SPARSE SIGNAL MODELING IN A SCALABLE CELP CODER

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ABSTRACT

This work presents a series of sparse signal modeling algorithms implemented in a variable rate CELP coder in order to compare their performances at a reasonable computational load. Multipulse excitation (MPE), Multi-Pulse Maximum Likelihood Quantization (MP-MLQ), Algebraic CELP (ACELP) and hybrid excitation schemes are analyzed under a common framework. New approaches are proposed, based on cyclic and parallel use of fast greedy algorithms. These algorithms yield a statistically significant reduction of signal approximation error at a controllable computational complexity. Main results were confirmed by comparing MOS values obtained with the PESQ algorithm

Index Terms— speech coding, CELP, scalable coding, sparse approximation, MP-MLQ, ACELP

1. INTRODUCTION

Most of speech coding standards appeared in the 90's of the last century (e.g. [1]) but nowadays, thanks to a rapid development of digital signal processors and programmable devices, more complex sparse approximation and compressive sensing techniques may be applied to the multipulse or stochastic excitation CELP coders [2], [3].

In the MP-MLQ and ACELP coders the exhaustive codebook search algorithm is not feasible in most cases, so the suboptimal algorithms, like the focused search [1], depth first [5], pre-selection [6], maximum take precedence [7], local, global and iteration free replacement [8], [9], [10], [11] were used. In the recent years new multi-layer excitation schemes for the CELP coder were proposed [12], combining the MPE approach and the ACELP approach.

The aim of this paper is to compare some of the codebook search algorithms and to propose new ones which may be implemented in a variable rate CELP coder. The CELP coder used for testing is the G.723.1 coder [1], [4] with the algebraic code excited linear prediction algorithm replaced by a series of sparse signal modeling algorithms. The criteria used in our comparison are the signal modeling accuracy and scalability (better signal quality for an increased number of codebook vectors being used for signal modeling).

It should be stressed, that our aim is not a construction of a new variable rate speech coder, competing with the ITU-T standards, like G.718 [13]. Our primary interest is in comparing the excitation schemes and codebook search algorithms. So we do not implement any bandwidth extension algorithm, we keep the narrowband speech whatever the bit rate.

This paper is organized as follows: In Sect.2 the basic excitation schemes of the CELP coder are described. In Sect.3 the codebook search algorithms for MP-MLQ and ACELP coders are compared. New algorithms based on M-best search and pulse replacement are proposed. In Sect.4 new hybrid CELP excitation schemes are tested. In Sect.5 the simulation results are briefly summed up.

2. SIGNAL MODELING IN CELP CODERS

The CELP coder may be regarded as a special sparse approximation algorithm (Fig.1). Spectral weighting of quantization noise is attained by using the de-emphasis filter (here $A(z/\gamma)/A(z)$), which models the masking threshold. The N-dimensional vectors of the perceptual speech signal $\bar{x}_t$ are modeled using the filtered vectors issued from two codebooks (the adaptive one and the constant one). Due to a small number of vectors being selected from both dictionaries, this is a kind of sparse approximation. It must be stressed, that the criterion used in this modeling is Euclidean: vectors are selected and a synthetic perceptual signal $\bar{x}_t^*$ is built so as to minimize the squared Euclidean norm $||\bar{e}||^2 = ||\bar{x}_t - \bar{x}_t^*||^2$. At successive stages of modeling the spectral flatness of the error signal $\bar{e}$ increases and the quantization noise accompanying the output speech signal $\bar{x}_s^*$ attains its proper spectral shape.

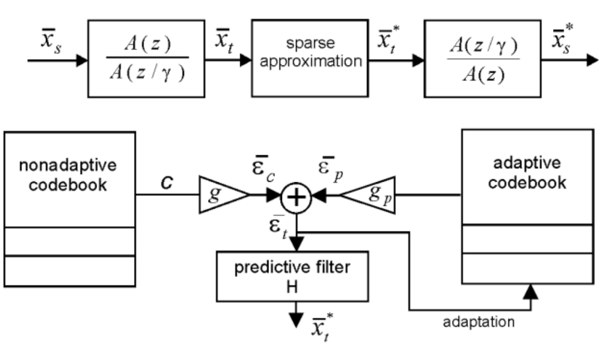

Fig.1. Simplified scheme of the CELP coder/decoder: pre-emphasis and de-emphasis filtering used for spectral weighting (above) and perceptual speech signal coding (below)

A vector of synthetic perceptual signal equals:

$$\bar{x}_t^* = \bar{x}_0 + H\,\bar{\varepsilon}_t = \bar{x}_0 + \bar{x}_c + \bar{x}_p \qquad (1)$$

where: $\bar{\varepsilon}_t$ - excitation signal, $\bar{x}_0$ - zero input response of the predictive filter $H(z)=1/A(z/\gamma)$, H - the lower triangular NxN Toeplitz matrix built on the impulse response of $H(z)$, $\bar{x}_c = H\,\bar{\varepsilon}_c$ - the signal issued from the constant codebook and $\bar{x}_p = H\,\bar{\varepsilon}_p$ - the signal issued from the adaptive codebook (long term prediction). Assuming that the long term prediction signal is known (in this paper we do not optimize this stage of signal modeling), the error energy equals:

$$||\bar{e}\,||^2 = ||\,\bar{x}_t - \bar{x}_t^*\,||^2 = ||\,\bar{x}_t - \bar{x}_0 - H\,\bar{\varepsilon}_p - H\,\bar{\varepsilon}_c\,||^2 = ||\,\bar{x} - \bar{x}^*\,||^2 \quad (2)$$

where $\bar{x} = \bar{x}_t - \bar{x}_0 - \bar{x}_p$ - the target signal and $\bar{x}^* = \bar{x}_c = H\bar{\varepsilon}_c$ - its model.

Having the codebook $C = [c^1, c^2, \ldots, c^L]$, consisting of L N-dimensional vectors (in most cases single pulses, i.e. $C=I$ is the unit matrix), the excitation signal $\bar{\varepsilon}_c$ may be obtained using the following approaches (excitation schemes):

a) ***multi-gain scheme***, used in the *Multipulse Excitation* (MPE) coders [2]:

$$\bar{\varepsilon}_c = \sum_{i=1}^{K} g_i\, c^{j(i)}, \qquad K < N \qquad (3)$$

This multi-gain excitation scheme leads to the “classical” sparse modeling techniques. Indeed, the sparse approximation

$$\bar{x}^* = H\bar{\varepsilon}_c = \sum_{i=1}^{K} g_i\, H c^{j(i)} = \sum_{i=1}^{K} g_i\, f^{j(i)} \qquad (4)$$

is searched, minimizing the error (2). The vectors $f^{j(1)}, f^{j(2)}, \ldots, f^{j(K)}$ are searched in the filtered codebook $F = HC = [f^1, f^2, \ldots, f^L]$.

b) ***one-gain scheme***, applied e.g. in GSM-EFR, GSM-AMR, G.729, G.723.1 coders:

$$\bar{\varepsilon}_c = g \sum_{i=1}^{K} s_i\, c^{j(i)} \qquad (5)$$

Here, the pulses have only two amplitudes (signs $s_i = \pm 1$) and one common gain g. There are two variants of this scheme. In the MP-MLQ *(Multi-Pulse - Maximum Likelihood Quantizer*) there are no restrictions or small restrictions concerning positions of the selected vectors (pulses), e.g. in the G.723.1 coder operating at bit rate 6.3 kbit/s either even or odd positions may be taken [1]. In the ACELP (*Algebraic CELP*) coders pulses are distributed in tracks and have usually 8-16 possible positions. Such excitation is used e.g. in the G.723.1 coder operating at 5.3 kbit/s [1].

c) ***hybrid scheme***, used in the G.718 coder [12], [13]:

$$\bar{\varepsilon}_c = \sum_{l=1}^{L'} g_l \sum_{i=K'(l-1)+1}^{K'l} s_i\, c^{j(i)} \qquad (6)$$

Here, there are L’ layers in which K’ pulses are distributed as in (5). In each layer, however, a separate gain (g_l) is used.

The *multi-gain excitation scheme* (3) is analyzed in [3] and [16]: several sparse approximation algorithms are compared, attention is focused on the Optimized Orthogonal Matching Pursuit (OOMP) algorithm [2], [14], [15], particularly on its fast implementation, which has been proposed under the name of Recursive Modified Gram-Schmidt (RMGS) algorithm [15],[16]. In this paper we analyze the *one-gain excitation scheme* (5) and the *hybrid scheme* (6), in which we also use the OOMP algorithm.

3. CODEBOOK SEARCH IN MP-MLQ AND ACELP

Having the target vector $\bar{x} = \bar{x}_t - \bar{x}_0 - H\bar{\varepsilon}_p$ its best approximation (model $\bar{x}^* = H\,\bar{\varepsilon}_c$) is searched, which minimizes the Euclidean norm $||\,\bar{x} - \bar{x}^*\,||$ and is described with (5). Testing of all possible combinations of pulse positions and signs is not feasible, so many suboptimal algorithms are proposed:

Gain first – Looking for positions and signs for a preselected gain. In the G.723.1 - 6.3kbit/s coder four gains are tested and a simple greedy algorithm is used for positions calculation [1], [4]. The criterion is the Euclidean norm.

Focused search – Pulses are allocated in K nested loops, but the inner loops are entered only if the approximation error $||\,\bar{x} - \bar{x}^*\,||^2$ is below the predefined threshold (G.729, G.723.1 at 5.3 kbit/s).

Depth first tree search [5] – The inner loops are entered but the outer loops are selected according to the approximation error.

Pre-selection [6] and ***maximum take precedence*** [7] – Preselection of pulse positions, according to the long-term prediction signal $\bar{\varepsilon}_p$ and back filtering of the target signal $\bar{x}$.

Local replacement [8] – Iterative replacement of least significant pulses (having a small influence on the approximation error) with more significant ones.

Global replacement [9], [10] – As above, but replacement is performed for any pulse. It is reported, that this methods yields, at lower computational load, comparable results to the *focused search* and *depth first* approaches [9], [10], [18]. In the first stage of this algorithm the initial positions and signs of K pulses are calculated. They may be obtained from the long-term prediction residual signal or may be found by a back filtering of the target vector $\bar{x}$ (a combination of both signals is usually used). In the second stage each pulse, one by one, is replaced to its better position. The criterion is maximum norm of the orthogonal projection of $\bar{x}$ on $H\bar{\varepsilon}_c$ or minimum angle between $\bar{x}$ and $H\bar{\varepsilon}_c$ (both are equivalent). This procedure is repeated in a cyclic manner. If in K trials there is no effective replacement (each pulse stays at its previous position) then the algorithm is stopped. In our implementation of the *global replacement* algorithm the following modification is proposed: the initial pulse positions and signs are calculated using the *minimum angle* algorithm.

Iteration free replacement [11] – Pulse replacement without calculation of the approximation error at each iteration.

Minimum angle [17] - It is a simple greedy algorithm, allocating K pulses in K steps by minimizing the angle between the target vector $\bar{x} = \bar{x}_t - \bar{x}_0 - H\bar{\varepsilon}_p$ and its model:

$$\bar{x}^* = H\,\bar{\varepsilon}_c = H\,g\sum_{i=1}^{K} s_i\,c^{j(i)} = g\sum_{i=1}^{K} s_i\,H\,c^{j(i)} = g\sum_{i=1}^{K} s_i\,f^{\,j(i)} \quad (7)$$

where $f^{\,j(i)} = H c^{j(i)}$ - the filtered pulse allocated at position $j(i)$, i.e. the impulse response of $H(z)$ shifted to $j(i)$.

The target signal is modeled by adding and subtracting of the vectors $f^{\,j(i)}$. Having a sum of K vectors a proper gain may be obtained by the orthogonal projection of the target vector $\bar{x}$ on this sum.

M-best implementation of a greedy algorithm - The M-best implementation calculates, in a parallel way, M sequences of pulses. At the first step the codebook vectors are sorted in ascending order according to the angle with the target vector. The first M vectors start M sequences. At the second step (generally, at the k^{th} step) there are almost ML possible sequences (to any of M sequences any of L-k+1 vectors may be appended), but only M of them are retained. The criterion is, of course, the angle between the target vector and its models. The identical sequences (permutations of the same vector indices) are not allowed. They are easily recognized because they form the same angle with the target vector. At the last step the best sequence is selected. The angle minimization algorithm is so simple, that even M=10 parallel runs yield no computational complexity problems.

Hybrid algorithm **-** In the first stage the initial pulse positions and signs are calculated using the *M-best* implementation of the minimum angle algorithm. In the second stage the *global pulse replacement* is performed, as described above.

We have tested some of these codebook search algorithms in the MP-MLQ and ACELP coders, both based on the G.723.1 coder structure [4]. The long and short time predictors, perceptual filters, frame and subframe (N=60) lengths are left unchanged. The postfilters are suppressed, because they affect the MOS values obtained with the PESQ algorithm. The codebook C consists of L=60 pulses of unit amplitude, i.e. the matrix C is a unit matrix. Scaling is obtained by changing the number of pulses K. In our scalable MP-MLQ coder there is only one grid containing all N=60 positions (two grids containing even and odd positions are suppressed). The number of pulses varies from K=4 to K=36. In our scalable ACELP coder four tracks are used, each one contains 15 positions. In each track the same number of pulses is allocated, from 1 to 9, according to the chosen bit rate. This approach differs from the G.723.1 coder, in which there are 4 tracks having unequal number of positions.

Two criteria are used for comparing the codebook search algorithms. The first one is the segmental SNR measured at the perceptual signal level (note that the sparse approximation algorithm uses the Euclidean norm $||\bar{x}_t - \bar{x}_t^*||$ so it is reasonable to use SNR for perceptual signal). At the speech signal level using of the SNR may be questioned, so we compare the MOS values obtained using the PESQ algorithm.

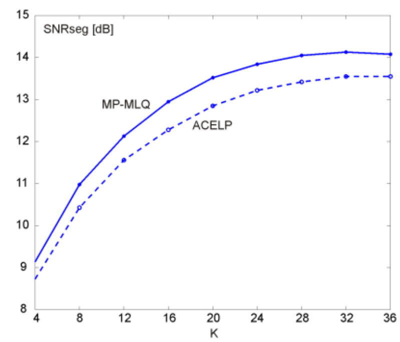

Fig.2. The segmental perceptual SNR [dB] for the *minimum angle* algorithm (4 phrases, 2 feminine and 2 masculine speakers)

For each tested algorithm, the segmental perceptual SNR values are evaluated and compared with the segmental perceptual SNR of the reference algorithm (i.e. the *minimum angle* – Fig.2): $\Delta SNR = SNR_{seg} - SNR_{seg}^{min.angle}\ [dB]$. Results for the MP-MLQ and the ACELP coder are shown in Fig.3. The confidence interval for ΔSNR values is about ± 0.04 dB.

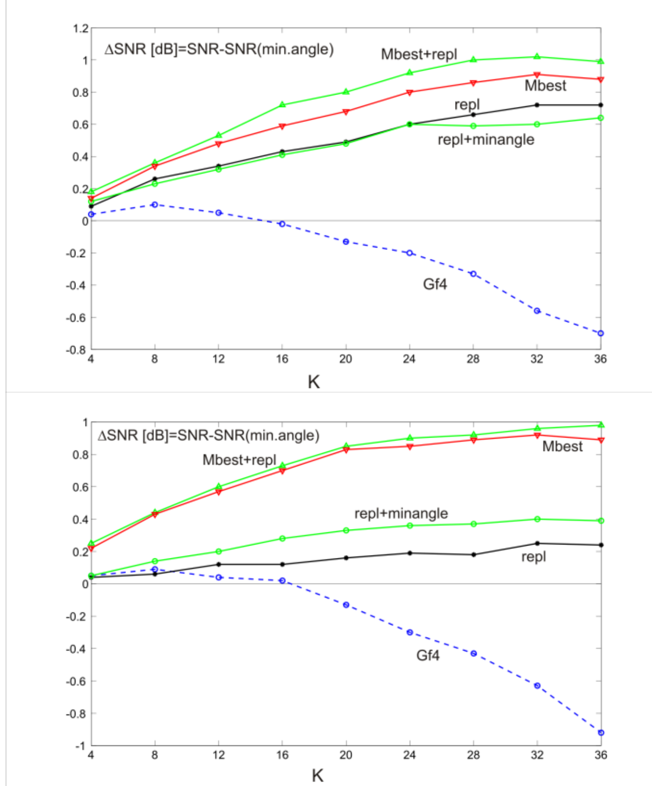

Fig.3. $\Delta SNR\,[dB]$ for the MP-MLQ coder (above) and the ACELP coder (below): Gf4 – *Gain first* with 4 gain candidates, repl – *global replacement*, repl+minangle - *global replacement* starting with minimum angle, Mbest – *M-best minimum angle* with 10 parallel sequences, Mbest+repl – *hybrid* algorithm

For both coders *gain first* algorithm performs no better than the reference algorithm, despite of its greater complexity. The *global replacement* algorithms perform better than the reference algorithm. The *M-best* implementation of the *minimum angle* algorithm is better than the *global replacement*. It is to be noted, that the *M-best* algorithm has a controllable computational cost (*M* times the cost of the *minimum angle* algorithm), whereas the number of iterations of the *global replacement* algorithm is variable. The *hybrid* approach outperforms the other codebook search algorithms. It has been juxtaposed with the *minimum angle* algorithm using K=12 vectors by comparing MOS values obtained with the PESQ algorithm [19]. According to the Wilcoxon signed rank test [20] for 10 speech phrases the mean MOS value for the *hybrid* codebook search algorithm is greater than the mean MOS value for the *minimum angle* algorithm. This result is significant at the 0.005 level for both the MP-MLQ and ACELP coders.

4. HYBRID EXCITATION SCHEMES

4.1. Using multiple gains

As the number of pulses (K) grows, there is a saturation of the SNR for MP-MLQ/ACELP coders (Fig.2) which is not observed for the MPE coders using the OOMP algorithm [3]. This saturation is due to single gain used in the excitation model (5) – not due to the codebook search algorithms (more complex codebook search algorithms yield only a slight improvement of perceptual SNR - Fig.3).

During the simulations of the MPE - OOMP coder it has been observed that the absolute value of gains diminish at subsequent iterations. This rule may be applied to the MP-MLQ model: the norms of vectors selected at subsequent iterations may be reduced:

$$\bar{\varepsilon}_c = g\sum_{i=1}^{K}\alpha_i\, s_i\, c^{j(i)} \tag{8}$$

where $\alpha_i > \alpha_{i+1}$ are the multiplicative factors which are constant and are not transmitted. The values of these factors are set up experimentally, by the observations of gains applied in the MPE coder (Fig.4).

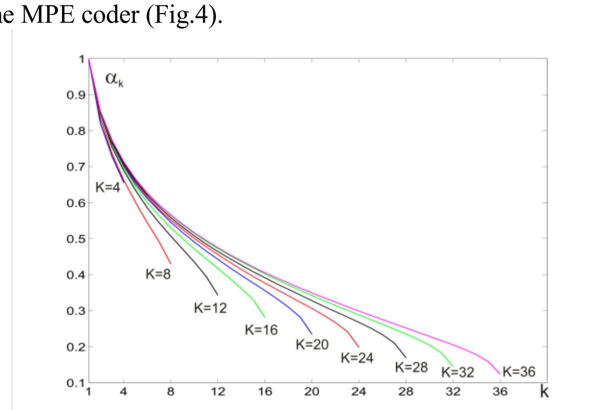

Fig.4 Gain reduction factors

Codebook search is performed by using a modified *minimum angle* approach. Note that the modified model (8) demands greater bit rate than the MP-MLQ model (5). This is due to transmission of the permutation of K vectors: in order to reconstruct the excitation signal we should know which vectors correspond to particular gains.

In Fig.5 the perceptual segmental SNR of the tested coders is drawn as a function of the bit rate. Bit rates used for LPC coefficients (0.8 kbit/s) and long term predictor lags (0.6 kbit/s) are the same as in the G.723.1 coder. The adaptive and nonadaptive codebook gains are coded in 7 bits each, yielding 1.86 kbit/s. In our implementation, the filtered codebook F is orthogonalized with respect to the filtered excitation issued from the adaptive codebook $\bar{x}_p = H\bar{\varepsilon}_p$ [15], [18].

The improvement of perceptual SNR obtained due to the variable gain excitation (8) is not sufficient to compensate for the increase of a bit rate – compare the MLQvg1 with MP-MLQ and ACELP in Fig.5. In order to reduce bit rate without affecting much signal quality, the multiplicative factors are kept constant for a group of K' vectors.

$$\bar{\varepsilon}_c = g\sum_{l=1}^{L'}\alpha_l \sum_{i=K'(l-1)+1}^{K'l} s_i\, c^{j(i)} \tag{9}$$

Thus the permutations of vectors within each group do not reckon. This modification (label "MLQvg4" in Fig 5) yields a good modeling accuracy, comparable to MP-MLQ at lower bit rates and a good scalability, offering improvement of accuracy at higher bit rates. Indeed, when using K=4 vectors for signal modeling, both coders are identical. However, for K=32 the MLQvg4 coder outperforms the MP-MLQ coder in terms of perceptual SNR and MOS measured with the PESQ algorithm. According to the Wilcoxon signed rank test (significance level 0.005) for 10 speech phrases the mean MOS value for the MLQvg4 coder is greater than the mean MOS value for the MP-MLQ coder. Of course the bitrates are not the same, but note, that the MP-MLQ coder, due to the saturation effect, has no chance, even for large K, to attain MOS values easily accessible for coders using the modified excitation (9).

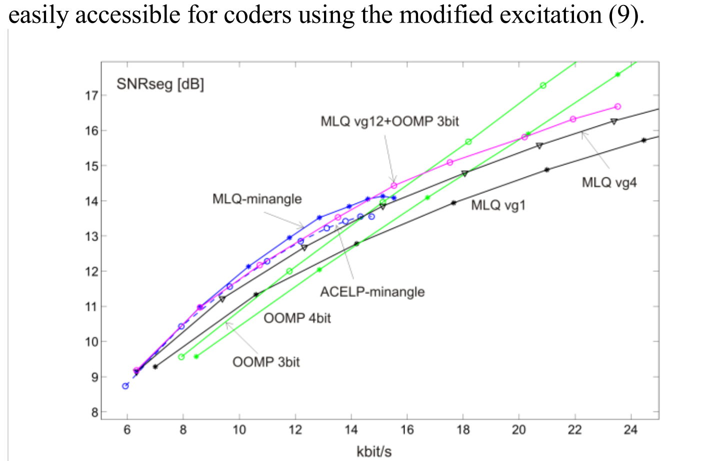

Fig.5 The segmental perceptual SNR [dB] as a function of bit rate for the tested CELP models and search algorithms (markers indicate number of vectors K=4,8,12,16,20,24,28,32,36)

4.2. Combining the MPE and MP-MLQ schemes

In our MPE-OOMP coders gains are quantized as follows: firstly the gain of a maximum absolute value is quantized at 7 bits. All the gains are divided by this reference value and their absolute values are quantized at b=3 or 4 bits.

The accuracy of the MPE-OOMP is worse than that of the MP-MLQ and ACELP at low bit rates. Compare the MPE-OOMP coder using K=4 vectors and b=3 bits per gain (OOMP-3bit in Fig. 5) and ACELP-minangle coder using K=8 vectors. Both coders have the same bit rate (almost 8 kbit/s), but the difference of perceptual SNR is 0.88 ± 0.04 dB. According to the Wilcoxon signed rank test (significance level 0.005) the mean MOS value for the ACELP-minangle algorithm is greater than the mean MOS value for the OOMP-3bit algorithm. However, at high bit rates the MPE- OOMP coders outperform the other ones.

In order to reduce the number of quantized gains without affecting much the signal quality a hybrid excitation model (6) may be used. Similar models have been proposed in [12] and applied in G.718 coder [13]. Here, only L' gains are quantized for $K = K'L'$ vectors used for signal modeling. In our implementation the codebook search algorithm uses L'-stage OOMP in the outer loop and the K' – stage *minimum angle* approach in the inner loop. The target signal model is obtained as a combination of vectors issued from the orthogonalized codebooks:

$$\bar{x}^* = \sum_{l=1}^{L'} g_l \sum_{i=K'(l-1)+1}^{K'l} s_i \, f_{orth(l)}^{j(i)} \tag{10}$$

The results for N=60, K'=12, b=3 bits and K=4,8,...,36 (Fig.5 – label "MLQvg12+OOMP3bit") show that this technique yields high perceptual SNR and good scalability.

5. CONCLUSIONS

Several codebook search algorithms used for the MP-MLQ and ACELP coders are tested and compared. The result is somewhat astonishing: a very simple greedy algorithm, namely the *minimum angle* approach [17], yields quite good modeling accuracy. More complex algorithms yield some improvement of the SNR at a perceptual signal level, but this improvement does not exceed much 1 dB. Nevertheless, this is a statistically significant improvement. It may be obtained using a hybrid codebook search algorithm, based on the *M-best* implementation of the *minimum angle* algorithm and the *global replacement* algorithm. The main disadvantage of the MP-MLQ and ACELP excitation models is a poor scalability: SNR saturates as the number of chosen vectors (pulses) increases.

In order to improve the scalability without increasing much the bit rate some hybrid excitation schemes are analyzed. The saturation of the SNR disappears if gains diminish in subsequent iterations of the *minimum angle* algorithm. The other solution of the SNR saturation problem is a combined OOMP and *minimum angle* approach, used for calculation of a hybrid (MPE and MP-MLQ) excitation model. New CELP excitation models and codebook search algorithms may serve to construct a simple scalable CELP based on the G.723.1 standard.

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