# Co-occurrence matrix 기반 비데오 영상 검색

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# Retrieval of video images based on Co-occurrence matrix

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Abstract: Multimedia data is now one of the widely used information in all the fields as the fast developments of computer techniques have been made. Traditional database systems based on textual information have limitations when applied to multimedia information. This is because simple textual descriptions are ambiguous and inadequate for searching multimedia information for multimedia databases and digital libraries. Thus, especially for image data, which is one of the important multimedia information types, there have been recently considerable interests in content-based image retrieval techniques, which can retrieve and browse image data on the basis of pictorial queries. Therefore, this paper presents an efficient method for describing texture information in image data.

#### I. Introduction

Many features of an image such as colour, texture, shape and symbolic descriptors have been used as the basis of content-based image retrieval [1]. This paper proposes video image retrieval algorithm especially using texture features. Texture is one of the most important defining characteristics of an image [2] However, there is no formal definition of a texture because it shows its characteristics by both each pixel value and texel values [3]. On the basis of texture characteristics, an image can be considered as the mosaic of different texture pattern regions. When each texture pattern region in an image is described by proper features, the images in databases can be retrieved and browsed in terms of texture patterns. For describing a texture region, this paper suggests the use of only six different texture features, which are produced by the co-occurrence matrix [4]. In order to describe directional characteristics of a texture region, each texture feature is realised along the four different directions: vertical, horizontal, and two diagonal directions. Also, Euclidean distance is applied to show the strength of a similarity between a query texture pattern and texture patterns in databases. Since each texture feature has its own different value domain, it is difficult to directly use the individual feature values in order to produce the correct strength of a similarity in the Euclidean distance. Therefore, we propose to normalise individual feature components of a texture pattern by using the standard deviations of the respective features over an entire database. The proposed algorithm in this paper is applied to a variety of texture patterns taken from real video images.

This paper is organised as follows. Section explains how to produce Co-occurrence matrices and its texture features. Also, a normalised Euclidean distance is defined in section III. Finally, the results of applying the proposed algorithm to real video images are shown in section IV.

# II. Co-occurrecne matrix

Haralick et al [4] suggested a co-occurrence matrix for extracting texture features to describe the spatial distribution of a texture. Co-occurrence matrices display the graylevel spatial-dependency along different angular relationships, horizontal, vertical and two

diagonal directions, in a neighbouring system A cooccurrence matrix is specified by the relative frequencies P(i, j, r, b) with which two pixels, separated by distance r, occur in a texture along the direction of angle  $\theta$ , one with graylevel 1 and the other with graylevel 1. A cooccurrence matrix is therefore a function of distance r, angle  $\theta$  and gravscales.

It is assumed that a textured image Y is defined over a  $m = m_x \times m_y$  finite lattice  $\Omega$ :

$$\Omega = \{(k, t), (m, n) : 1 \le (k, t), (m, n) \le M\}$$
 (1)

The co-occurrence matrices used in this paper shows texture characteristics along 0 degree, 45 degree, 90 degree and 135 degree as follows.

$$\begin{split} &P(i,j,r,0^\circ) = \#\{((k,l),(m,n) \in \Omega), |k-m| = 0, |l-n| = r, \\ &Y(k,l) = i, Y(m,n) = j\} \end{split} \qquad \text{e) Sum of squares: variance} \\ &P(i,j,r,45^\circ) = \#\{((k,l),(m,n) \in \Omega), ((k-m) = i,(l-n) = -i)) \text{ or} \\ &((k-m) = -r,(l-n) = r), Y(k,l) = i, Y(m,n) = j\} \\ &(3) \\ &P(i,j,r,90^\circ) = \#\{((k,l),(m,n) \in \Omega), |k-m| = r, |l-n| = 0, \\ &Y(k,l) = i, Y(m,n) = j\} \end{aligned} \qquad \text{f) Inverse difference moment:} \\ &Y(k,l) = i, Y(m,n) = j\} \\ &(4) \\ &P(i,j,r,135^\circ) = \#\{((k,l),(m,n) \in \Omega), ((k-m) = r,(l-n) = r)\} \text{ of } \\ &IDM = \sum_{i} \sum_{j} \left(\frac{1}{1+(i-j)^2} \left(\frac{P(i,j,r,\theta)}{R}\right)\right) \\ &((k-m) = -r,(l-n) = -r), Y(k,l) = i, Y(m,n) = j\} \end{aligned} \qquad \text{(5)}$$

where # denotes the number of elements. observed that the co-occurrence matrix is symmetrical because of P(i, j, r, b) = P(j, i, r, b).

The total number of pairs of compared pixels is different due to the angular relationships. To overcome this, it is necessary to normalise the frequencies of the occurrence matrices The frequency normalising constant R is explicitly defined as the frequency of pairs of compared pixels in each co-occurrence matrix. For examples, the constant R for the horizontal, vertical and the diagonal co-occurrence matrices are defined in (Eq. respectively

$$K_H = 2N_v (N_v - 1) \tag{6}$$

$$K_H = 2N_y(N_x - 1)$$
 (6)  
 $K_V = 2N_x(N_y - 1)$  (7)  
 $K_D = 2(N_x - 1)(N_y - 1)$  (8)

$$K_D = 2(N_x - 1)(N_y - 1)$$
 (8)

Using the above co-occurrence matrices, many different texture features are produced. However, there is a dilema between computing costs and the number of texture scatures. Therefore, this paper uses only six different texture features in order to keep reasonable computing costs. The definitions of the texture features used in this paper are also shown as follows [4][5][6].

a) Maximum probability:

$$f_{MP} = \max_{i,j} \left( \frac{P(i,j,r,\theta)}{R} \right) \tag{9}$$

b) Angular Second Moment: uniformity

$$f_{ASM} = \sum_{i} \sum_{j} \left\{ \frac{P(i, j, r, \theta)}{R} \right\}^{2} \tag{10}$$

c)Contrast:

$$f_{CON} = \sum_{n=0}^{N_{\rm c}-1} n^2 \left\{ \sum_{i=1}^{N_{\rm g}} \sum_{j=1}^{N_{\rm g}} \left( \frac{P(i,j,r,\theta)}{R} \right) \text{ where } i-j \models n \right\}$$
 (11)

d) Correlation

$$f_{COR} = \frac{\sum_{i} \sum_{j} (\eta) \frac{P(i, j, r, \theta)}{R} - \mu_{\chi} \mu_{\chi}}{\sigma_{\chi} \sigma_{\chi}}$$
(12)

e) Sum of squares: variance

$$f_{VAR} = \sum_{i} \sum_{j} (i - \mu)^2 \left( \frac{P(i, j, r, \theta)}{R} \right)$$
 (13)

I) Inverse difference moment;

$$Of_{IDM} = \sum_{i} \sum_{j} \left( \frac{1}{1 + (i - j)^{2}} \left( \frac{P(i, j, r, \theta)}{R} \right) \right)$$
 (14)

where  $\mu_{\rm g}$  is the total grayscale,  $\mu$  the mean of P and  $\mu_{\rm g}$ ,  $\mu_{\rm g}$ ,  $\sigma_{\rm g}$ ,  $\sigma_{\rm g}$  are the mean and standard deviation of  $P_1$ ,  $P_2$ , that are denoted as:

$$P_x = \sum \frac{P(\iota, j, r, \theta)}{R} \tag{15}$$

$$P_{v} = \sum_{i} \frac{P(i, j, r, \theta)}{R} \tag{16}$$

#### III. Normalised Euclidean distance

As explained in section II, a texture pattern of a video image is described in terms of its six different texture features, each of which shows four directional characteristics. In order to compare a query texture with textures in a video image database, this paper proposes a normalised Euclidean distance as a similarity function.

The strength of similarity between two patterns can be described through the Euclidean distance corresponding texture features as follows:

$$\begin{split} ED(Q,I) = & \left| f_{Q\_MP} - f_{I\_MP} \right| + \left| f_{Q\_ASM} - f_{I\_ASM} \right| + \\ & \left| f_{Q\_CON} - f_{I\_CON} \right| + \left| f_{Q\_COR} - f_{I\_COR} \right| + \\ & \left| f_{Q\_VAR} - f_{I\_VAR} \right| + \left| f_{Q\_IDM} - f_{I\_IDM} \right| \end{split} \tag{17}$$

 $f_Q$ ,  $f_I$  are texture features of a query and input textures, respectively. Since each texture feature has its own value domain, total Euclidean distance can be easily dependent on the Euclidean distance of the feature with larger feature value domain. Therefore, it is required to normalise the Euclidean distance in order to have a independent similarity function regardless of texture feature value domain. This paper uses the standard deviation of respective texture features over entire image database as follows:

$$ED(Q,I) = \frac{\left| f_{Q\_MP} - f_{I\_MP} \right|}{\left| SD_{MP} \right|} + \frac{\left| f_{Q\_ASM} - f_{I\_ASM} \right|}{\left| SD_{ASM} \right|} + \frac{\left| f_{Q\_CON} - f_{I\_CON} \right|}{\left| SD_{CON} \right|} + \frac{\left| f_{Q\_COR} - f_{I\_COR} \right|}{\left| SD_{COR} \right|} + \frac{\left| f_{Q\_IDM} - f_{I\_IDM} \right|}{\left| SD_{VAR} \right|} + \frac{\left| f_{Q\_IDM} - f_{I\_IDM} \right|}{\left| SD_{IDM} \right|}$$
(18)

#### 1V. Experimental results

Searching a texture pattern in a video image should be considered in a content-based retrieval system. This is because a pattern-based retrieval system is operated locally rather than globally. This section shows the retrieval results of a local query texture.

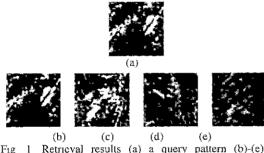


Fig 1 Retrieval results (a) a query pattern (b)-(e) Retrieval results

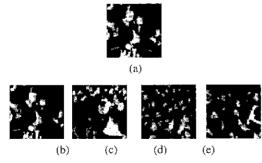


Fig. 2. Retrieval results (a) a query pattern (b)-(e)

Retrieval results

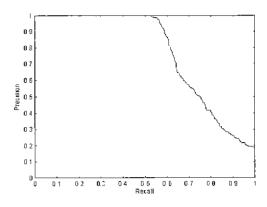


Fig. 3. Precision Vs. Recall

## V. Conclusion

The efficient retrieval video image algorithm using texture features are proposed in this paper. The proposed texture features are produced on the basis of Cooccurrence matrices. In order to precisely describe texture patterns, the texture features proposed in this paper consider four directional components such as vertical, horizontal, and two diagonal directions. Also, we suggest the normalised Euclidean distances between a query and video image feature sets in order to avoid domination of a certain feature value range. Since the normalised Euclidean distance improve the strength of similarity function, we just used only six different texture features and also produced competent results.

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