How to Choose the Best Color Space for the Guidance of an Indoor Robot?

C. Montagne, S. Lelandais and J. Triboulet
Complex Systems Laboratory, University of Evry, France

C. N'Zi
INPHB, Yamoussoukro, Côte d'Ivoire

Abstract

In order to help disabled people in their current life, our laboratory develops a system with a mobile robot supporting a camera and an arm manipulator, and guided remotely by the handicapped person. The robot moves in an indoor environment so, in the camera images, much of the informations are related to textures and colors. A previous work permits to localize and guide the robot in 3D space, by use of segments from gray levels stereoscopic vision. Our aim is to use color, so we have to choose the color space, which is the best to detect and match segments. We have built a color images database with some different scenes and we have defined two ways for obtaining a notation for each color space, or color axis. One is an absolute evaluation of the space called "weighted notation" and the other is a comparative evaluation based on the segment histograms from color and gray level images. So, after a test stage, we hope to be able to determine the best three space components, which will be used by the mobile robot.

Introduction

The LSC is implied in the robotics of assistance to the disabled people through ARPH[(1)] project. Developed with the AFM[(2)] support, this project consists in developing a mobile robot supporting one camera and one arm manipulator, and guided remotely by the handicapped person. The arm makes it possible to carry out various tasks of the current life as to open a gate or pour out water in glass. To carry out these tasks, the robot must move until its work place. Different manners are considered: the operator can lead the robot manually, by direct or indirect vision (via a camera), or the robot moves automatically towards the place or the object indicated by the operator. In this second case, the robot needs localization and navigation automatic methods. By definition, the mobile base moves within a domestic environment. This environment is characterized by a great diversity of colored and textured "objects" from floor to ceiling: fitted carpet, carpet, tiling, wallpaper, painted wall, wooden furniture, modern furniture, plastic objects, glass, etc. In a first time, our goal is to locate and guide the robot in such environment, without human intervention. A second objective will be to find colored objects in order to handle them.

Currently, we are able to locate and guide a base with a stereoscopic vision in gray levels.[1] As it is shown on figure 1, from a gray level image, the contour points of the scene objects are extracted by DERICHE gradient method.[2] Then the image is binarised from a hysteresis thresholding. Finally, segments are created from hysteresis segmentation. By matching the segments resulting from two stereoscopic images, the scene 3D representation is built. The matching method is a hybrid classification (bayesian and neuronal network) of segments in two classes: "good" or "bad" matched. Classification arguments are segment descriptors based on the geometry of the segment, the luminance and the texture of the areas on both sides of the segment, and the vicinity with other segments.

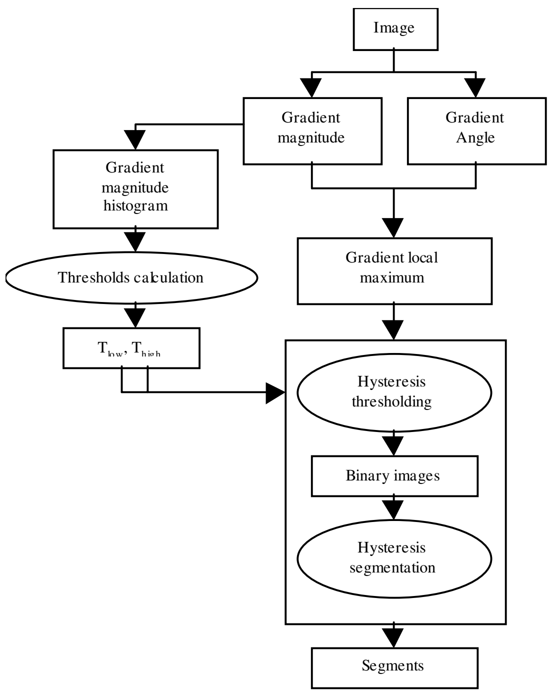

Figure 1. General algorithm for edge detection and segmentation

Color information is more complex than luminosity information but it is also more complete. We think this information is of primary importance for any in-door robotics application. Unfortunately, there are many manners to represent the colors. Our purpose is to choose a color space[3,4,5,6] (RGB, HSI, L*a*b*, ...) for our application. In this paper, we present in-door environment and the used methodology to select best color space.

Color Images Database

We indexed specific characteristics about in-door environment. This census appears useful to us for two reasons: first, to have technical data, and secondly to have indices for the color space choice.

General Constraints

Indoor environment is a life place, it is not easy to arrange it for the robot needs. Thus, a passive vision is required. This environment is not fixed: robot must be located compared to the significant landmarks in the scene (pieces of furniture, walls). The scene lighting (artificial or natural) is not controlled: algorithms must be robust to compensate this kind of parasites.

General Advantages

Many objects are polyhedric: horizontal, vertical and reducing lines are thus numerous. Forms, textures and colors are important visual indices.

We have begun a color images database assembly with 39 images from different rooms of some private houses. One example of these images is shown on figure 2.

Figure 2. In-door image example

Metrics Definition

The quality of localization and navigation depends on the quality of the matching step results. These results will be better if extracted segments are correct (i.e. a sufficient number for each image, good value of the descriptors, ...).

To choose an adapted color space, we need measuring tools giving useful comparative data. Because few works have been done about this particular subject (some works concern specialized applications and can not be directly used[7,8]), we have developed our own tools. Detected segments are a fundamental criterion. For robot localization and navigation, segments must be long. Indeed, we suppose a long segment corresponds to a significant scene element. Moreover, it is possible to forget small elements like plant foliage, ground squares, texture elements, and decorative objects.

We apply algorithms to each color axis and we analyze detected segments with usual statistics like segment quantity, mean size and standard deviation (of all segments or those having minimal size). We use also a "weighted notation" and a "segments histogram comparison" defined below.

Weighted Notation

We distribute built segments on a size scale whose step (in pixels) is fixed arbitrarily. Then, for each step, we calculate a notation by multiplying the step index with the number of associated segments. The final note (eq. 1) is the sum of all notes. This method is illustrated on figure 3.

$$note = \sum_{i=0}^{n} \left(i \cdot \sigma_i \right) \qquad \textbf{(1)}$$

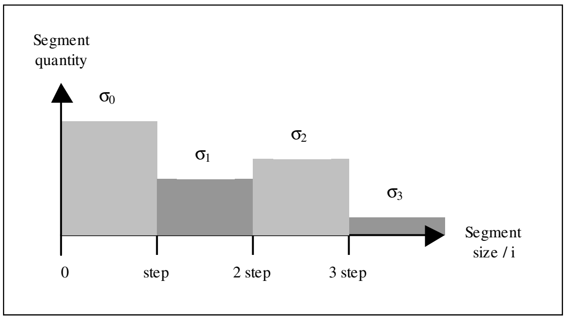

Figure 3. Weighted note (principle)

This computation favors great segments. So, the color axis, which provides the larger number of great segments, will obtain the best note and will be considered as the better axis. We have chosen the five most significant color spaces (RGB, xyz, HSI, L*a*b*, $I_1I_2I_3$), so we have fifteen color axes. On all the images from database, we have to apply this method and compare the obtained notation in order to select three axes from different spaces, or one complete space. A B-axis concrete example, from the original image shown on figure 2, is presented on figure 4. In this case, the step is equal to 25 pixels. So segments which have a size less than 25 pixels have a null contribution.

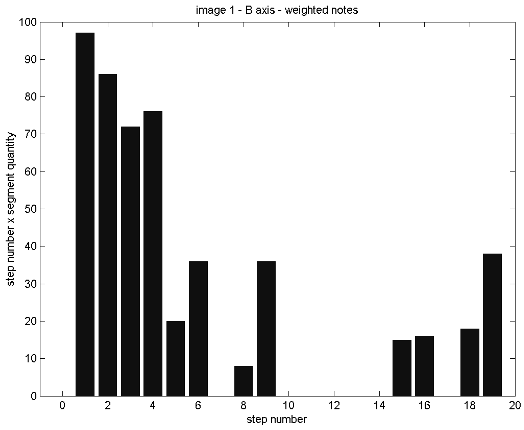

Figure 4. Weighted note (example)

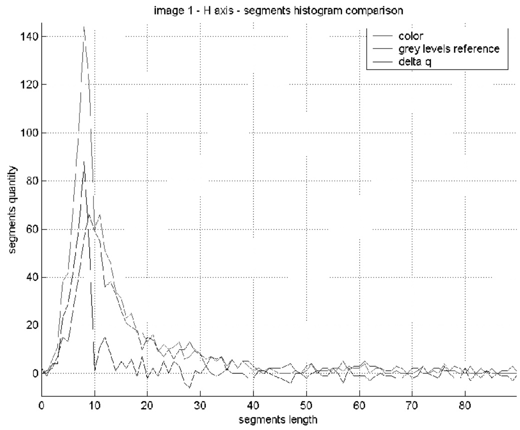

Figure 6. Segments histogram comparison (example)

Segments Histogram Comparison

In order to evaluate the quality of colored image with regard to black and white image from the same scene, we compare the histograms of the detected segments from these two images. The gray level image is obtained with the mean of the three components of the RGB space. This corresponds to the I_1-axis. Figure 5 represents the comparison principle between the color histogram and the gray level histogram.

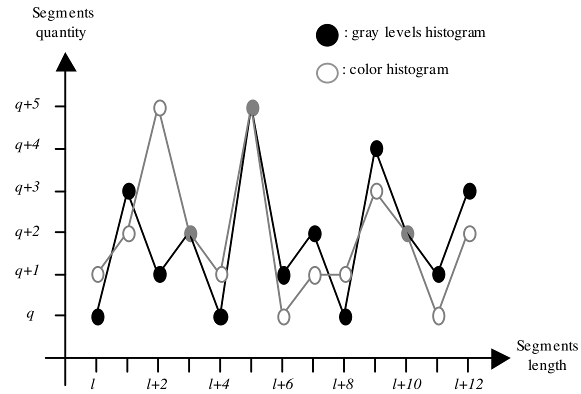

Figure 5. Segments histogram comparison (principle)

With these two curves, we compute also a notation, as explained below. For a given length, we have:

$$\Delta q = q - q_r \qquad (2)$$

with q the segment quantity from the colored image, and q_r the segment quantity from gray levels image reference. If:

$$\sum_{l=0}^{l_{\max}} (\Delta q_l) > 0 \qquad (3)$$

(i.e. there are more segments from color image than from the reference) then color information is most important than black and white information.

On figure 6, we present an example of two histograms. The third curve represents the difference between histograms, Δq.

But, this measurement does not hold account length of the segments. To correct this problem, we prefer to use the value:

$$\sum_{l=0}^{l_{\max}} (\Delta q_l \cdot l) \qquad (4)$$

If the variation Δq is significant but the segment length is weak, the global weight of this segment will be decreased. To manipulate simplest values, we can also use the step system used for the weighted notation. Equation 4 becomes:

$$\sum_{i=0}^{n} (\Delta q_i \cdot i) \qquad (5)$$

with i the step index, and:

$$\Delta q_i = \sum_{j=low_i}^{j=high_i} (q - q_r)_j \qquad (6)$$

For a given step i, we have a minimal length (low_i) and a maximal length ($high_i$) of segments. Figure 7 shows curves thus obtained.

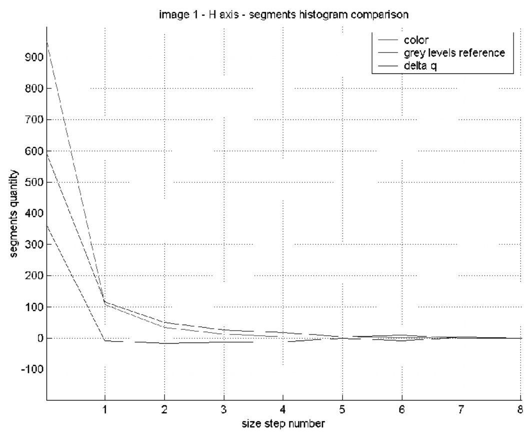

Figure 7. Step system applied to histogram comparison

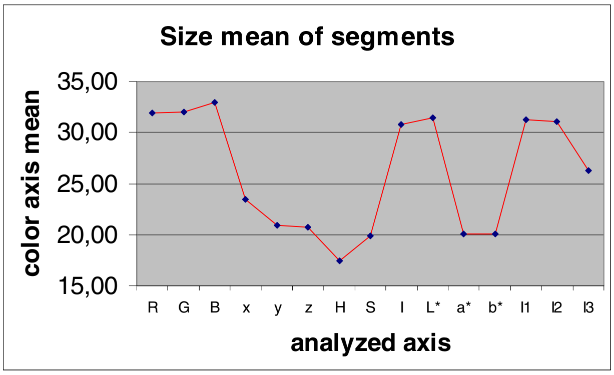

Figure 8a. Size mean of segments

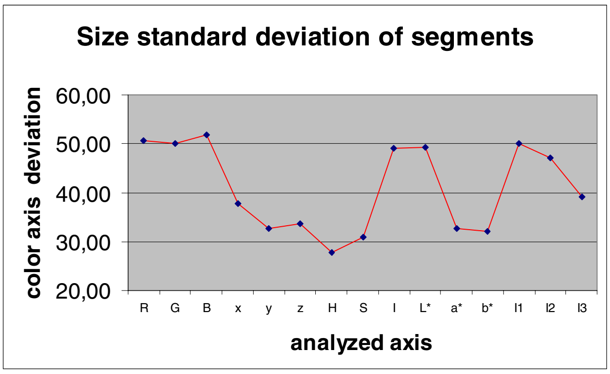

Figure 8b. Size standard deviation of segments

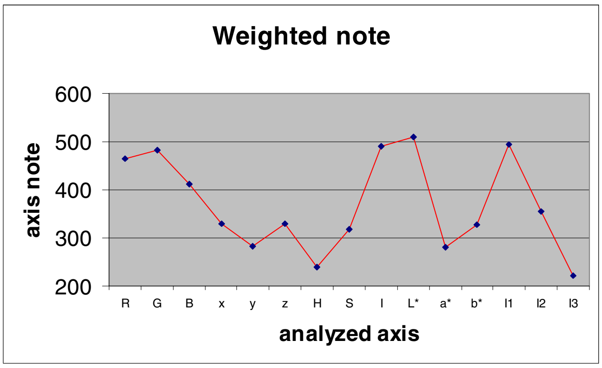

Figure 8c. Weighted note

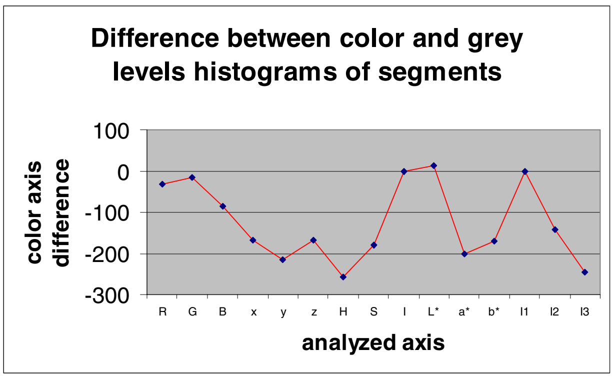

Figure 8d. Segments histogram comparison

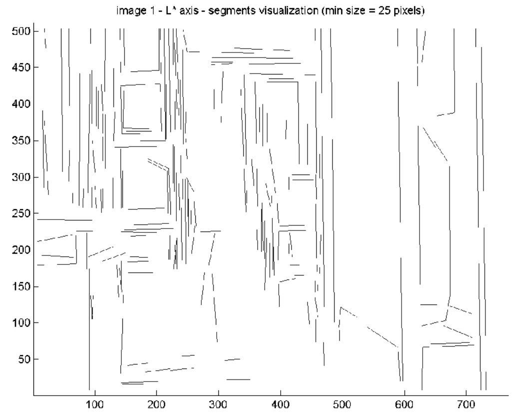

Figure 9. Visualization of built segments

Note that this last approach includes the weighted notation, but it allows to compare each color axes with the same reference.

Results

We compute four values from the image database: size mean and size standard deviation of segments, weighted note and segment histogram comparison. Results obtained are shown on four curves (figure 8a, 8b, 8c, 8d).

The axis, which provides the longer segments, is the blue axis. But six other axes lead to a size mean value very close of the blue axis value. They are: G, R, L*, I_1, I_2 and I axes. When standard deviation is important, it means there is an important difference of size between segments. So, some segments will be very long. The same previous seven axes lead to great values of standard deviation. The best result for weighted note is given by the L*-axis. As we said before (see eq. 6), it is the same situation for the segments histogram comparison. Five other axes give good results for these features: I_1, I, G, R and B axes. Only the L*-axis obtains positive evaluation for the histogram comparison. I_1 corresponds to the reference, so its result is equal to zero. Other axes have negative result. It means that we obtain in these images less segments than in the reference image. We obtain very close results if we analyze the max of each parameter on the database.

Table 1. Parameter Mean for Each Space

	RGB	xyz	HSI	L*a*b*	I1I2I3
mean	*32,29*	*21,69*	*22,71*	*23,85*	*29,53*
standard deviation	*50,86*	*34,74*	*35,93*	*38,05*	*45,45*
note	*453*	*313*	*349*	*372*	*356*
difference	*-45*	*-184*	*-147*	*-120*	*-130*

In the table 1, we present the mean values of each feature for each of the five spaces. In this case, RGB space looks better than L*a*b*, $I_1I_2I_3$ and HSI. The xyz space seems to be less interesting. To conclude this part, we can say intensity axes are the best in order to extract segments. RGB space gives good results because it is a space where the intensity is supported by the three axes. Figure 9 shows segments obtained from figure 2, for the L*-axis.

In order to obtain the more complete evaluation as possible, we are working on a vectorial gradient as DiZenzo[9] defines it. This computation uses combination of pixel color values from the three components of a color space.

Conclusion

Actually, it is possible to say that intensity axes, as L*, I or I_1, are individually good in order to obtain a sufficient number of segments. These segments are enough to localize and guide a robot. As a single color axis has less information than an intensity axis, it is not useful alone. But, this color information can enhance intensity information.

Now, we have to finish the test with the vectorial gradient. We think it is possible to improve the quality and the quantity of the built segments by finding a new representation space. In this space, we can merge intensity axis for one space with two color axes from another space.

In order to choose these color axes, we have to implement other evaluation tools. These tools will be inspired from works about image database indexing and retrieval.[10]

References

1. H. Loaiza, J. Triboulet, S. Lelandais, C. Barat, “Matching segments in stereoscopic vision”, *IEEE Instrumentation & Measurement Magazine*, vol.4, n°1, pp.37-42, March 2001.
2. R. Deriche, “Using Canny’s criteria to derive an optimal edge detector recursively implemented”, *The International Journal of Computer Vision*, pp.167-187, 1987.
3. Published under Murat Kunt direction, “Traitement numérique des images”, *Traitement de l’information : volume 2*, Collection Electricité, Presses Polytechniques et Universitaires Romandes, 1993.
4. Alain Tremeau, “Représentation numérique des images couleur”, *Spring School – Color Images*, Pau, France, March 2001.
5. Rafael C. Gonzales, Richard E. Woods, “Digital Image Processing”, *Addison-Wesley Publishing Co.*, Massachusetts, pp.221-251, 1993.
6. Yu-Ichi Ohta, Takeo Kanade, Toshiyuki Sakai, “Color information for region segmentation”, *Computer Graphics and Image Processing 13*, pp.222-241, 1980.
7. Jean-Christophe Terrillon, Yoshinori Niwa, Kazuhiko Yamamoto, “On the selection of an efficient chrominance space for skin color-based image segmentation with an application to face detection”, *QCAV 2001*, pp.409-414, May 2001, Le Creusot, France.
8. Alberto Albiol, Luis Torres, Edward J. Delp, “Optimum color spaces for skin detection”, *International Conference on Image Processing*, pp.122-124, October 2001,
9. Silvano Di Zenzo, “A note on the gradient of a multi-image”, *Computer Vison, Graphics and Image Processing*, vol.33, pp.116-125, 1986.
10. Stuart Gibson, Richard Harvey, J. Andrew Bangham, “Multi-dimensional histogram comparison via scale trees”, *International Conference on Image Processing*, pp.709-712, October 2001, Thessaloniki, Greece.

Biography

Christophe Montagne received his Engineer degree in engineering of the industrial systems from the University of Evry in 1999. Now, he starts a robotic thesis within the LSC. His current research works concern color integration in image processing for localization and guidance of mobile robots.

Sylvie Lelandais received her Ph. D. degree in automatic and signal processing from the Technological University of Compiègne in 1984. Her current research interests include color image processing, texture analysis, shape from texture, wavelets, and vision for robotic and biomedical image processing.

Jean Triboulet received his Ph. D. degree in robotics from the University of Evry in 1996. His major fields of interests are sensor calibration, 3D vision, and image processing for telerobotics and mobile robots.

Camille N’Zi received his Ph. D. degree in robotics from the University of Evry in 1995. Now, he is Assistant Professor at the INPHB at Yamoussoukro, Côte d’Ivoire. He is currently at LSC for research period. His fields of interests are about image processing and 3D vision.

M. Christophe Montagne
Complex Systems Laboratory
University of Evry
40, rue du Pelvoux
91020 Evry Cedex – FRANCE
Tel: (33) 01 69 47 75 04 / Fax: (33) 01 69 47 75 99
Email: cmontagne@club-internet.fr

---

(1) : *Assistance Robotisée à une Personne Handicapée (Robotized Assistance for an Handicapped Person).*
(2) : *Association Française contre la Myopathie (French Association against Myopathy)*