Available online at www.sciencedirect.com
ScienceDirect
Int. J. Electron. Commun. (AEÜ) 61 (2007) 469–477
International Journal of Electronics and Communications
www.elsevier.de/aeue

Similarity relation matrix-based color edge detection

Recep Demirci*

Technical Education Faculty, Electrical Education Department, Abant Izzet Baysal University, Beciyoruk Kampusu, 81620, Duzce, Turkey

Received 2 February 2006

Abstract

A novel edge detection algorithm for color images was described in this paper. In the proposed method, smoothness of each pixel in color image is firstly calculated by means of similarity relation matrix and is normalized to maximum gray level. In other words, color image in three-dimensional color spaces is mapped into one dimension. Accordingly the edges are performed in such a way that pixels lower than thresholds are assigned to be edge. Thus with proposed method, edge pixels in a color image are detected simultaneously without any complex calculations such as gradient, Laplace and statistical calculations.

Keywords: Edge detection; Similarity relation matrix; Smoothness thresholding

1. Introduction

Edge is commonly defined as a sudden change in the local color intensity of an image or a jump in intensity from one pixel to the next. On the other hand, a region in image that generally represents objects could be defined as a collection of pixels, which share the same or similar intensities. Thus boundaries of regions or objects in image are characterized by edges. Each other is closely related. In practice, either an image is firstly segmented as regions and then edges are detected, or other way around. It depends on applications or what we look for in image.

It is commonly accepted that the edge serves to simplify the analysis of images by drastically reducing the amount of data to be processed and by preserving useful structural information about object boundaries. During the past two decades edge detection has been a major topic of research providing many algorithms that perform well in a given application, but poorly in most others. Usually, edge detection is performed by smoothing, differentiating and tresholding. The most of edge detector so far has been based on the gradient of image. The computation of the gradient of an image has been performed by obtaining the partial derivatives in x and y directions by means of Roberts, Prewitt and Sobel operators [1,2].

Although, the gradient-based edge detection method has been widely applied in practice and a reasonable edge map has been obtained for most images, they suffer from some practical limitations. Firstly, they need a smoothing operation to alleviate the effect of high spatial frequency in estimating the gradient. Usually, this smoothing is applied to all pixels in the image including the edge regions, and so the edge is distorted and missed in some cases in particular at junctions or corners. Secondly, the gradient magnitude alone is insufficient to determine meaningful edges because of the ambiguity caused by underlying pixel pattern, especially in complex natural scenes. Thirdly, the gradient-based edge detection method increases the computational complexity because calculations, such as square root and arctangent, to produce the gradient vector are required.

* Tel.: +90 380 5413344; fax: +90 380 5413184.
E-mail address: demirci_r@ibu.edu.tr.

1434-8411/$ - see front matter © 2006 Elsevier GmbH. All rights reserved.
doi:10.1016/j.aeue.2006.08.004

The detailed comparison and evaluation of edge detectors has been performed by Heath et al. [3]. They employed people to evaluate performance of several edge detectors with a number of images and looked for correlations in judgments of participants. Recently, fuzzy logic-based edge detection algorithm have been introduced by researchers. Kim and Han has described edginess of pixels in terms of fuzzy rules [4] whereas the gradient magnitude and direction with fuzzy reasoning rules have been used to locate edges by others [5–7].

On the other hand, the edge detection process of color images is another important research issue. Typically, a color image consists of RGB channels. The color edge detection process must take into account the changes in intensity, chromaticity or both. So far, several color edge detection algorithms have been developed. These schemes can be classified into two different approaches. In the first approach, the three-channel image is processed as three gray-level images. We can use any gray-level edge detection scheme to detect the edge image for each color channel separately. Therefore, three edge images can be obtained for the RGB channels. Finally, a merging procedure is executed to combine these edge images into a targeted edge image. However, these sorts of algorithms have two major drawbacks. First, the inter-channel correlation is discarded in these schemes. Second, a high computational cost is consumed [8–10].

In the second approach, a two-stage structure is imposed on the design of color edge detection schemes. In the first stage, a channel reduction technique is employed to reduce the dimensionality of each color image from three to one. Next, an edge detection procedure for the reduced one-channel image is executed to detect image. The two-stage edge detection schemes or color image have two advantages. First, the channel reduction process is independent of the edge detection scheme. The correlation among the color channels is taken into consideration. Second, any gray-level edge detection scheme can be applied to the detection of edge images in the second stage. In other words, the computational cost can be reduced [11–14].

Generally, the detection of edge in an image could be defined as clustering of the pixels into two categories: edge and non-edges. The word clustering means to identify the number of subclasses of c clusters in a data universe X comprised of n data samples, partitioning X into c clusters ($2 \leqslant c < n$). It is assumed that the members of each cluster bear more mathematical similarity to each other than to members of other clusters. Let define a sample set of n data samples that we want to classify:

$$X = \{x_1, x_2, x_3, \ldots, x_n\}.$$

Each data sample, x_i, is defined by m features, i.e.,

$$x_i = \{x_{i,1}, x_{i,2}, x_{i,3}, \ldots, x_{i,m}\}, \tag{1}$$

where each x_i in the universe X is an m-dimensional vector of m elements or m features. Since the m features all may have different units, generally, we have to normalize each of the features to a unified scale before classification. Geometrically, each x_i is a point in M-dimensional feature space, and the universe of data sample, X, is a point set with n elements in the sample space. There are mainly two important issues in this regard: how to measure the similarity between pairs of data points and how to evaluate the partitions once they are performed.

In this paper, a two-stage edge detection algorithm has been proposed. Firstly, the color image in three dimensional color spaces is mapped into one dimension by means of the similarity relation matrix. This transformation produces a gray level image where the similar pixels show the smooth areas and dark pixels show the dissimilar areas, noise and edges. Secondly, the thresholding could be employed if it is preferred.

2. Similarity measure

2.1. Psychological sense

Similarity, a relationship between two perceptual or conceptual objects is one of the central problems of psychology. The concept of similarity is extremely important as it provides the foundation for organizing the world into categories and identifying new situations by comparing with past experiences. In daily life, we often come across situations where we have to distinguish similar groups or we have to classify some similar objects. Therefore, similarity measure becomes an important tool to decide the similarity degree between two groups or between two objects. What happens if one has to judge similarity between two different objects? This is a very important cognitive problem which is successfully dealt with by humans, yet difficult to address by machines.

Although similarity, as perceptual resemblance, has been under consideration by psychologists for more than a century, from initial experimental studies to recent sophisticated mathematical developments, the human perception and judgment of similarity has received little attention from the computer and engineering community. Psychologists have developed two main categorization models: Similarity-based categorization and Rule-based categorization. Similarity-based models propose that conceptual categories are performed as clusters held together by the similarity of their examples whereas the others argued that categorization is based on a more rule-like or theory-like semantic representation. Prototype Concept by Rocsh [15], Exemplar model (Generalized Context Model) by Nosofsky [16] and Feature Contrast Model by Tversky [17] are the most popular similarity models for classification.

According to the prototype concept, objects in the world can be clustered together on a number of correlated attributes. For example, creatures are noticeably distinguished from animated objects and plant in terms of their activities, their internal organs and a great many other respects. Within the class of creatures, there are also correlations between attributes. Possession of one attribute tends to correlate within the general class of creatures with the possession of other attributes. This cluster of inter-correlated attributes leads to the formation of prototype concepts. The prototype represents the idealized category of member of possessing all of the attributes in the cluster. Membership in the prototype concept is determined by judging how similar any instance is to the prototype [18].

Exemplar model (Generalized Context Model) of categorization assumes that humans represent categories by storing every exemplar (together with its category label) in memory. Category decisions are based on a similarity computation between a probe stimulus and stored exemplars. Many models of categorization are equivalent to a process in which the observer estimates the likelihood that a stimulus x belongs to one of several categories C_k where $k = 1, \ldots, K$. Let $\Theta_k = \{x_n; n = 1, \ldots, N_k\}$ be set of exemplars of category C_k stored in memory where N_k is number of exemplars in category C_k. According to Generalized Context Model, the posterior probability that stimulus x is classified in category C_k is given by

$$P(C_k|x) = \frac{b_k h_k(x)^\gamma}{\sum_{l=1}^{K} b_l h_l(x)^\gamma}, \tag{2}$$

where b_k is a response bias and $h_k(x)$ is given by a summed similarity between x and every stored exemplars of category C_k,

$$h_k(x) = \sum_{n=1}^{N_k} \exp\{-d(x, x_n)^q\}, \tag{3}$$

where $q = 1$ yields an exponential function and $q = 2$ yields a Gaussian function; $d(x, x_n)$ is a measure of the psychological distance from x to x_n. The γ parameter reflects the amount of determinism in responding. The quantity $h_k(x)$ can be interpreted as a measure of category similarity and therefore as a measure of evidence that stimulus x belongs to this category [19].

Another similarity approach known as, feature contrast model, was suggested by Tversky where similarity is determined by matching features of compared entities, and integrating these features by the formula

$$S(A, B) = \Theta f(A \cap B) - \alpha f(A - B) - \beta f(B - A). \tag{4}$$

The similarity of A to B, $S(A, B)$ is expressed as a linear combination of the measure of the common and distinctive features. The term $(A \cap B)$ represents the features that items A and B have in common. $(A - B)$ represents the features that A has but B does not. $(B - A)$ represents the features that B, but not A, possesses. The terms Θ, α and β reflect the weights given to the common and distinctive components, and the function f is often simply assumed to be additive.

2.2. Mathematical sense

One of the simplest similarity measures is distance between pairs of feature vectors in the feature space. If the distance between all pairs of sample data is computed somehow, then it is expected that the distance between points in the same cluster will be significantly less than the distance points in different clusters. A commonly used measure of similarity is based on distance functions. The general form of distance between a pair of M-by-1 vectors x_i and x_j is defined by

$$d_{i,j} = \|x_i - x_j\| = \left[\sum_{m=1}^{M} |x_{i,m} - x_{j,m}|^r\right]^{1/r}, \tag{5}$$

where $x_{i,m}$ and $x_{j,m}$ are the mth feature of sample data x_i and x_j, respectively. This function is also called the Minkowski r-metric. The traditional view is that the value $r = 1$ is called City-block distance and the value $r = 2$ is called the Euclidean distance. The closer the individual features of x_i and x_j are to each other, the smaller will the distance $d_{i,j}$ be, and the greater will therefore be the similarity between x_i and x_j.

Another measure of similarity is based on the idea of a dot product or inner product. Given a pair of vector x_i and x_j of the same dimension, their inner product is written in expanded form as follows:

$$x_i^{\mathrm{T}} x_j = \sum_{m=1}^{M} x_{i,m} x_{j,m}. \tag{6}$$

Then the normalized inner product

$$S(x_i, x_j) = \cos(\alpha) = \frac{x_i^{\mathrm{T}} x_j}{\|x_i\| \|x_j\|}, \tag{7}$$

which is the cosine of the angle between x_i and x_j has been used as a meaningfully measure of similarity the similarity between x_i and x_j. The inner product of may be viewed as a cross-correlation function. Recognizing that the inner product is a scalar, the more positive the product of is, the more similar (correlated) the vectors x_i and x_j are to each other.

2.3. Fuzzy approach

As it was discussed in the previous section, the notion of similarity involves an elaborate cognitive process rather than simply a mathematical model. Whenever the assessment of similarity should reproduce the judgment of a human observer based on qualitative features, it is appropriate to model it as a cognitive process that simulates human similarity perception. Fuzzy set theory has been very attractive tool for modeling and mimicking cognitive process, especially those concerning recognition aspects. Also fuzzy set theory is able to handle qualitative nonnumerical descriptions, class memberships and human reasoning. The first assessment of similarity and relations in terms of fuzzy logic was studied by Zadeh [20,21]. A new similarity measure between fuzzy sets and between elements was proposed by Wang where the min and max operator were used [22]. Although, Twersky's feature contrast model provides a solid foundation for building a similarity assessment model that is based on psychological experiments of human similarity judgment, it has a serious drawback: it is intended for binary features only. This means that similarity assessment is based on evaluating the features that the two stimuli either have or do not have. An extension of feature contrast model, called Fuzzy feature contrast (FFC) was proposed by Santini and Jain [23] where the functions given in Eq. (4) were replaced by membership functions. The further improved version of FFC called generalized Tversky index (GTI) was introduced by Tolias et al. [24]. With GTI model, the similarity between two objects could be assigned any value between 0 and 1. However in both method, the α and β weights assigned to the distinctive components were left to users.

2.4. Color similarity

An image is collection pixels which have feature vectors. The feature vector of a pixel is an m-dimensional vector of m elements or m features. The features of a pixel could be a gray level for gray scale images, or red, green, blue levels for color images. The artificial features: texture, noise etc., could also be added into feature vector. In image processing field, the similarity measure of two pixels has been generally assessed so far by means of Euclidian distance in color space. On the other hand, Wuerger et al. [25] showed in their research into proximity judgments in color space that perceptual color proximity is not Euclidean in nature. That means that distance information in Euclidean color space is not adequate for similarity judgment. The most general from of similarity measure based on the distance in color space could be given as below

$$S_1(x_i, x_j) = 1 - \frac{d_{ij}}{D_n} = 1 - \frac{\|x_i - x_j\|}{D_n}, \tag{8}$$

where is similarity between x_i and x_j, D_n is normalization coefficient. The variation of similarity with intensity difference according to Eq. (8) is shown in Fig. 1. In Generalized Context Model given in Eq. (3), the similarity was expressed in terms of an exponential or Gaussian function of distance [26,27]. When Eq. (3) is reorganized for color similarity in color space, following formula could be obtained

$$S_2(x_i, x_j) = \exp\left(\frac{-d_{ij}^q}{D_n}\right) = \exp\left(\frac{-\|x_i - x_j\|^q}{D_n}\right). \tag{9}$$

The characteristic of color similarity according to Eq. (9) with $q=1$ and 2 are shown in Figs. 2 and 3, respectively. The employment of Gaussian function with color distances to calculate similarity measure in term of color histograms was recently performed in applications for color image retrievals [28,29].

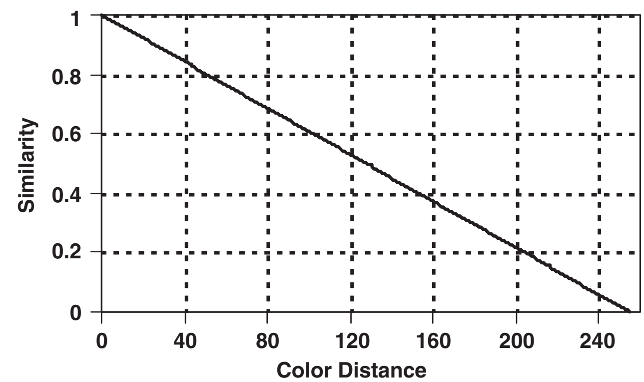

Fig. 1. Similarity versus color distance with Eq. (8) ($D_n = 255$).

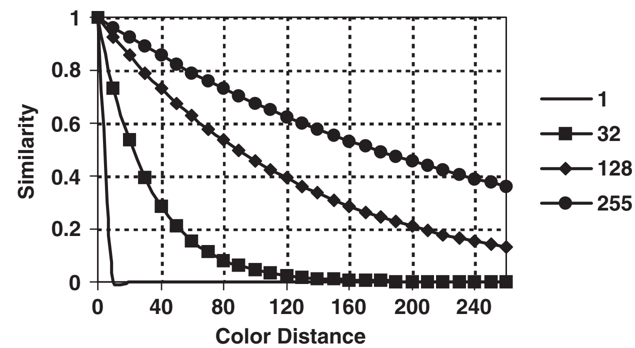

Fig. 2. Similarity versus color distance according to Eq. (9) with different D_n ($q = 1$).

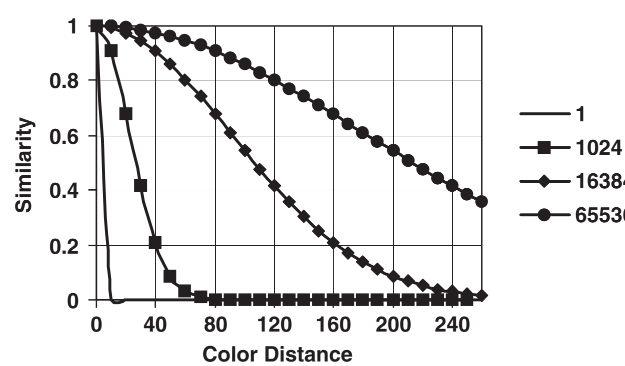

Fig. 3. Similarity versus color distance according to Eq. (9) with different D_n ($q = 2$).

The first application of FFC model in image was done by Seaborn et al. [30] where the α and β weights assigned to the distinctive components were not used whereas the comparatively test of FFC and GTI models in image processing field was introduced by Chaira and Ray [31].

3. Proposed algorithm

3.1. Formation of similarity relation matrix

An image consists of pixels, which are neighbor to each other. Let consider two neighbor pixels, which are in an image as shown in Fig. 4. Gray level differences of each color component between pixel P_1 and P_2 could be defined as follows:

$$\Delta R = |L_{R,1} - L_{R,2}|, \tag{10}$$

$$\Delta G = |L_{G,1} - L_{G,2}|, \tag{11}$$

$$\Delta B = |L_{B,1} - L_{B,2}|. \tag{12}$$

The color distance between any two pixels in color space is calculated by Euclidean norm as

$$d_{i,j} = \frac{1}{\sqrt{3}}(\Delta R^2 + \Delta G^2 + \Delta B^2)^{1/2}. \tag{13}$$

Mathematically and mathematical physiologically, the similarity of any neighboring two pixels could be calculated by means of Eqs. (8) and (9), respectively. A pixel in an image has eight neighboring pixels as shown in Fig. 5. Therefore, the similarity calculations for all the possible combinations are performed as shown in Fig. 6. This approach is well-suited with noisy exemplar approach proposed by Kahana and Sekular [26] where interstimulus similarity is used to categorize the noisy image. As interstimulus similarity is physiologically hart of many cognition theories, what we proposed here is compatible with physiological recognition theories. Consequently, similarity relation matrix is achieved as

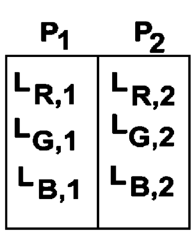

Fig. 4. Gray levels of neighboring pixels.

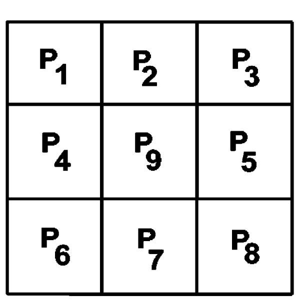

Fig. 5. Neighboring pixels in a color image.

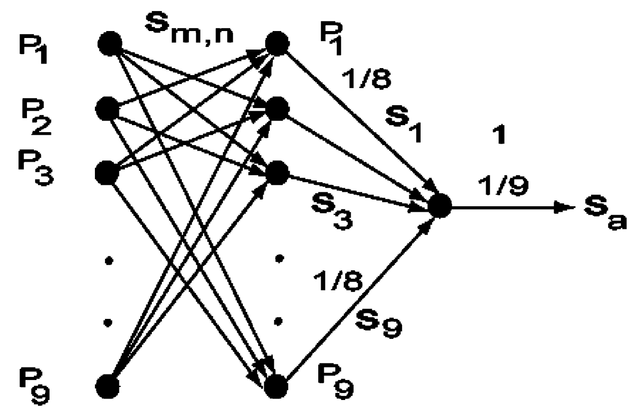

Fig. 6. Similarity network.

$$S_{m,n} = \begin{bmatrix} S_{1,1} & S_{1,2} & . & . & S_{1,9} \\ S_{2,1} & S_{2,2} & . & . & S_{2,9} \\ . & . & . & . & . \\ . & . & . & . & . \\ S_{9,1} & S_{9,2} & . & . & S_{9,9} \end{bmatrix}. \tag{14}$$

As the similarity of a pixel to itself is always equal to unity, there is no need to calculate them. The similarity relation matrix is symmetric. When all elements of the $S_{m,n}$, apart from diagonal, are unity, it means that the central pixel and its all neighbors have the same color level or it is perfectly smooth. The local smoothness of kth pixel could be estimated as follows:

$$S_k = \frac{1}{8}\sum_{n=1}^{9} S_{k,n} \quad \text{for } k \neq n. \tag{15}$$

As could be seen from Eq. (15) and Fig. 6, there is no need to consider the similarity of itself. Therefore, Eq. (15) gives the average how the kth pixel is similar to the others. On the other hand, the general average of the central and all neighboring pixels could be calculated as follows:

$$S_{\mathrm{a}} = \frac{1}{9}\sum_{n=1}^{9} S_k. \tag{16}$$

The S_{a} could be interpreted as the smoothness of the central pixel. Its values vary between zero and 1. On the other hand, the complement of the S_{a} $(1 - S_{\mathrm{a}})$ is considered to be dissimilarity or noisiness.

3.2. Local similarity thresholding (LST)

Kahana and Sekular [26] have described interstimulus dissimilarity as noise in their investigation by assuming that each stimulus is stored imperfectly in memory. Therefore they proposed to threshold the summed similarity of a

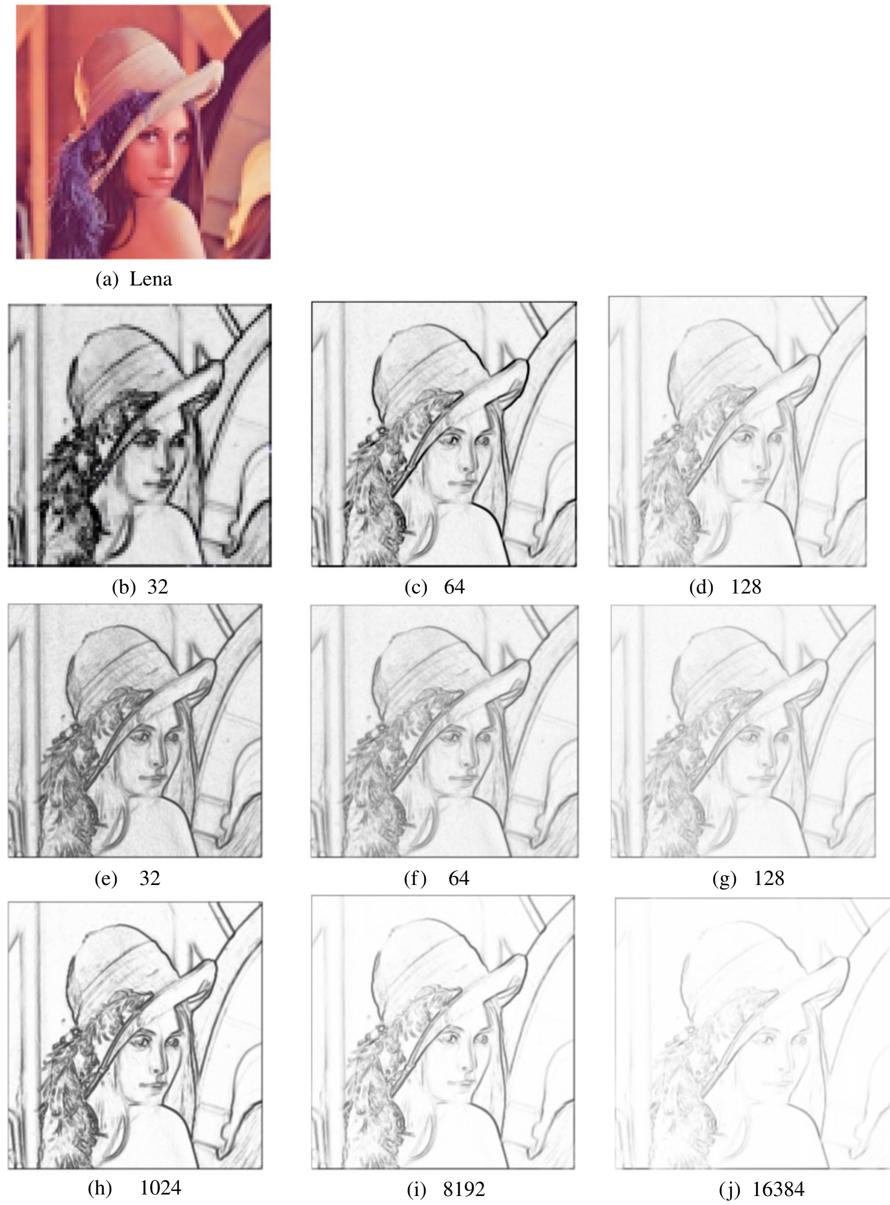

Fig. 7. Transformation of three-dimension color space into one dimension: S_{a}: (a) Lena (b)–(d) By means of linear function with D_n: 32, 64 and 128. (e)–(g) By means of exponential function with D_n: 32, 64 and 128. (h)–(j) By means of Gaussian function with D_n: 1024, 8192 and 16 384.

stimulus to make decision. Keeping in mind that the complement of the S_{a} is considered as dissimilarity or noisiness and assuming that each pixel is stimulus, we proposed a new version of similarity matrix as follows:

$$\widetilde{S}_{m,n} = \begin{cases} 1 & \text{if } S_{m,n} \geqslant S_{\mathrm{T}}, \\ 0 & \text{if } S_{m,n} < S_{\mathrm{T}}, \end{cases} \tag{17}$$

where S_{T} is similarity threshold. The interpretation of Eq. (17) is that if the similarity of two pixels is lower than S_{T}, they are considered to be dissimilar. So the local smoothness of kth pixel could be estimated as follows:

$$\widetilde{S}_k = \frac{1}{8}\sum_{n=1}^{9} \widetilde{S}_{k,n} \quad \text{for } k \neq n \tag{18}$$

and the general average of the central and all neighboring pixels could be calculated as follows:

$$\widetilde{S}_{\mathrm{a}} = \frac{1}{9}\sum_{n=1}^{9} \widetilde{S}_k. \tag{19}$$

With such approach, a color image in three-dimensional color spaces is mapped into one-dimensional gray image while the noise is weakened and the edge information is preserved.

4. Simulation results and discussion

The proposed algorithm was tested with the well-known Lena image shown in Fig. 7(a) which is a color image of size 256 × 256 with 255 gray levels. Fig. 7(b)–(d) show the smoothness image obtained by means of Eq. (8) with different normalization coefficients: 32, 64 and 128, respectively. When the similarity of pixels is calculated by means of exponential approach, Eq. (9), with different D_n: 32, 64 and 128, the transferred images shown in Fig. 7(e)–(g) have been obtained respectively. Moreover, Fig. 7(h)–(j) have been achieved when the Gaussian similarity measure is employed with different D_n: 1024, 8192 and 16 384, respectively. As could be seen, Gaussian similarity measure-based image conversion produces the similarity image with less noise than exponential and linear approach. At same time, the edge information is preserved. Also it was observed in three approaches that edge strengths are inversely related with normalization coefficients.

Although, the noise in the transferred image can be reduced by increasing normalization coefficients, at the same time, the edge strength is weakened. However, with our second approach: LST, three-dimension color space is transferred in one dimension by filtering noise and preserving edge strength in the color image. Fig. 8 shows the transferred image of Lena with LST while normalization coefficient is fixed as 32. Fig. 8(a)–(c) show the images with S_T: 0.25, 0.50 and 0.75, respectively, when linear similarity function is employed. Transformation of three dimension color space into one dimension with exponential function and different S_T: 0.25, 0.50 and 0.75 have been shown in Fig. 8(d)–(f), respectively. Moreover, LST images obtained with Gaussian functions with S_T: 0.25, 0.50 and 0.75 are shown in Fig. 8(g)–(i), respectively. It was mentioned in introduction that the edge pixel is universally defined as a sudden change

(a) 0.25 (b) 0.50 (c) 0.75

(d) 0.25 (e) 0.50 (f) 0.75

(g) 0.25 (h) 0.50 (i) 0.75

Fig. 8. Transformation of Lena image into one dimension with LST: $\widetilde{S}_a$: (a)–(c) By means of linear function with S_T: 0.25, 0.50 and 0.75. (d)–(f) By means of exponential function with S_T: 0.25, 0.50 and 0.75. (g)–(i) By means of Gaussian function with S_T: 0.25, 0.50 and 0.75.

in the local color intensity of an image or a jump in intensity from one pixel to the next. Keeping above definition in mind, if the central pixel does not belong to edge category or it has the same grey level as its neighboring pixels, its smoothness will be unity. If the S_a is far from unity, the central pixel could be edge or even noise. Consequently, by thresholding the smoothness, the pixels in an image could be clustered as edge and background.

It has been noticed from applications that the three-dimensional color images could be successfully transferred into one-dimension image with proposed algorithm.

The transformed image is a gray scale image in which the gray levels show the edginess strength. The edginess strength could be controlled by the normalization constants. As a result of this, very small variations in a color image could be detected. Moreover, with LST algorithm, the edginess strength as well as noisiness could be controlled by thresholding local similarity values.

5. Conclusion

In this paper, a two-stage color edge detection algorithm, where the similarity relation matrix is used for the channel reduction process has been proposed. The similarities of neighboring pixels have been calculated by means of mathematical and mathematical physiological similarity functions. Accordingly, the three-dimensional color images could be successfully transferred into one-dimension images, which show color discontinuous as gray levels. The further research to combine automatic thresholding selection methods with proposed algorithm is still in progress.

References

[1] Gonzalez RC, Woods RE. Digital Image Processing. Reading, MA: Addison-Wesley; 1993.

[2] Canny JF. A computational approach to edge detection. IEEE Trans Pattern Anal Mach Intell 1986;8(6):679–98.

[3] Heath H, Sarkar S, Sanocki T, Bowyer KW. Edge detector comparison: initial study and methodology. Comput Vision Image Understanding 1998;69:38–54.

[4] Kim TY, Han JH. Edge representation with fuzzy sets in blurred images. Fuzzy Sets Systems 1998;100:77–87.

[5] Kim DS, Lee WH, S Kweon I. Automatic edge detection using 3 × 3 ideal binary pixel patterns and fuzzy-based edge thresholding. Pattern Recognition Lett 2004;25:101–6.

[6] Yuksel ME, Yildirim MT. A simple neuro-fuzzy edge detector for digital images corrupted by impulse noise. AEU—Int J Electron Commun 2004;58:72–5.

[7] Liang LR, Looney CG. Competitive fuzzy edge detection. Appl Soft Comput 2003;3:123–37.

[8] Fan J, Aref WG, Hacid MS, Elmagarmid AK. An improved automatic isotropic color edge detection technique. Pattern Recognition Lett 2001;22:1419–29.

[9] Ruzon MA, Tomasi C. Edge, junction, and corner detection using color distributions. IEEE Trans Pattern Anal Mach Intell 2001;23:1281–95.

[10] Theoharatos C, Economou G, Fotopoulos S. Color edge detection using the minimal spanning tree. Pattern Recognition 2005;38:603–6.

[11] Trahanias PE, Venetsanopoulos AN. Color edge detection using vector order statistics. IEEE Trans Image Process 1993;2:259–64.

[12] Yang CK, Tsai WH. Reduction of color space dimensionality by moment-preserving thresholding and its application for edge detection in color images. Pattern Recognition Lett 1996;17:481–90.

[13] Yang CK, Tsai WH. Color image compression using quantization, thresholding, and edge detection techniques all based on the moment-preserving principle. Pattern Recognition Lett 1998;19:205–15.

[14] Tsai P, Chang CC, Hu YC. An adaptive two-stage edge detection scheme for digital color images. Real-time Imag 2002;8(4):329–43.

[15] Rosch E. Cognitive representation of semantic categories. J Exp Psychol: Gen 1975;104:192–233.

[16] Nosofsky RM. Attention, similarity and the identification-categorization relationship. J Exp Psychol: Gen 1986;115: 39–57.

[17] Tversky A. Feature of similarity. Psychol Rev 1977;84: 327–52.

[18] Hampton JA. Similarity-based categorization and fuzziness of natural categories. Cognition 1998;65:137–65.

[19] Rosseel Y. Mixture models of categorization. J Math Psychol 2002;46:178–210.

[20] Zadeh LA. Similarity relations and fuzzy ordering. Inf Sci 1971;3:177–200.

[21] Ross TJ. Fuzzy logic with Engineering Application. New York: McGraw-Hill; 1995.

[22] Wang WJ. New similarity measures on fuzzy sets and on elements. Fuzzy Sets Systems 1997;85:305–9.

[23] Santini S, Jain R. Similarity measures. IEEE Trans Pattern Anal Mach Intell 1999;21:871–83.

[24] Tolias YA, Panas SM, Tsoukalas LH. Generalized fuzzy indices for similarity matching. Fuzzy Sets Systems 2001;120:255–70.

[25] Wuerger SM, Maloney LT, Krauskopf J. Proximity judgments in color space: tests of a euclidean color geometry. Vision Res 1995;35:827–35.

[26] Kahana MJ, Sekuler R. Recognizing spatial patterns: a noisy exemplar approach. Vision Res 2002;42:2177–92.

[27] Stewart N, Brown GDA. Similarity and dissimilarity as evidence in perceptual categorization. J Math Psychol 2005;49:403–9.

[28] Zhai H, Chavel P, Wang Y, Zhang S, Liang Y. Weighted fuzzy correlation for similarity measure of color-histograms. Opt Commun 2005;247:49–55.

[29] Liang Y, Zhai H, Chavel P. Fuzzy color-image retrieval. Opt Commun 2002;212:247–50.

[30] Seaborn M, Hepplewhite L, Stonham J. Fuzzy colour category map for the measurement of colour similarity and dissimilarity. Pattern Recognition 2005;38:165–77.

[31] Chaira T, Ray AK. Fuzzy approach for color region extraction. Pattern Recognition Lett 2003;24(12):1943–50.

Recep Demirci was born in K. Maras, Turkey in 1968. He obtained his B.Sc. degree from the Gazi University in 1990 where he studied Electrical Education. He was a visiting researcher at the Purdue University, USA in 1992. He has got his Ph.D. degree from the Electrical Engineering Department, University of Wales Cardiff, UK in 1998. He completed his military service as a Lecturer at the Engineering Brigade in Izmir between 1998 and 2000. He has been working as an Assistant Professor at the Electrical Education Department, Technical Education Faculty, Abant Izzet Baysal University since 2000. His research interests include image processing, neural networks, fuzzy systems, and adaptive control.