Optimal Bit-allocation for Wavelet-based Scalable Video Coding

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Abstract—We investigate the wavelet-based scalable video coding problem and present a solution that takes account of each user’s preferred resolution. Based on the preference, we formulate the bit allocation problem of wavelet-based scalable video coding. We propose three methods to solve the problem. The first is an efficient Lagrangian-based method that solves the upper bound of the problem optimally, and the second is a less efficient dynamic programming method that solves the problem optimally. Both methods require knowledge of the user’s preference. For the case where the user’s preference is unknown, we solve the problem by a min-max approach. Our objective is to find the bit allocation solution that maximizes the worst possible performance. We show that the worst performance occurs when all users subscribe to the same spatial, temporal, and quality resolutions. Thus, the min-max solution is exactly the same as the traditional bit allocation method for a non-scalable wavelet codec. We conduct several experiments on the 2D+t MCTF-EZBC wavelet codec with respect to various subscribers’ preferences. The results demonstrate that knowing the users’ preferences improves the coding performance of the scalable video codec significantly.

Keywords—wavelet video coding; rate allocation;

I. INTRODUCTION

Scalable video coding (SVC) encodes a video into a single bitstream comprised of several subset bitstreams. A subset bitstream represents a lower resolution of the video in the spatial, temporal, or quality resolution. SVC is a natural compression solution for a video broadcasting system because it can simultaneously support all the subscribers of the system with heterogeneous display and computational capability. An important issue in SVC is how to measure the relative importance of a resolution to the overall coding performance.

Many researchers employ a weighting coefficient to represent the relative importance of a resolution [1], [2], but a good coding performance metric for SVC should consider the subscriber’s preference for different resolutions, which is not considered in these previous works. For example, if we want to produce bitstreams in two scenarios: one where all the subscribers prefer the QCIF display and the other where all the subscribers prefer the CIF display, then the optimal bitstreams for the two scenarios should be different. In the first scenario, the optimal bit allocation can only be obtained by allocating all the bits to the subbands that support the QCIF display. Obviously, this allocation cannot be optimal for the second scenario in which the optimal bit allocation must encode more spatial subbands to support a higher spatial resolution display with the CIF format. In [3], the lagrangian cost is used to measure the importance of an resolution. But it is suitable for the coding methods that use QP (quantization parameter), and the user preference is not considered either.

The contribution of this work is twofold: 1) based on the preference, we formulate the bit allocation problem for SVC, and show that the weighting coefficients can be derived from the subscriber’s preferences for different resolutions in a motion compensation temporal filtering(MCTF)-based 2D+t wavelet video codec [4]; and 2) we propose three bit-allocation algorithms to solve the problem. The first is an efficient Lagrangian-based method that solves the upper bound of the problem optimally, and the second is a less efficient dynamic programming method that solves the problem optimally. Both methods require knowledge of the user’s preference. For the case where the user’s preference is unknown, we solve the problem by a min-max approach, which objective is to optimize the bit allocation solution for the worst possible user preference distribution.

The remainder of this paper is organized as follows. In Section II, we describe the proposed SVC performance metric; and in Section III, we formulate the rate-distortion function of a wavelet-based scalable video coder. In Section IV, we introduce methods to solve the bit-allocation problem when preferences are known; and in Section V, we present a min-max based approach for the case where the subscriber’s preference is unknown. Section VI reports the experimental results, and Section VII contains some concluding remarks.

II. SVC’S PERFORMANCE AND SUBSCRIBERS’ PREFERENCES

A general video broadcasting system consists of a video source, a scalable video coder, broadcasting servers, the network, and subscribers. The scalable coder encodes a source video so that the network’s bandwidth requirement can be met and the subscriber’s demand can be satisfied. The satisfaction of the subscriber’s demand can be quantified to measure the system’s performance. In [5], the performance
of SVC is measured as follows:

\[ Q_{all} = \sum_{i \in N} Q_i, \quad (1) \]

where \( N \) denotes the set of subscribers, and \( Q_i \) denotes the satisfaction of subscriber \( i \)'s demand by SVC, which is usually measured by the PSNR. However, we found that the PSNR is not sufficient to satisfy the demand of a subscriber because he/she may prefer higher frame rates or spatial resolutions than the PSNR. Thus, we introduce the preference factor \( \psi \in [0,1] \) for each subscriber and combine it with the PSNR to obtain the following performance measurement:

\[ Q_{all} = \sum_{i \in N} \psi_i \text{PSNR}_i. \quad (2) \]

If we let \( S, T, \) and \( R \) denote the sets of spatial, temporal, and quality resolutions respectively, then a resolution in SVC can be represented by \((s, t, r)\), where \( s \in S \), \( t \in T \), and \( r \in R \). Denote subscriber \( i \)'s preference for the resolution \((s, t, r)\) as \( \psi_i(s,t,r) \), and let the PSNR of the resolution be \( \text{PSNR}_{i(s,t,r)} \). Then, Equation (2) can be re-written as follows:

\[ Q_{all} = \sum_{s \in S, t \in T, r \in R} \text{PSNR}_{i(s,t,r)} \sum_{i \in N} \psi_i(s,t,r). \quad (3) \]

The performance measurement can be normalized based on the subscriber’s preference so that we obtain

\[ Q_{average} = \frac{Q_{all}}{\sum_{s \in S, t \in T, r \in R} \sum_{i \in N} \psi_i(s,t,r)} \]

\[ = \sum_{s \in S, t \in T, r \in R} \text{PSNR}_{i(s,t,r)} \mu_{i(s,t,r)}, \quad (4) \]

where \( \mu_{i(s,t,r)} = \frac{\sum_{i \in N} \psi_i(s,t,r)}{\sum_{i \in N} \psi_i(s,t,r)} \) can be regarded as the preference of the system to the resolution. From the definition of \( \mu_{i(s,t,r)} \), we have \( \mu_{i(s,t,r)} \geq 0 \) and

\[ \sum_{s \in S, t \in T, r \in R} \sum_{i \in N} \psi_i(s,t,r), \quad (5) \]

The \( \text{PSNR}_{i(s,t,r)} \) can be calculated as follows:

\[ \text{PSNR}_{i(s,t,r)} = 10 \log_{10} \frac{255^2}{\bar{D}_{i(s,t,r)}}, \quad (6) \]

where \( \bar{D}_{i(s,t,r)} \) denotes the average mean square error (MSE) of the frames in resolution \((s, t, r)\). If we substitute Equation (6) into Equation (4) and use Equation (5), we have

\[ Q_{average} = 10 \log_{10} 255^2 - \log_{10}(\prod_{s \in S, t \in T, r \in R} \bar{D}_{i(s,t,r)}) \]

It is obvious that maximizing the average performance \( Q_{average} \) is equivalent to minimizing the geometric mean of the distortion

\[ \prod_{s \in S, t \in T, r \in R} \bar{D}_{i(s,t,r)}. \quad (8) \]

Note that, in SVC, each temporal resolution involves a different number of frames. If a scalable coder adopts the dyadic temporal structure, which assumes that the number of frames in temporal resolution \( t \) is \( 2^t \), then the overall distortion of the resolution \((s, t, r)\) in a GOP is

\[ \bar{D}_{(s,t,r)} = 2^t \bar{D}_{(s,t,r)}. \quad (9) \]

III. FORMULATION OF THE RATE-DISTORTION FUNCTION

In this section, we formulate the rate-distortion function of a wavelet-based scalable video coder. We use non-negative integers to index the spatial and temporal resolutions. The lowest resolution is indexed by \( 0 \), and a higher resolution is indexed by a larger number. Let \( p \) and \( q \) denote the number of spatial and temporal decompositions respectively; then, the spatial resolution index \( s \) and temporal resolution index \( t \) are in the ranges \( \{0, 1, \ldots, p\} \) and \( \{0, 1, \ldots, q\} \) respectively. Note that we use \((xy, mn)\) to denote the spatial-temporal subband, which is the \( y \)-th spatial subband after the \( x \)-th spatial decomposition and the \( n \)-th temporal subband after the \( m \)-th temporal decomposition. We let \( W_{s,t} \) denote the set of subbands used to reconstruct the video of spatial resolution \( s \) and temporal resolution \( t \), and an example of two spatial and three temporal resolutions with the corresponding \( W \) is shown in Figure 1.

For each quality resolution \( r \), let \( \beta_r[(xy, mn)] \) represent the number of bits assigned to subband \((xy, mn)\) for the quality resolution \( r \), and obviously, we have

\[ \beta_{r+1}[(xy, mn)] \geq \beta_r[(xy, mn)] \quad (10) \]

for each subband \((xy, mn)\). Let \( b_r \) denote the maximum number of bits for all the subbands of quality resolution \( r \) in a GOP, and then the bit constraint for the quality resolution \( r \) can be written as

\[ b_r = \sum_{z \in W_{p,q}} \beta_r[z], \quad (11) \]

where \( z \) ranges over all subbands in \( W_{p,q} \). Recall that the average distortion of all the subbands of the frames in the resolution \((s, t, r)\) is represented by \( \bar{D}_{(s,t,r)} \). We introduce a new notation \( \Theta(s, t, \beta_r) \) for \( \bar{D}_{(s,t,r)} \) to explicitly represent the average distortion in the wavelet domain as a function of \( \beta_r \), and then we have

\[ \Theta(s, t, \beta_r) = \frac{1}{2} \sum_{z \in W_{s,t}} w_{z}^s t \bar{D}_z(\beta_r[z]), \quad (12) \]
where \( w_{z}^{x} \) is the subband weighting derived from [6] and \( D_{z}(\beta_{z}[z]) \) indicates the distortion of subband \( z \) encoded with \( \beta_{z}[z] \) bits.

Let \( v \) be the number of quality resolutions indexed from \( 0, \ldots, v - 1 \), and let \( \{\beta_{0}, \cdots, \beta_{v-1}\} \) be the bit allocation profile. We can represent Equation (8) explicitly as \( D(\beta_{0}, \cdots, \beta_{v-1}) \) to indicate the dependence of the average distortion of a GOP on the bit allocation profile. Then, we obtain

\[
D(\beta_{0}, \cdots, \beta_{v-1}) = \prod_{r=0}^{v-1} \prod_{s=0}^{q-1} \prod_{t=0}^{\beta_{r}(s)} \Theta(s, t, \beta_{r})^{\mu(s, t, r)} (13)
\]

The rate-distortion problem (P) can now be formulated as finding the bit allocation profile \( \{\beta_{0}, \cdots, \beta_{v-1}\} \) that satisfies the constraints in Equations (10) and (11) and minimizes the distortion function specified in Equation (13):  

\[
\begin{align*}
\min D(\beta_{0}, \beta_{1}, \cdots, \beta_{v-1}) \\
\text{subject to} & \sum_{z \in W} \beta_{i}(z) = b_{i}, \quad \text{for } i = 0, \cdots, v - 1, \\
& \beta_{v-1}(z) \leq \beta_{v}(z) \quad \forall i = 1, \cdots, v - 1.
\end{align*}
\]

(14)

IV. SOLVING BIT-ALLOCATION WITH KNOWN PREFERENCES

The optimal bit-allocation problem (P) can be solved by solving a sequence of bit-allocation sub-problems \( (P_{r}) \), with quality resolution \( r = 0, \cdots, v - 1 \). The sub-problem \( (P_{r}) \) is defined as follows:

\[
\begin{align*}
\min D(\beta_{0}, \beta_{1}, \cdots, \beta_{v-1}) \\
\text{subject to} & \sum_{z \in W} \beta_{i}(z) = b_{i}, \quad \forall \beta_{r} \geq 0, \cdots, r \\
& \beta_{v-1}(z) \leq \beta_{v}(z) \quad \forall i = 1, \cdots, v - 1.
\end{align*}
\]

(15)

where \( W \) is the set of all subbands, and \( \{b_{i}\} \) is a given non-decreasing sequence that corresponds to the bit constraints. The problem \( (P_{r}) \) allocates bits from the quality resolution 1 to \( r \); hence, all the subscriptions for a quality resolution \( r > 1 \) will use the bit allocation result of the quality resolution \( r \). Thus, we have \( \beta_{r} = \beta_{r+1} = \cdots = \beta_{v-1} = \beta_{v} \) for \( r = 0, \cdots, v - 1 \) in Equation (15). The optimal bit-allocation problem (P) can be solved by solving \( (P_{0}) \), followed by \( (P_{1}) \) based on the solution of \( (P_{0}) \), and so on up to solving \( (P_{v-1}) \). In the following subsections, we propose two methods to solve \( (P_{r}) \). The first finds the upper bound of \( (P_{r}) \) by a Lagrangian-based approach, and the second finds the exact solution by using the less efficient dynamic programming approach.

A. Lagrangian-based Solution

The bit-allocation problem is usually analyzed by the Lagrangian multiplier method. By assuming that \( \prod_{i=a}^{b} f_{i} = 1 \) for any function \( f_{i} \) with \( b > a \), the objective of \( (P_{r}) \) can be re-written as

\[
D(\beta_{0}, \cdots, \beta_{v-1}, \beta_{r}, \cdots, \beta_{v}) = \prod_{s=0}^{p-1} \prod_{t=0}^{q-1} \prod_{k=0}^{\beta_{r}(s)} \Theta(s, t, \beta_{r})^{\mu(s, t, r)} \Theta(s, t, \beta_{v})^{\mu(s, t, v)}.
\]

(16)

Because \( \sum_{s \in S, t \in T, r \in R} \mu(s, t, r) = 1 \) (See Equation (5), by applying the generalized geometric mean - arithmetic mean inequality to Equation (16), we can obtain its upper bound as follows:

\[
D(\beta_{0}, \cdots, \beta_{v-1}, \beta_{r}, \cdots, \beta_{v}) \leq C + \sum_{s=0}^{p-1} \sum_{t=0}^{q-1} \sum_{k=0}^{\beta_{r}(s)} \Theta(s, t, \beta_{r})
\]

(17)

where the constant \( C = \sum_{s=0}^{p-1} \sum_{t=0}^{q-1} \sum_{k=0}^{\beta_{v}(s)} \Theta(s, t, \beta_{v}) \). Note that the constant \( C \) is computed from the bit allocation results from resolution 0 to resolution \( r - 1 \).

Now we can find the solution for the problem \( (P_{r}^{+}) \), which is the upper bound of the problem \( (P_{r}) \). The problem \( (P_{r}^{+}) \) is defined as

\[
\begin{align*}
\min_{\beta_{r}} \Omega_{r}(\beta_{r}) = & \sum_{s=0}^{p-1} \sum_{t=0}^{q-1} \sum_{k=0}^{\beta_{r}(s)} \Theta(s, t, \beta_{r}) \Theta(s, t, \beta_{v})^{\mu(s, t, v)} \\
\text{subject to} & \sum_{z \in W} \beta_{r}(z) = b_{r},
\end{align*}
\]

(18)

After substituting Equation (12) into Equation (18) for \( \Theta(s, t, \beta_{r}) \) and re-arranging the terms, we have

\[
\Omega_{r}(\beta_{r}) = \sum_{z \in W} \rho_{z}^{r} D_{z}(\beta_{z}[z]),
\]

(19)

where \( z \) is a subband, \( W \) is the set of all subbands, and \( \rho \) is the final weighting factor. Note that \( \rho \) is computed from the preference weighting \( \mu \) and the spatial-temporal weighting \( w_{z}^{x} \).

Now, replacing \( \Omega_{r}(\beta_{r}) \) in Equation (18) with Equation (19), the problem \( (P_{r}^{+}) \) can be solved optimally by using the Lagrangian approach with the Lagrangian function:

\[
L(\lambda, \beta_{r}) = \sum_{z \in W} \rho_{z}^{r} D_{z}(\beta_{z}[z]) - \lambda(b_{r} - \sum_{z \in W} \beta_{z}[z]).
\]

(20)

A necessary condition for optimal bit allocation can be satisfied by taking the partial derivative with respect to \( \lambda \) and \( \beta_{r} \) and setting the results to zero. Thus, the optimal bit allocation vector \( \beta_{r}^{*} \) for the quality resolution \( r \) must satisfy

\[
\frac{\partial L(\lambda, \beta_{r})}{\partial \beta_{z}[z]} = \rho_{z}^{r} \frac{\partial D_{z}(\beta_{z}[z])}{\partial \beta_{z}[z]} + \lambda = 0,
\]

(21)

and

\[
\frac{\partial L(\lambda, \beta_{r})}{\partial \beta_{z}[z]} = b_{r} - \sum_{z \in W} \beta_{z}[z] = 0.
\]

(22)

The two necessary conditions require that 1) the optimal bit allocation \( \beta_{r}^{*} \) must exist when the rate-distortion functions of all the subbands have the same weighted slope; and 2)
at that particular slope, the total number of bits of all the subbands is \( b_r \).

It is straightforward to show that if \( \tilde{D}_z(\beta_r[z]) \) is convex for any \( z \), then \( \sum_{z \in W} r'_z \tilde{D}_z(\beta_r[z]) \) with \( r'_z \geq 0 \) is a convex function; therefore, the necessary condition is also the sufficient condition for \( \beta^*_r \). We can use a similar approach to that in \( [7] \) to derive an efficient algorithm to find the optimal bit allocation vector. Thus, we modify the distortion function \( D_z(\beta_r[z]) \) to make it a convex function. We initialize \( \beta_r[z] = 0 \) for all subbands, and divide \( b_r \) into \( \lfloor b_r/\delta \rfloor \) segments with \( \delta \) bits for each segment. In each stage of our algorithm, we calculate \( \tilde{D}_z(\beta[z] + \delta) \) and select the subband \( z' \) that has the largest weighted absolute slope:

\[
\arg \max_{z \in W} r'_z \frac{\tilde{D}_z(\beta[z] + \delta) - \tilde{D}_z(\beta[z])}{\delta}.
\]

Then, we only modify the bit allocation vector of the component that corresponds to the subband \( z' \) by letting

\[
\beta_r[z] \leftarrow \begin{cases} 
\beta_r[z'] + \delta, & \text{if } \sum_{z \in W} \beta_r[z] \leq b_r - \delta, \\
\beta_r[z'] + (b_r - \sum_{z \in W} \beta_r[z]), & \text{otherwise}.
\end{cases}
\]

We repeat the above process several times until the constraint is achieved.

**B. Optimal Solution Based on Dynamic Programming**

Although the proposed Lagrangian-based method is efficient and theoretically sound, it optimizes the upper bound of the true objective function. In this section, we propose another optimal bit allocation method based on dynamic programming (DP). Although the proposed method uses more memory and requires more computation time than the Lagrangian-based method, it can find the optimal bit allocation for the true objective function.

To solve the bit-allocation problem with the DP-based method, we represent the problem as an acyclic directed graph \( G = (N, A) \), called a DP graph for short, where \( N \) is the set of nodes and the members of \( A \) are arcs. The arc from node \( i_k \) to node \( i_l \) is represented by \( i_k \rightarrow i_l \) where \( i_k \) and \( i_l \) are the source node and the sink node of the arc respectively. A path can be represented as a concatenation of arcs.

Let \( \text{seq} \) be a bijection mapping from the subbands to the integer set from 0 to \( |W| - 1 \), where \( |W| \) is the number of subbands; and let \( \text{seq}^{-1} \) be its inverse mapping from an integer to a subband. To construct the DP graph for the problem \( (P) \), we arrange the subbands \( z \) as a sequence \( \text{seq}(z) \in \{0, \cdots, |W| - 1\} \), and divide \( b_{v-1} \) into \( M = \lfloor \frac{b_{v-1}}{\varepsilon} \rfloor \) components. Let \( \mu = [\mu(s,t,r)] \) denote the subscriber’s preference vector. In addition, let \( \beta = [\beta_0, \cdots, \beta_{v-1}] \) and \( b = [b_0, \cdots, b_{v-1}] \) be, respectively, the subband bit allocation vector and the bit budget vector for all quality resolutions. The min-max approach for the problem \( (P) \) can be written as

\[
\min_{\beta} \max_{\mu} D(\beta_0, \beta_1, \cdots, \beta_{v-1})
\]

subject to
\[
\sum_{z \in W} \beta_i[z] = b_i, \quad \text{for } i = 0, \cdots, v-1,
\]

and
\[
\beta_{i-1}[z] \leq \beta_i[z], \quad b_{i-1} \leq b_i \quad \text{for } i = 1, \cdots, v-1.
\]
In other words, the min-max approach finds the best bit allocation vectors for the preference distribution that yields the largest distortion.

First, we show that the least favorable preference distribution $\mu^*$ is independent of the quality resolution $r$. For any subband bit allocation $\beta$, at the quality resolution $r$, the least favorable preference distribution maximizes the distortion $D(\beta_0, \beta_1, \cdots, \beta_{r-1}, \beta_r, \cdots, \beta_r)$. From Equation (16), we have

$$D(\beta_0, \cdots, \beta_{r-1}, \beta_r, \cdots, \beta_r) \leq \max_{s=0,\cdots,p-1} \max_{t=0,\cdots,q-1} \max_{k=0,\cdots,r} \Theta(s, t, \beta_k),$$

(27)

$$= \Theta(p-1, q-1, \beta_0),$$

(28)

where Equation (27) is derived from $0 \leq \mu(s,t,r) \leq 1$, and $\sum_{(s,t,r)} \mu(s,t,r) = 1$; and Equation (28) is obtained because the maximum distortion can be obtained when the bits $\beta_0$ for the coarsest quality resolution are assigned to the subbands in the highest spatial and temporal resolutions. Thus, the least favorable preference $\mu^*$ occurs when all users have preference 1 for the resolution $(p-1, q-1, 0)$.

After deriving the least favorable preference $\mu^*$, the problem can be solved easily by using the methods proposed previously. It is noteworthy that the above min-max problem finds the optimal bit allocation for the codec containing only one spatial, temporal, and quality resolution. This result corresponds to allocating the bits optimally for a non-scalable wavelet codec.

VI. EXPERIMENT RESULTS

We now evaluate the coding performance of the proposed bit allocation methods on a 2D+T wavelet encoder. In the experiment, a GOP has 32 frames. First, each frame is decomposed by applying a three-level 2-D wavelet transform with the 9-7 wavelets; then, the five-level MCTF method is applied to each spatial subband. The method uses the 5-3 wavelets for temporal decomposition of each spatial subband. When MCTF is applied, we assume that the motion vectors are given. The motion estimation step uses a full search with integer-pixel accuracy. The block size is $16 \times 16$, and the search range is $[16, -15]$ both vertically and horizontally. Finally, the 2-D EZBC method is used to encode the wavelet coefficients of the 2D+T wavelet codec.

The experiment is conducted on the video sequence Coastguard and assumes that the users subscribe to the different spatial and temporal resolutions. Figure 3 shows the R-D curves of each sequence versus different spatial and temporal preference profiles. It is obvious that the scalable bit allocation methods with known preferences (i.e., Lagrangian and DP) achieve a better coding performance than the method that lacks the preference information (i.e., min-max approach). The DP method outperforms the Lagrangian method in all cases. Note that the DP method finds the optimal bit allocation for the problem $(P)$, while the Lagrangian method finds the optimal solution for the upper bound of the problem.

VII. CONCLUSION

In this paper, we consider subscribers’ preferred resolutions when assessing the performance of a wavelet-based scalable video codec. We formulate the problem as a scalable bit allocation problem and propose different methods to solve it. Specifically, we show that the Lagrangian-based method can find the optimal solution of the upper bound of the problem, and that the dynamic programming method can find the optimal solution of the problem. We also consider applications where the subscribers’ preferences are not known, and use a min-max approach to find a solution. Our experimental results show that knowing the users’ preferences can improve the PSNR of the 2D+T wavelet scalable video codec. The average PSNR gain depends on the users’ preference distribution. It can range from 1 db to 8 db at a fixed bit rate. There is a significant performance gap between when the preferences are known over when they are unknown. Hence, in our future work, we will reduce the gap or derive a method that enables us to estimate the preference patterns in the encoder.

REFERENCES


Figure 1. An example of indexing the subbands according to the spatial (in (a)) and temporal resolution (in (b)) after two spatial and three temporal decompositions. In the example, \( W_{0,0} \) is \{20, 30\}; \( W_{1,0} \) is \{(20, 30), (21, 30), (22, 30), (23, 30)\}; \( W_{0,1} \) is \{20, 30, 21, 30\}; \( W_{1,1} \) is \{(20, 30), (21, 30), (22, 30), (23, 30), (20, 31), (21, 31), (22, 31), (22, 32)\} and so on.

Figure 2. The construction of the DP graph. The x-axis indicates the subbands and the y-axis indicates the rate. Note that all the nodes indexed by \((x, k-1)\), \((x, k)\), and \((x, k+1)\) belong to quality resolution \( r_{k+1} \).

Figure 3. Comparison of the performance under different spatial and temporal preferences with respect to the Coastguard sequence. Left: Four preference patterns are used to subscribe to three spatial resolutions, which are QuadQCIF, QCIF, and CIF. Right: Four preference patterns are used to subscribe to three temporal resolutions, which are 7.5 fps, 15 fps, and 30 fps.