MIXED COLOR/LEVEL LINES AND THEIR STEREO-MATCHING WITH A MODIFIED HAUSDORFF DISTANCE

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Abstract: Level lines and sets are competitive features to support recognition. Color is assumed more informative than intensity, so color-lines are preferred to exhibit the set basis. In the paper, they are defined after level lines, and then extracted and characterize. Greater information is kept by color lines resulting into more efficient grouping towards objects. A novel Hausdorff-inspired disparity finder is introduced fed in by color lines with respect to epipolar constraints. The efficient disparity map resulting from pixel wise line-matching between left and right images justifies our technical choices.

1 INTRODUCTION

Usual segmentation appears sensitive in practice to the view point and shadows (contrast changes). In this paper, morphologically stable sets are extracted and a Hausdorff distance provides for global and local pattern matching all in once. Level sets make a basis - the topographic map - easy to compute.

According to psychologists (Koschan a Abidi 2008), in most contexts color prevails on shape and texture: whence using color to make lines more distinctive seems sensible.

Defining color sets and lines is not straightforward because of the intrinsic tri-dimensional nature of color. Usually, color data are transformed from a 3D color space to a 1D Level Space, by combining the three components, either to specify a total order of colors or towards some optimal function of those. Here, our of the commonly used HSV space, the 1D level space is provided by a mixture of H and V weighted by S. After mixture line features have been extracted from two images to compare, matching is carried out with a coarse to fine strategy involving a modified Hausdorff distance (Huttenlocher 1993), to pair portions of lines.

As the disparity in stereoscopic images is computed from the distance of corresponding points, results of stereo shape matching and their comparison with the ground truth will assert the efficiency of our matching process, founding the algorithm evaluation.

The paper is organized as follows. Section 2 is a brief reminder on lines, color and matching for notations and basic algorithms. Section 3 details our procedure to enhance intensity lines into color lines. Then, Section 4 deals with pattern and point selections for matching towards disparity from line pairing. Finally, the validity and efficiency of the proposed procedure are evaluated through comparing our depth map with the ground truth.

2 BIBLIOGRAPHY

Level sets and lines. Level sets (Caselles 1999), the topographic map, prove invariant to contrast changes and naturally robust to occlusions. Converting images into sets and back is straightforward. Projections follow equation (1) or (2)

$$X_\lambda = \{x \in \Re^2, u(x) \le \lambda\} \tag{1}$$

$$X^\lambda = \{x \in \Re^2, u(x) \ge \lambda\} \tag{2}$$

where *u(x)* is the gray level at pixel *x* in the image and λ is the parameter – threshold – defining the lower (resp. upper) set X_λ (resp. X^λ). reconstruction follows equations (3)

$$u(x) = \inf_\lambda\{\lambda, u \in X^\lambda\} = \sup_\lambda\{\lambda, u \in X_\lambda\} \tag{3}$$

A level line is the border of a level set, therefore parameterized by the same λ. In practice it still depends on the threshold's step: as it is usually low

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valued in hope of an exhaustive topographic map, images generate more lines than necessary to matching. Color is likely to improve a priori the line separability then lowering their number.

Color Edges and Lines. Color was first proved to extend the notion of topographic map by (Coll & Froment 2000) who designs a total order in the HSV space. Gouiffès (2008) proposed to extract color sets from color bodies in the RGB 3-D histogram. Moreover the Hue in HSV proves ultimately discriminative and invariant to shadow, however it is ill-defined at low saturation. Compared to gray level, color provides more edge or line information.

Feature matching. Set-correspondence finding between two images can be classified into three principal algorithmic lines: Point matching, based on correlation windows on raw intensity data, but suffer on homogeneous areas. Geometrical Feature matching are the corners or curvature points or line segments with attributes. Region and shape matching strategies. The hypothesis is made here that corresponding patterns maintain the shape between images (Loncaric 1998).

The method we detail in the present paper exploits the shape stability granted by the invariance to contrast through color sets.

3 COLOR SETS AND LINES

3.1 Color Sets

Color image data can be represented in the RGB cube. The pixel intensity – i.e. level – amounts to projecting the given RGB point onto the principal diagonal of the cube (the gray level scale). The question then arises to find a transformation more adaptive to the image content. Gouiffes & Zavidovique (2008) proposed to use the dichromatic model to find body colors: vectors pointing to principal body colors are used separately instead of the sole cube diagonal. Related data – i.e. close enough in the RGB space – is projected onto that vector exhibiting associated level sets.

Our leading idea to build the transformation of the HSV color space into a 1-D level space takes after the vanishing of Hue, independently at both low light intensity and low saturation.

3.2 H,V Mixtures vs. S

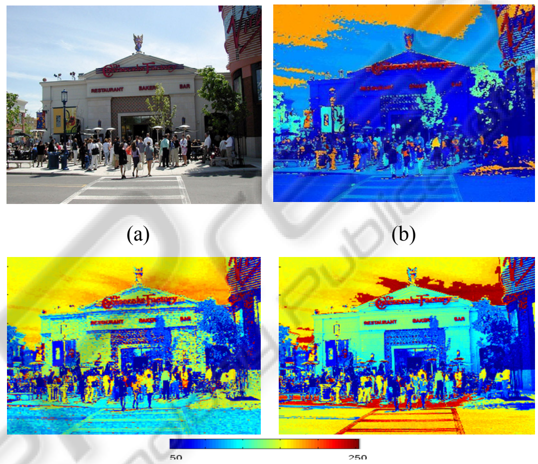
Considering the above-mentioned drawbacks of the HSV space, the following formulation of S is preferred:

$$S = Max(R,G,B) - Min(R,G,B) \qquad (4)$$

Second, we propose to use hue when it is relevant(high saturation) and intensity otherwise (low saturation). To ensure color sets homogeneous enough respective to what is expected from regions in image segmentation, we design a smooth transition with a sigmoid function Sig(s,k):

$$O_F(p) = Sig(s,k)H(p) + (1 - Sig(s,k))I(p) \qquad (5)$$

Sig(s,k) is thus parameterized by its slope s and inflection point k to be adapted from former α and β.



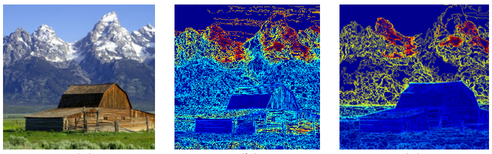
(a) (b) (c) (d)

Figure 1: (a) Original image, (b) pseudo-color image in the data space from the step function O_F and threshold on intensity, (c) pseudo-color image in the data space from the sigmoid mixture O_F and a threshold on intensity, (d) pseudo-color image from the same data space and a threshold on magnitude of the saturation, both (b) (c) and (d) use same scale of pseudo color.

Fig 1 compares the use of a sigmoid (Fig. 1(c)) is compared with the use of a Heaviside step function (see Fig 1 (b)). On top of regular noise, the artifacts of the step function are likely due to the frequency of switches between the intensity and hue scales when saturation lies in around the threshold. The overall consequence is a loss of some details when trying to lower the effect. The drawback of the sigmoid function, compared to the step function, is conversely its smoothness. When saturation is low, although hue does not keep much of an effect, a change of the RGB vector even to a close one might result into significant modification of the final result O_F due to the small signal situation. Pepper noise can occur on the image during the transition of the Sig function around point k. Fig.1(c) finally illustrates that issue: for example, on the road area, the wall of the restaurant, or among the crowd, the sigmoid combination outputs some sparse noise.

Sharpening the sigmoid to make it closer to a step function will reduce details. Since, again, the sigmoid is more biased by the hue and is exactly used to take advantage from it, the inflection point k is set to a low value. Figure 1(d) shows better results in that respect thanks to replacing the usual formula of the saturation – a ratio – by the difference version given in equation (4). Finally, Fig. 2 compares our lines with the classical gray level lines.

Our line extraction method derives from the one proposed by Bouchafa (2006) to direct close curve extraction.



(a) (b) (c)

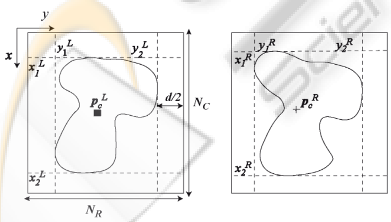
Figure 2: (a) Original color image, (b) gray level lines, (c) color lines. Note that (b) and (c) result from a same artificial look-up table to make lines more distinct.

4 COLOR LINE MATCHING

To speed the match up, our method begins to sort patterns by global features for a coarse stage. Then, at the fine stage, point matching is performed.

Coarse Scale Matching. Techniques of comparing border of sets between 2 shapes, such as, length, level of set, standard deviation and position shape, which is exploited from stereo vision knowledge.

Fine Matching. Published techniques relying on a reference point, e.g. Chang (1991), strongly depend on this point stability.



(a) (b)

Figure 3: Example of corresponding sets A and B and their centroids and notations.

The Hausdorff distance founds an interesting technique to get the process free from the center. Let $\boldsymbol{A} = \{a_1,...,a_n\}$ and $\boldsymbol{B} = \{b_1,...,b_m\}$ be two finite sets. Their Hausdorff distance is defined as

$$H(A,B) = Max\left(h(A,B), h(B,A)\right) \tag{6}$$

where

$$h(A,B) = \underset{a \in A}{Max}\ \underset{b \in B}{Min} \left\| a_i - b_j \right\| \tag{7}$$

and $\| \ \|$ is a norm in the affine space of the image.

In previous works, e.g. (Huttenlocher 1993) Hausdorff was used to locate shapes in a scene by using a template.

Here, a topographic map contains abundant lines which are close together, hampering the accuracy of the distance map in our application. Therefore a progressive scheme is rather tried: every tentative couple of left and right lines is extracted and superimposed within a common window W with center $\boldsymbol{p_c^W}$ of coordinates (x_c^W, y_c^W) and of size N_R N_C. However, using the center of W, $p^W_c = (N_C/2, N_R/2)$ as the reference point for mapping, two problems occur. First, direct mapping of the centroid of W may make some part to exceed the window. Second, right and left patterns to be matched can be dissimilar since they were filtered roughly, therefore large enough space d is needed to compensate.

Thus, a slightly more elaborated shifting strategy into W has to be designed (see Fig. 3). x_1^L, x_2^L, y_1^L, y_1^L are the coordinates of the bounding rectangle of the left pattern, and $p_c^L = (x_c^L, y_c^L)^T$ is the centroid (small square) of the line to be mapped in the comparison. It is likely different from the center of the window, illustrating the first problem.

Finally, both each point $\boldsymbol{p^L} = (x^L, y^L)$ of L_L and each point $\boldsymbol{p^R} = (x^R, y^R)$ of L_R are translated into W, of reference point $p^W = (xc^W, yc^W)$ and of size N_R x N_C respectively with vectors v_L^W and v_R^W :

$$\boldsymbol{p'}_L = \boldsymbol{p}_L + \boldsymbol{v'}_{LW} \quad with \quad \boldsymbol{v'}_{LW} = (x_c^W - x_c^L, y_c^W - y_c^L)^T \tag{8}$$

$$\boldsymbol{p'}_R = \boldsymbol{p}_R + \boldsymbol{v'}_{RW} \quad with \quad \boldsymbol{v'}_{RW} = (x_c^W - x_c^R, y_c^W - y_c^R)^T \tag{9}$$

where The new centroid p^W_c is then defined as:

$$\boldsymbol{p}_c^W = \begin{pmatrix} x_c^W \\ y_c^W \end{pmatrix} = \begin{pmatrix} N_R \\ N_C \end{pmatrix}^T \begin{pmatrix} (x_c^L - x_1^L)/(x_2^L - x_1^L) \\ (y_c^L - y_1^L)/(y_2^L - y_1^L) \end{pmatrix} \tag{10, 11}$$

and comparison window is the rectangle N_R x N_C:

$$N_R = x_2^L - x_1^L + d \tag{12}$$

$$N_C = y_2^L - y_1^L + d \tag{13}$$

where d is the extension of the window from the size of the line

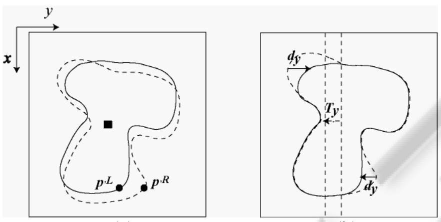
Note that, according to the stereovision application targeted in our paper, we assume that the epipolar constraint holds, Therefore, the translation on row x is similar in v'^W_L and v'^W_R. This assumption reduces significantly the complexity of the Hausdorff matching so made one-dimensional. After shifting the selected left line L_L to W (equation (8)) the distance map is computed with a city block distance. Then, candidate samples of right lines are mapped to W – equations (8,9) – and the Hausdorff distance is computed for all right line candidates in C_R as resulting from the coarse scale matching. The final homologous line is the line which provides the minimum Hausdorff distance - equation (6) .

Indeed, when finding the point-to-point or line-to-point distances, we use their minimum. Pattern-to-pattern distances, i.e. set of points to set of points, result from the furthest of those closest points. When a pattern is selected by the Hausdorff's condition, all points in the set will find their corresponding part.

$\boldsymbol{T}_y$ is the translation vector bound to the minimum Hausdorff distance (see Fig. 4), and $\boldsymbol{d}_y$ is the local Hausdorff vector between corresponding columns of points $\boldsymbol{p'}_L$ and $\boldsymbol{p'}_R$ (respectively y'_R and y'_L). The disparity D of corresponding points $\boldsymbol{p}^L$ and $\boldsymbol{p}^R$ is obtained from the stereo pair, following:

$$D(\boldsymbol{p}^L) = |y^L - y^R| = |y_c^L - y_c^R| - \|\boldsymbol{T}_y\| - \|\boldsymbol{d}_y\| \qquad (14)$$

Note that the disparity value is computed at all sample points of a line.



(a) (b)

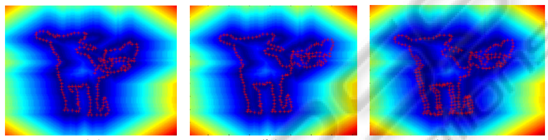
Figure 4: (a) Right line L_R (dotted line), superimposed on L_L (continuous line) when L_R was firstly projected into W which already had L_L as distance map, centroid of L_R is marked as $\mathbf{p_c}^{\mathbf{R}}$. (b) The Hausdorff method makes L_R translate to new centroid $\mathbf{q_c}^{\mathbf{R}} = \mathbf{p_c}^{\mathbf{R}} + \mathbf{T_y}$. Finally, the vector $\mathbf{d_y}$ goes from $\mathbf{p'}^{\mathbf{R}} + \mathbf{T_y}$ to $\mathbf{p'}^{\mathbf{L}}$.

Decomposing Lines. A single global distance to all points corresponds to a simple linear transformation between homologous points. Indeed, one region or line can relate to several depths. Also, one line likely refers to several objects at different depths. Rather than a complicate set of equations, the line can be decomposed into portions where the rigid motion applies well enough.

In figure 5, the line points extracted from the right image of a stereoscopic pair (red crosses) superimpose with the left line from the distance map. Blue means close and the redder the further.

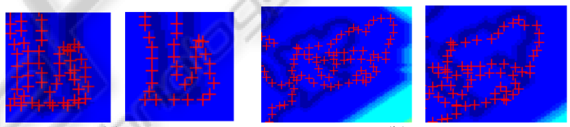
Let us call "centroid match" the process where the two centroids are superposed first and then the result for every pair of corresponding points is computed.

In fig.5 (a) the centroid match leads to large distances between corresponding points, up to missing corresponding points on the right border of the right leg (reader's right) that are paired with the left border of the right leg. In Fig. 5(b) Hausdorff makes both lines have correct co-points, generally better than before. The distance of corresponding points is reduced; however there are still some misfits in the tail (right area of the deer). Finally, Fig. 5(c) illustrates our technique. Obviously, the number of mismatched points was efficiently reduced. Fig. 6 shows some enlarged details of the points matching.



(a) (b) (c)

Figure 5: Illustration of the matching procedure. Right lines' (Red Cross symbol) superimposed on left lines' distance map (dark). (a) lines based on the same centroid at the center window, (b) lines after optimal Hausdorff translation, (c) result of the proposed method.



(a) (b)

Figure 6: (a) Enlarged version of the leg part in figure 17: left, centroid matching; right, modified Hausdorff. (b) close up on the tail part of figure 17: left, general Hausdorff, to compare with right, modified Hausdorff.

5 EXPERIMENT AND RESULTS

Color lines are evaluated first in comparing with gray level lines. They are then used to evaluate the efficiency of the modified Hausdorff distance. This distance is compared to classical line matching methods through the stereo matching quality for both color and gray lines. The database, 2003-2006, in Scharstein (2003, 2007) and Hirschmüller (2007) is our test bench.

5.1 Contribution of the Color Lines

The relevance of our color mixture lines wrt. gray level lines, is indicated by two criteria: 1) *the number of lines*, compactness of the topographic map. 2) The *average PSNR values* and number of lines computed on the image data base are collected in the table 1. Three different data are considered:

gray, abrupt mixture, and sigmoid. λ is the quantization step, both PSNR and “line number” are decreasing functions of λ. k sets the mix (section 3).

From the analysis of the table 1, we can note that the PSNR for the sigmoid mixture is lower than with Gray lines except when the saturation is greater than or equal to 0,4. The number of lines is appreciably lower in same conditions. That means images reconstructed from a topographic map after smooth-mixture are closer to the input image, while the topographic map is more compact. Fig. 7 shows examples of level and color sets.

Table1: Comparison results between images after color mixture data and gray level ones: average PSNR of each kind of data and the average number of lines.

	λ	k	PSNR	Nb. lines.
Gray	1	-	42.33	36474.30
	2	-	37.97	29234.31
	5	-	31.19	18666.96
		0.1	36.46	29378.13
		0.2	38.15	30617.52
	1	0.4	42.53	33416.48
		0.1	32.63	20784.17
Sigmoid method		0.2	34.41	22332.59
	2	0.4	38.68	25575.09
		0.1	27.97	11498.09
		0.2	29.77	12779.41
	5	0.4	33.51	15507.00

Figure 7: Examples of level and color sets: (a) Original color image, (b) Pseudo color image of gray level sets, (c) Pseudo color image of sigmoid color set: for all pseudo color images the step parameter is set equal to 5, the amplitude is coded on 8 bits and k = 0,2 for the mixture.

Line images are shown in Fig. 8. As expected, many lines appear on colorimetrically homogeneous objects. Shadows produce lots of irrelevant lines, unstable for matching since they do not correspond to real objects. With the sigmoid mixture, the topographic maps are more compact and lines correspond to salient physical items at sight.

This preliminary experimental evaluation suggests that our HSV mixture produces lines more appropriate for matching, i.e. more distinctive, quicker to compute, and more related to object-boundaries.

5.2 Matching Results

Figure 9 shows an example of results of our disparity computation method and figure 13 displays the error from the ground truth in every pixel. Most matching errors occur for large color lines related to several objects at different depths.

In Table 2 , N_T refers to the average number of line points computed in the whole data base. N_C is the number of correct points, those for which the disparity error is less than 5. E_T stands for the mean disparity error computed on the N_T points and E_C same on the N_C points.

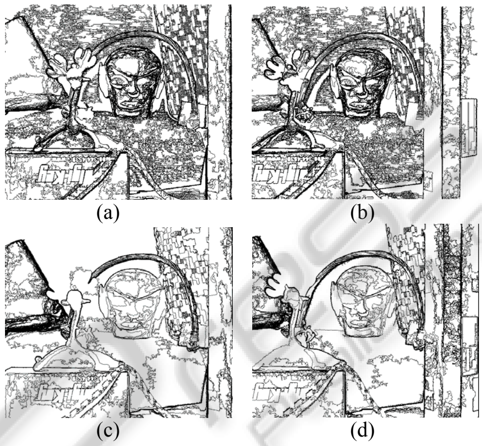


Figure 8: Examples of lines from the stereo pair of Fig.7. Step λ is set to 2, and the inflection point k is 0.2. (a), (b) are the gray level lines in left and right images respectively, (c) (d): Lines from sigmoid mixture.

The parameter $\%D_{E>5}$ (resp.$\%D_{E>1}$) is the percentage of points with a disparity error $\frac{\sum_x \sum_y |D_n(x,y) - D_r(x,y)|}{n}$ greater than 5 pixels (resp. 1 pixel), $D_n(x,y)$ being the disparity after our method at pixel (x,y) and D_r (x,y) the truth after the data base; n is the number of pixels.

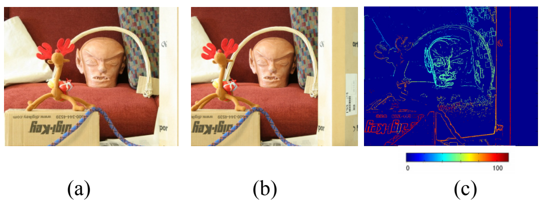


Figure 9: Example of matching: (a), (b) left and right stereoscopic images, (c) the disparity-line image and its color map value.

These criteria are computed for the Hausdorff distance and the centroid method. The Hausdorff method is used with gray and Sigmoid Mixture data (the parameter that we use is T_S = 0.2). Out of table 2, gray level data yields a larger number of points than the mixture in same technical conditions.

Most added points are not salient and those from shadow lines are unstable. Consequently, 19,3% of the gray lines have not been correctly matched, compared to only 13 % for the mixture lines. Too large a number of lines is also problematic in terms of computation times and resources. Eventually, disparity errors are always lower from mixture lines.

Table 2: Comparison of the results provided by the Hausdorff matching and classical centroid line matching.

	N_T	N_C	E_T	E_C	$\%D_{E>5}$	$\%D_{E>1}$
Hausdor						
Gray	6092	497	4,9	0,7	18	54
Mixture	3585	313	4,0	0,6	13,51	50,63
Centroid	3892	289	6,9	1,0	28,07	67,73

For comparison purposes, Table 2 collects also results from the Centroid technique on mixture data. N_T is normalized to find a number of lines comparable to Hausdorff's by controlling the T_a threshold of acceptable data as defined in section 4. Even if T_a is adjusted in the Hausdorff case, it could only worsen results since the matching condition states that a tighter threshold means more similar patterns. T_a depends on the line length not on the type of input data. Then on the same image sub-part, 26,6 % of the lines have not been correctly matched. Moreover, the errors E_T and E_C are significantly higher than Hausdorff 's (E_T : 69% and E_C : 59%).

The same N_T value is kept for gray vs. mixture lines not to bias results (same technique and parameters).

Contribution of the Modified Hausdorff Distance. Table 3 compares the classical and modified Hausdorff distances for the color mixture. In the latter case, lines are divided if their length is higher than an experimentally set threshold T_l, the value of which depends on the image size through natural stretching and shrinking in stereo (T_l=500 in our experiments). Same measures as before are collected

Table 3: Comparison of classical Hausdorff techniques and modified techniques.

	N_T	N_C	E_T	E_C	$\%D_{E>5}$	$\%D_{E>1}$
Classical	23185	18621	3,5744	1,0840	21,01	65,53
Modified	24585	21357	3,1402	0,8753	14,22	60

Because these techniques are based on a different Hausdorff matching, the threshold of acceptable data *Ta* is separately chosen to reach the same level of details in the disparity image.

According to table 3, the classical Hausdorff method yields a smaller number of points which means less detail compared to the modified Hausdorff. It produces even a smaller number of points, N_C, for which the disparity error is less than 5. Nevertheless, the average error E_C (Column 4) is 3,57 pixels for the global Hausdorff and only 3,14 pixels for the modified version. Likewise, the rate $\%D_{E>5}$ in column 5 is 21,01% vs.14,22%, meaning that 79% of the lines are correctly matched by the classical approach, while 85,8% are correctly matched with the modified version. And finally, Table 3 also shows that the disparity errors are always lower with the modified Hausdorff distance.

6 CONCLUSIONS

Our work studies color line matching and evaluates its relevance in a stereo matching application. A novel color topographic map is proposed with less irrelevant lines, more related to objects and more distinctive. Direct close curve extraction based on the color map reduces the memory and CPU greed. Color sets finally prove more stable in practice than usual results of region segmentation. The proposed modified Hausdorff shows its efficiency in finding more accurate correspondences for image registration.

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