國立交通大學

資訊科學與工程研究所

碩 士 論 文

基於時空域畫面複雜度的品質限制跳畫面演算法

A Quality Constrained Frame Skipping Algorithm based on Spatiotemporal Frame Complexity

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摘　　　要

近年來最佳化視訊編碼的限制問題已日漸成為研究的目標。本論文著重在以位元率和品質限制為條件的時空域品質衡量問題。基於編碼畫面的時間域相依性，我們提出一個可調式跳畫面機制來達到好的時空域品質衡量。在給定的區間內藉由所提出的 R-Q/D-Q 模型去預測所有的位元率與畫面失真的組合並且挑選那些畫面使得它在時間域上內插能達到較佳視覺效果。實驗結果顯示，我們的方法雖然簡單但非常有效地能夠解決所針對的問題，並且對於快速移動的視訊品質亦能給於適度的改善。總結而言，我們的方法能夠藉由所提出的畫面選擇方式來有效地達到已編碼畫面的品質要求。

A Quality Constrained Frame Skipping Algorithm
based on Spatiotemporal Frame Complexity

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ABSTRACT

This constrained problem of optimized video encoding has increasingly been the object of study in recent years. This thesis focuses on the problem of trading temporal quality for spatial quality subject to the rate- and quality- constraints. An adaptive frame skipping scheme is proposed to achieve a good tradeoff between spatial and temporal quality based on temporal dependency between the coded frames. The frame selection scheme chooses the frames that lead to the better visual quality in interpolation by estimating all possible combinations of the rate and distortion of the coded frames within the window using the proposed R-Q/D-Q models, respectively. Experimental results show that our scheme is simple but very effective, and have moderate improvements for high motion sequences in the various subjective-based objective measurements. To conclude, our scheme can effectively achieve the quality requirement of the coded frames in spatial domain by the proposed frame selection approach.

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CHAPTER 1

Introduction

1.1 Research Overview

Multimedia services such as surveillance, video-conferencing and media utilization are getting popular in recent years. Some of these applications require that the bit-rate and/or the decoded quality of video bitstreams satisfy certain constraints. For instance, the bit-rate may not exceed a target value due to the limitation on channel bandwidth, or there is a quality requirement for the coded frames. Within the extensive literature, however, comparatively little research has focused on the scenario where both the bit-rate and the distortion of the coded frames must be below a pre-determined level. In such a scenario, it is necessary to trade the temporal quality for the spatial quality, or vice versa, during the encoding. For doing so, a common technique is adaptive frame skipping.

1.2 Problem Statement

This thesis aims to develop a quality- and rate-constrained adaptive frame skipping scheme. Our objective is to determine which frames in a specified time window should be encoded and what the values of their quantization parameters (QP) are such that the following conditions are satisfied:

1. The bit-rate of the coded frames shall be less than a target value,
2. The distortion of each coded frame shall be below a given level,
3. When the skipped frames are interpolated, the overall distortion, including both the coded frames and the skipped ones, shall be minimized.

Stated in another way, our goal amounts to searching for the solution to the following constrained optimization problem:

$$[\mathbf{q}^*, \mathbf{s}^*] = \arg\min_{\mathbf{q},\mathbf{s}} \sum_{i=1}^{N} D_i(\mathbf{q}, \mathbf{s}) \tag{1.1}$$

$$s.t. \sum_{i=1}^{N} R_i(\mathbf{q}, \mathbf{s}) \leq R_t \text{ and } D_i(\mathbf{q}, \mathbf{s}) \leq D_{\max},$$

where D_i denotes the distortion of the i-th frame, R_i corresponds to the associated number of coded bits; the vector $\mathbf{s} = [s_1, s_2, ..., s_N]$ specifies the frame-skip pattern with $s_i = 1$ indicating the skip of the i-th frame; $\mathbf{q} = [q_1, q_2, ..., q_N]$ describes the quantization parameters; and R_t and $D_{\max}$ define the target bit-rate and the quality requirement, respectively.

As can be seen from Eq. (1.1), the distortion constraints in our problem are non-static: on one hand, the distortion of each coded frame has to be lower than $D_{\max}$, and on the other hand, which frames deserve coding is not known in advance. For such a complex problem, there generally does not exist a closed-form solution. To solve the problem, dynamic programming can be used. Its computational complexity, however, increases exponentially with the number of frames contained in the window, making it unfeasible and unpractical for real applications. As a result, we proposed in this thesis a heuristic algorithm.

1.3 Contributions

In brief, our algorithm proceeds as follows:

1. Within a time window, we first compute all possible frame-skip patterns.
2. For each admissible skip pattern,
   (a) We use a D-Q model to estimate the QP of the non-skipped frames.

   (b) We then use an R-Q model to estimate their coding bits.

3. For the skipped frames, we compute their distortions by conducting frame interpolation.
4. Finally, we choose, among all possible frame-skip patterns, the one that has more non-skipped frames while satisfying both the rate and the quality constraints.

Specifically, our main contributions in this work include the following:

- We proposed an empirical D-Q model based on the analysis of spatial-temporal frame complexity.
- We designed an adaptive frame skipping algorithm that uses the D-Q model, together with an R-D model, to determine the frame-skip pattern and the QP for the non-skipped frames.
- We also provided a detail analysis on how video content, distortion measures, and interpolation schemes may affect the frame selection and the reconstruction quality.

Experimental results indicate that our scheme has a significant improvement in R-D performance, as compared with the regular frame skipping and the other previous work. The improvement is most obvious in fast-motion sequences, and similar results are observed with the other objective measures, such as SSIM and VQM.

1.4 Organization

The remainder of this thesis is organized as follows: Chapter 2 contains a brief review of the related works and compares the problem settings of different schemes. Chapter 3 presents our adaptive frame skipping scheme and the proposed D-Q model. Chapter 4 provides simulation results and compares the performance of our scheme with that of the regular frame skipping and of the previous work. Finally, Chapter 5 summarizes our work and gives a list of future works.

CHAPTER 2

Background

2.1 Rate Control in H.264/AVC

Rate control plays an important role in the application of H.264. Rate control is employed to achieve good perceptual quality by regulating the variable bit rate output of video encoder to meet the target bit-rates and the user's desired constraints. In general, rate control can be separated into two levels: the frame and the macroblock (MB) levels. One is frame level bit allocation which we examine in this thesis to handle the spatial and temporal quality of video effectively. The other is bit allocation in the macroblock level by effectively distributing bit budgets among MBs. Like H.263 and MPEG-4, H.264 allows variable frame skipping to keep the rate constraint. The goal of frame skipping control is to satisfy the target bit allocation. Further, in order to achieve optimal rate control scheme, the rate-distortion (R-D) model is usually used for modeling the encoded bits or the distortion. Consequently, the quadratic rate-quantization model of H.264 is briefly discussed in the section 2.2. Besides, a number of studies have investigated the rate control scheme in the different experiment conditions. So rate control via variable frame rate by R-D model or other approaches are also discussed in the section 2.3.

2.2 Quadratic Rate-Distortion Model.

Rate control allocates a target number of bits to each frame and then computes QPs to meet the target bits. According to [1], a quadratic rate-distortion model was proposed as follows:

$$R_{texture} = \left(c_1 \frac{1}{QP} + c_2 \frac{1}{QP^2} \right) \times A, \tag{2.1}$$

where A is the mean of absolute difference of the residual component, QP denotes the quantization parameter and c_i denotes the model parameters that are fitted to the data. Due to the fact that the actual MAD is not available before the QP calculation, the MAD of the coding unit can be predicted by the linear model as follows:

$$\widehat{A}_l[i] = a \times A[i-1] + b, \tag{2.2}$$

where $\widehat{A}_l[i]$ presents the predicted MAD of frame i, $A[i-1]$ is the actual MAD at the co-located position in the previous frame, a and b are two parameters that will be updated after coding each frame. In brief, Eq. (2.1) was used to compute the corresponding QP after the target number of bits for the frame is computed.

2.3 Related Works

Fixed frame skipping (FFS), adopted in H.264/AVC of the JM reference software, is one of frame skipping scheme to encode video for meeting the rate constraints. Because it cannot flexibly select the frame to be coded and logically decide which frame should be dropped, some approaches such as adaptive frame skipping based on spatio-temporal complexity analysis have been proposed for solving the disadvantage of fixed frame skipping scheme. The related works about frame skipping scheme reported in the literature can be classified into two major categories. One is to adopt adaptive frame skipping based on spatio-temporal complexity analyses to achieve a good balance between spatial quality and temporal quality for rate-distortion optimized video coding. The other is to consider the reconstruction of the skipped frame using motion-compensated frame interpolation at decoder and then to choose the dropped frame by modeling the reconstructed quality of the dropped frame using motion-compensated frame interpolation at encoder to meet the user's requirements. In the following sections 2.3.1 and 2.3.2, we reviewed some approaches that have been proposed for finding rate-distortion optimized video coding with frame skipping scheme.

2.3.1 Rate-Distortion Optimized Frame Skipping

Vetro *et al.*[2] proposed a video coding algorithm considering the trade-off between spatial and temporal quality. The purpose of the algorithm is to find the optimal frame rate and quantization parameter selection to minimize the mean square error with rate-distortion model and frame skipping control subject to constraints on the target bit-rate and buffer occupancy. This algorithm is based on analytical model that estimated the distortion of encoded frames and the distortion of skipped frames reconstructed from previous coded frame by using frame replication. But, the prediction accuracy of the distortion model is not sufficient, especially for the video sequence with mixed motion activity.

Song *et al.*[4] formulated the problem as a rate-distortion (R-D) optimization process and solved the problem by the gradient search in low bit-rate condition. The main idea is to predefine Lagrange multiplier and then to calculate the histogram of difference (HOD) of last two in the previous sub-GOP (12 frames as a unit) to estimate which frames to be encoded for the current sub-GOP. However, the approach presents a limited performance when the high motion and low motion are mixed among each sub-GOP because the frame rate of the current GOP is predicted from the previous GOP information and the variable frame rate can only be changed from one basic unit to another.

2.3.2 Interpolation-Quality-Oriented Frame Skipping

Kuo [5] provided a video coding algorithm based on estimating quality of skipped frames for deciding which frames to be coded in low bit-rate channel. He proposed a variable frame skipping scheme that introduced motion-compensated frame interpolation in the encoding process. The experiment results revealed the suitable frame skipping had generated the better PSNR quality than that of the conventional coding with no frame skipping. Similar concept was also presented in Yang *et al.*[6], adaptive frame skipping, which is adopted in the video encoding process. Their algorithm was proposed based on a bidirectional motion estimation and adaptive overlapped block motion-compensated interpolation. Both of the two above-mentioned methods are used to model the reconstructed objective quality of the skipped frame using motion-compensated frame interpolation. However, the difference between them is the skipped frame selection strategy.

In summary, the previous studies were designed to determine the variable encoding frame rate through adaptive frame skipping scheme. The basic idea of adaptive frame skipping mechanism is to reduce bit usage in temporal domain and then the saved bits can be allocated to improve the spatial quality of video. Their scheme used the rate-distortion model and frame interpolation at encoder to estimate the objective quality of the dropped frame in the bit-rate constraint, respectively. However, no requirements for the objective quality of the coded frame have been considered. In the following, an adaptive frame skipping scheme subject to rate- and quality- constraint was proposed.

CHAPTER 3

Quality- and Rate-Constrained Frame Skipping

3.1 Algorithm Overview

In Section 1.2, we discussed the problem of adaptive frame-skip coding with quality- and rate- constraints. In this chapter, we propose a frame selection scheme that adaptively skips frames based on a pair of R-Q and D-Q models, and provides a way to determine the quantization parameter for each coded frame. The notion of our algorithm can be expressed in Figure 3.1. In order to trade off processing delay and R-D performance, we first define a window size to specify the continuous number of frames that will influence the level of frame skipping (e.g., the window size in Figure 3.1 is equal to 4). Among the frames contained in the window, we search for a frame-skip pattern that yields the best reconstruction quality subject to a rate constraint, which is computed as $R_w = (R_b \times N_w)/F$ with R_b, N_w, and F being the channel bandwidth, the number of frames in the window, and the initial frame rate, respectively. An example of such a pattern is given in Figure 3.1, where the frame F(t+3) is skipped such that (i)

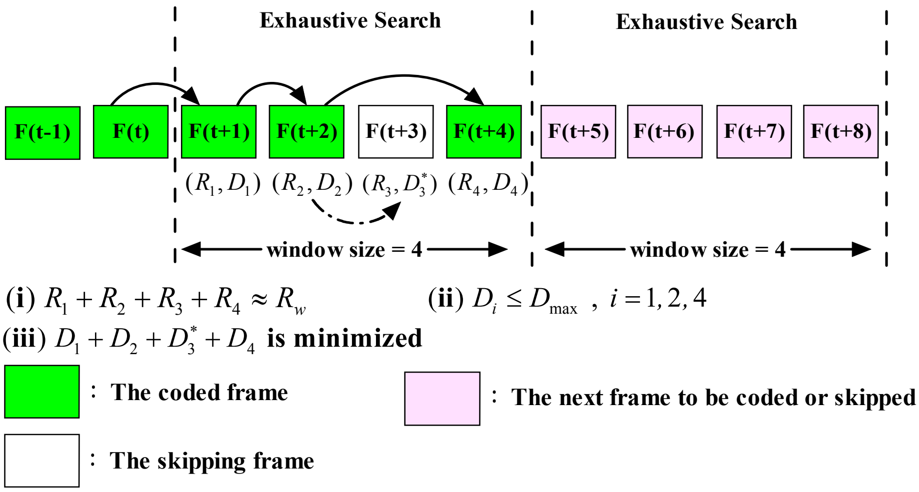


Figure 3.1: The notion of the proposed algorithm. Note to graphics illustrator: (1) The solid arrows indicate the path for estimating the bits and distortion of the coding frames by R-Q/D-Q models. (2) The dashed arrow indicates the reference frame used for frame replication.

$R_1 + R_2 + R_4 \simeq R_w$, (ii) $D_1, D_2, D_4 \leq D_{\max}$, and (iii) $D_1 + D_2 + D_3^* + D_4$ is minimized. Remarkably, the D_3^* represents the distortion (in mean squared error) of the skipped frame F(t+3) when it is interpolated by replicating F(t+2). As will be seen in Section 4.1, the way in which the skipped frames are interpolated has an important effect on frame skipping.

In search of an optimal frame-skip pattern, it is necessary to acquire the rate R_i and the distortion D_i of each coded frame. Collecting the R-D data associated with different frame-skip patterns actually requires coding the non-skipped frames. The complexity, however, may be so high that the approach becomes impractical. In order to reduce the computation, we employed a pair of R-Q and D-Q models that relate the estimated the rate and the distortion of each non-skipped frame to its quantization parameter. Unlike the conventional R-D models, ours allows the R-D estimation to be dynamically adapted to the change of the prediction distance. The design details are discussed in Section 3.2 and 3.3.

Figure 3.2 shows the flowchart of our algorithm, and the steps are as follows:

Step 1 Initialize the R-Q and D-Q models.

Step 2 Compute all possible frame-skip patterns within the window. For example, if the window size is 4, there are 2^4 frame-skip patterns.

For each non-skipped frame, we

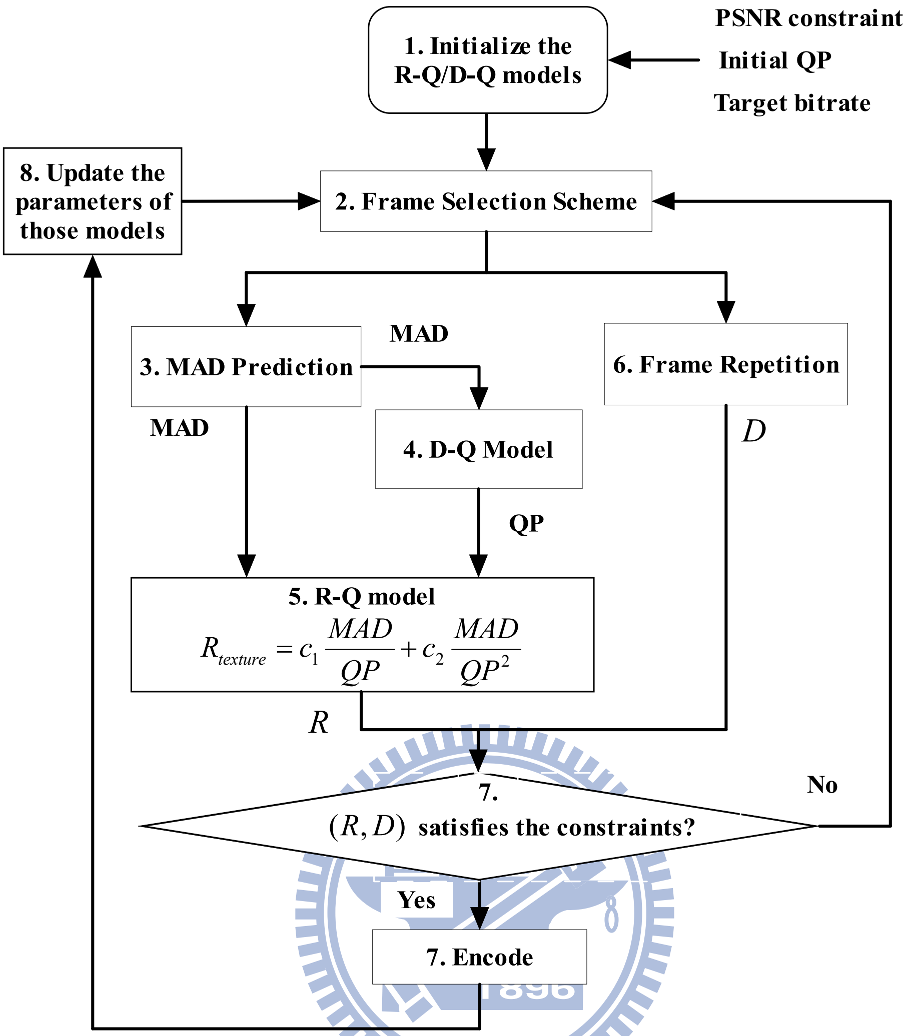


Figure 3.2: The proposed algorithm flowchart.

Step 3 Estimate the MAD of its prediction residues,

Step 4 Compute its QP with the D-Q model subject to the quality constraint,

Step 5 Estimate the bit rate associated with the chosen QP using the R-Q model,

Step 6 Measure the distortion of the skipped frame by assuming the use of frame replication.

Among all plausible frame-skip patterns, we

Step 7 Choose the one that has more non-skipped frames while satisfying both the rate and quality constraints.

Step 8 Lastly, the R-D models are updated and (restarting from step 3) the process is repeated until the entire sequence is coded.

3.2 Distortion-Quantizer (D-Q) Model

In our scheme, the QP for each non-skipped frame subject to the quality constraint must be determined. Therefore, a parametric model is needed to describe the relationship between the distortion and the QP of the non-skipped frames. Given the quality constraint (PSNR used as a measurement metric), the model can estimate the QP of the current frame based on the previous information (the distortion and the QP of the previous coded frame, etc.). Thus, we will adopt the D-Q model, proposed by Zhuo *et al.* [3], using a mathematical model to describe the relationships between the quantization parameter and the quality (PSNR used as a measurement metric) as follows.

$$PSNR = c_1 QP^2 + c_2 QP + c_3,$$

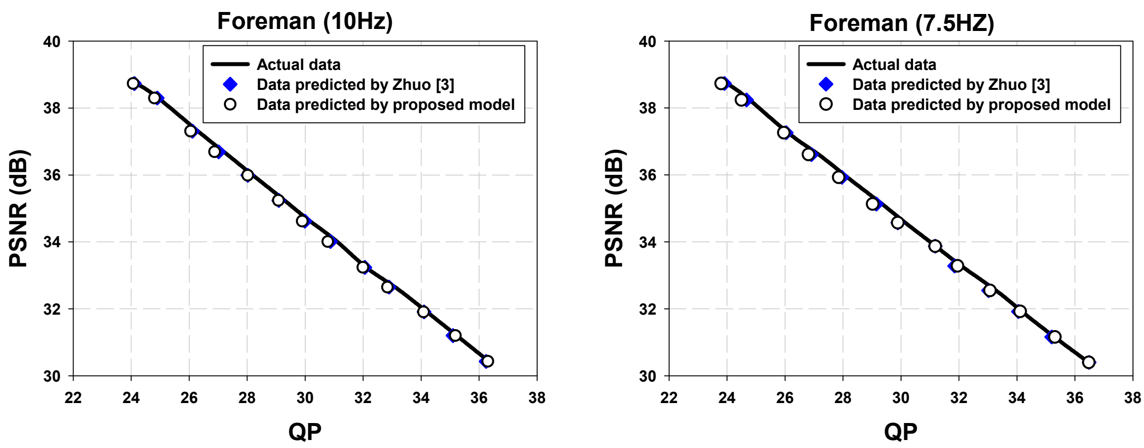
where QP denotes quantization parameter, $PSNR$ denotes the reconstructed video quality, and c_i,$i = 1, 2, 3$ are model parameters.

However, the account of the effect of temporal complexity in the model, such as the sum or mean absolute differences of the residual component or the mean square error of the residual component on estimating the QP of the frame to be coded, is neglected. The prediction accuracy of the model can be critically influenced by the distance between the current frame and its reference. Accordingly, the impact of temporal complexity should be considered.

Based on our observations from a lot of experiment results which are generated by using H.264 JM 12.3 [7], we find that the model is sensitive to $|\log \frac{1}{MAD}|$. In addition, when the quantization step size and $|\log \frac{1}{MAD}|$ are used for the input parameters of the model, the prediction accuracy of the model can be improved. So the quantization step size is used in place of the quantization parameter in the model. Therefore, the modified model can be formulated as follows:

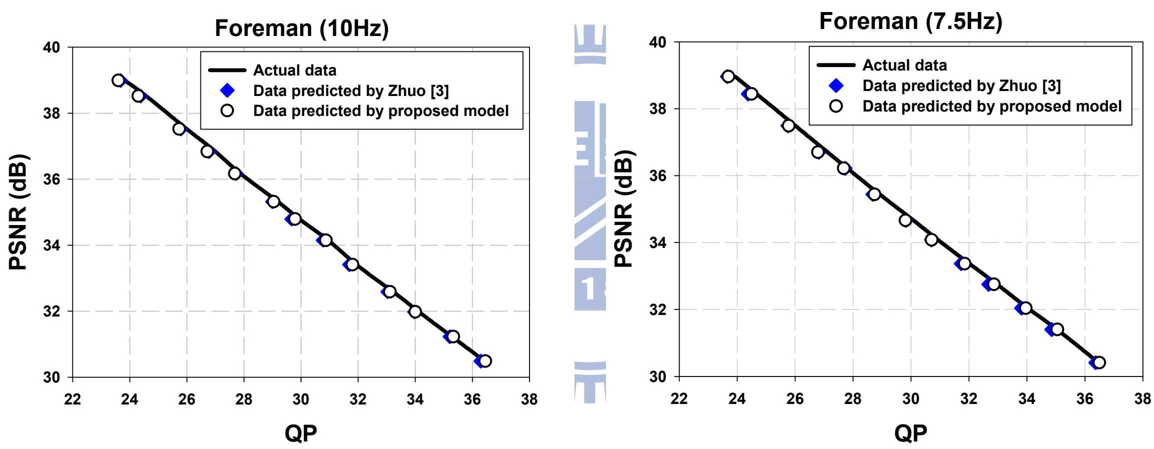
$$PSNR = c_1 \left(\left| \log \frac{1}{MAD} \right| \times Qstep \right)^2 + c_2 \left(\left| \log \frac{1}{MAD} \right| \times Qstep \right) + c_3,$$

where $Qstep$ represents the quantization step size, MAD represents mean absolute difference and c_i,$i = 1, 2, 3$ denote the model parameters that are fitted to the data. The PSNR-QP curves of Foreman sequence of the actual data, the model data by [3] and



(a) (b)

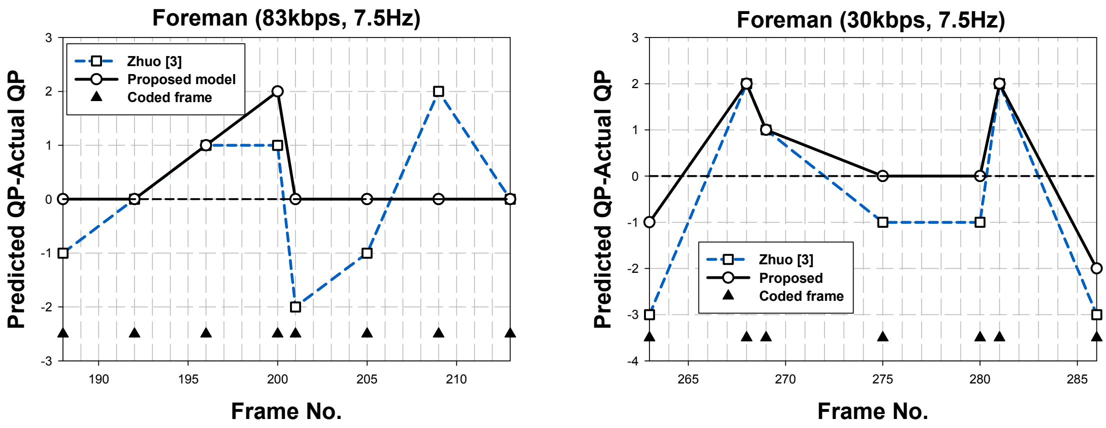
Figure 3.3: PSNR-QP curves of Foreman sequence with regular frame skipping for frame rate = 10, 7.5.



(a) (b)

Figure 3.4: PSNR-QP curves of Foreman sequence with irregular frame skipping for frame rate = 10, 7.5.

the proposed model data with regular and irregular frame skipping are shown in Figure 3.3 and Figure 3.4, respectively. Compare Figure 3.3 with Figure 3.4, the prediction accuracy of the two models are almost the same in sequential level. Therefore, the data in frame level are provided. As shown in Figure 3.5, the QP prediction error can be decreased substantially because the prediction distance between the current frame and its reference frame is taken into consideration in our model.



(a) (b)

Figure 3.5: The QP prediction error traces of Foreman sequence for frame rate = 7.5 in bit-rate (a) 83kbps, (b) 30kbps.

3.3 Rate-Quantizer (R-Q) Model

In order to estimate the number of bits required for coding each non-skipped frame, we adopt the quadratic R-D model in Eq. (2.1), where the MAD is predicted linearly by Eq. (2.2). Let $\widehat{A_L}[i]$ denote the predicted MAD of frame i by the linear model. It has been known that the linear MAD model performs poorly in video frames undergoing rapid temporal changes. For this reason, Liu et al. [8] proposed an adaptive MAD model that allows the MAD prediction to switch between the conventional linear model and their proposed direct model. Unlike the linear model, the direct model, as shown in Eq. (3.1), estimates the MAD of the frames to be coded.

$$\widehat{A_D}[i] = A[i-1] \times \left(1 + \frac{A[i-1]}{A_0[i-1]} \times \frac{A_0[i] - A_0[i-1]}{A_0[i-1]}\right), \tag{3.1}$$

where $A_0[i]$ is the MAD of the current frame i with zero motion, $\widehat{A_D}[i]$ is the predicted MAD of frame i by the direct model and $A[i-1]$ is the actual MAD of the $(i-1)$-th frame resulting from motion-compensated prediction. They found that the actual MAD of the current frame can be estimated by the actual MAD of the previous reference frame and the prediction error was reduced by a weighting factor that includes the previous known data since the fluctuation of $A_0[i]$ always reflects the fluctuation of $A[i]$.

In our scheme, we should predict the bits and the distortion of the frames within

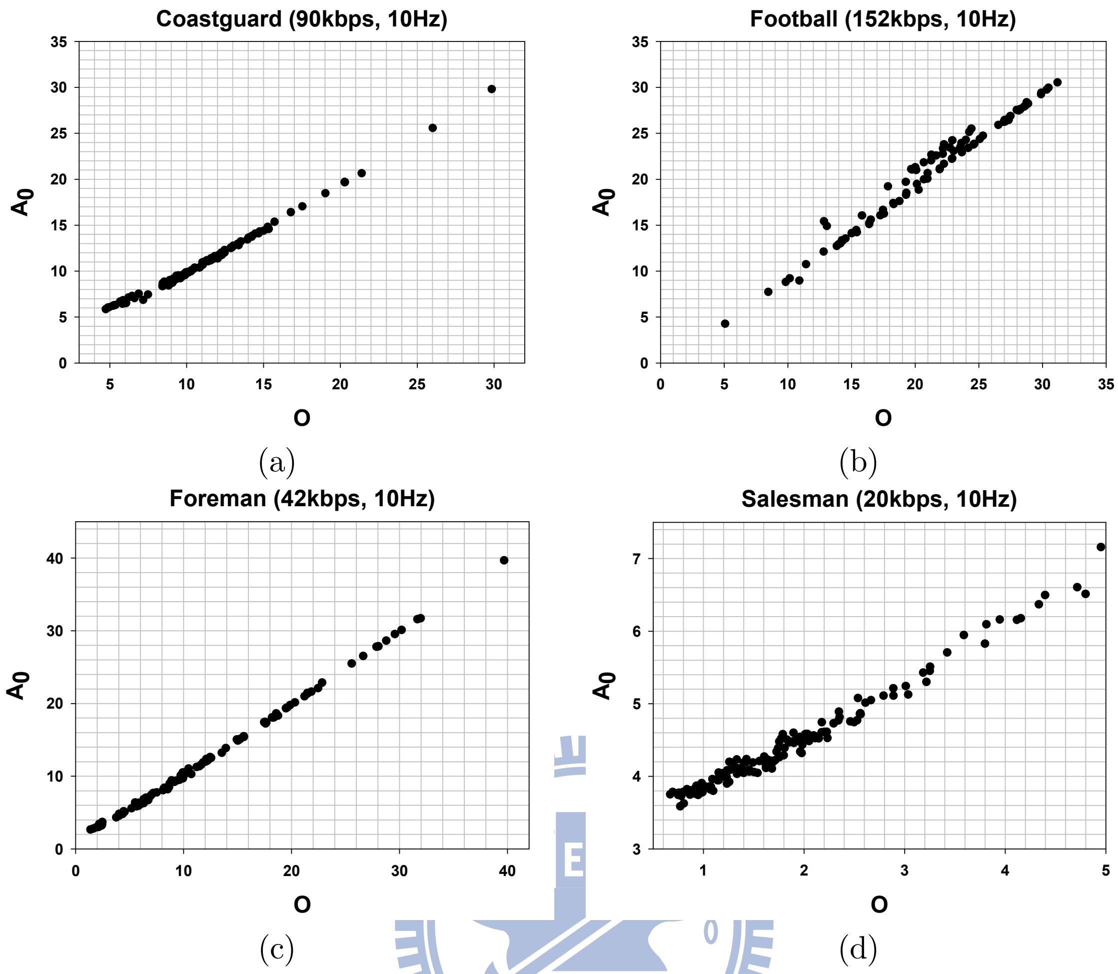


Figure 3.6: The relationships between O and A_0 of (a) Coastguard, (b) Football, (c) Foreman, (d) Salesman sequences.

the window, however, only the first frame within the window has the reconstructed reference frame and the actual MAD of the previous reference frame. In other words, the next frames within the window have no the above-mentioned the reconstructed reference frame and the actual MAD except the current frame. Let $\widehat{A_0}[i]$ and $O[i]$ denote the MAD of frame i when the previously-reconstructed frame and the previous source frame are used as the predictor, respectively. We expect $O[i]$ between the current frame i-th and the previous original frame $(i-1)$-th to be used to estimate $\widehat{A_0}[i]$ because their difference is only the quantization error. The linear relation between $\widehat{A_0}[i]$ and $O[i]$ is justified by extensive experiments, with some of the results shown in Figure 3.6. Therefore, the $\widehat{A_0}[i]$ of the i-th frame is modeled by a linear predictor as follows:

$$\widehat{A_0}[i] = a \times O[i] + b,$$

where a and b denote the model parameters. Except the first frame in the window, the actual MAD of the remaining frames is unknown. For those frames, we modify the direct model by using $\widehat{A_0}[i]$ in place of $A_0[i]$ and using the predicted MAD instead of the actual MAD. The Eq. (3.1) can be modified in the following:

$$\widehat{A_D}[i] = \widehat{A_P}[i-1] \times \left(1 + \frac{\widehat{A_P}[i-1]}{\widehat{A_0}[i]} \times \frac{\widehat{A_0}[i] - \widehat{A_0}[i-1]}{\widehat{A_0}[i-1]}\right), \tag{3.2}$$

where

$$\widehat{A_P}[i-1] = \begin{cases} \widehat{A_L}[i-1] & \Gamma_L[i-1] < \Gamma_D[i-1] \\ \widehat{A_D}[i-1] & \text{otherwise} \end{cases},$$

$$\Gamma_L[i] = \sum_{n=0}^{i} \left|\widehat{A_L}[n] - A[n]\right|,$$

$$\Gamma_D[i] = \sum_{n=0}^{i} \left|\widehat{A_D}[n] - A[n]\right|,$$

where $\widehat{A_P}[i]$ denotes the result which is adaptively switched between the linear model and the direct model, Γ_L and Γ_D denote the similarity measure of the direct model and the linear model, and i denotes the i-th frame within the window. Therefore, we use Eq. (3.1) to predict the first frame in the window and then use Eq. (3.2) to estimate others in the window.

CHAPTER 4

Experiments and Analyses

In this chapter, in order to evaluate the performance of the proposed coding method and to analyze the effects of the MAD and QP estimations on the frame selection scheme for the different window sizes, we conduct a set of experiments to illustrate:

1. To what extent the window size affects the accuracy of the MAD and QP estimations?
2. How the proposed scheme trades off the spatial and temporal quality?
3. Which subjective quality assessment used to be the distortion measure is compatible with human perceptional system in our experimental environment?

We integrate the proposed algorithm into the H.264/AVC reference software, Joint Model version 12.3, to exhibit its utility. The details of the testing conditions in the following experiments are presented in Table 4.1.

4.1 Joint Spatio-Temporal Bit Allocation

In order to demonstrate the benefit of frame skipping in low bit-rate condition, we adopt H.264 JM reference software to encode video sequences in fixed frame skipping.

Table 4.1: Testing conditions and encoder parameters

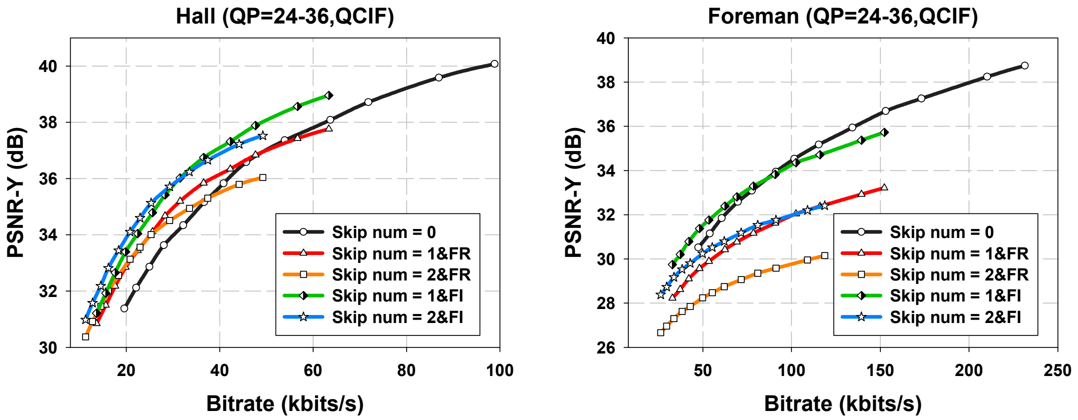
Codec	H.264/AVC JM12.3	*CPU*	Dual-Core 2.6GHz
Reference frame number	1	*Basic Unit*	99
Original frame rate	30 frames/sec	*Coding pattern*	IPPP...
Variable block size	Yes	*Video resolution*	176x144

Moreover, we use frame replication and motion-compensated frame interpolation to achieve a full frame rate video. For simplicity, we abbreviate frame replication as FR and motion-compensated frame interpolation as FI.

The five PSNR traces, indicating the qualities of full-frame-rate video reconstructions up-converted from 30, 15, 10fps by FR and FI, are shown in Figure 4.1. From the figure, three important observations can be made:

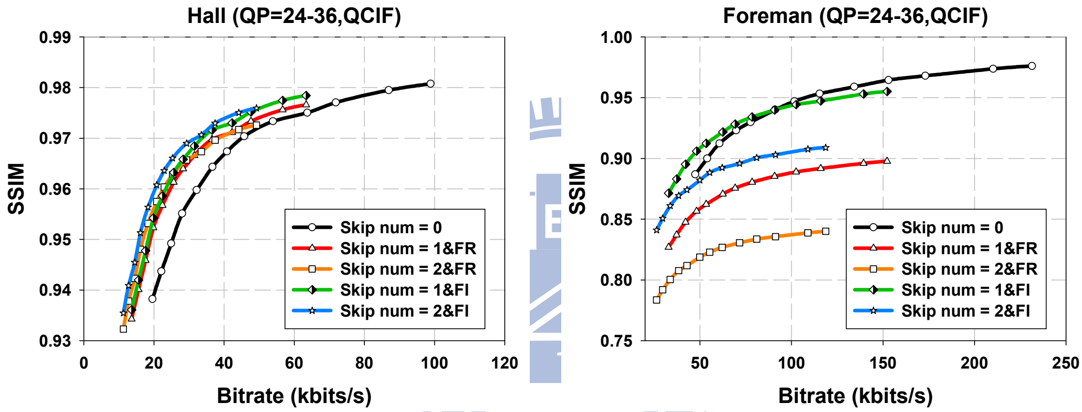
1. Compare part (a) and (b). The performance of reconstructing frame-skipped videos by FR and FI are more effective than that of encoding videos with full frame rate in low bit-rate condition, especially for low motion sequences.
2. Compare the two frame interpolation schemes. The performance of motion-compensated frame interpolation is better than that of frame replication and the influence of motion-compensated frame interpolation on frame recover is more obvious than frame repetition, especially for high motion sequences.
3. Compare the PSNR with subjective quality. The distortion of skipped frames dominates the whole distortion of reconstructed frames which include non-coded frames, especially for high motion sequences.

When we alter the quantization parameter and the frame rate simultaneously, the correlation between subjective quality and the PSNR become lower. For example, if we jointly change these two parameters, the PSNR may increase, whereas subjective quality may decrease. Therefore, in the following experiments, we will adopt various video quality assessments to demonstrate the benefit of skipped frame scheme in H.264. In addition to common objective quality measures, such as SSIM [9] and VQM [10][11], we also evaluate the performance by the new quality metric (NQM) [12] because it takes into account of the frame rate, motion speed and the PSNR. However, because NQM only considers the effect of frame replication in [12], we just use frame replication to reconstruct the skipped frames if we adopt NQM. Figure 4.2-4.4 present the rate-distortion curves of two different sequences in SSIM, NQM, and VQM, respectively.



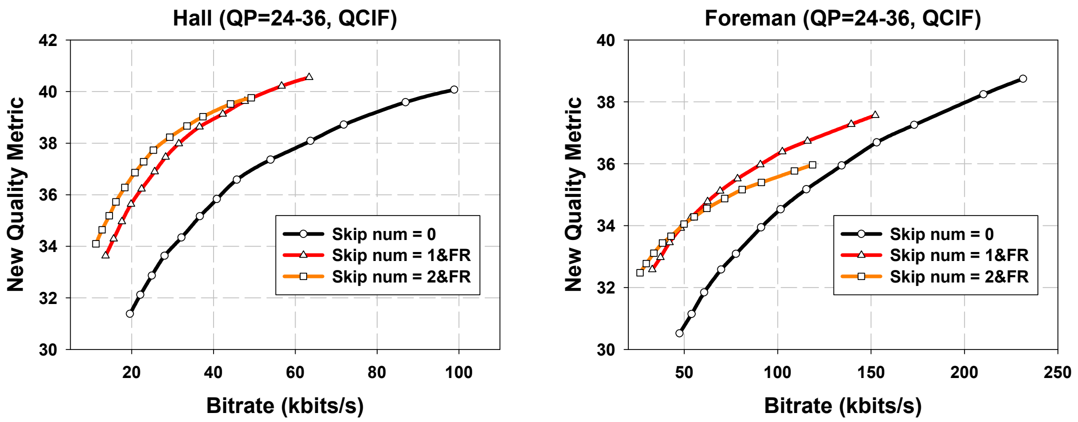
(a) (b)

Figure 4.1: Rate-distortion curves of (a) Hall and (b) Salesman sequences for regular frame skip number =0, 1, 2 in PSNR.



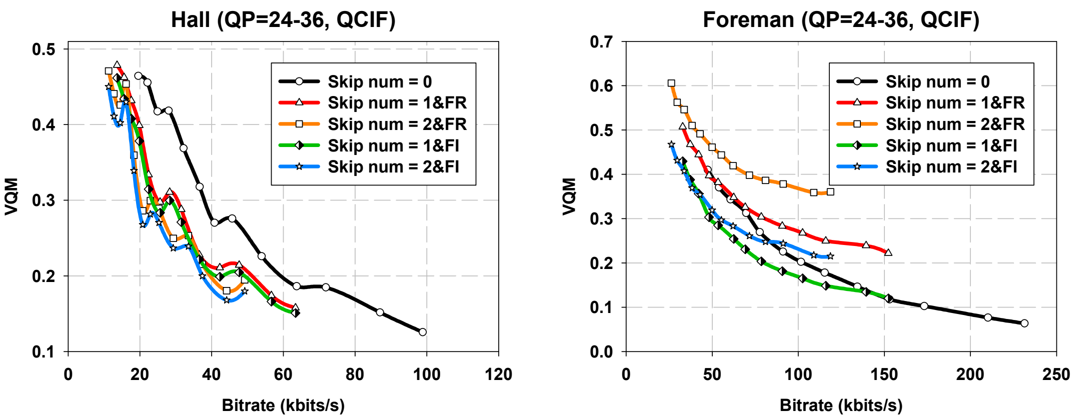
(a) (b)

Figure 4.2: Rate-distortion curves of (a) Hall and (b) Salesman sequences for regular frame skip number =0, 1, 2 in SSIM.



(a) (b)

Figure 4.3: Rate-distortion curves of (a) Hall and (b) Salesman sequences for regular frame skip number =0, 1, 2 in NQM.



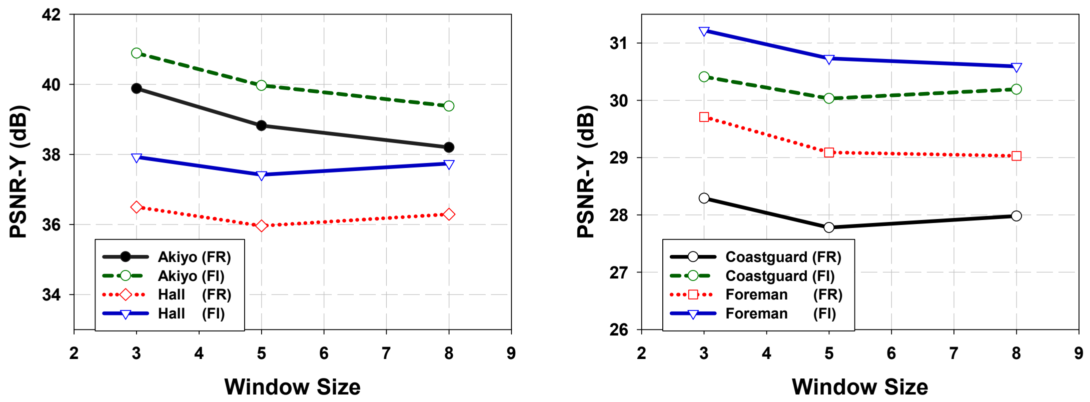
(a) (b)

Figure 4.4: Rate-distortion curves of (a) Hall and (b) Salesman sequences for regular frame skip number =0, 1, 2 in VQM.

Comparing Figure 4.1 and Figure 4.2, we find that the R-D performance in PSNR and SSIM are similar, but on the contrary, there are very different trends between the performance in PSNR and NQM in comparison of Figure 4.1 with Figure 4.3. The main difference is that the performance of reconstructed frame-skipping video is more efficient than that of the encoding video with full frame rate. On the other hand, we also find that, as shown in Figure 4.4, the R-D performance in VQM is different from the R-D performance in PSNR because the former reflects the human visual system effectively.

4.2 Quality of the Proposed R-Q/D-Q Models

In order to analyze the effect of window size on the performance of our proposed scheme, we vary the window size in our experiments and observe the performance. Given the target bit-rates and PSNR constraints, then we encoded video sequences to obtain the PSNR-Y for the difference window sizes. It should be noted that the PSNR-Y is computed on the whole sequence including repeated frames. Figure 4.5 shows the experiment results, which indicate that the smaller the window size, the better the PSNR-Y performance. However, more frames will be predicted and considered when the window size increases. In the sections 4.2.1 and 4.2.2, we will analyze the possible factors that affect the performance for the different window sizes from the experiments.



(a) (b)

Figure 4.5: The average PSNR-Y comparison of the (a) slow motion sequences and (b) high motion sequences for the window size=3, 5, 8.

4.2.1 MAD Prediction Accuracy

In this section, we analyze the effect of mismatch accuracy of our MAD prediction on the R-D performance. We carry out some experiments to compare our MAD prediction with the linear model. In our experiments, we examine the MAD prediction accuracy by using our MAD prediction for the window size = 3, 5, 8. Our MAD prediction and the linear model predict the same frames to be coded in the same conditions. In order to find the influence of variable frame rates and quantization parameters on MAD prediction, we evaluate the mismatch ratio between the predicted MAD and the actual MAD per frame, and we define

$$mismatch\ ratio(i) = \frac{\widehat{A}(i) - A(i)}{A(i)} \times 100\%$$

where $\widehat{A}(i)$ is the predicted MAD of ith frame and $A(i)$ is the actual MAD of ith frame. Figure 4.6 shows the MAD prediction mismatches which are generated by the linear model and by our MAD prediction in the window size=3, 5, 8, respectively. Therefore, two observations can be made: (1) the bigger the window size, the lower the chance that it will accurately predict the actual MAD, and (2) the mismatch ratio of our MAD prediction is smaller than that of the linear model.

In order to analyze the factor that affects the MAD prediction accuracy, we set the following two experiments to find the influence of the different frame skipping

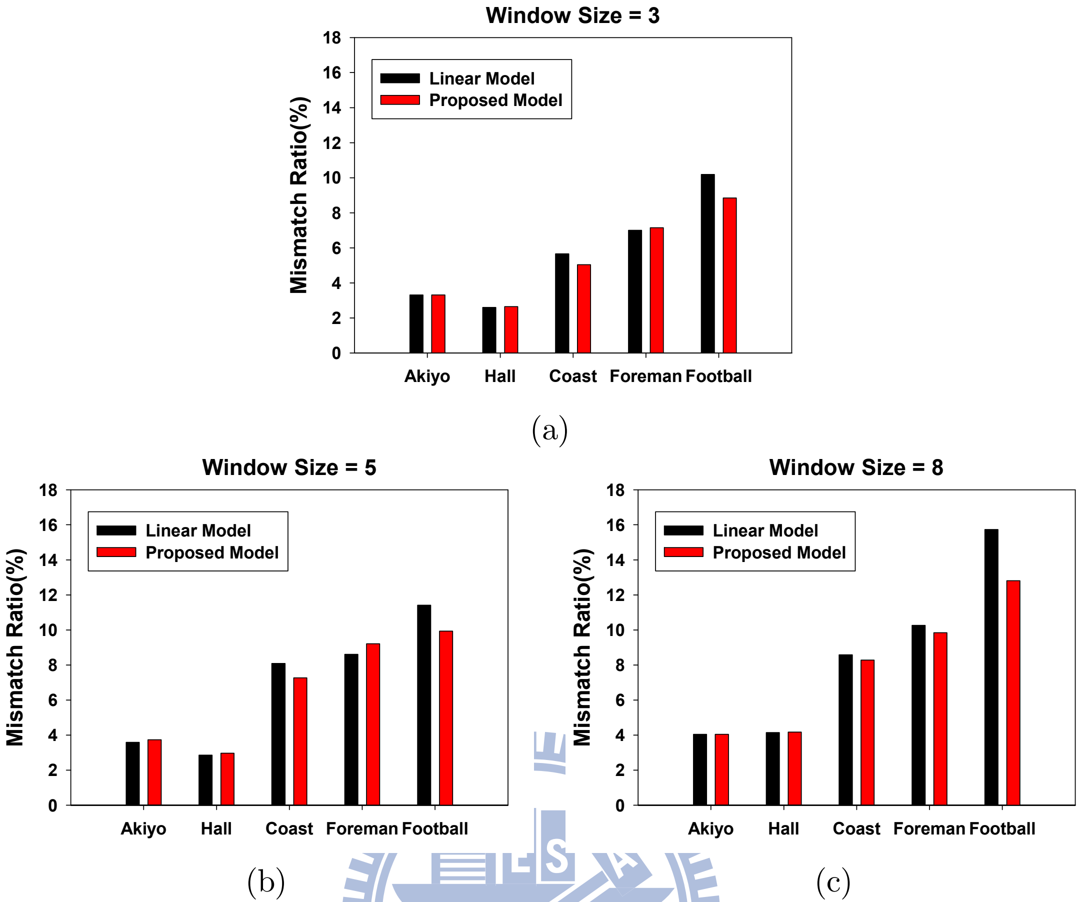


Figure 4.6: The MAD prediction mismatch comparison of the proposed MAD prediction and the linear model for the window size = 3, 5, 8.

approaches on our MAD prediction when the frame rate was 10.

- Experiment 1: Fixed frame skipping (FFS) with fixed QP
- Experiment 2: Variable frame skipping (VFS) with fixed QP

Note that variable frame skipping adopts the method which computes the mean square error (MSE) per two frames and then selects the frames to be coded with the highest MSE each three frames.

The comparison of the average mismatch ratio of the MAD prediction in the two experiment settings for the window size = 3, 5, 8 is shown in Figure 4.7. Two observations could be extracted from Figure 4.7: (1) The mismatch ratio of the MAD prediction in experiment 1 is higher than that of experiment 2. VFS easily results in more frames skipped and hence the fluctuation of the MAD is so high that the estimation of the actual MAD becomes harder. (2) the larger the window size causes more frames to be predicted, and hence the mismatch ratio of the MAD prediction is larger.

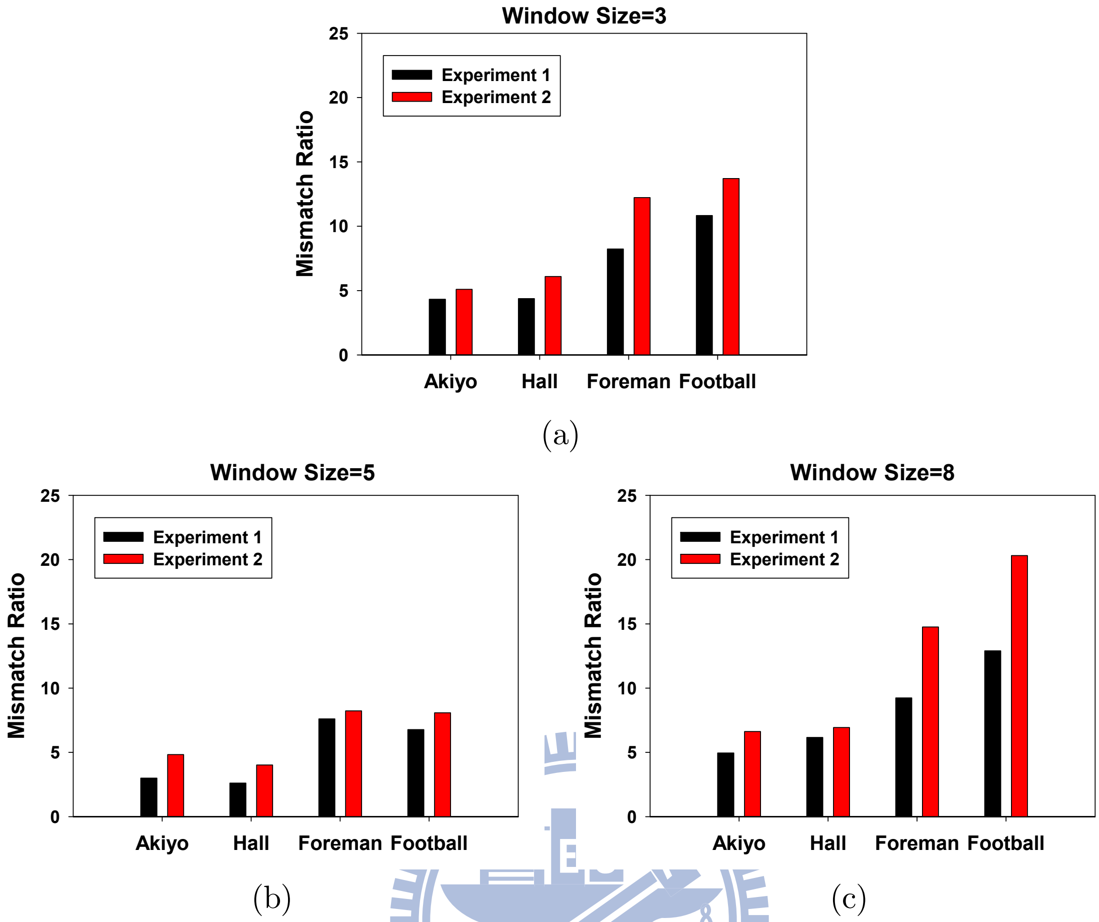


Figure 4.7: The average mismatch ratio of the MAD prediction in the window size=3, 5, 8.

4.2.2 QP Prediction Accuracy

In order to find the accuracy of the predicted QP by our proposed distortion model, we design the following experiment. The experiment can be described as following steps:

1. Encode a video sequence to get the PSNR and MAD of coded frames.
2. Use the PSNR and MAD from step 1 to estimate the QPs of coded frames by the proposed distortion model; in the meantime, the number of times predicted is based on the window size.
3. Compare the predicted QPs and the actual QPs to obtain the accuracy.

Figure 4.8 shows the results of the different sequences for the different window sizes. The details of the experiment results are presented in Table 4.2. From the figure and table, we found that when window size increased, the accuracy of predictive QPs decreased. Owing to the increase in the prediction distance between the predicted frame and the reference frame, the prediction error becomes larger.

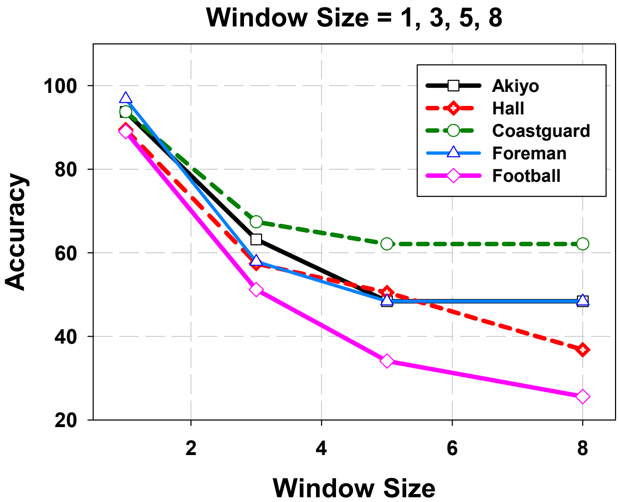


Figure 4.8: The QP prediction accuracy for the different window sizes.

Table 4.2: The accuracy of QP prediction of the differenet sequences for the different window size.

Sequences	window size = 1	window size=3	window size=5	window size=8
Foreman (15fps)	92.4%	56.6%	51.7%	51.7%
Foreman (10fps)	96.8%	57.9%	48.4%	48.4%
Football (15fps)	89.6%	61.6%	52.8%	47.2%
Football (10fps)	89%	51.2%	34.1%	25.6%
Hall (15fps)	91%	66.2%	56.6%	46.9%
Hall (10fps)	89.5%	47.4%	50.5%	36.8%
Akiyo (10fps)	93.7%	63.2%	48.4%	48.4%
Akiyo (6fps)	94.5%	80%	80%	72.7%
Coastguard (10fps)	93.7%	67.4%	62.1%	62.1%
Coastguard (6fps)	83.6%	63.6%	49%	47.2%
Pamphlet (10fps)	88.4%	55.8%	48.4%	37.9%
Pamphlet (6fps)	89.1%	49.1%	50.9%	27.3%
Salesman (10fps)	96.5%	76.4%	67.1%	66.2%
Salesman (6fps)	97.6%	60%	60%	33.8%

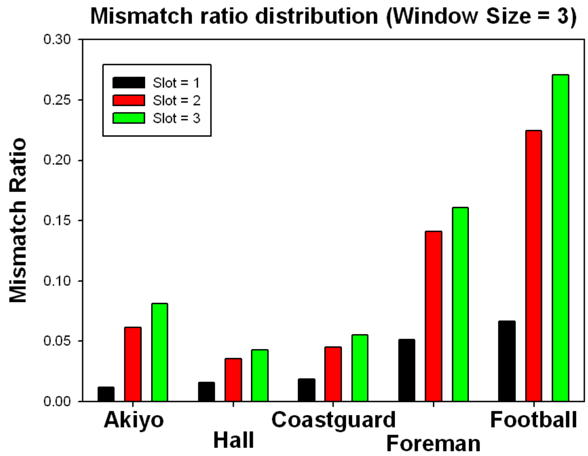


Figure 4.9: The MAD mismatch distribution of the experiment 1 within the window size = 3, 5, 8.

4.2.3 Chain Effect of QP and MAD Prediction

In order to analyze the effect of MAD prediction error on our scheme, we survey the distribution of the MAD prediction mismatch ratio in experiment 1. Figure 4.9 shows the distribution results. In Figures 4.9, we find that the larger window size provides more flexibility in frame selection, but introduces more propagation errors. Because the actual MAD is not available during the frame selection, the prediction error chain effect results in the error propagation problem.

From Figure 4.5, we see that there are two factors that affect the performance for the different window sizes. One is the error propagation. The other is the window size. Figure 4.10 shows the performance of Foreman sequence for the different window sizes. In the figure, we find that the performance for the different window size are almost the same in low bit-rate coding. In addition, considering the human perceptional system, it is always better to avoid long runs of skipped frames, which may cause an undesirable visual effect. Based on the above-mentioned observations, no matter what the window size to be set (we set to five here), our scheme must at least encode one frame in the window.

4.3 Performance Evaluation

After the window size selection analyses have been studied in details, in this section, we evaluate the performance of our proposed scheme. We use interpolation-quality-

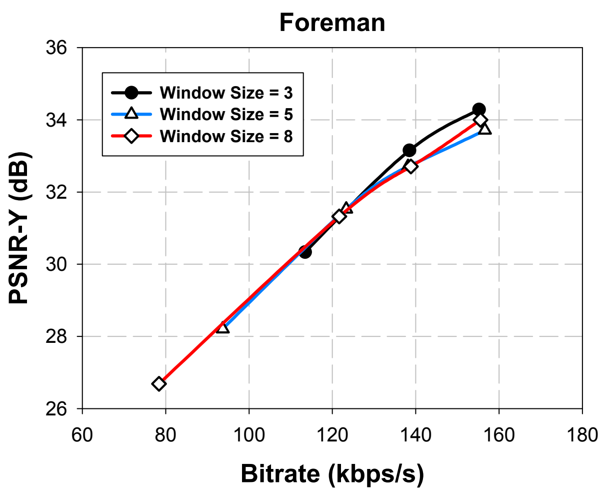


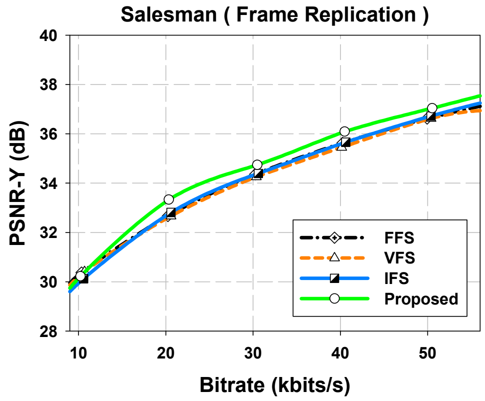
Figure 4.10: The performance of foreman sequence for the window size=3, 5, 8.

oriented frame skipping (IFS) to select the coded frame and then meet the frame rate which we want. In addition, we know that the fixed frame skipping scheme (FFS) and variable frame skipping scheme (VFS) introduced in the previous section. The three schemes are used as baseline for comparison. The experiment process is as follows:

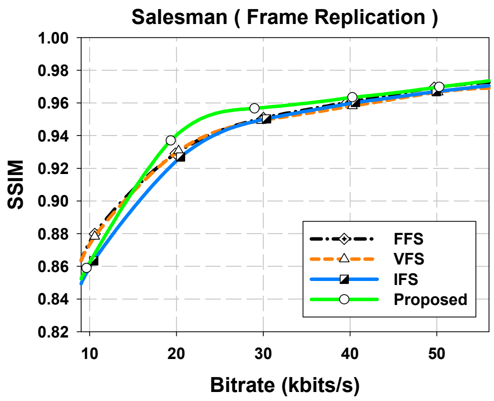
1. Set QP = 24.
2. Encode the test sequences with FFS, VFS, and IFS approaches at frame rate = 15, 10, 7.5, 6, respectively.
3. Obtain the distortion of the coded frames and the coded bit-rate and then measure the distortion of reconstructed test sequences which include the skipped frame reconstructed by frame repetition or motion-compensated frame interpolation. This gives a particular combination of rate (R) and distortion (D), an R-D operating point.
4. Repeat step 2 and add 1 to QP until QP = 36.
5. Select the operating points that give the best rate-distortion performance (i.e. the lowest distortion for a given rate R) and then these operating points form a convex hull.
6. Use the smallest PSNR as quality constraint and the coded bit-rate as rate constraint.

Through extensive experiments, we obtain the best R-D performance through the proposed scheme to compare the three schemes. Another objective quality measurement, such as SSIM, QM, and VQM, is adopted to evaluate the performance besides adopting the PSNR. The R-D performances of the different sequences are given in Figure 4.11-4.14, respectively. Therefore, from the figures, we can find that:

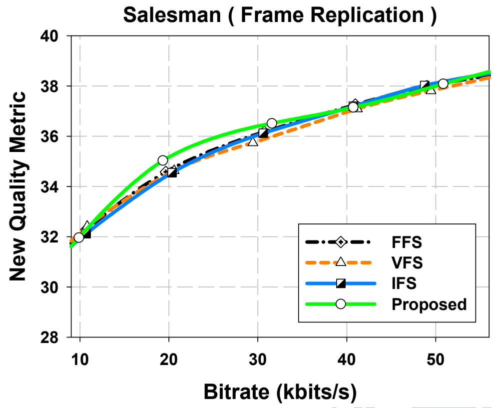
1. Compare the curves produced in the different quality assessments. As shown in Figure 4.11, we find that the R-D performance in PSNR and SSIM are similar, but on the contrary, there are very different trends between the performance in PSNR and NQM, especially for high motion sequences. On the other hand, all schemes show the similar performance with VQM.
2. Compare Figure 4.11(a) with Figure 4.11(e). We find that a tradeoff between spatial and temporal quality is limited in low bit-rate coding. In addition, by comparing Figure 4.12(a) with 4.12(e), we find that frame interpolation can improve more in FFS, VFS, and IFS. The main reason is more frames which are skipped in those schemes.
3. Compare the performances of four schemes in Figure 4.11. We find that the performance of the proposed method is superior to the performances of FFS, VFS, and IFS. The similar results can be found in Figure 4.12. Therefore, a good skipped frame selection is still needed.



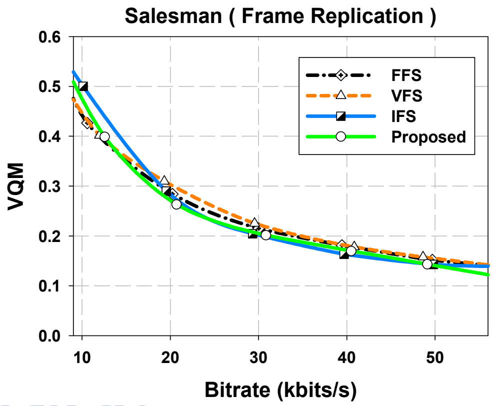
(a)



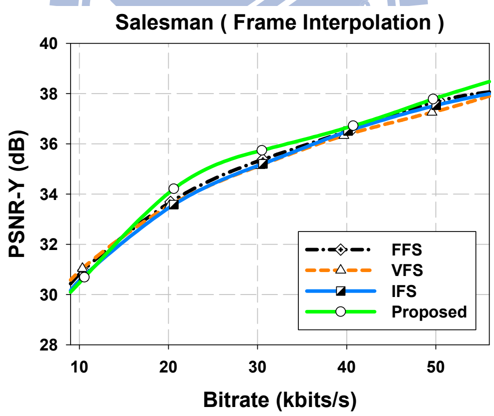
(b)



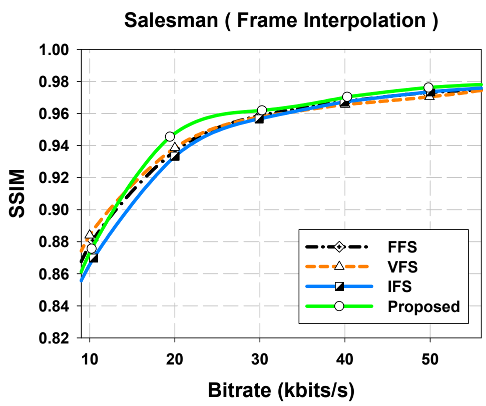
(c)



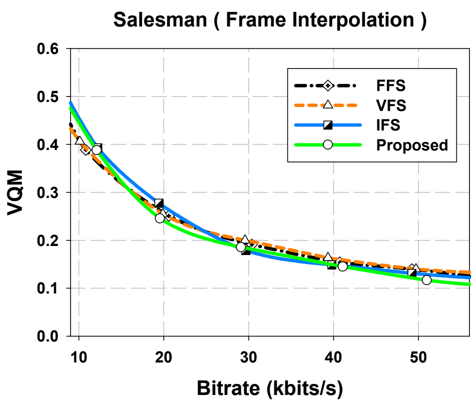
(d)



(e)

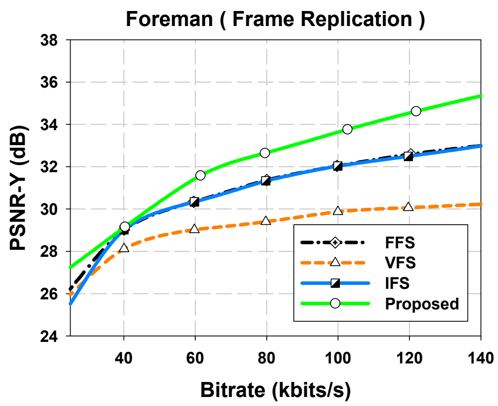


(f)

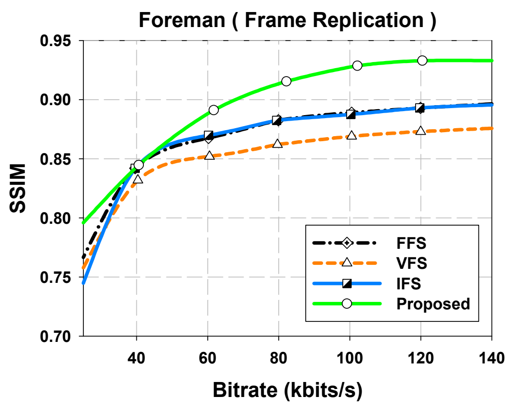


(g)

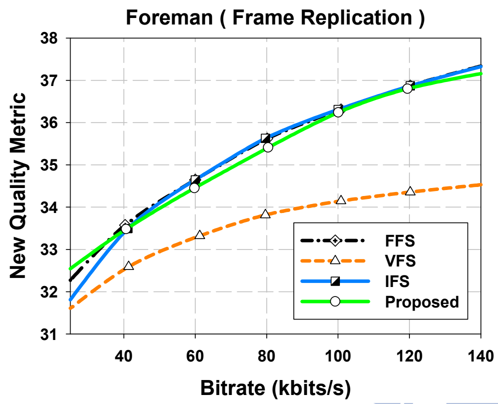
Figure 4.11: The R-D performance comparison of Salesman sequence reconstructed by frame replication and frame interpolation based on the different objective quality measurement.



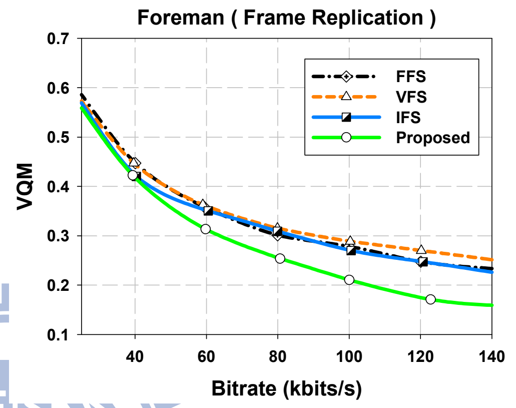
(a)



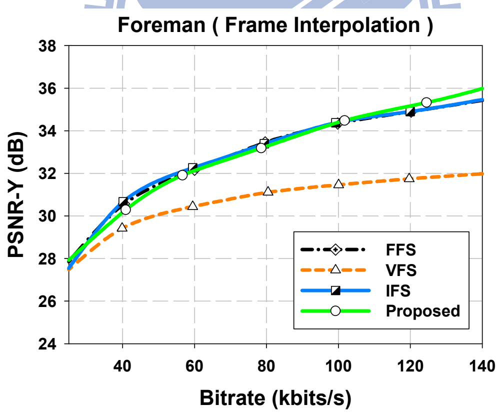
(b)



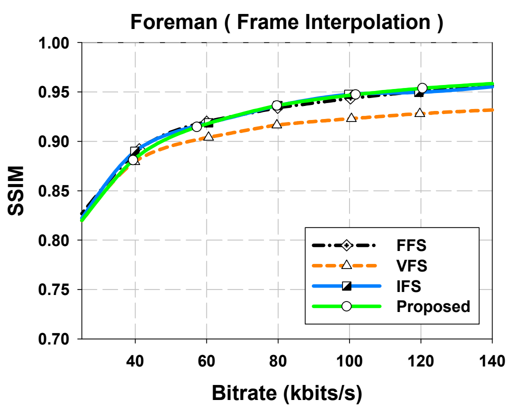
(c)



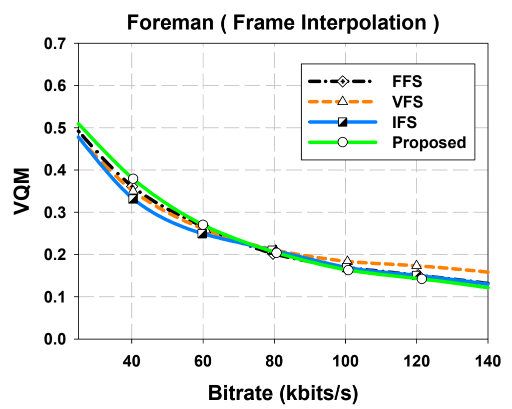
(d)



(e)



(f)



(g)

Figure 4.12: The performance comparison of Foreman sequence reconstructed by frame replication and frame interpolation based on the different objective quality measurement.

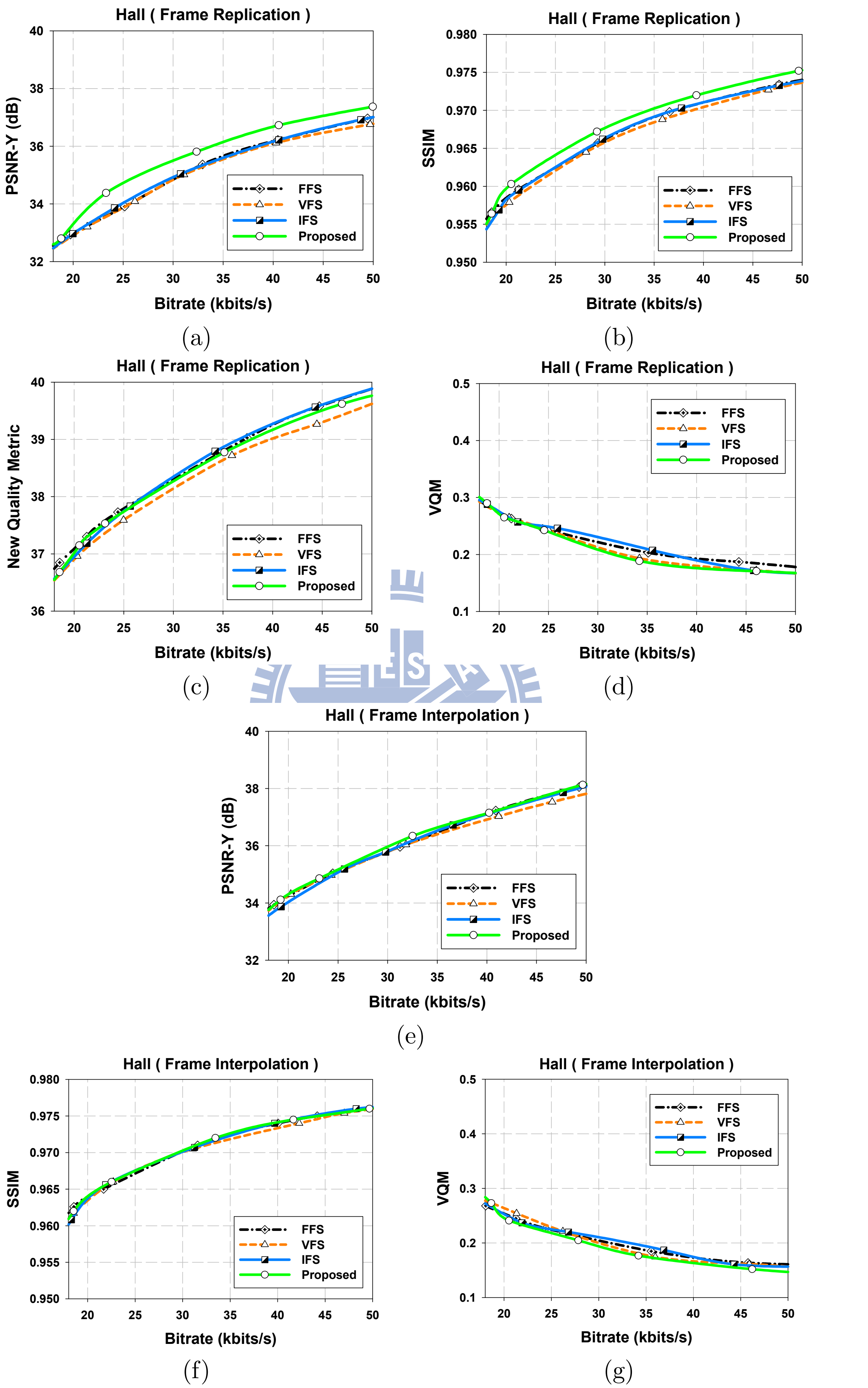


Figure 4.13: The performance comparison of Hall sequence reconstructed by frame replication and frame interpolation based on the different objective quality measurement.

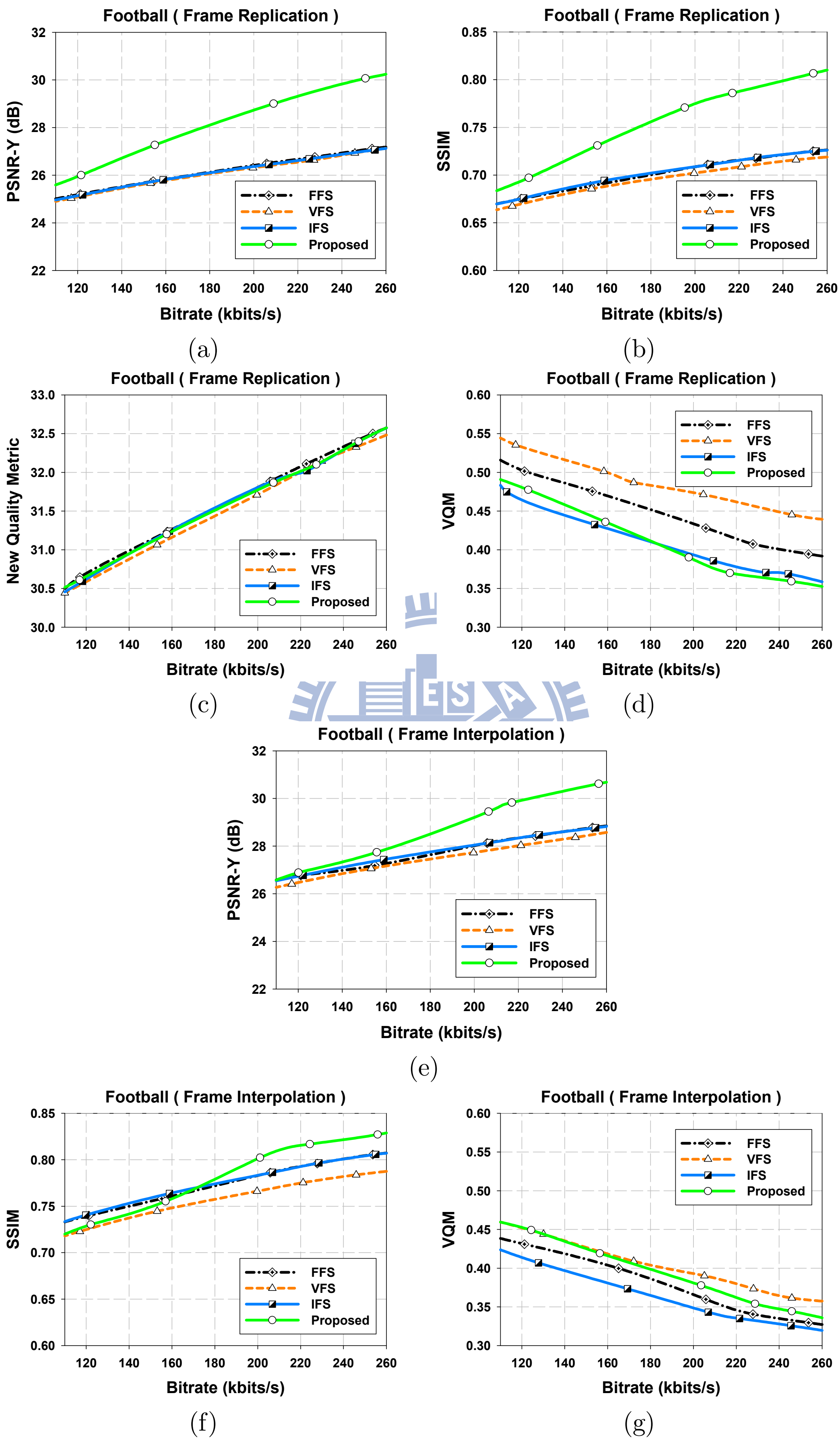


Figure 4.14: The performance comparison of Football sequence reconstructed by frame replication and frame interpolation based on the different objective quality measurement.

CHAPTER 5

Conclusions

In this thesis, we proposed an adaptive frame-skipping scheme which trades the temporal quality for the spatial quality, or vice versa, in order to satisfy both the rate and the quality constraints. Among the frames contained in a time window, our approach attempts to determine which should be encoded and what the values of their quantization parameters are. For each admissible frame-skip pattern, its R-D performance is estimated through a D-Q model and a R-Q model, both specifically take into account the effects of frame skipping. As compared with the regular frame skipping and the other previous work, our scheme reveals a significant improvement in R-D performance, especially in fast-motion sequences. Similar results are also observed with the other objective measures, such as SSIM and VQM.

We plan to further extend our study in several directions: (1) to establish a theoretical foundation for the empirical D-Q model, (2) to alleviate the error propagation in the prediction of the MAD and QP, and (3) to devise an adaptation scheme for the adjustment of window size.

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