World Academy of Science, Engineering and Technology
International Journal of Electronics and Communication Engineering
Vol:3, No:11, 2009

A New Approach for Image Segmentation using Pillar-Kmeans Algorithm

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International Science Index, Electronics and Communication Engineering Vol:3, No:11, 2009 waset.org/Publication/354

***Abstract*—**This paper presents a new approach for image segmentation by applying Pillar-Kmeans algorithm. This segmentation process includes a new mechanism for clustering the elements of high-resolution images in order to improve precision and reduce computation time. The system applies K-means clustering to the image segmentation after optimized by Pillar Algorithm. The Pillar algorithm considers the pillars' placement which should be located as far as possible from each other to withstand against the pressure distribution of a roof, as identical to the number of centroids amongst the data distribution. This algorithm is able to optimize the K-means clustering for image segmentation in aspects of precision and computation time. It designates the initial centroids' positions by calculating the accumulated distance metric between each data point and all previous centroids, and then selects data points which have the maximum distance as new initial centroids. This algorithm distributes all initial centroids according to the maximum accumulated distance metric. This paper evaluates the proposed approach for image segmentation by comparing with K-means and Gaussian Mixture Model algorithm and involving RGB, HSV, HSL and CIELAB color spaces. The experimental results clarify the effectiveness of our approach to improve the segmentation quality in aspects of precision and computational time.

***Keywords*—**Image segmentation, K-means clustering, Pillar algorithm, color spaces.

I. Introduction

THE image segmentation is an effort to classify similar colors of image in the same group. It clusters colors into several groups based on the closeness of color intensities inside an image. The objective of the image segmentation is to extract the dominant colors. The image segmentation is very important to simplify an information extraction from images, such as color, texture, shape, and structure. The applications of image segmentation are diversely in many fields such as image compression, image retrieval, object detection, image enhancement, and medical image processing.

Several approaches have been already introduced for image segmentation. The most popular method for image segmentation is K-means algorithm [1][2][12]. It is widely a used algorithm for image segmentation because of its ability to cluster huge data points very quickly. Hierarchical clustering is also widely applied for image segmentation [20][21][24]. Many researches used Gaussian Mixture Model with its variant Expectation Maximization [9][15].

This paper proposes a new approach for image segmentation that utilizes Pillar Algorithm to optimize K-means clustering. The Pillar algorithm performs the pillars' placement which should be located as far as possible from each other to withstand against the pressure distribution of a roof, as identical to the number of centroids amongst the data distribution. It designates the initial centroids' positions by calculating the accumulated distance metric between each data point and all previous centroids, and then selects data points which have the maximum distance as new initial centroids. The segmentation process by our approach includes a new mechanism for clustering the elements of high-resolution images in order to improve precision and reduce computation time.

In this paper, Section 2 describes the K-means algorithm. Our approach will be discussed in Section 3. Section 4 describes the experimental results using several color spaces with two comparing algorithms, and then followed by concluding remarks in Section 5.

II. The Basic Theory of K-means Clustering

This section briefly explains the basic theory of K-means clustering. Let $A=\{a_i \mid i=1,\ldots,f\}$ be attributes of f-dimensional vectors and $X=\{x_i \mid i=1,\ldots,N\}$ be each data of A. The K-means clustering separates X into k partitions called clusters $S=\{s_i \mid i=1,\ldots,k\}$ where $M \in X$ is $M_i=\{m_{ij} \mid j=1,\ldots, n(s_i)\}$ as members of s_i, where $n(s_i)$ is number of members for s_i. Each cluster has cluster center of $C=\{c_i \mid i=1,\ldots,k\}$. K-means clustering algorithm can be described as follows [26]:

1. Initiate its algorithm by generating random starting points of initial centroids C.
2. Calculate the distance d between X to cluster center C. Euclidean distance is commonly used to express the distance.
3. Separate x_i for i=1..N into S in which it has minimum $d(x_i,C)$.
4. Determine the new cluster centers c_i for i=1..k defined as:

$$c_i = \frac{1}{n_i}\sum_{j=1}^{n(s_i)} m_{ij} \in s_i \qquad (1)$$

5. Go back to step 2 until all centroids are convergent.

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The centroids can be said converged if their positions do not change in the iteration. It also may stop in the t iteration with a threshold ε [15] if those positions have been updated by the distance below ε:

$$\left|\frac{C^t - C^{t-1}}{C^t}\right| < \varepsilon \tag{2}$$

III. New Approach for Image Segmentation

The image segmentation is important to unify contiguous colors in the color vector space into representative colors [27]. It can improve significantly performance of the information extraction, such as color, shape, texture, and structure. This section describes our approach for image segmentation using our proposed Pillar algorithm [26] to optimize K-means clustering.

The image segmentation system pre-proceeds three steps: noise removal, color space transformation and dataset normalization. First, the image is enhanced by applying adaptive noise removal filtering. Then, our system provides a function to convert RGB of an image into HSL and CIELAB color systems. Because of different ranges of data in HSL and CIELAB, we apply the data normalization. Then, the system clusters the image for segmentation by applying K-means clustering after optimized by Pillar algorithm. Fig. 1 shows the computational steps of our approach for image segmentation.

A. Noise Removal

An adaptive noise removal filtering using the Wiener filter is applied for noise removal of images. The Wiener filter can be considered as one of the most fundamental noise reduction approaches and widely used for solution for image restoration problems [3, 23]. In our system, we use 3x3 neighborhoods of filtering size.

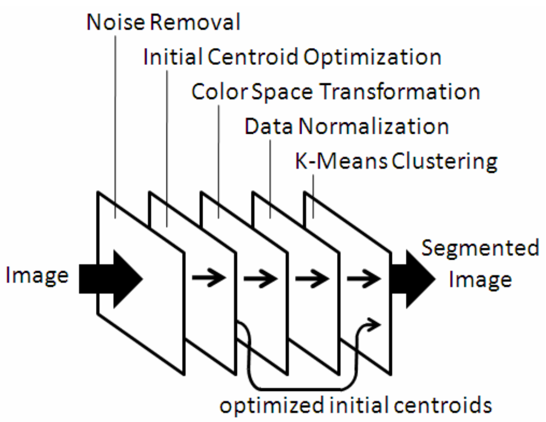

Fig. 1 Computational steps of our approach for image segmentation

B. Color Space Transformation

Our image segmentation system pre-proceeds the image by transforming the color space from RGB to HSL and CIELAB color systems. HSL is well-known as an improved color space of HSV because it represents brightness much better than saturation. Beside, since the hue component in the HSL color space integrates all chromatic information, it is more powerful and successful for segmentation of color images than the primary colors [11]. The CIELAB color system has the advantage of being approximately perceptually uniform, and it is better than the RGB color system based on the assumption of three statistically independent color attributes [22]. The CIELAB color space is also widely-used for image restoration and segmentation [8][15][16][25]. Considering the advantages of each color system of HSL and CIELAB, in our system we utilize both of them as hybrid color systems for image segmentation.

C. Data Normalization

Because of different ranges of data points in HSL and CIELAB color spaces, we need to normalize the datasets. In our system, Softmax algorithm [5][19] is used for the data normalization. The Softmax can reach softly toward its maximum and minimum value, but never getting there. The transformation using Softmax is more or less linear in the middle range, and has a smooth nonlinearity at both ends. The output range is between 0 and 1. A function in principle used to obtain the needed S-curve is the logistic function [27]:

$$f(x_i) = \frac{1}{1+e^{-x_i'}} \tag{3}$$

The logistic function produces the needed S-curve but not over the needed range of values, and there is also no way to select the range of linear response. In order to resolve this problem, {x} should be first transformed linearly to vary around the mean $\bar{x}$ in the following way:

$$x_i' = \frac{x_i - \bar{x}}{\lambda(\sigma_x / 2\pi)} \tag{4}$$

where:

$\bar{x}$ is the mean value of variable x

σ_x is the standard deviation of variable x

λ is the linear response measured in standard deviation. It describes in terms of how many normally distributed standard deviations of the variables are to have a linear response. In our case, we set λ=10 in order to make smoother for normalizing the datasets.

D. Image Segmentation using Pillar Algorithm

The system uses the real size of the image in order to perform high quality of the image segmentation. It causes high-resolution image data points to be clustered. Therefore we use the K-means algorithm for clustering image data considering that its ability to cluster huge data, and also outliers, quickly and efficiently [18][26]. However, Because of initial starting points generated randomly, K-means algorithm is difficult to reach global optimum, but only to one of local minima [6] which it will lead to incorrect clustering results [13]. Barakbah and Helen [18] performed that the error ratio of K-means is more than 60% for well-separated datasets. To avoid this phenomenon, we use our previous work regarding initial clusters optimization for K-means using Pillar algorithm [26]. The Pillar algorithm is very robust and superior for initial centroids optimization for K-means by positioning all centroids far separately among them in the data distribution.

This algorithm is inspired by the thought process of determining a set of pillars' locations in order to make a stable house or building. Fig. 2 illustrates the locating of two, three, and four pillars, in order to withstand the pressure distributions of several different roof structures composed of discrete points. It is inspiring that by distributing the pillars as far as possible from each other within the pressure distribution of a roof, the pillars can withstand the roof's pressure and stabilize a house or building.

It considers the pillars which should be located as far as possible from each other to withstand against the pressure distribution of a roof, as number of centroids among the gravity weight of data distribution in the vector space. Therefore, this algorithm designates positions of initial centroids in the farthest accumulated distance between them in the data distribution.

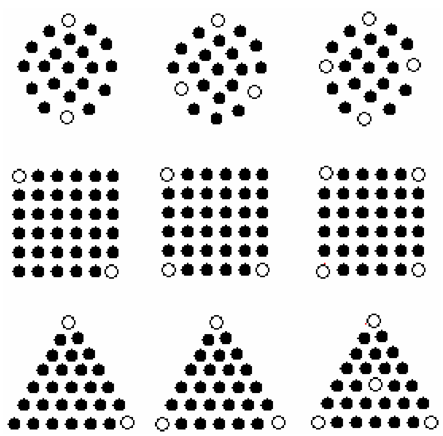

Fig. 2 Illustration of locating a set of pillars (white points) withstanding against different pressure distribution of roofs.

The Pillar algorithm is described as follows. Let $X=\{x_i \mid i=1,\ldots,n\}$ be data, k be number of clusters, $C=\{c_i \mid i=1,\ldots,k\}$ be initial centroids, $SX \subseteq X$ be identification for X which are already selected in the sequence of process, $DM=\{x_i \mid i=1,\ldots,n\}$ be accumulated distance metric, $D=\{x_i \mid i=1,\ldots,n\}$ be distance metric for each iteration, and m be the grand mean of X. The following execution steps of the proposed algorithm are described as:

1. Set $C=\varnothing$, $SX=\varnothing$, and $DM=[]$
2. Calculate $D \leftarrow \mathrm{dis}(X,m)$
3. Set number of neighbors $nmin = \alpha \,.\, n / k$
4. Assign $dmax \leftarrow argmax(D)$
5. Set neighborhood boundary $nbdis = \beta \,.\, dmax$
6. Set i=1 as counter to determine the i-th initial centroid
7. $DM = DM + D$
8. Select ж $\leftarrow x_{argmax(DM)}$ as the candidate for i-th initial centroids
9. SX=SX ∪ ж
10. Set D as the distance metric between X to ж.
11. Set $no \leftarrow$ number of data points fulfilling $D \leq nbdis$
12. Assign DM(ж)=0
13. If $no < nmin$, go to step 8
14. Assign $D(SX)$=0
15. $C = C \cup$ ж
16. $i = i + 1$
17. If $i \leq k$, go back to step 7
18. Finish in which C is the solution as optimized initial centroids.

However, the computation time may take long time if we apply the Pillar algorithm directly for all elements of high-resolution image data points. In order to solve this problem, we reduce the image size to 5%, and then we apply the Pillar algorithm. After getting the optimized initial centroids as shown in Fig. 3, we apply clustering using the K-means algorithm and then obtain the position of final centroids. We use these final centroids as the initial centroids for the real size of the image as shown in Figure 1, and then apply the image data point clustering using K-means. This mechanism is able to improve segmentation results and make faster computation for the image segmentation.

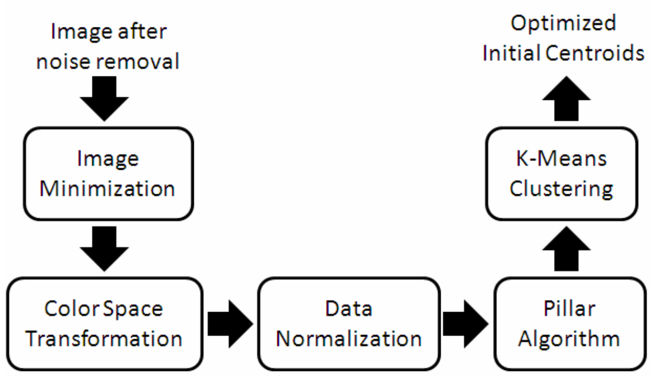

Fig. 3 Initial centroid optimization of K-means clustering for image segmentation.

IV. Experimental Results

To perform practical applicability of our proposed approach for image segmentation, we made a series of experiments and tested its performance using variance. Variance constraint [10] can express the density of the clusters with the variance within cluster and the variance between clusters [4][17]. The ideal cluster has minimum variance within cluster to express internal homogeneity and maximum variance between clusters to express external homogeneity [14]. Let $X=\{x_i \mid i=1,\ldots,N\}$ be data set, $S=\{s_i \mid i=1,\ldots,k\}$ be clustered X where $M \in X$ is $M_i=\{m_{ij} \mid j=1,\ldots,n(s_i)\}$ as members of s_i, variance within cluster can be defined as follows [26]:

$$v_w = \frac{1}{N-k}\sum_{i=1}^{k}\left(n(s_i)-1\right)v_i^{\,2} \tag{5}$$

where N is number of data points, k is number of clusters, and n_i is number of members in i-th cluster, while v_i is given as:

$$v_i^{\,2} = \frac{1}{n(s_i) - 1} \sum_{\substack{j=1 \\ \in s_i}}^{n(s_i)} \left(m_{ij} - \bar{s}_i \right)^2 \tag{6}$$

where m_j is members of i-th clusters.

Variance between clusters then can be defined as follows:

$$v_b = \frac{1}{k-1} \sum_{i=1}^{k} n(s_i) \left(\bar{s}_i - \bar{x} \right) \tag{7}$$

For our experimental study, we use the well known SIMPLIcity dataset of Wang et al. [7]. These images are manually divided into 10 categories which are people, beaches, historian buildings, buses, dinosaurs, elephants, roses, horses, mountains, and foods. We conducted the performance comparison between our approach for image segmentation and two comparing algorithms which are K-means algorithm and Gaussian Mixture Model (GMM) algorithm. For performing the K-means algorithm, we run 10 times of K-means and noticed its average results. For GMM algorithm, we use the spherical model with 50 numbers of iteration. In order to perform comparisons in several color spaces, we used 4 different color spaces which are RGB, HSV, HSL and CIELAB. We set the comparison parameters up with 4 and 5 numbers of clusters, and with respectively different data normalization algorithms: Z-Score and Softmax (λ=10).

Fig. 4 shows the performance comparison of variance within cluster (v_w) which expresses the internal homogeneity of image segmentation results. The low v_w conveys that the internal homogeneity of the clusters is so high that the variance inside each cluster becomes low. The comparison came from average results of 10 image experiments with 4 and 5 clusters in different color spaces. Fig. 4 shows that our approach for image segmentation using Pillar-Kmeans algorithm reached the lowest v_w in all color spaces and outperformed the two comparing algorithms in all color spaces. Fig. 5 shows the performance comparison of variance between clusters (v_b) which expresses the external homogeneity. The good clusters have high external homogeneity that defines the degree of separation between clusters. In Fig. 5, our approach also reached the highest v_b and outperformed the others. These two figures which represent the precision of segmentation result show the advantage of adequate segmentations by our proposed approach Pillar-Kmeans algorithm. Our approach is able to enhance the quality of the image segmentation.

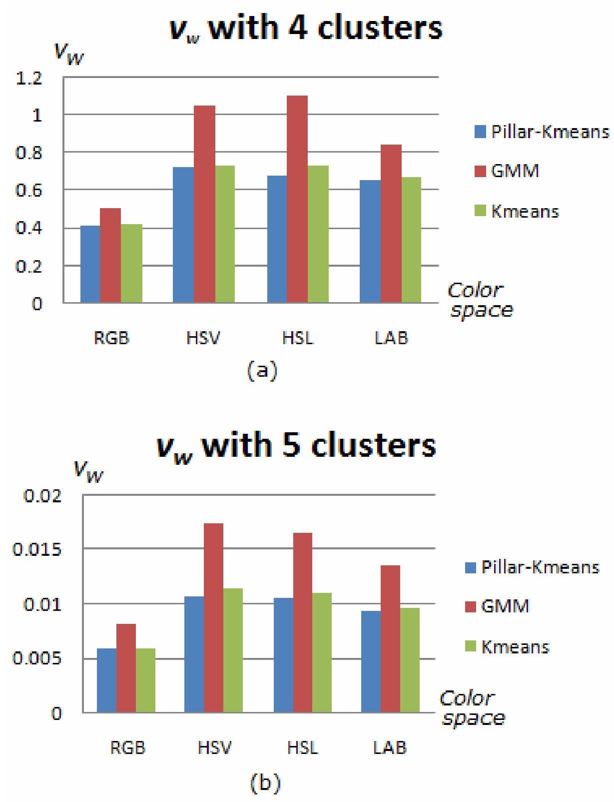

Fig. 4 Performance comparison of v_w

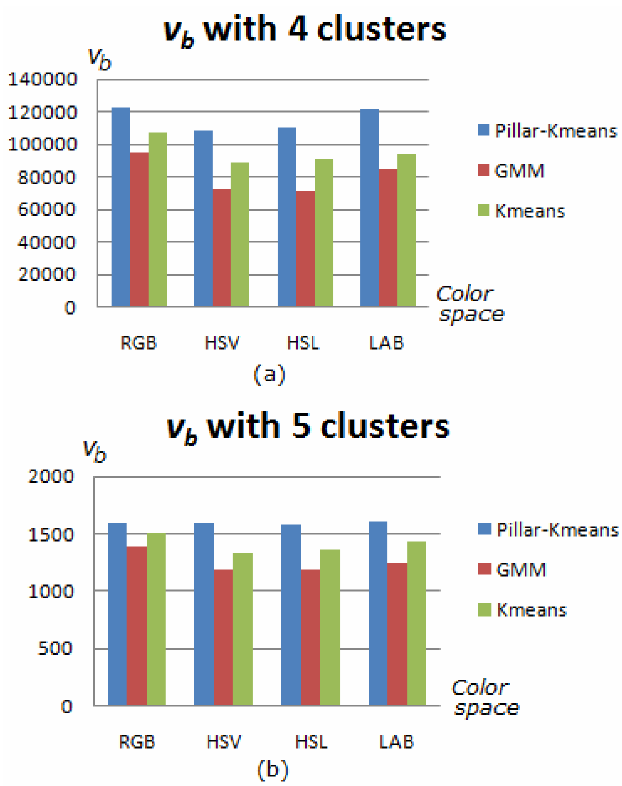

Fig. 5 Performance comparison of v_b

Fig. 6 shows one of visual comparisons of image segmentation between K-means algorithm, GMM, and our proposed Pillar-Kmeans algorithm. The Pillar-Kmeans performed the high quality of image segmentation rather than the two comparing algorithms.

Moreover, in the view point of execution time, our approach is able to reach the computational time as fast as K-means clustering in all color spaces, as shown in Fig. 7. It means that our proposed approach is able to make the image segmentation as fast as K-means and reach high quality of the segmented results.

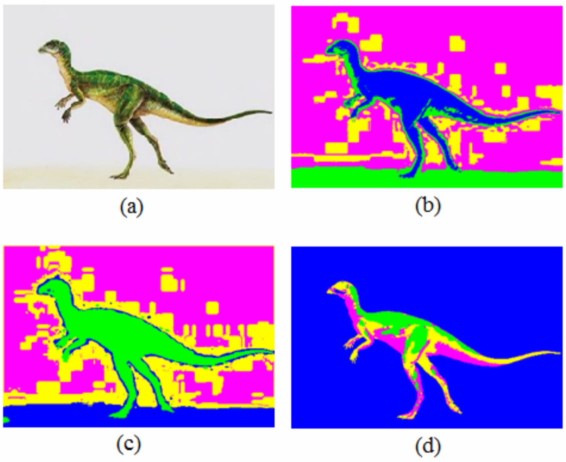

Fig. 6 Visual comparison of image segmentation (a) Image source. (b) K-means clustering. (c) GMM (d) Pillar-Kmeans algorithm

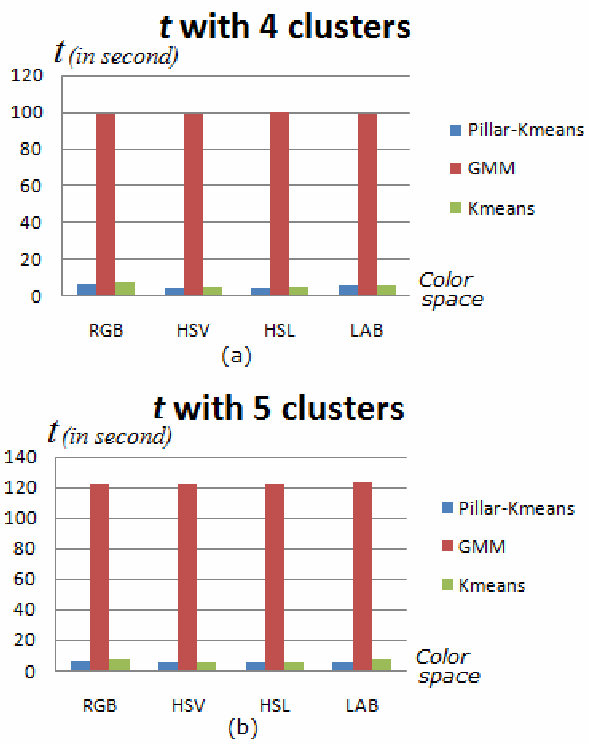

Fig. 7 Performance comparison of computational time

V. Conclusion

In this paper, we have presented a new approach for image segmentation using Pillar-Kmeans algorithm. The system applies K-means clustering after optimized by Pillar Algorithm. The Pillar algorithm considers the pillars' placement which should be located as far as possible from each other to withstand against the pressure distribution of a roof, as identical to the number of centroids amongst the data distribution. This algorithm is able to optimize the K-means clustering for image segmentation in aspects of precision and computation time. A series of experiments involving four different color spaces with variance constraint and execution time were conducted. The experimental results show that our proposed approach for image segmentation using Pillar-Kmeans algorithm is able to improve the precision and enhance the quality of image segmentation in all color spaces. It also performed the computational time as fast as K-means and kept the high quality of results.

Acknowledgment

This work was supported in part by the Japanese Ministry of Education, Culture, Sports, Science and Technology, and Keio University, under Grant Monbukagakusho scholarship and Mori Memorial Research Fund 2008/2009 for Graduate Student Researcher Development Grant, Keio University.

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