



## Colour Image Segmentation using K-means Clustering and KPE Vector Quantization Algorithm

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**Abstract**— *In this paper we introduce vector quantization based segmentation approach that is specifically designed to segment low-altitude, high resolution, aerial images, as a preprocessing step to 3D reconstruction. This approach uses vector quantization algorithms-K-Means clustering and KPE to form regions. It uses color similarity and volume difference criteria to merge adjacent regions. Experiments performed with real aerial images of varied nature demonstrate that this approach does not result in over segmentation or under segmentation allowing large-scale urban scenes to be segmented in an accurate, reliable and fully automatic way. The vector quantization seems to give far better results as compared to conventional on-the-fly watershed algorithm.*

**Keywords**— *segmentation, vector quantization*

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### I. INTRODUCTION

This paper deals with the specific problem of segmenting architectural elements such as roofs, walls and pavement in low-altitude aerial images, so that these segmented elements can later be used as the basis to build 3D reconstruction algorithms specifically tailored to recover the geometry of entire metropolitan areas in a fully automatic way[1][2].

Segmentation is the process of partitioning an image into disjoint and homogeneous regions. This task can be equivalently achieved by finding the boundaries between the regions; these two strategies have been proven to be equivalent indeed.[4][5][6] Regions of image segmentation should be uniform and homogeneous with respect to some characteristics such as gray tone or texture. Region interiors should be simple and without many small holes. Adjacent regions of segmentation should have significantly different values with respect to the characteristic on which they are uniform. Boundaries of each segment should be simple, not ragged, and must be spatially accurate [10][11][12].

Segmentation is an extremely important operation in several applications of image processing and computer vision, since it represents the very first step of low-level processing of imagery. As mentioned above, the essential goal of segmentation is to decompose an image into parts which should be meaningful for certain applications. In this paper, we are concerned with color image segmentation which is becoming increasingly important in many applications. For instance, in digital libraries large collections of images and videos need to be catalogued, ordered, and stored in order to efficiently browse and retrieve visual information.

Until a few years ago, segmentation techniques were proposed mainly for gray-level images. The reason is that, although color information permits a more complete representation of images and a more reliable segmentation of them, processing color images requires computation times considerably larger than those needed for gray-level images. This is no longer a major problem with an increasing speed and decreasing costs of computation; besides, relatively inexpensive color camera are nowadays largely available. Accordingly, there has been a remarkable growth of algorithms for segmentation of color images in this last decade. Most of the times, these are kind of dimensional extensions of techniques devised for gray-level images; thus they exploit the well-established background laid down in that field [7],[8][9]. In other cases, they are ad hoc techniques tailored on the particular nature of color information and on the physics of the interaction of light with colored materials.

In this paper, we use vector quantization technique. This segmentation technique basically has three steps to follow:

Step1: Apply Vector Quantization technique to form regions.

Step2: Region Merging

In section 2, we first describe the on-the-fly approach based on watershed segmentation. Proposed methodology is explained in Section 3. The segmentation results and discussion are provided in Section 4 and we conclude the paper in Section 5.

### II. ON-THE-FLY APPROACH[1]

Catchment basin merging algorithm (CBMA) [3] embeds an on-the-fly merging mechanism into VSWT [2], in order to reduce over-segmentation. The merging process is guided by a set of rules that take into account geometric attributes of the catchment basins such as depth, area and volume. A typical CBMA, would create new segmentation edges only between catchment basins whose volumes (or depths, or areas) in the previous iteration are larger than pre-defined thresholds.

### III. SEGMENTATION USING VECTOR QUANTIZATION

#### A. K-Means clustering)-VQ [14]

K-means clustering algorithm is fairly straightforward. Given a number k, separate all data in a given partition into k separate clusters, each with a center that doubles as a representative. There are iterations that reset these centers then reassign each point to the closest center. Then the next iteration repeats until the centers do not move.

#### B. Kekre's proportionate error algorithm(KPE)-VQ[15]

In this algorithm initial code vector is set as the average of the entire training sequence. Thus initially the codebook contains only one code vector. This code vector is then split into two by adding proportionate error instead of adding constant error. This algorithm gives better clustering.

#### C. Proposed technique

Vector quantization technique is applied on given image and then it is divided into regions. The regions are then merged based on color threshold and volume threshold values. The proposed technique has two steps to follow

1. Applying vector quantization technique to from regions
2. Region merging.

#### 1. Applying vector quantization technique:

Following Vector Quantization techniques are used in step1.

The K-Means Clustering Algorithm[14].

Kekre's proportionate error algorithm (KPE) [15].

In each vector quantization technique 2 types of training vectors are formed.

- Each training vector is of dimension three consisting of R, G, B components of one pixel.
- Each training vector is of dimension twelve consisting of R, G, and B components of 2 ×2 adjacent pixels.

The size of codebook is set to eight. Training vectors are reassigned to encoding regions in every iteration. Once the code book size reaches eight the process is stopped. In the original image, pixel value is replaced by the encoding region number to which the pixel is assigned.

#### 2. Region merging:

Region merging based on color similarity is performed after region formation as a posteriori step. All pixels pertaining to each segmented region have exactly the same label. Thus, a single scan through the labeled image suffices to compute the mean color and volume of each region. The labeled image is then scanned successively to combine two adjacent regions whose mean colors differ by less than a preset threshold and to merge a small region whose volume is less than a preset threshold into larger region.

### IV. EVALUATION FUNCTION Q(I) [16]

The evaluation function is defined as

$$Q(I) = \frac{1}{10000(N \times M)} \sqrt{R} \times \sum_{i=1}^R \left[ \frac{e_i^2}{1 + \log A_i} + \left( \frac{R(A_i)}{A_i} \right)^2 \right] \quad \dots (1)$$

where I is the segmented image, N×M the image size, and R the number of regions of the segmented image, while  $A_i$  and  $e_i$  are, respectively, the area and the average color error of the  $i$ th region;  $e_i$  is defined as the sum of the Euclidean distances between the RGB color vectors of the pixels of region  $i$  and the color vector attributed to region  $i$  in the segmented image. While  $R(A_i)$ , represents the number of regions having an area equal to  $A_i$ .

The smaller the value of  $Q(I)$ , the better the segmentation result should be. The body of the sum is composed of two terms: the first is high only for non-homogeneous regions (typically, large ones), while the second term is high only for regions whose area  $A$  is equal to the area of many other regions in the segmented image (typically, small ones). We may expect that the number of regions of area  $A_i$  in given an image will be small if area  $A_i$  has a high value; and in this case  $R(A_i)2/A_i$  contributes little to the sum. On the other hand, the number of regions of area  $A_i$  may be large if the area  $A_i$  has a low value; in this case  $R(A_i)2/A_i$  contributes strongly to the sum. Heuristically we can say that  $R(A_i)$  is almost always 1 for large regions, and can be much larger than 1 for small regions. In any case, the denominator  $A_i$  drastically forces the term  $R(A_i) /A_i$  to near zero for large regions, and lets it grow for small regions.

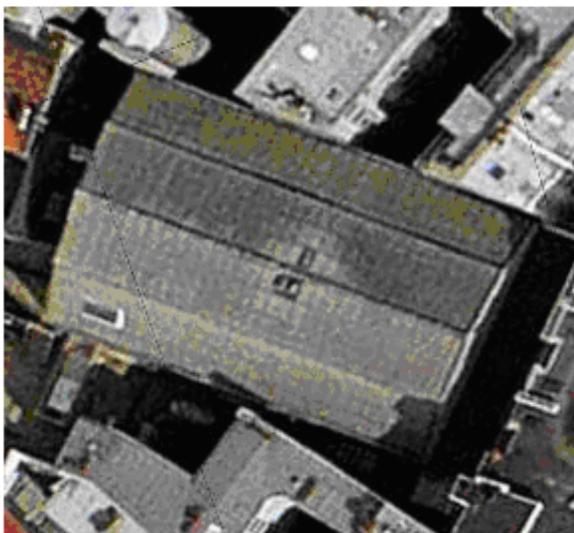
### V. EXPERIMENTAL RESULT

The algorithms are implemented on Celeron processor 1.73 GHz, 1MB cache, 1GB RAM machine to obtain result. We have tested these algorithms on 8 images of size around 250×250. We compare three approaches – on-the-fly, K-means clustering+RM, KPE+RM explained in sections 2 and 3 respectively - using the evaluation function described in section 4. Table 1 shows the values of Evaluation function 'Q' given in equation (1) obtained after the algorithms are applied on various scenes. The value shown in bold is the least value among all the values of evaluation function 'Q' obtained using RGB 1 pixel and RGB 2×2 block. The least value resents the best segmentation result.

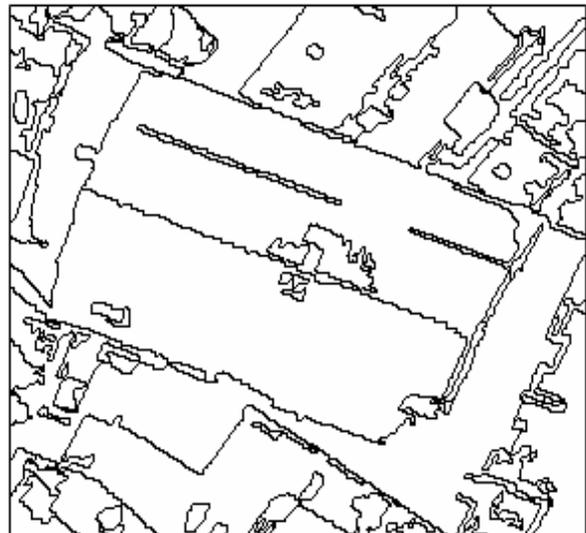
TABLE I: VALUES OF EVALUATION FUNCTION 'Q' FOR VARIOUS SCENES

Scene No.	Training Vector	Algorithms		
		K-Means Clustering + RM	KPE+RM	On-The-Fly
1	RGB 1 Pixel	<b>454.8486</b>	457.9944	1628.3
	RGB2×2 block	<b>423.3818</b>	439.0842	
2	RGB 1 Pixel	497.0836	<b>389.34</b>	1204.1
	RGB2×2 block	417.75	<b>370.15</b>	
3	RGB 1 Pixel	<b>1082.90</b>	1204.10	2423.7
	RGB2×2 block	1391.30	<b>1337.60</b>	
4	RGB 1 Pixel	2023.50	<b>1327.60</b>	5057
	RGB2×2 block	2011.20	<b>1920.20</b>	
5	RGB 1 Pixel	291.1735	<b>286.3662</b>	905.602
	RGB2×2 block	<b>1210.70</b>	1424.60	
6	RGB 1 Pixel	<b>498.15</b>	1369.20	1818
	RGB2×2 block	598.48	<b>563.97</b>	
7	RGB 1 Pixel	<b>884.9261</b>	890.7452	2756.5
	RGB2×2 block	<b>967.19</b>	1101.40	
8	RGB 1 Pixel	<b>547.8999</b>	623.8634	1632.5
	RGB2×2 block	<b>659.1562</b>	705.6068	

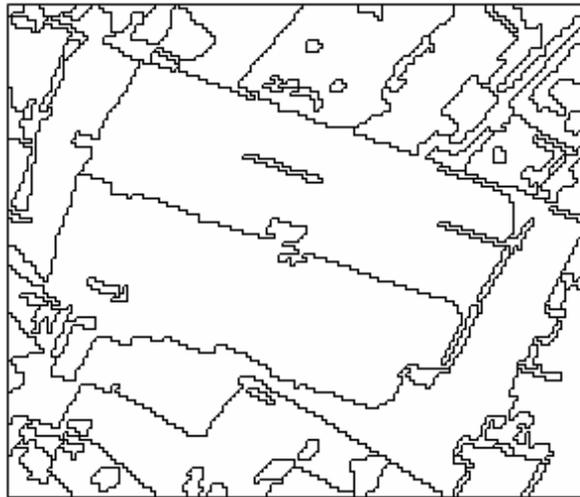
Figure 1 shows the result of applying these algorithms on scene 1.



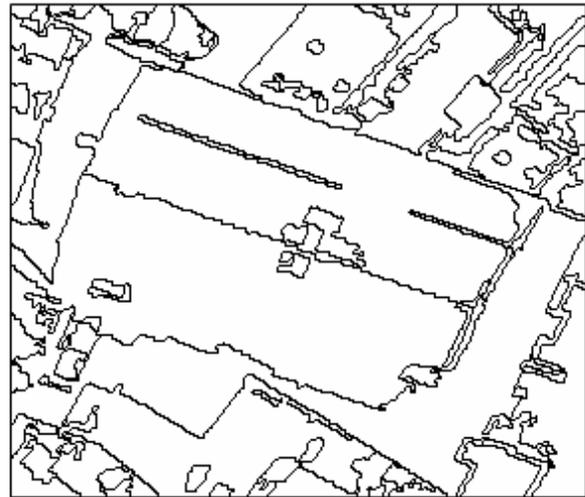
(a) Input Image: Suburban scene 1



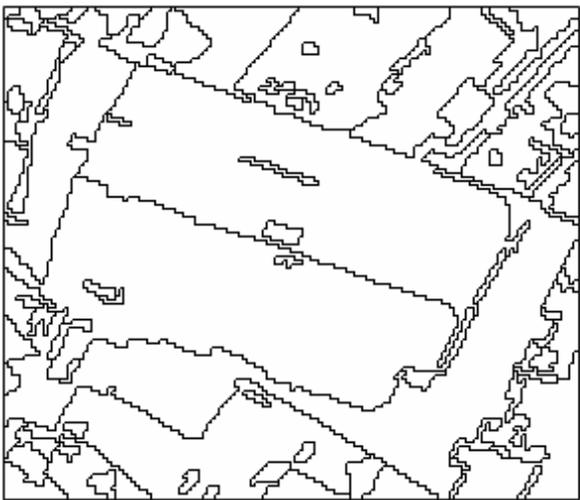
(b) K-means clustering +RM Training vector size=3



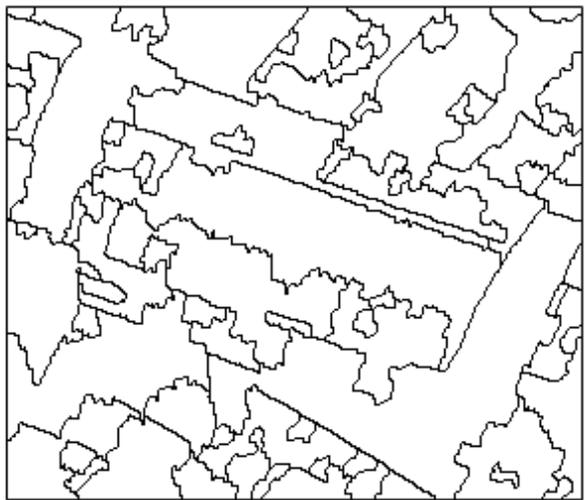
(c) K-means clustering +RM-  
Training vector size=12



(d) KPE+RM  
Training vector size=3



(e) KPE+RM  
Training vector size=12



(f) On-the-fly

Figure1: Segmentation of suburban scene 1

## VI. CONCLUSIONS

In this paper we have demonstrated that vector quantization technique can be used as the basis to construct fully automatic, reliable technique for segmenting architectural elements in low-altitude, high resolution, aerial images of urban scenes. The evaluation function ‘Q’ correctly retrieves the best segmentation result. It has been found that when the training vector size is 12 i.e. when a block of 4 pixels is taken into a training vector, a zigzag effect appears over the contours. When the training vector size is 3, we don’t see the zigzag effect over the contours. Between K-means clustering+RM and KPE+RM which approach gives better result is fully image dependent. However performance of these two algorithms is far better than on-the-fly watershed algorithm.

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