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Histogram of Radon transform with angle correlation matrix for distortion invariant shape descriptor

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ABSTRACT

A shape matching descriptor based on the histogram of Radon transform (HRT) with an angle correlation matrix is proposed. Our descriptor based on HRT is robust to shape rotation, scaling, and translation. Shape distortions provide sparse and dense distortions relative to the angle coordinate on our descriptor. Therefore, we compute an angle correlation matrix and apply the dynamic time warping for a non-linear angle matching to be robust to these transformations. Based on the beam search algorithm, we speed-up the time complexity of our method. Robustness to affine distortions for our approach is shown experimentally on different kinds of datasets and compared with the literature.

1. Introduction

Affine transformation invariance is a very important property required for shape descriptors for characters, symbols, and logos recognition. For instance, for scanning paper documents using a flat bed scanner shape rotation, scaling, and translation (RST transformations) become serious issues for the recognition. In addition, with the growing popularity of digital input devices [1] like Tablet PCs and smartphones, there is an increasing interest in designing systems that can recognize automatically hand-sketched or camera-captured symbols. These types of symbols are warped and thus have a high variation and distortion. Therefore, new descriptors are needed invariant to these new kinds of deformations. In this paper, we focus on the RST transformations and distortions – non-uniform scaling, shearing, and reflection –, we propose a novel shape matching method that is robust to such distortions.

Many shape descriptors have been proposed for the shape matching. The generic Fourier descriptor (GFD) proposed by Zhang and Lu [2] is a typical Fourier descriptor, and it is invariant to shape rotation. The phase-only correlation function (POC) proposed by Kuglin et al. [3] has been shown to be effective for shape matching. The correlation between two images is computed using their Fourier transform phase spectra and the results are invariant to shape translation. The Fourier–Mellin transform (FMT) proposed by Chen et al. [4] is invariant to the RST transformations. First, they perform the Fourier transform on the original image and then apply the log-polar mapping to the Fourier domain. In the matching step, the correlation between descriptors is computed by employing POC. Since the RST invariant methods are useful for many applications, many methods have been adapted using POC [5–7].

RST transformation invariant descriptors for the shape matching using the Radon transform have been proposed first by Tabbone et al. [8,9]. The Radon transform is defined as the line integral in the image space and this gives rise to some beneficial properties for the RST transformations. A translation in shapes becomes a one-dimensional translation relative to the radial coordinate of the Radon domain. Furthermore, scaling and rotation in shapes are projected to scaling and translation relative to the radial and angular coordinates of the Radon domain, respectively [10]. The $\mathcal{R}$-transform [9] (generalized in [11]) based on an integral function for the radial coordinate and the Fourier transform for the angular coordinate is proposed. The result is a one-dimensional descriptor that is robust to the RST transformations. The obtained descriptor was so compact that it has been used in several applications [12,13] where time complexity constraints are important. More recently, different adaptation of the Radon have been proposed. The histogram of Radon transform (HRT) [14] used the Radon transform and a two-dimensional histogram. This descriptor encodes the shape length at each orientation, and it is robust to the RST transformations. In [15], the authors combine the Radon transform and the dynamic time warping (DTW); they apply the dynamic time warping to the radial coordinate in the Radon domain directly. The descriptor is invariant to the RST transformations with a high complexity but not robust to distortions.

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In the case of invariant methods for any distortions, a method using ellipses was proposed to normalize such distortions [16,17]. This method estimates ellipses which approximates shapes. A distorted image is normalized by a transformation that changes the ellipses to a circle. After the normalization, any shape matching method that is invariant to the RST transformations is employed. The local descriptor ASIFT proposed by Morel and Yu [18] is also invariant to any distortions. ASIFT is an enhanced method of the conventional SIFT proposed by Lowe [19]. Their method detects and matches local features in images.

In this paper, we focus on a novel shape matching robust to the classical RST transformations and any distortions [20,21]. We discuss a new method based on HRT. When shape undergoes any distortions, we found that it makes sparse and dense distortions relative to the angular coordinate on our HRT descriptor. In order to obtain invariance to such horizontal distortions, we compute an angle correlation matrix and apply the dynamic time warping (DTW) to the angle coordinate. DTW is an elastic distance well adapted for non-linear matching methods. A fast computation method using the beam search algorithm [22] can be performed in our DTW.

This paper is an extension of [21], where we show the robustness of our method for shape distortions. Here, we improve the definition of the cost on our angle correlation matrix, furthermore, experiments using the different kind and commonly used datasets are carried out. In our comparison with other methods for affine distorted datasets, we show that our recognition performance are better than any other methods.

The remainder of this paper is organized as follows. The Radon transform and our descriptor HRT are recalled in Sections 2 and 3. Our shape matching methods – computing our angle correlation matrix, our dynamic time warping method, and our beam search algorithm are discussed in Section 4. Experimental results are given in Section 5, and finally our conclusions are drawn in Section 6.

2. Radon transform

We start by introducing the Radon transform. Let a coordinate (x, y) in the two-dimensional x–y plane be described as $\mathbf{x}$, and an original image represented as $f(\mathbf{x})$. The Radon transform of $f(\mathbf{x})$ is defined as

$$\mathcal{R}_f(\theta,\rho)=\int f(\mathbf{x})\delta(\mathbf{x}\cdot\xi-\rho)\,\mathrm{d}\mathbf{x}, \tag{1}$$

where $\xi=(\cos\theta,\ \sin\theta)$, and $\delta(\cdot)$ is a delta function. In other words, the Radon transform is the integral of $f(\mathbf{x})$ over lines

$$L_{\theta\rho}=\{\mathbf{x}\in R^2\,|\,\mathbf{x}\cdot\xi=\rho\}, \tag{2}$$

where ρ is the distance between the origin and $L_{\theta\rho}$, the unit vector ξ and the angle θ describe the orientation of the line $L_{\theta\rho}$. The line integral is computed by a delta function $\delta(\cdot)$. The Radon transform has useful properties with respect to RST transformations.

$P1$: *Rotation*. When a shape is rotated by θ_0, the Radon transform $\mathcal{R}_f(\theta,\rho)$ is circular shifted in the variable θ by a distance θ_0 as

$$\mathcal{R}_f(\theta,\rho)\rightarrow\mathcal{R}_f(\theta-\theta_0,\rho), \tag{3}$$

where $\mathcal{R}_f(\theta,\rho)$ is cyclic for the θ as

$$\mathcal{R}_f(-\theta,\rho)=\mathcal{R}_f(\pi-\theta,\rho). \tag{4}$$

$P2$: *Scaling*. When a shape is scaled by α, the Radon transform $\mathcal{R}_f(\theta,\rho)$ is scaled by α relative to the coordinate ρ. Moreover, the magnitude of $\mathcal{R}_f(\theta,\rho)$ is multiplied by α as

$$\mathcal{R}_f(\theta,\rho)\rightarrow\alpha\mathcal{R}_f\left(\theta,\frac{\rho}{\alpha}\right). \tag{5}$$

$P3$: *Translation*. When a shape is translated to $\mathbf{x}_0$, the Radon transform $\mathcal{R}_f(\theta,\rho)$ is translated to $\mathbf{x}_0\cdot\xi$ relative to the coordinate ρ as

$$\mathcal{R}_f(\theta,\rho)\rightarrow\mathcal{R}_f(\theta,\rho-\mathbf{x}_0\cdot\xi). \tag{6}$$

The results of the Radon transform of Fig. 1 are shown in Fig. 2. In the case of the RST transformations shown in Fig. 1(b), the Radon image shown in Fig. 2(b) is translated horizontally, scaled vertically,

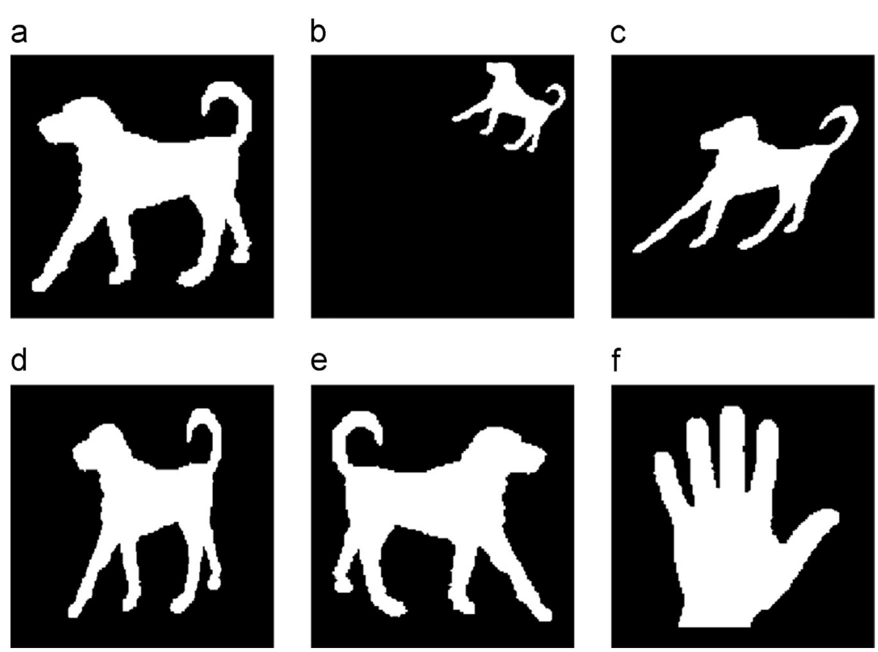

Fig. 1. (a) “Dog” image. (b) RST transformations. (c) Shearing. (d) Non-uniform scaling. (e) Reflection. (f) Original image “Hand”.