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LETTER

New Rotation-Invariant Texture Analysis Technique Using Radon Transform and Hidden Markov Models

Abdul JALIL[†a)], **Anwar MANZAR**[††], **Tanweer A. CHEEMA**[††], *and* **Ijaz M. QURESHI**[††], *Members*

SUMMARY A rotation invariant texture analysis technique is proposed with a novel combination of Radon Transform (RT) and Hidden Markov Models (HMM). Features of any texture are extracted during RT which due to its inherent property captures all the directional properties of a certain texture. HMMs are used for classification purpose. One HMM is trained for each texture on its feature vector which preserves the rotational invariance of feature vector in a more compact and useful form. Once all the HMMs have been trained, testing is done by picking any of these textures at any arbitrary orientation. The best percentage of correct classification (PCC) is above 98 % carried out on sixty texture of Brodatz album.
key words: *radon transform, hidden Markov models, rotation-invariant features*

1. Introduction

Texture analysis, which is a an important issue for researchers, finds many applications in image processing, pattern recognition and computer vision. In all these applications generally texture features are extracted and then fed to a classifier for classification. For texture analysis methods that are translation, rotation and scale invariant [1]. Ordinary wavelet transforms have been used widely for texture analysis [2]–[5], but unfortunately they are not rotation-invariant. They capture variation only along vertical, horizontal and diagonal directions. Some attempts were made towards rotation invariant texture analysis using wavelet transform [6]–[8]. Some have also proposed preprocessing step to make the analysis invariant to rotation by defining some principal direction [9], [10]. After finding its angle they have used wavelet decomposition in that particular direction. Mao and Jain [11] have used rotation-invariant symmetric autoregressive random field model in which neighborhood points of a pixel are defined on several circles around it. This approach, however, overlooks the global information of the texture. Some approaches have used HMM [12]–[14]. Chen and Kundu [13] decompose the image into subbands using quadrature mirror filter and then model these subbands by an HMM. Unfortunately, as the number of classes (textures) increases, the performance deteriorates. Do and Vitterli [14] have used a steerable wavelet domain HMM along with a maximum likelihood solution for model parameters. But they have experimented on a limited scale and used only thirteen images from Brodatz album. In this letter, we propose a new technique using a combination of Radon Transform (RT) and one-dimensional HMM (1-D HMM). Due to directional properties of RT we capture the directional information of each texture at any arbitrary orientation. Any orientation of texture gives us one set of feature vectors (FV). These feature vectors are considered as observation vectors in order to train 1-D HMM to give us rotationally invariant representation of this texture. One set of FV for a texture trains one HMM model and so for M textures we have M number of HMM model. For testing purpose we pick up any one of these textures with any arbitrary orientation, find its feature vectors using RT and find the best match between these feature vectors and those preserved by the HMMs. We have given comparison of the proposed scheme with some other popular schemes in the literature using percentage of correct classification (PCC) as figure of merit.

2. Feature Extraction Using Radon Transform

The very first step after formulating disk image is its feature extraction using RT. A disc image is the disc shape area from the middle of the image. It has been selected before calculating the Radon transform to make the method isotropic. The RT of two-dimensional (2-D) function $f(x, y)$ is defined as [15]

$$g(s, \theta) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y)\delta(x\cos\theta + y\sin\theta - s)dxdy \quad (1)$$

where θ is the angle formed by the line along which the integral is calculated while is the perpendicular distance of this line from the origin as shown in Fig. 1. $g(s, \theta)$ is 1-D projection of $f(x, y)$ at an angle θ with distance s from the origin. In the case of an image which is discrete, the integration along a line with orientation θ and distance s from the origin changes into a summation of the gray scale values of the pixels lying along that line. It is then averaged by dividing this sum by the total number of pixels on that line. The RT of any texture is taken along lines at different orientations θ and different offsets from the origin, s. The angle θ is varying from 0^o to 180^o in discrete steps of $\Delta\theta$. For any fixed value of θ_i, there will be projections of the image along different lines at different values of s from the origin as shown in Fig. 1. The number of lines, denoted as N, determines the length of the feature vector $\mathbf{o}_i$which is given as

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[†]The author is with the Department of Computer and Information Sciences, PIEAS, Islamabad, Pakistan.
[††]The authors are with the Centre of Intelligent Systems Engineeirng IIUI, Islamabad, Pakistan.
a) E-mail: jalil@pieas.edu.pk
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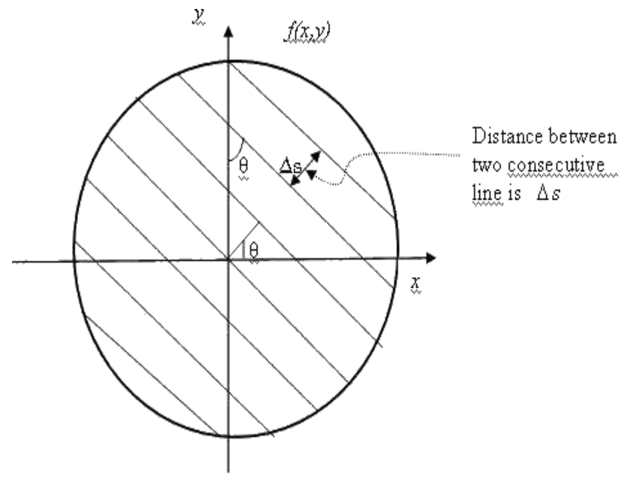

Fig. 1 Radon transform of the image.

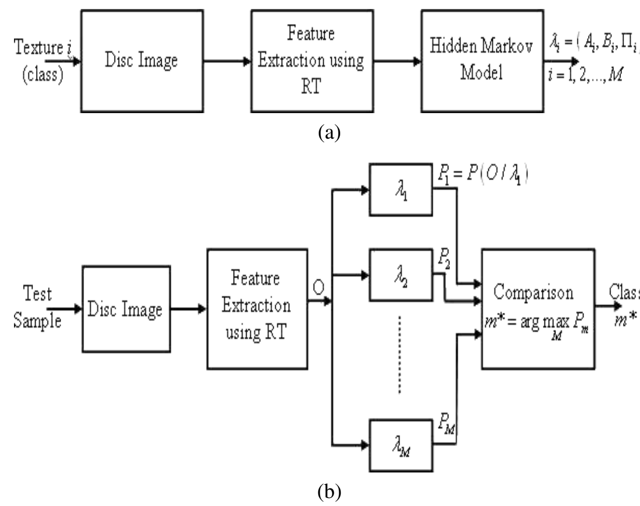

Fig. 2 (a) Block diagram for the training phase. (b)Blck diagram for the testing phase of the textures with different orientations.

$$\mathbf{o}_i = [o_{i1} o_{i2} \cdots o_{iN}]^T \tag{2}$$

where o_{ik} is value of $g(s, \theta)$ for $\theta = \theta_i$ and $s = s_k$ where $N = 2s/\Delta s$ whereby Δs is the value of the discrete step of the offset and s is the maximum offset from the origin in any direction.L is the number of such feature vectors and it is equal to the total number of discrete steps of θ between 0^o and 180^o. If we take $\Delta\theta = 2$ then L, the number of feature vectors, will be 90. These feature vectors (FV) formulate observation sequence for a particular texture. Any orientation of a texture gives us the observation sequence

$$\mathbf{O} = [\mathbf{o}_1 \mathbf{o}_2 \cdots \mathbf{o}_L]_{N \times L} \tag{3}$$

The above FV sequence $\mathbf{O}$ is for one texture at one orientation. If we take more FV sequences for a texture at different orientations, our HMM training should become more robust. This process is repeated for other textures of Brodatz Album. For M number of textures there are M number of FV sequences. For classification and testing purpose one may use direct matching through correlation between FVs.Once we have some target texture to be tested, we first find out its FV sequence. Then we may take direct correlation between FV sequence of target texture and all the reference FV sequences one by one. The one with maximum correlation shall give us the class to which the target texture belongs. Unfortunately after large experimentation we find that percentage of correct classification is less than 30%. The main reason for such adverse results is that each FV sequence belongs to same texture but at particular orientation. Now once we take a target texture and find its FV sequence at a different orientation than the orientation at which its reference FV sequence was taken, its FVs are cyclically shifted. With the result, that correlation between the reference FV of a texture at some orientation and target FV of the same texture but at some other orientation, the correlation is quite low. It is possible to improve the situation by keeping many FVs one texture at manny orientations. But this will result in massive data base and testing will becoming time consuming and expensive. This dilemma can be overcome if we use a classifier that can be trained on these FVs to capture the rotational invariance of the texture features. Discrete Hidden Markov Model (HMM) is one such strong candidate. Once HMM is trained on a set of FVs pertaining to different orientations, the HMM parameters adjusted are robust against any rotation of the texture.

3. Training of Hidden Markov Model for Classification Purpose

Figure 2 (a) is a schematic diagram giving all the steps for training phase of each texture. The observation sequence formulated in the above section is used to train an HMM model. This sequence of observations is modeled by one HMM whose salient features are given below. For elaborate review of HMMs one may see [16].

State transition probability matrix$A = a_{ij}$ where $a_{ij} = p_r(q_{t+1} = j | q_t = i)$, $i, j = 1, 2, \cdots N$ where q_t is the state at time t and N is the number of states in the model.

Observation probability density matrix $B = \{b_j(o_t)\}$ where $b_j(o_t) = p_r(o_t | q_t = j)$

Initial state probability $\Pi = \{\pi_i\}$ where $\pi_i = p_r(q_1 = i), i = 1, 2, \cdots N$

Each texture with different orientations is represented by one model which is usually denoted by $\lambda_i = (A_i, B_i, \Pi_i)$, $\imath = 1, 2, \cdots M$ where M is the number of Brodatz textures. One model is trained for each texture independently. For M textures we have M HMM models. The training program for HMM uses learning problem which states: Given observation sequence $\mathbf{O} = [\mathbf{o}_1 \mathbf{o}_2 \cdots \mathbf{o}_L]$, adjust the model parameters of the HMM $\lambda_m = (A_m, B_m, \Pi_m)$ in order to maximize $P(\mathbf{O}|\lambda_m)$ which is the probability to have these FVs $\mathbf{O}$ given the HMM,λ_m. The most popular algorithm used to solve this learning problem is Baum-Welch algorithm which is being presented as follows [16]:

First of all two variables are defined. The first variable is $\xi_t(i, j)$ which is the probability of being in state i at time t

and in state j at time $t+1$.

$$\begin{aligned}\xi_t(i,j) &= p(q_t = i, q_{t+1} = j|\mathbf{O},\lambda)\\ &= \frac{p(q_t = i, q_{t+1} = j, \mathbf{O}|\lambda)}{p(\mathbf{O}|\lambda)}\\ &= \frac{p(q_t = i, q_{t+1} = j, \mathbf{O}|\lambda)}{\sum_{i=1}^{N}\sum_{j=1}^{N} p(q_t = i, q_{t+1} = j, \mathbf{O}|\lambda)}\end{aligned} \tag{4}$$

The second variable is $\gamma_t(i)$ which is the a posterior probability is given as

$$\begin{aligned}\gamma_t(i) &= p(q_t = i|\mathbf{O},\lambda)\\ &= \frac{p(q_t = i, \mathbf{O}|\lambda)}{\sum_{i=1}^{N} p(q_t = i, \mathbf{O}|\lambda)}\\ &= \frac{\alpha_t(i)\beta_t(i)}{\sum_{i=1}^{N}\alpha_t(i)\beta_t(i)}\end{aligned} \tag{5}$$

where α_s and β_s are forward and backward variables respectively, defined as follows

$$\alpha_t(i) = P(o_1, o_2, \cdots, o_t|\lambda) \tag{6}$$

$$\beta t(i) = P(o_{t+1}, o_{t+2}, \cdots, o_T|q_t, \lambda) \tag{7}$$

Having calculated ξ_s and γ_s and using (4) and (5), the HMM parameters are updated according to the following equations

$$\overline{\pi} = \gamma_1(i), 1 \le i \le N \tag{8}$$

$$\overline{a_{ij}} = \frac{\sum_{t=1}^{T-1}\xi_t(i,j)}{\sum_{t=1}^{T-1}\gamma_t(i)}, 1 \le i \le N,\ 1 \le i \le N \tag{9}$$

$$\overline{b_j(k)} = \frac{\sum_{\substack{t=1\\ o_t=v_k}}^{T}\xi_t(i,j)}{\sum_{t=1}^{T-1}\gamma_t(i)}, 1 \le i \le N,\ 1 \le i \le O \tag{10}$$

The training is done off-line and only once. For each new texture, a new class is considered and so a new model is trained. There is no need to retrain the others. A particular tolerance factor is given in order to ensure proper training and convergence of the HMM. All the vectors put together capture directionality of the image in all direction from 0 to 180 degrees. The HMM trained on these vectors preserves the rotational invariance. Even if we take the same image at some other rotation, its feature vectors are still the same, except that they are cyclically rotated. If an HMM is trained on these cyclically rotated feature vectors, the parameters of HMM i.e. $\lambda_m = (A_m, B_m, Pi_m)$, come out to be still the same. Moreover, once testing is done, we are not using exactly the same orientation of the images from which we extracted the feature vectors and trained the HMM. In fact we used different orientations of the image, extracted the feature vectors and used evaluation problem for carrying out the testing. Percentage of correct classification (PCC) is used as figure of merit for testing the proposed algorithm.

4. Testing and Classification

Figure 2 (b) gives the steps for testing phase of any texture with any orientation. We use evaluation problem [16] of HMM for testing and classification purpose. The evaluation problem states: Given the observation sequence or set of vectors $\mathbf{O} = [\mathbf{o}_1\mathbf{o}_2\cdots\mathbf{o}_L]$ and an HMM λ_m, how do we efficiently compute $P(\mathbf{O}|\lambda_m)$ which is the probability of the observation sequence generated by the given model, λ_m. In testing, we find out the observation sequence $\mathbf{O} = [\mathbf{o}_1\mathbf{o}_2\cdots\mathbf{o}_L]$ by using RT on the texture at any orientation being tested for classification. Then evaluate $P(\mathbf{O}|\lambda_m)$ for all$m = 1, 2\cdots, M$. Finally the class is found by using maximum likelihood principle.

$$m^* = arg\left\{\underbrace{max}_{\mathbf{m}} P(\mathbf{O}|\lambda_m)\right\} \tag{11}$$

This unknown texture is m^* of the Brodatz album.

5. Simulation

For simulation purpose, we have used sixty textures taken from Brodatz album (D1-D60) as given in Fig. 3. Each texture is treated as a class. The RT of every texture is taken at constant discrete steps between 0^o to 180^o. The discrete steps of θ have been taken as $6^o, 4^o, 3^o$ and 2^o , thus making number of feature vectors L = 30, 45, 60 and 90, respectively. The number of states has been given as N =1,2, 3, 4, and 6 in order to see its effect on PCC. For testing we use all 60 textures at 20 arbitrary orientations which become 1200 in total. From Table 1, we observe that as the number of features, L, increases, the value of PCC becomes higher and higher. The states in HMM do not have any explicit physical meaning. One cannot say that increase or decrease of states would result in a better model in terms of PCC. For larger values of L (60 and 90), N = 5 seems to be the best choice in terms of PCC. Although one may increase the number of

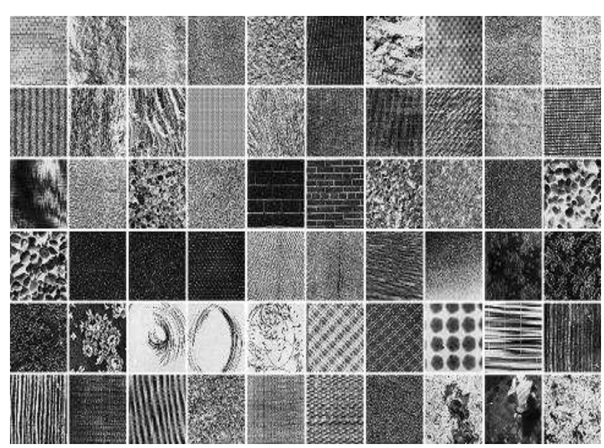

Fig. 3 First 60 textures from Brodatz album (D01-D60). First row D01-D10, second row D11-D20, and so on, and sixth row D51-D60.

Table 1 1200 test samples have been carried out along with their associated PCC %.

L N	1	2	3	4	5	6
30	92.05	93.66	95.75	95.50	95.00	94.08
45	93.55	94.00	96.91	96.41	96.83	95.83
60	94.81	95.70	97.91	97.33	97.66	97.00
90	94.99	95.50	98.16	97.83	98.25	97.83

Table 2 Comparison of the best results of the proposed method with some of the methods from the literature.

Methods from the Literature			Proposed Methods
Chen and Kundu	Khouzani and Zadeh	Ojala et al	
(10 textures)	(25 textures)	(16 textures)	(60 textures)
93.33%	97.90%	95.80%	98.250%

training feature vectors in order to get a better HMM for any texture, but it becomes computationally cumbersome. The best value of PCC achieved in this letter is 98.25%. The comparison of our result has been given with some techniques in the literature in the form of Table 2. While the proposed technique gives 98.25%, it has been tested on first 60 textures from Brodatz album which were isotropic, as well as, anisotropic. Chen and Kundu [13] which gives 95 has been tested on 10 textures only. Ojal et. al. [17] gives PCC as 97.90% and is tested on 16 textures while Jafri and Khouzani [10] has 97.4 PCC which is tested on 25 textures only. Moreover, textures used by these authors for testing are mainly anisotropic.

6. Conclusion

The proposed technique, which is rotation invariant, uses Radon transform to capture the feature vectors and HMMs for training and classification. In this new technique there is no need to defining a principal direction which is used in anisotropic textures [18]. This technique has the advantage of being equally valid for anisotropic as well as isotropic textures. The RT based HMM has an advantage over wavelet transform based HMM. The two dimensional wavelet transform 2DWT captures features only in the horozontal, vertical and diagonal direction [10] while RT captures the directional features of the texture at all angles from 0^o to 180^o. Thus HMM trained on these FVz preserve rotational invariance which HMMs trained on wavelet based FVs do not. Lastly, we see this proposed technique giving better PCC than the ones compared with in the papers [10], [13], [17].

References

[1] J. Zhang and T. Tan, "Brief review of invariant texture analysis methods," Pattern Recognit., vol.35, pp.735–747, 2002.
[2] T. Chang and C.C.J. Kuo, "Texture analysis and classification with tree-structure wavelet transform," IEEE Trans. Image Process., vol.2, no.4, pp.429–441, Oct. 1993.
[3] M. Unser, "Texture classification and segmentation using wavelet frames," IEEE Trans. Image Process., vol.4, no.11, pp.1549–1560, 1995.
[4] A. Liane and J. Fan, "Texture classification by wavelet packet signature," IEEE Trans. Pattern Anal. Mach. Intell., vol.15, no.11, pp.1186–1191, Nov. 1993.
[5] J.R. Smith and S.F. Chang, "Transform features for texture classification and discrimination in large image databases," Proc. IEEE ICIP, 1994.
[6] D. Charalampidis and T. Kasparis, "Wavelet-based rotational invariant roughness features for texture classification and segmentation," IEEE Trans. Image Process., vol.11, no.8, pp.825–837, Aug. 2002.
[7] R. Manthalkar, P.K. Biswas, and B.N. Chatterji, "Rotation and scale invariant texture features using discrete wavelet packet transform," Pattern Recognit. Lett., vol.24, pp.2455–2462, 2003.
[8] G.M. Haley and B.S. Manjunath, "Rotation-invariant texture classification using a complete space-frequency model," IEEE Trans. Image Process., vol.8, no.2, pp.255–269, 1999.
[9] C.-M. Pun and M.-C. Lee, "Log-polar wavelet energy signatures for rotation and scale invariant texture classification," IEEE Trans. Pattern Anal. Mach. Intell., vol.25, no.5, pp.590–603, May 2003.
[10] K. Jafari-Khouzani and H. Soltanian-Zadeh, "Rotation invariant multiresolution texture analysis using radon and wavelet transforms," IEEE Trans. Image Process., vol.14, no.6, pp.783–795, June 2005.
[11] J. Mao and A.K. Jain, "Texture classification and segmentation using multiresolution simultaneous autoregressive models," Pattern Recognit., vol.25, no.2, pp.173–188, 1992.
[12] W.-R. Wu and S.-C. Wei, "Rotation and gray-scale transform-invariant texture classification using spiral resampling, subband decomposition, and hidden Markov model," IEEE Trans. Image Process., vol.5, no.10, pp.1423–1434, Oct. 1996.
[13] J.-L. Chen and A.A. Kundu, "Rotation and gray scale transform invarianttexture identification using wavelet decomposition and hidden Markov model," IEEE Trans. Pattern Anal. Mach. Intell., vol.16, no.2, pp.208–214, Eeb. 1994.
[14] M.N. Do and M. Vetterli, "Rotation invariant characterization and retrieval using steerable wavelet-domain hidden Markov models," IEEE Trans. Multimedia, vol.4, no.4, pp.517–526, Dec. 2002.
[15] A.K. Jain, Fundamentals of Digital Image Processing, Pearson Education, 1989.
[16] L.R. Rabiner, "A tutorial on hidden Markov models and selected applications in speech recognition," IEEE Proc., vol.77, no.2, pp.257–286, Feb. 1989.
[17] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," IEEE Trans. Pattern Anal. Mach. Intell., vol.24, no.7, pp.971–987, July 2002.
[18] K. Jafri-Khouzani and H. Soltanian-Zadeh, "Radon transform orientation estimation for rotation invariant texture analysis," IEEE Trans. Pattern Anal. Mach. Intell., vol.27, no.6, pp.1004–1008, June 2005.