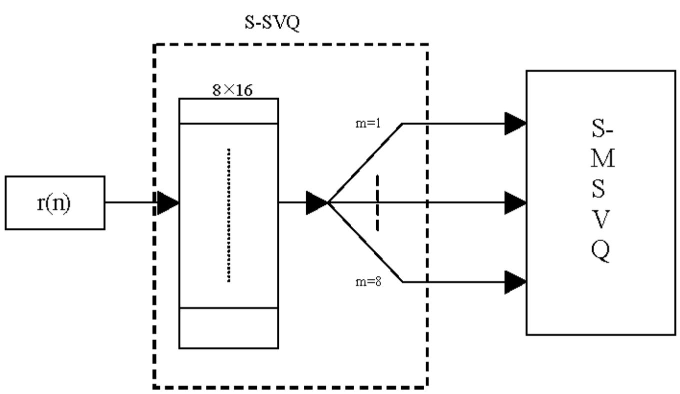


Fig. 2: Hybrid model of S-SVQ and S-MSVQ for ISF quantization

Each input vector is first switched to one of *m* clusters, based on (3) and then split and quantized using the corresponding codebook.

S-SVQ has better rate-distortion efficiency and lower computational complexity, as compared to SVQ [11, 12]. Indeed, it is a hybrid scheme that combines the advantages of SVQ, i.e. lower computational complexity and split vector quantizer. Another method in this field is S-MSVQ. As mentioned earlier, S-MSVQ is based on SVQ and M-SVQ that improves the rate-distortion efficiency. The basic idea of S-MSVQ is to divide the quantization into successive stages, where the first stage performs a relatively crude quantization and the second stage quantizes the error vector between original and quantized output of the first stage. When there is high correlation between the components, S-MSVQ is preferable as compared to SVQ. The rate-distortion efficiency of S-MSVQ is better. However, the complexity of S-MSVQ is higher than SVQ.

In this way, a hybrid model of S-SVQ and S-MSVQ is proposed in this paper to collect all the advantages of S-SVQ and S-MSVQ. In this model, the vector space is first classified into 8 clusters ($m=8$) and then for each of the mentioned clusters, which has a group of vectors, all of the vectors are split into 2 subvectors, $r_1(n)$ and $r_2(n)$, of dimensions 9 and 7, respectively. Fig. 2 shows the block diagram of proposed hybrid model. In this figure, the block of S-MSVQ has the same structure as Fig. 1.

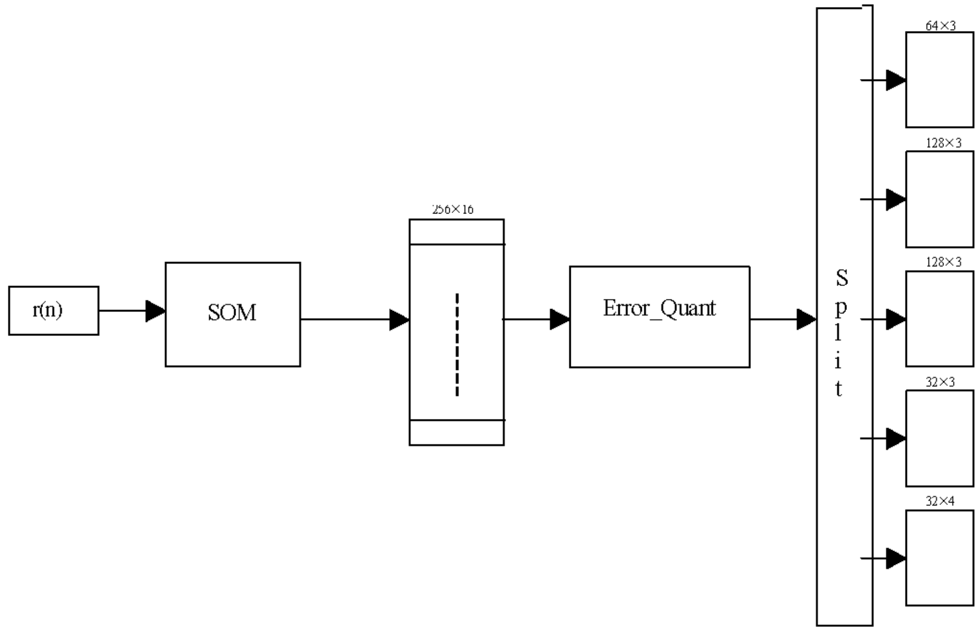


Fig. 3: Hybrid model of SOM and S-MSVQ for ISF quantization

**Hybrid of SOM and S-MSVQ:** In this section, a new hybrid scheme for ISF quantization is introduced by employing SOM for codebook generation. Using SOM in the application of codebook generation is noteworthy in various areas such as image processing [27-30]. SOM is a good solution to classification problems. The steps of codebook generation using SOM are as follow:

Step 1: gather the training data;
Step 2: specify the suitable map size for current application, because of its dependency on the codebook size;
Step 3: Find the best-matching node and its neighbors;
Step 4: Update the weights of network.

Figure 3 shows the ISF quantization scheme using hybrid model of SOM and S-MSVQ. The specifications of SOM, which is used in generating new codebook, are listed in Table 2. As shown in Table 2, SOM generates a codebook with the size of 256×16. It is noted that the map size is 16×16 (256) and the input vector has 16 components.

**Hybrid of GHSOM and S-MSVQ:** In this section, ISF quantization is performed using GHSOM for codebook generation. Although, SOM is one of the stable networks in high-dimensional data applications, but it has some problems and limitations because of a single self-organizing layer with a fixed number of neurons. A model which resolves these problems is GHSOM,

Table 2: SOM specifications in hybrid model

| Specification | Value or type |
|---|---|
| Map size | 16×16 |
| Neighborhood function | Gaussian |
| Distance metric | Euclidean |
| Number of input features | 16 |
| Training mode | Batch |
| Rough Training | |
| Initial learning rate | 0.5 |
| Initial radius | 3 |
| Final radius | 1 |
| Fine Training | |
| Initial learning rate | 0.05 |
| Initial radius | 1 |
| Final radius | 1 |

which is a dynamically growing architecture that grows into a hierarchical structure of SOMs according to the input data. The structure of a GHSOM is shown in Fig. 4. One of the most advantages of GHSOM is capability of adding independent SOMs according to the input data requirements. Also, it is not necessary to predefine the size of each SOM.

The starting point in growth process is to find the overall deviation of input data as measured with the single-unit SOM at layer 0. A weight vector, $m_0$, is assigned to this unit that is the average of input data:

$$m_0 = [\mu_{0_1}, \mu_{0_2}, \ldots \mu_{0_n}]^T \quad (4)$$

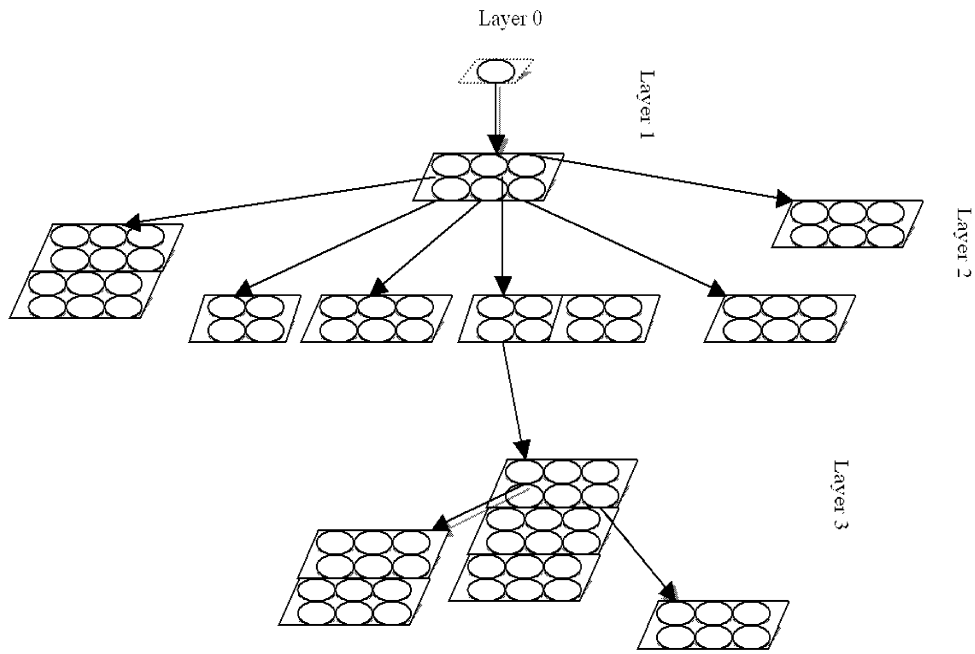


Fig. 4: GHSOM structure

For this unit, which is a single unit in layer 0, the mean quantization error (MQE) is defined as:

$$mqe_0 = \frac{1}{d}\|m_0 - x\| \quad (5)$$

**Where:**
$d$ is the number of input data elements.

After calculating $mqe_0$, GHSOM is trained with its first layer SOM which initially consists of a rather small number of units, e.g. a grid of 3×2 units as shown in Fig. 4. In this Figure, the map in layer 1 consists of 3×2 clusters and provides a rather rough organization of the input data. The six independent maps in the second layer offer a more detailed view of the data. The same process which was performed in layer 0, is repeated in other layers. It is noted that the process of learning in GHSOM is similar to SOM in which the weight vector of winner and the units in vicinity of winner are adapted in such a way as to resemble more closely the input pattern.

Weight adaptation process is performed as follows in which learning-rate parameter, α, is decreasing with time:

$$m_i(t+1) = m_i(t) = \alpha(t)h_{ci}(t)[x(t) - m_i(t)] \quad (6)$$

**Where:**
$h_{ci}(t)$ is the neighborhood function, $x(t)$ represents the current input pattern and $c$ refers to the winner at iteration $t$. For all of the neurons in first layer, $mqe_1$ is calculated using an equation similar to Eq. (5). Indeed, each layer of the GHSOM is responsible for explaining some portion of the input data deviation. Based on the mean quantization error (MQE) in all of the units of each SOM, we decide whether each of the SOM's layers should be grown or not. If MQE of each layer of SOM satisfies inequality (7), a new row or a new column of units is added to this SOM.

$$MQE_m \geq \tau_m mqe_0 \quad (7)$$

**Where:**
$\tau_m$ is a fraction of quantization error in layer 0 and $\tau_m mqe_0$ is considered the same for all other layers.

The procedure of adding continues until a suitable size of the map is reached. Let, threshold $\tau_m$ as a fraction of quantization error in layer 0. The $mqe_i$ with a value grater than $\tau_m$ is considered as $mqe_e$ and indicates the maximum dissimilarity between the weight vector and input pattern. Now, the new row or column is inserted. Selection of a row or a column depends on the position of neighbor having the most dissimilar weight vector. The average weight vectors of existing neighbors are chosen as the initial value of new units' weight vectors. Once, the insertion phase is terminated, the process is repeated.

The block diagram of the proposed model is shown in Fig. 3, with SOM replaced by GHSOM. The size of designed codebook is 40×16. The GHSOM specifications are listed in Table 3.

Table 3: GHSOM specifications in hybrid model

| Specification | Value or type |
|---|---|
| Codebook size | 40×16 |
| Neighborhood function in all cases<br>1: layer_1st_neigh<br>2: sub_layer_neigh<br>3: grow_map_neigh | Gaussian |
| Distance metric | Euclidean |
| Number of input features | 16 |
| Training mode | Batch |
| Initial radius of layer_1st_radius | 1.5 |
| Final radius of layer_1st_radius | 0.5 |
| Initial radius of sub_layer_radius | 0.1 |
| Final radius of sub_layer_radius | 0.1 |
| Initial radius of grow_map_radius | 0.8 |
| Final radius of grow_map_radius | 0.1 |
| Breadth (which controls the breadth of maps) | 0.6 |
| Depth (which controls the depth of maps) | 0.1 |

**Experimental Results:** The performance of three proposed models, in terms of computational complexity, spectral distortion (SD) and number of bits per frame are compared with traditional S-SVQ and S-MSVQ ISF quantization methods. For this purpose, an AMR-WB in 12.65 kbit/s mode is implemented [3]. The training dataset consists of 1048576 vectors and the test set consists of 10240 vectors from 51 different speakers (twenty five men and twenty six women). FARSDAT speech database is used in this work. FARSDAT is a Farsi continuous speech corpus including 6000 utterances from 300 speakers with various accents [31].

The number of additions, multiplications and comparisons of five different ISF quantization methods, for one frame of speech, are reported in Table 4. As a result, the proposed "GHSOM+S-MSVQ" hybrid model has the least computational complexity.

Spectral distortion (SD), as another performance criterion, is defined as follows [32]:

Table 4: Computational complexity comparison of different ISF quantization methods

| | Number of operations | | | | |
|---|---|---|---|---|---|
| Operation | S-SVQ | S-MSVQ | Hybrid of S-SVQ and S-MSVQ | Hybrid of SOM and S-MSVQ | Hybrid of GHSOM and S-MSVQ |
| Addition | 11512 | 9664 | 9912 | 9920 | 3224 |
| Multiplication | 6784 | 5280 | 5408 | 5280 | 1824 |
| Comparison | 2056 | 896 | 904 | 640 | 424 |

Table 5: Average spectral distortion of S-MSVQ as compared to three proposed hybrid models

| Method | S-MSVQ | Hybrid of S-SVQ and S-MSVQ | Hybrid of SOM and S-MSVQ | Hybrid of GHSOM and S-MSVQ |
|---|---|---|---|---|
| Avg. SD (dB) | 0.6059 | 0.6061 | 0.6060 | 0.6061 |

Table 6: Number of bits per frame in different ISF quantization methods

| Method | S-SVQ | S-MSVQ | Hybrid of S-SVQ and S-MSVQ | Hybrid of SOM and S-MSVQ | Hybrid of GHSOM and S-MSVQ |
|---|---|---|---|---|---|
| Number of bits | 46 | 46 | 49 | 38 | 36 |

$$SD_k = \sqrt{(x_k - \hat{x}_k)^2} \tag{8}$$

**Where:**

$x_k$ and $\hat{x}_k$ are LPC coefficients before and after quantization in frame $k$, respectively.

The average SD of S-MSVQ ISF quantization method and three proposed hybrid models are shown in Table 5. As can be seen, the average spectral distortion is approximately the same for S-MSVQ and three hybrid models.

The number of bits per frame in S-SVQ, S-MSVQ and three proposed hybrid models are reported in Table 6. As a result, the proposed "GHSOM+S-MSVQ" hybrid model has the least number of bits per frame.

## CONCLUSIONS

In this paper, three hybrid models for quantization of ISF in adaptive multi-rate wideband (AMR-WB) speech coder were proposed: "S-SVQ+S-MSVQ", "SOM+S-MSVQ" and "GHSOM+S-MSVQ". Experimental results showed that the "GHSOM+S-MSVQ" hybrid model performs better than traditional S-SVQ and S-MSVQ and two other hybrid models. In this way, the number of multiplications, additions and comparisons in "GHSOM+S-MSVQ", as compared to S-MSVQ, was reduced 66.6%, 65.5% and 52.7%, respectively. The number of bits per frame in proposed "GHSOM+S-MSVQ" model, as compared to S-MSVQ, was also reduced 21.7% with no significant change in spectral distortion, as well.

## REFERENCES


1. ITU-T G.729 Recommendation, 1995. Coding of Speech at 8kbps Using Conjugate-Structure Algebraic Code Excited Linear Prediction (CS-ACELP).
2. Bessette, B., R. Salami, R. Lefebvre, M. Jelinek, J. Rotola-Pukkila, J. Vainio, H. Mikkola and K. Jarvinen, 2002. The Adaptive Multirate Wideband Speech Codec (AMR-WB). IEEE Transactions on Speech and Audio Processing, 10: 620-636.
3. ITU-T G.722.2 Recommendation, 2002. Wideband Coding of Speech at Around 16kbit/s Using Adaptive Multi-Rate Wideband (AMR-WB).
4. Järvinen, K., 2000. Standardisation of the Adaptive Multi-Rate Codec. In the Proceedings of International Conference on Signal Processing, pp: 1313-1316.
5. Adoul, J.P. and R. Lefebvre, 1995. Wideband Speech Coding. in B. Kleijn and K. Paliwal, (Eds): Speech Coding and Synthesis (Elsevier, Amsterdam), pp: 289-309.
6 So, S. and K. Paliwal, 2007. A Comparative Study of LPC Parameter Representations and Quantisation Schemes for Wideband Speech Coding. Digital Signal Processing, 17: 114-137.
7. 3GPP TS 26.190, 2001. AMR Wideband Speech Codec; Transcoding Functions.
8. Sugamura, N. and F. Itakura, 1986. Speech Analysis and Synthesis Methods Developed at ECL in NTT-from LPC to LSP. Speech Communication, 5: 213-229.
9. Saito, S. and K. Nakata, 1985. Fundamentals of Speech Signal Processing (Academic Press).
10. Karayiannis, N.B. and P.I. Pai, 1996. Fuzzy Algorithms for Learning Vector Quantization. IEEE Transactions on Neural Networks, 7: 1196-1211.
11. So, S. and K. Paliwal, 2004. Efficient Vector Quantisation of Line Spectral Frequencies Using the Switched Split Vector Quantiser. In the Proceedings of International Conference on Spoken Language Processing, pp: 2641-2644.
12. So, S. and K. Paliwal, 2007. Efficient Product Code Vector Quantisation Using the Switched Split Vector Quantiser. Digital Signal Processing, 17: 138-171.
13. Combescure, P., J. Schnitzler, K. Fischer, R. Kirchherr, C. Lamblin, A. le Guyader, D. Massaloux, C. Quinquis, J. Stegmann and P. Vary, 1999. A 16, 24, 32 kbits/s Wideband CELP Speech Codec Based on ATCELP. In the Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing, pp: 5-8.
14. Linde, Y., A. Buzo and R.M. Gray, 1980. An Algorithm for Vector Quantizer Design. IEEE Transactions on Communications, 28: 84-95.
15. Hernandez-Gomez, L.A. and E. Lopez-Gonzalo, 1993. Phonetically-Driven CELP Coding Using Self-Organizing Maps. In the Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing, pp: 628-631.
16. Easton, M.G. and C.C. Goodyear, 1991. A CELP Codebook and Search Technique Using a Hopfield Net. In the Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing, pp: 685-688.
17. Wu, S., G. Zhang, X. Zhang and Q. Zhao, 2008. A LD-aCELP Speech Coding Algorithm Based on Modified SOFM Vector Quantizer. In the Proceedings of International Symposium on Intelligent Information Technology Application, pp: 408-411.
18. Wu, L., M. Niranjan and F. Fallside, 1994. Fully Vector-Quantized Neural Network-Based Code Excited Nonlinear Predictive Speech Coding. IEEE Transactions on Speech and Audio Processing, 2: 482-489.
19. Sheikhan, M., V. Tabataba Vakili and S. Garoucy, 2009. Complexity Reduction of LD-CELP Speech Coding in Prediction of Gain Using Neural Networks. World Applied Sciences J., 7(Special Issue of Computer and IT): 38-44.
20. Sheikhan, M., V. Tabataba Vakili and S. Garoucy, 2009. Codebook Search in LD-CELP Speech Coding Algorithm Based on Multi-SOM Structure. World Appl. Sci. J., 7(Special Issue of Computer and IT): 59-68.
21. Sheikhan, M. and S. Garoucy, 2010. Reducing the Codebook Search Time in G.728 Speech Coder Using Fuzzy ARTMAP Neural Networks. World Applied Sci. J., 8: 1260-1266.
22. Kohonen, T., 2001. Self-Organizing Maps (Springer, 3rd edn.).
23. Kohonen, T., 1998. The Self-Organizing Maps. Neurocomputing, 21: 1-6.
24. Rauber, A., D. Merkl and M. Dittenbach, 2002. The Growing Hierarchical Self-Organizing Map: Exploratory Analysis of High-Dimensional Data. IEEE Transactions on Neural Networks, 6: 1331-1341.
25. Dittenbach, M., A. Rauber and D. Merkl, 2002. Uncovering Hierarchical Structure in Data Using the Growing Hierarchical Self-Organizing Map. Neurocomputing, 48: 199-216.

26. Itakura, F., 1975. Line Spectrum Representation of Linear Predictive Coefficients of Speech Signals. J. the Acoustical Society of America, 57: S35.
27. Chen, Q., K. Kotani, F.F. Lee and T. Ohmi, 2008. A VQ-Based Fast Face Recognition Algorithm Using Optimized Codebook. In the Proceedings of International Conference on Wavelet Analysis and Pattern Recognition, pp: 298-303.
28. Amerijckx, C., M. Verleysen, P. Thissen and J. Legat, 1998. Image Compression by Self-Organized Kohonen Map. IEEE Transactions on Neural Networks, 9: 503-507.
29. Laha, A., N.R. Pal and B. Chanda, 2004. Design of Vector Quantizer for Image Compression Using Self-Organizing Feature Map and Surface Fitting. IEEE Transactions on Image Processing, 13: 1291-1303.
30. Nasrabadi, N.M. and Y. Feng, 1988. Vector Quantization of Images Based Upon the Kohonen Self-Organization Feature Maps. In the Proceedings of International Conference on Neural Networks, 1: 101-108.
31. Bijankhan, M., J. Sheikhzadegan, M.R. Roohani, Y. Smareh, C. Lucas and M. Tebiani, 1994. The Speech Database of Farsi Spoken Language. In the Proceedings of International Conference on Speech Science and Technol., pp: 826-831.
32. Martin, R., 2005. Speech Enhancement Based on Minimum Mean-Square Error Estimation and Supergaussian Priors. IEEE Transactions on Speech and Audio Processing, 13: 845-856.