Application of Co-Occurrence Frequency Image

Takayuki Fujiwara Hiroyasu Koshimizu Manabu Hashimoto

Chukyo University
101, Tokodachi, Kaizu-cho, Toyota, 470-0393, JAPAN
tfuji@sist.chuyko-u.ac.jp

Abstract

We have revealed that the co-occurrence frequency image (CFI) based on the co-occurrence histogram (CH) of the gray level value of an image has a new potential to introduce a new scheme for image feature extraction. Our method and filters are very similar to the previous methods in result but quite different in process from those which have been used so far. Thus, we could show a possibility for introducing a new paradigm for basic image processing methods by means of CFI. We found that the CFI has better generalization performance than the texture analysis method and therefore CFI has high potentiality for the application to image processing methods. In addition in this paper, we extended CH and CFI from binary to ternary for enforcing the potential.

1. Introduction

Though co-occurrence matrix [1 - 3] has a promising potential due to the two-dimensional statistics of the image, further discussions beyond the texture discrimination have not been sufficiently proposed so far. These technological backgrounds are originated by the facts: that one-dimensional statistic (histogram) is stable and powerful tool in image analysis, that the co-occurrence matrix was proposed exclusively for texture analysis [3 - 5], and that the co-occurrence matrix needs large computation costs. The co-occurrence matrix was not used in the whole region of the image in the previous methods. On the other hand, the proposed method has been used in the co-occurrence frequency distribution of an image.

Image processing is generally constructed based on the gray information such as one-dimensional statistical gray histogram, co-occurrence histogram, gradient, texture, etc [6]. However, no practical image processing method based on the co-occurrence histogram had been proposed excepting the texture identification [3 - 5]. Since the gray histogram is the most influential for extracting the global image properties, image processing methods have been always expected to be improved or extended.

The co-occurrence histogram or co-occurrence matrix is also such influential basic image feature especially for the texture feature analysis. We have proposed a paradigm of the image feature called "Co-occurrence Frequency Image (CFI)" as a complete extension of the gray histogram and frequency image [7], and we try to investigate the method for feature extraction of the image by using the CFI.

This paper describes a couple of filters for image enhancements such as a method of image binarization based on CFI and an investigation of N-ary CH and CFI. In section 2, CFI is summarized, and in section 3, the feature extraction method by using Band-Pass filter is introduced. In section 4, some proposals of the filter and its experimental results are presented. In section 5, method of image binarization based on CFI is presented. In section 6, definition of the ternary CH and CFI is introduced and some experimental results of Ternary CH and CFI are presented.

2. Genera Idea of CFI

We used the co-occurrence histogram (CH) or co-occurrence Frequency (CF) that is defined based on a pair of pixels $f(i, j)$ and $f(i+K, j+L)$ in the image as shown in eq. (1). The parameters of K and L denote the relationship between a pair of pixels and therefore we call this formalization as KL-method. Figure 1 shows the framework of the CH in KL-method. Successively we also proposed R-method (Figure 2) that is not depend on the direction for the definition of a pair of pixels as eq. (2). The parameter R is given value and denotes the radius. This method uses the average of gray values on the circumference of circle.

$$h_2(k,l) = \sum_{ij \in N,M} w(i,j,k,l),$$
$$w(i,j,k,l) = \begin{cases} 1 & f(i,j)=k, f(i+K, j+L)=l \\ 0 & otherwise \end{cases} \tag{1}$$

$$fr(i,j) = \sum_{d=1}^{R\times 4} f_{i+R\cos(\frac{d\theta}{R\times 4}),\ j+R\sin(\frac{d\theta}{R\times 4})}$$
(R = 0, 1, ..., N or M, i = 0, 1, ..., N, j = 0, 1, ..., M) (2)

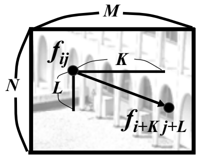
Let CH or CF be the co-occurrence frequency value of a given image. Let us introduce the Co-occurrence Frequency Image (CFI) of which each pixel consists of the corresponding address of the CF of the input image. Figure 3 shows an example of CFI. These images are computed by eq. (3).

$$F_2(i,j) = h_2(f(i,j), f(i+K, j+L))$$

, where value of $F_2(i, j)$ denotes the co-occurrence frequency and the parameter K and L is given value in the case of KL-method.

The distribution of frequency value in CFI expresses the basic feature of the image more complicatedly than Frequency Image from one-dimensional statistic. We propose a scheme of feature extraction based on

CFI-based band-pass filter as shown in Figure 4. Here *th* is the thresholding parameter of the frequency value. In case of low frequency, the pair of pixels have generally sharp gradient, and this thresholding means the parameter of edge detection that represents the border between minority and majority values of CH as shown in Figure 4.



$f_{i+K,\,j+L}$

f_{ij}	0	···	64	65	···	128	129	···	192	193	···	255
0	0	···	0	0	···	0	0	···	0	0	···	0
···	···	···	···	···	···	···	···	···	···	···	···	···
64	0	···	34	34	···	0	1	···	0	1	···	0
65	0	···	34	32	···	0	0	···	0	0	···	0
···	···	···	···	···	···	···	···	···	···	···	···	···
128	0	···	0	0	···	50	51	···	3	7	···	0
129	0	···	0	1	···	58	49	···	5	5	···	0
···	···	···	···	···	···	···	···	···	···	···	···	···
192	0	···	0	0	···	5	6	···	91	101	···	0
193	0	···	0	0	···	5	2	···	89	112	···	0
···	···	···	···	···	···	···	···	···	···	···	···	···
255	0	···	0	0	···	0	0	···	0	0	···	0

Figure 1. Framework of Co-occurrence histogram ($K, L = 1, 1$).

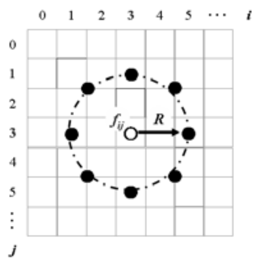


Figure 2. A pair of pixels (R-method).

Figure 3. Example of Co-occurrence Frequency Image.

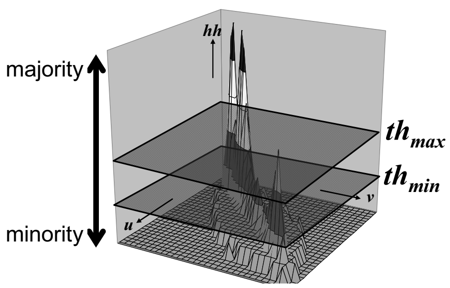


Figure 4. CH and its threshold.

3. Feature Extraction Based on CFI

The distribution of frequency value in CFI expresses the basic feature of the image more complicatedly than FI. CFI-based band-pass filter is defined by eq. (4).

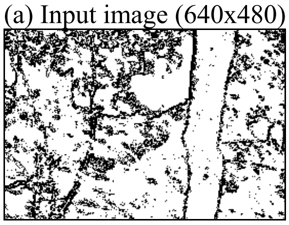
$$G(i,j) = \begin{cases} f(i,j) & th_{\min} \le cfi(i,j) \le th_{\max} \\ 0 & otherwise \end{cases} \tag{4}$$

Here $th_{\min}$ and $th_{\max}$ are the thresholding parameters of the frequency value.

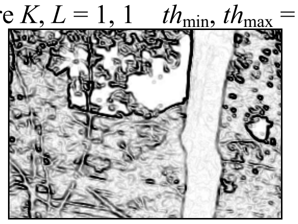
This CFI-based filter for edge detection designed by setting $th_{\min}$ and $th_{\max}$ be lower is similar to but not coincident with any well known edge detectors such as Sobel gradient. Figure 5 shows an example of a set of CFI's together with an example of Sobel edge extraction.

These images are magnified image of 640x480 pixels. Comparing CFI edge given in Figure 5(b) with Sobel edge given in Figure 5(c), it is known that these are approximately similar but the details are exactly different. The value of CH could be generally lower in case of the edge detection, because the number of the pairs of pixels $f(i, j)$ and $f(i+K, j+L)$ consisting edge is very small. Our method can be used not only for detecting the co-occurrence features of the given image but also for providing a new paradigm to design such filters that could generate several functions such as edge detection by combining the input image and its CFI.

(a) Input image (640x480)



(b) Result of CFI-based low-pass filter (where $K, L = 1, 1$ $th_{\min}, th_{\max} = 0, 4$)



(c) Result of Sobel filter (3x3)

Figure 5. An example of a set of CFI's together with an example of Sobel edge extraction.

4. Designing Adaptive Filters Based on CFI

4.1. A sharpening filter based on CFI

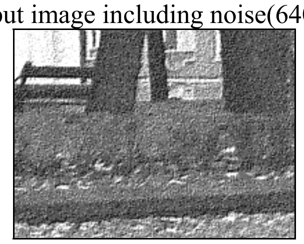
A simple edge enhancement could be realized by using CFI-based band pass filter. This fact encourages us to extend this idea for designing CFI-based filter more. A sharpening filter is designed by combining the original image and the result of edge detection by means of the low-pass filter defined by eq. (5).

$$E(i,j) = f(i,j) + \xi(i,j) \cdot (f(i,j) - f(i+K, j+L))$$

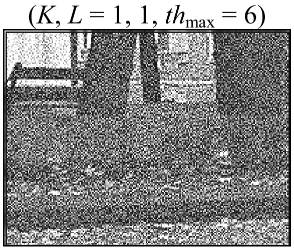
$$\xi(i,j)=\begin{cases}1 & F_2(i,j)\le th_{\max}\\ 0 & otherwise\end{cases} \quad (5)$$

, where $\xi(i, j)$ denotes the weight function specified based on the value of $F_2(i, j)$. CFI-based method can exclusively select the edge region, and can mask the non-edge region so that the texture is never smoothed out or excessively enhanced within this region, because CFI is based on the co-occurrence frequency. As shown in Figure 6, the texture of the trunk region of the trees seems very natural in this sharpening processing.

(a) Input image including noise(640x480)



(b) Result of sharpening based on CFI (K, L = 1, 1, $th_{\max}$ = 6)



(c) Result of sharpening filter by Laplacian (3 x 3)
Figure 6. The result of sharpening for an image with random noise.

4.2. A smoothing filter based on CFI

In order to reduce the typical side effect of the smoothing such as the edge blur, we propose a smart smoothing method based on CFI as follows. Basic idea is to apply smoothing operation selectively to the flat region and we implemented this idea by eq. (6).

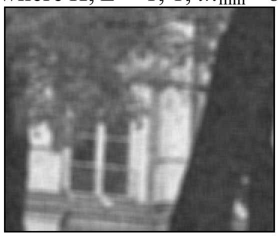
$$S(i,j)=\begin{cases}\psi(i,j)\sum_{m=-N}^{N}\sum_{n=-N}^{N}\frac{f(i+m,j+n)}{M} & th_{\min}\le F_2(i+m,j+n)\\ f(i,j) & otherwise\end{cases} \quad (6)$$

, where $\psi(i, j)$ denotes the weight function based on the value of $F_2(i, j)$ and M denotes the number of pixels in this filter. This filter computes summation of values under given condition based on CFI.

The experimental results when $\psi(i, j) = 1$ and the smoothing size of the filter is 5x5 are shown in Figure 7. These images are magnified image of 640x480 pixels. As clearly known from these results, CFI-based smoothing filter could be an edge preserving characteristic. CFI-based method could select the flatness texture without noise, and realize an edge preserving characteristics.

(a) Input image including noise(640x480)

(b) Result of smoothing based on CFI (where K, L = 1, 1, $th_{\min}$= 8)

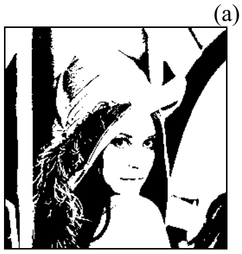


(c) Result of smoothing filter (5x5)
Figure 7. The results of smoothing filters applied to an image with random noise.

5. Thresholding Algorithm for Binarization Based on CFI

CFI is classified into either low or high co-occurrence frequency regions, and low co-occurrence frequency region in CFI means an edge region. Basing on this property, we propose a new thresholding algorithm for image binarization, where the thresholding parameter can be defined feasibly by means of median gray value of the pixels involved in the low co-occurrence frequency region. The experimental results are shown in Figure 8.

(a) Input image



(b) Result of proposed method (Threshold=111, R=1,

(c) Result of discriminant analysis

$th_{\min}$, $th_{\max}$ = 0, 6)   (Threshold=117)

Figure 8. The experimental results of image binarization.

6. Ternary CH and CFI

We have revealed that CFI based on CH composed of binary parameter space is promising in image feature extraction. Then this means that CH is a straightforward extension of the histogram in statistics. Moreover we try to extend it to multi-dimensional CH and CFI. In this section, we introduce a scheme of a ternary CH and CFI with some experimental result. Let ternary CH or CF be ternary co-occurrence frequency value of a given image with the similar definition as the scheme of binary CH and CFI.

Ternary CFI $F_3(i, j)$ is defined by eq. (7).

$$F_3(i,j) = h_3(\alpha,\beta,\gamma) \tag{7}$$

, where h_3 have 3 arguments; first and second arguments are used as the same parameters in binary CH, and third argument denotes the augmented parameter for expressing ternary co-occurrence frequency value.

We propose new framework of ternary CH for KL-method and R-method, respectively. In the ternary KL-method, third value for ternary CH is defined as the parameter $f(i\text{-}K, j\text{+}L)$ in a direction perpendicular to the direction of K and L as shown in Figure 9(a). In the ternary R-method, the third value for ternary CH is defined by the average of gray values on the ring with the radius of double R as shown in Figure 9(b). The experimental results of CH and CFI generation are shown in Figure 10. Brief investigation gave the fact of the clear difference between these results such as Figure 10(d) and 10 (e) for prospecting some clear application of ternary CFI. Successively more detailed investigations could be expected for finding out more intensive local statistical features of the given image.

7. Conclusion

We have proposed a new image feature of co-occurrence frequency image, and we proposed some application of CFI and band-pass filters based on CFI. In addition in this paper, we extended CH and CFI from binary to ternary and showed some experimental performance of it. As the future subjects, this method requires the more detailed investigations for choosing and customizing the parameters K, L, $th_{\min}$ and $th_{\max}$ of CFI.

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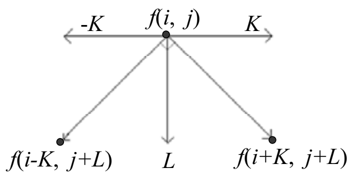
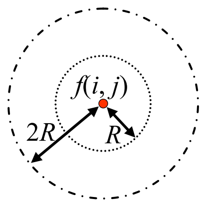
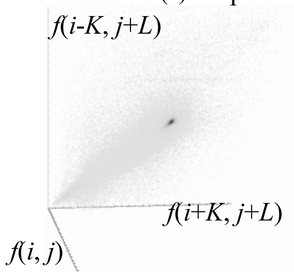




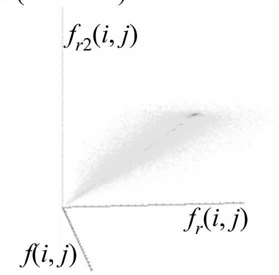
(a) KL-method   (b) R-method

Figure 9. A third value of ternary CH

(c) Input image (640x480)

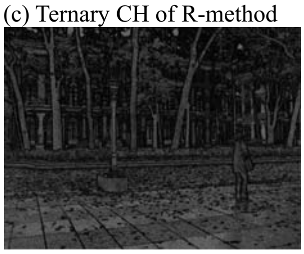


(b) Ternary CH of KL-method



(c) Ternary CH of R-method

(d) Ternary CFI of KL-method



(e) Ternary CFI of R-method

Figure 10. The experimental results of ternary CH and CFI