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Image compression scheme based on curvelet transform and support vector machine

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ABSTRACT

In this paper, we propose a novel scheme for image compression by means of the second generation curvelet transform and support vector machine (SVM) regression. Compression is achieved by using SVM regression to approximate curvelet coefficients with the predefined error. Based on characteristic of curvelet transform, we propose a new compression scheme by applying SVM into compressing curvelet coefficients. In this scheme, image is first translated by fast discrete curvelet transform, and then curvelet coefficients are quantized and approximated by SVM, at last adaptive arithmetic coding is introduced to encode model parameters of SVM. Compared with image compression method based on wavelet transform, experimental results show that the compression performance of our method gains much improvement. Moreover, the algorithm works fairly well for declining block effect at higher compression ratios.

1. Introduction

From early days to now, the basic objective of image compression is the reduction of size for transmission or storage while maintaining suitable quality of reconstructed images. For this purpose, many compression techniques, i.e., scalar/vector quantization, differential encoding, predictive image coding, transform coding have been introduced. Among all these, transform coding is most efficient especially at low bit rate (Iqbal, Javed, & Qayyum, 2007).

In the past few years, wavelets and related multi-scale representations pervade all areas of signal processing (Abdallah, Hamza, & Bhattacharya, 2007; Liu, Yeh, Chen, & Hsu, 2004; Mallat, 1989). The reason for the success of wavelets is the fact that wavelet bases represent well a large class of signals, and therefore allow us to detect roughly isotropic features occurring at all spatial scales and locations. However, there has been a growing awareness to the observation that wavelets may not be the best choice for presenting natural images recently. This observation is due to the fact that wavelets are blind to the smoothness along the edges commonly found in images. In other words, wavelet cannot provide the 'sparse' representation for an image because of the intrinsic limitation of the wavelet. Hence, recently, some new transforms have been introduced to take advantage of this property. The ridgelet and curvelet transforms (Candès & Donoho, 2000) are examples of two new transforms, which are developed to sparsely represent natural images. They are very different from wavelet-like systems that have been developed. Curvelet and ridgelet take the form of basis elements which exhibit very high directional sensitivity and are highly anisotropic. The fast discrete curvelet transform (FDCT) (Candès & Donoho, 2004; Candès, Demanet, Donoho, & Ying, 2005) improves upon earlier implementation – based upon the first generation of curvelet – in the sense that they are conceptually simpler, faster and far less redundant.

SVM is a learning system that uses a hypothesis space of linear functions in a high-dimensional feature space to estimate decision surfaces directly rather than modeling a probability distribution across training data (Perez-Cruz, Afonso-Rodriguez, & Giner, 2003). It uses support vector (SV) kernel to map the data from input space to a high-dimensional feature space, which facilitates the problem to be processed in linear form. SVs are samples that have non-zero multipliers at the end of optimization process which is referred to equation. SVM always finds a global minimum because it usually tries to minimize a bound on the structural risk, rather than the empirical risk (Burges, 1998; Burges & Schoclkopf, 1997; Seo, 2007; Trontl, Smuc, & Pevec, 2007).

In this paper, we present a novel scheme for image compression based on the second generation curvelet transform and support vector machine (SVM) regression. In the proposed method, the original image is first decomposed into curvelet coefficients by using the second generation curvelet transform. Then different scales of quantized coefficients are selected for arithmetic coding and entropy coding. The lowest sub-band is encoded by differential pulse code modulation (DPCM) for including a large amount of image energy. The finer scale sub-bands are compressed by SVM regression, which approximates the curvelet coefficients using a fewer support vectors and weights. And some of the finer scale sub-bands are

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discarded directly due to containing a little amount of energy and having little noticeable effect on the image quality.

The remainder of the paper is organized as follows: Sections 2 and 3 discuss the theoretical basis of curvelet and SVM regression. In Sections 4 and 5, implement of the compression algorithm is described in detail. Section 6 gives the experimental results. Conclusion and orientations for future works are discussed in Section 7.

2. The second generation of curvelet transform

The curvelet transform has gone through two major revisions. The first curvelet transform (commonly referred to as the "curvelet 99" transform now) used a complex series of steps involving the ridgelet analysis of the radon transform of an image (Candès & Donoho, 2000). The performance was exceedingly slow. Soon after their introduction, researchers developed numerical algorithms for their implementation (Donoho & Duncan, 2000), and reported on a series of practical successes (Starck, Murtagh, Candès, & Donoho, 2003).

Now curvelets have actually been redesigned in an effort to make them easier to use and understand. In this new method, the use of the ridgelet transform was discarded, thus reducing the amount of redundancy in the transform and increasing the speed considerably. The second generation curvelet transform is considerably simpler, faster and less redundant than the "curvelet 99" transform.

2.1. Continuous-time curvelet transforms

We work throughout in two dimensions, i.e., R^2, with spatial variable x, with ω a frequency-domain variable, and with r and θ polar coordinates in the frequency-domain.

We start with a pair of windows $W(r)$ and $V(t)$, which we will call the "radial window" and "angular window", respectively. These are smooth, non-negative and real-valued, with W taking positive real arguments and supported on $r \in (1/2, 2)$ and V taking real arguments and supported on $t \in [-1, 1]$.

For each $j \geqslant j_0$, we introduce the frequency window U_j defined in the Fourier domain by

$$U_j(r,\theta) = 2^{-3j/4} W(2^{-j}r) V\left(\frac{2^{\lfloor j/2 \rfloor}\theta}{2\pi}\right) \tag{1}$$

where $\lfloor j/2 \rfloor$ is the integer part of $j/2$.

According to the formula (1), U_j is a polar "wedge" window, as show in Fig. 1.

Define the waveform $\varphi_j(x)$ by means of its Fourier transform. We may think $\varphi_j(x)$ as a "mother" curvelet in the sense that all curvelets at scale 2^{-j} are obtained by rotations and translations of $\varphi_j(x)$. Introduce the equispaced sequence of rotation angles $\theta_l = 2\pi \cdot 2^{-\lfloor j/2 \rfloor} \cdot l$ with $l = 0, 1, \ldots$ such that $0 \leqslant \theta_l < 2\pi$, and the sequence of translation parameters $k = (k_1, k_2) \in Z^2$.

With these notations, we define curvelets by

$$\varphi_{j,l,k}(x) = \varphi\left(R_{\theta_l}\left(x - x_k^{j,l}\right)\right) \tag{2}$$

where R_θ is the rotation by θ radians.

A curvelet coefficient is then simply the inner product between an element $f \in L^2(R^2)$ and a curvelet $\varphi_{j,l,k}$,

$$c(j,l,k) := \langle f, \varphi_{j,l,k}\rangle = \int_{R^2} f(x)\overline{\varphi_{j,l,k}(x)}\,dx \tag{3}$$

Reconstruction formula is

$$f = \sum_{j,l,k} \langle f, \varphi_{j,l,k}\rangle \varphi_{j,l,k} \tag{4}$$

2.2. Digital curvelet transforms

In the continuous-time definition (3), the window U_j smoothly extracts frequencies near the dyadic corona and near the angle. Coronae and rotations are not especially adapted to Cartesian arrays. Instead, it is convenient to replace these concepts by Cartesian equivalents; here, "Cartesian coronae" based on concentric squares (instead of circles) and shears, as show in Fig. 2.

Define the "Cartesian" window

$$\widetilde{U}_j(\omega) := \widetilde{W}_j(\omega) V_j(\omega) \tag{5}$$

$\widetilde{W}_j(\omega)$ is a window of the form

$$\widetilde{W}_j(\omega) = \sqrt{\varphi_{j+1}^2(\omega) - \varphi_j^2(\omega)}, \quad j \geqslant 0 \tag{6}$$

where φ is defined as the product of low-pass one-dimensional windows

$$\varphi_j(\omega_1, \omega_2) = \varphi(2^{-j}\omega_1)\varphi(2^{-j}\omega_2) \tag{7}$$

The function φ obeys $0 \leqslant \varphi \leqslant 1$, might be equal to 1 on $[-1/2, 1/2]$, and vanishes outside of $[-2, 2]$. The digital curvelet transform coefficient is obtained by

$$c(j,l,k) = \int \hat{f}(\omega)\widetilde{U}_j\left(S_{\theta_l}^{-1}\omega\right) e^{i\left\langle S_{\theta_l}^{-T} b, \omega x\right\rangle} d\omega \tag{8}$$

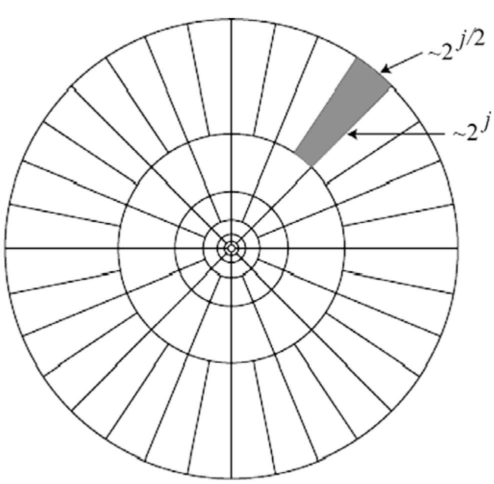

Fig. 1. Continuous curvelet support in the frequency domain.

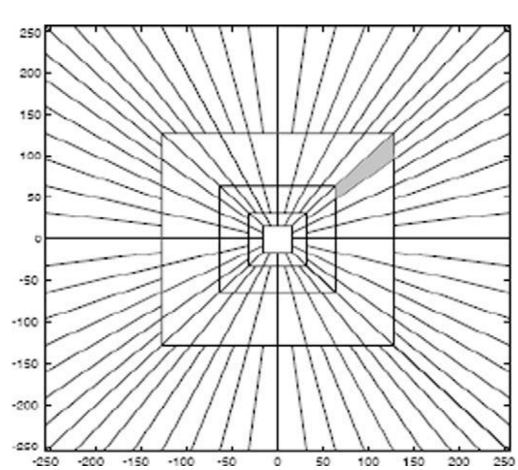

Fig. 2. Digital curvelet tiling of space and frequency.