Forest Fire Detection Algorithm Based on Digital Image

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Abstract—A series of computer vision-based fire detection algorithms is proposed in this paper. These algorithms can be used in parallel with conventional fire detection systems to reduce false alarms. They can also be deployed as a standalone system to detect fire combined with a video acquisition device. This paper chiefly discussed the segmentation problem. It adopted the L*a*b*, YCbCr color space and kmeans clustering algorithm to isolate the forest fire detection. This algorithm is characterized by high stabilization and versatility, improves fire detection in real time and accurate, and has been used in the forest fires detecting. And this performed well in experiments.

Index Terms—YCbCr color space, K-means clustering algorithm, Fire detection system

I. INTRODUCTION

In China, forests are a very rare natural resource. Forest fires happen frequently and the loss is very serious each year. Strong combustion not only burns forest and plants on the ground, but also changes forestry structure, forest biology, climate and soil performance. So the forest function of preventing water and soil from being washed away and that of regulating weather both decrease. Meanwhile, the earth's surface becomes bare, and soil temperature increases. Then soil organisms are destroyed and the former forest area becomes wasteland.

Traditional fire detecting technology has some drawbacks which are hardly a solution. On the one hand, Detector must be installed near the fire, otherwise it will not be able to effectively detect the fire; On the other hand, this detection system if used in large space inside (such as hangar and large warehouse, etc.) outdoors or have strong airflow places (such as forest reserve, etc.) it is difficult or impossible to effectively detect fire. Due to single criterion, traditional fire detecting technology can't meet the demand of sensitivity and reliability. The current fire detecting technology is too laggard to discover the hidden trouble in advance and prevent the fine effectively.

With the development of the computer technology, Digital image processing technology has been widely used in various fields, and on that basis, a fire detecting technology was proposed for digital image processing [1-4].

Compared to the conventional fire detection technology, the fire detection technology which is based on the digital image can monitor the forest for 24 h realtime, making a quick reaction in the early stages of the fire, analyzing and dealing with the real-time data. These fire detection technologies vastly shorten the fire warning time which is advantageous in realizing the prediction of the fire and control. At the same time, the clear image will increase the reliability of the criterion, and reduces the error ratios [5-10].

In the case of forest fire detection, it is possible to detect the fire by distinguishing between the color of the forest(green) and the fire (red), or by using the difference between sequential images to detect the rapid formation of smoke. A detection system for forest fire generally uses a stationary image.

Forest fire detection systems are one of the most important components in surveillance systems used to monitor buildings and environment as part of an early warning mechanism that reports preferably the start of forest fire. Due to the rapid developments in digital camera technology and video processing techniques, there is a big trend to replace conventional forest fire detection techniques with computer vision- based systems.

Even though normalized RGB color space overcomes to some extent the effects of variations in illumination, further improvement can be achieved if one uses YCbCr color space which makes it possible to separate luminance/illumination from chrominance. This paper chiefly discussed the segmentation problem, it adopted the CIE L*a*b*, YCbCr color space and K-means

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clustering algorithm to isolate the fire .The result shows that system has better control performance and robustness [11-12].

II. BASIC THEORY

A color image can be represented by multiple color space models, such as RGB (red, green, and blue), YCbCr (luminance, chrominance-blue, and chrominancered), and CIE LAB. RGB describes a color based on the three primary colors and light system theory. YCbCr describes a color in accordance with the principles of brightness and chromatic aberration.

A. YCbCr Color Space

YCbCr color spaces used as a part of the color image pipeline in video and digital photography systems. Y is the luma component and Cb and Cr are the bluedifference and red-difference chroma components. Y (with prime) is distinguished from Y which is luminance, meaning that light intensity is nonlinearly encoded based on gamma corrected RGB primaries.

YCbCr is not an absolute color space; rather, it is a way of encoding RGB information. The actual color displayed depends on the actual RGB primaries used to display the signal. Therefore a value expressed as YCbCr is predictable only if standard RGB primary chromaticties are used.

YCbCr color space is defined in the ITU-R BT.601-5 and ITU-R BT.709-5 standards of ITU (International Telecommunication Union). These documents define YCbCr as a color space for digital television systems. These documents give concrete definitions for coefficients of conversion between RGB and YCbCr color spaces, for normalization and quantization of digital signals. A majority of parameters defined for the digital YCbCr color space remains the same for the YPbPr color space used in the analog television systems. YCbCr and YPbPr color spaces are closely related. Individual color components of YCbCr color space are luma Y, chroma Cb and chroma Cr. Chroma Cb corresponds to the U color component, and chroma Cr corresponds to the V component of a general YUV color space.

The difference between YCbCr and RGB is that YCbCr represents color as brightness and two color difference signals, while RGB represents color as red, green and blue. In YCbCr, the Y is the brightness (luma), Cb is blue minus luma (B-Y) and Cr is red minus luma (R-Y).

YCbCr which refers to the luminance component Y, Cb refers to the blue color component, and Cr refers to the red color component. The human eyes are more sensitive for the component Y, so people will not aware the changes of the image quality after sampling to reduce chrominance component in through the chrominance components. The main sub sampling format has the YCbCr 4:2:0, YCbCr 4:2:2 and YCbCr 4:4:4. The YCbCr 4:2:0 means every four pixel has four luminance components, two chrominance component (YYYYCbCr), and sampling only odd scan line, which is the most

commonly used format for the portable video equipment (mpeg-4) and video conference (H. 263). The YCbCr 4:2:2 means every 4 pixel has 4 luminance component, 4 chrominance component (YYYYCbCrCbCr), which is the most commonly used format for DVD, digital TV, HDTV and other consumer video equipment. The all pixels dot-matrix for YCbCr 4:4:4 is YYYYCbCrCb-CrCbCrCbCr, and which is most commonly used format for high quality studio video applications and professional video products.

The forest fire monitoring image are mostly color, the stored pictures are 24 color bitmap by R G B color space. Consulting relative references, the flame color of those pictures are distributed more uniformly in YCbCr color space [13]. The conversion formula from RGB color space to YCbCr is as formula one follow.

 $RGB \rightarrow YCbCr$

$$Y = 0.299 * R + 0.587 * G + 0.114 * B;$$

Cb = 0.5 - 0.168736 * R - 0.331264 * G + 0.5 * B;
Cr = 0.5 + 0.5 * R - 0.418688 * G - 0.081312 * B;

(1)

Among them, Y is the luminance component, Cr reflects the difference between the red component and the illumination value of the input RGB signal, and Cb reflects the difference between the blue component and the illumination value of the input RGB signal, the value ranges for those components is between 0 and 255.

B. CIE LAB Color Space

CIE L*a*b* (CIELAB) is the most complete color space specified by the International Commission on Illumination (French Commission international de l'éclairage, hence its CIE initialize). It describes all the colors visible to the human eye and was created to serve as a device-independent model to be used as a reference, and CIE L*a*b* color space is established by International Commission on Illumination (CIE) in 1976. The CIE made it as an uniform color space approximation, and made three primary locations like L*a*b*(the * will be omited later, abbreviate it to LAB). A LAB color space is a color-opponent space with dimension L for lightness and a and b for the color-opponent dimensions, based on nonlinearly compressed CIE XYZ color space coordinates.

The LAB color space includes all perceivable colors which means that its gamut exceeds those of the RGB and CMYK color models. One of the most important attributes of the LAB-model is device independence. This means that the colors are defined independent of their nature of creation or the device they are displayed on. The LAB color space is used e.g. in Adobe Photoshop when graphics for print have to be converted from RGB to CMYK, as the LAB gamut includes both the RGB and CMYK gamut. Also it is used as an interchange format between different devices as for its device independency.

In LAB color space, L is brightness; a's positive number means red, a's negative number means green; b's positive number means yellow, b's negative number means blue. In other words, the three coordinates of CIE LAB represent the lightness of the color ($L^* = 0$ yields black and $L^* = 100$ indicates diffuse white; seculars white may be higher), its position between red/magenta and green (a*, negative values indicate green while positive values indicate magenta) and its position between yellow and blue (b*, negative values indicate blue and positive values indicate yellow). The asterisk (*) after L, a and b are pronounced star and are part of the full name, since they represent L*, a* and b*, to distinguish them from Hunter's L, a, and b, described below.

Unlike the RGB and CMYK color models, LAB color is designed to approximate human vision. It aspires to perceptual uniformity, and its L component closely matches human perception of lightness, although it doesn't take the Helmholtz–Kohlrausch effect into account. It can thus be used to make accurate color balance corrections by modifying output curves in the a and b components, or to adjust the lightness contrast using the L component. In RGB or CMYK spaces, which model the output of physical devices rather than human visual perception, these transformations can only be done with the help of appropriate blend modes in the editing application [14].

LAB color space can't contain all colors that human beings can feel like XYZ color space although it has an advantage for color uniformity, therefore, transform RGB color space to XYZ color space at first, and then transform XYZ color space to LAB color space. The conversion formulaes are as formula two and formula three follows.

 $RGB \Rightarrow XYZ:$ X = (0.4124 * R + 0.3576 * G + 0.1805 * B) / 0.95047; Y = 0.2126 * R + 0.7152 * G + 0.0722 * B; Z = (0.0193 * R + 0.1192 * G + 0.9505 * B) / 1.08883;(2) $XYZ \Rightarrow CIELAB :$

$$if(X > 0.008856) \quad \text{then } fx = pow(X, 1/3);$$
else $fx = 7.787 * X + 16/116;$

$$if(Y > 0.008856) \quad \text{then } fy = pow(Y, 1/3);$$
else $fy = 7.787 * Y + 16/116;$

$$if(Z > 0.008856) \quad \text{then } fz = pow(Z, 1/3);$$
else $fz = 7.787 * Z + 16/116;$

$$L * = (116 * fy - 16) / 100;$$

$$a * = (500.0 * (fx - fy) + 110.0) / 220.0;$$

$$b * = (200.0 * (fy - fz) + 110.0) / 220.0;$$
(3)

III. FLAME PIXEL IDENTIFICATION METHOD BASED ON YCBCR COLOR SPACE

A. The Fire Characteristics in the YCbCr Space

Statistics found that the value of the collected flame pixel just focus on an ellipse area in (Cb,Cr) color space.

The flame pixel statistics of Figure 1 as follow.



Figure 1. Typical flame images

For convenience, the value of Cb and Cr quantificated to 30 levels gray, and we will get the gray value of Cb and Cr (The order from grayscale 0 to 30)

Cb (number i means the number of pixels Cb's grayscale is i):

0	0	0	0	760	3121
4370	3058	3003	2836	2961	2199
2187	1864	1592	7	0	0
0	0	0	0	0	0
0	0	0	0	0	0

Cr (number j means the number of pixels Cr's grayscale is j):

5	/				
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	456	2227
2545	1980	2862	4221	7864	5803
0	0	0	0	0	0

(Cb,Cr) (aij means the number of line i and j column which the Cb's grayscale is i and Cr's grayscale is j):

		-	-							
0	0								 0	0
						632	128		 	
					376	1117	1621	7	 	
				252	1368	518	1215	1017	 	
			69	1265	376	55	269	1024	 	
			1199	426	4	4	291	1079	 	
		386	1171	3	0	7	269	972	 	
	4	1322	103	0	0	18	328	720	 	
	90	485	0	0	0	5	56	149	 	
	342	34	0	0	0	0	0	8	 	
	20								 	
0									 	0

Of course, the actual statistics can collect a large number of fire images, and statistics after extraction flame pixel.

Statistics suggest that the distribution of Cb and Cr probably close to normal distribution, and in the (Cb, Cr) color space, the distribution also largely in line with bipartite normal distribution. Using this result, we can can make the flame segmentation by using these flame of specific distribution in (Cb, Cr) space.

B. The Flame Segmentation based on YCbCr Color Space

Statistics suggest that the distribution of Cb and Cr probably close to normal distribution, and in the (Cb, Cr) color space, the distribution also largely in line with bivariate normal distribution. The function of bivariate normal distribution is as formula four follow.

$$F(x,y) = \frac{1}{2\pi\sigma_{x}\sigma_{y}} \exp\left[-\frac{1}{2}\left[\frac{(x-\mu_{x})^{2}}{\sigma_{x}^{2}} + 2\frac{(x-\mu_{x})(y-\mu_{y})}{\sigma_{x}\sigma_{y}} + \frac{(y-\mu_{y})^{2}}{\sigma_{y}^{2}}\right]\right]$$
(4)

Among them, μ_x is the expectation of x, σ_x is the standard deviation of x, μ_y is the expectation of y, σ_y is the standard deviation of y. In here, making the variable x and y transform into Cb and Cr. According to the probability statistics related knowledge, we can use the simple variance and standard deviation of Cb and Cr replace those expectation and standard deviation. So, the the formula after the transformation is as formula five follow.

$$f(C_{r}Cb) = \frac{1}{2\pi S_{C}S_{Cb}} \exp\left\{-\frac{1}{2}\left[\frac{(Cr-\overline{C}r)^{2}}{S_{Cr}^{2}} - 2\frac{(Cr-\overline{C}t)(Cb-\overline{C}b)}{S_{C}S_{Cb}^{2}} + \frac{(Cb-\overline{C}b)^{2}}{S_{Cb}^{2}}\right]\right\}$$

$$(5)$$

Cr, Cb, S_{Cr} , S_{Cb} are simple variance and simple standard deviation, and the calculation formula is as formula six follow.

$$\overline{Cr} = \frac{1}{N} \cdot \sum_{i=1}^{N} Cr_{i};$$

$$S_{Cr}^{2} = \frac{1}{N} \cdot \sum_{i=1}^{N} (Cr_{i} - \overline{Cr})^{2}$$
(6)

The calculation formula of Cb is similar to Cr. In the

formula five, the $2\pi S_{Cr} S_{Cb}$ is fixed value, so the value of f for this part can be omitted for convenience of calculations. After, for a given pixel, we will find the value of Cr and Cb, and then find the corresponding probability s which means the probability of flame pixel. Given a threshold T, the pixel will be supposed to flame pixel if f(Cr, Cb) > T. In order to determine T, figuring out their probability of the acquisition of the flame pixel, and making T value can pass almost of these flame pixels. The decision rule of the flame pixel as follow.

if f(Cr(x, y), Cb(x, y)) > T then fire pixel; else not fire pixel;

After the statistical analysis, the values would be gotten, the value of \overline{Cr} is 0.246431, and the value of \overline{Cb} is 0.682332, the value of S_{Cr}^{2} is 0.00414649, the value of S_{Cb}^{2} is 0.0050133, and the threshold T is 3e-5. The performance of image segmentation is shown in Figure 2.



Original image A



Image A after segmentation



Original image B



Image B after segmentation Figure 2. Segmentation results based on YCbCr color space

IV. SEGMENTATION FLAME BASED ON K-MEANS CLUSTERING METHOD

A. Step of Segmentation Flame based on K-means Clustering Method

The term "k-means" was first used by James MacQueen in 1967,[15] though the idea goes back to Hugo Steinhaus in 1957.[16] The standard algorithm was first proposed by Stuart Lloyd in 1957 as a technique for pulse-code modulation, though it wasn't published outside Bell labs until 1982.[17] In 1965, E.W.Forgy published essentially the same method, which is why it is sometimes referred to as Lloyd-Forgy, too.[4] A more efficient version was proposed and published in Fortran by Hartigan and Wong in 1975/1979[18-19].

The most common algorithm uses an iterative refinement technique. Due to its ubiquity it is often called the k-means algorithm; it is also referred to as Lloyd's algorithm, particularly in the computer science community.

The k-means clustering in particular when using heuristics such as Lloyd's algorithm is rather easy to implement and apply even on large data sets. As such, it has been successfully used in various topics, ranging from market segmentation, computer vision, geostatistics, and astronomy to agriculture. It often is used as a preprocessing step for other algorithms, for example to find a starting configuration.

The K-means clustering algorithm is an iterative algorithm, each iteration one time, the class center will refresh once, after several times of iteration, the class center tend to be stable. The specific ways to segment flame based on K-means clustering algorithm is shown as follow.

(1)Select a color space, the space distance algorithm, and a threshold T, if the old and new mean distances are all less than T, the center would be supposed to stability.

(2) Take K different pixels from the image as the initial cluster center. The different pixel means if the distances are greater than T, it is different.

(3) For every pixel of the image, calculating the distance between the pixel and each cluster average, made this pixel allocating to the cluster for minimum distance.

(4) Calculating the new mean of each cluster, and the calculation formula is shown in formula seven.

$$\overline{v} = \frac{\sum_{\text{all pixels in class}} v_i}{N}$$
(7)

Among of this formula, $\overline{\nu}$ means the average value cluster of v color space, and the range for summing are all pixel in this cluster, N means the number of those pixel.

(5) Comparing the distance between the new mean and the old mean, if the value of the distance is greater than T, repeat step 3 and step 4, or continue to step 6.

(6) For every cluster, if the cluster mean is no different than the value of those flames pixel in the color space, the all pixels in this cluster are flame pixels, or are not flame pixel.

B. Result analysis

In the experiment, chosen the L * a * b * color space, and the distance algorithm is shown in formula eight.

$$\alpha |L_{1}^{*} - L_{2}^{*}| + \beta |a_{1}^{*} - a_{2}^{*}| + \gamma |b_{1}^{*} - b_{2}^{*}|$$
(8)

Among of this formula $(L *_1, a *_1, b *_1)$ and $(L *_2, a *_2, b *_2)$ are two points of L*a*b* color space, and $\alpha + \beta + \gamma = 1$. Experiments have shown a decent result for $\alpha = 0.2$, $\beta = \gamma = 0.4$ and value of T is 1e-2.

For the mean and standard deviation on previous statistics flame pixel in L * a * b * space, those values can be used to determine whether the difference is or not. And the value of the mean and standard deviation is shown as follow.

$$(\overline{L^*}, \overline{a^*}, \overline{b^*}) = (0.837825, 0.525517, 0.735679)$$

$$(S_{L^*}, S_{a^*}, S_{b^*}) = (0.1589633, 0.0897174, 0.1923818)$$

The decision rule as follow.

if
$$|u_{L^*} - \overline{L^*}| \le S_{L^*}$$
 and $|u_{a^*} - \overline{a^*}| \le S_{a^*}$
and $|u_{b^*} - \overline{b^*}| \le S_{b^*}$ then fire pixel class

else not fire pixel class;

 $(u_{L^*}, u_{a^*}, u_{b^*})$ is a mean for estimated cluster. Directly figure out the mean $(\overline{L^*}, \overline{a^*}, \overline{b^*})$ and the distance by using the formula eight, and then given a proper threshold value to determine the fire pixel, after the experiment, the effect is often better by using $(\overline{L^*}, \overline{a^*}, \overline{b^*})$ and $(S_{L^*}, S_{a^*}, S_{b^*})$. The performance of image segmentation based on K-means clustering method is shown in Figure 3.



Original image A



Image A after segmentation



Original image B



Image B after segmentation Figure 3. Segmentation results based on K-means clustering method

V. FLAME RECOGNITION BASED ON YCBCR AND LAB COLOR SPACE

Even though the RGB color space can be used for pixel classification, it has disadvantages of illumination dependence. It means that it is not possible to separate a pixel's value into intensity and chrominance. Furthermore, the illumination of image if has changed, the fire pixel classification rules can not perform well. The chrominance can be used in modeling color of fire rater than modeling its intensity. So it is needed to transform RBG color space to other color spaces where the separation between intensity and chrominance is more discriminate. Because of the linear conversion between RGB and YCbCr color spaces. In this pepper, we use YCbCr color space to model fire pixels.

The effect of the segmentation algorithm shown that the flame pixel identification method is faster and high recognition rate. But the results are affected significantly from threshold and in some cases it is easily to produce many grains. YCbCr color space in which chrominance and luminance are separated is adopted because of its high suitability to the face detection application comparing with other color spaces. Under the condition of strong light in the day, the recognition is better by using YCbCr color space. Under the condition of clear flame and the single surrounding environment, the Kmeans clustering method is better, but the recognition result is unremarkable when the flame is litter, and the effect is relevant to the value K. Flame recognition based on YCbCr and LAB color space would be more effectively by experiment. The algorithm flow diagram is shown in Figure 4.



Figure 4. Algorithm flow diagram

Due to the preliminary extraction, iterative times is significantly reduced when using k-means algorithm iterations, through the experiment, the K value for 5 is just about enough. The performance of image segmentation based on combining the two methods is shown in Figure. 5.



Original image A



Image A after segmentation



Original image B



Image B after segmentation



Original image C



Image C after segmentation

Figure 5. Segmentation results based on YCbCr color space

VI. CONCLUSION

Forest fire effective detection has a very important significance; this paper has discussed the forest fire prediction algorithm which is based on the image processing. Through the image processing knowledge, using the fire flame characteristics to detect fire. This article mainly introduced the two kinds of methods to flame segmentation which are based on flame pixel identification method and the traditional k-means clustering method. By those methods, it can be easily to implement through the simple statistics.

In the actual experiment, it found that the misjudgments rate is low when breaking out of fire but the fire alarm did not report, and the misjudgments rate is ont ideal when there is no fire but the fire alarm report. It mainly because the flame features extraction in the flame of the feature is less, only looked at a few flame characteristics. In fact, there are many flame feature to be discovered, and the system can also be used by artificial intelligence algorithm based on the neural network, made the machine self learning, thus reduce misjudgment rate, enhance the system efficiency, stability, etc.

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REFERENCES

- Turgay Celik, , Hasan Demirel, Huseyin Ozkaramanli, Mustafa Uyguroglu."Fire detection using statistical color model in video sequences", Journal of Visual Communication and Image Representation. Vol.18, Issue 2, April 2007, P176–185.
- [2] Hong Jin, Rong-Biao Zhang. "A Fire and Flame Detecting Method Based on Video", Proceedings of the Eighth International Conference on Machine Learning and Cybernetics, Baoding. 2009: 2347-2352.
- [3] Aiping Jiang, Lian Liu, "Forest Fire Image Segmentation Based on Multi-fractal and Contourlet Transform", AISS: Advances in Information Sciences and Service Sciences, Vol. 4, No. 7, pp. 200 ~ 207, 2012
- [4] Zaid A. Ali Al-Marhabi, LiRen Fa, FanZi Zeng, Maan Younus Abdullah Alfathi,Alhamidi Radman, "Achieving WSN Performance and Forest Monitoring System With WSC", IJACT: International Journal of Advancements in Computing Technology, Vol. 4, No. 12, pp. 77 ~ 84, 2012.
- [5] Yongqiang Jiao, Jonathan Weir, WeiQi Yan, "Flame Detection in Surveillance", JOURNAL OF MULTIMEDIA, VOL. 6, NO. 1, FEBRUARY 2011, p22-32.
- [6] Wenhui Li, Peixun Liu, Ying Wang, Huiying Li, Bo Fu, Hongyin Ni, "Early Flame Detection in Video Sequences based on D-S Evidence Theory", JOURNAL OF COMPUTERS, VOL. 8, NO. 3, MARCH 2013, p818-825.
- [7] Çelik Turgay, Demirel Hasan1. "Fire detection in video sequences using a generic color model", Fire Safety Journal.Feb2009, Vol. 44 Issue 2, p147-158.
- [8] Jose M. Chaves-González, Miguel A. Vega-Rodríguez, Juan A. Gómez-Pulido, Juan M. Sánchez-Pérez. "Detecting skin in face recognition systems: A colour spaces study". Digital Signal Processing. Vol 20, Issue 3, May 2010, P806–823.
- [9] Tung Xuan Truong, Jong-Myon Kim. "Fire flame detection in video sequences using multi-stage pattern recognition techniques". Engineering Applications of Artificial Intelligence, Vol. 25, Issue 7, October 2012, P1365–1372.
- [10] Juan Chen, Qifu Bao. "Digital Image Processing based Fire Flame Color and Oscillation Frequency Analysis". Procedia Engineering, Vol. 45, 2012, P595–601.

- [11] Dongil Hana, Byoungmoo Leeb. "Flame and smoke detection method for early real-time detection of a tunnel fire". Fire Safety Journal, Vol. 44, Issue 7, October 2009, P951–961.
- [12] TurgayC- elik _, HasanDemirel, "Fire detection in video sequences using a generic color model", Fire Safety Journal 44 (2009) 147–158.
- [13] Rafael C.Gonzalez, Richard E.Woods. Digital Image Processing Third Edition. Publishing House of Electronics Industry, 2010.
- [14] Margulis, Dan (2006). Photoshop LAB Color: The Canyon Conundrum and Other Adventures in the Most Powerful Colorspace. Berkeley, Calif. : London: Peachpit ; Pearson Education. ISBN 0-321-35678-0.
- [15] MacQueen, J. B. (1967). "Some Methods for classification and Analysis of Multivariate Observations". 1. Proceedings of 5th Berkeley Symposium on Mathematical Statistics and Probability. University of California Press. pp. 281– 297.MR 0214227. Zbl 0214.46201. Retrieved 2009-04-07.
- [16] Steinhaus, H. (1957). "Sur la division des corps matériels en parties". Bull. Acad. Polon. Sci. (in French) 4 (12): 801–804. MR 0090073. Zbl 0079.16403.
- [17] Lloyd, S. P. (1957). "Least square quantization in PCM". Bell Telephone Laboratories Paper. Published in journal much later: Lloyd., S. P. (1982). "Least squares quantization in PCM". IEEE Transactions on Information Theory 28 (2): 129–137. doi:10.1109/TIT.1982.1056489. Retrieved 2009-04-15.
- [18] E.W. Forgy (1965). "Cluster analysis of multivariate data: efficiency versus interpretability of classifications". Biometrics 21: 768–769.
- [19] J.A. Hartigan (1975). Clustering algorithms. John Wiley & Sons, Inc.



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