Pattern Recognition ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at ScienceDirect

Pattern Recognition

journal homepage: www.elsevier.com/locate/pr

Geometric invariant features in the Radon transform domain for near-duplicate image detection ☆

Yanqiang Lei [a], Ligang Zheng [b], Jiwu Huang [c,*]

[a] School of Information Science and Technology, Sun Yat-sen University, Guangzhou 510006, China
[b] School of Computers, Guangzhou University, Guangzhou 510006, China
[c] College of Information Engineering, Shenzhen University, Shenzhen 518060, China

ARTICLE INFO

Article history:
Received 9 September 2012
Received in revised form
24 October 2013
Accepted 12 May 2014

Keywords:
Geometric invariants
Radon transform
Near-duplicate image detection

ABSTRACT

Radon transform has been widely used in content-based image representation due to its excellent geometric properties. In this paper, we propose a family of geometric invariant features based on Radon transform for near-duplicate image detection. According to the theoretical analysis between geometric operations (translation, scaling, and rotation) and Radon transform, we present a geometric invariant feature model. Based on the feature model, we developed four kinds of geometric invariant features. In addition, a uniform sampling technique is introduced to combine different features. The comprehensive performance of the combined feature is better than that of a single one. Extensive experiments show that the proposed features are robust, not only to rotation and scaling, but also to other operations, such as compression, noise contamination, blurring, illumination modification, cropping, etc., and achieve strong competitive performance compared with the state-of-the-art image features.

1. Introduction

With the rapid advancement of multimedia and Internet technologies, the amount of digital images that are easily accessible to users has become overwhelmingly large. Nowadays, it is very common for a digital image to have many near-duplicates on the Internet, as can be easily observed by using a search engine, such as Google or Bing. This phenomenon will inevitably lead to a huge waste of storage and network resources in addition to problems such as copyright infringement. Therefore, effectively detecting near-duplicated images has become an important issue. Note that "near-duplicates" refer to transformed versions of the original image. The commonly used transformations (sometimes called content-preserving operations) include geometric operations, blurring, noise contamination, enhancement, and compression.

Near-duplicate image detection methods achieve their goals by measuring the similarity between the features of the query and the target. So, exploiting effective features is one of the most fundamental tasks. As we know, robustness, discriminability, storage load, and computational complexity, are the four key issues of the features. Here, robustness represents the ability of a feature to resist the commonly used image transformations. Discriminability refers to the ability of a feature to distinguish images which are not near-duplicated pairs. Storage load indicates the size of the extracted feature, and the computational complexity denotes the time for generating the feature. An ideal feature is a compact descriptor with low computational cost, which, at the same time, performs excellent robustness and discriminability. Up until now, a single image feature has hardly been able to achieve good performance in the four aspects at the same time. Usually, there would be a trade-off among them in practical applications. Now, we first review the effective image features which have been developed for near-duplicate image detection. In [1], Xu et al. employed the difference of multi-resolution histograms (MHD) to perform the detection. The main advantage of an MHD is its low computation. The vector of locally aggregated descriptors (VLAD) [2] and bag-of-features (BOF) [3] are those techniques that aggregate local descriptors (e.g., SIFT [4]) into global representations. In recent years, VLAD and BOF have provided strong competition in near-duplicate image detection. GIST [5], which was proposed to describe a scene, is another well-known image representation. It achieves excellent robustness to many kinds of image manipulation [6]. In [7], Zheng et al. introduced the salient covariance matrix (SCOV) as a compact descriptor to near-duplicate image detection. Each of the above-mentioned features has its own advantages. But, as mentioned previously, a single feature can hardly achieve perfect performance. Based on our experiments, MHD and

Abbreviation: Enhanced Radon feature, (ERF); Moment pattern, (MP); High-order invariant moment, (HOIM); Integral of Fourier transform, (IOFT); Arc length and area ratio, (ALAR)

☆Supported in part by the 973 Program (2011CB302204), NSFC (U1135001, 61332012, 61300205).

* Corresponding author.
E-mail addresses: Yanqianglei@yahoo.com (Y. Lei), zlg.sysu@gmail.com (L. Zheng), jwhuang@szu.edu.cn (J. Huang).

http://dx.doi.org/10.1016/j.patcog.2014.05.009
0031-3203/© 2014 Elsevier Ltd. All rights reserved.

GIST cannot tolerate rotation at all. VLAD and BOF are sensitive to noise contamination and blurring. SCOV shows poor performance to rotation and illumination modification.

In this paper, we focus on developing geometric invariant features in the Radon transform domain for near-duplicate image detection. The motivation of this study is twofold. First, we can extract features based on Radon transform [8] which are provably invariant to geometric operations (e.g., rotation, scaling, and translation), where rotation and scaling are two popular transformations used to generate near-duplicated images. Second, the features derived from Radon transform are not only invariant to geometric operations, but also robust against compression, noise contamination, blurring, illumination modification, and cropping. Recently, many geometric invariant features have already been reported based on Radon transform in different applications, such as shape description [9–13], object recognition [14–16], image authentication [17,18], and texture analysis [19–24]. However, most of them cannot be directly applied to detect near-duplicates, since they usually lead to high storage load or ignore the tolerance to other image operations. In our work, we have also discussed the existing Radon transform-based invariants which can be extended to near-duplicate image detection, such as the methods in [9,18].

The contributions of this study include the following three points. First, we present a model for generating geometric invariant features based on Radon transform. Once the image is mapped to the Radon space, we formulate the problem of feature extraction as a two-step model. The first step constructs a translation and scaling invariant for each column of the Radon image, while the second stage extracts a rotation invariant based on the intermediate vector obtained in the previous step. The features of such a model can guide works which plan to investigate image invariants in Radon transform. Second, we develop four kinds of geometric invariant features based on the proposed model, where the effect of translation is eliminated by re-shift processing; scaling invariants are constructed by the theories of probability, moment, Fourier transform, and curve, and the rotation invariant is achieved by discrete Fourier transform (DFT). Those invariant features compete strongly compared with the existing methods in near-duplicate image detection. Third, according to the model's properties, we propose a uniform sampling technique to combine different features. Such a technique will not increase the feature dimensionality.

The remainder of this paper is organized as follows. In Section 2, we construct the geometric invariant features in the Radon transform domain. Section 3 shows the image database and performance evaluation. Experimental results and discussions are presented in Sections 4 and 5, respectively. Finally, concluding remarks of the paper and future works are given in Section 6.

2. Geometric invariant features in the Radon transform domain

Radon transform [8] of an image is the integral transform consisting of the integral of a function over straight lines, as shown in Fig. 1. Radon transform of a 2-D image $f(x,y)$ can be defined as

$$g(r,\theta)=\mathcal{R}\{f(x,y)\}=\iint f(x,y)\delta(r-x\cos\theta-y\sin\theta)\,dx\,dy, \quad (1)$$

where r is the distance from the origin to the projection line, θ denotes the projection angle, and $\delta(*)$ is the pulse function. Radon transform has excellent properties [15,18] that are beneficial in constructing geometric invariants:

- *Periodicity*:

$$g(r,\theta)=g(r,\theta+2k\pi), \quad \forall k\in\mathbb{Z}. \quad (2)$$

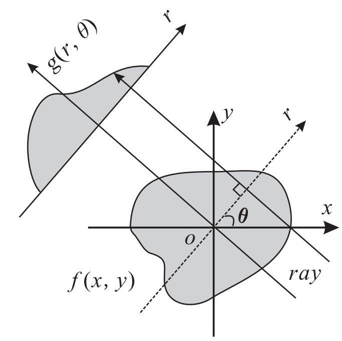

Fig. 1. The Radon transform of an image at direction θ.

- *Semi-symmetry*:

$$g(r,\theta)=g(-r,\theta\pm\pi). \quad (3)$$

- *Translation*:

$$\mathcal{R}\{f(x-x_0,y-y_0)\}=g(r-x_0\cos\theta-y_0\sin\theta,\theta). \quad (4)$$

- *Scaling*:

$$\mathcal{R}\left\{f\left(\frac{x}{\lambda},\frac{y}{\lambda}\right)\right\}=\lambda g(\frac{r}{\lambda},\theta). \quad (5)$$

- *Rotation*:

$$\mathcal{R}\{f(x\cos\theta_0-y\sin\theta_0,x\sin\theta_0+y\cos\theta_0)\}=g(r,\theta+\theta_0). \quad (6)$$

where (x_0,y_0), λ, and θ_0 represent the corresponding parameters of translation, scaling, and rotation. Note that a constraint defined as (7) must be satisfied to enable the above-mentioned properties, where $\mathcal{D}$ is the support domain of the original image content:

$$f(x,y)=0 \quad \text{if } (x,y)\notin\mathcal{D}. \quad (7)$$

In fact, Radon transform converts an image into another image (called Radon image in this paper). With the above-mentioned properties, we conclude that the translation and scaling information are encoded into the columns (r coordinates), and the rotation information is encoded into the rows (θ coordinates), as shown in Figs. 2 and 3. Note that the projection magnitude $g(r,\theta)$ also contains the scaling information. We can only consider the case of $\theta\in[0,2\pi)$ due to the *periodicity*. In addition, if the constructed invariants are irrelevant to the direction of the r coordinates, we can further constrain θ in the range of $[0,\pi)$, owing to *semi-symmetry*. Once the Radon image is obtained, investigating the geometric invariant features can be converted to the following two issues:

(i) To calculate a value that is invariant to translation and scaling for each column of the Radon image.
(ii) To calculate the rotation invariant for the intermediate vector generated by the above step.

2.1. Translation and scaling invariant

As mentioned previously, the translation and scaling invariant will be constructed in each column of the 2-D Radon image. According to (4) and (5), Fig. 3 shows the intuitive effects of translation and scaling for a single column. With the constraint in (7), the effect of translation can be easily eliminated by the following