AREA-BASED MATCHING ALGORITHM ASSESSMENT FROM SATELLITE IMAGES

GERALD JEAN FRANCIS BANON AND SERGIO DONIZETE FARIA

Instituto Nacional de Pesquisas Espaciais - INPE, Divisão de Processamento de Imagens - DPI, CP 515, 12.201-970 São José dos Campos, SP, Brazil
e-mail: {banon,faria}@dpi.inpe.br

ABSTRACT

An experimental assessment of eight area-based matching algorithms is presented. The algorithms have been selected from the literature within the last three decades. They are presented using a uniform notation. Based on a degree of matching between a set and a point, a special measure of matching precision is introduced. The eight algorithms are used to locate 50 different patterns in remote sensing images. The patterns are extracted from one image at one date and the pattern matching is performed on an image at another date. The experimental assessment results in a matching algorithm ranking which shows that the best algorithm is the one based on the correlation coefficient.

Keywords: correlation coefficient, pattern matching, pattern recognition.

INTRODUCTION

One important problem in image analysis is to find the exact location of a given *pattern* (template) in a digital image that we refer to as *search image*. This problem, called image matching appears, for example, in object detection or in digital image registration.

Over the last three decades several matching algorithms have been introduced. In this work, we are presenting the result of an experimental assessment of eight different algorithms referred as *area-based matching* because the patterns consist of rectangular images and the algorithms deal explicitly with the gray levels. Our assessment will be based upon an application-oriented criterion defined in terms of a matching precision measure.

The solution to image matching consists of computing a *similarity measure*. More precisely, for each pixel position x in the search image domain for which there exists a sub-image (of the search image) centered at x and having the same size as the pattern, we compute a similarity measure between the pattern and the sub-image. Then we select among all the previous pixel positions the ones having the greatest similarity. We call *matching region* the set of these selected positions.

In the next section we present the similarity measures used in eight matching algorithms. In the third section, we introduce a measure of matching precision that is used in the fourth, to experimentally assess the matching algorithms. Finally, in the last section, we come up to some conclusions.

MATCHING ALGORITHMS

Each matching algorithm is based upon a distance or a similarity measure. In this section, we are recalling the ones we have selected in our comparative work.

Let E be a non-empty set and let $\mathbf{R}$ be the set of real numbers. Let f and g be two images from E to $\mathbf{R}$. We denote by f' and g' their centralized (i.e., the zero average) versions, and by f'' and g'' their normalized (i.e., the zero average and unit variance) versions. We denote by $\#E$ the number of points of the image domain.

Let $d_1(f,g)$ be the Euclidean distance between the normalized version of *f* and *g*:

$$d_1(f,g) \stackrel{\Delta}{=} \sum_{x \in E} \left(f''(x) - g''(x)\right)^2 . \tag{1}$$

Let **n** be the interval of integers between 1 and *n*, and let $\{g_i\}_{\mathbf{n}}$ be a family of *n* images from *E* to **R**. We know that minimizing $d_1(f,g_i)$ over **n** is equivalent to maximizing $s_1(f,g_i)$ over **n**, where $s_1(f,g)$ is the *correlation coefficient* between *f* and *g*:

$$s_1(f,g) \stackrel{\Delta}{=} \frac{\sum_{x \in E} f'(x) g'(x)}{\left(\sum_{x \in E} f'^2(x) \sum_{x \in E} g'^2(x)\right)^{1/2}} . \tag{2}$$

We can use $s_1(f,g)$ as a first similarity measure between *f* and *g*.

Let $d_2(f,g)$ be the City Block distance between the centralized versions of *f* and *g*:

$$d_2(f,g) \stackrel{\Delta}{=} \sum_{x \in E} \left| f'(x) - g'(x) \right| . \tag{3}$$

Barnea and Silverman (1972) use this distance to perform a fast digital image registration. Maragos (1988) shows that minimizing $d_2(f,g_i)$ over **n** is equivalent to maximizing $s_2(f,g_i)$ over **n**, where $s_2(f,g)$ is the so-called *morphological correlation* between *f* and *g*:

$$s_2(f,g) \stackrel{\Delta}{=} \sum_{x \in E} \min\{f'(x), g'(x)\}. \tag{4}$$

Based on two robust estimations of the correlation coefficient of two binormal random variables, Brunelli and Messelodi (1995) propose two similarity measures. Let $s_3(f,g)$ and $s_4(f,g)$ be the expressions defined by:

$$s_3(f,g) \stackrel{\Delta}{=} 1 - \frac{\sum_{x \in E} \left| f'(x) - g'(x) \right|}{\sum_{x \in E} \left(|f'(x)| + |g'(x)| \right)}, \tag{5}$$

$$s_4(f,g) \stackrel{\Delta}{=} (1/\#E) \sum_{x \in E} 1 - \frac{|f'(x) - g'(x)|}{|f'(x)| + |g'(x)|} . \tag{6}$$

The expressions $s_3(f,g)$ and $s_4(f,g)$ correspond to the Brunelli and Messelodi similarity measures when *f* and *g* have the same variance. Actually, the similarity measures of Brunelli and Messelodi use the normalized versions of *f* and *g* instead of their centralized versions.

In the context of mathematical morphology, Khosravi and Schafer (1996), and Banon and Faria (1997) propose, respectively, the measures of similarity $s_5(f,g)$ and $s_6(f,g)$:

$$s_5(f,g) \stackrel{\Delta}{=} \min_{x \in E}\{g(x) - f(x)\} - \max_{x \in E}\{g(x) - f(x)\}, \tag{7}$$

$$s_6(f,g) \stackrel{\Delta}{=} \sum_{x \in E} 1_{[-l/2, l/2]}\left(f'(x) - g'(x)\right), \tag{8}$$

where, 1_I is the characteristic function of the real interval *I* defined by $1_I(s) \overset{\Delta}{=} \begin{cases} 1 \text{ if } s \in I \\ 0 \text{ otherwise} \end{cases}$ for any *s* in **R**, and *l* is a positive real constant representing an interval length.

Finally, based on the Kolmogorov-Smirnov statistic, Fernàndez (1997) uses the Chessboard distance. In this work, we use, as distance between *f* and *g*, the Chessboard distance between the centralized versions of *f* and *g*:

$$d_3(f, g) \overset{\Delta}{=} \max_{x \in E} \left| f'(x) - g'(x) \right|. \tag{9}$$

MATCHING PRECISION MEASURE

To assess the above matching algorithms, we introduce an application-oriented criterion defined in terms of a matching precision measure.

Let *F* be a rectangle of $\mathbf{Z}^2$ and let $d(x, y)$ be the Euclidean distance between two points *x* and *y* of *F*. Let $d_{\min}(x, A)$ the minimum distance between a point *x* and a subset *A* of *F*, that is, $d_{\min}(x, A) \overset{\Delta}{=} \min_{y \in A}\{d(x, y)\}$. Similarly, let $d_{\max}(x, A)$ the maximum distance between a point *x* and a subset *A* of *F*, that is, $d_{\max}(x, A) \overset{\Delta}{=} \max_{y \in A}\{d(x, y)\}$.

We denote by $\beta(A, x)$ the *matching degree* between a subset *A* and a point *x* of *F*:

$$\beta(A, x) \overset{\Delta}{=} \alpha_1(A)\alpha_2(A, x)\alpha_3(A, x), \tag{10}$$

where,

$$\alpha_1(A) \overset{\Delta}{=} \max\{((10 - \# A)/9), 0\}, \tag{11}$$

$$\alpha_2(A, x) \overset{\Delta}{=} \max\{((3 - d_{\min}(x, A))/3), 0\}, \tag{12}$$

$$\alpha_3(A, x) \overset{\Delta}{=} \max\{((3 - d_{\max}(x, A))/3), 0\}. \tag{13}$$

The coefficients 9 and 10 in (11) have been chosen by considering that α_1 should be zero for matching region areas greater than 9 points. The coefficient 3 in (12) and (13) has been chosen by considering that α_2 and α_3 should be zero for distances greater than 2 points.

We verify that β assumes values in the real interval [0, 1], 1 meaning a perfect matching (i.e., $A = \{x\}$). Fig. 1 shows five different subsets *A* and the corresponding matching degree $\beta(A, x)$.

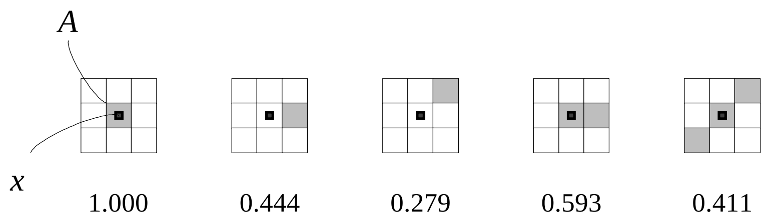


Fig. 1. *Some degrees of matching between a point and a subset.*

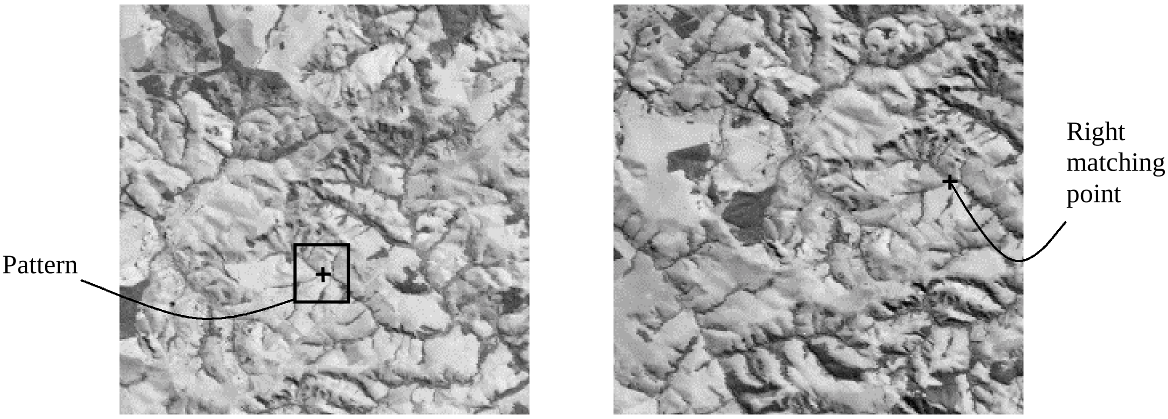
If A is the matching region produced by a matching algorithm in searching for the right *matching position* x of a given pattern in the search image, then its *measure of matching precision* will be $\beta(A, x)$.

EXPERIMENTAL ASSESSMENT

The experimental assessment has been performed using *five* pairs of remote sensing images (Faria and Banon, 1998a-e).

The patterns are extracted from one image at a given date, called the *reference image*, and submitted to the matching algorithms in order to be located in another image (the search image) of the same region but at a different date.

Fig. 2 shows one such pair of images.



Reference image Search image

Fig. 2. *Example of a pattern in the reference image and the corresponding right matching point in the search image.*

For each pair of images, *ten* patterns of size 23 by 23 have been extracted from the reference image. The final matching precision has been obtained by averaging the individual matching precision (see Expression (10)) over the 50 (*five* by *ten*) resulting patterns. The assessment has been made possible by manually selecting, in the search images, the 50 corresponding right matching points.

In this experiment, the constant l of Eq. 8 has been set to 20.

Table 1 shows, in decreasing order of matching precision, the eight tested matching algorithms.

Table 1. *Ranking of the selected matching algorithms*.

Matching algorithm	Equation	Measure of matching precision
Correlation coefficient	(2)	0.958
Brunelli and Messelodi, 1995	(5)	0.912
Barnea and Silverman, 1972; Maragos, 1988	(3) (4)	0.882
Brunelli and Messelodi, 1995	(6)	0.758
Banon and Faria, 1997	(8)	0.678
Fernàndez, 1997	(9)	0.166
Khosravi and Schafer, 1996	(7)	0.154

CONCLUSIONS

In this experimental work, we have assessed eight matching algorithms from the point of view of the matching precision criterion in remote sensing applications. The assessment has been made using five pairs of remote sensing images from different scenes.

Ideally, the matching region produced by a matching algorithm should be reduced to a singleton containing the desired location. Nevertheless, in practical situations, such as in remote sensing, we might get a greater matching region. Furthermore, the matching region might not even contain the correct location. This is precisely what we have taken into account by introducing a matching precision measure.

All the algorithms encountered in the literature are alternatives to the algorithm based on the correlation coefficient. However, our experimental result shows that no measure of similarity is better than the correlation coefficient, based on a matching precision criterion. Actually, some other measures might be attractive for some other reasons, like the implementation efficiency of the morphological correlation of Maragos.

More details on the pattern size effect and on the implementation efficiency can be found in Faria and Banon's technical report (2001).

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