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Rotation invariant co-occurrence features based on digital circles and discrete Fourier transform ☆

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ABSTRACT

Grey-level co-occurrence matrices (GLCM) have been on the scene for almost forty years and continue to be widely used today. In this paper we present a method to improve accuracy and robustness against rotation of GLCM features for image classification. In our approach co-occurrences are computed through digital circles as an alternative to the standard four directions. We use discrete Fourier transform normalisation to convert rotation dependent features into rotation invariant ones. We tested our method on four different datasets of natural and synthetic images. Experimental results show that our approach is more accurate and robust against rotation than the standard GLCM features.

1. Introduction

Grey-level co-occurrence matrices are among the most long-standing texture descriptors in use, their origin dating back to the pioneering work of Haralick et al. [23]. Though many other methods have been proposed since their appearance – see Ref. [44] for a comprehensive overview – GLCM continue to be very common and widely adopted still today. Bibliometric data reveal that the number of relevant scientific papers has even increased during the last years (see Table 1). GLCM features are particularly appealing for their conceptual simplicity, ease of implementation and the low number of features they produce. A recent comparative experiment on image classification under non-ideal conditions [27] showed that GLCM features tend to perform better when few classes (10 or less) are involved, a situation in which they can compete with newer and more powerful methods. Besides, co-occurrence features can be combined with other descriptors that convey complementary information through suitable fusion schemes [13]. Recent applications of GLCM span very diverse areas of image processing, including surface inspection [17,7], environmental monitoring [3,29], content-based image retrieval [39] and image reconstruction [4]. Among the numerous application areas, co-occurrence matrices seem to be particularly common in medical image analysis [24,28,6,37,20] and remote sensing [8,42,30,26].

Co-occurrence matrices have been extended in various directions, leading to several variations such as generalised co-occurrence matrices [16], which consider the distribution of local maxima; integrative co-occurrence matrices [36], which operate on colour images and, more recently, pattern co-occurrence matrices [40,21], which analyse the co-occurrence of local patterns. By contrast, the original formulation has not changed significantly since its appearance. This is not uncommon: when a method matures and new ones appear, scientific interest tends to switch from the former to the latter. Newer methods receive more attention, and the older becomes frozen, somewhat immutable, with few chances of improvement. Something of this type we believe has happened with co-occurrence matrices, at least for what it concerns rotation invariant features.

Motivated by the wide diffusion of the method – even in very critical areas like medical image analysis and computer-assisted diagnosis, we wished to investigate whether it was possible to improve robustness and accuracy of the method in rotation invariant classification tasks. This is a major concern, for in many applications images can occur in different and uncontrolled rotation angles. The common approach to obtaining rotationally-invariant features from co-occurrence matrices consists of averaging [23,1,11] or – equivalently – summing up [38, p. 215] the matrices corresponding to the same distance and different directions. We believe that this procedure reduces significantly and somewhat unnecessarily the discrimination capability of the resulting features. We therefore propose some improvements to compute more

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0167-8655/

Table 1
Co-occurrence matrices – bibliometric overview. Source: Scopus®. Query: TITLE (“co-occurrence matrices” OR "GLCM") OR AUTHKEY ("co-occurrence matrices" OR “GLCM”). Accessed on January 27, 2014.

Source type	Year							
	2006	2007	2008	2009	2010	2011	2012	2013
Conference proc.	34	33	48	74	95	113	103	63
Journals	28	30	35	47	45	60	67	93

efficient rotationally-invariant features from GLCM. Our study considers the effects of two design factors that determine how GLCM features are computed. These are: (1) the spatial arrangement of pairs of pixels; and (2) the way to convert GLCM features into rotation invariant ones. In the remainder of the paper we first discuss such design factors (Section 2), then evaluate their effects through an image classification experiment (Section 3). We present and analyse the results in Section 4 and conclude with final considerations in Section 5.

2. Design factors

Grey-level co-occurrence matrices estimate the joint occurrence probability of grey levels at a given distance and direction. The method is intrinsically directional, hence sensitive to rotation. In order to achieve rotation invariant descriptors, we need to remove the dependence on direction and obtain features that depend on distance only. Such a goal can be obtained through the following steps: (1) for each pixel in the image, consider all pixels that are located approximately at a given distance from it (we refer to this entity as neighbourhood); (2) extract rotation dependent features for each direction defined by the neighbourhood; (3) convert the rotation dependent features into rotation-independent ones. We discuss each step in the remainder of this section, with particular emphasis on steps (1) and (3), which represent the chief objective of this study. Less emphasis will be devoted to step (2), for the extraction of rotation dependent co-occurrence features is quite a standard operation that does not require further explanations. Following the terminology of Design of Experiments (see Ref. [14, p. 148]), the type of neighbourhood and the procedure to obtain rotation invariant features will be the *design factors* of our study; the possible solutions for each factor will be referred to as *variations*.[1] A combination of variations will be referred to as a *treatment*. In the following subsections we discuss the design factors and variations considered in the study.

2.1. Type of neighbourhood

Let I_0 denote the grey value of a pixel and I_j, $j \in \{1, \ldots, N\}$ the grey values of a set of pixels approximately equidistant from it, with the convention that I_1 stands horizontally on the right of I_0 and the others follow counter-clockwise from I_1 (Fig. 1). Note that, since the image is scanned by one-pixel steps, it is not necessary, due to symmetry, to consider the entire neighbourhood: only one half suffices (for a detailed explanation see Ref. [38, p. 280]).

We consider two variations for the type of neighbourhood: the original formulation proposed by Haralick et al. [23], based on four directions – this is by far the most used in practice –, and the digital circles proposed by Petrou and García Sevilla [38].

2.1.1. Original formulation

In Haralick’s formulation the neighbourhood is formed by the central pixel plus four peripheral pixels equally spaced at angular intervals of 45°. For a given distance d, the relative coordinates of the peripheral pixels with respect to the central one are: $(0, d)$, $(-d, d)$, $(-d, 0)$, $(-d, -d)$. In this scheme the number of pixels in the neighbourhood is constant, therefore independent of d. Fig. 2 shows the neighbourhoods corresponding to distances $d = 1, 2, 3$. In the remainder, we use the subscript ‘$*$’ to refer to this variation.

[1] To our ear this term sounds better, in this context, than the more common *level*.

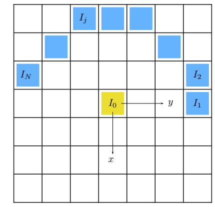

Fig. 1. Neighbourhood of pixels.

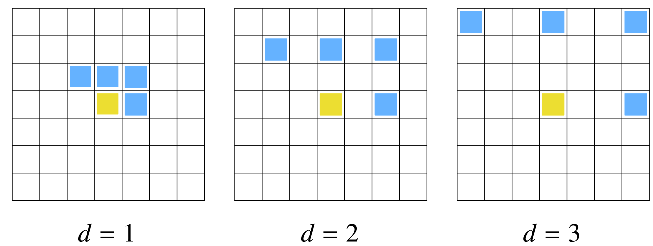

Fig. 2. Type of neighbourhood: original, four-direction.

2.1.2. Digital circles

As an alternative to the neighbourhood described above, Petrou and García Sevilla [38] suggested the use of digital circles. The definition of circle in the continuous space does not translate immediately into the digital domain, thus the way to define digital circles is not unique (for a discussion on this topic see the work of Mukherjee et al. [33]). Herein we used the same strategy proposed in Ref. [38]: a pixel belongs to a neighbourhood of radius d if its distance to the central pixel is in the range $[d - 1/2, d + 1/2)$. With this setting, the number of pixels forming the neighbourhood depends on d, and asymptotically approaches $[\pi d]$, where $[\cdot]$ indicates ‘the nearest integer of’. The resulting neighbourhoods for $d = 1, 2, 3$ are shown in Fig. 3. In the remainder, we use the subscript ‘$\circ$’ to refer to this variation.

2.2. Extraction of rotation dependent features

Consider a generic grey-scale image $\mathbf{I}$. From any neighbourhood containing N peripheral pixels we get N angular dependent co-occurrence matrices, each corresponding to the direction defined by pixels 0 and j (see Fig. 1). Now let $\mathbf{M}_j$ indicate any such co-occurrence matrix and $f_j^{(k)}$ a generic parameter extracted from it, with $1 \leqslant k \leqslant K$, being K the total number of parameters (let these, for instance, be *contrast*, *correlation*, *energy*, etc. – see Section 3.2).

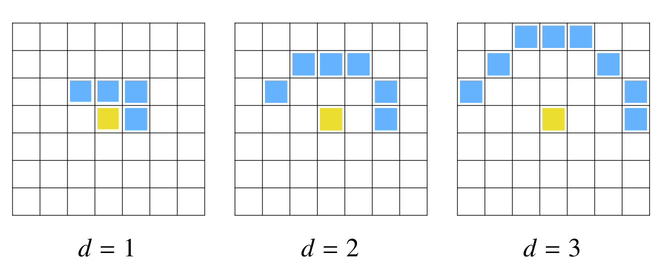

Fig. 3. Type of neighbourhood: digital circles.