STEREO VISION MATCHING OVER SINGLE-CHANNEL COLOR-BASED SEGMENTATION

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Abstract: Stereo vision is one of the most important passive methods to extract depth maps. Among them, there are several approaches with advantages and disadvantages. Computational load is especially important in both the block matching and graphical cues approaches. In a previous work, we proposed a region growing segmentation solution to the matching process. In that work, matching was carried out over statistical descriptors of the image regions, commonly referred to as characteristic vectors, whose number is, by definition, lower than the possible block matching possibilities. This first version was defined for gray scale images. Although efficient, the gray scale algorithm presented some important disadvantages, mostly related to the segmentation process. In this article, we present a pre-processing tool to compute gray scale images that maintains the relevant color information, preserving both the advantages of gray scale segmentation and those of color image processing. The results of this improved algorithm are shown and compared to those obtained by the gray scale segmentation and matching algorithm, demonstrating a significant improvement of the computed depth maps.

1 INTRODUCTION

Stereo vision is a common procedure used to obtain a 3D representation of a scene where the information is provided from two different image projections of the same scene. This particular process is carried out automatically by human vision. However, implementing this technique in a computer vision system presents many diverse problems which will be discussed throughout this study.

All multi and stereo view vision based approaches must take into consideration a process known as Matching. This consists in identifying the same physical points in different images (Pons and Keriven, 2007). The difference between these images is referred to as the disparity, from which the depth information can be recovered.

We propose in this paper an improvement of a previous work (Revuelta Sanz et al., 2010b). In this previous work, stereo vision has been achieved by matching the region descriptors instead of matching blocks or edges located in both images. Regarding color images matching, algorithms found in the literature show to have important computational load, whichever is the color space chosen to process the image (see (Kuan et al., 2008; Mushrif and Ray, 2008; Ozden and Polat, 2007) for examples). The segmentation and the descriptors extraction of each region were obtained by means of a region growing and indexing algorithm (Revuelta Sanz et al., 2010a), gray scale based. The contribution to this algorithm is the inclusion of color information in the region growing process, and our results will only be compared to those obtained with the gray scale version. The goal of this complementary functionality is to take advantage of the color information in image segmentation, improving the depth maps accuracy, while preserving the simplicity of the gray scale approach.

This paper is organized as follows. After this introduction, section 2 explains the details of the proposed pre-processing tool. In the same section the effects of this pre-processing are shown. In section 3, the segmentation and matching process of pairs of images is described. Results of the application of the described algorithm are shown in section 4, and discussed in section 5, comparing

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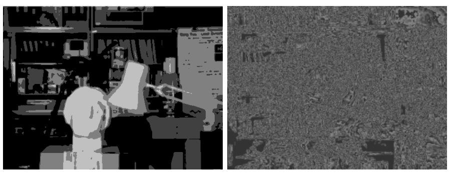
these results with those obtained by the gray scale version of the algorithm.

2 COLOR IMAGE PROCESSING

The field of research referred to as color image processing has been widely studied over the past few decades, this is partly due to the fact that it is closely related to the process of human vision (Millán and Valencia, 2006). However, several different parameters must be considered when this segmentation is to be performed on gray scale (Zhang et al., 2007) and color images (Kuan, Kuo, & Yang, 2008).

The color is commonly presented as the combination of three components, Red-Green-Blue (RGB). Other possibilities come from transpositions of this space into three other coordinates, such as YIQ or YUV, HSL, HSV, etc. The basic principles of the improved and novel algorithm proposed in this paper are listed as follows:

- Not every bit of a pixel carries the same information: most relevant bits have more information than the least bits.
- During the process of image segmentation it is only important to compare relevant information.
- A pseudo-color image (PCI from hereinafter) can be built from a color image and maintains the majority of the advantages associated with both color and gray scale segmentation.



(a) (b)

Figure 1: Two most (a) and least (b) significant bits of the red channel acquired from the Tsukuba right image.

These facts allow reducing the complexity of the segmentation process, while at the same time maintains the most relevant color features. For that purpose, we identify the dominant colors in an image, and set the rest of the bits with information regarding relevant color levels. This process can be carried out using the following steps: RGB conversion to Hue, Saturation and Value (HSV) color space, color clustering with the hue component (assigning homogeneous values to pixels when their color is close enough) and calculation of the pseudo-color gray scale image. These images will be segmented and matched as explained in (Revuelta Sanz, Ruiz Mezcua, Sánchez Pena, & Thiran, 2010b). This is done with the following instructions:

```
counts=INF;
while(counts > MAX_NUM_OF_COLORS)
    counts=0;
    Variation_Threshold++;
    for 0 < i < 360, do:
      newHistogram[i] = counts;
      if histogram[i] is local minima [i] with
variation > Variation_Threshold, do:
        counts++;
     else
       if   histogram[i]   is   isolated   color
component with level > Level_Threshold, do:
        counts++;
      end if;
      end if;
 end for;
end while;
```

The maximum number of colors (MAX_NUM_OF_COLORS) is a constant that forces the threshold increase of the local minima variation to fit the palette of colors to the desired one. The Variation_Threshold variable is originally set to 100, and incremented in steps of 100. Although, this is not a crucial data since it will be adjusted in the iterative loop.

The newHistogram array stores the same H value until the algorithm finds a local minima or an isolated group of colors above another threshold, when counts increases its value representing a new color. Figure 2 presents both the hue component of and histogram (ranged in 180º) and the corresponding LUT after the transformation. As presented in figure 2, the array obtained may not be considered as a proper histogram, but as a 1D-LUT where a value (ranging between 1 and 8) is assigned to every Hue value of each pixel in the original image. Originally gray pixels will be processed in a gray scale format.

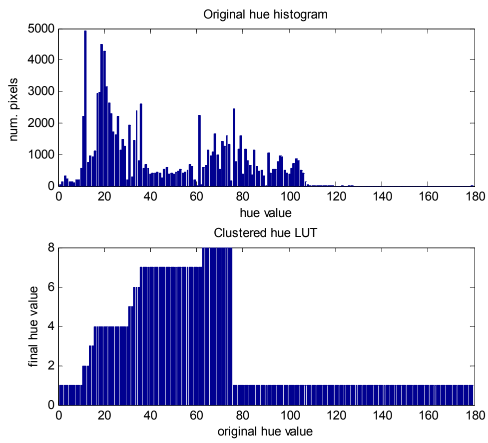
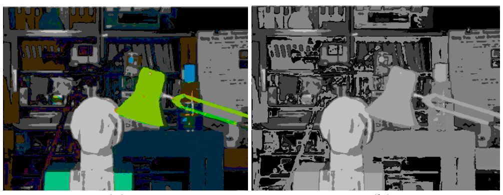


Figure 2: (up) Original histogram of Tsukuba right image (ranged [1:180], horizontal axis) and (down) Clustered Look-Up-Table to 8 colors (ranged [1,8], vertical axis).

The complete transformation for each pixel is as follows:

```
if O(Si,j) > SAT_THRESHOLD & O(Vi,j) >
VAL_THRESHOLD, do:
  F(Hi,j) = O(Hi,j);
  F(Si,j) = 255;
  F(Vi,j) = O(Vi,j)&MASK;
else
  F(Hi,j) = O(Hi,j);
  F(Si,j) = 0;
  F(Vi,j) = O(Vi,j)&MASK;
end if;
```

In this pseudo code, the terms O(…) and F(…) are the original and final images, respectively. $H_{i,j}$, $S_{i,j}$ and $V_{i,j}$ are the *Hue*, *Saturation* and *Value* component , respectively, of the (i-th,j-th) pixel and MASK is the constant that maintains the two MSBs rejecting the rest ones. The result of the aforementioned process is the conversion of the original image to a scalar image. Figure 3 illustrates two representations of the final PCI image (false colors have been introduced to aid visual perception). Since the level of *Saturation* has been reduced to one bit (whether or not it is completely saturated), the color palette is forced to be represented by 8 colors. As effect of the minimum saturation constraint, some pixels are left in gray scale. The *Value* of every pixel is truncated to its two MSBs, the complete pixel information can thus be stored in 6 bits, which maintain the most relevant information of each pixel. As a result, a gray-scale image can be built, which is then segmented as a non ambiguous gray scale image, as shown in figure 3.b.



(a) (b)

Figure 3: (a) Tsukuba right image after color clustering (1 byte/pixel). False color representation. (b) PCI shown in a gray scale image.

In these images, each byte has the following structure:

Table 1: Clustered pseudo color byte structure.

S	C_1	C_2	C_3	V_8	V_7	0	0

In this table, S is the saturation bit, C_x the descriptor of the dominant color (allowing 8 different colors) and V_8 and V_7 the two MSB of the Value component. It is important to notice that this transform is not equivalent to a Euclidean distance measurement in any color space. Moreover, its non-linear transform allows an important save of memory and computational load, maintaining important information.

3 PCI SEGMENTATION AND MATCHING

We present herein an analysis of the segmentation process required in computer vision. This task has been used to separate different regions or areas located within the same image of support Ω (Pham et al., 2000):

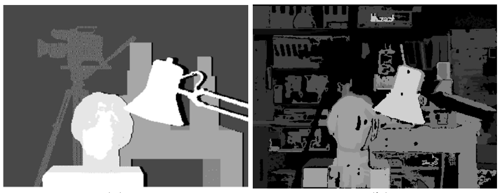
$$\Omega = \sum_{k=1}^{K} S_k \qquad (1)$$

In this equation, S_k represents the k-th region and $S_k \cap S_j = \emptyset$ for $k \neq j$. When applied to binary images the process of segmenting demonstrates no interpretation uncertainties. However, several different parameters must be considered when this segmentation is to be performed on gray scale (Zhang, Xiong, Zhou, & Wong, 2007) and color images (Kuan, Kuo, & Yang, 2008).

The segmentation and matching is done with the algorithm presented in (Revuelta Sanz, Ruiz Mezcua, Sánchez Pena, & Thiran, 2010b). The main advantage of the segmentation process is that it allows statistical descriptors to be extracted from every region on the fly thus reducing the computational cost as each pixel is only processed once. A detailed description of the extraction features may be found in (Revuelta Sanz, Ruiz Mezcua, & Sánchez Pena, 2010a).

4 RESULTS

The pre-processing and segmentation procedures have been implemented using an OpenCV library along with a specific C program designed for this particular application. To verify the reliability of this procedure, it has been applied to the Tsukuba pair of color images, which have a resolution of 384x288 pixels. Figure 4 shows the real depth map and the computed one.

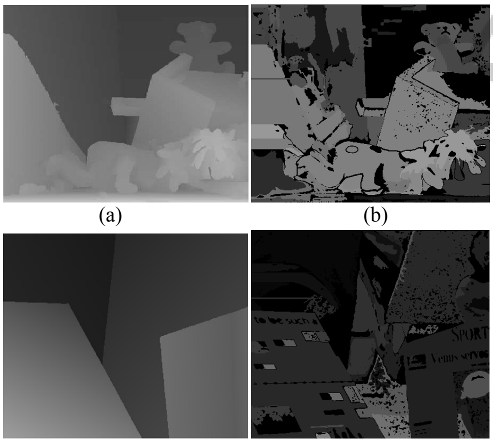


(a) (b)

Figure 4: (a) Real depth of Tsukuba images. In black, the occluded parts. (b) The computed depth map. In black, unmatched regions and occluded parts.

The time required by the algorithm to obtain this result is 77.4 ms (12 fps), achieving a real-time performance. The quantitative results, obtained by means of the Middlebury web page (Middlebury, 2010), show that the error in non-occluded pixels achieves the 46.9% of pixels for a threshold of 2.

Further tests on different color standard image pairs have also been carried out, using the same database. Image processing results on each image of the Teddy and Venus pairs are presented in the following figure, close to the true depth maps.



(a) (b)

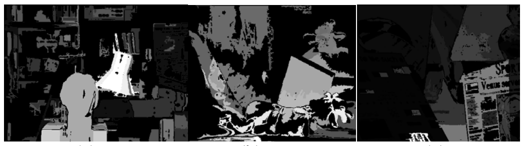
(c) (d)

Figure 5: (a) Teddy true and (b) computed depth map. (c) Venus true and (d) computed depth map.

In these cases, the time required to compute the depth maps is 114.2 ms (8 fps) for the Teddy image, and 111.8 ms (8 fps) for the Venus image. In these cases, the error in non-occluded pixels ("nonocc" in the database notation) for the Teddy and Venus image pairs is 60 and 77.2%. These results are discussed in the following section.

5 DISCUSSION

The main goal of the pre-processing and color clustering algorithm has been achieved. We propose now a qualitative comparative analysis between the proposed algorithm for color images and the previously developed algorithms applied to gray scale images (Revuelta Sanz, Ruiz Mezcua, Sánchez Pena, & Thiran, 2010b). The depth map computed using truncated gray scale images on the same set of image pairs are presented in the following figure 6.



(a) (b) (c)

Figure 6: Segmentation based on gray scale version of (a) Tsukuba, (b) Teddy and (c) Venus images pairs (Revuelta Sanz, Ruiz Mezcua, Sánchez Pena, & Thiran, 2010b).

The errors appreciated in this figure are a result of the lack of information of the gray scale image.

By using the color based algorithm presented in this paper most of these errors have been corrected. All remaining results are seen to improve when using the novel color-based algorithm, where more detailed depth maps have been obtained. However several errors are still present which are related to the segmentation process. An example of such errors may be observed and measured in the different areas of the left panel of the Venus pair, which provoke errors shown in figure 5.d. These can be explained by the nature of the segmentation algorithm. As the areas with the same value (regardless of the image being in gray or color scales) are processed as being the same region, any depth differences within the same region have not been computed, and only a mean value is provided. This particular effect may also be appreciated when observing the floor of figure 5.b. Additionally, some differentiated areas inside this panel (color blocks, for example) have been processed as different regions thus, the depth has been computed separately. Finally, the high rate of errors measured in images 5.b and 5.d are also due to the following reason: the depth is computed from the difference of the centroids horizontal coordinate in both images. This centroid can be displaced if the segmentation in one image includes some parts that are not included in the corresponding image and region segmentation. Hence, the centroid different appears to be different of the exact value and, finally, all pixels segmented and labelled as belonging to that region will have a depth value slightly distorted but big enough to compute as errors.

To conclude, the additional information provided by color images is advantageous when an improved segmentation algorithm is to be implemented. The main problems associated with such color-based segmentation, i.e. three-channel processing, has been solved by the composition of a pseudo-color image which preserves the critical information within a single channel, where no additional computational load is required for the segmentation process.

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REFERENCES

Middlebury Database. 2010. http://vision.middlebury.edu/stereo/data/

Kuan, Y.-H., Kuo, C.-M., & Yang, N.-C., 2008. Color-based image salient region segmentation using novel region merging strategy. *IEEE transactions on multimedi*a 10[5], 832-845.

Millán, M. S. & Valencia, E., 2006. Color image sharpening inspired by human vision models. *Applied Optics* 45[29], 7684-7697.

Mushrif, M. M. & Ray, A. K., 2008. Color image segmentation: Rough-set theoretic approach. *Pattern recognition letters* 29[4], 483-493.

Ozden, M. & Polat, E., 2007. A color image segmentation approach for content-based image retrieval. *Pattern recognition* 40[4], 1318-1325.

Pham, D. L., Xu, C., & Prince, J. L., 2000. Current Methods in Medical Image Segmentation. *Annual Review of Biomedical Engineering* 2, 315-337. Annual Reviews Inc.

Pons, J.-P. & Keriven, R., 2007. Multi-View Stereo Reconstruction and Scene Flow Estimation with a Global Image-Based Matching Score. I*nternational Journal of Computer Vision* 72[2], 179-193.

Revuelta Sanz, P., Ruiz Mezcua, B., & Sánchez Pena, J., 2010a. M. Efficient Characteristics Vector Extraction Algorithm using Auto-seeded Region-Growing. *Proceedings of the 9th IEEE/ACIS International Conference on Computer and Information Science ICIS* 2010, 215-221.

Revuelta Sanz, P., Ruiz Mezcua, B., Sánchez Pena, J. M., & Thiran, J.-P. 2010b, *Stereo Vision Matching using Characteristics Vectors* EPFL-REPORT-150511.

Zhang, K., Xiong, H., Zhou, X., & Wong, S., 2007. A 3D Self-Adjust Region Growing Method for Axon Extraction. *Image Processing, 2007. ICIP 2007. IEEE International Conference on* 2[II], 433-436. San Diego, California, IEEE Signal Processing Society.