A NEW IMAGE TEXTURE EXTRACTION ALGORITHM BASED ON MATCHING PURSUIT GABOR WAVELETS

M. Yaghoobi[1], *H.R. Rabiee*[1], *M. Ghanbari*[1, 2], *M.B. Shamsollahi*[3]
[1]Digital Media Lab (http://www.aictc.com/dml), Sharif University of Technology
[2] Department of Electronic Systems Engineering, University of Essex, UK
[3]Department of Electrical Engineering, Sharif University of Technology

ABSTRACT

Feature vector extraction, based on local image texture, is a primitive algorithm for many other applications, like segmentation, clustering and identification. If these feature vectors are a good match to the human visual system (HVS), we can expect to get the appropriate results by using them. Gabor filters has been used for this purpose successfully. In this paper we introduce a novel refinement, with the use of Matching Pursuit (MP) to improve the Gabor based texture feature extractor. With this improvement, we show that the separability of different textures will increase. Another consideration in this work is computation complexity. Therefore, we limit the basis function set to reduce MP computation time.

1. INTRODUCTION

Texture processing is the fundamental part of many image processing algorithms. With using texture features, we can segment images based on textural properties of different regions. Although there is no mathematical definition for texture, we can express it as a kind of pattern repetition in image regions or local image frequency components. In this paper, local frequencies of image are used as the texture indicators.

Many feature based algorithms, at the first step extract "feature vectors" based on the image characteristic in the frequency domain [1-2]. The algorithms in this class mainly operate in the frequency space, instead of the special space.

Normally, if one wants to segment the image with texture based feature vectors, distances between different classes in the feature space are very important. When within class distances are small and between class distances are large, relatively, we could get relatively better results with simple features [4].

Many of the recent feature extractors use filter banks for texture segmentation [1-4]. In this kind of feature extractors, after the subband filtering operations, a nonlinear operator acts on the filtered image. In some applications, for achieving better results, a smoothing filter will be applied after that. Band-selective filter banks are the appropriate choices for texture feature extraction. These filters could effectively capture the texture patterns in images; therefore they are appropriate for texture extraction [4]. One important branch of these filter banks are Log-Polar Gabor filters [2]. For best adaptation with human visual system, we should compensate constant part (DC) of them and gain Log-Polar Gabor-Wavelet. (Mother Wavelet is admissible if it has zero mean, with good attenuation in infinity).

The goal in this paper is to present a novel refinement to Gabor-Wavelet with Matching Pursuit to get better class separation in texture feature extraction. The idea of using Matching Pursuit (MP) in signal processing applications, which was presented for the first time in [3], could find a semi-optimal expansion of signals with the predefined set of functions (Dictionary). Due to greedy nature of this algorithm we must incorporate some changes to reduce its computation time. To achieve this we have used the expansion coefficients for feature generation instead of direct filtering. Therefore, the resulting feature space has a more separable characteristic. We use fisher criteria and some sample textures to demonstrate the effectiveness of this algorithm.

The survey literature and our new algorithm are presented in sections 2 through 6. Section 7 illustrates the experimental results and in section 8 the conclusions are presented.

2. FILTER BASED FEATURE VECTOR EXTRACTION

There are three important types of texture feature extractors, Statistical, Model based and Filter based [4]. In this paper, we consider the filter based approach. As shown in figure 1, for feature generation we have three steps:

1. Filter bank: Input image should be filtered:

$$I(m,n) * h(m,n) == \sum_{m'=-\infty}^{+\infty} \sum_{n'=-\infty}^{+\infty} I(m',n').\overline{h(m-m',n-n')} \quad (2.1)$$

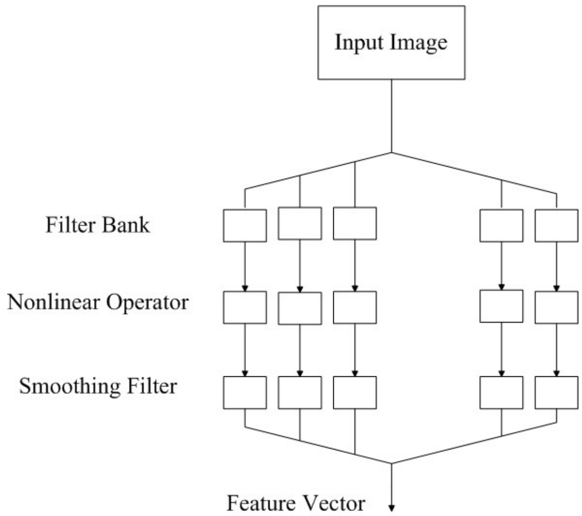

Figure 1: Filter-bank texture feature extraction

Where I(m,n) and *h(m,n)* are input image and filter function, respectively.

2. Nonlinear operator: this operator is used for compensation of the sign of filtered images and making the required similarity to human visual system [1]. For this purpose sigmoid function, square function and absolute value could be used. We have used the absolute value measure in this research.

3. Smoothing filters: nonlinear operators introduce some high frequency artifacts, which can be compensated by using smoothing filters. Low pass filters, that are chosen based on appropriate filter bandwidths, are suitable for this purpose.

The feature vectors are generated by assigning the corresponding pixels of the smoothing filters output. Therefore, dimension of feature vectors are equal to the number of filter banks.

Gabor-Wavelet filters are chosen at least for two reasons:

I. Best time-frequency localization [2].

II. High similarity with human visual system [5].

It is shown in [6] that this type of filters is appropriate for texture feature extraction. This will be discussed in the next section.

3. GABOR-WAVELET FILTER

As mentioned in the previous sections, Gabor-Wavelet filters are appropriate for image texture discrimination, therefore we introduce them briefly. The canonical form of Gabor functions is as follows:

$$G(x,y) = Ne^{-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)} .e^{-i(\omega_0 x)} \quad (3.1)$$

Where N $,\sigma_x$ $,\sigma_y$ $,\omega_0$ are normalization coefficient, variance in *x* and *y* directions and modulation frequency, respectively. Moreover, one can drive the desired functions from (3.1) with affine transformation. The most common forms of these transforms that are used in our algorithm are as follows:

A) Rotation around origin: the typical rotation matrix operator can be used for this purpose:

$$R_L^{\theta} = \begin{pmatrix} Cos\theta & Sin\theta \\ -Sin\theta & Cos\theta \end{pmatrix} \quad (3.2)$$

That is the left side operator for $\begin{pmatrix} x \\ y \end{pmatrix}$ vector.

B) Transferring: transfer in space domain is shown by this notation:

$$G_{x_0,y_0}(x,y) = G(x-x_0, y-y_0) \quad (3.3)$$

C) Scaling:

$$G_a(x,y) = \frac{1}{\sqrt{ab}} G\left(\frac{x}{a},\frac{y}{b}\right) \quad (3.4)$$

Where $\frac{1}{\sqrt{ab}}$ is the normalization factor and for simplicity we chose *a=b*.

With the first two operators, we obtain the general form of Gabor-Wavelet that is used in many previous works.

$$G_{a,x_0,y_0}(x,y) = Ne^{-\frac{1}{2}\left(\frac{(xCos\theta+ySin\theta)^2}{\sigma_x^2}+\frac{(-xSin\theta+yCos\theta)^2}{\sigma_y^2}\right)} .e^{-i(\omega_0 xCos\theta+\omega_0 ySin\theta)} \quad (3.5)$$

Four directions (for θ) and all dyadic scales (2^s) are sufficient for making a complete basis set for image representation [2]. We chose 4 directions, but non dyadic, with less number of scales for our algorithm (Because reconstruction is not important for feature extraction).

4. MATCHING PURSUIT

Matching Pursuit (MP) is a sequential algorithm for finding a semi-optimal solution for function expansion based on a redundant dictionary*.

$$f(x) \in \underset{k\in K}{Span}\{g_k(x)\} \Rightarrow f(x) = \sum_{k\in K} a_k g_k(x) \quad (4.1)$$

Where $g_k(x)$ is the basis function (Gabor-Wavelet in this paper) and $\{a_k\}$ are the coefficients of the expansion. Clearly, finding the optimal solution is an NP-hard problem in MP, therefore we settle for a semi-optimal solution.

The first step in MP is to compute the inner product of input function and the basis functions in the dictionary

* Collection of basis function

(atoms). We select the atom that has the greatest value (by other means the atom that best matches to the input function) for the second step.

$$f = \langle f, g_{\gamma_0} \rangle g_{\gamma_0} + R^1 f \quad , f \in L^2(C^n) \qquad (4.2)$$

Where $\langle f, g_{\gamma_0} \rangle$ is inner product of f and g_{γ_x} and $R^1 f$ is residual in the first step. Because g_{γ_0} is orthogonal to $R^1 f$, we have:

$$\|f\|^2 = |\langle f, g_{\gamma_0} \rangle|^2 + \|R^1 f\|^2 \qquad (4.3)$$

Therefore, energy of f ($\|f\|^2$) is reduced with the value of $|\langle f, g_{\gamma_0} \rangle|$.

In the next iteration, f will be replaced by $R^1 f$ and the process repeats with new values. In regards to the energy reduction of $R^k f$ in kth iteration, the algorithm is stable and we can continue the algorithm until we reach the desired residual energy (error energy):

$$f = \sum_{n=0}^{N-1} \langle R^n f, g_{\gamma_n} \rangle g_{\gamma_n} + R^N f \qquad (4.4)$$

$$\|f\|^2 = \sum_{n=0}^{N-1} |\langle R^n f, g_{\gamma_0} \rangle|^2 + \|R^N f\|^2 \qquad (4.5)$$

When the dictionary is not complete, after sufficient number of iterations, we get the projection of input signal on span of the dictionary. Therefore the residual function is orthogonal to the dictionary span.

5. FISHER CRITERIA FOR CLASS SEPARATION

In order to compare the different feature spaces, we need a criterion to show separability of different classes. Linear discriminators and fisher criteria are the classical tools to achieve this goal.

Fisher transform is a linear transform that maps the feature space to a hyperplane [9]. This hyperplane is used to maximize between-class distances and minimize within-class variances.

$$z = w^T x_M \qquad (5.1)$$

$$F(w) = \frac{w^T S_B w}{w^T S_W w} \qquad (5.2)$$

S_B and S_w are between class and within class scatter matrices:

$$S_W = C_{x_{M1}} + C_{x_{M2}} \qquad (5.3)$$

$$S_B = (m_1 - m_2)(m_1 - m_2)^T \qquad (5.4)$$

Where $C_{x_{m_i}}$ and m_i are covariance matrix and mean value of ith class, respectively.

For maximizing $F(w)$, we must select w as follows:

$$w = S_W^{-1}(m_1 - m_2) \qquad (5.5)$$

Here $F(w)$ is named "fisher criteria" value to show the classes separation (in this case two classes).

6. FEATURE VECTOR GENERATION WITH MP

In Section 2, we introduced the feature vector extraction process using filter banks. Because MP is not a filter-bank, we should present an algorithm to generate these vectors. An algorithm is presented for this purpose previously in [7]. In that algorithm, Gaussian envelopes of each atom are used to generate images for different type of atoms. For example, atoms with the same scale and orientation, are reconstructed (with Gaussian envelope) in separate images. Then one must assign the absolute value of each image pixel to the corresponding feature vector element. We showed in [8] that if we use MP expansion with large number of iterations the resulted feature vectors are better than Gabor filter bank feature vectors.

In this paper we present a new method to produce vectors that needs less MP iterations (therefore less computation). Two changes, made in the previous method, are as follows:

I) Image texture is presented with medium size Gabor functions. It means that wide atoms and narrow atoms don't have textural information. Wide atoms mostly present image darkness and brightness and narrow atoms represent the edges in the image. With selecting such a dictionary we reduce the computation time (wide atoms need more multiplication in convolution computation).

II) If we use MP with small number of iterations, we couldn't get better results than Gabor-Wavelet. So we present a new feature vector to compensate for this problem. In the modified feature vector we place Gabor-Wavelet feature vector in the first part and the MP based vector is placed afterward. For two last components of the feature vector, we use residual image and reconstructed image of the input. In the experimental results section we will see the class separation improvement in the feature space.

7. EXPRIMENTAL RESULTS

Comparing different feature spaces need to have a mathematical criterion that we discussed in the previous section. We need some sample texture images to build the feature space .Therefore we chose 4 different textures of Brodatz album [10] (these textures are shown in Figure 2).

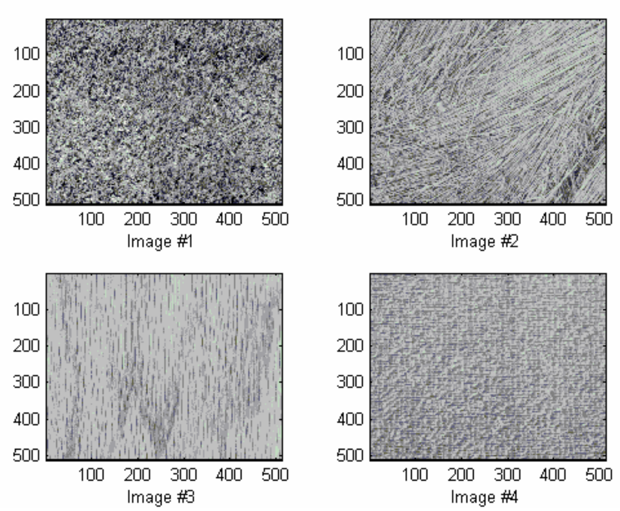

Figure 2: Sample texture image

These textures are D9, D15, D68 and D84. As it can be seen in Figure 2, mean values of all images are approximately equal and the differences between these images are their texture pattern. Therefore, for discrimination of this type of images we must use texture-based features. We would like to compare Gabor-Wavelet feature vector and our new refined feature vector. Therefore, we have computed the fisher criteria for the every two selected images of these sets and for the above feature spaces. We show the corresponding results in Tables 1 and 2.

Table 1: Fisher criteria for refined feature vector
(With scale of 10000)

Image #	1	2	3	4
1		6.5834	14	7.5636
2	6.5834		7.6071	5.2095
3	14	7.6071		8.5043
4	7.5636	5.2095	8.5043	

Table 1: Fisher criteria for Gabor-Wavelet feature vector
(With scale of 10000)

Image #	1	2	3	4
1		5.6444	12	6.6615
2	5.6444		5.0732	4.2692
3	12	5.0732		7.9449
4	6.6615	4.2692	7.9449	

We could clearly see improvement in each pair of the respected cells in those tables. Improvement in feature criteria guaranties more class separation with linear discriminators. But, as we have stated in the previous sections, this criteria leads to a better class separation in most classifiers.

8. CONCOLUSION

A new feature vector generator has been introduced in this paper that is able to refine the Gabor based algorithms. We showed that with the use of matching pursuit expansion, we could improve the linear discrimination. Our matching pursuit feature vectors outperform our previous method [8]. But considering the computation complexity (reducing iteration), Gabor feature vector shows better results. Of course, with mixing these vectors, we will obtain the best results. Finally, we showed that this refinement is enhanced with "Fisher Discrimination Criterion".

9. ACKNOWLEDGMENT

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