Color Features Comparison for Segments Matching

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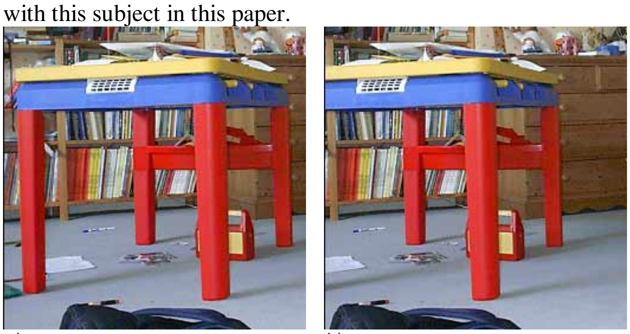
Abstract

In the field of the localization of in-door mobile robot, a method consists in extracting line segments from two stereoscopic images and in pairing line segments from the first image with those from the second image. With pairs of line segments, it is possible to measure distances between robot and objects of the environment. The pairing phase requires parameters characterizing the line segments which are discriminating, otherwise the line segments can be badly paired. This paper proposes a method of pairing based on two parameters using information color. More precisely, the two parameters use levels from a color axis which is given according to the color contents of the pair of images. The first parameter is a set of homogeneous colors which are in the areas close to a line segment. These colors are obtained from neighboring gray level dependence matrices but color axis levels replace gray levels. The second parameter is a distance between pixels composing the areas close to a line segment. This distance is the earth mover's distance. Results show a good success rate of the two parameters. The homogeneity colors are also more discriminating than the EMD. These results are extended to experimentation on more two hundred pair of images.

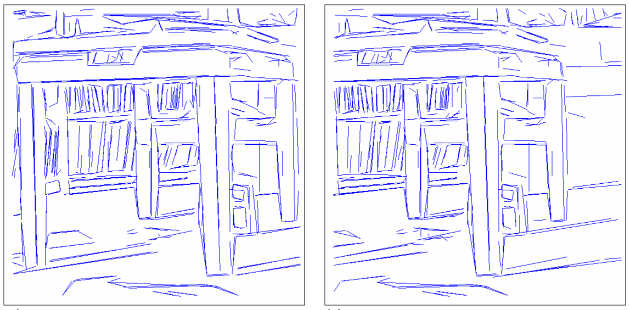
1. Introduction

The IBISC laboratory (French acronym for data processing, integrative biology, and complex systems) is implied in the robotics of assistance to the disabled people through ARPH project (Assistant Robot for Handicapped People) [1]. This project is developed with the AFM (French Muscular Dystrophy Association) support. This project consists in a device composed by one control unit and one mobile base. The base supports one arm manipulator. By using the arm, a handicapped person is able to carry out various tasks of the current life. The various control modes included or not the handicapped person. Thus, the base must be able to be completely autonomous. To ensure this capacity, various sensors equip the base. Currently, after a first approach in black and white [2], we work on the localization and the guidance of this base with a stereoscopic vision system using two color cameras. Color interests us because of work environment. Indeed, to put landmarks in life place is not interesting and we must use in-door elements to extract useful information. We find very different colors and textures in an in-door environment, according to room functionalities and inhabitant feelings. In a previous work [3], we showed color information was significant to proceed to a supervised line segment extraction from image, according to the lengths and directions. Indeed, combination of extracted line segments, from three color axes, leads to exhaustive information. But, it is necessary to organize this information. Now, we work on line segment pairing: figures 1 and 2 show examples of line segment sets to be paired. The method adopted in [2] consists in characterizing each line segment by a whole of sixteen parameters of different nature: geometrical, of brightness, textural in areas close to the line segment. Then couples of line segments from two images are automatically affected in two classes: "good" or "bad" matched. To do that, we use a combination of bayesian and neural methods. Now, we wish to introduce color information into the parameters of line segment characterization. We lead with this subject in this paper.



a) *b)*

***Figure 1.** Stereoscopic images: a) left, b) right.*



a) *b)*

***Figure 2.** Line segments to be paired: a) left, b) right.*

2. Parameters based on color

Our purpose is to use information based on the color to characterize the areas close to the line segments (see figure 3).

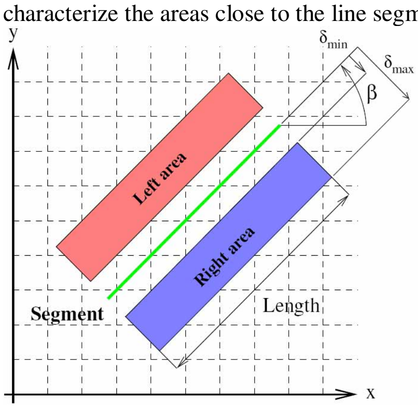


***Figure 3.** Line segment vicinity.*

It requires using representative and discriminating parameters. Thus they will be useful for the line segment matching. However, images we use for our application have a great variability: colors, textures, reflections, … If we do not take this variability into account, then features will not be discriminating, specially color features, and line segment matching will not be efficient. So we propose to compute our parameters according to one color axis which will be the best to characterize areas along the line segments. The parameters we retained are a set of four homogeneous colors (two by areas) and a distance between pixels of the two areas according to the selected color axis.

2.1. Overall process

Our purpose is part of an overall process which begins with acquisition of stereoscopic images and finishes with 3D rebuilding of the environment (see figure 4).

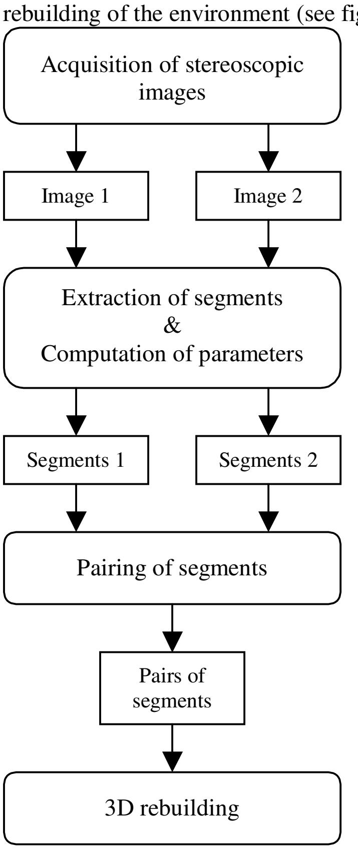


Figure 4. *Overall process.*

2.2. Color axis choice

To maximize the effectiveness of the two parameters, we propose to select, for each pair of stereoscopic images, one color axis. First, on one of the two images, we use the Baker's Transformation [4] [5] to extract a sample of size 16x16 (see figure 5). This sample is representative of initial image colors according to the BT. We convert this sample on various color axes: 28 in all, chosen among RGB, rgb, $I_1I_2I_3$, L*a*b*, L*u*v*, HSI, YT_1T_2, YUV, YIQ, XYZ and xyz spaces [6] [7]. And we calculate the standard deviation of each projected sample. We choose the axis which leads to the greatest standard deviation. After that, we convert the two images on the selected axis color and we calculate the two parameters on these images. The parameters are computed independently of the line segment extraction: the selected color axis can be different from the original color space. Figure 6 illustrates these various steps.

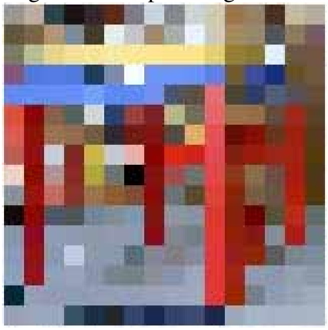


Figure 5. *16x16 rgb sample from left image (figure 1a).*

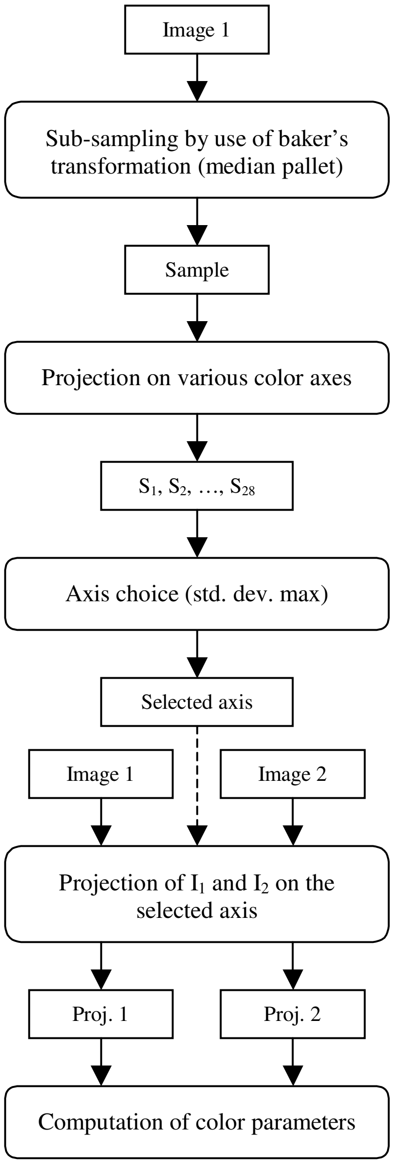


Figure 6. *Sub-process for computation of color parameters.*

2.3. First parameter: homogeneous colors

Generally, a line segment results from an edge between two homogeneous areas: it is interesting to characterize such a line segment by colors which compose these areas. In the vein of coocurence matrices [8] and gray level run length matrices [9], Sun and Wee introduce neighboring gray level dependence matrices [10]. A NGLDM measures local homogeneities [11] i.e. pixels which are homogeneous with their vicinity. We decided to treat on a single color axis, so we can employ NGLDM directly. Given an image $I(i,j)$, $i=1,2,\ldots,n$ and $j=1,2,\ldots,m$. Let K be the set of color axis levels. The NGLDM Q of I is defined as:

$$Q_{d,a}(k,s) = card\{\ (i,j)\ |\ I(i,j)=k \text{ and } card\{\ (q,r)\ |\ \rho((i,j),(q,r))\leq d \text{ and } |I(i,j)-I(q,r)|\leq a\ \}=s\ \} \qquad (1)$$

In this formula, d is a selected vicinity distance around a pixel, a is a selected similarity value between two color axis levels, $\rho((i,j),(q,r))=max(|i-q|,|j-r|)$ is the distance between the elements (i,j) and (q,r), $k=1,2,\ldots,K$ and $s=0,1,\ldots,S$ with $S=(2d+1)^2-1$ is the number of pixels in the vicinity of a pixel. Figure 7 illustrates the NGLDM computation. For this example, parameters are: $d=1$ i.e. pixel vicinity is composed of the $S=8$ pixels around, and $a=2$ i.e. levels $k-2$, $k-1$, k, $k+1$, $k+2$ are "close".

1	1	4	3
1	1	3	4
1	1	6	6
1	6	6	2

"Image"

$Q_{1,2}$		Quantity of close pixels (∈[0;S])								
		0	1	2	3	4	5	6	7	8
Level (∈[1;K])	1	0	0	1	1	2	2	1	0	0
	2	1	0	0	0	0	0	0	0	0
	3	0	0	0	1	0	0	1	0	0
	4	0	0	0	1	0	1	0	0	0
	5	0	0	0	0	0	0	0	0	0
	6	0	0	1	2	1	0	0	0	0

Figure 7. *Example of NGLDM computation.*

With Q we calculate:

$$P(k,s) = \frac{Q(k,s)}{\sum_{u=1}^{K}\sum_{v=0}^{S} Q(u,v)} \qquad (2)$$

$$P(s|k) = \frac{P(k,s)}{\sum_{v=0}^{S} P(k,v)} \qquad (3)$$

$P(s|k)$ is the probability for a pixel of color axis level k to have s close pixels in the range $[k-a;k+a]$. Finally, "local homogeneities" are values of $P(s|k)$ with $S-h$ ρ s ρ S. In our case, we consider, for each areas close to a line segment, the two color axis levels which maximize "local homogeneities" with $a=2$, $d=1$ ($S=8$) and $h=2$. This last parameter (h) defines the homogeneity notion: a pixel of homogeneous level has from 6 to 8 "close" pixels in its vicinity.

2.4. Second parameter: EMD

We choose a second parameter which is the earth mover's distance introduced by Rubner [12] which permits to measure perceptual dissimilarities. This distance measures the quantity of energy which is necessary to transform a distribution into another. In our case, the distance between pixels of the two close areas of a line segment is:

$$d_{EMD}(P,Q) = \sum_{k=1}^{m+n+1} |\hat{p}-\hat{q}|(r_{k+1}-r_k)$$
$$\text{with } \hat{p}=\sum_{i=1}^{m}[p_i \leq r_k]w_{pi} \text{ and } \hat{q}=\sum_{j=1}^{n}[q_j \leq r_k]w_{qj} \qquad (5)$$

P and Q are the histograms of the two sets of pixels (according to the selected color axis). The set $r_1,r_2,\ldots,r_{m+n}$ corresponds to $p_1,p_2,\ldots,p_m,q_1,q_2,\ldots,q_n$. m and n are the numbers of color axis levels of P and Q. $[x]$ is 1 if x is true else 0. w_{pi} and w_{qj} are the respective weights of components p and q.

2.5. Pairing

To test the effectiveness of the two parameters, we calculate its for all line segments (see figure 2) and we calculate two matrices which describe the probabilities of good pairing between a line segment i from left image and a line segment j from right image. The first matrix is based on:

$$p_{ij} = \left(1-\frac{|H_1(i)-H_1(j)|}{n}\right)\cdot\left(1-\frac{|H_2(i)-H_2(j)|}{n}\right) \cdot\left(1-\frac{|H_3(i)-H_3(j)|}{n}\right)\cdot\left(1-\frac{|H_4(i)-H_4(j)|}{n}\right) \qquad (6)$$

n is the number of color axis levels, $H_{1,2,3,4}$ are the four line segment homogeneities (two by close areas). The second matrix is based on:

$$d_{ij} = |d_{EMD}(i)-d_{EMD}(j)| \qquad (7)$$

If we consider for one line segment i the line segment j which maximizes p_{ij} or minimizes d_{ij} then we say line segments i and j are paired. To be more precise and to avoid certain pairing errors, we operate in a cross way i.e. we check for the line segment j if line segment i maximizes (minimizes) also p_{ji} (d_{ji}).

3. Results

3.1. Results on one example

From the example images of figures 1 and 2, we obtain the following results.

First, our process indicates the Blue axis to be the color axis used for computation of the parameters. Figure 8 shows the projected samples sorted by descending order of the standard deviations.

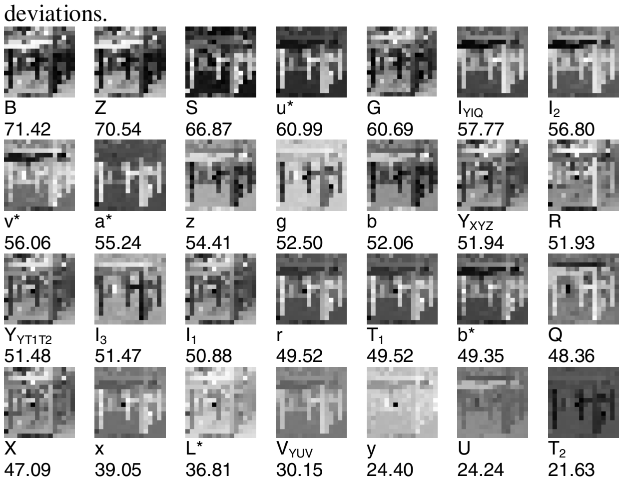


Figure 8. *Projected samples and standard deviations of figure 1a.*

We can see variations of contrast from these samples: we consider that a low contrast (i.e. a low std. dev.) will not characterize sufficiently the line segments but a high contrast will be able to do it.

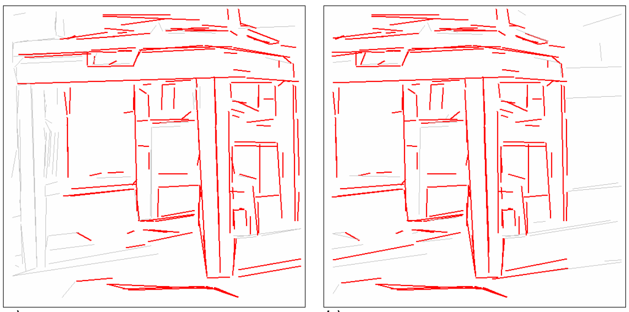
Secondly, table 1 shows results of the pairing step.

Table 1. Pairing results of line segments from figure 2 (Blue is the selected color axis).

Line segments of:	Quantity	Paired by homogeneity		Paired by EMD
- left image	233	186		173
- right image	190			
Parameter:	**Pair of line segments**	**Good pairs**	**Bad pairs (out of zone)**	**Bad pairs (on zone)**
Homogeneity	186 (100%)	152 (81.72%)	21 (11.29%)	13 (6.99%)
EMD	173 (100%)	126 (72.83%)	29 (16.76%)	18 (10.41%)

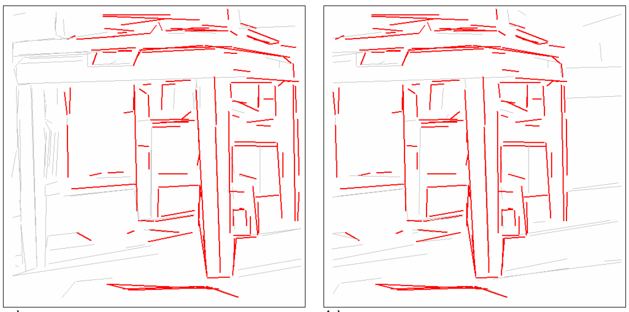
The quantity of line segments is lower than on the figure 2 because we added a selection of the line segments before the pairing. In this table, "out of zone" indicates pairs of line segments which are not in the common part of the stereoscopic images: these pairs can be removed geometrically. "On zone" indicates pairs of line segments in the common part: these pairs are truly bad. These results show that we obtain good pairings with the two parameters based on color information.

Figures 9 and 10 illustrate these results. Figure 9 shows the well-paired line segments when we use the homogeneity parameter. Figure 10 shows the same thing when we use the EMD parameter. Badly-paired line segments or not paired line segments appear in light gray. We see clearly that the "out of zone" line segments are not paired and that homogeneity parameter is more effective than the EMD parameter.



a) b)

Figure 9. *Well paired line segments (in red) by the homogeneity: a) left, b) right.*



a) b)

Figure 10. *Well paired line segments (in red) by the EMD: a) left, b) right.*

3.2. Results on image database

To confirm these results, we have also experimented our method on 248 pairs of in-door images. In this experiment, we compare the results of an automatic pairing (see section 2.5) with those of a manual pairing (i.e. ground truth). The experiment aim is to answer at the question: "does automatic pairing pair the line segments which were paired manually?" For the manual pairing, we limit the quantity of line segments: it is lower than 50 line segments per image. In practice, the manual pairing leads to approximately 20 pairs of line segments by pair of images (≈ 5000 pairs of line segments in all).

First, table 2 shows the distribution of color axes which were selected for the computation of the two parameters.

Table 2. Selected color axis for image database experiment.

R	G	B	r	g	b	I_1
17	1	23	3	1	4	0
6.85%	0.4%	9.27%	1.21%	0.40%	1.61%	0%
I_2	I_3	L*	u*	v*	a*	b*
8	4	4	4	7	2	0
3.23%	1.61%	1.61%	1.61%	2.82%	0.81%	0%
S(HSI)	Y	T_1	T_2	U	V	I
14	0	0	0	0	0	11
5.65%	0%	0%	0%	0%	0%	4.44%
Q	X	Y	Z	x	y	z
4	33	19	76	1	4	8
1.61%	13.31%	7.66%	30.65%	0.4%	1.61%	3.23%

Z axis is chosen mainly and five others axes are chosen in more than 5% of the cases: they are Red, Blue, Saturation, X and Y axes. We can remove "0% axes" of our process or replace them by others. But, in practice, we did not see a correlation between the choice of a color axis and the pairing: there are no axes which systematically involve good or bad pairing. Thus, we consider useful to do the preliminary choice of one color axis according to the contents of the image.

Now, table 3 shows the global results of the pairing step.

Table 3. Global results.

Pairs of line segments:	Homogeneity	EMD
- good	77.77%	52.92%
- bad	22.23%	47.08%

The homogeneity parameter finds 3/4 of the manual pairs. It appears effective for a color-based parameter. The EMD parameter appears worse because it finds only 1/2 of the manual pairs.

We also compute another statistics: we analyze the part of well-paired pairs by homogeneity which are also well-paired by EMD (see table 4).

Table 4. Distribution of the pairings between homogeneity and EMD parameters.

Homogeneity	EMD	% of pairs
Good	Good	49.84%
Good	Bad	27.94%
Bad	Good	3.09%
Bad	Bad	19.14%

Mainly, line segments are well paired when we use the homogeneity parameter and also when we use the EMD parameter. The interest of this table appears in the second and third data. There are more line segments which are well paired only by the homogeneity than line segments which are well paired only by the EMD. That confirms the greatest effectiveness of the homogeneity parameter: globally, homogeneity results include EMD results.

Finally, to appreciate our current results, we compare them with those obtained with other methods and data (see table 5). These other methods are partly at the origin of our work and use epipolar classification (parameters based on geometry) [13], and bayesian/neural classification (with 16 parameters based on geometry, brightness and texture) [2].

Table 5. Comparison with other methods and data.

"Methods":	% of good pairing	Experiment conditions
Homogeneity	77.77 %	248 pairs of images
EMD	52.92 %	5000 pairs of line segments
Epipolar	36 %	45 pairs of images
Epipolar with angle and position constraint	77 %	698 pairs of line segments
Bayes	93.21 %	180 pairs of images
Neural network	92.35 %	2640 pairs of line segments

Although these results are independent between them, we can see the use of our first color parameter is on level of epipolar classification (which uses geometrical parameters). However, we are below methods more sophisticated using various types of parameters.

4. Conclusion

Work presented here is related to the matching of line segments. It requires the development of a fast data processing sequence. This sequence must be also robust to allow adaptation with different contexts in term of luminosity, colors and textures. We developed a method allowing us to optimize work space retained for calculation of the characterization parameters of the line segments in color images. We also proposed two parameters based on the color which are very significant for the line segment pairing phase. To reinforce the validity of this work, we plan complementary works. The first will relate to the comparison between this approach and the original pairing method (bayesian and neural classifications) and also a pairing epipolar method [13]. This comparison would be done on the same data. We think also of adding our parameters in the bayesian and neural classifications. Another development will be to use fully a color space and not a single axis. In addition we think it could be interesting, since we carry out an adaptive selection of axis/space, to define different parameters according to retained axis/space. But this requires an in-depth work on the characteristics of spaces and many tests allowing to evaluate the opportunity of such a step.

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Author Biography

Christophe Montagne received his Engineer degree in engineering of the industrial systems from the University of Evry (1999) and his PhD degree in robotics from the University of Evry (2005). His research works concern color integration in image processing for localization and guidance of mobile robots. He also works on color quantization and image indexing and retrieval.

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André Smolarz was born in France in 1955. He graduated in mechanic engineering in 1978, from the Université de Technologie de Compiègne (UTC), where he also received, in 1982, a PhD degree in Statistical Pattern Recognition. He is currently an Associate Professor at the Université de Technologie de Troyes (UTT). His research interests are texture modeling and analysis, classification and statistical pattern recognition.