

Combining Support Vector Machine Learning with the Discrete Wavelet Transform and Contourlet Transform in Image Compression

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Abstract:

In this paper, the results of combining support vector machine (SVM) learning with discrete wavelet transform and contourlet transform in image compression are compared. The algorithm combines SVM learning with the discrete wavelet transform (DWT) and contourlet transform (CCT) of the image. An SVM selects the minimum number of training points, called support vectors which ensure modeling of the data within the specified level of accuracy. It is this property that is exploited as the basis for an image compression algorithm. Now, the SVMs learning algorithm performs the compression in a spectral domain of DWT and CCT coefficients.

Peak signal to noise ratio (PSNR) is computed for the images compressed using wavelet and contourlet transforms. Results show that contourlet transform based image compression is more effective in capturing smooth contours (due to anisotropy property) than wavelet transform based compression.

Keywords—Image Compression; Support Vector Machine(SVM); Discrete Wavelet Transform(DWT); Contourlet Transform(CCT); (Peak Signal to Noise Ratio)PSNR

I. INTRODUCTION

The main aim of image compression is to reduce the redundancy and remove unnecessary information in the image in order to store or transmit the data in an efficient form. There are two kinds of image compression, lossy and lossless compression. Lossy compression is also known as noisy or irreversible compression, as some amount of data is lost or in other words all original data cannot be obtained when the image is uncompressed. This technique is commonly used in compressing multimedia data such as audio or video, in applications such as tele-videoconferencing. Lossless compression is also known as noiseless or reversible compression because no data is lost and all the original data can be obtained when the image is uncompressed. Lossless technique is used document and medical imaging and facsimile transmission.

In image compression, the wavelet transform produces less blocking artifacts than the DCT. They perform well in image de-noising too. However, 2D wavelet transform is a tensor-product implementation of the 1D wavelet transform. It provides local frequency representation of image regions over a range of spatial scales. It does not represent 2D singularities effectively. Therefore it does not work well in retaining the

directional edges in the image, and it is not sufficient in representing the contours that are not horizontal and vertical [6].

The Contourlet transform (CTT) is a true 2-D geometrical image based transform, which was introduced by M.N.Do and M. Vetterli [5]. It overcomes the difficulty in exploring the geometry in digital images due to the discrete nature of the image data. It possesses the important properties of directionality and anisotropy which wavelet do not possess. It can represent a smooth contour with fewer coefficients compared with wavelets [6].

SVM are used for classification, regression, and density estimation. Typically, the training vectors are mapped to a higher-dimensional space using a kernel function, and the linear separating plane with the maximal margin between classes is found in this space. SVM training involves optimizing over several parameters. SVMs can also be applied to regression problems. An input parameter to a SVM is an insensitivity zone (tolerance). The goal of the SVM is to produce an output which is within this insensitivity zone.

In the algorithm presented in this paper, SVM learning is applied after mapping the image to frequency domain. The PSNR and MSE of the compressed images when SVM learning is applied to image after mapping it to frequency domain using DWT and CCT are compared. These quality measurement values are also drawn for images compressed using DWT and CCT without the application of SVM

learning. As the results show the image compressed by applying SVM learning to contourlet co-efficient have a better quality compared to others.

This paper is organized as follows: Section II discusses the basics of Discrete Wavelet Transform (DWT). Section III has basics of contourlet transform (CCT). Section IV gives an overview of image compression using SVM. Section V describes the implementation. The results are included in section VI, and conclusions are drawn in section VII.

II. DISCRETE WAVELET TRANSFORM

The wavelet transform is widely used in signal processing and image compression. Image coding standard, JPEG-2000, is based on DWT. Wavelet transform decomposes a signal into a set of basis functions. These basis functions are called wavelets. All wavelets are obtained from a single wavelet, called mother wavelet by dilations and shifting. The DWT has been introduced as a highly efficient and flexible method for sub-band decomposition of signals. In DWT, signal energy concentrates on specific wavelet co-efficients. This characteristic is useful for compressing images.

Wavelets convert the image into a series of wavelets that can be stored more efficiently than pixel blocks. Wavelets have rough edges; they are able to render pictures better by eliminating the blockiness. In DWT, a time-scale representation of the digital signal is obtained using digital filtering techniques.

The signal to be analyzed is passed through filters with different cut-off frequencies at different scales. A 2-D DWT can be seen as a 1-D wavelet scheme which transform along the rows and then a 1-D wavelet transform along the columns. The 2-D DWT operates in a straight forward manner by inserting array transposition between the two 1-D DWT. The rows of the array are processed first with only one level of decomposition. This essentially divides the array into two vertical halves, with the first half storing the average coefficients, while the second vertical half stores the detail coefficients. This process is repeated again with the columns, resulting in four sub-bands.

Image consists of pixels that are arranged in two dimensional matrix, each pixel represents the digital equivalent of image intensity. In spatial domain, adjacent pixel values are highly correlated and hence redundant. In order to compress images, these redundancies existing among pixels needs to be eliminated. DWT processor transforms the spatial domain pixels into frequency domain information that are represented in multiple sub-bands, representing different time scale and frequency points. One of the prominent features of JPEG2000 standard, providing it the resolution scalability, is the use of the 2D-DWT to convert the image samples into a more compressible form.

III. CONTOURLET TRANSFORM

The contourlet transform (CCT) is the two-dimensional extension of the wavelet transform using multi-scale and directional filter banks. The contourlet expansion is composed of basis images oriented at various directions in multiple scales, with flexible aspect ratio. The main difference between contourlets and other multi-scale directional systems is that the

contourlet transform allows for different and flexible number of directions at each scale, while achieving nearly critical sampling.

Contourlet representation contains basis elements oriented at variety of directions much more than few directions that are offered by other separable transform technique. One way to obtain a sparse expansion for images with smooth contours is first apply a multistage wavelet like transform to capture the edge points, and then local directional transform to gather the nearby edge points into contour segments. With this insight, one can construct a double filter bank structure where the laplacian pyramidal (LP) filter is used to capture the point discontinuities, followed by a directional filter bank (DFB) to link point discontinuities into linear structures.

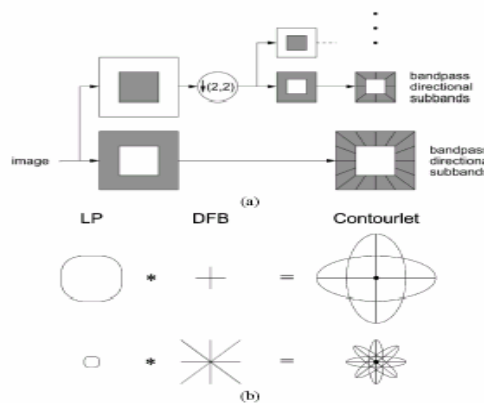


Fig 1 PDFB Filters

The LP decomposition at each level generates a down sampled low pass version of the original and the difference between the original and the prediction, resulting in a band pass image. This process is continued to obtain a set of band-pass filtered images. Thus the Laplacian pyramid is a set of band pass filters (as shown in Fig 2).

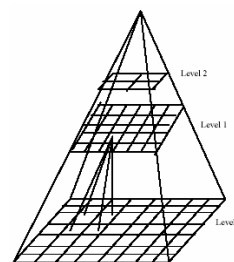


Fig 2 Laplacian Pyramid

The directional filter bank is a critically sampled filter bank that can decompose images into any power of two's number of directions (as shown in Fig 3.).

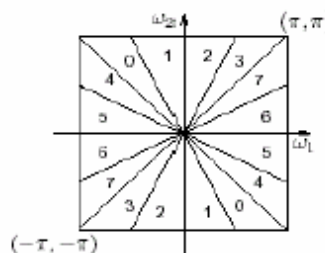


Fig 3. Directional Filter

The overall result is an image expansion using basic elements like contour segments, and thus it is named contourlet transform.

The combination of this double filter bank is named pyramidal directional filter bank (PDFB).

IV. IMAGE COMPRESSION USING SVM

SVM is an algorithm introduced by Vapnik and his coworkers [7]. It is originally developed for the problems of classification and tries to find the optimal hyper-plane by solving a linearly constrained quadratic programming (QP) problem. Then, with the introduction of ϵ -insensitive loss function, SVM has been extended to solve a nonlinear regression estimation problem, called the SVR. Moreover, the SVR approach with the ϵ -insensitive loss function can use a small subset of the training data, namely the SVs, to approximate the unknown functions within a tolerance epsilon band.[10]

The general regression problem is to approximate an unknown function $f(x)$ from a given set of (input, output) data $(x_1, y_1), \dots, (x_l, y_l) \in X \times Y$, where $X \subseteq \mathbb{R}^d$ and $Y \subseteq \mathbb{R}$. In the SV methods, the nonlinear regression problem in the input space \mathbb{R}^d is considered as a linear one $f(x) = w^T \phi(x) + b$ in some feature space F that induced by the nonlinear mapping $\phi: x \rightarrow \phi(x)$, where $w \in F$ is a normal vector, and $b \in \mathbb{R}$ a bias term. Thus the standard formulation of the SVR given by Vapnik is stated as the following (1), where ξ_i, ξ_i^* and C are, respectively, positive slack variables to deal with training samples with a prediction error larger than ϵ ($\epsilon > 0$) and the penalization applied to these samples. The $C > 0$ determines the trade-off between the flatness of f and the amount up to which deviations larger than ϵ are tolerated. This corresponds to dealing with the so-called ϵ -insensitive loss function $|\xi|_\epsilon$ described by (2).

$$\min \frac{\|w\|^2}{2} + C \sum_{i=1}^l (\xi_i + \xi_i^*),$$

$$s. t. \begin{cases} y_i - f(x_i, w) \leq \epsilon + \xi_i, \\ f(x_i, w) - y_i \leq \epsilon + \xi_i^*, \\ \xi_i, \xi_i^* \geq 0, \end{cases} \quad (1)$$

$$|\xi|_\epsilon = \begin{cases} |\xi| - \epsilon & \text{if } |\xi| > \epsilon, \\ 0 & \text{if } |\xi| \leq \epsilon. \end{cases} \quad (2)$$

By introducing a dual set of variables, a Lagrange function is constructed from the objective function and the corresponding constraints. It can be shown that this function has a saddle point with respect to the primal and dual variables at the solution. Then the primal problem is typically transformed into the dual optimization problem, as shown in (3). And its solution is given by (4), where α_i and α_i^* are the Lagrange multipliers corresponding to ξ_i and ξ_i^* , l is the number of SVs and $k(x_i, x)$ is the kernel function. The Gaussian RBF kernels $k(x_i, x) = k(x_i, x, \sigma) = \exp(-\|x_i - x\|^2 / 2\sigma^2)$ are very popular for their universal approximation in the widely used kernels. Note that only samples with non-zero Lagrange α_i and α_i^* are counted in the solution and are called support vectors. The immediate advantage of the method is that good approximating functions can be obtained with a (relatively) small set of SVs, leading to the concept of sparsity and, in turn, to the idea of inherent compression.[10]

$$\max - \sum_{i,j=1}^l (\alpha_i - \alpha_i^*) (\alpha_j - \alpha_j^*) k(x_i, x_j) / 2 - \epsilon \sum_{i=1}^l (\alpha_i + \alpha_i^*) + \sum_{i=1}^l y_i (\alpha_i - \alpha_i^*)$$

$$s. t. \begin{cases} \sum_{i=1}^l (\alpha_i - \alpha_i^*) = 0 \\ 0 \leq \alpha_i, \alpha_i^* \leq C \end{cases} \quad (3)$$

$$f(x) = W^T \phi(x) + b = \sum_{i=1}^l (\alpha_i - \alpha_i^*) k((x_i - x) + b), \quad (4)$$

$$0 \leq \alpha_i, \alpha_i^* \leq C$$

V. IMPLEMENTATION

Input image is decomposed into approximate and detailed coefficients by employing DWT. After decomposing the image into sub bands, each sub band represents the image in different frequency range. Most of the energy will be compacted in low frequency sub bands as it is sensitive to human eyes. Image reconstruction is possible by using only the low frequency wavelet coefficients, however, to get a better quality of picture SVM regression is used to compress other sub-bands which represents the finer details, this SVM regression is applied to coefficients of finer detail sub-bands to approximate the wavelet coefficients using support vectors and weights.

The same is done for the input image which is decomposed into different sub-bands according to contourlet transform. The PSNR value is calculated for each of these images compressed using DWT and CCT, and conclusions are drawn.

VI. RESULTS

In this section, experimental results are tabulated. The PSNR values for images compressed using DWT or CCT and with or without SVM are compared.

The SVM parameters used are: gaussian kernel is used, ϵ is 0.001 and $C = 1000$. With these parameters the PSNR value for the given image is found to be maximum. The results are tabulated for different images in Table 1.

Image	PSNR (in dB)			
	DWT	CCT	DWT with SVM	CCT with SVM
Lena.png	24.65	26.43	27.68	31.05
Zoneplate.png	22.57	24.77	25.69	30.88
Peppers.png	26.42	27.21	28.86	30.91

Table 1. PSNR values for different images compressed using DWT or CCT

As an example, lena.png images are shown. Fig(4) shown is the original image. Fig (5) and Fig (6) is the 2 level decomposition using contourlet transform and wavelet transform respectively, Fig (7) and Fig (8) represent the compressed images using contourlet and dwt transform respectively. Fig(9) and Fig (10) are the images compressed combining CCT and SVM, and DWT and SVM respectively.



Fig 4. Lena.png (original image)



Fig 9. CCT with SVM Compression



Fig 10. DWT with SVM Compression

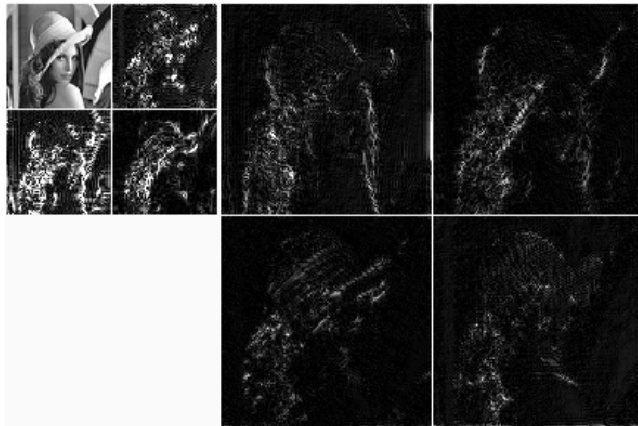


Fig 5 Contourlet coefficients

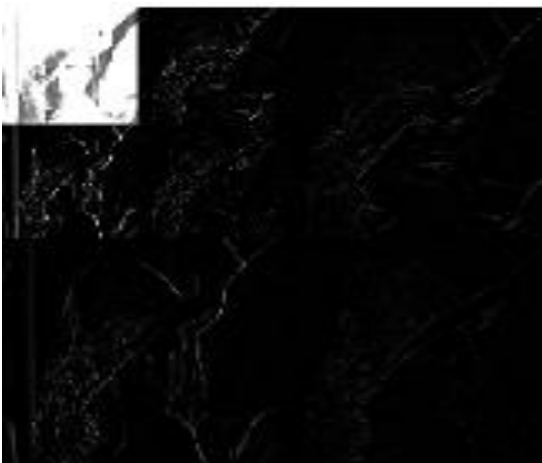


Fig 6. Wavelet coefficients



Fig 7. CCT compression



Fig 8. DWT Compression

VII. CONCLUSION

We have presented image compression algorithm which takes advantage of SVM learning. The algorithm exploits the trend of the DWT/CCT coefficients after the image has been transformed from the spatial domain to the frequency domain via the DWT/CCT. SVM learning is used to estimate the DWT/CCT coefficients within a predefined error. The SVM is trained on the absolute magnitude of the DWT/CCT coefficients as these values require less SVs to estimate the underlying function. The net result of the SVM learning is to compress the DWT/CCT coefficients much further.

We have presented results showing that by combining SVM learning with CCT produces better results compared to SVM learning applied to DWT. The results show that PSNR value is better for the former method than the latter. Also by applying SVM learning to CCT/DWT coefficients the PSNR and MSE values are found to be improved.

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