



Rotation-discriminating template matching based on Fourier coefficients of radial projections with robustness to scaling and partial occlusion

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ABSTRACT

We consider brightness/contrast-invariant and rotation-discriminating template matching that searches an image to analyze A for a query image Q . We propose to use the complex coefficients of the discrete Fourier transform of the radial projections to compute new rotation-invariant local features. These coefficients can be efficiently obtained via FFT. We classify templates in “stable” and “unstable” ones and argue that any local feature-based template matching may fail to find unstable templates. We extract several stable sub-templates of Q and find them in A by comparing the features. The matchings of the sub-templates are combined using the Hough transform. As the features of A are computed only once, the algorithm can find quickly many different sub-templates in A , and it is suitable for finding many query images in A , multi-scale searching and partial occlusion-robust template matching.

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1. Introduction

1.1. The problem

In this paper, we consider the rotation-discriminating and brightness/contrast-invariant template matching problem, where the algorithm must search a grayscale image to analyze A for a query image Q . A template matching is rotation-invariant if it can find rotated instances of Q in A and is rotation-discriminating if it determines the rotation angle of Q for each matching. We define that two images \mathbf{x} and \mathbf{y} are equivalent under brightness/contrast variation if there are contrast correction factor $\beta > 0$ and brightness correction factor γ such that $\mathbf{y} = \beta\mathbf{x} + \gamma\mathbf{1}$, where $\mathbf{1}$ is the matrix of 1's.

In the literature, there are many techniques to solve this problem. The most obvious solution is the “brute-force” algorithm. It makes a series of conventional brightness/contrast-invariant template matchings between Q rotated by many different angles and A . Conventional brightness/contrast-invariant template matching usually uses the normalized cross-correlation (NCC). Computation of NCC can be accelerated using fast Fourier transform (FFT) and integral images [1] or bounded partial correlation [2]. However, even using fast NCC, the brute-force rotation-invariant algorithm is slow because fast NCC must be applied repeatedly for many angles.

Some techniques solve rotation-invariant template matching using previous segmentation/binarization, for example [3,4]. Given a grayscale image to analyze A , they first convert it into a binary image using some segmentation/thresholding algorithm. Then, they separate each connected component from the background. Once the shape is segmented, they obtain scale-invariance by normalizing the shape's size. Next, they compute some rotation-invariant features for each component. These features are compared with the template's features. The most commonly used rotation-invariant features include Hu's seven moments [5] and Zernike moments [6]. Unfortunately, in many practical cases, images Q and A cannot be converted into binary images and thus this method cannot be applied.

Ullah and Kaneko use local gradient orientation histogram to obtain rotation-discriminating template matching [7]. Marimon and Ebrahimi present a much faster technique that also uses gradient orientation histogram [8]. The speedup is mainly due to the use of integral histograms. The gradient orientation histograms are not intrinsically rotation-invariant and a “circular shifting” is necessary to find the best matchings.

The recently developed matching algorithms based on scale and rotation-invariant key-points, like SIFT [9] and GLOH [10], present very spectacular computer performance together with true scale-invariance. These algorithms are particularly fit for finding query images with rich textures. However, they can fail to find some simple shapes with little grayscale variations.

Many other techniques use circular projections (also called ring projections) for the rotation-invariant template matching, for example [11–13]. The underlying idea of these techniques is that features

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computed over circular or annular regions are intrinsically rotation-invariant. The circular projection can be followed by radial projection to obtain scale and rotation-discriminating template matching [14]. This technique can be drastically accelerated using dedicated hardware, like FPGA (field programmable gate array) [15]. However, these techniques are slow in conventional computers, because circular and radial projections are time-consuming processes in non-parallel computers.

1.2. The outline of the algorithm

Choi and Kim [16] have proposed an interesting approach to accelerate circular projection-based rotation-invariant template matching. Their method computes circular projections for each pixel (x,y) in A (that is, the mean grayscales of the circular rings centered at (x,y)) forming a one-dimensional vector $C(A(x,y))$. The circular projection reduces the 2-D information of the neighborhood of $A(x,y)$ into a one-dimensional rotation-invariant vector. To reduce even more the data, the method computes the first low-frequency complex Fourier coefficients c_1, c_2, \dots of $C(A(x,y))$, and uses them as rotation-invariant features. Actually, this technique computes the Fourier coefficients directly, without explicitly computing the circular projections, by convolving A with appropriate kernels via FFT. The features of Q are compared with the features of each pixel $A(x,y)$ to select the pixels candidate for the matching. A secondary filter based on the rotation-invariant Zernike moments is used to further test the candidate pixels. Rotation-dependent features cannot be used in this test because circular projections do not discriminate the rotation angle.

We propose to improve Choi and Kim's algorithm by using new rotation-invariant and rotation-discriminating features derived from radial projection, together with the circular features. In order to provide a short name to the new algorithm, we will call it "Forapro" template matching (Fourier coefficients of radial projections). We compute, for each pixel (x,y) in A , the mean grayscales of the radial lines centered at (x,y) , forming a one-dimensional vector of radial projections $R(A(x,y))$. Then, we compute the first low-frequency complex inverse Fourier coefficients r_1, r_2, \dots of $R(A(x,y))$. Actually, we do not compute the radial projections, but the Fourier coefficients directly. Convolutions in the frequency domain are used to compute quickly the Fourier coefficients, employing appropriate kernels and FFT. Using special instruction sets, like MMX (multi-media extensions) or SSE (streaming SIMD extensions), available in most of the nowadays processors, FFT can be computed 5–20 times faster than good conventional software implementations. Differently from the circular case, the radial coefficients are not intrinsically rotation-invariant. However, it is possible to derive many rotation-invariant features and one rotation-discriminating feature from the radial coefficients.

We show experimentally that the rotation-invariant radial features are more adequate for finding templates than circular ones. However, the maximal accuracy is obtained by using both the radial and circular features. We classify query images in "stable" and "unstable" ones and show that any local feature-based template matching can fail when searching for unstable query images. Thus, we extract one or more stable circular sub-templates $T_1, \dots, T_N \subset Q$, find them in A , and test for false positive errors using Hough transform or NCC. This secondary test is essential, because any feature-based template matching reduces the original 2-D information into a set of features, and consequently many non-equivalent templates may be mapped into the same features, producing false positive errors.

Template matchings based on pre-computed rotation- and brightness/contrast-invariant features are advantageous principally when the algorithm must search an image A for a large number

of templates. In this case, the vector of rotation-invariant features $v_f(A(x,y))$ is computed only once for each pixel $A(x,y)$. Then, each template T_i can be found quickly in A by computing the vector of features $v_f(T_i(x_0, y_0))$ at the central pixel (x_0, y_0) of T_i and comparing it with $v_f(A(x,y))$. If the distance is below some threshold, then the neighborhood of $A(x,y)$ is "similar" (in rotation- and brightness/contrast-invariant sense) to the template image T_i and (x,y) is considered a candidate for the matching. This property makes our algorithm suitable for: finding many different query images in A ; multi-scale searching and partial occlusion-robust template matching.

Our compiled programs and some test images are available at www.lps.usp.br/~hae/software/forapro. Note that these programs are intended only for testing the ideas developed in this paper, and thus many parameters were purposely left to be set by hand.

The remainder of the paper is organized as follows: Section 2 presents the new features and the concept "stability"; Section 3 presents the new template matching algorithms; Section 4 presents experimental results; and Section 5 presents our conclusions.

2. New features

2.1. Radial IDFT coefficients

Given a grayscale image A , let us define the radial projection $R_\alpha^\lambda(A(x,y))$ as the average grayscale of the pixels of A located on the radial line with one vertex at (x,y) , length λ and inclination α :

$$R_\alpha^\lambda(A(x,y)) = \frac{1}{\lambda} \int_0^\lambda A(x + t \cos(\alpha), y + t \sin(\alpha)) dt. \quad (1)$$

In practice, a sum must replace the integral, because digital images are spatially discrete. The vector of M discrete radial projections at pixel $A(x,y)$ with radius λ can be obtained by varying the angle α :

$$R_{A(x,y)}^\lambda[m] = R_{2\pi m/M}^\lambda(A(x,y)), \quad 0 \leq m < M. \quad (2)$$

Figs. 1(b) and 2(a) depict $M = 36$ radial projections at the central pixel of Fig. 1(a).

Vector of radial projections $R_{A(x,y)}^\lambda[m]$ characterizes the neighborhood of $A(x,y)$ of radius λ . If A rotates, then this vector shifts circularly. This property is illustrated in Fig. 2, the vector of radial projections of Fig. 1(a). The k -th Fourier coefficient of a vector of radial projections R is (we omit indices $A(x,y)$ and λ)

$$r[k] = \sum_{m=0}^{M-1} R[m] \exp(-j2\pi km/M), \quad 0 \leq k < M. \quad (3)$$

The Fourier coefficients of a vector of radial projections can be computed directly convolving A with an appropriate kernel K , without explicitly calculating the radial projections. Fig. 3(a) depicts the "sparse DFT kernel" K (with $M = 8$ angles) such that the convolution $A * \check{K}$ yields the first Fourier coefficient of the radial projections (where $\check{K}(x,y) = K(-x, -y)$ is the double reflection of K):

$$\begin{aligned} (A * \check{K})(x,y) &= \sum_p \sum_q A(p,q) \check{K}(x-p, y-q) \\ &= \sum_p \sum_q A(p,q) K(p-x, q-y). \end{aligned} \quad (4)$$

It is well known that the convolution $A * \check{K}$ can be computed by multiplications in the frequency domain:

$$A * \check{K} \Leftrightarrow \mathbf{A} \check{\mathbf{K}}, \quad (5)$$

where \mathbf{A} and $\check{\mathbf{K}}$ are respectively the discrete Fourier transforms of A and \check{K} .

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