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KALMAN FILTER BASED ERROR CONCEALMENT ALGORITHM

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ABSTRACT

Video transmitted over unreliable environment, like wireless channels or in generally any network with unreliable transport protocol, is always subject to packet loss due to network congestion and channel noise.By using compressed video, errors could propagate to the subsequent frames with resulting worse video quality. On the one hand, traditional error control and recovery schemes for data communication were adapted to combat transmission errors.In this paper we have dealed with Kalman Filter based error concelament. We have tried to find motion vector for lost macroblock boundary matching algorithm. After that we have filtered obtained motion vectors with Kalman filter in order to obtain more accurately estimation.

Index Terms— One, two, three, four, five, six, seven, eight, nine, ten

1. INTRODUCTION

Video transmitted over wireless environment, e.g. WiFi networks based on IP protocol or in generally any network with unreliable transport protocol, is facing the losses of videopackets due to network congestion and noises of different kinds. By using highly effective videocodecs problem is becoming more important. Visual quality degradation could propagate to the subsequent frames due to redundancy elimination in order to gain high compression ratio.
On the one hand, traditional error control and recovery methods for data communication were adapted to combat transmission errors. These techniques introduced some redundancy which is helpful in lossless reconstruction of damaged video signal, but they also increase amount of data needed to be transmitted. On the other hand, signal reconstruction and error concealment have been proposed to obtain close approximation of the original signal or attempt to make the output signal at the decoder less objectionable to human eyes. While in data transmissions is such procedure impossible, in video communication it is sufficient. Error concealment utilizes statistical redundancy which is always presented in video streams due to various reasons, e.g. coding delay and implementation complexity.
Error concealment methods can be classified into three categories: 1) spatial, 2) temporal, 3) hybrid. Spatial error concealment techniques use the information from the surrounding correctly received or already concealed blocks to reconstruct damaged area. Typical representative of this class is weighted pixel averaging. Temporal error concealment techiques use the information of the corresponding blocks from the previous/successive blocks to conceal corrupted block. Typical representative of temporal error concealment methods is boundary matching algorithm. Hybrid error concealment techniques use as information from the spatial domain as information from the temporal domain. Lost motion vector estimation techniques developed over the times employ several mechanism: 1) lost motion vector is replaced with zero motion vector, 2) lost motion vector is replaced with spatially corresponding vector in the previous frame, 3) lost motion vector is replaced with average of the surroundings correctly received vectors, 4) lost motion vector is replaced with median of the surroundings correctly received vectors. All of these techniques, i.e. temporal error concealment techniques, are very effective when high temporal correlation between following frames exists and also is suitable for P frames in compressed video sequences. Recently, it grows also an interest in error concealment methods based on Bayesian filter theory. Hence we have followed this way in our paper.
In this paper we have dealed with Kalman Filter based error concelament. We have tried to find motion vector for lost macroblock with boundary matching algorithm. After that we have filtered obtained motion vectors with Kalman filter.

2. BAYESIAN FILTERING

In Bayesian approach we attempt to construct the posterior PDF of the state given all measurements. All available information is used to form such PDF. So this PDF represents complete solution.
Let $\mathbf{x}_k$, $k \in \mathbb{N}$, be the state sequence:

$$\mathbf{x}_k = \mathbf{f}_k(\mathbf{x}_{k-1}, \mathbf{u}_{k-1}, \mathbf{v}_{k-1}) \quad (1)$$

where $\mathbf{f}_k$ is in generally non-linear function of the previous state $\mathbf{x}_{k-1} \in \mathbb{R}^{n_x}$, $\mathbf{v}_{k-1} \in \mathbb{N}^{n_v}$ is state noise, $\mathbf{u}_{k-1} \in \mathbb{R}^{n_u}$ is known input, n_x, n_v, n_u are dimensions of the state, process and input noise vectors.
Next, let $\mathbf{z}_k$ be the measurement:

$$\mathbf{z}_k = \mathbf{h}_k(\mathbf{x}_k, \mathbf{n}_k) \tag{2}$$

where $\mathbf{z}_k \in \mathbb{R}^{n_z}$, $\mathbf{h}_k$ is in generally non-linear measurements function, $n_k \in \mathbb{N}^{n_n}$ is measurement noise, n_z and n_n are dimensions of the measurement and measurement noise vectors.
We want to find estimate of the $\mathbf{x}_k$ based on all available measurements at time *k* (marked as $\mathbf{z}_{1:k}$) by constructing the posterior PDF $p(\mathbf{x}_k, \mathbf{z}_{1:k})$. It is assumed, that initial PDF $p(\mathbf{x}_0|\mathbf{z}_0) \equiv p(\mathbf{x}_0)$ is available. Posterior PDF can be obtained recursively in two stages, namely prediction and update. Suppose that required PDF $p(\mathbf{x}_{k-1}|\mathbf{z}_{1:k-1})$ at time step *k-1* is available. Then using the system model it is possible to obtain the prior PDF of the state at the time step *k* [1]:

$$p(\mathbf{x}_k|\mathbf{z}_{1:k-1}) = \int p(\mathbf{x}_k|\mathbf{x}_{k-1}) p(\mathbf{x}_{k-1}|\mathbf{z}_{1:k-1}) \, \mathrm{d}\mathbf{x}_{k-1} \tag{3}$$

Prediction step usually deforms, spreads state PDF due to noise.
Measurement $\mathbf{z}_k$ is available at time step *k*, so it can be used to update the the prior. Using Bayes' rule we obtain:

$$p(\mathbf{x}_k|\mathbf{z}_{1:k}) = \frac{p(\mathbf{z}_k|\mathbf{x}_k) p(\mathbf{x}_k|\mathbf{z}_{1:k-1})}{p(\mathbf{z}_k|\mathbf{z}_{1:k-1})} \tag{4}$$

where the normalizing constant is:

$$p(\mathbf{z}_k|\mathbf{z}_{1:k-1}) = \int p(\mathbf{z}_k|\mathbf{x}_k) p(\mathbf{x}_k|\mathbf{z}_{1:k-1}) \, \mathrm{d}\mathbf{x}_k \tag{5}$$

In the update equation (5), the measurement $\mathbf{z}_k$ is used to modify the predicted prior from the previous time step to obtain PDF of the state.
Equations (3) and (4) theoretically allow optimal Bayesian solution. But it is only conceptual solution and integrals in these equations are intractable. Solution exists in some restricted cases such as Kalman Filter and grid-based filters.

2.1. Kalman Filter

Kalman filter together with its basic variants are commonly used tools in statistical signal processing, especially in the context of causal, real-time applications.
There are several approaches in the derivation of the Kalman Filter. We can assume Gaussian distribution of the deriving process and of the initial state. In the next phase, we derive the posterior distribution of the states given the observations, taking the mean of the resulting distributions as the estimation of the state. The second approach combines a recursive-weighted least-squares method with special weighting of the previous estimate of the states in the role of additional measurements [2].

To model state of the internal process let's assume that posterior density in time *k-1*, $p(\mathbf{x}_{k-1}|\mathbf{z}_{k-1})$, is Gaussian. Hence, $p(\mathbf{x}_k|\mathbf{z}_k)$ is also Gaussian. Next, random variables $\mathbf{v}_{k-1}$ and $\mathbf{n}_k$ are independent with normal probability distributions and with covariances labeled as Q_{k-1} and R_k. $\mathbf{f}_k(\mathbf{x}_{k-1}, \mathbf{v}_{k-1})$ and $\mathbf{h}_k(\mathbf{x}_k, \mathbf{n}_k)$ are linear function. Hence, equations (1) and (2) for derivation of the optimal Bayesian solution can be rewritten to the form:

$$\mathbf{x}_k = \mathbf{F}_k \mathbf{x}_{k-1} + \mathbf{B}_k \mathbf{u}_k + \mathbf{v}_{k-1} \tag{6}$$

$$\mathbf{z}_k = \mathbf{H}_k \mathbf{x}_k + \mathbf{n}_k \tag{7}$$

where F_k and H_k are matrices defining the linear function [3]. In practice, these matrices and covariance matrices Q_{k-1}, R_k might change with each time step or measurement. As the Kalman filter is recursive estimator, only estimated state from the previous time step and measurement at the current time step are needed to compute current state [4].
Kalman Filter is based on Bayesian filtering, and thus it works also in the two phases: Predict and Update. Predict stage can be described with following two equations:

$$\hat{\mathbf{x}}_{k|k-1} = \mathbf{F}_k \hat{\mathbf{x}}_{k-1|k-1} + \mathbf{B}_{k-1} \mathbf{u}_{k-1} \tag{8}$$

where $\hat{\mathbf{x}}_{k|k}$ is the estimate of the state at time *k* given observations up to time *k* and

$$\mathbf{P}_{k|k-1} = \mathbf{F}_k \mathbf{P}_{k-1|k-1} \mathbf{F}_k^T + \mathbf{Q}_{k-1} \tag{9}$$

where $\mathbf{P}_{k|k}$ is the error covariance matrix.
Update stage can be described with the following equations:

$$\tilde{\mathbf{y}}_k = \mathbf{z}_k - \mathbf{H}_k \hat{\mathbf{x}}_{k|k-1} \tag{10}$$

where $\tilde{\mathbf{y}}_k$ is innovation term,

$$\mathbf{S}_k = \mathbf{H}_k \mathbf{P}_{k|k-1} \mathbf{H}_k^T + \mathbf{R}_k \tag{11}$$

where $\mathbf{S}_k$ is innovation covariance and $\mathbf{R}_k$ is covariance of $\mathbf{n}_k$,

$$\mathbf{K}_k = \mathbf{P}_{k|k-1} \mathbf{H}_k^T \mathbf{S}_k^{-1} \tag{12}$$

where $\mathbf{K}_k$ is Kalman gain,

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k \tilde{\mathbf{y}}_k \tag{13}$$

is update state estimate and

$$\mathbf{P}_{k|k} = (I - \mathbf{K}_k \mathbf{H}_k) \mathbf{P}_{k|k-1} \tag{14}$$

is update estimate covariance.

With using least-square methods we obtain the same results. By using least-square method all the distributions are described by their means and covariances in the derivation procedure.

3. AUTOREGRESSIVE PROCESS

In dependence on motion amount in video scene, spatially or temporally neighboring motion vectors can be highly correlated. So motion vector can be predicted from spatially or temporally neighboring motion vectors. Autoregressive random process is used to model the correlation between motion vectors [5].
Let $B_i(m,n)$ be the block at the location (m,n) in the *i*th frame. Motion vector of this macroblock will be highly correlated to the motion vector of $B_i(m-1,n)$. It is also assumed that (x,y) components of motion vector are independent and have zero mean and the same variance. Let $x_{vx}(m,n)$, $x_{vy}(m,n)$ are the components of motion vector [6]:

$$x_{vx}(m,n) = a_1 x_{vx}(m-1,n) + w_{vx}(n,m) \quad (15)$$

$$x_{vy}(m,n) = a_2 x_{vy}(m-1,n) + w_{vy}(n,m) \quad (16)$$

The noise term $w_{vx}(m,n)$, $w_{vy}(m,n)$ are normally distributed as

$$w_{vx} \approx N(0, s_{vx}(m,n)) \quad (17)$$

$$w_{vy} \approx N(0, s_{vy}(m,n)) \quad (18)$$

where

$$\begin{aligned} s_{vx}(m,n) &= E[w_{vx}^2(m,n)] = s_{vy}(m,n) = \\ &= E[w_{vy}^2(m,n)] = s(m,n) \end{aligned}$$

Recovered motion vector can be obtained with one of the popular estimation techniques, like BMA. Let $y_{vx}(m,n)$, $y_{vy}(m,n)$ are components of such vector [6]:

$$y_{vx}(m,n) = x_{vx}(m,n) + r_{vx}(m,n) \quad (19)$$

$$y_{vy}(m,n) = x_{vy}(m,n) + r_{vy}(m,n) \quad (20)$$

Again as in previous case, the noise term $r_{vx}(m,n)$ and $r_{vy}(m,n)$ are normally distributed:

$$r_{vx} \approx N(0, t_{vx}(m,n)) \quad (21)$$

$$r_{vx} \approx N(0, t_{vy}(m,n)) \quad (22)$$

where

$$\begin{aligned} t_{vx}(m,n) &= E[r_{vx}^2(m,n)] = t_{vy}(m,n) = \\ &= E[r_{vy}^2(m,n)] = t(m,n) \end{aligned}$$

Equations 15 – 18 are similar to the typical Kalman filtering problem. The parameters a_1 and a_2 can be estimated by using the least square error method.

4. KALMAN FILTER BASED ERROR CONCEALMENT

Kalman filter based error concealment can be described by following steps (2D notation(m,n) is abbreviated to the 1D notation(m)) [6]:

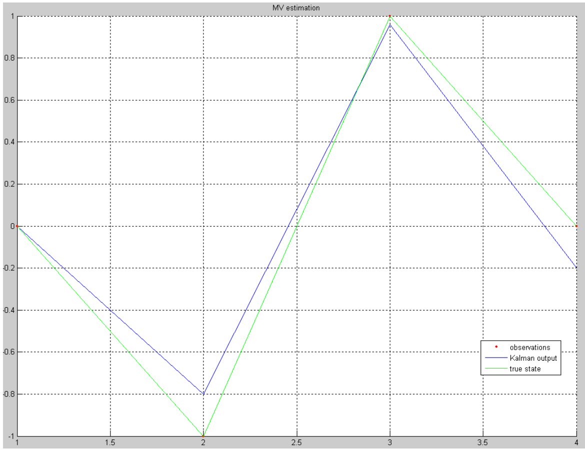
1. Error detection
2. Initialization – $x_{vx}(0) = x_{vy}(0) = 0$ and $p_{vx}(0) = p_{vy}(0) = 0$
3. Get the noisy motion vector measurements by using BMA
4. Kalman filtering
   - $x_{vx}(m|m-1) = a_1 x_{vx}(m-1|m-1)$
     $x_{vy}(m|m-1) = a_2 x_{vy}(m-1|m-1)$
   - $p_{vx}(m|m-1) = a_1 p_{vx}(m-1|m-1) a_1 + $
     $+ s(m)$
     $p_{vy}(m|m-1) = a_2 p_{vy}(m-1|m-1) a_2 + $
     $+ s(m)$
   - $k_{vx}(m) = \frac{p_{vx}(m|m-1)}{p_{vx}(m|m-1)+t(m)}$
     $k_{vy}(m) = \frac{p_{vy}(m|m-1)}{p_{vy}(m|m-1)+t(m)}$
   - Update predicted motion vectors – finally estimated motion vectors
     $x_{vx}(m|m) = x_{vx}(m|m-1) + k_{vx}(m)[y_{vx}(m) -$
     $- x_{vx}(m|m-1)]$
     $x_{vy}(m|m) = x_{vy}(m|m-1) + k_{vy}(m)[y_{vy}(m) -$
     $- x_{vy}(m|m-1)]$
   - $p_{vx}(m|m) = [1 - k_{vx}] p_{vx}(m|m-1)$
     $p_{vy}(m|m) = [1 - k_{vy}] p_{vy}(m|m-1)$
5. Repeat steps 3-4

5. EXPERIMENTAL RESULTS

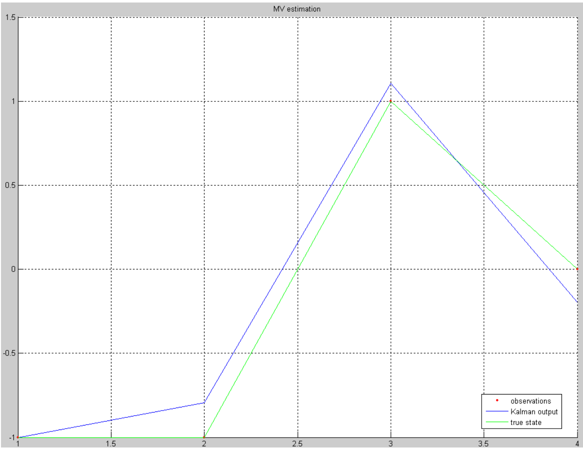
The Kalman based error concealment technique was tried on several standard video sequences like Foreman and Mobile. All tests were made in Matlab. The values for the system parameters and also for s_n and t_n can be found in [5].

Figure a) and b) shows Kalman filter performance in estimation of the lost motion vectors. In this simulation it was assumed that four neighboring vectors are available So macroblock with the lost motion vector is surrounded with correctly received macroblocks and therefore missing motion vectors can be relatively easily and correctly obtained through Kalman filter estimation. Difference between these two figures is in values of surrounding motion vectors. While in first case the values of the surrounding motion vector have varied, in second case are first two values the same. But the result of the approximation is relatively the same.
Effectiveness of Kalman filter error concealment method can be also viewed in the Table 1. In this table we can see results for typical video sequence named Foreman. This sequence include medium amount of moving edges. We have compared performance of BMA algorithm, Kalman filter based concealment method and typical and widely used spatial error concealment method known as weighted pixel averaging, in which is value of the lost pixel computed as inverse distance between

lost pixel and pixel to be concealed. In this test sequence Kalman filter based error concealment gives slightly better results then traditional BMA algorithm. Weighted pixel averaging has problem with losses on the building corners what results in worse performance in comparison with other two methods. Second test sequence, Mobile, is challenging task for many error concealment methods, it contains a lot of moving edges what is difficult to conceal with spatial error concealment methods. Performance results confirmed effectiveness of the previous simulation, again Kalman filter based scheme gives the best results and the weighted pixel averaging the worst.



(a) MV estimation, Foreman sequence, varying values



(c) MV estimation, Foreman sequence

Table 1. PSNR comparison for Foreman sequence

EC scheme	PSNR[dB] Foreman	PSNR[dB] Mobile
WPA	25.9715	22.458
BMA	27.9012	24.016
KF	28.101	24.110

6. CONCLUSION

In this paper we have described Kalman filtering based error concealment method. Also we have compared this method with conventional error concealment method, like BMA and weighted pixel averaging. Motion vectors obtained through boundary matching algorithm represents input for Kalman filter, which is trying to reduce inaccuracy in prediction process. Experiment results shown that such approach to the visual quality improvement helps to increase PSNR for about 0.1–0.2 dB. Effectiveness of the Kalman filter based error concealment and of course of other concealment methods is markedly dependent on the character of video sequence. As we have shown, spatial error concealment method offers poor results in concealment of lost in video sequence with a lot of motion. This method can be easily used in any video codec which uses motion compensation scheme and in regard of its computational cost can be used in various environments.

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8. REFERENCES

[1] N. J. GORDON, D. J. SALMOND, and A. F. M. SMITH, "Novel approach to nonlinear/non-gaussian bayesian state estimation," *Radar and Signal Processing*, vol. 140, no. 2, pp. 107–113, 1993.

[2] S. GANNOT and A. YEREDOR, "The kalman filter and its application to speech processing," *Springer Handbook of Speech Processing and Speech Communication*, pp. 135–157, 2008.

[3] M. S. ARULAMPALAM, S. MASKELL, N. GORDON, and T. CLAPP, "A tutorial on particle filters for online nonlinear/non-gaussian bayesian tracking," *IEEE Transactions on Signal Processing*, vol. 50, no. 2, pp. 174–188, 2002.

[4] G. WELCH and G. BISHOP, "An introduction to the kalman filter," *Siggraph Course Notes, course 8*, 2001.

[5] Ch.-M. Kuo, Ch.-H. Hsieh, Y.-D., Jou, H.-Ch. Lino, and P.-Ch. Lu, "Motion estimation for video compression using kalman filtering," *IEEE Transactions on Broadcasting*, vol. 42, no. 2, pp. 110–116, 2996.

[6] Z.-W. Gao and W.-N. Lie, "Video error concealment by using kalman-filtering technique," *ISCAS 2004*, pp. II–69–II–72, 2004.