Color stereo matching using correlation measures

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ABSTRACT
In the context of computer vision, stereo matching can be done using correlation measures. Few papers deal with correlation from color images so the underlying problem of this paper is about how correlation can be used with color images. A new protocol that can help to choose a color space and to generalize the correlation measures to color is proposed. Nine color spaces and three different methods have been investigated to evaluate their suitability for stereo matching. The results obtained from our evaluation protocol show us to what extent stereo matching can be improved with color.

KEY WORDS
color, correlation, matching.

1 Introduction

Matching is an important task in computer vision because the accuracy of the 3D reconstruction depends on the accuracy of the matching. A lot of matching algorithms have been proposed [19]; the present paper focuses on matching using correlation measures [1] whose main hypothesis is based on the similarity of the neighborhoods of the corresponding pixels. Hence, in this context, we consider that a correlation measure evaluates the similarity between two pixel sets.

Although the use of color images is more and more frequent in computer vision [8, 14] and can improve the accuracy of stereo matching [17], few papers present correlation measures with color images [10, 17]. The most common approach is to compute the mean of the three color components [15] or to use only one of the color components [8]. In this paper, our purpose is also to take into account color in dense matching using correlation. The main novelty of our work is a protocol that enables to choose a color space and to generalize the correlation measures from gray level to color.

In order to set up this protocol, nine color spaces are evaluated and three methods are proposed: to compute the correlation with each color component and then to merge the results; to process a principal component analysis and then to compute the correlation with the first principal component; to compute the correlation directly with colors. As for this latter, at least two difficulties appear: the computation of the difference between two colors and the evaluation of the rank of a set of colors. Moreover, an evaluation protocol which enables to study the behavior of each method with each color space is required to highlight the best way to adapt correlation measures to color and the improvement of the efficiency of stereo matching using correlation.

The paper is structured as follows. Firstly, the most used color spaces are presented. Secondly, three methods and the rules for adapting the measures are given. The third part shows our evaluation protocol. Finally, the results are discussed and conclusions drawn.

2 Color spaces

A color space is a mean by which color can be specified, created and visualized. The choice of color space is important and a lot of color spaces have been proposed [4, 12, 20]. Here, the color spaces that are most used are distinguished into four families [22] (Table 1):

- Primary systems: RGB, XYZ [22];
- Luminance-chrominance systems: $L^*u^*v^*$ [20], $L^*a^*b^*$ [20], AC_1C_2 [21] and YC_1C_2 [12];
- Perceptual system: HSI [10];
- Statistical independent component system: $I_1I_2I_3$ [16] and $H_1H_2H_3$ [4].

3 Color stereo matching using correlation

3.1 Algorithm and notations

The three steps of the algorithm are, for each pixel in the left image:

NAME	DEFINITION
XYZ	$\begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = \begin{pmatrix} 0.607 & 0.174 & 0.200 \\ 0.299 & 0.587 & 0.114 \\ 0.000 & 0.066 & 1.116 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix}$
$L^*u^*v^*$	$L^* = \begin{cases} 116\,(Y/Y_w)^{\frac{1}{3}} - 16 & \text{if } Y/Y_w > 0.01 \\ 903.3\,Y/Y_w & \text{otherwise} \end{cases}$ $u^* = 13L^*(u' - u'_w)$ with $u' = \frac{4X}{X+15Y+3Z}$ $v^* = 13L^*(v' - v'_w)$ with $v' = \frac{9Y}{X+15Y+3Z}$ X_w, Y_w, Z_w are the white reference components
$L^*a^*b^*$	$a^* = 500(f(X/X_w) - f(Y/Y_w))$ $b^* = 200(f(Y/Y_w) - f(Z/Z_w))$ $f(x) = \begin{cases} x^{1/3} & \text{if } x > 0.008856 \\ 7.787x + \frac{16}{116} & \text{otherwise} \end{cases}$
AC_1C_2	$\begin{pmatrix} A \\ C_1 \\ C_2 \end{pmatrix} = \begin{pmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{\sqrt{3}}{2} & \frac{-\sqrt{3}}{2} & 0 \\ \frac{-1}{2} & \frac{-1}{2} & 1 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix}$
YC_1C_2	$\begin{pmatrix} Y \\ C_1 \\ C_2 \end{pmatrix} = \begin{pmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ 1 & \frac{-1}{2} & \frac{-1}{2} \\ 0 & \frac{-\sqrt{3}}{2} & \frac{\sqrt{3}}{2} \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix}$
HSI	$I = \frac{R+G+B}{3}, S = 1 - 3\frac{\min(R,G,B)}{R+G+B}$ $H = \begin{cases} \arccos H_1 & \text{if } B \leq G \\ 2\pi - \arccos H_1 & \text{otherwise} \end{cases}$ $H_1 = \frac{(R-G)+(R-B)}{2\sqrt{(R-G)^2+(R-B)(G-B)}}$
$I_1I_2I_3$	$\begin{pmatrix} I_1 \\ I_2 \\ I_3 \end{pmatrix} = \begin{pmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{2} & 0 & \frac{-1}{2} \\ \frac{-1}{4} & \frac{-1}{4} & \frac{1}{2} \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix}$
$H_1H_2H_3$	$\begin{pmatrix} H_1 \\ H_2 \\ H_3 \end{pmatrix} = \begin{pmatrix} 1 & 1 & 0 \\ 1 & -1 & 0 \\ \frac{-1}{2} & 0 & -\frac{1}{2} \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix}$

Table 1: The nine color spaces investigated.

1. The search area, region of the image where we expect to find the corresponding pixel, is determined in the right image;
2. For each pixel in the search area, the correlation score is evaluated;
3. The pixel giving the best score is the matched pixel.

The left and right images are denoted by I_v with $v = l, r$ and the following notations are used:

- The size of the correlation windows is $(2n+1) \times (2m+1)$ and $N = (2n+1)(2m+1)$, n, $m \in \mathbb{N}^*$;
- The gray level of the pixel in the image I_v at coordinates (i, j) is noted $I_v^{i,j}$;
- The vectors $\mathbf{f}_v$ with $v = l, r$ contain the gray levels of the pixels in the left and right correlation windows: $\mathbf{f}_v = (\cdots I_v^{i+p,j+q} \ldots)^T = (\cdots f_v^k \cdots)^T$, where f_v^k is the element k of vector $\mathbf{f}_v$, $p \in [-n; n]$, $q \in [-m; m]$, $k \in [0; N-1]$ and the transposed vector of $\mathbf{f}$ is noted $\mathbf{f}^T$;
- The ordered values of vector $\mathbf{f}$ are noted: $(f)_{0:N-1} \leq \ldots \leq (f)_{N-1:N-1}$.

3.2 Three methods

In the sequel, we use XYZ space with coordinates x, y and z but the formulae are valid for all the color spaces. We introduce the following notations:

- $\mathbf{c}_v^k = (x_v^k\ y_v^k\ z_v^k)^T$ with $v = l, r$ are the colors of the elements k in the correlation windows;
- Matrices $\mathbf{F}_v$ with $v = l, r$ contain the colors of the pixels in the left and right correlation windows: $\mathbf{F}_v = (\cdots \mathbf{c}_v^k \cdots)^T$, $k \in [0; N-1]$.

The three proposed methods of the protocol are:

- METHOD 1: to compute the correlation measure with each component and to merge the results:

$$\mathrm{M_c}(\mathbf{F}_l, \mathbf{F}_r) = \gamma(\mathrm{M_g}(\mathbf{x}_l, \mathbf{x}_r), \mathrm{M_g}(\mathbf{y}_l, \mathbf{y}_r), \mathrm{M_g}(\mathbf{z}_l, \mathbf{z}_r))$$
$$\gamma \in \{\text{minimum}, \text{maximum}, \text{median}, \text{mean}, \text{belli}\} \quad (1)$$

  $\mathrm{M_c}$ is a color correlation and $\mathrm{M_g}$ a gray level correlation. The vectors $\mathbf{x}_v$, $\mathbf{y}_v$, $\mathbf{z}_v$ with $v = l, r$ contain all the components of the colors in the correlation windows and the fusion of Belli [2] is defined by:

$$\mathrm{M_c}(\mathbf{F}_l, \mathbf{F}_r) = \frac{\mathrm{M_g}(\mathbf{x}_l,\mathbf{x}_r)^2 + \mathrm{M_g}(\mathbf{y}_l,\mathbf{y}_r)^2 + \mathrm{M_g}(\mathbf{z}_l,\mathbf{z}_r)^2}{\mathrm{M_g}(\mathbf{x}_l,\mathbf{x}_r) + \mathrm{M_g}(\mathbf{y}_l,\mathbf{y}_r) + \mathrm{M_g}(\mathbf{z}_l,\mathbf{z}_r)} \quad (2)$$

- METHOD 2: to process a principal component analysis, PCA, like Cheng [7], and then to compute the correlation measure with the first principal component. The PCA can be done on all the images (METH 2.1) or on the correlation window (METHOD 2.2) and in this latter variant:

$$\mathrm{M_c}(\mathbf{F}_l, \mathbf{F}_r) = \mathrm{M_g}(\mathrm{PCA}(\mathbf{F}_l), \mathrm{PCA}(\mathbf{F}_r)) \quad (3)$$

- METHOD 3: to compute the correlation measure directly with colors; for this method, we give the rules for adapting the measures:
  - L_P norm with $P \in \mathbb{N}^*$ defined by:

$$\|\mathbf{f}_v\|_P = \left(\sum_{k=0}^{N-1} |f_v^k|^P\right)^{\frac{1}{P}} \text{ becomes}$$
$$\|\mathbf{F}_v\|_P = \left(\sum_{k=0}^{N-1} \|\mathbf{c}_v^k\|_P{}^P\right)^{\frac{1}{P}} \text{ with} \quad (4)$$
$$\|\mathbf{c}_v^k\|_P{}^P = (x_v^k)^P + (y_v^k)^P + (z_v^k)^P$$

    Euclidean norm is noted: $\|\mathbf{f}_v\| = \|\mathbf{f}_v\|_2$ and $\|\mathbf{F}_v\| = \|\mathbf{F}_v\|_2$. This is the Frobenius norm;

∘ Scalar product defined by:

$$\mathbf{f}_l \cdot \mathbf{f}_r = \sum_{k=0}^{N-1} f_l^k f_r^k \qquad \text{becomes}$$
$$\mathbf{F}_l \cdot \mathbf{F}_r = \sum_{k=0}^{N-1} x_l^k x_r^k + y_l^k y_r^k + z_l^k z_r^k \tag{5}$$

∘ Means noted:

$$\overline{\mathbf{f}_v} = \frac{1}{N} \sum_{k=0}^{N-1} f_v^k \qquad \text{becomes}$$
$$\overline{\mathbf{F}_v} = \frac{1}{N} (\underbrace{1 \cdots 1}_{N \text{ columns}})^T \begin{pmatrix} \sum_{k=0}^{N-1} x_v^k & \sum_{k=0}^{N-1} y_v^k & \sum_{k=0}^{N-1} z_v^k \end{pmatrix} \tag{6}$$

The two major problems are to compute the difference between two colors and to evaluate the rank of a set of colors. To describe the difference of colors in a space, a distance is needed. The most common is the L_2 norm [10], but here the L_P norm is chosen with $P \in \mathbb{N}^*$:

$$d(\mathbf{c}_l, \mathbf{c}_r) = ((x_l - x_r)^P + (y_l - y_r)^P + (z_l - z_r)^P)^{\frac{1}{P}} \tag{7}$$

This norm is not suitable for HSI space and this distance is commonly used [10]:

$$d(\mathbf{c}_l, \mathbf{c}_r) = \sqrt{(I_l - I_r)^2 + S_l^2 + S_r^2 - 2S_l S_r cos\theta}$$
$$\theta = \begin{cases} |H_l - H_r| & \text{if } |H_l - H_r| \leq \pi \\ 2\pi - |H_l - H_r| & \text{otherwise.} \end{cases} \tag{8}$$

The term $\mathbf{D}(\mathbf{F}_l, \mathbf{F}_r) = \begin{pmatrix} \dots & d(\mathbf{c}_l^i, \mathbf{c}_r^i) & \dots \end{pmatrix}^T$ is the vector of distances between colors of the correlation windows and d is like equations (7) or (8).

To sort a color vector, four possibilities are given:

- SORT 1: to sort the first principal component of a PCA, like [7];
- SORT 2: to compute the bit mixing code and to sort these codes [6];
- SORT 3: to sort only one of the components;
- SORT 4: to use the lexicographic order:

$$\begin{aligned} &\text{if } (x_v^k > x_v^i) \text{ or } (x_v^k = x_v^i \text{ and } y_v^k > y_v^i) \\ &\text{or } (x_v^k = x_v^i \text{ and } y_v^k = y_v^i \text{ and } z_v^k > z_v^i) \\ &\text{then } \mathbf{c}_v^k > \mathbf{c}_v^i \\ &\text{else } \mathbf{c}_v^k < \mathbf{c}_v^i \end{aligned} \tag{9}$$

In our previous work [5], the commonly used correlation measures were classified into five families: cross-correlation-based measures, classical statistics-based measures, derivative-based measures, ordinal measures and robust measures. The way of adapting every measures into each family is illustrated by an example.

Cross-correlation-based measures – The Zero mean Normalized Cross-Correlation noted:

$$\text{ZNCC}(\mathbf{f}_l, \mathbf{f}_r) = \frac{(\mathbf{f}_l - \overline{\mathbf{f}_l}) \cdot (\mathbf{f}_r - \overline{\mathbf{f}_r})}{\|\mathbf{f}_l - \overline{\mathbf{f}_l}\| \|\mathbf{f}_r - \overline{\mathbf{f}_r}\|} \qquad \text{becomes}$$
$$\text{ZNCC}(\mathbf{F}_l, \mathbf{F}_r) = \frac{(\mathbf{F}_l - \overline{\mathbf{F}_l}) \cdot (\mathbf{F}_r - \overline{\mathbf{F}_r})}{\|\mathbf{F}_l - \overline{\mathbf{F}_l}\| \|\mathbf{F}_r - \overline{\mathbf{F}_r}\|} \tag{10}$$

Classical statistics-based measures – The Zero mean Normalized Distances given by:

$$\text{ZND}_P(\mathbf{f}_l, \mathbf{f}_r) = \frac{\|(\mathbf{f}_l - \overline{\mathbf{f}_l}) - (\mathbf{f}_r - \overline{\mathbf{f}_r})\|_P{}^P}{\sqrt{\|\mathbf{f}_l - \overline{\mathbf{f}_l}\|_P{}^P \|\mathbf{f}_r - \overline{\mathbf{f}_r}\|_P{}^P}} \quad \text{become}$$
$$\text{ZND}_P(\mathbf{F}_l, \mathbf{F}_r) = \frac{\|\mathbf{D}(\mathbf{F}_l - \overline{\mathbf{F}_l}, \mathbf{F}_r - \overline{\mathbf{F}_r})\|_P{}^P}{\sqrt{\|\mathbf{F}_l - \overline{\mathbf{F}_l}\|_P{}^P \|\mathbf{F}_r - \overline{\mathbf{F}_r}\|_P{}^P}} \tag{11}$$

Derivative-based measures – These measures [1] use filters to compute the image derivatives. These filters are applied separately on the three channels. To compute the norm and the orientation of the gradient vector field, we use the method of Lee-Cok [13] or the sum of the gradient vector [14]. The Pratt measure:

$$\text{PRATT}(\mathbf{f}_l, \mathbf{f}_r) = \text{ZNCC}(\text{R}_p(\mathbf{f_l}), \text{R}_p) \qquad \text{becomes}$$
$$\text{PRATT}(\mathbf{F}_l, \mathbf{F}_r) = \text{ZNCC}(\text{R}_p(\mathbf{F}_l), \text{R}_p(\mathbf{F}_r)) \tag{12}$$

The vectors $\text{R}_p(\mathbf{f_v})$ and the matrices $\text{R}_p(\mathbf{F_v})$ are obtained after using the Pratt filter [18].

Ordinal measures – These measures [3, 9, 23] use ordered gray levels of the pixels in the correlation window. To sort the color vectors, we use the four methods: SORT 1 to 4. The Increment Sign Correlation [9]:

$$\text{ISC}(\mathbf{f}_l, \mathbf{f}_r) = \frac{1}{N-1}(\mathbf{b_l} \cdot \mathbf{b_r} + (1 - \mathbf{b_l}) \cdot (1 - \mathbf{b_r}))$$
$$\text{becomes} \tag{13}$$
$$\text{ISC}_P(\mathbf{F}_l, \mathbf{F}_r) = \frac{1}{N-1}(\mathbf{c}_r \cdot \mathbf{c}_l + (1 - \mathbf{c}_r) \cdot (1 - \mathbf{c}_l))$$

The vectors $\mathbf{b}_v$ and $\mathbf{c}_v$ are obtained after applying the Kaneko transform [9]. This transform compares the pixels in the correlation window. So, for, the vectors $\mathbf{c}_v$, this transform is applied after sorting the vector of colors with one of the method SORT 1 to 4.

Robust measures – These ones use the tools of robust statistics. The Smooth Median Powered Deviation [5]:

$$\text{SMPD}_P(\mathbf{f}_l, \mathbf{f}_r) = \sum_{i=0}^{h-1} (|\mathbf{f}_l - \mathbf{f}_r - \text{med}(\mathbf{f}_l - \mathbf{f}_r)|^P)_{i:N-1}$$
$$\text{becomes, with } \mathbf{D} = \mathbf{D}(\mathbf{F}_l, \mathbf{F}_r), \tag{14}$$
$$\text{SMPD}_P(\mathbf{F}_l, \mathbf{F}_r) = \sum_{i=0}^{h-1} (|\mathbf{D} - \text{med}(\mathbf{D}))|^P)_{i:N-1}$$

4 Evaluation protocol

Ten pairs of color images with ground truth are used: a random-dot stereogram and nine real images proposed by Scharstein and Szeliski [19] and that can be found at: `http://www.middlebury.edu/stereo/data.html`. Six of these images are made up piecewise of planar objects (typically posters, some with cut-out edges) and three images are complex scenes. Because of the lack of space, the results of only two pairs (Figure 1) are shown.

For the evaluation, ten criteria are chosen:

- Percentage of correct and false matches (CO, FA);
- Percentage of accepted matches (AC): if the distance between the calculated and the true correspondent is one pixel then the calculated correspondent is accepted. When the percentage of correct matches is low, if this criterion is large then the method gives a good estimation of the disparities;
- Percentage of false positives and false negatives (FP, FN): the method finds the pixel is matched whereas it is not matched and vice versa;
- Percentage of correct matched pixels in occluded areas: the morphological dilation of the set of pixels with no corresponding pixels in the other image of the pair is considered (DI, black and gray pixels in 1.(d) and 1.(h)). The results in the set of pixels without correspondent (OC, black pixels in 1.(d) and 1.(h)) and in the set of pixels near the pixels without correspondent (NO, gray pixels in 1.(d) and 1.(h)) are distinguished;
- Execution time (T) and disparity maps.

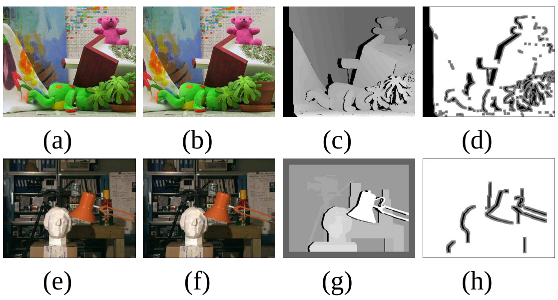

Figure 1: (a)-(b) "Teddy" images. (c) Disparity map: the clearer the pixel is, the closer the point to the image plane and the larger the disparity. The black pixels are occluded pixels. (d) Occluded areas, black: pixels without correspondent, gray: region around the black pixels. (e)-(h) Same images with "head and lamp".

The size of the correlation window is 9×9 (the most suitable size for this kind of images found in [5]). The images are rectified so the search area is limited to the size 61×1 (121×1 with "teddy"): 30 (60 with "teddy") pixels before and after the pixel of interest. Moreover, the symmetry constraint is added in order to try to locate the occluded pixels. The correlation is performed twice by reversing the roles of two images. The matches for which the reverse correlation falls onto the initial point in the left image are considered as valid, otherwise the pixel is considered as occluded. The three methods and the nine color spaces[1] are tested and compared with gray level correlation.

5 Experimental results

The results with "teddy" are shown in tables 2 and 3, for one measure of each family. The table 2 gives the parameters to obtain the best results for each method. The results of the best methods are noted in bold letters. The table 3 presents the results for the best method for color matching and the results of gray level matching. The best results are noted in bold letters and when the color matching always gives the best results, the name of the corresponding column is noted in bold letters.

MEA	METHOD 1		METHOD 2		METHOD 3	
	SPACE	FUSION	SPACE	VAR	SPACE	OTHER
NCC	$\mathbf{H_1H_2H_3}$	**max**	$H_1H_2H_3$	2.2	$H_1H_2H_3$	
D_1	XYZ	max	$H_1H_2H_3$	2.2	$\mathbf{H_1H_2H_3}$	$\mathbf{L_\infty}$
PRATT	**XYZ**	**max**	RGB	2.1	$H_1H_2H_3$	
ISC	**XYZ**	**belli**	$H_1H_2H_3$	2.2	$L^*u^*v^*$	SORT 4
$SMPD_2$	**XYZ**	**med**	$H_1H_2H_3$	2.1	$H_1H_2H_3$	L_2

MEA = measure, VAR = variant, max = maximum, med = median.

Table 2: Best results with each method for "Teddy".

MEA	TYPE	**CO**	AC	FA	FP	**FN**	**DI**	OC	**NO**	T
NCC	GL	52.28	23.86	30.56	2.74	14.42	69.96	76.09	65.74	**52**
	C	**55.16**	**24.13**	**30.41**	**2.63**	**11.80**	**70.56**	**77.05**	**66.11**	141
D_1	GL	49.52	**22.62**	29.83	**2.83**	17.83	70.93	**75.31**	67.92	**63**
	C	**51.55**	21.94	**29.31**	2.94	**16.19**	**71.88**	74.34	**70.19**	140
PRATT	GL	29.05	8.22	30.73	3.81	36.40	58.51	66.77	52.84	**86**
	C	**45.21**	**17.26**	**28.41**	**3.47**	**22.92**	**65.03**	**69.75**	**61.79**	225
ISC	GL	44.88	19.20	**28.16**	2.70	24.27	68.96	76.52	63.77	**126**
	C	**52.56**	**22.33**	28.55	**2.59**	**16.31**	**73.07**	**77.45**	**70.07**	245
$SMPD_2$	GL	49.88	23.21	30.46	2.34	17.32	74.51	79.65	70.97	**568.9**
	C	**56.48**	**25.34**	**30.06**	**2.21**	**11.24**	**77.68**	**80.70**	**75.61**	2109

MEA = measure, GL = gray level, C = color

Table 3: Color and gray level matching for "Teddy".

[1] Here, $X_w = 250.155$, $Y_w = 255$ and $Z_w = 301.41$.

The results with all the images and particularly with “teddy” permit these remarks:

- METHOD 1 and 3 always have variants that give better results than the gray level method whereas METHOD 2 does not;
- METHOD 1 and 3 always have variants that improve the percentage of correct pixels and false negatives;
- METHOD 1 is better than METHOD 3 but METHOD 3 is less expensive;
- For METHOD 1:
  - Best color space is often XYZ (54% of the cases);
  - Best fusion is often with the operator maximum (48% of the cases);
- For METHOD 2:
  - Best color space is often $H_1H_2H_3$ (42% of the cases);
  - Best method is often 2.1 (65% of the cases);
- For METHOD 3:
  - Best color space is often $H_1H_2H_3$ (50% of the cases);
  - Best results are obtained with SORT 4;
  - All the L_P norms give equivalent results.

The disparity maps obtained with color images are the best (figures 2 and 3).

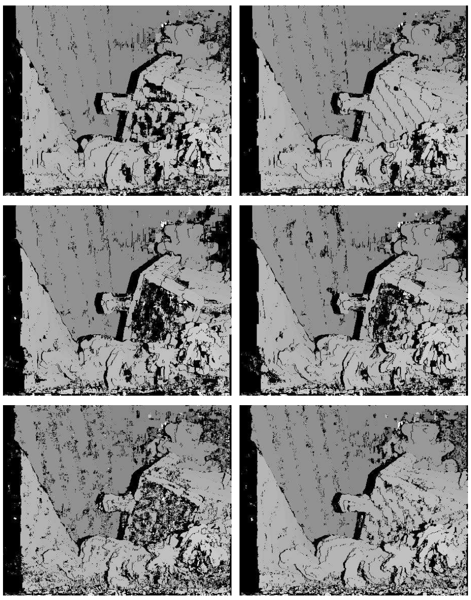

Figure 2: Disparity maps for “Teddy”.

6 Conclusion

This paper deals with color stereo matching using correlation and illustrates how to generalize gray level correlation to color. A protocol is proposed, for which nine color spaces are tested and three different methods are experimented. The results highlight that color always improve the results even if the best color space and the best method are not easy to distinguished. In fact, the choice of the color space and the method depends on the measure, the images and the execution time constraint. Nevertheless, there is an important result: we can conclude that METHOD 1 with XYZ space or METHOD 3 with $H_1H_2H_3$ space are often the best (64% of the cases). An extension of this work would be to consider different areas in order to determine if color can be used, for example, like Koschan [11] who distinguishes chromatic and achromatic areas.

Figure 3: Disparity maps for “Head and lamp”.

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