MOTION COMPENSATED FRAME RATE UP-CONVERSION USING 3D FREQUENCY SELECTIVE EXTRAPOLATION AND A MULTI-LAYER CONSISTENCY CHECK

Michel Bätz, Fabian Brand, Andrea Eichenseer, and André Kaup

Multimedia Communications and Signal Processing
Friedrich-Alexander University Erlangen-Nürnberg (FAU), Cauerstr. 7, 91058 Erlangen, Germany

ABSTRACT

A high temporal resolution is desirable in many applications such as entertainment systems, automotive systems, or video surveillance. Apart from using cameras with a higher temporal resolution, it is also possible to employ frame rate up-conversion methods to obtain an enhanced temporal resolution. In principle, those algorithms can be grouped into approaches that rely on a motion estimation and approaches that do not. Both strategies typically process a video sequence frame by frame and take into account only the directly adjacent frames to compute the intermediate frame. In this paper, we propose a frame rate up-conversion technique that employs a motion compensated three-dimensional reconstruction algorithm. As a result, the proposed method takes into account more than two frames and is capable of jointly reconstructing up to a certain amount of missing frames in a video sequence. Furthermore, we present a multi-layer consistency check to further improve the reconstruction. On average, simulation results show a luminance PSNR gain compared to a conventional frame rate up-conversion method of 0.5 dB. Visual examples substantiate our objective results.

***Index Terms*—** Temporal Resolution Enhancement, Video Processing, Frame Rate Up-Conversion, Signal Extrapolation

1. INTRODUCTION

Increasing the temporal resolution is desirable in many applications. In video surveillance, for instance, properly tracking fast moving objects or people requires a high frame rate so that the tracking algorithm can follow the objects. In entertainment systems, video streams with a low temporal resolution need to be interpolated for playback on a screen with a high refresh rate. One possibility to obtain a higher temporal resolution is to use more expensive video cameras that are capable of capturing a higher frame rate. However, this also limits the exposure time, possibly leading to darker or more noisy images. Another approach is to apply frame rate up-conversion (FRUC) methods. The concept of increasing the temporal resolution by a post processing step is similar to the task of spatial resolution enhancement, where super-resolution methods are employed [1]. Basically, FRUC approaches can be divided into two categories: non-motion compensated methods and motion compensated (MC) methods. While non-motion compensated FRUC approaches are less computationally expensive compared to their motion compensated counterpart, they also have an inferior performance regarding reconstruction quality since they cannot properly deal with motion. On the other hand, a highly accurate motion estimation (ME) is necessary so as to avoid the introduction of artifacts.

Numerous FRUC methods are proposed in the literature, ranging from non-motion compensated approaches such as frame repetition, linear averaging, or central weighted median [2] over simple MC methods such as MC shifting, MC fetching, or MC linear averaging [2] to more advanced methods as proposed in [3, 4, 5].

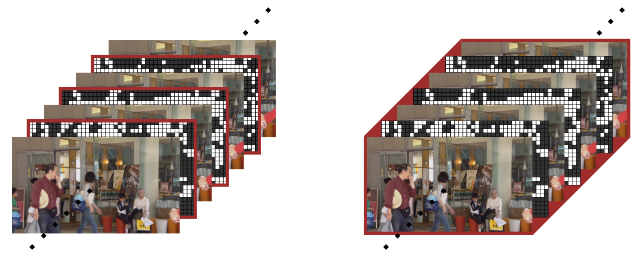

Fig. 1. Hole filling of the remaining missing pixels after motion compensated FRUC. Conventional case (left) only makes use of a 2D support, while the proposed case (right) makes use of a 3D support incorporating more temporal information.

Both categories of FRUC approaches typically rely only on the two directly adjacent, available frames and reconstruct a video sequence of higher frame rate in a frame by frame fashion. Using only the two neighboring frames, however, provides a rather limited temporal support which may lead to an inferior reconstruction quality and the frame by frame processing may yield temporally inconsistent results. Furthermore, holes that remain in the intermediate frame after the motion compensation step are typically reconstructed by conventional two-dimensional interpolation techniques [6, 7, 8, 9]. However, these interpolation methods, only operate on the motion compensated intermediate frame and cannot incorporate samples from neighboring frames. Making use of a larger temporal support should prove advantageous due to the temporal correlation in video sequences. In this paper, we therefore propose a novel motion compensated frame rate up-conversion method which employs three-dimensional frequency selective extrapolation (3D-FSE) [10, 11] and a multi-layer consistency check. Fig. 1 shows the 2D support for hole filling in conventional FRUC approaches (left) and the novel 3D support (right). While 3D-FSE allows for incorporating more temporally adjacent frames into the reconstruction process, it also reconstructs a certain amount of frames in the video sequence jointly. The proposed additional multi-layer consistency check further improves the reconstruction quality by providing adaptive weights for the reconstruction. Comparisons between the different FRUC approaches show the benefit of the proposed technique.

The remainder of the paper is structured as follows. The basic concepts of FRUC are provided in Section 2. Section 3 presents the proposed frame rate up-conversion method based on 3D-FSE together with the novel multi-layer consistency check. Subsequently, simulation results are discussed in Section 4 and Section 5 concludes this paper.

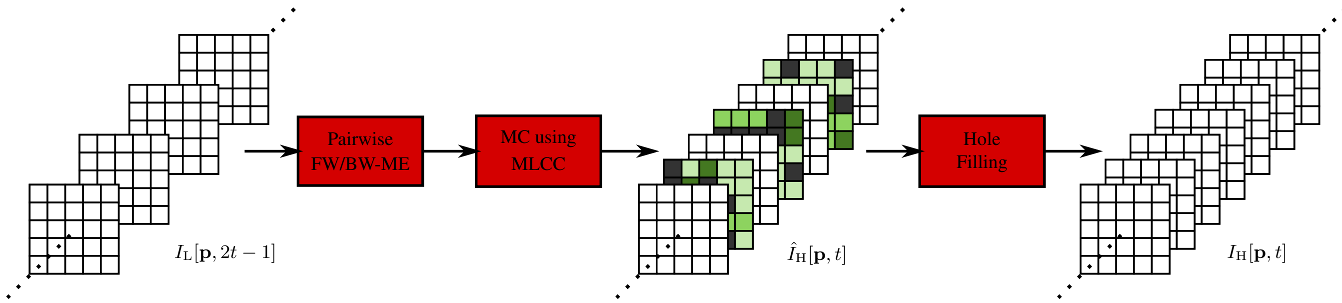

Fig. 2. Proposed FRUC framework. The workflow can be grouped into three steps: a pairwise forward and backward motion estimation (FW/BW-ME), a two-sided weighted motion compensation (MC) including a novel multi-layer consistency check (MLCC), and the 3D hole filling. White denotes known samples, black missing ones, and green illustrates motion compensated samples from different layers.

2. TRADITIONAL FRAME RATE UP-CONVERSION

FRUC algorithms can be grouped into non-motion compensated and motion compensated approaches. As the latter usually yields better results, we focus on that class in this paper. Motion compensated FRUC methods can be further divided into unilateral and bilateral approaches [3]. For unilateral approaches, the motion estimation provides motion vectors (MV) from the previous frame to the next frame or vice versa. For bilateral approaches, the motion estimation needs to provide MVs centered on the intermediate frame to be reconstructed and symmetrically pointing to the previous and next frame, respectively. A straightforward bilateral approach is motion compensated linear averaging (MCLA) [2] which can be written as

$$\hat{I}_{\mathrm{H}}[\mathbf{p},\tau] = \frac{1}{2}\left(\hat{I}_{\mathrm{H}}[\mathbf{p}-\frac{\mathbf{v}}{2},\tau-1] + \hat{I}_{\mathrm{H}}[\mathbf{p}+\frac{\mathbf{v}}{2},\tau+1]\right), \quad (1)$$

where $\hat{I}_{\mathrm{H}}[\mathbf{p},\tau]$ is the intermediate frame at time τ to be reconstructed in the video sequence with higher frame rate, $\hat{I}_{\mathrm{H}}[\mathbf{p},\tau-1]$ is the previous available frame, and $\hat{I}_{\mathrm{H}}[\mathbf{p},\tau+1]$ is the next available frame. The pixel position is denoted by $\mathbf{p} = (m,n)$ and $\mathbf{v}$ is the corresponding MV valid at time τ. The advantage of bilateral approaches is that they do not generate overlaps or holes in the images that would need to be reconstructed afterwards. However, it is not an easy task to estimate MVs at the intermediate frame and hence, bilateral methods typically lead to inferior reconstruction results. On the other hand, unilateral approaches can yield overlaps and holes which need to be treated properly. The proposed method will be based on a unilateral MC.

For the actual motion estimation, conventional block-based motion estimation techniques [12] or more advanced optical flow methods can be employed. In this paper, we rely on the dense optical flow method proposed in [13, 14] for all FRUC methods. The following section presents the novel frame rate up-conversion framework.

3. FRAME RATE UP-CONVERSION USING 3D-FSE

An overview of the proposed FRUC method is shown in Fig. 2 in the form of a block diagram. The temporally low resolution video sequence $I_{\mathrm{L}}[\mathbf{p},2t-1]$ serves as input to the FRUC framework which, in contrast to conventional FRUC approaches, processes the complete video sequence jointly to obtain the final video sequence of higher frame rate $I_{\mathrm{H}}[\mathbf{p},t]$. The proposed framework mainly consists of three steps: a pairwise forward and backward ME, a two-sided weighted MC including the novel multi-layer consistency check (MLCC), and a hole filling process using a three-dimensional reconstruction approach. After the first two steps, the motion compensated sequence $\hat{I}_{\mathrm{H}}[\mathbf{p},t]$, which still contains holes, is obtained.

For the first step, the aforementioned optical flow method is used in a pairwise manner between each available frame in $I_{\mathrm{L}}[\mathbf{p},2t-1]$ both from the previous to the next frame (forward) and vice versa (backward). The two MV fields are necessary for our chosen two-sided weighted MC approach.

Two-sided Weighted Motion Compensation

The unilateral motion compensation that we use builds upon the FRUC approach proposed in [3], but is extended towards subpixel accuracy, makes use of MVs from an optical flow instead of a block matching technique, and handles overlaps slightly differently. First, a forward intermediate frame $\hat{I}_{\mathrm{H,fw}}$ is estimated as

$$\hat{I}_{\mathrm{H,fw}}[\mathbf{p}+\frac{\mathbf{v}_{\mathrm{fw}}}{2},\tau] = \frac{1}{2}\left(\hat{I}_{\mathrm{H}}[\mathbf{p},\tau-1] + \hat{I}_{\mathrm{H}}[\mathbf{p}+\mathbf{v}_{\mathrm{fw}},\tau+1]\right), \quad (2)$$

where $\mathbf{v}_{\mathrm{fw}}$ is the corresponding forward MV. If multiple trajectories hit the same pixel in the intermediate frame, a weighted average of these is computed. The weighting itself is based on the inverse sum of squared differences (SSD). In [3], the overlaps are handled with a partial average-based MC method, but according to the reported results, both ways to deal with overlaps perform similarly. For the actual subpixel handling, the frames are upsampled by the desired accuracy and the MVs are assigned to the corresponding upsampled block which is then shifted. After obtaining the forward estimate $\hat{I}_{\mathrm{H,fw}}$, the backward estimate $\hat{I}_{\mathrm{H,bw}}$ is calculated analogously. Finally, both estimations are combined according to

$$\hat{i}_{\mathrm{H}} = \begin{cases} \frac{\hat{i}_{\mathrm{H,fw}}+\hat{i}_{\mathrm{H,bw}}}{2}, & \text{if } \hat{i}_{\mathrm{H,fw}} \neq \mathcal{H} \ \wedge \ \hat{i}_{\mathrm{H,bw}} \neq \mathcal{H} \\ \hat{i}_{\mathrm{H,fw}}, & \text{if } \hat{i}_{\mathrm{H,fw}} \neq \mathcal{H} \ \wedge \ \hat{i}_{\mathrm{H,bw}} = \mathcal{H} \\ \hat{i}_{\mathrm{H,bw}}, & \text{if } \hat{i}_{\mathrm{H,fw}} = \mathcal{H} \ \wedge \ \hat{i}_{\mathrm{H,bw}} \neq \mathcal{H} \\ \mathcal{H}, & \text{otherwise,} \end{cases} \quad (3)$$

where $\hat{i}_{\mathrm{H}}$ denotes a single pixel in $\hat{I}_{\mathrm{H}}[\mathbf{p},\tau]$ and $\mathcal{H}$ represents a hole in the image. This process is repeated for all intermediate frames to be reconstructed in the video sequence.

Multi-Layer Consistency Check

Before the actual two-sided weighted motion compensation is performed, the available MVs from the forward and backward motion estimation are cross-checked similarly to [15] so as to remove coarse outliers. In general, each forward MV is followed to its destination position and the closest backward MV is then retraced to its destination position. If the starting and destination position match, the MV passed the cross-check. Instead of performing a hard cross-check, we propose to employ a soft multi-layer consistency check in

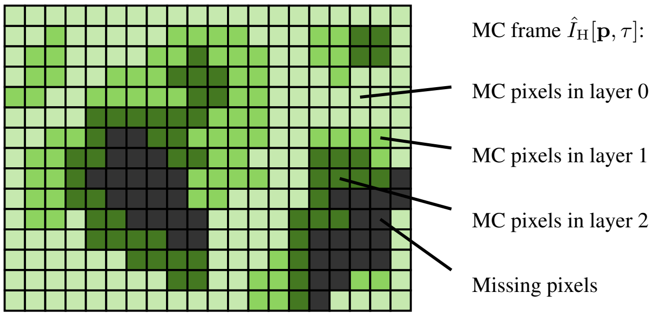

Fig. 3. Exemplary illustration of the novel multi-layer consistency check for three layers. The layers consist of all motion compensated pixels whose corresponding MVs passed a certain consistency check level. The higher the layer, the softer the cross-check.

this paper and assign specific weights for each layer which are then passed to the hole filling algorithm. The concept of this MLCC technique is illustrated in Fig. 3 for three layers. The higher the layer, the softer the cross-check and the smaller the weight assigned. For example, the region corresponding to layer 0 depicts all motion compensated pixels whose corresponding MVs passed the cross-check with a maximum error of 0.5 pixel. The region corresponding to layer 1 comprises all motion compensated pixels whose corresponding MVs passed the cross-check with a maximum error of 1.5 pixel and so on. Note that the layers are processed sequentially from low to high, i. e., from a harder to a softer cross-check. Furthermore, higher layers can only fill holes remaining from previous layers and do not interfere with already motion compensated positions. All MC pixels from layers $l > 0$ only serve as support for the hole filling algorithm, but will be replaced by the generated model which is described in the next section.

Hole Filling Using 3D-Frequency Selective Extrapolation

After the motion compensation, the remaining holes need to be filled and the area made up by layers $l > 0$ needs to be replaced for achieving a better reconstruction quality. To do so, we make use of frequency selective extrapolation (FSE) [9, 16, 17] and extend it to also cover MC pixels. FSE works in a blockwise manner; the area used to reconstruct a block is called extrapolation area $\mathcal{L}$. Fig. 4 shows an exemplary 2D extrapolation area and its subsets. The currently processed block of size b is marked in red and is surrounded by a support margin of d_{s} in each direction. All pixels inside $\mathcal{L}$ can be divided into four classes: known pixels $\mathcal{A}$ (white), previously reconstructed pixels $\mathcal{R}$ (blue), lost pixels $\mathcal{B}$ (black), and motion compensated pixels $\mathcal{M}$ (green). Only pixels in $\mathcal{B}$ and $\mathcal{M}$ for $l > 0$ are filled or replaced by FSE, respectively. In general, FSE generates a sparse, parametric signal model as a weighted superposition of Fourier basis functions in an iterative way. For the 2D case, this can be written as

$$g_{\mathrm{2D}}[\mathbf{p}] = \sum_{(k,l)\in\mathcal{K}} \hat{c}_{(k,l)}\varphi_{(k,l)}[\mathbf{p}], \tag{4}$$

where $g_{\mathrm{2D}}[\mathbf{p}]$ denotes the generated 2D signal model, the 2D Fourier basis functions are denoted by $\varphi_{(k,l)}$, and $\hat{c}_{(k,l)}$ are the corresponding estimated expansion coefficients. Moreover, the set of all iteratively chosen basis function is given by $\mathcal{K}$. The basis function $\varphi_{(k,l)}$ which minimizes the weighted residual energy is picked in each iteration. The corresponding weighting function w_{fse} controls the influence of each sample on the model generation and can be written as (5). The variables $\mathbf{p}_{\mathrm{c}}$, ρ, δ, and δ_l represent the centroid of the current block, the decay strength, the attenuation weight of previously

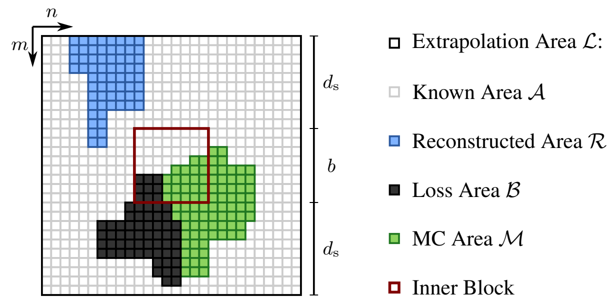

Fig. 4. Exemplary 2D extrapolation area $\mathcal{L}$ and its subsets.

Table 1. FSE parameter profiles for 2D/3D-FSE.

FSE parameter		2D-FSE	3D-FSE
Block / cube size	b	4	4
Spatial border width	d_{s}	14	10
Temporal border width	d_{t}	0	4
FFT size		32	32
Number of iterations		100	500
Decay strength	ρ	0.7	0.7
Attenuation weight	δ	0.5	0.2
Weight for layer l	δ_l	$1/(l+1)$	
Orthogonality correction	γ	0.5	0.5

reconstructed samples, and the weight of each layer l, respectively. We define δ_l such that the higher the layer, the less it influences the actual reconstruction. For the computation of the centroid $\mathbf{p}_{\mathrm{c}}$, both the loss area $\mathcal{B}$ and the MC area $\mathcal{M}$ for $l > 0$ inside the inner block are taken into account. As we want to make use of a larger temporal support, we use 3D-FSE [10, 11] instead of 2D-FSE which generates a 3D signal model $g_{\mathrm{3D}}[\mathbf{p}, t]$ and is a straightforward extension from the 2D variant. Furthermore, we adapt the processing order to better deal with the problem of FRUC such that cubes are processed in a slicewise fashion starting with the slice containing the least missing pixels.

$$w_{\mathrm{fse}}[\mathbf{p}] = \begin{cases} \rho^{\left\|\mathbf{p}-\mathbf{p}_{\mathrm{c}}\right\|_2}, & \text{for } \mathbf{p} \in \mathcal{A} \\ \delta\rho^{\left\|\mathbf{p}-\mathbf{p}_{\mathrm{c}}\right\|_2}, & \text{for } \mathbf{p} \in \mathcal{R} \\ \delta_l\delta\rho^{\left\|\mathbf{p}-\mathbf{p}_{\mathrm{c}}\right\|_2}, & \text{for } \mathbf{p} \in \mathcal{M} \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

4. SIMULATION RESULTS

In this section, the proposed motion compensated FRUC approach using 3D-FSE and the novel MLCC is analyzed with regard to reconstruction quality. The resulting frames of the video sequences are evaluated both visually and objectively using the luminance PSNR. All tests were conducted on the eight video sequences *BQSquare* and *BlowingBubbles* (416×240); *BQMall*, *PartyScene*, *BasketballDrill*, and *RaceHorses* (832×480); and *panslow* and *spincalendar* (1280×720). For the purpose of simulation, the first 101 frames of each sequence were used and every other frame was dropped so as to realize a lower temporal resolution. The PSNR was then evaluated for the 50 reconstructed frames. For the optical flow computation, the default parameters were selected. The parameters for both the 2D-FSE and 3D-FSE can be found in Table 1. Note that for 2D-FSE, all MC pixels are assigned to the set $\mathcal{A}$, i. e., set $\mathcal{M}$ is only used for 3D-FSE.

In the following, the seven compared FRUC approaches are listed. The first three approaches operate in a frame by frame

Table 2. Average $\mathrm{PSNR_Y}$ results (in dB) for a temporal resolution enhancement by a factor of 2.

Sequence		MCLA	MC-2FSE	MC-2FSE-XC	3FSE	MC-3FSE	MC-3FSE-XC	MC-3FSE-XC12
(416 × 240)	*BQSquare*	33.48	**36.13**	35.39	21.58	36.26	36.42	**36.52**
	BlowingBubbles	32.55	**33.41**	32.28	21.83	33.45	33.59	**33.73**
(832 × 480)	*BQMall*	31.21	**31.32**	28.84	17.72	31.38	32.36	**32.45**
	PartyScene	29.03	**29.51**	27.56	19.55	29.55	29.83	**30.14**
	BasketballDrill	30.29	**30.42**	25.88	19.55	30.44	29.45	**30.72**
	RaceHorses	26.36	**26.60**	23.94	15.60	26.62	26.11	**27.07**
(1280 × 720)	*panslow*	37.09	**37.48**	36.93	27.32	37.48	**37.53**	**37.53**
	spincalendar	33.92	**34.76**	31.89	21.98	34.76	**35.93**	35.43
Average Gain		–	**0.71**	−1.40	−11.10	0.75	0.91	**1.20**

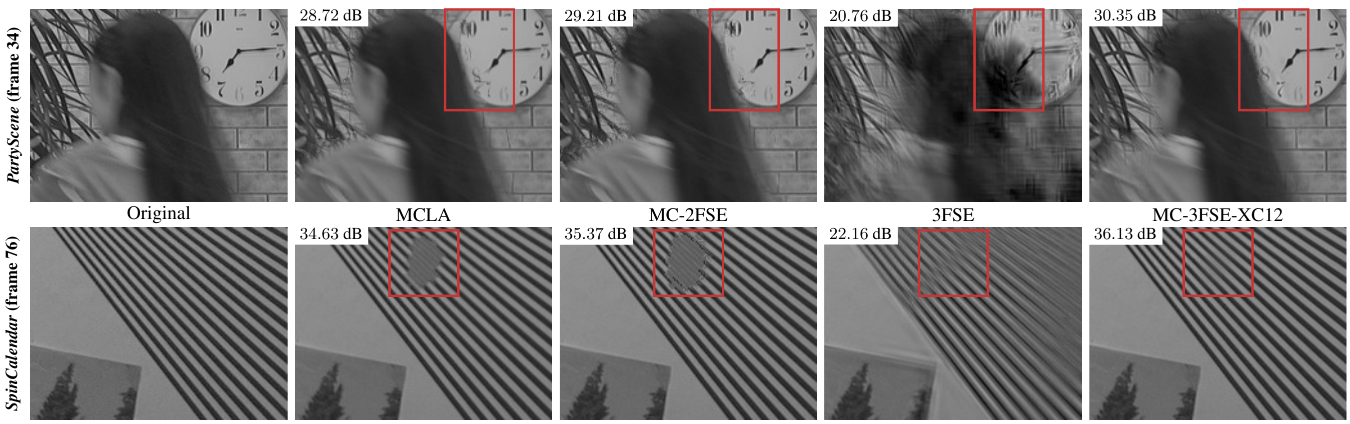

Fig. 5. Visual quality comparison of image detail examples for two different sequences using an upscaling of factor 2. Areas of interest are highlighted in red (best viewed enlarged on screen).

fashion and are: MCLA [2]; MC-2FSE, which corresponds to the approach from [3] but is extended by a subpixel-accurate motion compensation and uses 2D-FSE instead of the intra-predicted hole interpolation to provide a fairer comparison to the 3D-FSE-based methods; and MC-2FSE-XC, which is a variant of the latter performing an additional hard cross-check as described in [15]. The other four approaches reconstruct a certain amount of frames in the video sequence jointly and are: non-motion compensated 3D-FSE (3FSE), which is a straightforward application of 3D-FSE as mentioned in [10] with a centroid adaptation and a modified processing order; the proposed FRUC method without MLCC (MC-3FSE); the proposed FRUC method with just one cross-check layer (MC-3FSE-XC); and the proposed FRUC method with twelve layers (MC-3FSE-XC12). Note that the twelfth layer is a special case where all remaining MVs with an error of larger than 10.5 pixels are used to calculate a last MC layer. This last layer is assigned one common weight no matter the related MV error.

The corresponding average luminance PSNR values are listed in Table 2 together with the average gain compared to MCLA. It is evident that a cross-check in the case of 2D reconstruction is rather counterproductive, as it yields larger holes that need to be filled without any guidance from previous or next temporal frames. Furthermore, the results show that using 3D-FSE without any motion compensation is also not helpful although an enlarged temporal support is available. Applying a cross-check for the 3D approaches is advantageous in contrast to the 2D case since larger holes can be better filled due to the 3D support. Finally, it is apparent that incorporating the proposed MLCC with twelve layers gives the best results overall. Only for the sequence *spincalendar*, the performance with MLCC is worse. The reason for that are the highly periodic structures for which additional slightly incorrect support is not helpful. Compared to the best 2D approach, i. e., MC-2FSE, the proposed MC-3FSE-XC12 achieves an average gain of 0.5 dB. To substantiate the discussed objective quality results, visual examples are shown in Fig. 5 for four selected FRUC approaches and two video sequences. It is obvious that the proposed MC-3FSE-XC12 approach can successfully preserve the details in the clock (top) and reduce artifacts in periodic structures (bottom).

5. CONCLUSION

In this paper, a motion compensated FRUC approach based on three-dimensional frequency selective extrapolation was proposed. While conventional frame rate up-conversion methods rely only on the two adjacent frames and perform the reconstruction frame by frame, our approach is capable of incorporating more than two adjacent frames into the reconstruction process and jointly fills holes in the video sequence. Taking more than two frames into account for the reconstruction is advantageous as a larger support is available for the actual hole filling step which in turn leads to better results. Additionally, a multi-layer consistency check was presented that is capable of further increasing the reconstruction quality. Our proposed method was evaluated on real video sequences for an upscaling factor of 2. It was shown that our approach achieves an average gain in luminance PSNR of 0.5 dB over a conventional FRUC technique. According to the visual findings, the proposed method can successfully reduce artifacts. Future work will include employing a volume alignment to the FRUC approach as previously proposed for error concealment and evaluating the framework on compressed data.

6. ACKNOWLEDGEMENT

This work was supported by Bosch Sicherheitssysteme Engineering GmbH, Nuremberg, Germany.

7. REFERENCES

[1] S. C. Park, M. K. Park, and M. G. Kang, "Super-Resolution Image Reconstruction: A Technical Overview," *IEEE Signal Processing Magazine*, vol. 20, no. 3, pp. 21–36, May 2003.

[2] G. de Haan, "Digital Video Post Processing," 2010.

[3] U. S. Kim and M. H. Sunwoo, "New Frame Rate Up-Conversion Algorithms With Low Computational Complexity," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 24, no. 3, pp. 384–393, March 2014.

[4] G. G. Lee, C.-F. Chen, C.-J. Hsiao, and J.-C. Wu, "Bi-Directional Trajectory Tracking With Variable Block-Size Motion Estimation for Frame Rate Up-Convertor," *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, vol. 4, no. 1, pp. 29–42, March 2014.

[5] H. Liu, R. Xiong, D. Zhao, S. Ma, and W. Gao, "Multiple Hypotheses Bayesian Frame Rate Up-Conversion by Adaptive Fusion of Motion-Compensated Interpolations," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 22, no. 8, pp. 1188–1198, August 2012.

[6] H. Takeda, S. Farsiu, and P. Milanfar, "Kernel Regression for Image Processing and Reconstruction," *IEEE Transactions on Image Processing*, vol. 16, no. 2, pp. 349–366, February 2007.

[7] J. Dahl, P. C. Hansen, S. H. Jensen, and T. L. Jensen, "Algorithms and software for total variation image reconstruction via first-order methods," *Numerical Algorithms*, vol. 53, no. 1, pp. 67–92, July 2009.

[8] M. V. Afonso, J. M. Bioucas-Dias, and M. A. T. Figueiredo, "An Augmented Lagrangian Approach to the Constrained Optimization Formulation of Imaging Inverse Problems," *IEEE Transactions on Image Processing*, vol. 20, no. 3, pp. 681–695, March 2011.

[9] J. Seiler and A. Kaup, "Complex-Valued Frequency Selective Extrapolation for Fast Image and Video Signal Extrapolation," *Signal Processing Letters*, vol. 17, no. 11, pp. 949–952, November 2010.

[10] K. Meisinger and A. Kaup, "Spatiotemporal Selective Extrapolation for 3-D Signals and Its Applications in Video Communications," *IEEE Transactions on Image Processing*, vol. 16, no. 9, pp. 2348–2360, September 2007.

[11] J. Seiler and A. Kaup, "Motion compensated three-dimensional frequency selective extrapolation for improved error concealment in video communication," *Journal of Visual Communication and Image Representation (VCIR)*, vol. 22, pp. 213–225, March 2011.

[12] M. Santamaría and M. Trujillo, "A Comparison of Block-Matching Motion Estimation Algorithms," in *Proceedings of the IEEE 7th Colombian Computing Congress*, Medellín, Colombia, October 2012, pp. 1–6.

[13] C. Zach, T. Pock, and H. Bischof, "A Duality Based Approach for Realtime TV-L1 Optical Flow," in *Proceedings of the 29th DAGM Symposium on Pattern Recognition*, Heidelberg, Germany, September 2007, pp. 214–223.

[14] J. Sánchez Pérez, E. Meinhardt-Llopis, and G. Facciolo, "TV-L1 Optical Flow Estimation," *Image Processing On Line*, vol. 3, pp. 137–150, July 2013.

[15] M. Bätz, A. Eichenseer, J. Seiler, M. Jonscher, and A. Kaup, "Hybrid Super-Resolution Combining Example-Based Single-Image and Interpolation-Based Multi-Image Reconstruction Approaches," in *Proceedings of the IEEE International Conference on Image Processing (ICIP)*, Quebec City, Canada, September 2015.

[16] J. Seiler and A. Kaup, "Optimized and Parallelized Processing Order for Improved Frequency Selective Signal Extrapolation," in *Proceedings of the European Signal Processing Conference*, Barcelona, Spain, August 2011, pp. 269–273.

[17] W. Schnurrer, M. Jonscher, J. Seiler, T. Richter, M. Bätz, and A. Kaup, "Centroid Adapted Frequency Selective Extrapolation for Reconstruction of Lost Image Areas," in *Proceedings of the IEEE International Conference on Visual Communications and Image Processing*, Singapore, Singapore, December 2015, pp. 1–4.