CORRESPONDENCE MATCHING BASED ON HIGHER ORDER STATISTICS FOR MULTI-VIEW PLUS DEPTH VIDEO SEQUENCES

S. Colonnese, P. Oliveira**, A. Rosato*, L. Ungaro**, A. Beghdadi***, M. Biagi*, G. Scarano**

*DIET, Università La Sapienza di Roma
**Universidade do Porto, Faculdade de Engenharia
***L2TI, Institut Galilée - Université Paris 13

ABSTRACT

This work addresses the problem of correspondence matching in multiview video sequences when co-acquired depth maps are available, as in the novel Multiview Video plus Depth (MVD) format. For the purpose of activity-based correspondence matching, we exploit the view depth information, allowing a thorough geometrical analysis of the video scene, and the statistical analysis of the inter-frame differences.

In this paper we outline a correspondence matching procedure exploiting mutual information between active areas in different sequences. For activity detection we make use of the depth information and the estimated Higher Order Statistics of the inter-frame differences, which are resilient to luminance variations.

The procedure encompasses two steps, namely: i) a selection of points candidate for matching search, and ii) the search of the most similar points; this procedure does not require any preliminar activity detection or segmentation stage.

Index Terms— Correspondence matching, Higher Order Statistics, Multiview Video plus Depth (MVD) format.

1. INTRODUCTION

The problem of processing multi-view sequences representing the same scene under different point of views in order to find corresponding points occurs in a variety of applications, such as computer vision, video surveillance, image registration, image fusion [1]. Correspondence matching procedures based on activity matching rely on the claim that a real point, viewed in two concurrent frames of two different views, could be classified as belonging to the background (still) or foreground (moving) plane. Thus, collecting this binary classification information for an image point along a certain number of video frames generates an activity vector representative of a real point in the 3d space. Thereby, points of different views having similar activity vectors are likely to originate from the same real point; this forms the basis for activity based correspondence matching. In [2], activity based correspondence matching is realized by adopting a Hamming distance criterion between activity vectors, whereas on [3] the distance is defined taking into account the mutual information between activity vectors as well. This approach proves resilient to luminance errors due to noisy, low-contrasted acquisitions. On the other hand, both the procedures in [2, 3], being based on a preliminar background/foregorund classification procedure, depend on a foreground detection preprocessing stage whose performance severely affects the overall correspondence matching performance.

Several approaches to activity detection and segmentation [4], [5],[6] rely on Higher Order Statistics of the inter-frame differences. Besides, depth map acquisition or estimation [7] is gaining relevance for activity detection and segmentation purposes, especially in the framework of multiview video [8]. In [9], the authors propose a method for detecting temporal changes of the three-dimensional structure of an outdoor scene from its multi-view images captured at two separate times. In [10], an automatically learning multi-view detector is described. In [11], the authors present an automatic foreground object detection method for videos captured by different moving cameras that exploit correspondences between differently acquired views, whereas in [12] the authors propose an automatic segmentation system exploiting multiple images. In [13] the authors present a layered stereoscopic moving-object segmentation method based on the higher-order statistics (HOS) of the frame-difference and processing it by multiple depth-layer masks [14]. Thereby, the geometrical and statistical information carried by the availability of enriched video format encompassing multiple views and depth images [15] boosts the development of advanced correspondence matching techniques exploiting the available information in a joint fashion.

Herein, following the approach in [3], we investigate correspondence matching based on mutual information, but we introduce the following novel contributions. Firstly, we base our analysis in depth and HOS sequences rather than binary segmentation maps used in other correspondence matching works. Thus, the preliminar foreground/background segmentation is avoided, and the depth and HOS sequences, having pixels' values quantized to more than two levels, provide richer information than the binary background-foreground sequences in [3], while still assuring resilience to luminance noise. Secondly, we introduce a self-information-based criterion for the selection of pixels eligible for correspondence matching. The pixel selection stage has an important impact on the overall performance, and it allows avoiding any computationally demanding activity detection stage. We present here preliminar promising results that assess the satisfactory performance of our correspondence matching procedure even in absence of any post-processing validation and regularization stage, which is often required by state-of-the-art algorithms [3].

2. SIGNAL MODEL FOR CORRESPONDENCE MATCHING PURPOSES

Let us consider a multiview sequence, i.e. a set of video sequences acquiring the same real scene for the same time interval from different points of view. Let us denote by $I_t^{(i)}(u,v)$, the t-th frame extracted from the i-th camera view sequence. Each point (u,v) of the frame is the projection on the image plane of a real point (x,y,z), i.e. $(u,v)=\Pi^{(i)}(x,y,z)$.

Let us denote by $B^{(i)}$ the set of points (u,v) which are obtained by projection in the camera plane of real points (x,y,z) belonging to the static background. Similarly, let us denote by $F^{(i)}$ the points representing the projection of foreground moving objects. The frame support $D^{(i)}$ can be partitioned as follows:

$$D^{(i)} = B^{(i)} \cup F^{(i)},\ B^{(i)} \cap F^{(i)} = \oslash \tag{1}$$

Extending the analytical framework proposed in [4], we write $I_t^{(i)}(u,v)$ as:

$$I_t^{(i)}(u,v) = b_t^{(i)}(u,v) + m_t^{(i)}(u,v), \tag{2}$$

being $b_t^{(i)}(u,v) \neq 0$ iff$(u,v) \in B^{(i)}$ and $m_t^{(i)}(u,v) \neq 0$ iff$(u,v) \in F^{(i)}$. As aforementioned, we assume that a real point (x,y,z) is contemporaneously seen as belonging to the background or to the foreground in two contemporary frames belonging to two different views.

Thus, collecting such information on the image point (u,v) along a certain number T of video frames generates an activity vector $\mathbf{a}(u,v)$. Although in each frame of the same view the pixel (u,v) of the 2d representation can be associated to different real world points $(u,v)=\Pi^{(i)}(x,y,z)$ in different frames of the same view, the temporal evolution of the activity vectors in corresponding point is coherent in the different views. Specifically, the activity vector is defined as:

$$\mathbf{a}^{(i)}(u,v) = [a^{(0)}(u,v) \dots a^{(T-1)}(u,v)] \tag{3}$$

being $a^{(k)}(u,v)$ a binary foreground indicator function defined as $a^{(k)}(u,v)=1$ iff$(u,v) \in F^{(i)}$. Image point correspondence matching between different views is then realized by distance matching of the corresponding activity vector; in [2], a Hamming distance criterion is exploited, whereas in [3] the distance is defined taking into account the vector entropy as well. Both procedures, being based on a background/foregorund classification procedure, depend on a foreground detection preprocessing stage whose performance severely affects the final correspondence matching results.

Herein, we make a twofold observation, that is:

- in several activity detection approaches, the foreground indicator function defined as $a^{(k)}(u,v)=1$ iff$(u,v) \in F^{(i)}$ is observed to be correlated with the difference between consecutive video frames; this is widely exploited in a variety of algorithms for activity detection purposes, as pointed out in [17];
- within the stationarity interval of the multiview acquisition geometry, a deterministic relation can be found between the distances of the real point (x,y,z) with respect to the centers of the different cameras.

Stemming on these observations, we formally introduce the definitions of the video depth maps as well as of the inter-frame differences and of their HOS. In the following, we describe the correspondence matching procedure based on such information.

Let us first introduce the concept of depth maps. Each point (u,v) of the image frame is the projection of a real point (x,y,z) on the image plane; the distance of (x,y,z) with respect to the camera center, is stored in the so called depth map, and it is indeed related to object surfaces in the acquired scene. Let us denote by $d_t^{(i)}(u,v)$, the depth map relative to the t-th frame of the i-th camera view sequence. Although the depth map may be limited in range and spatial resolution and may suffer of acquisition noise, especially on the edges, it carries relevant information on real world objects and it can be exploited for segmentation purposes. In [11], the non Gaussian areas of a video frame are matched to a co-acquired depth map in order to discriminate low-depth region (foreground) from high-depth region (background).

In the multiview framework, given an image point (u,v) within the frame $I_t^{(i)}(u,v)$ and its depth map value $d_t^{(i)}(u,v)$, its 3D positions and, as a consequence, its distance with respect to a different camera can be computed if the relative locations of the multiview cameras are known. A particular case is found when the distance between cameras is much smaller than the object-to camera distance. Hence, a real point (x,y,z) has different projection points $(u_{i_1},v_{i_1}) = P^{(i_1)}(x,y,z)$, $(u_{i_2},v_{i_2}) = P^{i_2}(x,y,z)$ in different cameras, but its distance from the cameras is approximately the same, i.e. $d_t^{(i1)}(u_{i1},v_{i1}) \approx d_t^{(i2)}(u_{i2},v_{i2})$. In a nutshell, an object is expected to belong either to the low-depth region (foreground) or to the high-depth region (background) in both cameras.

Let us now introduce the HOS of the inter-frame differences. The inter-frame difference at temporal distance t_0 is written as

$$\Delta_t^{(i)}(u,v) = I_t^{(i)}(u,v) - I_{t-t_0}^{(i)}(u,v)$$
$$= \begin{cases} b_t^{(i)}(u,v) - b_{t-t_0}^{(i)}(u,v), (u,v) \in B_t^{(i)} \cap B_{k-t_0}^{(i)} \\ m_t^{(i)}(u,v) - b_{t-t_0}^{(i)}(u,v), (u,v) \in F_t^{(i)} \cap B_{k-t_0}^{(i)} \\ b_t^{(i)}(u,v) - m_{t-t_0}^{(i)}(u,v), (u,v) \in B_t^{(i)} \cap F_{k-t_0}^{(i)} \\ m_t^{(i)}(u,v) - m_{t-t_0}^{(i)}(u,v), (u,v) \in F_t^{(i)} \cap F_{k-t_0}^{(i)} \end{cases} \quad (4)$$

Remarkably, the background difference tends to assume a Gaussian statistic, and this feature has been exploited for foreground extraction in single view video. Specifically, the fourth-order cumulant of a Gaussian random variate is zero. Thereby, when applied to the inter-view differences, its sample local estimate on a $W \times W$ window can be matched against a threshold to reject local noise contribution.

Then, in principles we have

$$K_t^{(i)}(u,v) = E\left\{(\Delta_t(u,v) - E\{\Delta_t(u,v)\})^4\right\} - 3\left(E\left\{(\Delta_t(u,v) - E\{\Delta_t(u,v)\})^2\right\}\right)^2 \quad (5)$$

whereas its sample version is computed by replacing the expected value with a spatial local average of the variates under concern on a $W \times W$ window around (u,v). Besides, following the approach in [4], for the purpose of a fast estimate of the local sequence activity the sample cumulant evaluation can be substituted by the computation of the sample fourth-order moment or even of a suitable Hybrid Nonlinear Moment [16]. Herein, we refer to the sample moment:

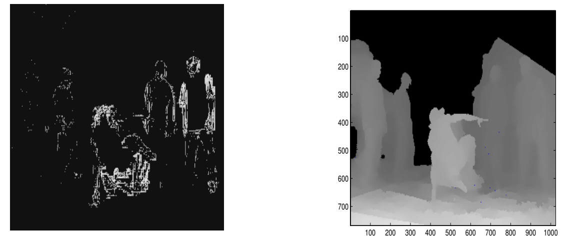
$$\hat{k}_t^{(i)}(u,v) = \overline{\left(\Delta_t(u,v) - \overline{\Delta_t(u,v)}\right)^4} \quad (6)$$

that, after a thresholding stage meant to eliminate noise contributions, provides an effective tool for HOS-based activity vector estimation. An example of depth and HOS sequences is reported in Fig.1.

Given this underlying correlation of the depth maps and HOS with object segmentation, here, we extend the activity analysis originally applied to a binary foreground/background segmentation map [3] both to the depth domain $d_t^{(i)}(u,v)$ and to the domain of the HOS of inter-frame differences $\hat{k}(u,v)$.

3. DEPTH BASED AND HOS BASED CORRESPONDENCE MATCHING

Firstly, we analyze the activity detection correspondence matching based on the mutual information between depth-based activity vector. Let us build the depth-based activity



(a) $\hat{k}_t^{(i)}(u,v)$ (b) $d_t^{(i)}(u,v)$

Fig. 1. Thresholded and quantized HOS and depth maps.

vector $\mathbf{a_d^i}(u,v)$ of the i-th view by collecting depth information for $k = 0, \cdots T-1$, i.e.:

$$\mathbf{a_d^{(i)}}(u,v) = \left[d_0^{(i)}(u,v)\ d^{(i)}(u,v)\ \ldots d_{T-1}^{(i)}(u,v)\right] \quad (7)$$

We aim at matching the pixel (u,v) characterized by the depth-based activity vector $\mathbf{a_d^{(i)}}(u,v)$ of the i-th view with a pixel (u',v') of the j-th view characterized by the most similar depth-based activity vector $\mathbf{a_d^{(j)}}(u',v')$ of the j-th view. Following the approach in [3], the similarity is herein expressed in terms of mutual information between vectors. To compute the similarity measure, we build the co-occurrence matrix $C^d(u,v;u',v')$ of the values of depth extracted at the locations $(u,v;u',v')$ from the different views at the same temporal index t, namely the corresponding elements of the two activity vectors $\mathbf{a_d^{(i)}}(u,v)$, $\mathbf{a_d^{(j)}}(u',v')$. Specifically, the c_{l_1,l_2}^d element of the co-occurrence matrix $C^d(u,v;u',v')$ counts the number of occurrences of the event

$$\mathcal{E} = \left\{d_t^{(i)}(u,v) = l_1 \text{ and } d^{(j)}(u',v') = l_2\right\} \quad (8)$$

throughout the observed sequence, i.e. $t = 0, \cdots T-1$, normalized by the number of frames T. Thereby, the probability of co-occurrence of two depth values l_1, l_2 is roughly estimated as c_{l_1,l_2}^d. With these positions, the similarity measure $\mathcal{S}^d$ between the pixel (u,v) of the i-th view and a pixel (u',v') of the j-th view is computed as:

$$\mathcal{S}^d(u,v;u',v') = \sum_{l1=0}^{L_d-1}\sum_{l2=0}^{L_d-1} c_{l_1,l_2}^d \cdot \log_2 \frac{c_{l_1,l_2}^d}{\sum_l c_{l,l_2}^d\ \sum_l c_{l_1,l}^d} \quad (9)$$

Besides, following the same procedure, we can introduce the activity vectors based on the HOS of the inter-view differences $\hat{k}(u,v)$ for $k = 0, \cdots T-1$, i.e.

$$\mathbf{a_{HOS}^{(i)}}(u,v) = \left[\hat{k}_0^{(i)}(u,v)\ \hat{k}_1^{(i)}(u,v)\ \ldots \hat{k}_{T-1}^{(i)}(u,v)\right] \quad (10)$$

To perform the HOS-based correspondence matching, we then build the co-occurrence matrix of the depth values

$C^{HOS}(u, v; u', v')$ and finally resort to the HOS based similarity metric:

$$\mathcal{S}^{HOS}(u, v; u', v') = \sum_{l1=0}^{L_{HOS}-1} \sum_{l2=0}^{L_{HOS}-1} c_{l_1,l_2}^{HOS} \cdot \log_2 \frac{c_{l_1,l_2}^{HOS}}{\sum_l c_{l,l_2}^{HOS} \sum_l c_{l_1,l}^{HOS}} \tag{11}$$

being L_{HOS} the number of levels of the quantized HOS information.

Remarkably, each pixel can be characterized can be characterized by the self-information of the corresponding activity vector. Specifically, referring to the depth-based correspondence matching procedure, if the depth is quantized using L_d levels, each pixel (u, v) is characterized by the entropy

$$H(\mathbf{a}_{\mathbf{d}}^{(\mathbf{i})}(u, v)) = \sum_{l=0}^{L_d-1} p_l \log_2(1/p_l) \tag{12}$$

where p_l represents the probability of the l-th depth level, $l = 0, \ldots L_d - 1$. For the case of HOS based matching, the point (u, v) is characterized by a different entropy measure $H(\mathbf{a}_{\mathbf{HOS}}^{(\mathbf{i})}(u, v))$.

In Fig.2(a) we plot a bidimensional map of the entropy of the activity vector in the depth domain, namely $H(\mathbf{a}_{\mathbf{d}}^{(\mathbf{i})}(u, v))$. Interestingly enough, the self-information due to the activity as measured in the HOS domain is not related to the luminance discontinuities, exploited by correspondence matching methods such as SIFT [21] or SURF [22], but rather on the changes occurring in a certain location (u, v) throughout the T observed frames. A similar behavior is observed in Fig.2(b), where we plot a bidimensional map of the entropy of the activity vectors $H(\mathbf{a}_{\mathbf{HOS}}^{(\mathbf{i})}(u, v))$ in the HOS domain. The activity vector self-information is herein used for the purpose of selecting the pixels to be matched, as shown in the following Section.

(b) Depth-based Entropy

(a) HOS-based Entropy

Fig. 2. Entropy maps of the activity vectors.

4. EXPERIMENTAL RESULTS

We present here experimental results obtained by applying the above introduced HOS/depth correspondence matching

(a) i-th view

(b) j-th view

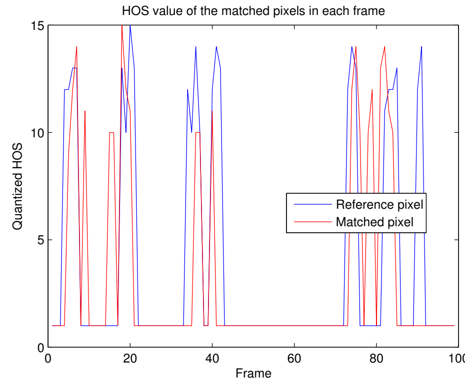
Fig. 3. Correspondence matching in the HOS domain.

procedure on the test sequence Breakdancer [19, 20] having a spatial resolution of 768×1024 pixels and a temporal resolution of 25 frames per seconds. We discuss the performance of correspondence matching performances obtained using the above introduced similarity metrics, using $T = 100$; this choise provides a good balance between computational cost and estimation performances. Each HOS map is thresholded and logarithmically quantized to $L_{HOS} = 16$ levels, the depth maps are thresholded, clipped, and uniformly quantized at $L_d = 128$ levels; the quantization stage reduces the estimation/acquisition noise effect and decreases the computational complexity. Then, two steps are applied, namely: i) selection of points candidate for matching research, based on the activity vectors self-information, and ii) search of the most similar points according to the activity vectors mutual-information. The results shown here are not directly comparable with state-of-the-art methods since, differently from what presented in [3] and in most litera-

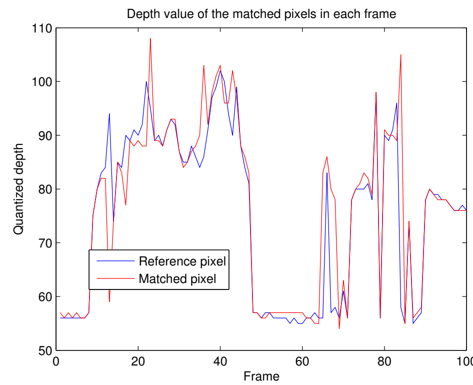
(a) i-th view

(b) j-th view

Fig. 4. Correspondence matching in the depth domain.



(a) HOS-based activity vectors



(b) Depth-based activity vectors

Fig. 5. Plot of two activity vectors evaluated in the HOS and depth domain for two matched points (u, v) and (u', v').

ture methods, here no post-processing is applied for the purposes of validation and regularization of the matched points. Besides, w.r.t. [3], where two independent pre-processing stages are applied, namely foreground/background segmentation and activity detection, here only entropy based pixel selection is applied.

In Fig.3(a) and (b), we show an example of corresponding pixels pairs found based on the HOS information whereas in Fig.4(a) and (b) an example of corresponding pixels pairs for the depth based case. In both the Figures we recognize that the proposed methods are able to match points which are in a low contrasted luminance areas (see the highlighted points labeled as A) but are well characterized in terms of HOS difference or depth, respectively. Points which are in a high contrasted luminance areas (highlighted points labeled as B) can be recognized as well. In Fig.5(a) and (b), we examplify one matched vectors' pair for the HOS and depth based cases, respectively; further results are available at [23].

From the above results, a few remarks can be drawn. First, both the HOS and depth domain lead to effective correspondence matching, and are therefore coandidate for activity based correspondence matching. The HOS based approach inherently realizes a change detection and does not require a preliminary segmentation stage. The segmentation stage can be also avoided when dealing with depth maps, since the acqusition stage itself provides information about the layered objects present in the scene. Besides, the HOS and depth based approach presents different strengths, since the first can work also in absence of depth information whereas the second works also in case or noisy, low-contrasted images or even images acquired in the dark for surveillance purposes. The preliminary results shown here pave the way for further joint processing of these information, possibly combined on the basis of their estimated reliability [18].

5. CONCLUSION

In this paper, we have investigated two strategies for finding corresponding pixels in different views of the same scene based on their activity; as a by-product of the study, an information-based criterion for selecting the pixels to be matched is given. The first approach characterizes the pixels activity using the co-acquired video depth maps, whereas the second approach exploits the Higher Order Statistics of the inter-frame difference. With respect to state-of-the-art works, both the strategies avoid preliminar pre-processing stages and open the path towards joint exploitation of statistical and geometrical features for multiview video scene analysis.

6. REFERENCES

[1] Ce Liu, J. Yuen, A. Torralba, “SIFT Flow: Dense Correspondence across Scenes and Its Applications,” IEEE Trans. on Pattern Analysis and Machine Intelligence, vol.33, no.5, pp.978,994, May 2011.

[2] E.B. Ermis, P. Clarot, P. Jodoin, V. Saligrama, “Activity Based Matching in Distributed Camera Networks,” IEEE Trans. on Image Processing, vol.19, no.10, pp.2595,2613, Oct. 2010

[3] Soon-Young Lee, Jae-Young Sim, Chang-Su Kim, Sang-Uk Lee, “Correspondence Matching of Multi-View Video Sequences Using Mutual Information Based Similarity Measure,” IEEE Trans. on Multimedia, vol.15, no.8, pp.1719,1731, Dec. 2013.

[4] A. Neri, S. Colonnese, G. Russo, P. Talone, “Automatic moving object and background separation” Signal Processing, Vol. 66 no. 2, April 1998.

[5] V. Reddy, C. Sanderson, B.C. Lovell, “Improved Foreground Detection via Block-Based Classifier Cascade With Probabilistic Decision Integration,” IEEE Trans. on Circuits and Systems for Video Technology, vol.23, no.1, pp.83,93, Jan. 2013.

[6] Qingqing Fu, M. Celenk, “Marked watershed and image morphology based motion detection and performance analysis,” 8th Int. Symp. on Image and Signal Processing and Analysis (ISPA), 2013, pp.159,164, 4-6 Sept. 2013.

[7] S. Colonnese, S. Rinauro, G. Scarano, “Bayesian depth map interpolation using edge driven Markov Random Fields”, Computational Modelling of Objects Represented in Images: Fundamentals, Methods and Applications III - Proceedings of the International Symposium, CompIMAGE 2012 , pp. 143-146.

[8] S. Colonnese, F. Cuomo, T. Melodia, “An Empirical Model of Multiview Video Coding Efficiency for Wireless Multimedia Sensor Networks,” IEEE Trans. on Multimedia, Vol.15 n.8 December 2013.

[9] Ken Sakurada, Takayuki Okatani, Koichiro Deguchi, “Detecting Changes in 3D Structure of a Scene from Multi-view Images Captured by a Vehicle-Mounted Camera,” Computer Vision and Pattern Recognition (CVPR), 2013 IEEE Conf. on, pp.137,144, 23-28 June 2013.

[10] X. Perrotton, M. Sturzel, M. Roux, “Implicit hierarchical boosting for multi-view object detection,” Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conf. on, pp.958,965, 13-18 June 2010.

[11] Shih-Wei Sun, Yu-Chiang Frank Wang, Fay Huang, Hong-Yuan Mark Liao, “Moving foreground object detection via robust SIFT trajectories”, Jour. of Visual Communication and Image Representation, Vol. 24, Issue 3, April 2013, Pages 232-243.

[12] O. Aghazadeh, J. Sullivan, S. Carlsson, “Multi view registration for novelty/background separation,” Computer Vision and Pattern Recognition (CVPR), 2012 IEEE Conf. on,pp.757,764, 16-21 June 2012.

[13] Yibin Chen, Canhui Cai, Kai-Kuang Ma, Xiaolan Wang, “Layered moving-object segmentation for stereoscopic video using motion and depth information”, Jour. of Visual Communication and Image Representation, Vol. 24, no. 7, October 2013, Pages 829-837.

[14] U. Takyar, T. Maugey, P. Frossard, “Extended Layered Depth Image Representation in Multiview Navigation,” IEEE Signal Processing Letters, vol.21, no.1, pp.22,25, Jan. 2014.

[15] Ying Chen, A. Vetro, “Next-Generation 3D Formats with Depth Map Support,” MultiMedia, IEEE, vol.21, no.2, pp.90,94, Apr.-June 2014

[16] G.Scarano, D.Caggiati, G.Jacovitti, “Cumulant series expansion of hybrid nonlinear moments of n variates”, *IEEE Transactions on Signal Processing*, vol.41, no.1, pp.486-489, January 993.

[17] Hongliang Li, K.N. Ngan, “Video Segmentation and Its Applications”, in Image/Video Segmentation: Current Status, Trends, and Challenges, Springer 2011, pp 1-23.

[18] S. Colonnese, S. Rinauro, G. Scarano, “Generalized Method of Moments Estimation of Location Parameters: Application to Blind Phase Acquisition,” IEEE Trans. on Signal Processing, vol.58, no.9, pp.4735,4749, Sept. 2010.

[19] http://research.microsoft.com/en-us/downloads/5e4675af-03f4-4b16-b3bc-a85c5bafb21d/

[20] C.L.Zitnick, S.B.Uyttendaele, S.Winder, R. Szeliski, “High-quality video view interpolation using a layered representation”, ACM Trans. on Graphics (TOG), Vol. 23, No. 3, pp. 600-608.

[21] D.G. Lowe, “Distinctive image features from scale-invariant keypoints”, International journal of Computer Vision, 2004, 60.2: 91-110.

[22] H.Bay, A. Ess, T. Tuytelaars, L. Van Gool, “Speeded-up robust features (SURF)” Computer vision and image understanding, 110(3), 346-359, 2008.

[23] http://infocom.uniroma1.it/˜colonnese/Correspondence_matching.html