6.1 Introduction

In signal processing, a filter bank is an array of band-pass filters that separates the input signal into multiple components, each one carrying a single frequency sub-band of the original signal. The process of decomposition performed by the filter bank is called analysis (meaning analysis of the signal in terms of its components in each sub-band); the output of analysis is referred to as a sub-band signal with as many sub-bands as there are filters in the filter bank. The reconstruction process is called synthesis, meaning reconstitution of a complete signal resulting from the filtering process. This splitting of frequency bands can be used for improving the coding efficiency of the transmitted signal, thereby improving the available bandwidth.

Based on the composing filters, the filter banks can be classified as finite impulse response (FIR) and infinite impulse response (IIR) filter banks. In filter bank design problem, the task in hand is to reconstruct the received signal as close as possible to the original input signal. When this is achieved exactly then the filter bank is said to have a perfect reconstruction property. The reconstruction error is used to evaluate the overall performance of the filter bank and the stop-band energy, pass-band energy, stop-band ripple, pass-band ripple, transition bandwidth etc. assess the performance of the composing filters (Rafi et al., 2013).

The filter bank design problem requires the linear phase property and can be provided by the use FIR filters. However, the filter order has to be chosen very high which results in an unacceptable delay. In contrast to FIR filters, an alternative is to use much lower order IIR filters with the same frequency selectivity as the FIR filters. This means that IIR filters require
fewer multipliers and adders for digital implementation and are more efficient. Although, IIR filter banks offer low system delay and high stop-band attenuation, their design is very complex. They are either limited to the two-channel case or suffer from stability problems. Moreover, the linear phase approach with IIR filters causes the problem of causality (Agrawal and Sahu, 2015). In fact, the difficulty in designing such IIR filter banks is to satisfy the perfect reconstruction condition and the causal-stable requirement of the filters.

During the past two decades, design of multirate filter banks has received considerable attention due to their wide applications in numerous engineering fields such as one-dimensional or multi-dimensional signal processing, communication network, and power system network (Indrebo et al., 2004; Lollmann and Vary, 2007; Blanco-Velasco et al., 2008; Bai et al., 2009; Shyu et al., 2011). Among various multirate filter banks, a two-channel system is the most widely used and constitutes basic element of a multirate system. Two-channel filter banks can be classified into three types: quadrature mirror filter (QMF) banks, orthogonal filter banks, and biorthogonal filter banks (Bregovic and Saramaki, 2003). These filter banks can be designed to have either the perfect reconstruction (PR) or nearly perfect reconstruction (NPR) property (Vaidyanathan, 1993). QMF banks and biorthogonal filter banks can be created with the use of either linear-phase or nonlinear-phase filters, whereas for orthogonal filter banks, nonlinear-phase filters are always used.

Originally, the concept of QMF bank was introduced by Croisier et al. (1976) to reduce or eliminate the effect of aliasing error in sub-band coding of speech signals. A QMF bank is basically a filter whose magnitude response is the mirror image around $\pi/2$ of that of another filter. The QMF banks have been extensively used for splitting a signal into two or more sub-bands in the frequency domain, so that each sub-band signal can be processed in an independent manner and sufficient compression may be achieved. Eventually, at some point in the process, the sub-band signals are recombined so that the original signal is properly reconstructed. These filters find applications in many signal processing fields, such as design
of wavelet bases (Chan et al., 2004; Sablatash, 2008), image compression (Prakash et al., 2012; Kumar and Nagaraju, 2009), antenna systems (Chandran, 2003; Sharma et al., 2014), wideband beam forming for sonar (Charafeddine and Groza, 2013) etc. due to advancement in QMF bank. In comparison to earlier band-pass filter based sub-band coding systems, aliasing distortion is eliminated in QMF bank based sub-band coding systems; therefore, the transition width of the filters is not much important. Also, lower order filters with wider transition band can be used. Therefore, computation complexity is reduced in case of sub-band coding system based on QMF banks. Moreover, lower bit rates are possible, without degrading the quality of decoded speech signals. QMF based sub-band coders provide more natural sounding, pitch prediction, and wider bandwidth than earlier sub-band coders.

QMF filter sections are cascaded in a tree structure to generate multichannel filter banks. There are two types of tree structures, namely, uniform and octave filter bank structures. In uniform $M$-channel filter bank (full grown tree), at every level, the low-pass and the high-pass channels are divided into two parts, whereas, only the low-pass channel is divided into two parts, in a non-uniform octave filter bank (Agrawal and Sahu, 2013).

A typical two-channel QMF bank, splits the discrete input signal into two sub-band signals having equal bandwidth, using the low-pass and high-pass analysis filters. These sub-band signals are decimated by a factor of two to achieve signal compression or to reduce processing complexity. The decimated signals are typically coded and transmitted. At the receiver, the two sub-band signals are decoded and then interpolated by a factor of two and finally passed through low-pass and high-pass synthesis filters. The outputs of the synthesis filters are combined to obtain the reconstructed signal. The reconstructed signal suffers from three types of errors: aliasing distortion (ALD), amplitude distortion (AMD), and phase distortion (PHD), due to the fact that the analysis and the synthesis filters are not ideal (Upendar et al., 2010). In most of applications, a common requirement is that reconstructed signal should be as close to the transmitted signal as possible. Therefore the main stress while
designing filters for the QMF bank is to eliminate or minimize these three distortions to obtain a PR or NPR system.

The design techniques for QMF bank are classified as optimization-based or non-optimization based. Various optimization based techniques (Sahu et al., 2006; Upendar et al., 2010; Ho et al., 2010; Ghosh et al., 2012) have been developed for the design of two-channel linear phase NPR QMF bank using constrained or unconstrained optimization. In these design methods, ALD is cancelled completely by selecting the synthesis filters in terms of the analysis filters, whereas PHD is eliminated using the linear phase FIR filters. The overall transfer function of such an alias and phase distortion free system turns out to be a function of the filter tap coefficients of the low-pass analysis filter only, as the high-pass and low-pass analysis filters are related to each other by the mirror image symmetry condition around the quadrature frequency $\pi/2$. The AMD is minimized by optimizing the filter tap weights of the low-pass analysis filter using computer aided techniques. Design techniques for PR QMF can be found in literature (Spurbeck and Mullis, 1998; Goh and Lim, 1999; Bregovic and Saramaki, 2000). In PR QMF bank, all three distortions, namely, ALD, AMD, and PHD, are eliminated simultaneously.

Relevant previous state-of-the-art work on the design of linear phase two-channel QMF banks can be classified into a number of different approaches. The least-squares (Johnston, 1980; Andrew et al., 1997) and weighted least-squares (WLS) (Chen and Lee, 1992; Lu et al., 1998) design methods had been applied previously. Jain and Crochiere (1984) and Andrew et al. (1997) presented an eigenvector-eigenvalue approach to find the optimum prototype filter tap weights in time domain. Chen and Lee (1992) proposed a WLS method for QMF bank in frequency domain. Lu et al. (1998) developed a method based on self convolution technique to reformulate a fourth order objective function as a quadratic function. But due to complex optimization techniques these methods are not suitable for higher order filter banks. Various iterative methods (Sahu et al., 2006; Kumar et al., 2010;
Ho et al., 2010) have been applied for the design problem of two-channel QMF bank based on single objective or multi-objective, and constraint or unconstraint nonlinear optimization. Sahu et al. (2006) have developed an efficient technique by considering filter responses in transition band as well as in pass-band and stop-band regions. Ho et al. (2010) presented a modified field function method for the design of QMF bank by finding the global minimum of the nonconvex optimization problem. The conventional design methods may fail to achieve the optimal design for highly nonlinear and complex objective functions. Gradient based methods (Xu et al., 1998; Lu et al., 1998; Sahu et al., 2006; 2006) may easily be trapped at local minima on search space and some methods (Chen and Lee, 1992) requiring intensive matrix inversion calculations therefore, not suitable for designing QMF bank in real-time. Consequently, nowadays researchers have been attempting the design methods for QMF bank based on modern global optimization algorithms. Yu and Lim (2001) applied genetic algorithm for the design of multiplier-less lattice QMF. Neural networks (Jou, 2007), differential evolution (Ghosh et al., 2011, 2012) and swarm intelligence (Upendar et al., 2010; Rafi et al., 2013) based approaches have been presented for the design of optimum QMF bank.

In recent years, swarm intelligence has become very popular among researchers for solving optimization problems from various engineering fields. The swarm intelligence models the population of interacting agents that are able to self-organize. Typical examples are: an ant colony, an immune system, a flock of birds, fish schooling and bees swarming around their hive. Particle swarm optimization algorithm has emerged as a powerful tool for solving non-linear equations in multi-dimensional space and it has been applied successfully for the design of two-channel QMF bank (Upendar et al., 2010). Rafi et al. (2013) proposed an improved particle swarm optimization method for designing linear phase QMF banks. Ghosh et al. (2012) presented an approach based on adaptive-differential evolution algorithm for the design of two-channel QMF banks.
Artificial bee colony (ABC) algorithm is a recently introduced optimization algorithm for both constrained and unconstrained problems based on intelligent foraging behavior of honeybee swarms and has many advantages over earlier swarm intelligence algorithms (Karaboga, 2005). The scout bee phase is a peculiar stage of ABC algorithm in comparison to PSO and DE algorithms that provides diversity in the population. Karaboga and Basturk (2009) successfully applied ABC algorithm for design of digital IIR filter. The present work takes into consideration the designing two-channel linear phase QMF bank. The QMF bank is constructed by using IIR digital all-pass filters (DAFs). Utilizing the theory of two-channel QMF banks with two IIR DAFs, the design problem is appropriately formulated in an appropriate Chebyshev approximation for the desired group delay responses of the IIR DAFs and the magnitude response of the low-pass analysis filter. As a result, the design problem can be solved by using the ABC optimization algorithm. The problem formulation for the two-channel QMF bank using IIR digital all-pass filters is explained in the subsequent section. The detailed description of the proposed oppositional ABC algorithm for solving the filter bank design problem and the simulation results are also given in this chapter.

6.2 Digital IIR Filter Bank Design Problem

A filter bank consists of an analysis filter bank followed by synthesis filter bank. Signals are partitioned into sub-bands for coding purposes. This is the simplest way to decompose a signal into one high-frequency component and one low-frequency component. The input signal is processed simultaneously by a low-pass filter and high-pass filter. The available frequent range is $\Omega = 0$ to $\Omega = \pi$ which is half the sampling rate, is usually portioned into two halves. The filtered signals have a bandwidth of $b = \pi/2$ thus the sampling rate can be halved (Qahwaji et al., 2011 and Zhou et al., 2008). Filter banks decompose signal spectra in a number of directly adjacent frequency bands and recombine the signal spectra by the use
of low-pass, band-pass and high-pass filters. The decomposition is performed in analysis filter banks and reconstruction in synthesis filter banks.

Figure 6.1 depicts the two-channel QMF filter bank with a system architecture shown in Figure 6.1. $H_0(z)$ and $H_1(z)$ designate the low-pass and high-pass analysis filters, respectively, and $F_0(z)$ and $F_1(z)$ designate the low-pass and high-pass synthesis filters, respectively.

The reconstructed signal $\hat{x}(n)$ suffers from three types of errors: ALD, PHD, and AMD. ALD can be cancelled totally by selecting the synthesis filters adroitly in terms of the analysis filters such that the synthesis filters $F_0(z) = H_1(-z)$ and $F_1(z) = -H_0(z)$ and PHD eliminated by using the linear phase FIR filters (Vaidyanathan, 1990; Vaidyanathan, 1993). The frequency response of the analysis filter $H_0(z)$ and $H_1(z)$ are shown in Figure 6.2. There exists a mirror-image symmetry about the frequency $\omega = \pi/2$ between $H_0(z)$ and $H_1(z)$, therefore, $H_0(z) = H_1(-z)$.

The overall transfer function of such an alias and phase distortion free system is a function of the filter tap weights of the low-pass analysis filter only and is given by the following equation (Sahu et al., 2006, Vaidyanathan, 1990):

$$\hat{x}(z) = \frac{1}{2} \left[ H_0^2(z) - H_0^2(-z) \right] x(z)$$ (6.1)
Let \( T(e^{jw}) \) denote the frequency response of the QMF bank. Equation (6.1) reveals that producing a reconstructed signal \( x'(n) \) that is a delayed replica of \( x(n) \) requires:

\[
T(e^{jw}) = H_0^2(e^{jw}) - H_0^2(e^{j(w+\pi)}) = e^{-j\pi d w} \text{ for all } w
\]

(6.2)

where, \( d \) is the system delay of the QMF bank.

![Figure 6.2: Frequency response of the analysis filters, \( H_0(z) \) and \( H_1(z) \)](image)

This imposes constraints not only that \( H_0(z) \) should be an ideal low-pass analysis filter, but also that its behaviour for all \( \omega \) should satisfy the condition given in Equation (6.2). The designs of QMF banks using conventional FIR or IIR structures for \( H_0(z) \) usually induce both magnitude and phase distortions. The analysis and synthesis structures of the two-channel QMF bank using digital all-pass filters shown by Figure 6.3 and 6.4, respectively, where \( A_1(z^2) \) and \( A_2(z^2) \) are two real IIR DAFs.

![Figure 6.3: The analysis system of the DC-based QMF bank](image)

Hence,

\[
H_0(z) = \frac{A_1(z^2) + z^{-1}A_2(z^2)}{2}
\]

(6.3a)
Substituting Equations (6.3a) and (6.3b) into Equation (6.2) yields the frequency response of the QMF bank as follows:

\[ T(e^{jw}) = \frac{1}{2} e^{-jw} A_1(e^{j2w}) A_2(e^{j2w}) \]  

(6.4)

From Equation (6.4), it is clear that the resulting QMF bank possesses perfect magnitude response, i.e., there is no magnitude distortion. Moreover, \( H_0(z) \) and \( H_1(z) \) satisfy the all-pass complementary and power complementary properties. They are termed the doubly-complementary (DC) filter pair (Vaidyanathan, 1993). Therefore, the design problem is to find the real coefficients for the IIR DAFs \( A_1(z_2) \) and \( A_2(z_2) \) such that the resulting phase response \( \text{Arg}\left[T(e^{jw})\right] \) of the DC-based QMF bank can approximate a desired phase characteristic in the minimax sense. The real IIR DAFs \( A_1(z_2) \) and \( A_2(z_2) \) with frequency responses are given as:

\[ A_1(e^{j2w}) = e^{-j2N_1w} \frac{\sum_{n=0}^{N_1} a_1(n) e^{j2nw}}{\sum_{n=0}^{N_1} a_1(n) e^{-j2nw}} = e^{j\theta_1(w)} \]  

(6.5a)

And,

\[ A_2(e^{j2w}) = e^{-j2N_2w} \frac{\sum_{n=0}^{N_2} a_2(n) e^{j2nw}}{\sum_{n=0}^{N_2} a_2(n) e^{-j2nw}} = e^{j\theta_2(w)} \]  

(6.5b)
Without loss of generality, both of the coefficients \( a_j(\theta) \) and \( a_2(\theta) \) are set equal to one. Then, the phase responses \( \theta_i(w), i=1,2 \) are given by:

\[
\theta_i(w) = -2N_i w - 2\phi_i(w) = -2N_i w - 2\tan^{-1}\left\{ \frac{-N_j}{I + \sum_{n=1}^{N_j} a_i(n) \cos(2nw)} \right\} \tag{6.6}
\]

Substituting Equation (6.6) into Equations (6.3a) and (6.3b) yields:

\[
H_0(e^{jw}) = \frac{1}{2} [e^{j\theta_1(w)} + e^{-jw} e^{j\theta_2(w)}] = \exp\left( j \frac{\theta_1(w) + \theta_2(w) - w}{2} \right) \cos\left( \frac{\theta_1(w) - \theta_2(w) + w}{2} \right) \tag{6.7}
\]

And, \( H_1(e^{jw}) = \frac{1}{2} [e^{j\theta_1(w)} - e^{-jw} e^{j\theta_2(w)}] = \exp\left( j \frac{\theta_1(w) + \theta_2(w) - w}{2} \right) \sin\left( \frac{\theta_1(w) - \theta_2(w) + w}{2} \right) \tag{6.8} \)

Therefore, the frequency response of the DC-based QMF bank can be given as:

\[
T(e^{jw}) = \frac{1}{2} \exp[j(-w + \theta_1(w) + \theta_2(w))] = \frac{1}{2} \exp[- j(2N_1 + 2N_2 + 1)w] \tag{6.9}
\]

From Equation (6.9), reveals that the QMF bank possesses a linear phase with group delay \( g_d = 2N_1 + 2N_2 + 1 \) and without magnitude distortion. The design problem can then be formulated as follows:

- From Equations (6.4) and (6.9), the constraint on the group delays of the IIR DAFs \( A_1(z_2) \) and \( A_2(z_2) \) is stated as follows:

\[
GD_1(w) + GD_2(w) + l = g_d \tag{6.10}
\]

where,

\[
GD_i(w) = -\frac{d}{dw} \theta_i(w) = -2 \left( \sum_{n=0}^{N_i} (n - N_i) a_i(n) e^{j2nw} + \sum_{n=0}^{N_j} na_i(n) e^{-j2nw} \right) \tag{6.11}
\]

for \( w \in [0, \pi / 2] \) and \( i = 1, 2 \).

- The magnitude of the low-pass analysis filter must be zero in \( w \in [\pi / 2, \pi] \), i.e.,
Digital IIR Filter Bank Design using OABC

\[
|H_o(e^{j\omega})| = \left| \frac{A_1(e^{j2\omega}) + e^{-j\omega} A_2(e^{j2\omega})}{2} \right| \\
= \frac{1}{2} \left( \sum_{n=0}^{N_1} a_1(n)e^{j(n-N_1)2\omega} - \sum_{n=0}^{N_1} a_1(n)e^{-j(n-N_1)2\omega} + \sum_{n=0}^{N_2} a_2(n)e^{jN_22\omega} - \sum_{n=0}^{N_2} a_2(n)e^{-jN_22\omega} \right) = 0 
\] (6.12)

The objective function based on the Chebyshev criteria is then formulated as follows:

\[
\text{Minimize} \left\| \text{Aprx}_1(a, w) \right\|_{w, \omega} + \alpha \left\| \text{Aprx}_2(a, w) \right\|_{w, \omega} 
\] (6.13)

where, \(\|x\|_\infty\) denotes the Chebyshev norm of \(x\) and \(a = [a_1^T a_2^T]^T\) with \(a_j = [a_j(1), a_j(2), ..., a_j(N_j)]^T\) the filter coefficient vector and,

\[
\text{Aprx}_1(a, w) = -2 \left\{ \sum_{n=0}^{N_1} (n-N_1) a_1(n)e^{j2\omega} - \sum_{n=0}^{N_1} a_1(n)e^{-j2\omega}\right\} \\
= \sum_{n=0}^{N_2} (n-N_2) a_2(n)e^{j2\omega} - \sum_{n=0}^{N_2} a_2(n)e^{-j2\omega} + I - g_d 
\] (6.14)

\[
\text{Aprx}_2(a, w) = \frac{1}{2} \left( \sum_{n=0}^{N_1} a_1(n)e^{j2(n-N_1)\omega} + e^{-j\omega} \sum_{n=0}^{N_2} a_2(n)e^{-j2(n-N_2)\omega} \right) \\
+ \frac{1}{2} \sum_{n=0}^{N_2} a_2(n)e^{-j2(n-N_2)\omega} 
\]

\(\alpha\) is a preset relative weight between the two error terms.

### 6.3 Solution Methodology

The IIR QMF bank design can be specified as a problem that searches the prototype filter coefficients which improve the overall performance of the filter bank by minimizing the amplitude distortion. The OABC algorithm, discussed in Section 4.4 of Chapter 4, is used to solve the unconstrained optimization problem formulation for two-channel QMF bank. The main structure of the algorithm contains the evolution of best food source by placing the employed bees, onlooker bees and scout bees in every iteration, until the maximum number of
cycles or end condition reached. Step by step description to obtain the optimized filter coefficients using the proposed OABC optimization algorithm is described in Table 6.1.

6.4 Results and Discussions

For designing the two-channel QMF, the step by step procedure described in section 6.5 is implemented. The effectiveness of the proposed OABC algorithm has been examined in terms of five significant parameters: peak stop-band ripple of $H_0(z)$ (PSR), the maximal variation of pass-band group delay of $H_0(z)$ (MVPGD), the maximal variation of the group delay (MVDG), maximum variation of the phase response (MVPR) of the designed filter bank $\hat{T}(e^{j\omega})$ and the maximal variation of the filter-bank response (MVFBR) defined as follows:

$$PSR = 20\log_{10}\left(\max_{\omega \in [0, \pi]} |H_0(e^{j\omega})| \right) \text{ (dB)} \quad (6.22)$$

$$MVPGD = \max_{\omega \in [0, \pi]} \left| GD\left\{H_0(e^{j\omega})\right\} - \left( N_1 + N_2 + \frac{1}{2} \right) \right| \text{ sample} \quad (6.23)$$

$$MVGD = \max_{\omega \in [0, \pi]} \left| GD\left\{\hat{T}(e^{j\omega})\right\} - (2N_1 + 2N_2 + 1) \right| \text{ sample} \quad (6.24)$$

$$MVPR = \max_{\omega \in [0, \pi]} \left| \text{Phase}\left\{\hat{T}(e^{j\omega})\right\} + (2N_1 + 2N_2 + 1)\omega \right| \text{ radian} \quad (6.25)$$

$$MVFBR = \max_{\omega \in [0, \pi]} \left| \hat{T}(e^{j\omega}) - \frac{1}{2}e^{j(2N_1+2N_2+1)\omega} \right| \quad (6.26)$$

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Initialize the value of the OABC control parameters: bee colony size ($NP$), maximum number of generations ($MGEN$), predefined parameter ($limit$), $NDUP$.</td>
</tr>
<tr>
<td>2.</td>
<td>Initialize the population of food sources, $X_i$ using Equation (4.2).</td>
</tr>
<tr>
<td>3.</td>
<td>Evaluate the population using Equation (4.4).</td>
</tr>
<tr>
<td>4.</td>
<td>Apply opposition using Equation (4.6) and again evaluate the fitness.</td>
</tr>
<tr>
<td>5.</td>
<td>Sort the population from best to worst and keep the best habitats.</td>
</tr>
<tr>
<td>6.</td>
<td>Initialize the generation counter, $g = 1$ and Improve=1</td>
</tr>
<tr>
<td>7.</td>
<td>Trial=0 ($i=1, 2, ..., NP$)</td>
</tr>
<tr>
<td>8.</td>
<td>while ($g &lt; MGEN$) do</td>
</tr>
<tr>
<td></td>
<td>for $i=1$ to $NP$</td>
</tr>
<tr>
<td></td>
<td>Employed bees' phase: For the employed bees, produce new food source, $V_i$ from $X_i$ based on $X_k$ such that $k \neq i$, using Equation (4.3).</td>
</tr>
</tbody>
</table>

Table 6.1 Step by Step procedure of the OABC algorithm for digital IIR filter bank design
Digital IIR Filter Bank Design using OABC

10: Calculate the fitness of the food source, $V_j$ using Equation (4.4).
   if (new food source is better) then
11:   Select the new food source.
12: else
13:   $Trial_i = Trial_i + 1$
end if
end for
14: Calculate the probability values for food sources using Equation (4.5).
for $i$ = 1 to $NP$
   if random $<$ $P_i$
15:    Onlookers bees phase: Depending on $P_i$, produce new food sources, $V_j$ for onlooker bees
         from food source, $X_{ij}$ based on $X_k$ such that $k \neq i$, using Equation (4.3).
16:    Calculate the fitness of the food source, $V_j$ using Equation (4.4).
   if (new food source is better) then
17:      Select the new food source.
18: else
19:      $Trial_i = Trial_i + 1$
end if
end if
end for
20: Scout bees' phase: $Big_l = \max\{Trial_i (i=1, 2, ..., NP)\}$.
   if ($Big_l > limit$ ) then
21:      Replace $l^{th}$ food source with a newly generated food source using Equation (4.2).
end if
22: Procure the global best solution (food source) achieved so far.
   if (global best is not improved) then
23:      Improve = Improve + 1
   else
24:      Improve = 1
end if
   if (MOD (Improve, NDUP) = 0) then
25:      Ensure the population does not have duplicates.
end if
26: $g = g + 1$
end do

For the purpose of comparison, the order of $A_1(z)$ and $A_2(z)$ for the real IIR DAFs i.e. $N_1$ and $N_2$ is taken as 9 and 8, respectively. The pass-band edge frequency of the low-pass analysis filter $H_0(z)$ is taken as, $w_p = 0.4\pi$ and the stop-band edge frequency is taken as, $w_s = 0.6\pi$. Many simulations have been performed to set the values of control parameters and the values of the various control parameters that have been used in the OABC algorithm for its implementation for designing the two-channel digital IIR QMF bank are given in Table
6.2. Table 6.3 lists the significant design results and their comparison with the results proposed by Lee and Yang (2003) and Lee and Shieh (2013) for two-channel IIR QMF bank with similar design specifications i.e. length of the filter, pass-band and stop-band edge frequencies.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Notation</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population size</td>
<td>$NP$</td>
<td>100</td>
</tr>
<tr>
<td>Maximum number of iterations</td>
<td>$MGEN$</td>
<td>100</td>
</tr>
<tr>
<td>Maximum number of trial limits</td>
<td>$limit$</td>
<td>5</td>
</tr>
<tr>
<td>Number of iterations to check duplication</td>
<td>$NDUP$</td>
<td>20</td>
</tr>
</tbody>
</table>

Table 6.3: Design results for the filter bank using OABC algorithm

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>PSR (dB)</td>
<td>-54.7222</td>
<td>-50.6398</td>
<td>-50.6808</td>
</tr>
<tr>
<td>MVPGD</td>
<td>0.1359</td>
<td>0.0535</td>
<td>0.0456</td>
</tr>
<tr>
<td>MVGD</td>
<td>2.0120</td>
<td>0.1069</td>
<td>0.0111</td>
</tr>
<tr>
<td>MVPR</td>
<td>0.1366</td>
<td>0.0093</td>
<td>0.0092</td>
</tr>
<tr>
<td>MVFBR</td>
<td>0.0046</td>
<td>0.0682</td>
<td>0.0046</td>
</tr>
</tbody>
</table>

From the above table it is observed that the performance of the proposed method is significantly better than all the other methods in terms of measure of peak stop-band ripple, the maximal variation of pass-band group delay, the maximal variation of the group delay and maximum variation of the phase response of the designed filter bank $\hat{T}(e^{j\omega})$. In terms of the maximal variation of the filter bank response, the proposed method show significantly better performance than the result of the method proposed by Lee and Shieh (2013) while its performance is equivalent to the method proposed by Lee and Yang (2003).

Table 6.4 lists the resulting filter coefficients obtained using the proposed method. Also, the frequency response, the phase response error and the group delay error of the designed filter bank are depicted in Figures 6.4 and Figure 6.5, respectively. From the simulation
results, it can be observed that the proposed OABC optimization algorithm has the capability to provide better phase response and more equiripple magnitude response of the QMF bank.

Table 6.4: The resulting filter coefficients of the digital IIR filter bank

<table>
<thead>
<tr>
<th>n</th>
<th>a₁(n)</th>
<th>a₂(n)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1.0000000000</td>
<td>1.0000000000</td>
</tr>
<tr>
<td>1</td>
<td>0.2488388000</td>
<td>-0.2631544000</td>
</tr>
<tr>
<td>2</td>
<td>-0.0784477400</td>
<td>0.1552796000</td>
</tr>
<tr>
<td>3</td>
<td>0.0367690900</td>
<td>-0.1015403000</td>
</tr>
<tr>
<td>4</td>
<td>-0.0176505100</td>
<td>0.0564582100</td>
</tr>
<tr>
<td>5</td>
<td>0.0059801400</td>
<td>-0.0352370100</td>
</tr>
<tr>
<td>6</td>
<td>-0.0017297820</td>
<td>0.0198208500</td>
</tr>
<tr>
<td>7</td>
<td>-0.0010165800</td>
<td>-0.0112849600</td>
</tr>
<tr>
<td>8</td>
<td>0.0019982920</td>
<td>0.0047114110</td>
</tr>
<tr>
<td>9</td>
<td>-0.0009629820</td>
<td>0.0047114110</td>
</tr>
</tbody>
</table>

Figure 6.5: Magnitude responses of $H_\theta(z)$ (Low-pass Response Curve) and $H_f(z)$ (High-pass Response Curve)

Figure 6.6: Phase error and group delay error of the filter bank
6.5 Conclusion

As QMF banks find application in most of the communication and signal processing systems to achieve the goals of sub-band coding and short-time spectral analysis, more and more research is being carried out on their designing. The present work also takes into account the designing of two-channel linear-phase QMF bank. The QMF bank is constructed by using IIR DAFs. Employing the theory of two-channel QMF banks with two IIR DAFs, the design problem is formulated in an appropriate Chebyshev approximation for the desired group delay responses of the IIR DAFs and the magnitude response of the low-pass analysis filter. The conventional ABC algorithm suffers from some inadequacies. It possesses a good exploration but lacks in exploitation as it shows insufficiency while searching the solution space resulting in a weak exchange of information and hence is not able to return optimal solutions. To remedy this problem, in the present work, the opposition based learning strategy is incorporated in ABC, which compared to the random initialization, helps to further accelerate the search convergence rate. The oppositional learning strategy takes a start with some initial random solutions that are improved over time by moving towards optimal solution. Hence, a modified version called oppositional artificial bee colony algorithm is proposed. Then, the proposed OABC algorithm is implemented for solving the non-linear multidimensional optimization problem of the two-channel QMF bank with linear phase. The simulation results clearly indicate that the overall performance of the proposed method is more robust than other existing methods, therefore, it is suitable for various signal processing application such as video processing and image compression.