ROTATIONALLY-BLIND TEXTURE CLASSIFICATION USING FRAME SEQUENTIAL APPROXIMATION ERROR CURVES

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ABSTRACT

In this paper we report a new set of rotation invariant features for texture classification. The proposed feature set is based on principles of image approximation using multiresolution (MR) frame decompositions. Features are obtained from sequential approximation error curves (SAECs) obtained from the reconstruction error of texture approximations. These approximations are formed by the sequential addition of frame coefficients in decreasing magnitude order. Feature selection consist of taking points along the SAEC. It is found that SAECs are oblivious to rotation, allowing the generation of *rotationally blind* feature sets. Hence, the computational complexity of classification systems is reduced by eliminating the need for feature post-processing (e.g., DFT-encoding) to achieve rotation invariance (RI). We test the rotationally-blind feature sets for texture classification using different MR frame decompositions and data sets. We show that the proposed SAEC-based feature set achieve classification rates competitive with other schemes using a smaller feature set.

Index Terms— Rotation invariance, texture, frames, directional filter bank

1. INTRODUCTION

Texture is an inherent property of objects and scenes. It is considered one of the key elements used by our visual system. Texture is one of the descriptors established by the MPEG-7 standard for Content Based Image Retrieval (CBIR) systems. From a digital image analysis perspective, classification and segmentation algorithms based on texture have been an important and prolific area of research over the last decades.

The objective of texture analysis is to use texture to describe the contents of an image using a compact set of features. An important problem in texture analysis is to find feature sets that are compact and have strong discriminative properties that allow accurate differentiation over many classes of textures. Additionally, it is highly desirable to design feature sets that are robust to variations in illumination, scale, perspective (e.g., stretching and skewing) and orientation (e.g., rotation).

To achieve rotation invariance (RI) a few schemes have been proposed over the years. One of the early approaches was the use of circular auto-regressive (AR) models [1] and Gaussian-Markov random fields (GMRFs) [2]. The combination of GMRFs with wavelets was proposed by Porter and Canagarajah in [3]. Ojala, et al. [4] reported RI feature sets using uniform Local Binary Patterns (LBPs).

Multichannel approaches are particularly well suited for RI texture analysis. Greenspan, et al., [5] used a Steerable Pyramid and DFT-encoding to obtain RI energy-based features. Haley and Manjunath [6] used an analytical Gabor representation to derive a complete feature set based on frequency magnitude, phase, and autocorrelations of the subband coefficients. Hill, et al., [7] used the dual-tree complex wavelet transform (DT-CWT) with DFT-encoding. More recently the use of the Bamberger Directional Filter Bank (BDFB) and Bamberger Pyramids has been extensively studied for RI texture classification [8].

In this paper we present a new set of RI features for texture classification. The proposed scheme derives from the multichannel paradigm. In our case, a texture is decomposed using multiresolution (MR) frames. The novel methodology analyzes the evolution of the reconstruction error obtained from texture approximations. These approximations are formed by the sequential addition of frame coefficients in decreasing magnitude order. We show that these features provide good feature sets for classification with the additional property of being blind to rotation distortions.

2. MEASURING TEXTURE FROM MULTIRESOLUTION FRAMES

MR Frames are redundant signal representation which provide more flexibility than MR bases like wavelets. In a recent tutorial paper [9] the properties and advantages of frames for analysis tasks were described in detail. Frames have been used for texture analysis for a long time, where they are commonly known as multichannel decompositions [10, 11]. In general it has been found that frames outperform bases because they provide more stable channel statistics and energy estimates.

In this paper we develop our initial results using a Bamberger Pyramid which has been successfully applied in RI texture classification [8]. More specifically, we use a Fully Undecimated Bamberger Pyramid (FUBP), a highly redundant MR frame. Multichannel decompositions that split the frequency plane in directionally selective channels can achieve RI using a DFT-encoding step [5, 7, 8]. In this paradigm, a feature vector $\mathbf{f} = [\ e_1 \quad e_2 \quad \ldots \quad e_M\ ]^T$, is formed for the set of directional subbands at each resolution. The feature set consists of the energies e_i for each channel. The ℓ_1 and ℓ_2 norms have been employed as energy estimates. Next the DFT of the feature vector $\mathbf{f}$ is computed as $\mathbf{F} = \mathbf{W}\mathbf{f}$, where $\mathbf{W}$ is the DFT matrix. A rigid texture rotation is encoded in $\mathbf{f}$ as a circular shift which is encoded in $\mathbf{F}$ as a complex exponential factor. Hence an RI feature vector is achieved by taking the magnitude of the first $M/2-1$ coefficients of $\mathbf{F}$.

A well known property of natural images is that they are compressible or close to sparse under different representations like wavelets, wavelet frames, FUBP, etc. This property implies that most of the image information is captured on a set of K *significant* coefficients such that $K << N$, where N is the total number of coefficients in the decomposition. In Figure 1 a curve depicting reconstruction error vs. the number of reconstruction coefficients for the Lena image. The FUBP is used as the image decomposition. The coefficients are added sequentially to the reconstruction following a descending magnitude order. As expected, the reconstruction error drops to zero rapidly. For conciseness we identify these curves as Sequential Approximation Error Curves (SAEC).

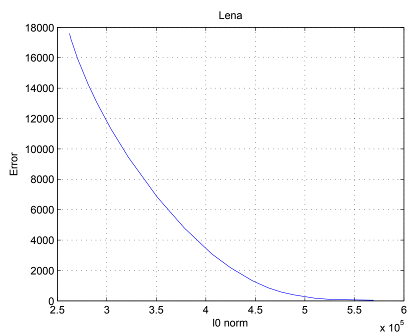

Fig. 1. SAEC for Lena showing good compressibility properties.

Large coefficients capture the significant perceptual components of an image like edges and low frequency detail. A natural question to ask is if textures would exhibit compressible behavior. This would be highly dependent on the texture statistical and structural properties. We evaluate texture compressibility by calculating the SAECs for several textures from the Brodatz database using the FUBP as the MR decomposition. We present the SAECs for d4 (pressed cork), d29 (beach sand), d55 (straw mating), d103 (loose burlap) in Figure 2. We note that the curves have a fast decay initially, but at some point a knee is reached making the decay to zero slower that in the Lena image case. A possible explanation for the evolution of these curves is that the overall structure of the structure is captured by a small percentage of the significant coefficients (fast decay), and the randomness and "feel" of the textures is captured by the majority of the coefficients (slow decay). We conclude that textures are partially compressible. It is also significant to note that SAECs vary significantly among the textures.

Next, we perform a similar experiment using the USC database of rotated textures [6]. The data set consists of 13 texture classes rotated at seven different angles. We are interested on evaluating the effect of rotation on the SAECs for a given texture. We calculated the SAECs for each 640×640 texture. We show the curves for the brick texture rotated at 0, 60 and 120 degrees in Figure 3. Surprisingly, the SAECs are invariant to rotation. This behavior was observed for all 13 texture classes over all angles. This suggests that frame coefficients steer the texture information proportionally to the rotation angle across orientations and scales in such away that the energy of sequential reconstructions is invariant to rotations.

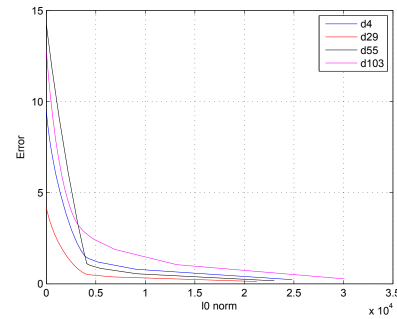

Fig. 2. Comparison of approximation error as a function of coefficients used in the reconstruction for different Brodatz textures.

3. ROTATIONALLY BLIND TEXTURE FEATURES

Considering the more specific problem of texture classification, SAECs provide information on the structural and statistical content of the texture as a function of reconstruction error. The curves show strong variations in their shapes for different textures but remain invariant to rotation. In fact, we could say that SAECs are oblivious or blind to texture rotation. A set of rotationally blind features has the advantage of removing any post-processing steps needed to achieve RI. For multichannel schemes this could be the DFT-encoding step or other more computationally expensive methods [6].

We propose to form a feature set by taking points along SAECs. A computational drawback is that we would need to do a large number of reconstructions as a function of the total number of coefficients. To reduce computation requirements of SAECs the following simplifications are proposed. First, a sequential thresholding scheme is used where the SAEC is evaluated over a small set of points. Second, the approximation errors can calculated in the frame domain avoiding the calculation of the inverse frame transform. An algorithm for SAEC computation is presented in Figure 4.

Some points about the algorithm follow. The matrix $\mathbf{\Phi}$ represents a general MR transform. The sequence of thresholds is generated as a function of the maximum magnitude coefficient M, and a scaling factor α where $0 < \alpha < 1$. The function $\Theta_T(\cdot)$ implements a hard thresholding function with threshold T. The expression $\| \bar{\mathbf{Y}} \|_0$ denotes the ℓ_0 norm of $\bar{\mathbf{Y}}$ (number of non-zero coefficients).

The algorithm returns the SAEC information in the arrays $e[i]$

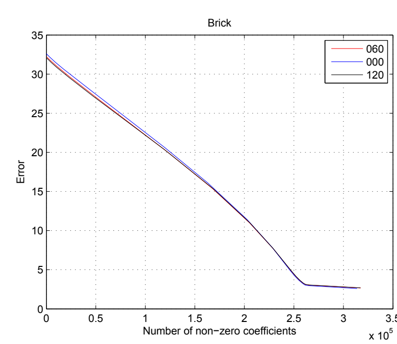

Fig. 3. l0 norm plots for 3 textures at different angles to show features are rotation invariant

Input: X ▷ sample texture
Output: $e[i]$, $l_0[i]$
$\mathbf{Y} = \mathbf{\Phi}^T \mathbf{X}$ ▷ image transformation
$M = max(|\mathbf{Y}|)$
$\alpha = 0.95$
$i = 0$
while $\alpha > 0$ **do**
  $T = \alpha M$
  $\bar{\mathbf{Y}} = \Theta_T(\mathbf{Y})$
  $e[i] = \frac{\|\mathbf{Y} - \bar{\mathbf{Y}}\|_2}{L}$
  $l_0[i] = \| \bar{\mathbf{Y}} \|_0$
  $\alpha = \alpha - 0.05$
  $i = i + 1$
end while

Fig. 4. Algorithm for SAEC calculation

and $l_0[i]$. In this case, 19 points are produced for each array. In order to make the SAECs better suited for feature extraction, at this time we consider only the error array $e[i]$. This allows us to align all the error values over uniformly spaced points along the abscissa. Figure 5 shows the SAECs produced by the algorithm for different textures. As in the previous case, the plots show that SAECs vary considerably from one texture class to another. Note that the abscissa is given in term of $1 - \alpha$.

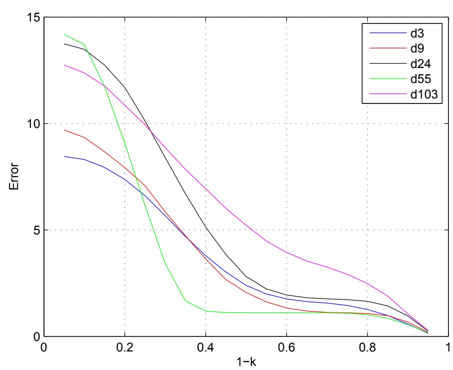

Fig. 5. SAECs for different Brodatz textures using the algorithm from Figure 4. The plot shows reconstruction error vs. 1-α

4. TEXTURE CLASSIFICATION

In this section we evaluate the proposed feature set. In order to compare our proposed features with other feature sets we choose the Bayes distance classifier. This classifier has been a extensively tested in texture classification [12, 10, 6, 13, 8]. The Bayes distance is given by

$$d_k(\mathbf{f}) = (\mathbf{f} - \mathbf{m}_k)^T \mathbf{C}_k^{-1} (\mathbf{f} - \mathbf{m}_k) + \log(\det(\mathbf{C}_k)) \quad (1)$$

where $\mathbf{m}_k$ and $\mathbf{C}_k$ correspond to the mean feature vector and covariance matrix for the kth texture class. These parameters are obtained using Maximum Likelihood estimates from training data. Classification is performed by assigning test vector $\mathbf{v}$ to class k^* according to

$$k^* = \arg\min_k \{d_k(\mathbf{f})\} \quad (2)$$

for $k = 1, 2, \ldots, N_K$, where N_K is the number of texture classes in our classification system.

To study the effect of different frame decompositions we present results using the Fully-Undecimated Bamberger Pyramid (FUBP), the Undecimated Discrete Wavelet Transform (UDWT) using the 9-7 filters and three resolution levels, and the Steerable Pyramid (SP). The FUBP and SP implement similar frequency plane partitioning with four pyramid levels and eight directional bands on the two mid-band pyramid levels. We note that the FUBP is fully redundant while the SP has a lower redundancy factor.

We present three texture classification scenarios. First we test the feature set without considering rotation. For our experiments we use the set of 30 textures from Brodatz database previously tested in other works [12, 13]. Each 512×512 texture is subdivided into 100 overlapping subimages of size 64×64. The SAEC for each subimage is calculated using the algorithm from Figure 4. From the 100 subimages, 50 are used for training and 50 are used for testing. Hence we have 1500 subimages for training and the remaining 1500 for testing.

Classification is performed over the testing set. Feature vectors are formed by picking points from the SAEC. We use feature vectors of dimension four, six, seven and eight, where the points are evenly space along the 19 elements of the array $e[i]$. The classification results for the frame representations are tabulated in Table 1. We observe that for the FUBP and UDWT there is a gradual increase in classification rate up to seven or eight features. Beyond eight features the classification performance decreases (not shown). The best classification performance was given by the UDWT using eight features. The BDFB follows closely, but the lower redundancy of the UDWT makes it a more attractive choice. The SP has significantly lower performance compared to the other two MR frames.

Table 1. Correct classification rates (in %) for Brodatz textures using SAECs

Num. Features	FUBP	UDWT	SP
4	86.73	90.47	84.6
6	92.20	95.80	87.2
7	94.80	95.80	85.8
8	94.73	96.13	85.0

These results are lower than those reported using the BDFB with 99.62% classification [13], and the Tree Structured Wavelet Transform with 98% correct classification [12]. However, in these two cases, the classification results were obtained with 10 features.

For the second scenario, we test the proposed feature set for rotation invariance. We use the texture data from [6]. We use 13 texture classes with six rotation angles ($0°$, $30°$, $60°$, $90°$, $120°$ and $150°$). Each texture of size 512×512 pixels is divided into sixteen 128×128 subimages. Eight subimages from every texture are used for training and the remaining 8 are used for testing. Hence, we use $624 (13 \times 8 \times 6)$ images for training and 624 for testing. Classification results are shown in Table 2. The best results are given by the FUBP and UDWT using six features. We obtain 95% correct classification rate in both cases. There are some additional observations to make from this table. First, the SP fails at providing good results; this is a somewhat unexpected result give the directional selectivity of this representation and its previous use in RI classification [5]. Further investigation is needed to understand these results. Second, the UDWT performs as well as the FUBP. This is an unexpected result given the limited directional selectivity of the UDWT. In fact the UDWT cannot be used with DFT-encoding to achieve RI features.

Table 2. Rotation invariant correct classification rates (in %) using SAECs

Num. Features	FUBP	UDWT	SP
4	93.75	93.11	59.62
6	95.51	95.83	45.19
7	93.27	74.52	39.42
8	20.67	81.73	32.69

These classification rates are comparable to other works using the same data set. Haley and Manjunath [6] achieved 96.8% correct classification using 204 features. Rosiles, et al. [8] obtained 96.96% correct classification using 12 features. In conclusion, the proposed feature set achieves competitive rotation invariant classification using significantly less features and without the need of feature post-processing steps to generate RI features.

Finally, in our third scenario we evaluate the FUBP features when the training set consist of a textures at a single angle, and the testing set consists of texture samples rotated at angles different from the training set. We use the same data set of rotated textures tested previously. Each texture class has 16 128×128 training images and 80 testing images per class. The experiment in performed six times changing the training angle at each instance. Classification results are shown in Table 3 for 4,6,7 and 8 features. The best classification rate of 94.69% was obtained using 4 features and the 30° training set. We note that for seven and eight features the results show large swings in classification rate. The causes of these variations is currently under study, but there seems to be a strong dependance on on the points selected along the SAEC curve to form the feature vectors.

Table 3. Classification rates for the FUBP using only images at one angle for training (in %).

# feats.	0°	30°	60°	90°	120°	150°
4	86.2	94.6	92.1	88.6	80.5	83.17
6	88.9	92.6	92.6	90.8	87.9	87.40
7	10.7	24.8	26.3	90.9	25.8	27.02
8	22.1	19.1	92.0	19.8	25.4	86.73

5. CONCLUSIONS

In this paper we have presented a novel set of rotationally blind features for texture classification. The features are obtained from Sequential Approximation Error Curves (SAECs). The key finding is that these curves are blind to rigid rotations on textures. This property generates rotation invariant features without additional feature post-processing like DFT-encoding. This property reduces the computational complexity of texture classification systems. Experimental results show that the SAEC feature sets have competitive classification performance for the UDWT and FUBP with respect to well known schemes. Moreover, the number of SAEC features needed to achieve these results are significantly less than the competing schemes. We consider the performance of the UDWT-SAEC features for RI classification to be remarkable, given the excellent classification results despite the limited directional selectivity of the UDWT. This implies that other factors not related to the orientation selectivity of the frame play a role to generate RI features. Important questions remain open for exploration in the future. First, a theoretical framework is needed to understand the RI properties of SAECs. Second, an optimal feature selection scheme for SAECs needs to be developed as indicated by the variability and instability of the classification results in some cases. Finally, we need to explore the invariance of SAECs to other geometrical distortions like scaling and perspective.

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