Motion-Compensated Temporal Filtering for Critically-Sampled Wavelet-Encoded Images

Vildan Atalay Aydin and Hassan Foroosh

Abstract

We propose a novel motion estimation/compensation (ME/MC) method for wavelet-based (in-band) motion compensated temporal filtering (MCTF), with application to low-bitrate video coding. Unlike the conventional in-band MCTF algorithms, which require redundancy to overcome the shift-variance problem of critically sampled (complete) discrete wavelet transforms (DWT), we perform ME/MC steps directly on DWT coefficients by avoiding the need of shift-invariance. We omit upsampling, the inverse-DWT (IDWT), and the calculation of redundant DWT coefficients, while achieving arbitrary subpixel accuracy without interpolation, and high video quality even at very low-bitrates, by deriving the exact relationships between DWT subbands of input image sequences. Experimental results demonstrate the accuracy of the proposed method, confirming that our model for ME/MC effectively improves video coding quality.

Index Terms

Motion Estimation, Motion Compensated Temporal Filtering, Video Coding, Discrete Wavelet Transform

I. INTRODUCTION

Reliable motion estimation/compensation can substantially reduce the residual energy in the coding of video data. Motion estimation methods are either global [6], [20]–[22], [24]–[27], [30], [31], [60]–[62], [64], [65], [118], [119], or local [57]–[59], [110] in their nature in terms of treating the transformation relating two images. There is also a separate but related body of work on camera motion quantification, which requires online or offline calibration of camera [9], [28], [40]–[42], [42]–[44], [46], [50]–[52], [63], [72], [73], [80], [81], [88]–[91], [96]. While these methods and their variations have been proposed in the past for motion compensation in different applications, space-time subband/wavelet coding [102] is by far the method of choice for coding and compressing images and videos due to its superior performance. Its effectiveness, however, can be significantly improved with motion compensation, which is the topic of the proposed method in this paper.

II. RELATED WORK

Still image coding [8] and video coding [146] are important topics of research in coding and compression of multimedia data. On the other hand, scalable video coding [103], [142] is an emerging trend in numerous multimedia applications with heterogeneous networks, due to their ability to adapt different resolution and quality requirements. Recently, a large body of research has focused on wavelet-based methods [8], [53], [93], [106], where motion compensated temporal filtering (MCTF) is shown to play an essential role in both scalable video coding and still image coding. MCTF is performed either directly on input images, or on their transforms. Thus, MCTF methods can be categorized into two groups depending on the order of temporal and spatial transforms. MCTF techniques which perform temporal decomposition before a spatial transform include, Secker and Taubman [106], and Pesquest-Popescu and Bottreau [104] who used lifting formulation of three dimensional temporal wavelet decomposition for motion compensated video compression. Kim et al. [92] proposed a 3-D extension of set partitioning in hierarchical trees (3D-SPHIT) by a low bit-rate embedded video coding scheme. More recently, Xiong et al. [145] extended spatiotemporal subband transform to in-scale motion compensation to exploit the temporal and cross-resolution correlations simultaneously, by predicting low-pass subbands from next lower resolution and high-pass subbands from neighboring frames in the same resolution layer. Furthermore, Chen and Liu [53] used an adaptive Lagrange multiplier selection model in rate-distortion optimization (RDO) for motion estimation. In order to achieve more accurate motion data, Esche et al. [56] proposed an interpolation method for motion information per pixel using block based motion data, and Rüfenacht et al. [105] anchor motion fields at reference frames instead of target frames to resolve folding ambiguities in the vicinity of motion discontinuities.

Vildan Atalay Aydin and Hassan Foroosh are with the Department of Computer Science, University of Central Florida, Orlando, FL, 32816 USA (e-mail: vatalay@knights.ucf.edu, foroosh@cs.ucf.edu).
Fig. 1. A block diagram of the proposed in-band Motion Compensated Temporal Filtering model.

Although the methods cited above have good performance, they suffer from drifting and operational mismatch problems. Therefore, performing spatial transform before temporal decomposition was introduced to overcome these drawbacks. However, since complete DWT is shift variant, in order to achieve in-band ME/MC (i.e. directly in the wavelet domain), several methods were proposed to tackle this problem by redundancy. Van der Auwera et al. [142] used a bottom-up prediction algorithm for a bottom-up overcomplete discrete wavelet transform (ODWT). Park and Kim [103] proposed a low-band-shift method by constructing the wavelet tree by shifting low-band subband in each level for horizontal, vertical, and diagonal directions for one pixel and performing downsampling. Andreopoulos et al. [8] defined a complete to overcomplete discrete wavelet transform (CODWT), which avoids inverse DWT generally used to obtain ODWT. More recently, Liu and Ngan [93] use partial distortion search and anisotropic double cross search algorithms with the MCTF method in [8] for a fast motion estimation. Amiot et al. [7] perform MCTF for denoising, using dual-tree complex wavelet (DT-CW) coefficients.

All MCTF methods summarized above perform motion estimation/motion compensation either in the temporal domain before DWT, or in the wavelet domain with the help of redundancy (e.g. ODWT, DT-CW, etc.), due to the fact that complete DWT is shift-variant and motion estimation directly on DWT subbands is a challenging task. However, redundancy in these methods leads to high computational complexity [93]. Inspired by the fact that shift variance keeps the perfect reconstruction and nonredundancy properties of wavelets and breaks the coupling between spatial subbands, and that wavelet codecs always operate on complete DWT subbands [8], we propose a novel in-band ME/MC method, which avoids the need of shift invariance, and operates directly on the original DWT coefficients of the input sequences. Since Haar wavelets are widely utilized in MCTF methods due to the coding efficiency based on their short kernel filters [8], our method is built on Haar subbands. For accurate ME/MC, we define the exact relationships between the DWT subbands of input video sequences, which allows us to avoid upampling, inverse DWT, redundancy, and interpolation for subpixel accuracy.

The rest of the paper is organized as follows. We introduce the problem and our proposed solution in Section III. We define the derived exact inter-subband relationships in Section IV, demonstrate the experimental results in Section V, and finally conclude our paper in Section VI.

III. Motion Compensated Temporal Filtering

In this section, we explain our proposed method for in-band motion compensated temporal filtering, operating directly on DWT subbands.

The wavelet transform provides localization both in time and frequency; therefore, it is straightforward to use wavelets in MCTF. In order to perform ME/MC in MCTF, wavelet subbands of the transformed signal need to be predicted. However, due to decimation and expansion operations of DWT, direct band-to-band estimation is generally not practical [103]. The proposed method overcomes this challenge by revealing the relationships between subbands of reference and target frames. The proposed in-band MCTF method is demonstrated in Fig. 1. Given a video sequence, first, DWT is performed on each frame for spatial decomposition, then a temporal decomposition is performed by splitting video frames into groups. ME/MC (P in Fig. 1) is performed by block matching, using reference frames (DWT(I_{2t})) to predict the target frames (DWT(I_{2t+1})). Employing the found motion vectors (MV), reference frames are mapped onto the target frames to generate error frames, C in Fig. 1 which are then quantized (Q), encoded/decoded by a wavelet codec, together with the MVs.

We employ Haar wavelet decomposition in spatial transform due to the benefits mentioned earlier. Since the method in Section IV is accurate for any arbitrary subpixel translation defined as a multiple of $2^k$, where $k$ is the decomposition level, our method does not need interpolation for subpixel accuracy. A block matching method with unidirectional full search is used for ME/MC steps which is a common method used for MCTF. Our cost function is based on mean square error minimization using all subbands, as follows:
(dx, dy) = \arg \min_{x,y} \{(A - \hat{A})^2 + (a - \hat{a})^2 + (b - \hat{b})^2 + (c - \hat{c})^2\}, \tag{1}

where A, a, b, c denote the original target frame wavelet subbands, and \(\hat{A}, \hat{a}, \hat{b}, \hat{c}\) are the estimated subbands for the same target image, using the method described in Section IV and a reference frame.

IV. INTER-SUBBAND RELATIONSHIP

In-band (wavelet domain) shift method along with the related notation are provided in this section.

A. Notation

Here, we provide the notation used throughout the paper beforehand, in Table I for a better understanding of the proposed method and to prevent any confusions.

| Notation | Description |
|----------|-------------|
| \(I_t\) | Input video frame at time \(t\) |
| A, a, b, c | Haar wavelet transform approximation, horizontal, vertical, and diagonal subbands of input image, respectively |
| F, K, L | Coefficient matrices to be multiplied by approximation, horizontal, vertical, and diagonal DWT subbands |
| \(h\) | Number of hypothetically added levels in case of non-integer shifts |
| \(s\) | Integer shift amount after the hypothetically added levels (\(h\)) |

Bold letters in the following sections demonstrate matrices and vectors. The subscripts \(x\) and \(y\) indicate the horizontal and vertical translation directions, respectively. Finally, the subscript \(k\) indicates the \(k\)th video frame, where \(k = 1, 2, \ldots\)

B. In-band Shifts

Our goal for the MCTF method described in Section III is to achieve ME/MC in the wavelet domain using DWT subbands, given a video frame sequence. For this purpose, wavelet subbands of the transformed signal should be predicted using only DWT subbands of the reference frame. Therefore, we derive the relationship between the subbands of transformed and reference images, which can be described by in-band shift (in the wavelet domain) of the reference image subbands. Below, we derive the mathematical expressions which demonstrate these relationships.

Let \(A, a, b, c\) be the first level approximation, horizontal, vertical, and diagonal detail coefficients (subbands), respectively, of a 2D reference frame at time \(t\), \(I_t\), of size \(2m \times 2n\), where \(m\) and \(n\) are positive integers. Since decimation operator in wavelet transform reduces the size of input frame by half in each direction for each subband, we require the frame sizes to be divisible by 2. Now, the 1st level subbands of translated frame in any direction (i.e. horizontal, vertical, diagonal) can be expressed in matrix form using the 1st level Haar transform subbands of reference frame as in the following equations:

\[
\begin{align*}
A_s &= F_y A F_x + F_y a K_1 + L_1 b F_x + L_1 c K_1 \\
a_s &= -F_y a K_1 + F_y a K_2 - L_1 b K_1 + L_1 c K_2 \\
b_s &= -L_1 a K_1 - L_1 a K_2 + L_2 b F_x + L_2 c K_1 \\
c_s &= L_1 a K_1 - L_1 a K_2 - L_2 b F_x + L_2 c K_2
\end{align*}
\]

As already mentioned in Section IV-A, \(F, K,\) and \(L\) stand for coefficient matrices to be multiplied by the lowpass and highpass subbands of the reference frame, where subscripts \(x\) and \(y\) indicate horizontal and vertical shifts. \(A_s, a_s, b_s, c_s\) are translated frame subbands in any direction. The low/high-pass subbands of both reference and transformed frames are of size \(m \times n\), \(F_y\) and \(L_{1,2}\) are \(m \times m\), whereas \(F_x\) and \(K_{1,2}\) are \(n \times n\).

By examining the translational shifts between subbands of two input frames in the Haar domain, we realize that horizontal translation reduces \(L\) to zero and \(F_y\) to the identity matrix. This could be understood by examining the coefficient matrices defined later in this section (namely, Eq. (5)), by setting the related vertical components to zero (specifically, \(s_y\) and \(h_y\)). Likewise, vertical translation depends solely on approximation and vertical detail coefficients, in which case \(K\) is reduced to zero and \(F_x\) is equal to the identity matrix.

Here, we first define the matrices for subpixel shift amounts. The algorithm to reach any shift amount using the subpixel relationship will be described later in this section.
For subpixel translation, contrary to the customary model of approximating a subpixel shift by upsampling an image followed by an integer shift, our method models subpixel shift directly based on the original coefficients of the reference frame, without upsampling and the need for interpolation. To this end, we resort to the following observations:

1. Upsampling an image $I$, is equivalent to adding levels to the bottom of its wavelet transform, and setting the detail coefficients to zero, while the approximation coefficients remain the same, as demonstrated in Fig. 2 for upsampling by $2^1$ as an example, where gray subbands show added zeros.

2. Shifting the upsampled image by an amount of $s$ is equivalent to shifting the original image by an amount of $s/2^h$, where $h$ is the number of added levels (e.g. $h = 1$ in Fig. 2).

These observations allow us to do an in-band shift of the reference subbands for a subpixel amount, without upsampling or interpolation, which saves both memory and reduces the computational cost. Transformed signals therefore can be found by using the original level subbands of the reference image with the help of a hypothetically added level ($h$) and an integer shift value ($s$) at the added level.

Now, the aforementioned coefficient matrices, $F_x$, $K_1$, and $K_2$ can be defined, in lower bidiagonal Toeplitz matrix form as follows.

$$ F_x = \frac{1}{2^{h_x+1}} \begin{bmatrix} 2^{h_x+1} - |s_x| & 2^{h_x+1} - |s_x| \\ |s_x| & 2^{h_x+1} - |s_x| \\ & \ddots & \ddots \\ & & |s_x| & 2^{h_x+1} - |s_x| \end{bmatrix} $$

$$ K_1 = \frac{1}{2^{h_x+1}} \begin{bmatrix} -s_x & -s_x \\ s_x & -s_x \\ & \ddots & \ddots \\ & & s_x & -s_x \end{bmatrix} $$

$$ K_2 = \frac{1}{2^{h_x+1}} \begin{bmatrix} 2^{h_x+1} - 3|s_x| & 2^{h_x+1} - 3|s_x| \\ -|s_x| & 2^{h_x+1} - 3|s_x| \\ & \ddots & \ddots \\ & & -|s_x| & 2^{h_x+1} - 3|s_x| \end{bmatrix} $$

where $s_x$ and $h_x$ demonstrate the integer shift amounts at the hypothetically added level and the number of added levels for $x$ direction, respectively.

$F_y$, $L_1$, and $L_2$ matrices are defined in a similar manner by upper bidiagonal Toeplitz matrices, using $y$ direction values for $s$ and $h$. 

Fig. 2. Upsampling illustration.
As mentioned earlier, \( F_x \) and \( K_{1,2} \) are \( n \times n \), while \( F_y \) and \( L_{1,2} \) are \( m \times m \). Sizes of these matrices also indicate that in-band shift of subbands is performed using only the original level Haar coefficients (which are of size \( m \times n \)) without upsampling. When the shift amount is negative, diagonals of the coefficient matrices interchange. The matrices are adapted for boundary condition by adding one more column/row at the end, for the MCTF method proposed in Section III where subband sizes are also adjusted to be \((m + 1) \times (n + 1)\).

The relationship defined above for subpixel shifts, can be used to produce any shift amount based on the fact that wavelet subbands are periodically shift-invariant. Table II demonstrates the calculation of any shift using subpixels, where \( \% \) stands for modulo, \( |s| \) and \( \lceil s \rceil \) are the greatest integer lower than, and smallest integer higher than the shift amount \( s \). Using circular shift of subbands for the given amounts in each shift amount case, and setting the new shift amount to the new shift values in Table II we can calculate any fractional or integer amount of shifts using subpixels.

| Shift amount Circular shift New shift amount |
|---------------------------------------------|
| \( s \% 2 = 0 \) \( s/2 \) \( 0 \) |
| \( s \% 2 = 1 \) \( |s|/2 \) \( 1 \) |
| \( |s| \% 2 = 0 \) \( |s|/2 \) \( s - |s| \) |
| \( s \% 2 = 0 \) \( |s|/2 \) \( s - |s| \) |

If the shift amount (or the new shift amount in Table II) is not divisible by 2, in order to reach an integer value at the \((N + h)\)th level, the shift value at the original level is rounded to the closest decimal point which is divisible by \( 2^h \).

V. Experimental Results

In this section, we demonstrate the results obtained with our method compared to the methods which perform in-band MCTF for video coding. We report our results on CIF video sequence examples with resolutions 352 \( \times \) 240 and 352 \( \times \) 288. We set our block size to 8 \( \times \) 8 or 16 \( \times \) 16 depending on the resolution of the sequences (in order to have integer number of blocks in subbands) and the required accuracy. Even though our MCTF method is based on 1-level DWT, we perform 2 more spatial decomposition levels after ME/MC steps before encoding, since compared methods use 3 spatial decomposition levels in total. Motion vectors and error frames are encoded using context-adaptive variable-length coding (CA VLC) and global thresholding with Huffman coding methods, respectively.

Fig. 3. Rate-distortion comparison for the Football sequence.

Fig. 3 shows the comparison of our method with respect to two conventional in-band methods, which are direct wavelet subband matching (band-to-band) and wavelet-block low-band-shift (LBS) \cite{103} for CIF video sequence "Football". The graph demonstrates rate-distortion curves for a predicted frame of the Football sequence, where the shown bitrates are for error frame only (same as in the compared methods), and the accuracy for our method is set to 1/4 pixel. As seen in this figure, our method improves PSNR compared to conventional in-band methods by \( 0.1 - 1 \) dB in general.

We demonstrate our results for several video sequences at different bitrates in Fig. 4 where bitrates include the luminance component only for the reference frame, the error frame, and MVs. The graph on the left shows the results with 1/2 pixel accuracy using 16 \( \times \) 16 blocks, and the one on the right uses 1/4 pixel accuracy with 8 \( \times \) 8 blocks. We also show the residual
images for a predicted frame of the Foreman sequence in Fig. 5, for 0.1 and 0.02 bpp, respectively. The examples show how our method reduces the residual signal energy even at very low bitrates by providing more accurate reconstruction (prediction).

VI. CONCLUSION

We propose a novel method for wavelet-based (in-band) ME/MC for MCTF in for video coding, where DWT is applied before temporal decomposition, and ME/MC steps are performed directly on DWT subbands. We avoid the need for shift-invariance property for non-redundant DWT (required by conventional methods for ME/MC), by deriving the exact relationships between DWT subbands of reference and transformed video frames. Our method avoids upsampling, inverse-DWT (IDWT), and calculation of redundant DWT while achieving high accuracy even at very low-bitrates. Experimental results demonstrate the accuracy of presented method for ME/MC, confirming that our model effectively improves video coding quality by reducing the residual energy in the error frames. The proposed ME/MC scheme can also be adapted for several image/video processing applications such as denoising, or scalable video coding.

REFERENCES

[1] Muhamad Ali and Hassan Foroosh. Natural scene character recognition without dependency on specific features. In Proc. International Conference on Computer Vision Theory and Applications, 2015.
[2] Muhamad Ali and Hassan Foroosh. A holistic method to recognize characters in natural scenes. In Proc. International Conference on Computer Vision Theory and Applications, 2016.
[3] Muhammad Ali and Hassan Foroosh. Character recognition in natural scene images using rank-1 tensor decomposition. In Proc. of International Conference on Image Processing (ICIP), pages 2891–2895, 2016.
[4] Mais Alnasser and Hassan Foroosh. Character recognition in natural scene images using rank-1 tensor decomposition. In Proc. of International Conference on Image Processing (ICIP), pages 2891–2895, 2016.
[5] Mais Alnasser and Hassan Foroosh. Rendering synthetic objects in natural scenes. In Proc. of IEEE International Conference on Image Processing (ICIP), pages 493–496, 2006.
[6] Mais Alnasser and Hassan Foroosh. Phase shifting for non-separable 2d haar wavelets. IEEE Transactions on Image Processing, 16:1061–1068, 2008.
[7] Carole Amiot, Catherine Girard, Jérémie Pescatore, Jocelynn Chanussot, and Michel Desvignes. Fluorosocopic sequence denoising using a motion compensated multi-scale temporal filtering. In ICIP, pages 691–695. IEEE, 2015.
[8] Yiannis Andreopoulos, Adrian Munteanu, Geert Van der Auwera, Jan PH Cornelis, and Peter Schelkens. Complete-to-overcomplete discrete wavelet transforms: theory and applications. IEEE Transactions on Signal Processing, 53(4):1398–1412, 2005.
[9] Nazim Ashraf and Hassan Foroosh. Robust auto-calibration of a ptz camera with non-overlapping fov. In Proc. International Conference on Pattern Recognition (ICPR), 2008.
[10] Nazim Ashraf and Hassan Foroosh. Human action recognition in video data using invariant characteristic vectors. In Proc. of IEEE Int. Conf. on Image Processing (ICIP), pages 1385–1388, 2012.
[11] Nazim Ashraf and Hassan Foroosh. Motion retrieval using consistency of epipolar geometry. In Proceedings of IEEE International Conference on Image Processing (ICIP), pages 4219–4223, 2015.
[12] Nazim Ashraf, Imran Junejo, and Hassan Foroosh. Near-optimal mosaic selection for rotating and zooming video cameras. Proc. of Asian Conf. on Computer Vision, pages 63–72, 2007.
[13] Nazim Ashraf, Yuping Shen, Xiaochun Cao, and Hassan Foroosh. View-invariant action recognition using weighted fundamental ratios. Journal of Computer Vision and Image Understanding (CVIU), 117:587–602, 2013.
[14] Nazim Ashraf, Yuping Shen, Xiaochun Cao, and Hassan Foroosh. View-invariant action recognition using weighted fundamental ratios. Computer Vision and Image Understanding, 117(6):587–602, 2013.
[15] Nazim Ashraf, Yuping Shen, and Hassan Foroosh. View-invariant action recognition using rank constraint. In Proc. of IAPR Int. Conf. Pattern Recognition (ICPR), pages 3611–3614, 2010.
[16] Nazim Ashraf, Chuan Sun, and Hassan Foroosh. Motion retrieval using low-rank decomposition of fundamental ratios. In Proc. IEEE International Conference on Image Processing (ICIP), pages 1905–1908, 2012.
[17] Nazim Ashraf, Chuan Sun, and Hassan Foroosh. Motion retrieval using low-rank decomposition of fundamental ratios. In Image Processing (ICIP), 2012 19th IEEE International Conference on, pages 1905–1908, 2012.
[18] Nazim Ashraf, Chuan Sun, and Hassan Foroosh. View-invariant action recognition using projective depth. Journal of Computer Vision and Image Understanding (CVIU), 123:41–52, 2014.
[19] Nazim Ashraf, Chuan Sun, and Hassan Foroosh. View invariant action recognition using projective depth. Computer Vision and Image Understanding, 123:41–52, 2014.
[20] Vildan Atalay and Hassan Foroosh. In-band sub-pixel registration of wavelet-encoded images from sparse coefficients. Signal, Image and Video Processing, 2017.
[21] Vildan A. Aydin and Hassan Foroosh. Motion compensation using critically sampled dwt subbands for low-bitrate video coding. In Proc. IEEE International Conference on Image Processing (ICIP), 2017.
[22] Murat Balci, Mais Alnasser, and Hassan Foroosh. Alignment of maxillofacial ct scans to stone-cast models using 3d symmetry for backscattering artifact reduction. In Proceedings of Medical Image Understanding and Analysis Conference, 2006.
[23] Murat Balci, Mais Alnasser, and Hassan Foroosh. Image-based simulation of gaseous material. In Proc. of IEEE International Conference on Image Processing (ICIP), pages 489–492, 2006.
[24] Murat Balci, Mais Alnasser, and Hassan Foroosh. Subpixel alignment of mri data under cartesian and log-polar sampling. In Proc. of IAPR Int. Conf. Pattern Recognition, volume 3, pages 607–610, 2006.
[25] Murat Balci and Hassan Foroosh. Estimating sub-pixel shifts directly from phase difference. In Proc. of IEEE International Conference on Image Processing (ICIP), pages 1057–1060, 2005.
[26] Murat Balci and Hassan Foroosh. Estimating sub-pixel shifts directly from the phase difference. In Proc. of IEEE Int. Conf. Image Processing (ICIP), volume 1, pages I–1057, 2005.
[27] Murat Balci and Hassan Foroosh. Inferring motion from the rank constraint of the phase matrix. In Proc. IEEE Conf. on Acoustics, Speech, and Signal Processing, volume 2, pages ii–925, 2005.
[28] Murat Balci and Hassan Foroosh. Metrology in uncalibrated images given one vanishing point. In Proc. of IEEE International Conference on Image Processing (ICIP), pages 361–364, 2005.
[29] Murat Balci and Hassan Foroosh. Real-time 3d fire simulation using a spring-mass model. In Proc. of Int. Multi-Media Modelling Conference, pages 8–pp, 2006.
[30] Murat Balci and Hassan Foroosh. Sub-pixel estimation of shifts directly in the fourier domain. IEEE Trans. on Image Processing, 15(7):1965–1972, 2006.
[31] Murat Balci and Hassan Foroosh. Sub-pixel registration directly from phase difference. Journal of Applied Signal Processing-special issue on Super-resolution Imaging, 2006:1–11, 2006.
[32] M Berthod, M Werman, M Shekarforoush, and J Zerubia. Refining depth and luminance information using super-resolution. In Proc. of IEEE Conf. Computer Vision and Pattern Recognition (CVPR), pages 654–657, 1994.
[33] Marc Berthod, Hassan Shekarforoush, Michael Werman, and Josiane Zerubia. Reconstruction of high resolution 3d visual information. In IEEE Conf. Computer Vision and Pattern Recognition (CVPR), pages 654–657, 1994.
[34] Aadvil Bhutta and Hassan Foroosh. Blind blur estimation using low-rank approximation of ceptrum. Image Analysis and Recognition, pages 94–103, 2006.
[35] Adeel A Bhutta, Imran N Junejo, and Hassan Foroosh. Selective subtraction when the scene cannot be learned. In Proc. of IEEE International Conference on Image Processing (ICIP), pages 3273–3276, 2011.
[36] Hakan Boyraz, Syed Zain Masood, Baoyuan Liu, Marshall Tappen, and Hassan Foroosh. Action recognition by weakly-supervised discriminative region localization.
[37] Ozan Cakmakci, Gregory E. Fasshauer, Hassan Foroosh, Kevin P. Thompson, and Jannick P. Rolland. Meshfree approximation methods for free-form surface representation in optical design with applications to wear-born displays. In Proc. SPIE Conf. on Novel Optical Systems Design and Optimization XI, volume 7061, 2008.
[38] Ozan Cakmakci, Brendan Moore, Hassan Foroosh, and Jannick Rolland. Optimal local shape description for rotationally non-symmetric optical surface design and analysis. Optics Express, 16(3):1583–1589, 2008.
[39] Ozan Cakmakci, Sophie Vo, Hassan Foroosh, and Jannick Rolland. Application of radial basis functions to shape description in a dual-element off-axis magnifier. Optics Letters, 33(11):1237–1239, 2008.
[40] X Cao and H Foroosh. Metrolgy from vertical objects. In Proceedings of the British Machine Conference (BMVC), pages 74–1.
[41] Xiaochun Cao and Hassan Foroosh. Camera calibration without metric information using 1d objects. In Proc. International Conf. on Image Processing (ICIP), volume 2, pages 1349–1352, 2004.
[42] Xiaochun Cao and Hassan Foroosh. Camera calibration without metric information using an isosceles trapezoid. In Proc. International Conference on Pattern Recognition (ICPR), volume 1, pages 104–107, 2004.
[43] Xiaochun Cao and Hassan Foroosh. Simple calibration without metric information using an isosceles trapezoid. In Proc. of IAPR Int. Conf. Pattern Recognition (ICPR), volume 1, pages 104–107, 2004.
[44] Xiaochun Cao and Hassan Foroosh. Camera calibration using symmetric objects. IEEE Transactions on Image Processing, 15(11):3614–3619, 2006.
[45] Xiaochun Cao and Hassan Foroosh. Synthesizing reflections of inserted objects. In Proc. IAPR Int. Conference on Pattern Recognition, volume 2, pages 1225–1228, 2006.
[46] Xiaochun Cao and Hassan Foroosh. Camera calibration and light source orientation from solar shadows. Journal of Computer Vision & Image Understanding (CVIU), 105:60–72, 2007.
[128] Yuping Shen and Hassan Foroosh. View invariant recognition of body pose from space-time templates. In Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2008.
[129] Yuping Shen and Hassan Foroosh. View-invariant action recognition from point triplets. IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI), 31(10):1898–1905, 2009.
[130] Yuping Shen, Fei Lu, Xiaochun Cao, and Hassan Foroosh. Video completion for perspective camera under constrained motion. In Proc. of IAPR Int. Conf. Pattern Recognition (ICPR), volume 3, pages 63–66, 2006.
[131] Chen Shu, Luming Liang, Wenzhang Liang, and Hassan Foroosh. 3D pose tracking with multitemplate warping and sift correspondences. IEEE Trans. on Circuits and Systems for Video Technology, 26(11):2043–2055, 2016.
[132] Chuan Sun and Hassan Foroosh. Should we discard sparse or incomplete videos? In Proceedings of IEEE International Conference on Image Processing (ICIP), pages 2502–2506, 2014.
[133] Chuan Sun, Imran Junejo, and Hassan Foroosh. Action recognition using rank-1 approximation of joint self-similarity volume. In Proc. IEEE International Conference on Computer Vision (ICCV), pages 1007–1012, 2011.
[134] Chuan Sun, Imran Junejo, and Hassan Foroosh. Motion retrieval using low-rank subspace decomposition of motion volume. In Computer Graphics Forum, volume 30, pages 1953–1962. Wiley, 2011.
[135] Chuan Sun, Imran Junejo, and Hassan Foroosh. Motion sequence volume based retrieval for 3D captured data. Computer Graphics Forum, 30(7):1953–1962, 2012.
[136] Chuan Sun, Imran Junejo, Marshall Tappen, and Hassan Foroosh. Exploring sparseness and self-similarity for action recognition. IEEE Transactions on Image Processing, 24(8):2488–2501, 2015.
[137] Chuan Sun, Marshall Tappen, and Hassan Foroosh. Feature-independent action spotting without human localization, segmentation or frame-wise tracking. In Proc. of IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 2689–2696, 2014.
[138] Amara Tariq and Hassan Foroosh. Scene-based automatic image annotation. In Proc. of IEEE International Conference on Image Processing (ICIP), pages 3047–3051, 2014.
[139] Amara Tariq, Asim Karim, and Hassan Foroosh. A context-driven extractive framework for generating realistic image descriptions. IEEE Transactions on Image Processing, 26(2):619–632, 2017.
[140] Amara Tariq, Asim Karim, and Hassan Foroosh. Nelasso: Building named entity relationship networks using sparse structured learning. IEEE Trans. on on Pattern Analysis and Machine Intelligence, 2017.
[141] Amara Tariq, Asim Karim, Fernando Gomez, and Hassan Foroosh. Exploiting topical perceptions over multi-lingual text for hashtag suggestion on twitter. In The Twenty-Sixth International FLAIRS Conference, 2013.
[142] G Van der Auwera, A Munteanu, P Schelkens, and J Cornelis. Bottom-up motion compensated prediction in wavelet domain for spatially scalable video coding. Electronics Letters, 38(21):1251–1253, 2002.
[143] Jiangjian Xiao, Xiaochun Cao, and Hassan Foroosh. 3D object transfer between non-overlapping videos. In Proc. of IEEE Virtual Reality Conference, pages 127–134, 2006.
[144] Jiangjian Xiao, Xiaochun Cao, and Hassan Foroosh. A new framework for video cut and paste. In Proc. of Int. Conf. on Multi-Media Modelling Conference Proceedings, pages 8–pp, 2006.
[145] Ruiqin Xiong, Jizheng Xu, and Feng Wu. In-scale motion compensation for spatially scalable video coding. IEEE Transactions on Circuits and Systems for Video Technology, 18(2):145–158, 2008.
[146] Mai Xu, Yilin Liang, and Zuolin Wang. State-of-the-art video coding approaches: A survey. In IEEE International Conference on Cognitive Informatics & Cognitive Computing, pages 284–290, 2015.
[147] Changqin Zhang, Xiaochun Cao, and Hassan Foroosh. Constrained multi-view video face clustering. IEEE Transactions on Image Processing, 24(11):4381–4393, 2015.