Efficiency of displacement estimation techniques

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An analytical description of displacement estimation which allows an objective evaluation and comparison of various displacement estimation techniques is presented. For evaluation and this by the impact of the 2D motion model of the displacement estimator and the amplitude and spatial resolution of the encoded displacement vector field can be quantified. The rate-distortion function describes the relationship between the encoding bit-rate required for transmission of the measured displacement vector field and the variance of the spatial and amplitude resolution of the encoded displacement vector field is described. The 2D motion model is considered by low pass filtering simulations of various displacement estimation techniques, the 2D motion models which are described by the nearest neighbour, affine and bilinear displacement vector interpolation, at different amplitude and spatial resolutions. The analytical description allows one to optimize a displacement estimation technique for motion compensated image sequence coding.

Abstract
An enhanced description of displacement estimation which allows an objective evaluation and comparison of various displacement estimation techniques is presented. For evaluation and by the impact of the 2D motion model of the displacement estimator and the amplitude and spatial resolution of the encoded displacement vector field can be quantified. The rate-distortion function describes the relationship between the encoding bit-rate required for transmission of the measured displacement vector field and the variance of the spatial and amplitude resolution of the encoded displacement vector field is described. The 2D motion model is considered by low pass filtering simulations of various displacement estimation techniques, the 2D motion models which are described by the nearest neighbour, affine and bilinear displacement vector interpolation, at different amplitude and spatial resolutions. The analytical description allows one to optimize a displacement estimation technique for motion compensated image sequence coding. © 1997 Elsevier Science B.V.

Keywords: Image coding; Generalized displacement estimation; Displacement coding; Rate distortion theory

I. Introduction
For efficient coding of moving images block-based motion compensated coding is applied in todays coding standards. The motion is represented by displacement vector fields, which are measured with help of displacement estimation techniques. In order to improve the efficiency of block-based motion compensated coding - displacement estimation with variable displacement amplitude resolution [5].

- displacement estimation with variable spatial resolution [2, 10].
- displacement estimation using 2D transformations [3, 11, 13, 15, 16, 19] have been proposed in the recent literature and are currently investigated in MPEG-4 [6, 7].

In displacement estimation with variable amplitude resolution, the amplitude resolution of the displacement vector is not kept fixed at integer or half pel resolution as in todays standards, but can vary adaptively among various resolutions, e.g. 0.5, 0.25 or 0.125 pixels.

In displacement estimation with variable spatial resolution the spatial distance of displacement
vectors varies adaptively, e.g. among $4 \times 4$, $8 \times 8$, $16 \times 16$, $32 \times 32$ and $64 \times 64$. Thus the displacement vector field can be represented with increased spatial resolution near the boundaries of moving objects.

Displacement estimation techniques using 2D transformations can be described by sparse displacement estimation combined with subsequent spatial interpolation. Although the subsequent spatial interpolation is not always carried out explicitly, it is inherent in the 2D transformation. Typical interpolation techniques applied are the affine or bilinear interpolation of estimated displacement vectors at node locations of a regular triangular or quadrilateral mesh overlaid on the image. The attachment of a single estimated displacement vector to a whole block in traditional block matching can be viewed as nearest neighbour interpolation of displacement vectors at node locations of a regular quadrilateral mesh.

The aim of this work is an objective assessment of the efficiency of the displacement estimation techniques in a video coding system by their rate-distortion functions. The rate-distortion function of a displacement estimation technique describes the relationship between the theoretical lower bound of its displacement estimation error and the encoding bit-rate required for transmission of an estimated sparse displacement field.

Both, the theoretical lower bound of the displacement estimation error and the encoding bit-rate of the estimated sparse displacement vector field, depend on its amplitude and spatial resolution. The theoretical lower bound of the displacement estimation error additionally depends on the kind of displacement vector interpolation. An objective assessment of the various estimation techniques independent of any test sequence and any implemented optimisation strategy is only possible with an analytical description of displacement estimation.

For this purpose, in its first part, this paper describes displacement estimation analytically giving additional insight into the sources of displacement errors. In the second part, rate-distortion theory is combined with the analytical description of displacement estimation to appraise the encoding bit-rate for the displacement vector fields.

The rate-distortion functions of displacement estimation techniques presented in this paper relate the lower bound of the displacement estimation error to the encoding bit-rate of the displacement information. An analytical description that relates the variance of the displacement estimation error to the encoding bit-rate of the prediction error image needed to gain a predefined image quality is presented in [4]. Combining the results of the work presented in this paper with the work presented in [4], it is seen as a good start to reach the goal of finding the theoretically optimum bit allocation for the displacement information and the prediction error image.

In Section 2 the analytical description of displacement estimation is derived. Section 3 extends the analytical description by consideration of displacement coding. In Section 4 the model parameters for the exact displacement signal are given. Experimental results are presented and discussed in Section 5. Section 6 contains the conclusions.

2. Analytical description of displacement estimation

In this work the exact displacement signal is assumed to be known. It is viewed as a two-dimensional signal, with two components, that exists in the image plane. It cannot be measured directly, but it leads to the temporal changes observable in the image sequence. Each component of the displacement signal is assumed to be discrete in time, but space- and amplitude-continuous (the amplitude is real valued). Discontinuities in their amplitude and spatial resolution. The theoretical lower bound of the displacement estimation error additionally depends on the kind of displacement vector interpolation. An objective assessment of the various estimation techniques independent of any test sequence and any implemented optimisation strategy is only possible with an analytical description of displacement estimation.

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The examined techniques require that both the estimation filter and the reconstruction filter are applied separately to the two components of the displacement signals. Thus for simplicity of the following description all signals are viewed as one-component signals.

The aim of the following is to relate the power spectral density $S_{x}(f_{x}, f_{y})$ of the exact displacement signal $d(x, y)$ to the power spectral density $S_{s}(f_{x}, f_{y})$ of the displacement error signal $e_{d}(x, y)$. The exact displacement signal $d(x, y)$ is assumed to be a real zero-mean ergodic wide-sense stationary stochastic process. It is important to note here that due to the sampling, the sampled displacement signal $d_{s}(x, y)$, the quantised displacement signal $d_{q}(x, y)$, the reconstructed displacement signal $d_{r}(x, y)$ and the displacement error signal, are no longer wide-sense stationary. However, they can be described as wide-sense cyclostationary, which means that their mean and autocorrelation fluctuate periodically in time. In other words, their mean and autocorrelation are invariant to a shift of the origin by integral multiples of $T_{x}$ in the $x$-direction and/or of $T_{y}$ in the $y$-direction, where $T_{x}$ and $T_{y}$ denote the horizontal and vertical sampling periods. Cyclostationary processes may be treated as they were stationary, by simply averaging the statistical parameters over one cycle $[16]$.

To reach the goal of relating the power spectral density of the exact displacement signal to the power spectral density of the displacement error signal, in a first step the estimation filtering, the sampling, the quantisation, and the reconstruction filtering are described separately. Combining these descriptions in a second step, the desired relation is derived.

2.1. Estimation filtering

Let $H_{1}(f_{x}, f_{y})$ denote the frequency response of the estimation filter. The power spectral density
2.2 Sampling

The power spectral density \( S_{dd}(f_x, f_y) \) of the sampled displacement signal, denoted by \( d(x, y) \), is given by normalised shifted copies of the power spectral density of the filtered displacement signal [18]:

\[
S_{dd}(f_x, f_y) = \frac{1}{T_{dx} T_{dy}} \sum_{n_x=-\infty}^{\infty} \sum_{n_y=-\infty}^{\infty} S_{dd}\left( f_x + \frac{n_x}{T_{dx}}, f_y + \frac{n_y}{T_{dy}} \right),
\]

with \( T_{dx} \) and \( T_{dy} \) denoting the horizontal and vertical sampling periods. For the simplicity of further writing let us simplify (2) by

\[
S_{dd}(f_x, f_y) = \sum_{n_x} \sum_{n_y} S_{dd}\left( f_x + \frac{n_x}{T_{dx}}, f_y + \frac{n_y}{T_{dy}} \right),
\]

\[
S_{dd}(f_x, f_y) = \sum_{n_x} \sum_{n_y} S_{dd}\left( f_x + \frac{n_x}{T_{dx}}, f_y + \frac{n_y}{T_{dy}} \right) \times H_d(f_x + \frac{n_x}{T_{dx}}, f_y + \frac{n_y}{T_{dy}}),
\]

valid when the quantisation step size is small with respect to the variance of the sampled displacement signal. The power spectral density \( S_{dd}(f_x, f_y) \) of the quantisation noise signal is assumed to be white with variance \( \sigma_q^2 \).

Assuming uniform quantisation of \( d(x, y) \) with step size \( A \) and \( K \) quantisation steps and a probability density function \( p_d(d) \) of the displacement signal, the quantisation error variance can be calculated as

\[
\sigma_q^2 = \int_{-A/2}^{A/2} d^2 p_d(d) \, \mathrm{d}d,
\]

2.3. Quantisation

The influence of the quantiser is described by a quantisation noise signal denoted by \( q_d(x, y) \). The quantisation noise signal is assumed to be independent of the sampled displacement signal, which is constructed displacement signal, denoted by \( \bar{d}(x, y) \), of the quantised displacement signal is then given by

\[
S_{dd}(f_x, f_y) = S_{dd}(f_x, f_y) + \sigma_q^2,
\]

The power spectral density \( S_{dd}(f_x, f_y) \) of the quantised displacement signal is given by

\[
S_{dd}(f_x, f_y) = \frac{1}{T_{dx} T_{dy}} S_{dd}(f_x, f_y) H_d(f_x, f_y)^2,
\]

2.4. Reconstruction filtering

Considering the cyclostationarity of the reconstructed displacement signal, denoted by \( \tilde{d}(x, y) \), its averaged power spectral density \( S_{dd}(f_x, f_y) \) is given by [18]:

\[
S_{dd}(f_x, f_y) = \frac{1}{T_{dx} T_{dy}} S_{dd}(f_x, f_y) H_d(f_x, f_y)^2,
\]

where \( H_d(f_x, f_y) \) denotes the frequency response of the reconstruction filter.

2.5. Power spectral density of the displacement error signal

With the given separate descriptions, it is now straightforward to relate the power spectral density of the displacement error signal to the power spectral density of the displacement signal. The autocorrelation function \( R_{dd}(\tau_x, \tau_y) \) of the cyclostationary displacement error signal,

\[
R_{dd}(\tau_x, \tau_y) = \mathbb{E}\{\bar{d}(x, y)\bar{d}(x-\tau_x, y-\tau_y)\} = E[\tilde{d}(x, y) - d(x, y)]E[\bar{d}(x-\tau_x, y-\tau_y) - \bar{d}(x-\tau_x, y-\tau_y)] = R_{dd}(\tau_x, \tau_y) - R_{dd}(\tau_x, \tau_y) - R_{dd}(\tau_x, \tau_y) + R_{dd}(\tau_x, \tau_y),
\]

depends on the spatial reference given by the sampling points. \( R_{dd}(\tau_x, \tau_y) \) denote the cross-correlation between the exact displacement signal and the reconstructed displacement signal. We can treat the displacement error signal as stationary, by averaging over one cycle. The power spectral density \( S_{dd}(f_x, f_y) \) of the displacement error signal is then given by

\[
S_{dd}(f_x, f_y) = S_{dd}(f_x, f_y) - 2S_{dd}(f_x, f_y) + S_{dd}(f_x, f_y),
\]

with \( f_x = f_x, f_y \),

\[
S_{dd}(f_x, f_y) = \frac{1}{T_{dx} T_{dy}} S_{dd}(f_x, f_y) H_d(f_x, f_y)^2
\]

2.6. Estimation and reconstruction filter frequency responses

To examine the different 2D transformation models, the frequency responses of the reconstruction filter for nearest neighbor interpolation, the affine, and the bilinear interpolation, have been calculated (see [Appendix A]):

\[
H_{\text{nn}}(f_x, f_y) = \text{rect}(f_x, f_y) \text{sinc}(\pi T_{dx}, f_y) \text{sinc}(\pi T_{dy}, f_x),
\]

\[
H_{\text{aff}}(f_x, f_y) = \text{rect}(f_x, f_y) \text{sinc}(\pi T_{dx}, f_y) \text{sinc}(\pi T_{dy}, f_x) \text{rect}(\pi T_{dx}, f_x) \text{rect}(\pi T_{dy}, f_y),
\]

\[
H_{\text{bil}}(f_x, f_y) = \text{rect}(f_x, f_y) \text{sinc}(\pi T_{dx}, f_y) \text{sinc}(\pi T_{dy}, f_x) \text{rect}(\pi T_{dx}, f_x) \text{rect}(\pi T_{dy}, f_y),
\]

\[
H_{\text{w}}(f_x, f_y) = \frac{1}{T_{dx} T_{dy}} S_{dd}(f_x, f_y) H_d(f_x, f_y)^2.
\]

Inserting now Eqs. (11) and (12) into Eq. (10) after some simplifications leads to the desired relationship between the power spectral density of the exact displacement signal and the power spectral density of the displacement error signal:

\[
S_{dd}(f_x, f_y) = S_{dd}(f_x, f_y) \text{sinc}^2(\pi T_{dx}, f_y) \text{sinc}^2(\pi T_{dy}, f_x)
\]

The performance of the displacement estimation technique is then assessed by the error variance \( \sigma_{q_d}^2 \) which can be calculated using Parseval's relation

\[
\sigma_{q_d}^2 = \int_{-A/2}^{A/2} \int_{-A/2}^{A/2} S_{dd}(f_x, f_y) \, \mathrm{d}f_x \, \mathrm{d}f_y,
\]
Estimation and reconstruction filter. As a quality measure for the reconstructed displacement vector field the displacement error variance has been used.

In this section the analytical description is extended to allow an objective assessment of the efficiency of the displacement estimation techniques in a video coding system by their rate-distortion functions. The rate-distortion function of a displacement estimation technique describes the relationship between the encoding bit-rate required for transmission of an estimated sparse displacement vector field and the corresponding theoretical lower bound of its displacement error.

The transmission rate needed to code an estimated sparse displacement vector field is affected by its spatial resolution and by its amplitude resolution. Assuming that the signal to be coded consists of real-valued samples (amplitude-continuous source), rate-distortion theory may be used to determine a rate-distortion function, which relates a predefined transmission rate for this signal (in bits/sample) to the corresponding minimum variance of the noise. The coding noise shall include all errors introduced during coding. It is related to the sampled signal. For an objective assessment of the spatial resolution of estimated sparse displacement vector fields, it is thus necessary to combine rate-distortion theory with the analytical description presented in the previous section. The relation between transmission rate and displacement reconstruction error variance then serves for an objective comparison of different spatial resolutions.

The coding process can be described by passing the signal to be transmitted, e.g. the sampled displacement signal, through a filter with the coder transfer function $G(f)$ and the addition of coding noise $S_{\text{coding}}(f)$. The coding noise shall include all errors introduced during coding. It is related to the sampled signal. For an objective assessment of the spatial resolution of estimated sparse displacement vector fields, it is thus necessary to combine rate-distortion theory with the analytical description presented in the previous section. The relation between transmission rate and displacement reconstruction error variance then serves for an objective comparison of different spatial resolutions.

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of the specific implementation of the encoder used for the displacement vector field encoding. Assume that the displacement vector field to be coded is passed through the 'optimum forward channel'. This channel describes the transformation between coder input and decoder output for the lowest transmission rate with respect to a predefined distortion. For the case of a zero-mean Gaussian source with memory, it consists of a nonideal band-limiting filter with a transfer function [9]

\[ G(f) = \max \left\{ 0, 1, -\frac{\theta}{S_{dd}(f)} \right\} \]  

(29)

followed by an addition of a band-limited, non-white Gaussian noise with a power spectral density

\[ S_{\text{sp,n,n}}(f) = \Theta \max \left\{ 0, 1 - \frac{\theta}{S_{dd}(f)} \right\} \]  

(30)

Now for the assumption that the two components of the displacement vector field have a Gaussian joint probability density function (p.d.f.) and the two components with distortion \( \Theta \) is given by [9]

\[ R_{\text{u,n,n}}(\Theta) = \frac{1}{2} \max \left\{ 0, \log \frac{S_{\text{dd},A}(f)}{\Theta} \right\} \]  

(31)

bit per coded vector.  

It is obvious now, that only frequency-bands with power spectral density above \( \Theta \) are coded. By varying the parameter \( \Theta \) we can now analyse the rate-distortion functions of the given idealised coders for various sampling ratios and displacement reconstruction filters. 

Again, (31) gives an upper bound for non-Gaussian sources with equal power spectral density.

4. Model assumptions and parameters

In the previous sections an analytical description of displacement estimation and coding has been presented. For a quantitative evaluation of (14) the exact displacement signal and the quantisation noise signal must be described by parametric models which, in the statistic mean, represent their power spectral densities in image sequences.

4.1. Model assumptions

Here an isotropic autocorrelation function has been chosen to describe the exact displacement signal:

\[ R_D(\Delta x, \Delta y) = \sigma_d^2 e^{-\Delta x^2 + \Delta y^2} \]  

(32)

This model is characterised by the model parameter \( \sigma_d^2 \) and \( \Delta \). The power spectral density \( S_{\text{dd}}(f) \) can be calculated from (32) by Fourier transformation of \( R_D(\Delta x, \Delta y) \) and band-limitation to the half of the horizontal and vertical sampling frequencies of the image signal \( f_{x,a} \) and \( f_{x,v} \):

\[ S_{\text{dd}}(f_{x,a}, f_{x,v}) = \frac{\sigma_d^2}{2\pi} \left\{ \frac{f_{x,a}^2}{f_{x,a}^2 + f_{x,v}^2} \right\}^{\frac{v^2}{2}}, \]  

for \( |f_{x,a}| \leq f_{x,a}/2, |f_{x,v}| \leq f_{x,v}/2 \),

(33)

0, else.

The power spectral density \( S_{\text{dd}}(f) \) has been measured using the Welch's method [17] for all images of the four test sequences. Furthermore the variance \( \sigma_d^2 \) and the correlation coefficient \( \phi_d \) of horizontally neighboured displacement vectors of the pejus displacement vector fields have been measured. With

\[ \phi_d = \frac{R_{\text{d},f_{x,a} f_{x,v}}}{\sigma_{d,x} \sigma_{d,y}}, \]  

(38)

\( \sigma_d^2 \) has been calculated by

\[ \sigma_d^2 = -\frac{2\Delta \ln \phi_d}{2\pi}, \]  

(39)

where \( \Delta \) determines the spatial resolution of the displacement field.

For an analytical description of the probability density function (p.d.f.) of the displacement signal a generalized Gaussian p.d.f. [12] has been chosen:

\[ p_D(d) = \frac{1}{\sigma_d \Gamma(v/2)} \left( \frac{d}{\sigma_d} \right)^{v/2} e^{-d^2/(2\sigma_d^2)} \]  

(37)

with

\[ r(v) = f(v^2), \quad f: \Gamma \]  

and model correlation coefficients on the other side. The parameter \( \nu \) is given in Table 1 for \( v = 0.3 \).

5. Quantitative evaluations

The analytical description is now used for an examination of displacement estimation and displacement vector field coding.

5.1. Examination of displacement estimation

The first two simulations address the performance of the different reconstruction filters. For this, the frequency response of the implicit estimation filter is set to one: \( H(\omega) = 1 \). No amplitude quantisation was performed: \( S_{\text{q},f_{x,a}}(f) = 0 \). In the first simulation the different reconstruction filters are examined for various spatial resolutions. As can be seen in Fig. 3, the displacement error

<table>
<thead>
<tr>
<th>Displacement amplitude resolution</th>
<th>1</th>
<th>1.2</th>
<th>1</th>
<th>1.8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Displacement quantisation error variance</td>
<td>0.04</td>
<td>0.013</td>
<td>0.004</td>
<td>0.001</td>
</tr>
</tbody>
</table>
variance $\sigma_n^2$ increases almost linearly with the spatial distance of samples. The lowest error is achieved with the Wiener filter. The affine and bilinear interpolation achieve a performance similar to the Wiener filter. The displacement error variance for nearest neighbour interpolation is almost 2 times the error variance of the affine and bilinear interpolation.

The second simulation addresses the influence of the amplitude resolution of the estimated vector field. The frequency response of the implicit estimation filter was chosen corresponding to the interpolation filter.

As can be seen the calculated figures coincide well with the measured figures for fine displacement amplitude resolutions. The small differences which can be noticed for full pel amplitude resolution are due to the description of the quantisation. Although the coarse step size has been considered in the quantiser model for the calculation of the quantisation error variance, its influence on the auto-correlation of the displacement error signal and on the cross-correlation between the displacement signal and the displacement error signal has been neglected. The displacement error signal has been assumed to have a white power spectral density (no auto-correlation) and to be additive to the displacement signal (no cross-correlation). This explains the small errors for coarser displacement amplitude resolutions.

A comparison of Fig. 4 with Fig. 5 shows a significant reduction of the displacement error variance for nearest neighbour interpolation than in the case of bilinear interpolation.

To confirm these theoretical results, for the third simulation the pelwise given displacement vector fields used for the definition of the model power spectral density were sampled and reconstructed using nearest neighbour and bilinear interpolation. The resulting displacement error variances $\sigma_n^2$ for these cases were measured. Exemplary results are given in Table 2 for nearest neighbour interpolation and bilinear interpolation with various amplitude resolutions of the displacement vectors and a spatial distance of 16x16 pel.

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The fourth simulation addresses the influence of the implicit estimation filter. A comparison between different amplitude resolutions of the displacement vectors for different spatial resolutions and for bilinear and nearest neighbour interpolation is given in Fig. 4. It can be seen that the displacement error variance decreases with the increase of the amplitude resolution of the displacement vectors. A large gain is reached by using half pel resolution instead of full pel resolution, whereas higher resolution than half pel leads to only marginal benefits. In general, the displacement error variance is more affected by the amplitude resolution in the case of nearest neighbour interpolation than in the case of bilinear interpolation.

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due to the estimation filter. This fact can be explained by Fig. 6. It shows how the reconstruction error is formed by using different estimation and reconstruction filters. When no estimation filter is used, the error is formed by the difference between the sampled signal and the reconstructed signal at the sampling points. At all other points a significant reconstruction error might occur and the displacement error variance might be large (see Fig. 6a) for the case of \(H(\hat{f}(\tau)) = 1\). The estimation filter is calculated in such a way that the displacement error variance of the reconstructed displacement signal is minimized. However, as a result of the minimization the reconstructed displacement signal at the sampling points is no longer exact (see Fig. 6b) for the case of \(H(\hat{f}(\tau)) = H_{\text{nearest}}(\tau)\) and \(H(\hat{f}(\tau)) = H_{\text{nearest}}(\tau)\). It is now averaged over the six nearest neighbours in the local neighbourhood. The reconstruction error is significantly reduced by applying the bilinear estimation and reconstruction filter \(H(\hat{f}(\tau)) = H_{\text{nearest}}(\tau)\) and \(H(\hat{f}(\tau)) = H_{\text{nearest}}(\tau)\). A comparison between Figs. 6(b) and 6(c) shows how the sampled signals differ when different estimation filters are used. This supports the fact that the same motion compensation method as has been used for the displacement estimation should be used for the motion compensated prediction of the image signal.

As one final result we can see from Fig. 5 that when the estimation filter is considered in the analytical description, the displacement error variance for a spatial distance of 16 pel and full pel amplitude resolutions in case of nearest neighbour interpolation is 1.56 times the error variance of bilinear interpolation.

The results given have been obtained as an average for the four test sequences. Of course the absolute figures given depend on the test sequence and the kind and the amount of 2D motion within the scene. If the scene contains mainly 2D translational motion and thus the correlation coefficient of horizontally neighboured samples of the exact displacement field are higher than assumed here, the slope of the curves given in Figs. 3-5 will be smaller. However, the relation between the curves will stay the same. If the scene contains a large amount of 2D motion and thus the displacement variance is higher than assumed here, the displacement error variance will also be higher than that given in Fig. 5 for coarse displacement amplitude resolutions (e.g. full pel displacement amplitude resolutions).

5.2. Examination of displacement vector field coding

The next simulations address the influence of the sampling ratio on the transmission rate needed to achieve a predefined displacement error variance. For these simulations the frequency response of the implicit estimation filter is set to one: \(H(\hat{f}(\tau)) = 1\). For the case of the reconstruction filter being the nearest neighbour interpolation filter or the bilinear interpolation filter, the resulting rate-distortion functions for encoding the displacement vector field with the assumption of a Gaussian source with memory according to Eq. (31) are depicted in Fig. 7.

As can be seen the spatial resolution of displacement vectors is a limiting factor for the achievable displacement error variance. Thus, if a low displacement error variance is desired, a low spatial distance of displacement vectors has to be chosen. For high displacement error variances the different distortion functions merge. For the quality criterion of displacement error variance it is unimportant whether errors are included due to displacement vector field sampling or due to displacement vector amplitude quantisation. It can be seen further that for each spatial resolution of the displacement vector field, the rate-distortion function for the bilinear interpolation filter is below the corresponding rate-distortion function for the nearest neighbour interpolation filter.

For an optimum coding the spatial resolution of the vector fields must be chosen in such a way that the working point of the encoder lies on the lower bounding curve. This lower bounding curve is the same as the given rate-distortion curve for spatial distance of displacement vectors of one. However, as can be seen in Fig. 7 for a distortion of \(\sigma^2 = 0.19\) in the case of nearest neighbour interpolation and \(\sigma^2 = 0.12\) in the case of bilinear interpolation, a spatial distance of displacement vectors of 16 is sufficient. Regarding again Table 2 we see that these limits are given by 1 pel displacement vector amplitude resolution. For coding displacement vector fields with less distortion, it seems to be advantageous to increase the spatial resolution instead of the amplitude resolution of the displacement vectors in order to code a displacement vector field at a minimum transmission rate. Of course in a real codec the influence of the displacement error onto the prediction error image has to be taken into account. One way to find a theoretically optimal bit allocation for the displacement information and the prediction error might be to combine the analytical description presented here with the analytical description of motion compensating prediction presented in [4].

To compare these theoretical results with the transmission rates for displacement vector fields in today’s video coding standards, rate-distortion values have been measured. For this purpose again the pelwise given displacement vector fields used for the definition of the model power spectral density were sampled with a spatial distance of 16 and 8 pel and the amplitude has been quantized with amplitude resolutions of 1, 1.2 and 1.4 pel. Distortion values for a spatial distance of 16 pel have already been given in Table 2. To measure the transmission rate, in one simulation the sampled and quantised displacement vector fields have been coded without spatial prediction, whereas in another simulation the spatial displacement vector prediction method of the H.263 [5] video coding...
standard has been applied. According to the H.263 video coding standard a displacement vector prediction is obtained by first quantising the displacement vectors to full pel, half pel or quarter pel amplitude resolution and then calculating a median displacement vector of the left, upper and upper left neighbour. To be independent of the implemented Huffman coding tables, which cannot be optimum, the entropy of the error between the displacement vector prediction and the quantised displacement vectors is calculated. This entropy gives the lower bound for the transmission rate achievable by entropy encoding, e.g. Huffman coding.

For a qualitative assessment of the measured entropy values and corresponding distortion values, the rate-distortion curves for the assumption of a memoryless Gaussian source \( R_{G,m}(\sigma^2_e) \) and a Gaussian source with memory \( R_{G.mie}(\sigma^2_e) \), Eq. (31), have been calculated. Remember that \( R_{G,mie}(\sigma^2_e) \) gives an upper bound for signals with the same power spectral density but non-Gaussian p.d.f., when still a Gaussian p.d.f. of the quantisation error signal is assumed. As we know the p.d.f. of displacement vector fields is non-Gaussian.

By exploiting the spatial correlation of displacement vector fields a reduction of transmission rate is achieved. Again, \( R_{G,mie}(\sigma^2_e) \) gives an upper bound for signals with non-Gaussian p.d.f., when still a Gaussian p.d.f. of the quantisation error signals is assumed. Consequently, if Gaussian p.d.f. of the quantisation error signals can further be assumed, an optimum exploitation of the spatial correlations of displacement vector fields drops transmission rates to \( R_{G,m}(\sigma^2_e) \) or even below.

6. Conclusions

An analytical description of displacement estimation is presented which allows an objective evaluation and comparison of various displacement estimation techniques. An additional value of the analytical description of displacement estimation is seen in its potential for an in-depth understanding of the different error sources of displacement estimation. Displacement estimation is described analytically by low pass filtering, spatial sampling, quantisation and reconstruction of an exact displacement vector field.

For the purpose of analysis the rate-distortion theory is applied. Distortion is introduced by a limited displacement vector amplitude resolution (quantisation) and a limited spatial resolution of displacement vector fields (sampling). From the view of this general description of displacement vector field coding, the term 'lossless encoding of displacement vector fields' as used frequently in the literature describes the encoding of displacement information which is already distorted. The displacement reconstruction filter applied to transmitted displacement vector fields reduces the distortion, i.e. the displacement error variance.

Comparisons of various displacement reconstruction techniques applied to displacement vector fields with various amplitude and spatial resolutions show that the bilinear interpolation filter performs always better than the nearest neighbour interpolation filter and very close to optimum Wiener filter. The affine interpolation filter performs slightly worse than the bilinear interpolation filter. The theoretical results obtained for various displacement vector amplitude resolutions, various spatial resolutions, and various displacement reconstruction techniques confirm the results achieved by heuristics.

During displacement estimation a local neighbourhood in the image signal is used to determine one displacement vector. Thus, if the picture elements in the local neighbourhood have been displaced differently the estimated displacement vector is not a sample of the displacement signal, but an averaged value of the displacements in the local neighbourhood. This effect is described by passing the displacement signal through an estimation filter before sampling. For each reconstruction filter there exists a corresponding optimal estimation filter, the transfer function of which is presented. Simulations show that a corresponding pair of estimation and reconstruction filter leads to a significant decrease of the displacement error variance. This means for practical implementations that the same reconstruction filter as has been used for the displacement estimation must be used for the motion compensated prediction of the image signal.

The rate-distortion analysis shows that allowing an infinite displacement vector amplitude resolution, the spatial resolution of the displacement vector field is a limiting factor for the achievable distortion, i.e. the displacement error variance. Thus, if a low displacement error variance is desired a high spatial resolution of displacement vector fields has to be chosen. The rate-distortion analysis confirms that for a full pel displacement vector amplitude resolution a spatial distance of displacement vectors of 16 x 16 pel is a good choice. For coding displacement vector fields with a lower distortion, the results propose to increase the spatial resolution instead of the amplitude resolution of the displacement vectors in order to code a displacement vector field at a lower transmission rate.

In a video coding system the influence of the displacement error onto the motion compensated prediction error of the luminance and chrominance samples has to be taken into account additionally. In order to find the theoretically optimum bit allocation for the displacement information and the prediction error image the analytical description presented here can be combined with the analytical description of motion compensating prediction presented in [4].

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Appendix A. Calculation of reconstruction filter frequency responses

The reconstruction filter serves for the spatial interpolation of a sparse displacement vector field. The interpolation techniques under consideration here are the affine and bilinear interpolation of estimated displacement vectors at node locations of a regular triangular or quadrilateral mesh. The attachment of a single estimated displacement vector to a whole block in traditional block matching is viewed as nearest neighbour interpolation of displacement vectors at node locations of a regular quadrilateral mesh.

To describe the reconstruction of the displacement signal within one mesh element (patch) of a regular quadrilateral mesh a local coordinate system with coordinates \(X, Y\) has been chosen. Its coordinates \((X_0, Y_0)\) of the upper left node of the patch has been chosen. Its coordinates \((X_0, Y_0)\) for which a displacement vector shall be calculated:

\[
X_0 = \text{INT}(x_0/M) M, \quad Y_0 = \text{INT}(y_0/N) N. \tag{A.1}
\]

where \(\text{INT}(\cdot)\) denotes the integer operation and \(M, N\) the horizontal and vertical distance of nodes of the mesh. The distance of nodes of the mesh corresponds to the horizontal and vertical sampling period of the displacement signal

\[
M = T_e, \quad N = T_e. \tag{A.2}
\]

The local coordinates of the point under consideration are then given by

\[
X = x_0 - X_0, \quad Y = y_0 - Y_0. \tag{A.3}
\]

For reconstruction of \(d(X, Y)\) from the quantised four nearest samples \(d_{0,0} = d_0(0,0), d_{M,0} = d_0(M,0), d_{0,N} = d_0(0,N)\) and \(d_{M,N} = d_0(M,N)\) of the filtered displacement signal (Fig. 9), by use of nearest neighbour interpolation, bilinear interpolation, or affine interpolation, we get

\[
d_{\text{nearest}}(X, Y) =\begin{cases} 
  d_{0,0} & \text{for } 0 < X < M/2, \quad 0 < Y < N/2, \\
  d_{M,0} & \text{for } M/2 < X < M, \quad 0 < Y < N/2, \\
  d_{0,N} & \text{for } 0 < X < M, \quad N/2 < Y < N, \\
  d_{M,N} & \text{for } M/2 < X < M, \quad N/2 < Y < N, 
\end{cases} \tag{A.4}
\]

\[
d_{\text{bilinear}}(X, Y) = \frac{1}{2} \left( 1 + \frac{X}{M} \right) \left( 1 + \frac{Y}{N} \right) d_{0,0} + \frac{X}{M} \left( 1 + \frac{Y}{N} \right) d_{M,0} + \frac{1}{2} \left( 1 + \frac{X}{M} \right) \left( 1 + \frac{Y}{N} \right) d_{0,N} + \frac{Y}{N} \frac{1}{2} \left( 1 + \frac{X}{M} \right) d_{M,N} \text{for } 0 < X < M, \quad 0 < Y < N, \tag{A.5}
\]

\[
d_{\text{affine}}(X, Y) =\begin{cases} 
  \left( 1 + \frac{X}{M} \right) d_{0,0} + \left( \frac{X}{M} - 1 \right) \frac{Y}{N} d_{M,0} + \frac{Y}{N} d_{0,N} & \text{for } 0 < X < M, \quad 0 < Y < N, \\
  \left( 1 + \frac{Y}{N} \right) d_{0,0} + \left( \frac{Y}{N} - 1 \right) \frac{X}{M} d_{0,N} + \frac{X}{M} d_{M,N} & \text{for } 0 < X < M, \quad N/2 < Y < N. 
\end{cases} \tag{A.6}
\]

Regarding the general description for two dimensional filtering,

\[
d(X, Y) = d(X, Y) * h(Y, X) = \iiint d_0(X', Y') h_2(X-X', Y-Y') dX' dY'. \tag{A.7}
\]

The filter impulse responses are obtained by comparing the coefficients

\[
b_{2,\text{nearest}}(X, Y) = \begin{cases} 
  1 & \text{for } 0 < |X| < M/2, \quad 0 < |Y| < N/2, \\
  0 & \text{else,}
\end{cases} \tag{A.8}
\]

\[
b_{2,\text{bilinear}}(X, Y) = \begin{cases} 
  (1 - X/M)(1 - Y/N) & \text{for } 0 < X < M, \quad 0 < Y < N, \\
  (1 + X/M)(1 - Y/N) & \text{for } -M < X < 0, \quad 0 < Y < N, \\
  (1 - X/M)(1 + Y/N) & \text{for } 0 < X < M, \quad -N < Y < 0, \\
  (1 + X/M)(1 + Y/N) & \text{for } -M < X < 0, \quad -N < Y < 0, 
\end{cases} \tag{A.9}
\]

\[
b_{2,\text{affine}}(X, Y) = \begin{cases} 
  1 - X/M & \text{for } 0 < X < M, \quad 0 < Y < N, \\
  1 + X/M - Y/N & \text{for } -M < X < 0, \quad 0 < Y < N, \\
  1 + Y/N & \text{for } -M < X < 0, \quad -N < Y < N, \\
  1 + Y/N - X/M & \text{for } 0 < X < M, \quad N < Y < N, \\
  1 + Y/N & \text{for } 0 < X < M, \quad X < N, \\
  1 + X/M & \text{for } -M < X < 0, \quad N < Y < N, \\
  1 + X/M & \text{for } -M < X < 0, \quad X < N, \\
  0 & \text{else.}
\end{cases} \tag{A.10}
\]

Now the frequency responses \(H(f)\) can be calculated by Fourier Transformation of the reconstruction filter impulse responses:

\[
H_{2,\text{nearest}}(f_x, f_y) = MN \sin(\pi M f_x) \sin(\pi N f_y), \tag{A.11}
\]

\[
H_{2,\text{bilinear}}(f_x, f_y) = MN \sin^2(\pi M f_x) \sin^2(\pi N f_y), \tag{A.12}
\]

\[
H_{2,\text{affine}}(f_x, f_y) = MN \sin(\pi M f_x) \sin(\pi N f_y) \sin(\pi (M f_x + N f_y)). \tag{A.13}
\]

Eqs. (15) (17) then follow with (A.2).
Appendix B. Calculation of estimation filter frequency responses

The estimated displacement vector in general is not a sample of the true displacement signal, but is an averaged value of the displacements in the local neighbourhood. This effect has be modelled by low pass filtering the true displacement signal before sampling. To simplify the calculations it is assumed in the following that displacement estimation can be expressed as a minimisation of the squared difference between the exact displacement signal and a displacement signal, which is implicitly interpolated from the sparse displacement vector field to be estimated. This implicit displacement signal depends on the 2D transformation model of the displacement estimator. The assumption of minimizing the squared difference between the two displacement signals is valid, when during displacement estimation the squared difference between the motion compensated previous frame and the original frame is evaluated in large measurement windows.

Now we have to determine the frequency response $H_i(f_0, f_1)$ for each frequency $f_0 = (f_{0x}, f_{0y})^T$ in such a way, that the displacement error variance according to Eq. (14) with (13) and (4) becomes minimum:

$$\sigma_0^2 = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left( H_i(f_0, f_1) H_i(f_0, f_1) - 1 \right)^2 \right) df_0 df_1 \rightarrow \text{MIN}. \quad (B.1)$$

Please remember, that all considered frequency responses are real. By partial derivation of $\sigma_0^2$ with respect to $H_i(f_0, f_1)$ we get, as long as $H_i(f_0, f_1)$ does not depend on $H_i(f_0, f_1)$, a condition for $H_i(f_0, f_1)$:

$$1 \frac{\partial \sigma_0^2}{\partial H_i(f_0, f_1)} = - SD(f_0, f_1) \left( H_i(f_0, f_1) H_i(f_0, f_1) - 1 \right) \left( 1 \frac{1}{T_{a, x} T_{a, y}} H_i(f_0, f_1) + \sum_{n \in \mathbb{Z}, m \neq 0} H_i(f_0, f_1) \left( 1 \frac{1}{T_{a, x} T_{a, y}} H_i(f_0, f_1) - m \frac{T_{a, x}}{T_{a, y}} n \frac{T_{a, y}}{T_{a, x}} \right)^2 \right) \rightarrow 0 \quad \text{for each } f_0 = (f_{0x}, f_{0y})^T, \quad (B.2)$$

which can be solved for $H_i(f_0, f_1)$:

$$H_i(f_0, f_1) = \frac{1}{1 \frac{1}{T_{a, x} T_{a, y}} \sum_{n \in \mathbb{Z}, m \neq 0} H_i(f_0, f_1) \left( 1 \frac{1}{T_{a, x} T_{a, y}} H_i(f_0, f_1) - m \frac{T_{a, x}}{T_{a, y}} n \frac{T_{a, y}}{T_{a, x}} \right)^2} \quad (B.3)$$

For an evaluation of Eq. (B.3) it is useful to simplify the denominator, because of the infinite summation. The denominator describes normalised shifted copies of $(H_i(f_0, f_1))^2$. It is thus the Fourier transform of a sampled "signal" given by $H_i(f_0, f_1) h_1(x - n, y - m)$, where the operator $(**)$ denotes two-dimensional convolution. We can thus write for $H_i(f_0, f_1)$:

$$H_i(f_0, f_1) = \frac{1}{1 \frac{1}{T_{a, x} T_{a, y}} \sum_{n \in \mathbb{Z}, m \neq 0} H_i(f_0, f_1) \left( 1 \frac{1}{T_{a, x} T_{a, y}} H_i(f_0, f_1) - m \frac{T_{a, x}}{T_{a, y}} n \frac{T_{a, y}}{T_{a, x}} \right)^2} \quad (B.4)$$

The reconstruction filter under consideration here have short impulse responses and (B.4) can be evaluated easily. The desired estimation filter frequency responses are given in Eqs. (20)-(22).

References


Ralf Buschmann was born in Bielefeld, Germany, in 1963. He received the Dipl.-Ing. degree in electrical engineering from the University of Hannover, Germany, in 1989. Since 1989, he has been with the Institut für Theoretische Nachrichtentechnik und Informationsverarbeitung at the University of Hannover, where he has been involved in the RACE research projects R202 "MONA LISA" and R2119 "HAMLET". His current research interest is in displacement estimation for video coding.
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