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# Rotation invariant analysis and orientation estimation method for texture classification based on Radon transform and correlation analysis

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ABSTRACT

Some recent rotation invariant texture analysis approaches such as multiresolution approaches yield high correct classification percentages, but present insufficient noise tolerance. This paper describes a new method for rotation invariant texture analysis. In the proposed method, Radon transform is utilized to project a texture image onto projection space to convert a rotation of the original texture image to a translation of the projection in the angle variable, and then Radon projection correlation distance is introduced. A *k*-nearest neighbors' classifier with Radon projection correlation distances is employed to implement texture classification and orientation estimation. Theoretical and experimental results show the high classification accuracy of this approach as a result of using the Radon projection correlation distance instead of repetitious usage of discrete transforms. It is also shown that the proposed method presents high noise tolerance and yields high accuracy in orientation estimation in comparison with Khouzani's method.



## 1. Introduction

Texture analysis plays an important role in computer vision and image processing. Over the last three decades, many texture analysis methods have been proposed, most of them assume that the texture has the same orientation, which is not always the case. Ideally, texture analysis should be invariant to translation, scaling, and rotation.

Recently, some researchers focused on rotation invariant texture analysis, and proposed various methods [1]. Kashyap and Khotanzad proposed a circular symmetric autoregressive random field(CSAR) model for texture rotation invariant analysis [2]. In their mode, for each pixel, the neighborhood points were defined on only one circle around it. This means that only the points on the circle were used. Based on Kashyap's work, Mao and Jain reported a rotation invariant symmetric autoregressive random (RISAR) model [3], in which the neighborhood points of a pixel were defined on several circles around it. Cohen et al. modeled a texture image as Gaussian Markov random field and utilized maximum likelihood technique to implement texture classification [4]. Chen and Kundu employed a quadrature mirror filter and hidden Markov model to improve the performance of Cohen's method, but increased the dimensions of the feature space [5]. Pietikainen et al. utilized a set of locally rotation invariant features based on auto-correlation and local binary patterns to describe textures [6], and their next work presented the binary patterns based on circular symmetric neighborhood sets to implement rotation invariant analysis [7]. These models implement rotation invariant analysis only based on the local details of texture images, present low correct classification percentages (CCPs) and are highly sensitive to noise.

To improve correct classification percentages, multiresolution approaches including Gabor filters, wavelet transforms, and wavelet frames have been used for rotation invariant texture analysis. Haley and Manjunath modified the Gabor model into the form of a polar 2-D Gabor wavelet [8], where each texture was modeled as a multivariate Gaussian distribution. Muneeswaran et al. proposed an approach, in which the rotation invariance was achieved by using two wavelets with their directional properties [9]. Arivazhagan et al. proposed an approach using Gabor wavelets [10]. In their approach, texture features were found by calculating the mean and variance of the Gabor filtered image. Rotation normalization was achieved by the circular shift of the feature elements. Abdulkadir et al. presented a wavelet packet neural network [11]. The proposed schema was composed of a wavelet packet feature extractor and a multi-layer perceptron classifier. Multiresolution approaches yield high correct classification percentages, but present insufficient noise tolerance [12].

In recent literatures, Radon transform has been employed in rotation invariant texture analysis. A method based on ridgelet

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transform and frequency-orientation space decomposition was proposed [13–14]. Ridgelet transform can be divided into two stages: the Radon transform stage and the 1-D wavelet transform stage. Xiao and Wu roposed a method using Radon and Fourier transforms [15]. Khouzani and Soltanian-Zadeh proposed an approach using Radon and wavelet transforms [16]. Their next work presented an orientation estimation method for rotation invariant texture analysis [17]. Radon transform is line integrals of an image, and results in a relatively high SNR increase [18]. Hence, these methods are relatively robust to additive noise, but the repetitious usage of discrete transforms may lead to inaccuracy in texture classification. This paper proposed a new method for rotation invariant texture classification and orientation estimation. In the proposed method, Radon transform is utilized to project a texture image onto projection space to convert a rotation of the original texture image to a translation of the projection in the angle variable, and then Radon projection correlation distances were determined. A $k$-nearest neighbors' classifier with Radon projection correlation distances is employed to implement texture classification and orientation estimation. Theoretical and experimental results show the high classification accuracy of this approach in terms of CCPs as a result of using the correlation analysis directly on the Radon projection instead of repetitious usage of discrete transforms. It is also shown that this method presents high noise tolerance and yields high accuracy in orientation estimation compared with Khouzani's method [17]. The outline of this paper is as follows: In Section 2, we briefly review Radon transform. The proposed approach is presented in Section 3. In Section 4, noise robustness has been proven. Experimental results are described in Section 5, and conclusions are presented in Section 6.

## 2. Radon transform and some of its properties

The Radon transform of a two-dimensional function $f(x, y)$ is defined as [18]

$$R(t,\theta)\{f(x,y)\} = \int\int f(x,y)\delta(t - x\cos\theta - y\sin\theta)\,dx\,dy \tag{1}$$

where $\delta(t)$ is the Dirac function, $t$ is the perpendicular distance of a straight line from the origin $O$ [see Fig. 1], $\theta$ is the angle between the distance vector and the $x$-axis, i.e., $\theta \in [0, \pi)$.

Radon transform has useful properties about translation, rotation as outlined in Eqs. (2) and (3).

Translation:

A translation of $f(x, y)$ results in an angle dependent translation along the spatial variable of the projection

$$R(t,\theta)\{f(x - x_0, y - y_0)\} = P(t - t_0, \theta) \tag{2}$$

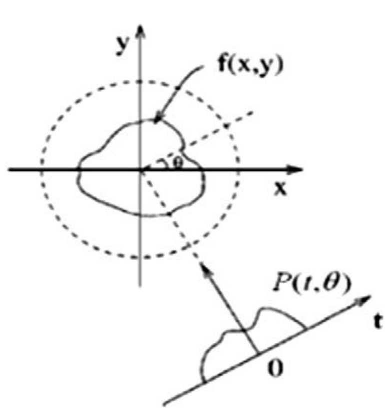


**Fig. 1.** The Radon transform of a two-dimensional function $f(x, y)$.

where $P(t, \theta)$ is the Radon transform of $f(x, y)$, $t_0 = x_0 \cos\theta + y_0 \sin\theta$.

Rotation:

A rotation of $f(x, y)$ by angle $\phi \in [0, 2\pi)$ leads to a circular shift of its Radon transform in the variable $\theta$.

$$R(t,\theta)\{f_\phi(x,y)\} = P(t, \theta + \phi) \tag{3}$$

where $f_\phi(x, y)$ is the rotated version of $f(x, y)$ with the rotation angle $\phi$.

## 3. The proposed approach

Assume that $P_1(t, \theta)$ and $P_2(t, \theta)$ are the Radon transforms of two texture images $f_1(x, y)$, $f_2(x, y)$ respectively. The correlation function of $P_1(t, \theta)$, $P_2(t, \theta)$ is given by

$$C(\tau, t) = \int_0^{2\pi} P_1(t,\theta)P_2(t,\theta+\tau)\,d\theta \tag{4}$$

**Definition 1.** Let $\tau_i$ be the value of $\tau$ corresponding to the maximum of $C(\tau, t_i)$, the Radon projection correlation distance between the two texture images is defined as

$$d(f_1(x,y), f_2(x,y)) = \frac{1}{k}\sum_{i=1}^{k}(\tau_i - \mu)^2 \tag{5}$$

where $k$ denotes the total number of $t$, and $\mu$ represents the mean value of $\tau_i$, i.e.,

$$\mu = \frac{1}{k}\sum_{i=1}^{k}\tau_i \tag{6}$$

**Claim 1.** The Radon projection correlation distance between the same texture images is zero.

**Proof.** Let $f_1(x, y)$, $f_2(x, y)$ be the same texture images, we have $P_1(t, \theta) = P_2(t, \theta)$. Then Eq. (4) can be rewritten as □

$$C(\tau, t) = \int_0^{2\pi} P_1(t,\theta)P_1(t,\theta+\tau)\,d\theta \tag{7}$$

According to the properties of correlation analysis, as $\tau = 0$, the function $C(\tau, t)$ gets its maximum for each value of $t$. Thus, we have

$$d(f_1(x,y), f_2(x,y)) = 0 \tag{8}$$

**Claim 2.** The Radon projection correlation distance between a texture image and its rotated version is zero.

**Proof.** Let $f_\phi(x, y)$ is the rotated version of a texture image $f(x, y)$ with the rotation angle $\phi$, according to the properties of Radon transform, we have □

$$P_\phi(t, \theta) = P(t, \theta + \phi) \tag{9}$$

where $P_\phi(t, \theta)$ denotes the Radon transform of $f_\phi(x, y)$. The correlation function of $P_\phi(t, \theta)$, $P(t, \theta)$ is given by

$$C(\tau, t) = \int_0^{2\pi} P_\phi(t,\theta)P(t,\theta+\tau)\,d\theta \tag{10}$$

Substituting (9) into (10), we have

$$C(\tau, t) = \int_0^{2\pi} P(t,\theta+\phi)P(t,\theta+\tau)\,d\theta \tag{11}$$

Let $\beta = \theta + \phi$, we have $\theta = \beta - \phi$, and $d\theta = d\beta$, Eq. (11) can be rewritten as

$$C(\tau, t) = \int_0^{2\pi} P(t,\beta)P(t,\beta+\tau-\phi)\,d\beta \tag{12}$$