Chap 4. Estimation of Decoded Video Distortion with MRF-based ISCD

\chapter{Estimation of Decoded Video Distortion with MRF-based ISCD}

\label{chapter:estimation}

Although the equation (\ref{eq:distortion\_final}) is able to estimate the average decoded distortion, it is imcomplete for the decoder with MRF source decoding. Because the decoded bit information accuracy is further improved by the MRF source decoder and the iterative process, bit error rate (BER) after the channel decoder, denoted by $fr(\gamma)$ in Chapter \ref{b:intro}, is not equivalent to the finally decoded BER. Hence, if the goal is to design an UEP scheme for ISCD decoders, it is important to expand (\ref{eq:distortion\_final}) to a more general form considering the iterative joint channel-source decoding in the decoder.

Since the 3D-MRF model based SISO source decoder in Section \ref {bb:sisodecoder} is employed, a expanded estimator is introduced in Section \ref{jj:est\_iscd} Finally, the simulation results for respective spatial, temporal, and 3D MRF decoders are presented in Section \ref{jj:res}.

Chap 4.1 Estimation of Distortion for ISCD Decoder with MRF Source Decoder

\section{Estimation of Distortion for ISCD Decoder with MRF Source Decoder}

\label{jj:est\_iscd}

Firstly, the ISCD decoding structures are depicted in Section \ref{bb:3d\_mrf\_iscd}, MRF-based source decoder can significantly enhance the bit accuracy and increase the decoded video quality based on the correlation in neighbourhood system. In other words, the BER of the output frame is smaller than $fr(\gamma)$, the bit error rate just after channel decoding, and the drop in BER is related to the neighbourhood system in each bit-plane. As a result, the estimator for the ISCD decoded distortion should as well consider the MRF model of the bit-planes and (\ref{eq:distortion\_final}) is expanded to

\begin{equation}

E[\hat{D\_k}] = \frac{1}{4}\sum\_{n=1}^{m}{(2^{2n}\cdot BER\_{k,n})},

\label{eq:distortion\_mrf}

\end{equation}

where $BER\_{k,n}$ denotes the average bit error rate between $\textbf{u}\_{k,n}$ and $\tilde{\textbf{u}}\_{k,n}$ in the final output frame,

\begin{equation}

P(\tilde{u}\_{k,n}^i = u) = \left\{\begin{array}{ll}

BER\_{k,n} & ,\quad u \neq u\_{k,n}^i \\

1- BER\_{k,n} & ,\quad u = u\_{k,n}^i \\

0 & ,\quad otherwise

\end{array}\right. .

\label{eq:ber\_definition}

\end{equation}

Besides, the estimation for the value of $BER\_{k,n}$ depends on $fr(w\_{k,n}\gamma\_0)$, where $w\_{k,n}$ is $w\_n$ for the $k$-th frame, and $BER\_{k,n}$ is highly related to the SISO MRF source decoder as well.

\begin{figure}[!htb]

\centering

\includegraphics[width=0.8\textwidth]{fig/iscd\_concept.pdf}

\caption{\label{fig:iscd\_concept}A conceptual diagram of ISCD decoder}

\end{figure}

In Fig.\ref{fig:iscd\_concept}, $\hat{u}^i\_{k,n}$ denotes the output bit through hard deciding $L\_c^{(O)}(u^i\_{k,n})$,which is the output of BCJR decoder, and $\tilde{u}^i\_{k,n}$ is the final output bit through hard deciding $L\_s^{(O)}(u^i\_{k,n})$, which is the output of MRF SISO decoder. As proposed in (\ref{eq:est\_u}), the correlation between $\textbf{u}\_{k,n}$ and channel decoder output $\hat{\textbf{u}}\_{k,n}$ can be described only by $fr(w\_{k,n}\gamma\_0)$. However, to derive $BER\_{k,n}$ after an SISO source decoder, an SISO estimator $L\_{k,n}$ is introduced to the encoder

\begin{align}

L\_{k,n}\equiv & E\left[\ln{\frac{P(\tilde{u}\_{k,n}^i=u\_{k,n}^i | u\_{k,n}^i)}{ P(\tilde{u}\_{k,n}^i\ne u\_{k,n}^i | u\_{k,n}^i)}}\right] \\

= & E[ (2u\_{k,n}^i-1)\cdot L\_{k,n}^i], \nonumber

\label{eq:llr\_uep\_definition}

\end{align}

where

\begin{equation}

2u\_{k,n}^i-1 = \left\{\begin{array}{ll}

1 &, u\_{k,n}^i =1 \\

-1 &, u\_{k,n}^i = 0

\end{array}\right. .\nonumber

\end{equation}

$L\_{k,n}$ is the expectation of the soft information similar to the SISO information in section \ref{bbb:siso\_s\_decoder}, and therefore it can be estimated through the aid of MRF model based SISO source decoder. $L\_{k,n}^i$ is calculated like $L^{(O)}\_i$ in (\ref{eq\_app\_LLR\_final\_short}) to (\ref{eq\_app\_LLR\_temporal}), and the term $L\_i$ in these equations can be estimated as

\begin{equation}

L\_i = \left\{\begin{array}{ll}

\ln{\frac{1-fr(\gamma\_{k,n})}{fr(\gamma\_{k,n})}} &, \quad u\_{k,n}^i = 1 \\

-\ln{\frac{1-fr(\gamma\_{k,n})}{fr(\gamma\_{k,n})}} &, \quad u\_{k,n}^i = 0

\end{array}\right. , \forall i \in \{1,\cdots,N\},

\end{equation}

where $\gamma\_{k,n}$ is the short of $w\_{k,n}\cdot \gamma\_0$. As a consequence, (\ref{eq:llr\_uep\_definition}) can be modified as

\begin{equation}

\begin{aligned}

L\_{k,n}=& \ln{\frac{1-fr(\gamma\_{k,n})}{fr(\gamma\_{k,n})}}+E\left[\sum\_{i'\in N\_i^{[s]}}{\beta\_{k,n}^{[s]}(P(\hat{u}\_{i'}=u\_{k,n}^i|L\_{i'})-P(\hat{u}\_{i'}\ne u\_{k,n}^i|L\_{i'}))}\right] \nonumber \\

&+ E\left[\sum\_{i'\in N\_i^{[t]}}{\beta\_{k,n}^{[t]}(P(\hat{u}\_{i'}=u\_{k,n}^i|L\_{i'})-P(\hat{u}\_{i'}\ne u\_{k,n}^i|L\_{i'}))}\right],

\end{aligned}

\end{equation}

where the first term is the estimated $L\_i$ which is only related to $fr(\gamma\_{k,n})$, and the last two terms are respectively referred to the estimated gain from spatial and temporal MRF decoder. Moreover, $\beta\_{k,n}^{[s]}$ and $\beta\_{k,n}^{[t]}$ can be calculated according to section \ref{bbb:parameter\_est}. Then, $BER\_{k,n}$ can be derived as

\begin{equation}

\begin{aligned}

BER\_{k,n}=&\frac{1}{1+e^{L\_{k,n}}} \\

=&\frac{fr(\gamma\_{k,n})}{fr(\gamma\_{k,n})+(1-fr(\gamma\_{k,n}))\cdot e^{E[L\_i^{(E,s)}]+E[L\_i^{(E,t)}]}},

\end{aligned}

\label{eq:ber\_llr}

\end{equation}

where

\begin{align}

E[L\_i^{(E,s)}] = & \frac{1}{N}\sum\_{i=1}^{N}{\sum\_{i'\in N\_i^{[s]}}{\beta\_{k,n}^{[s]}(P(\hat{u}\_{i'}=u\_{k,n}^i|L\_{i'})-P(\hat{u}\_{i'}\ne u\_{k,n}^i|L\_{i'}))}} \nonumber \\

E[L\_i^{(E,t)}] = & \frac{1}{N}\sum\_{i=1}^{N}{\sum\_{i'\in N\_i^{[t]}}{\beta\_{k,n}^{[t]}(P(\hat{u}\_{i'}=u\_{k,n}^i|L\_{i'})-P(\hat{u}\_{i'}\ne u\_{k,n}^i|L\_{i'}))}} .

\label{eq:avg\_llr}

\end{align}

It is worth noting that (\ref{eq:avg\_llr}) can further be deduced into a simplified form. Take $E[L\_i^{(E,s)}]$ for example,

\begin{align}

E[L\_i^{(E,s)}] = & \frac{1}{N}\sum\_{i=1}^{N}{\sum\_{i'\in N\_i^{[s]}}{\beta\_{k,n}^{[s]}(P(\hat{u}\_{i'}=u\_{k,n}^i|L\_{i'})-P(\hat{u}\_{i'}\ne u\_{k,n}^i|L\_{i'}))}} \nonumber \\

=& \frac{\beta\_{k,n}^{[s]}}{N}\sum\_{i=1}^{N}{\sum\_{i'\in N\_i^{[s]}}{ (2P(\hat{u}\_{i'}=u\_{k,n}^i|L\_{i'})})-1)},

\label{eq:avg\_llr\_s1}

\end{align}

where

\begin{align}

P(\hat{u}\_{i'}=u\_{k,n}^i|L\_{i'}) = \left\{\begin{array}{ll}

BER\_{N\_{k,n}} &, u\_{i'}\ne u\_{k,n}^{i} \\

1- BER\_{N\_{k,n}} &, u\_{i'}= u\_{k,n}^{i} \\

0 &, \text{otherwise}

\end{array}\right. .

\label{eq:hat\_u}

\end{align}

where $BER\_{N\_{k,n}}$ denotes the average bit error rate at the bit-plane where the neighbourhood system of $\textbf{u}\_{k,n}$ is situated. Since $BER\_{N\_{k,n}}$ depends on the MRF neighbourhood system type, it is investigated respectively with spatial MRF decoder and temporal MRF decoder. Firstly, when spatial MRF model is applied, the neighbourhood system of $\textbf{u}\_{k,n}$ is still located in the same bit-plane $\textbf{u}\_{k,n}$, which implies that $BER\_{N\_{k,n}^{[s]}}=fr(\gamma\_{k,n})$. Nevertheless, in the temporal MRF model, the neighbourhood system of $\textbf{u}\_{k,n}$ is in the $n$-th bit-plane of reference frame $k'$, which can be the previous or the next frame. In the decoder structure in Fig. \ref{fig\_iscd\_t}, consecutive decoding is adopted so that the iteratively decoded information is stored to offer the next frame an initial reference state. As a result, $BER\_{N\_{k,n}^{[t]}}$ can be seen as $BER\_{k',n}$, where $k'$ is the reference frame index of $f\_k$, and usually is $k-1$. Finally, (\ref{eq:hat\_u}) can be further combined with

\begin{equation}

BER\_{N\_{k,n}} = \left\{\begin{array}{ll}

fr(\gamma\_{k,n}) &, \text{ spatial MRF model is adopted} \\

BER\_{k',n} &, \text{ temporal MRF model is adopted, and reference frame index } k' < k \\

fr(\gamma\_{k',n}) &, \text{ temporal MRF model is adopted, and } k' > k

\end{array}\right. .

\label{eq:ber\_N}

\end{equation}

After substituting (\ref{eq:hat\_u}) into (\ref{eq:avg\_llr\_s1}),

\begin{align}

E[L\_i^{(E,s)}] = & \frac{\beta\_{k,n}^{[s]}}{N}\sum\_{i=1}^{N}\left[ 2 BER\_{N\_{k,n}}\cdot \#\{u\_{N\_i^{[s]}}\ne u\_{k,n}^i\} + 2(1- BER\_{N\_{k,n}})\cdot \#\{ u\_{N\_i^{[s]}}= u\_{k,n}^i \}\right. \nonumber \\

& \quad \left. - (\#\{u\_{N\_i^{[s]}}\ne u\_{k,n}^i\}+ \#\{ u\_{N\_i^{[s]}}= u\_{k,n}^i \}) \right] \nonumber \\

= & \frac{\beta\_{k,n}^{[s]}}{N} \sum\_{i=1}^{N}\left[ (1-2 BER\_{N\_{k,n}})\cdot(\#\{u\_{N\_i^{[s]}}= u\_{k,n}^i\}- \#\{ u\_{N\_i^{[s]}}\ne u\_{k,n}^i \})\right] \nonumber \\

= & \frac{\beta\_{k,n}^{[s]}(1-2 BER\_{N\_{k,n}})}{N}\sum\_{i=1}^{N}{(\#\{u\_{N\_i^{[s]}}= u\_{k,n}^i\}- \#\{ u\_{N\_i^{[s]}}\ne u\_{k,n}^i \})},

\label{eq:avg\_llr\_s2}

\end{align}

where $\#\{\cdot\}$ is the counting function. (e.g. $\#\{u\_{N\_i^{[s]}}=u\_{k,n}^i\}$ is the total number of bits which belong to neighbourhood of $u\_{k,n}^i$ and equal to $u\_{k,n}^i$) Similarly, $E[L\_i^{(E.t)}]$ can be reduced as well,

\begin{equation}

E[L\_i^{(E,t)}] = \frac{\beta\_{k,n}^{[t]}(1-2 BER\_{N\_{k,n}})}{N}\sum\_{i=1}^{N}{(\#\{u\_{N\_i^{[t]}}= u\_{k,n}^i\}- \#\{ u\_{N\_i^{[t]}}\ne u\_{k,n}^i \})}.

\label{eq:avg\_llr\_t}

\end{equation}

In hence, combining with (\ref{eq:avg\_llr\_s2}) and (\ref{eq:avg\_llr\_t}), (\ref{eq:ber\_llr}) can be modified as

\begin{equation}

BER\_{k,n}= \frac{fr(\gamma\_{k,n})}{fr(\gamma\_{k,n})+(1-fr(\gamma\_{k,n}))\cdot e^{ (\beta\_{k,n}^{[s]} \overline{N}\_{k,n}^{[s]}(1-2 fr(\gamma\_{k,n}))+\beta\_{k,n}^{[t]} \overline{N}\_{k,n}^{[t]}(1-2BER\_{N\_{k,n}}))}},

\label{eq:ber\_llr\_final}

\end{equation}

where

\begin{align}\label{eq:ber\_llr\_ne\_s}

\overline{N}\_{k,n}^{[s]} = & \frac{\sum\_{i=1}^{N}{(\#\{u\_{N\_i^{[s]}}= u\_{k,n}^i\}- \#\{ u\_{N\_i^{[s]}}\ne u\_{k,n}^i \})}}{N}, \\

\overline{N}\_{k,n}^{[t]} = & \frac{\sum\_{i=1}^{N}{(\#\{u\_{N\_i^{[t]}}= u\_{k,n}^i\}- \#\{ u\_{N\_i^{[t]}}\ne u\_{k,n}^i \})}}{N},

\label{eq:ber\_llr\_ne\_t}

\end{align}

and

\begin{equation}

BER\_{N\_{k,n}} = \left\{\begin{array}{ll}

BER\_{k',n} &, \text{ temporal reference frame index } k' < k \\

fr(\gamma\_{k',n}) &, \text{ } k' > k

\end{array}\right. .

\end{equation}

Finally, the updated distortion estimator (\ref{eq:distortion\_mrf}) for advanced ISCD decoder structures is built, and then the estimation structures as well as the simulation results are shown in next section.

Chap 4.2 Numerical Result

\section{Numerical Result}

\label{jj:res}

In this section, the result of the estimator would be verified through comparing it to the simulation result. The simulation scenario is similar to the first condition in section \ref{ccc:res}, where the encoder is given a requested average transmission power. Besides, the channel correction code is also the RSC code with generator matrix (\ref{eq:generator\_matrix}), BPSK modulation and AWGN channel is adopted as well. EEP scheme is applied in simulation as well as in the updated estimator (\ref{eq:distortion\_mrf}) and (\ref{eq:ber\_llr\_final}), that is all weights in $\{w\_{k,n}\}$ are set to 1. On the decoder side, for the sake of simplicity, the discussion is divided into three parts, only spatial-MRF based ISCD, only temporal-MRF based ISCD, and 3D-MRF based ISCD. As a result, each part matches with one estimator structure.

Besides, there are four videos for transmission, and the characteristic of each video is shown in Table.\ref{table:video}. Each video is fed into both the estimator and the simulation in every following part.

\begin{table}[ht]

\caption{Comparison of the characteristic and the spec of 4 test sequences.}

\centering

\begin{tabular}{ccccccc}

\\ [0.3ex] \hline \hline \\ [-1.5ex]

\multicolumn{1}{l}{}& \textbf{resolution} & \textbf{pixel format} & \textbf{\#frame} & \textbf{FPS} & \textbf{motion} & \textbf{homogeneity} \\ [0.5ex]

\hline \\ [-1.5ex]

\textit{\textbf{Foreman}} &352x288 &Y (8bits) &300 &15 & normal & normal \\

\textit{\textbf{Stefan}} &352x288 & Y (8bits) & 90 & 15 & large & small \\

\textit{\textbf{Hall}} & 352x288 & Y (8bits) & 300 & 15 & small & large \\

\textit{\textbf{Akiyo}} & 352x288 & Y (8bits) & 300 & 15 & very small & normal\\ [1ex]

\hline

\end{tabular}

\label{table:video}

\end{table}

Chap 4.2.1 Distortion for ISCD Decoder with Spatial MRF Decoder

\subsection{Distortion for ISCD Decoder with Spatial MRF Decoder}

\label{jjj:temporal}

\begin{figure}[!htb]

\centering

\includegraphics[width=0.9\textwidth]{fig/distortion\_est\_s.pdf}

\caption{\label{fig:distortion\_est\_s}A distortion estimator diagram for spatial MRF ISCD decoder.}

\end{figure}

In the first part for the spatial MRF based ISCD decoder, the simplified estimator structure is depicted in Fig.\ref{fig:distortion\_est\_s}, where $BER\_{k,n}$ is dependent only on the spatial neighbourhood system. In hence, parameter estimation block calculates $\beta\_{k,n}^{[s]}$ for each bit-plane, and the spatial MRF decoder calculates $\overline{N}\_{k,n}^{[s]}$ in (\ref{eq:ber\_llr\_ne}). It is worth noting that after one frame is split into bit-planes, the estimator is a parallel-operation structure, which can executes independently within each bit-plane. The parallel-operation structure is denoted by the multi-pipelines in Fig.\ref{fig:distortion\_est\_s}. Finally, distortion estimator block collects the all required information including $\beta\_{k,n}^{[s]}$, $\overline{N}\_{k,n}^{[s]}$, and $fr(\gamma\_{k,n})$ for all bit-planes, and then computes the expected average distortion according to (\ref{eq:distortion\_mrf}).

\begin{figure}[!htb]

\centering

\includegraphics[width=\textwidth]{fig/hall\_intra\_est\_eep.pdf}

\caption{\label{fig:hall\_intra\_est}Simulation result and the estimated quality using "Hall" sequence in different frame index and SNRs.}

\end{figure}

Fig.\ref{fig:hall\_intra\_est} depicts the comparison between estimated quality and simulated quality in different SNR conditions and in different frames of "Hall" sequence. Fig.\ref{fig:hall\_intra\_est} shows that the estimated result, denoted by the dash lines, approaches closely the simulated result, denoted by the solid lines, at each frame index. Because the scene in "Hall" sequence is relatively static throughout the video, the characteristic including movement of objects and the homogeneity in each frame are similar. As a result, the decoded quality is also stable in any SNR condition. It is verified that the proposed estimator performs well for the spatial MRF based ISCD using "Hall" sequence.

\begin{figure}[!htb]

\centering

\includegraphics[width=\textwidth]{fig/foreman\_intra\_est\_eep2.pdf}

\caption{\label{fig:foreman\_intra\_est}Simulation result and the estimated quality using "Foreman" sequence in different frame index and SNRs.}

\end{figure}

In additional to the "Hall" sequence which is relatively static throughout the video, the "Foreman" sequence is also used to evaluate the accuracy of the proposed estimator. Different from "Hall" sequence, "Foreman" sequence contains both static part and dynamic part. In "Foreman" sequence, there is Foreman's big face slightly swinging in the beginning, and there is a large camera movement that changes the scene much in the ending. Fig.\ref{fig:foreman\_intra\_est} depicts the comparison between estimated quality and simulated quality in different SNR conditions and in different frames of "Foreman" sequence. In Fig.\ref{fig:foreman\_intra\_est}, the estimated result, denoted by the dash lines, is again close to the mean of the simulated result, denoted by the solid lines. It is noticed that the decoded quality decreases obviously after the camera movement, and it is because the scene in the end is more complicated and more inhomogeneous than the beginning scene. As a consequence, it is shown that spatial MRF based ISCD works better when the homogeneity of the scene is larger. In conclusion, the proposed estimator can perform precise prediction for the decoded distortion before transmitting the video when spatial MRF based ISCD is adopted.

Chap 4.2.2 Distortion for ISCD Decoder with Temporal MRF Decoder

\subsection{Distortion for ISCD Decoder with Temporal MRF Decoder}

\label{jjj:spatial}

\begin{figure}[!htb]

\centering

\includegraphics[width=\textwidth]{fig/distortion\_est\_t.pdf}

\caption{\label{fig:distortion\_est\_t}A distortion estimator diagram for temporal MRF ISCD decoder.}

\end{figure}

In the second part, Fig.\ref{fig:distortion\_est\_t} depicts the structure diagram of the proposed estimator for the decoded distortion when using temporal MRF based ISCD. While the temporal only MRF based ISCD utilizes mere temporal MRF model to calculate $\beta\_{k,n}^{[t]}$ and $\overline{N}\_{k,n}^{[t]}$, motion estimation first executes with the reference frame, usually the previous frame. After the motion vectors are generated, both of the frames are split into bit-planes. Then $\beta\_{k,n}^{[t]}$ can be calculated through (\ref{eq\_beta\_est}), and $\overline{N}\_{k,n}^{[t]}$ is computed according to (\ref{eq:ber\_llr\_ne\_t}). Similar with the structure in Fig.\ref{fig:distortion\_est\_s}, operations after the bit-planes are built can be divided into $m$ parallel pipelines to execute more efficiently. Finally distortion estimation block collects the required information including $\beta\_{k,n}^{[t]}$ and $\overline{N}\_{k,n}^{[t]}$ in each bit-plane to compute the expected distortion according to (\ref{eq:ber\_llr\_final}). In contrast to Fig.\ref{fig:distortion\_est\_s}, distortion estimation block in Fig.\ref{fig:distortion\_est\_t} adds a set of required arguments $BER\_{N\_{k,n}}$. Because of the feature that temporal MRF based ISCD can store the previously decoded information, the distortion is highly related to the final bit error rate in the last frame (\ref{eq:ber\_llr\_final}).

\begin{figure}[!htb]

\centering

\includegraphics[width=\textwidth]{fig/stefan\_inter\_est\_eep.pdf}

\caption{\label{fig:stefan\_inter\_est}Simulation result and the estimated quality using the "Stefan" sequence in different frame index and SNRs.}

\end{figure}

Fig.\ref{fig:stefan\_inter\_est} shows the performance of temporal MRF based ISCD, depicted in the solid lines, and the estimated quality, depicted in dash lines, when using the "Stefan" sequence. "Stefan" sequence is a video with both large object movement and camera global movement throughout the sequence. Therefore, the performance of the temporal MRF based ISCD is varying more drastically. Even so, the proposed estimator is able to approach the distortion closely at each frame index. The only defect is the slight overestimation in $SNR=0$ dB condition. Nevertheless, the variation tendency of the decoded quality is still identical enough.

\begin{figure}[!hbt]

\centering

\includegraphics[width=\textwidth]{fig/akiyo\_inter\_est\_eep.pdf}

\caption{\label{fig:akiyo\_inter\_est}Simulation result and the estimated quality using the "Akiyo" sequence in different frame index and SNRs.}

\end{figure}

Fig.\ref{fig:akiyo\_inter\_est} is another comparison chart that shows the accuracy of proposed estimator for temporal MRF based ISCD when using "Akiyo" sequence. In "Akiyo" sequence, there is only one reporter sitting and talking, and thus this video is very static. In hence, the uncompressed "Akiyo" sequence is rich in temporal redundancy, and temporal MRF based ISCD is exactly a suitable solution for this sequence. From the simulation result represented in solid lines in Fig.\ref{fig:akiyo\_inter\_est}, the decoding quality is significantly raised to at least $40$ dB as just mentioned. Besides, it is worth noting that the proposed estimator is a little inaccuracy while the SNR is higher. Take the $SNR=4$ dB condition for example, although the simulation result oscillates seriously, it can still be noticed that the estimated quality is approximately $5$ dB lower than the average of simulation results. It might result from the PSNR formula in (\ref{eq:psnr}). According to (\ref{eq:psnr}), PSNR metric is much more sensitive to the variation or the deviation on the distortion $D$ when $D$ is smaller. However, on the whole, the proposed estimator still works well enough to predict the decoded quality as shown in dash lines in Fig.\ref{fig:akiyo\_inter\_est}.

Chap 4.2.3 Distortion for ISCD Decoder with 3D-MRF Decoder

\subsection{Distortion for ISCD Decoder with 3D-MRF Decoder}

\label{jjj:iscd\_3d}

\begin{figure}[!hbt]

\centering

\includegraphics[width=\textwidth]{fig/distortion\_est\_3d.pdf}

\caption{\label{fig:distortion\_est\_3d}A distortion estimator diagram for 3D-MRF based ISCD decoder.}

\end{figure}

In the last part, the structure diagram of the proposed estimator for the expected distortion with 3D-MRF based ISCD is presented in Fig.\ref{fig:distortion\_est\_3d}. In actual, this structure combines the structures in Fig.\ref{fig:distortion\_est\_s} and Fig.\ref{fig:distortion\_est\_t} after the bit-planes separation. Besides, the redundancies in spatial MRF model and temporal MRF model are jointly taken into consideration in distortion estimation in order to compute the expected distortion according to (\ref{eq:distortion\_mrf}) and (\ref{eq:ber\_llr\_final}) . Since both the estimators for spatial and temporal MRF ISCD are confirmed to be powerful enough to predict the respective decoded quality, the estimator for 3D-MRF ISCD should be precise as well.