New algorithm for QMF Banks Design and Its Application in Speech Compression using DWT

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***Abstract**: This paper presents a new algorithm for designing Quadrature Mirrors Filters (QMF) banks using windowing techniques. In the proposed algorithm the cut off frequency of the prototype filters is iteratively varied such that the perfect reconstruction at frequency (ω=0.5π) in ideal condition is approximately equal to 0.707. The designed QMF banks are used as mother wavelet for speech compression algorithm based on Discrete Wavelet Transform (DWT). The evaluation tests prove the efficiency of the proposed algorithm in speech compression using wavelets. The comparison results between the proposed algorithms with other existing algorithms used for designing QMF banks show an important reduction in Reconstruction Error (RE) and number of iterations.*

Keywords: *QMF, speech compression, DWT, windowing techniques.*

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1. Introduction

Quadrature Mirrors Filters (QMF) bank is most commonly used in digital signal processing area, such as sub-band coding [5, 12] audio, image or video processing [3, 5, 8, 9, 30] Electrocardiogram (ECG) analysis [24], networks communication systems [14] and many other applications. However, the performance of the designed QMF in different fields relies on their efficient designing. Then, several efforts have been made to design and optimize QMF banks.

Johnston [17] has introduced and designed a family of filters based on QMF banks, using a Hook and Jeaves [15] optimization routine with a Hanning window. But, this method is not appropriate in the case of filters with larger taps. Kennedy and Eberhart [11, 19] has introduced an iteratively method for designing a QMF banks. This algorithm is optimized in [16], in which authors have used different window function and varied iteratively the cut off frequency to minimize the Reconstruction Error (RE) of the designed prototype filters.

In the recent years, many algorithms have been introduced for the design of QMF banks with near perfect reconstruction [6, 7, 10, 21, 22, 23, 29, 33]. In [6, 22] authors use the algorithms presented in [16] and optimized it with some modification. But, the optimized algorithms are effectively used for filters with larger taps [6, 7, 31].

In the above context, this paper presents a new algorithm for QMF banks design using windowing techniques. The optimized QMF banks are then exploited in the field of speech compression; more particularly in the speech compression algorithm using wavelets. The paper is organized as follows. Section 2, presents an overview of the analysis and synthesis of a signal with two-channel QMF bank. Section 3, discusses the proposed algorithm for designing QMF banks using windowing techniques. Section 4, describes the principle of wavelet analysis using QMF banks, and also the principle of speech compression algorithm based on wavelets techniques. Finally, section 5 presents an evaluation tests of the optimized wavelet filters in the field of speech compression using Discrete Wavelet Transform (DWT) and a comparison performances between the proposed algorithm and other existing algorithms used for designing QMF banks given in [6, 16, 22], for same specifications design.

2. Analysis and Synthesis with Two Channel QMF Bank

QMF bank is a two-channel filter bank. The basic structure of QMF bank is shown in Figure 1. In the analysis step, the input signal $x(n)$ is decomposed into two frequency bands by low-pass filter $H_0(z)$ and high-pass filter $H_1(z)$. Then, each obtained sub-band is down sampled by factor of two. In the synthesis step, each sub-band is up-sampled by factor of two, then filtered by low-pass synthesis filter $G_0(z)$ and high-pass synthesis filter $G_1(z)$. Finally, the filtered sub-bands are recombined to reconstruct signal $y(n)$.

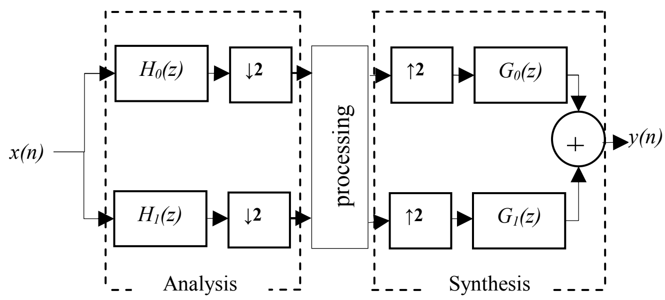


Figure 1. Tow channel QMF bank.

The input-output of the QMF bank in the Z-transform is given by Equation 1:

$$\begin{aligned} Y(z) &= \frac{1}{2}[H_0(z)G_0(z) + H_1(z)G_1(z)]X(z) \\ &+ \frac{1}{2}[H_0(-z)G_0(z) + H_1(-z)G_1(z)]X(-z) \\ &= T_{lin}(z)X(z) + A_{alias}(z)X(-z) \end{aligned} \tag{1}$$

Where, $T_{lin}(z)$ and $A_{alias}(z)$ are respectively called the linear (distortion) transfer function and the aliasing distortion transfer function.

The aliasing distortion can be eliminated by the conditions given in Equation 2:

$$\begin{aligned} H_1(z) &= H_0(-z) \\ G_0(z) &= H_0(z) \\ G_1(z) &= -H_0(-z) \end{aligned} \tag{2}$$

Then, Equation 1 becomes:

$$Y(z) = \frac{1}{2}\left[H_0^2(z) - H_0^2(-z)\right]X(z) \tag{3}$$

Hence, the complexity of QMF bank designing is reduced to design one single prototype filter $H_0(z)$. Let $z=e^{j\omega}$ and $H_0(z)$ a Finite Impulse Response filter (FIR) with N order, the transfer function of QMF bank using Equation 3 becomes:

$$T(e^{j\omega}) = \frac{e^{-j\omega N}}{2}\left\{\left|H_0(e^{j\omega})\right|^2 - (-1)^N\left|H_0(e^{j(\omega-\pi)})\right|^2\right\} \tag{4}$$

From Equation 4, if N is odd then at $\omega=0.5\pi$ the transfer function $T(e^{j\omega})$ is equal to zeros then, the perfect reconstruction is not required. If N is even, the transfer function $T(e^{j\omega})$ is given in Equation 5 and the perfect reconstruction condition is given by Equation 6 [4, 34]:

$$T(e^{j\omega}) = \frac{e^{-j\omega N}}{2}\left\{\left|H_0(e^{j\omega})\right|^2 + \left|H_0(e^{j(\omega-\pi)})\right|^2\right\} \tag{5}$$

$$\left|H_0(e^{j\omega})\right|^2 + \left|H_0(e^{j(\omega-\pi)})\right|^2 = 1 \tag{6}$$

3. Proposed Algorithm for QMF Banks Design

In QMF bank, the analysis and synthesis filters can be designed from a one single prototype filter $H_0(z)$. So, to design $H_0(z)$ with minimum of RE the following Equation 7 must be satisfied:

$$T(e^{j\frac{\pi}{2}}) = \left\{\left|H_0(e^{j\frac{\pi}{2}})\right|^2 + \left|H_0(e^{j(-\frac{\pi}{2})})\right|^2\right\} = 1 \quad at\ \omega = 0.5\pi \tag{7}$$

The Peak Reconstruction Error (PRE) is give by Equation 8:

$$PRE = max\left\{20log\left(\left|H_0(e^{j\omega})\right|^2 + \left|H_0(e^{j(\omega-\pi)})\right|^2\right)\right\} \tag{8}$$

Figure 2 shows the flowchart of the proposed algorithm. This algorithm is developed in MATLAB language and used for iteratively optimizing the cut off frequency (ω_c) using the condition given in Equation 7. In the proposed algorithm, the window type (Blackman, Hanning, Bartlett, Kaiser, …), the filter order (N), the pass-band ripple (A_p), the stop-band attenuation (A_s), the olerance (Tol), three cut off (ω_{c1},ω_{c2} and ω_{c3}) and the magnitude response in the ideal condition ($MRI=0.707$) are all initialized.

When the program starts, three prototype filters are designed. Then the magnitude response ($MRC_{i/i=1,\ 2,\ 3}$) and the error ($ERROR_{i/i=1,2,3}$) for each filter are calculated Figure 2. If tolerance is not satisfied $\{m=min\ (ERROR_{i/i=1,\ 2,\ 3}) > Tol\}$, three new cut off frequencies; ω_{c1}, ω_{c2} and ω_{c3} are calculated according to the following conditions:

1. *If* $m=MRC_1$ *then*
   $\omega_{c1}=\omega_{c1}$
   $\omega_{c2}=(\omega_{c1}+\omega_{c2})/2$
   $\omega_{c3}=\omega_{c2}$
2. *if* $m=MRC_2$ *then*
   $\omega_{c1}=(\omega_{c1}+\omega_{c2})/2$
   $\omega_{c2}=\omega_{c2}$
   $\omega_{c3}=(\omega_{c2}+\omega_{c3})/2$
3. *if* $m=MRC_3$ *then*
   $\omega_{c1}=\omega_{c12}$
   $\omega_{c2}=(\omega_{c2}+\omega_{c3})/2$
   $\omega_{c3}=\omega_{c3}$

Then, three new prototype filters are redesigned using the new cut off frequencies values (ω_{c1}, ω_{c2}, ω_{c3}). The iterations are stopped when the tolerance is satisfied ($m<Tol$), in this case the cut off frequency (ω_c) is defined as the minimum of the cut off frequencies $\omega_{ci/i=1,\ 2,\ 3}$:

$$\omega_c = min\ (\omega_{c1}, \omega_{c2}, \omega_{c3}) \tag{9}$$

This algorithm has been used for optimizing wavelet filters using windowing techniques. Table 1 illustrates some examples of developed filters (filters coefficients) and the obtained cut off. Here, six optimized filters are presents with filter taps 16 and 18. In all cases, the used window functions are: Hanning, Triangular and Kaiser. For Kaiser Window, the shape of window *beta* is fixed at 4.228 (for beta=0, the window is Rectangular). The initial cut off frequencies are: $\omega_{c1}=0.2$, $\omega_{c2}=0.5$ and $\omega_{c3}=0.8$ and the tolerance is fixed at 10^{-5}.

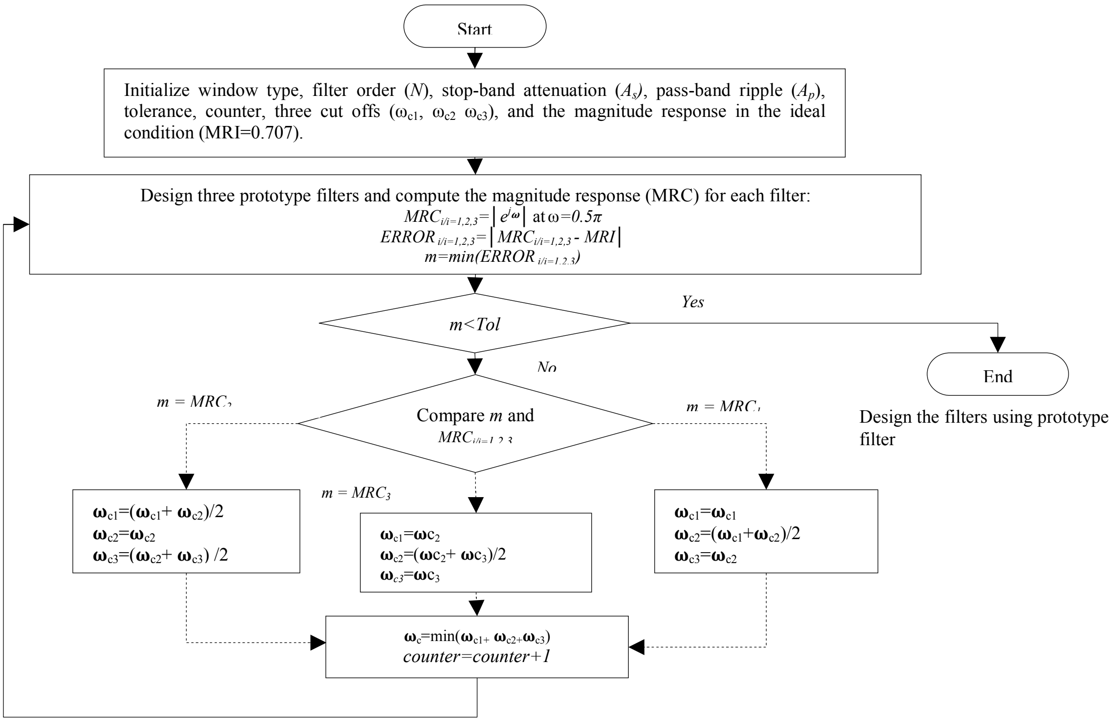


Figure 2. Block diagram of the proposed algorithm for designing QMF banks.

Table 1. Optimized wavelet filters coefficients using Hanning, Triangular and Kaiser Window.

Filter Taps(N)	Optimized Hanning (ω_c=0.5544)	Optimized Hanning (ω_c=0.5476)	Optimized Triangular (ω_c=0. 0.5533)	Optimized Triangular (ω_c= 0.5513)	Optimized Kaiser (ω_c=0.5466, beta=4.228)	Optimized Kaiser (ω_c=0.5411, beta=4.228)
1	0	0	0.001272998904561	0.001818116722793	0.000950082041332	0.002586347797257
2	-0.002001811335709	0.000473036715055	-0.009268425456495	0.003061800406147	-0.008633231927406	0.001276061399554
3	-0.001487102484462	-0.006280967377351	-0.002591953649765	-0.013780269012256	-0.000378674858179	-0.013901874516885
4	0.024403471188687	-0.000596645573818	0.032716947809036	-0.002413547473805	0.034060951068255	0.001832245090568
5	-0.009287101317910	0.031910258797848	-0.010702858795385	0.037047778389499	-0.016063909624410	0.039926434913383
6	-0.089339919388638	-0.015001083970880	-0.086435368640044	-0.012752788860883	-0.094297231386774	-0.021492151428878
7	0.096675163019950	-0.093534530406852	0.092844117625704	-0.089542107768001	0.105582699417707	-0.096877432209532
8	0.481037300318082	0.104481622746041	0.482164542202388	0.095925486417887	0.477964060380589	0.111687927831305
9	0.481037300318082	0.478548309069956	0.482164542202388	0.480635531178618	0.477964060380589	0.475248742506584
10	0.096675163019950	0.478548309069956	0.092844117625704	0.480635531178618	0.105582699417707	0.475248742506584
11	-0.089339919388638	0.104481622746041	-0.086435368640044	0.095925486417887	-0.094297231386774	0.111687927831305
12	-0.009287101317910	-0.093534530406852	-0.010702858795385	-0.089542107768001	-0.016063909624410	-0.096877432209532
13	0.024403471188687	-0.015001083970880	0.032716947809036	-0.012752788860883	0.034060951068255	-0.021492151428878
14	-0.001487102484462	0.031910258797848	-0.002591953649765	0.037047778389499	-0.000378674858179	0.039926434913383
15	-0.002001811335709	-0.000596645573818	-0.009268425456495	-0.002413547473805	-0.008633231927406	0.001832245090568
16	0	-0.006280967377351	0.001272998904561	-0.013780269012256	0.000950082041332	-0.013901874516885
17		0.000473036715055		0.003061800406147		0.001276061399554
18		0		0.001818116722793		0.002586347797257

4. QMF Bank Application in Speech Compression using Wavelets

In this section, the designed QMF banks are used as mother wavelets in Speech compression algorithm based on DWT. The appropriate QMF bank for speech compression using wavelets is that which maximizes the Compression Ratio (CR) while keeping a good quality of the reconstructed speech signal.

The Wavelet Transform (WT) more particularly the DWT has emerged as a powerful mathematical tool in digital signal processing area, and especially in speech compression. It provides a compact representation of a signal in time-frequency using multi-resolution techniques; introduced by *S.* Mallat [26] and described in detail by Meyer [27]. In order to, decompose the original speech signal by DWT, Mallat pyramid algorithm or transformation by QMF banks is used Figure 3. This algorithm consists in dividing the frequency band of the signal in to two sub-bands; one contains the low-pass ($H_0(z)$) components and other contains the high-pass ($H_1(z)$) components. Then, the low-pass band is again divided into low and high-pass sub-bands and so on.

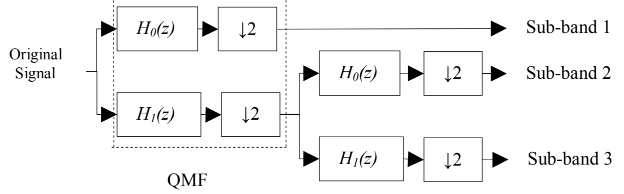


Figure 3. DWT decomposition using QMF banks.

The idea of signal compression using wavelets is primarily linked to the relative scarceness of the wavelet domain representation for the signal [20]. Agbinya [2] was shown that the wavelets concentrate speech information (energy and perception) into a few neighboring coefficients. Therefore, after decomposing the signal by the DWT and applying the thresholding, many coefficients will be zeroed (coefficients have negligible magnitudes) and others retained. Compression is then achieved by efficiently encoding the obtained coefficients.

Generally, the speech compression algorithm using wavelets is achieved in three major steps [1, 2, 13, 18, 25, 32], The first step consists in applying the DWT on the original speech signal. Then, the obtained coefficients are thresholded and encoded. Finally, quantization followed by entropy encoding is applied. More precisely the process of speech compression using DWT Figure 4 involves a number of different stages, each of them are discussed below:

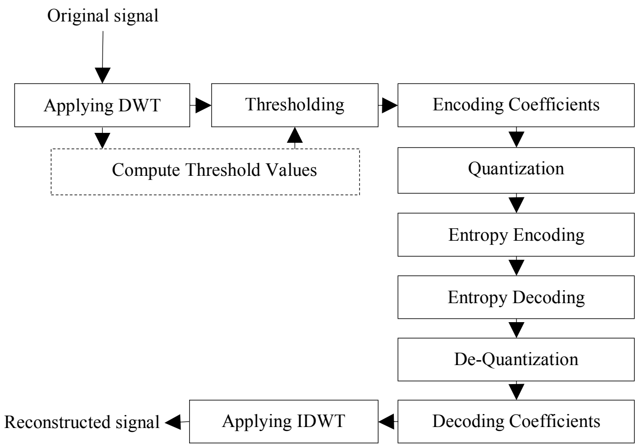


Figure 4. Block Diagram of speech compression using DWT.

- *Stage 1*: Choosing the mother wavelet, the decomposition level and applying the DWT on the original speech signal. Several criteria can be considered for choosing an optimal mother wavelet, the main objective is to maximize the Signal to Noise Ratio (SNR) and minimize the error variance between the original and reconstructed signal [20]. Generally, the choice of the optimal mother wavelet depends of the average energy concentrated in the approximation part of the wavelet coefficients. Agbinya [2] show that the adequate decomposition level for speech compression should be less or equals to five, with no further advantage gained in processing beyond scale five. In this research work, different mother wavelet filters are designed using the proposed algorithm based on windowing techniques and 5 level decomposition of DWT are applied.
- *Stage 2*: After decomposing the speech signal by using DWT, the obtained sub-bands are thresholded. Generally, there are two ways to computing the threshold values: Global threshold (the threshold value is manually set) and level depending thresholding using Birge-Massart strategy [28]. When the thresholds values are calculated, typically hard or soft thresholding is applied for truncate the small coefficients.
- *Stage 3*: The obtained wavelet coefficients after thresholding contains a string values of zeros, compression is achieved by efficiently encoding them. Then, the encoded coefficients are converted to other coefficients, with fewer possible discrete values by the mean of a quantization algorithm such as: Uniform, scalar or vector quantization algorithm. To remove the redundancy caused by the quantization, entropy encoding (Huffman or arithmetic coding) is used. The output bitstream of entropy encoding is multiplexed and transmitted. Here, to encode the thresholded wavelet coefficients two byte are used [20]: One byte to indicate the start sequence of zeros in the wavelet coefficients vector and the second byte representing the number of consecutive zeros.

For reconstruct the speech signal, the received bitstream demultiplexed and entropy decoding is used to extract the quantized coefficients. Then, an inverse quantization is applied to extract the encoded sub-bands followed by inverse DWT.

5. Tests and Results

In this section, a MATLAB program has been written to implement the proposed algorithm for QMF design described in this paper. Three tests were performed to evaluate the efficiency of the developed algorithm, using objective performance measures: CR, SNR, Peak Signal to Noise Ratio (PSNR) and Normalized Root Mean Square Error (NRMSE). The first test is an evaluation of optimized wavelet filters in the field of speech compression. The second is a comparative performance study between the developed wavelet filters and the Daubechies mother wavelets. The third is a comparative study between the proposed algorithm with other existing algorithms given in [6, 16, 22] used to design QMF banks, for some specifications; PRE and Number of Iteration (NI). The obtained results are calculated using the following formulas:

- *SNR*:

$$SNR = \frac{\Sigma x(n)^2}{\Sigma \left| x(n) - y(n) \right|^2} \tag{10}$$

- *PSNR*:

$$PSNR = 10log_{10}\left(\frac{Nx(n)^2}{\left\| x(n) - y(n) \right\|^2}\right) \tag{11}$$

- *NRMSE*:

$$NRMSE = \sqrt{\frac{(x(n) - y(n))^2}{(x(n) - \mu_x(n))^2}} \tag{12}$$

- *CR*:

$$CR = \frac{size\ of\ original\ signal}{size\ of\ compressed\ signal} \tag{13}$$

Where, $x(n)$ and $y(n)$ are respectively the original and the reconstructed speech signal, N is the length of the reconstructed speech signal and $\mu_x(n)$ is the mean of the speech signal.

Table 2 illustrates the obtained results, when the designed QMF banks are used as mother wavelets for speech compression algorithm based on DWT. Here, the used sentences are taken from TIMIT Database for Texas Instruments: male voice “sx37.wav” and female voice “sx22.wav” sampled all at 16000 Hz. For the QMF banks design algorithm, the initial cut off frequencies are: $\omega_{c1}=0.2$, $\omega_{c2}=0.5$ and $\omega_{c3}=0.8$.

Table 2. Evaluation performance using different window of length N=18.

Window function	Audio file	CR	SNR	PSNR	NRMSE	ω_c	RE (10^{-5})	NI
Bartlett-Hann	sx37.wav	5.1433	20.0194	38.7931	0.0998	0.5483	3.1311	14
	sx22.wav	4.3203	19.1696	36.7221	0.1100	0.5483	3.131	14
Bartlett	sx37.wav	5.0899	19.7833	38.5570	0.1025	0.5504	2.9822	14
	sx22.wav	4.2339	19.0554	36.6078	0.1115	0.5504	2.982	14
Kaiser	sx37.wav	5.1919	20.0174	38.7911	0.0998	0.5411	2.5786	15
	sx22.wav	4.3578	19.1088	36.6613	0.1108	0.5411	2.5786	15
Blackman-Harris	sx37.wav	4.9454	19.8794	38.6531	0.1014	0.5718	3.3039	14
	sx22.wav	4.1687	18.8996	36.4520	0.1135	0.5718	3.3039	14
Blackman	sx37.wav	5.0785	19.9981	38.7717	0.1000	0.5603	9.5921	13
	sx22.wav	4.2482	19.1902	36.7427	0.1098	0.5603	9.5921	13
Chebyshev	sx37.wav	5.0593	20.0287	38.8024	0.0997	0.5643	5.839	13
	sx22.wav	4.2203	19.0471	36.5995	0.1116	0.5643	5.839	13
Bohman	sx37.wav	5.0614	20.0358	38.8095	0.0996	0.5631	2.4504	15
	sx22.wav	4.2187	19.1410	36.6934	0.1104	0.5631	2.4504	15
Flattop	sx37.wav	4.2432	18.8706	37.6443	0.1139	0.6041	1.4216	15
	sx22.wav	3.5573	17.2373	34.7898	0.1374	0.6041	1.4216	15
Hanning	sx37.wav	5.1484	19.7976	38.5713	0.1024	0.5476	6.0914	13
	sx22.wav	4.3285	19.0345	36.5869	0.1118	0.5476	6.0914	13
Hamming	sx37.wav	5.1448	20.1984	38.9720	0.0977	0.5490	4.6831	14
	sx22.wav	4.3203	19.2415	36.7940	0.1091	0.5490	4.6831	14
Gauss	sx37.wav	5.1258	20.1545	38.9282	0.0982	0.5539	4.1732	14
	sx22.wav	4.2828	19.1432	36.6957	0.1104	0.5539	4.1732	14
Nuttallwin	sx37.wav	4.9692	19.8802	38.6539	0.1014	0.5708	9.6440	13
	sx22.wav	4.1784	18.9375	36.4899	0.1130	0.5708	9.6440	13
Parzen	sx37.wav	5.0565	20.0252	38.7989	0.0997	0.5634	1.0175	13
	sx22.wav	4.2213	19.0572	36.6097	0.1115	0.5634	1.0175	13
Triangular	sx37.wav	5.0963	19.3022	38.0759	0.1084	0.5514	3.7372	14
	sx22.wav	4.2334	18.2768	35.8293	0.1219	0.5514	3.7372	14

The tolerance is equal to 10^{-5}. For the Kaiser Window, the used shape of window *beta* is fixed at 4.228. The RE is calculated using the formula: $RE=|MRI\text{-}MRC|$.

In the speech compression algorithm using DWT, the speech signal is analysed by frames of 256 samples.

Then, five decomposition levels, a global threshold and a hard thresholding function are applied.

According to Table 2, it is clear that the optimized wavelet filters are able to compress speech signal, when they are used as mother wavelets for speech compression algorithm based on DWT. It is also observed that the performance parameters CR, SNR, PSNR and NRMSE depend on the used window type.

Figure 5 illustrates the time domain representation of the original speech signal (sx112.wav: TIMIT Database) and its reconstructed version. It is evident that the reconstructed speech signal is similar to the original. In this case, the used window is Modified “Bartlett-Hanning window” of length $N=20$, the cutoff frequency ω_c is equal to 0.5439. The obtained $CR=5.151$ and $SNR=18.021$dB.

Table 3 and Figure 6 illustrate the comparative performance study between the optimized QMF banks and the classical Daubechies wavelets, for same specifications such as: The decomposition level, the threshold values and the thresholding function. It can be observed that the global performances are significantly improved by using the optimized wavelet filters. It is also observed that the CR decreasing for wavelet filters with large taps and fixed SNR.

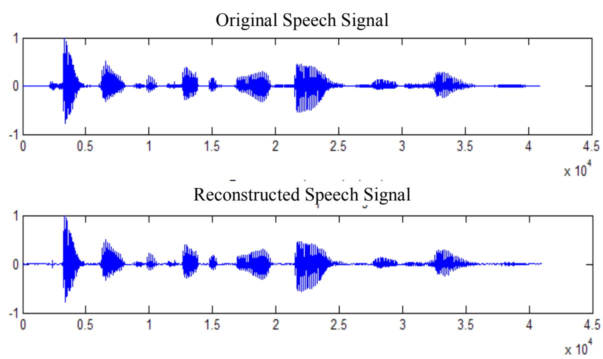


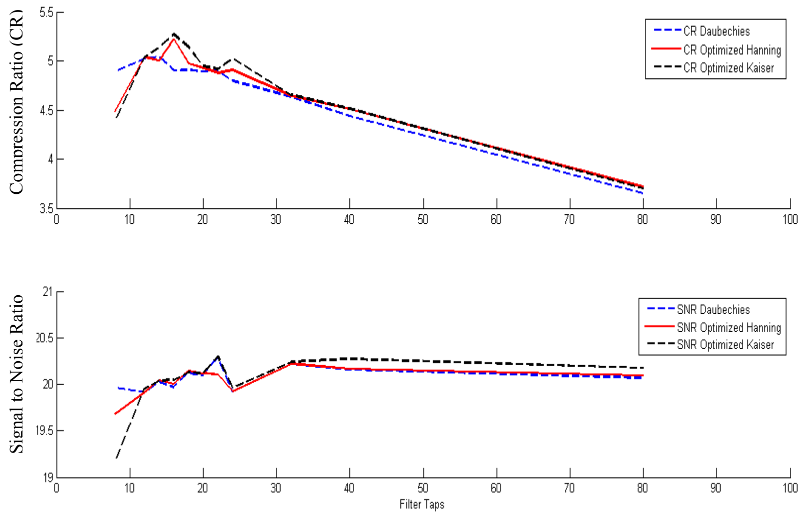
Figure 5. Time domain representation of the original speech signal (sx112.wav) and its reconstructed version.

Table 4 illustrates the comparison of performance between the proposed algorithm for QMF banks design and the algorithm given in [6, 16, 22], using Kaiser Window and the some specifications such as: The filter order, the pass-band ripple (A_p), the stop-band attenuation (A_s).

From Table 4, it is clear that the proposed algorithm is better, in term of PRE and NI.

Table 3. Comparison of performance using daubechies mother wavelets.

Wavelet filters		Filter order 8	12	14	16	18	20	22	24	32	40	80
Daubechies	CR	4.8920	5.0208	5.0452	4.9000	4.9053	4.8901	4.8980	4.7950	4.6355	4.4391	3.6509
	SNR	19.9623	19.9092	20.0204	19.9687	20.1209	20.1003	20.2877	19.9199	20.2156	20.1552	20.0674
	PSNR	38.7360	38.6828	38.7941	38.7424	38.8946	38.8740	39.0614	38.6936	38.9893	38.9289	38.8410
	NRMSE	0.1004	0.1011	0.0998	0.1004	0.0986	0.0989	0.0967	0.1009	0.0975	0.0982	0.0992
Optimized Hanning	CR	4.4842	5.0368	5.0021	5.1579	4.9481	4.9259	4.8769	4.9046	4.6433	4.5087	3.7134
	SNR	19.6790	19.9143	20.0429	20.0042	20.1347	20.1168	20.1049	19.9223	20.2197	20.1667	20.0957
	PSNR	38.4527	38.6880	38.8165	38.7778	38.9084	38.8905	38.8786	38.6960	38.9934	38.9404	38.8693
	RMSE	0.1038	0.1010	0.0995	0.0999	0.0984	0.0987	0.0988	0.1009	0.0975	0.0981	0.0989
Optimized Kaiser	CR	4.3807	5.0361	5.1360	5.2927	5.1396	4.9461	4.9153	5.0270	4.6546	4.5104	3.6978
	SNR	19.1641	19.9587	20.0368	20.0040	20.1313	20.1166	20.2970	19.9655	20.2396	20.2695	20.1772
	PSNR	37.9377	38.7324	38.8105	38.7777	38.9050	38.8903	39.0707	38.7392	39.0132	39.0431	38.9509
	NRMSE	0.1101	0.1005	0.0996	0.0999	0.0984	0.0987	0.0966	0.1004	0.0973	0.0969	0.0980



Filter Taps

Figure 6. Variation of CR and SNR via filter taps.

Table 4. Comparison performance study using Kaiser Window.

Algorithms	Filter order (N)	A_s	A_p	PRE(dB)	ω_c	NI
Jain *et al.*[16]	52	80	0.00078	0.0170	0.5192	153
Kumar *et al.* [22]	52	80	0.00078	0.0091	0.5193	16
Proposed	52	80	0.00078	0.0009	0.5162	13
Jain *et al.* [16]	56	80	0.00043	0.0175	0.5178	150
Kumar *et al.* [22]	56	80	0.00043	0.0094	0.5179	17
Proposed	56	80	0.00043	0.0005	0.5158	14
Jain *et al.* [16]	66	80	0.00008	0.0168	0.5151	152
Kumar *et al.* [22]	66	80	0.00008	0.0090	0.5151	16
Proposed	66	80	0.00008	0.0001	0.5150	13
Jain *et al.* [16]	78	60	0.00607	0.0647	0.5107	139
Kumar *et al.* [22]	78	60	0.00607	0.0376	0.5109	16
Proposed	78	60	0.00607	0.0068	0.5084	14
Jain *et al.* [16]	82	60	0.00434	0.0605	0.5102	141
Kumar *et al.* [22]	82	60	0.00434	0.0354	0.5104	18
Proposed	82	60	0.00434	0.0047	0.5079	11
Jain *et al.* [16]	92	60	0.00173	0.0634	0.5091	147
Kumar *et al.* [22]	92	60	0.00173	0.0368	0.5092	16
Proposed	92	60	0.00173	0.0022	0.5099	15

6. Conclusions

In this paper, a new algorithm for QMF banks design using windowing techniques is proposed. When the designed QMF banks are exploited in speech compression algorithm based on DWT, the evaluation tests prove the efficiency of the proposed algorithm in speech compression and especially for filters with medium taps. The comparison results with other existing algorithms used for designing QMF banks show an important reduction in term of RE and NI.

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