

Discrete Anamorphic Stretch Transform for Image and Video Compression

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Abstract:

To deal with the exponential increase of digital data, new compression technologies are needed for more efficient presentation of information. We introduce a physics-based transform that enables image compression by increasing the spatial coherency. We also present the Stretched Modulation Distribution, a new density function that provides the recipe for the proposed image compression. Experimental results show pre-compression using our method can improve the performance of JPEG 2000 format. And also enables video compression by taking video as of series of individual images or “frames and Discrete Anamorphic Stretch Transform (DAST) is operated on the images one by one followed by secondary compression such as JPEG image compression algorithm.

Keywords:

Anamorphic transform, diffractive data compression, dispersive data compression, image compression, physics based data compression, space-bandwidth engineering, warped stretch transform.

I.INTRODUCTION:

Image compression leading to efficient representation of information is critical for dealing with the storage and transmission of high resolution images and videos that dominate the internet traffic. JPEG [1] and JPEG 2000 [2] are the most commonly used methods for image compression. To reduce the data size, JPEG and JPEG 2000 use frequency decomposition via the discrete cosine transform (DCT) [1] or wavelet transform [2] as well as the frequency dependence of the human psychovisual perception.

In this letter, we introduce the Discrete Anamorphic Stretch Transform (DAST) and its application to image compression. DAST is a physics-inspired transformation that emulates diffraction of the image through a physical medium with specific nonlinear dispersive property. By performing space-bandwidth compression, it reduces the data size required to represent the image for a given image quality. This diffraction-based compression is achieved through a mathematical restructuring of the image and not through modification of the sampling process as in compressive sensing (CS) [3]–[7]. Our technique does not need feature detection and is non-iterative.

DAST is a nonlinear transform, both in terms of amplitude and in terms of the phase operation. Here we introduce the discrete-time representation of the Anamorphic Stretch Transform and its generalization to n -th order and to two dimensional data. We also present the Stretched Modulation Distribution, a new discrete density function that provides the recipe for the proposed image compression. It explains graphically, how the transform reshapes the image and how image compression is achieved. Experimental demonstrations study the effect of DAST on image coherence and bandwidth and show its application to enhance JPEG format when used as pre-compression.

II.DAST + JPEG FOR IMAGE COMPRESSION:

In DAST image is represented by two dimensionally discrete spatial variables n and m by $B[n, m]$. It is first passed through the DAST and then is uniformly re-sampled (down-sampled) at a rate below the Nyquist rate of original image. To recover the original image from the compressed one, the compressed image is first up-sampled and then inverse DAST is applied to recover the original image.

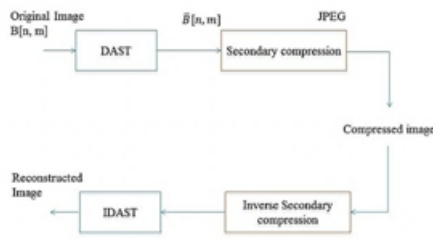


Fig. 2.1: DAST+JPEG for image compression

This method warps the image such that as the increases the image spatial size proportional bandwidth is reduced. This increases the spatial coherence and reduces the amount of data needed to represent the image. Mathematically, DAST is defined as follows:

$$\bar{B}[n, m] = \left| \sum_{K_1, K_2=-\infty}^{\infty} K(n - K_1, m - K_2) \cdot B(K_1, K_2) \right|^N$$

Where $||$ is the absolute operator. For DAST operation, the original image is convolved with DAST Kernel $K[n, m]$, and then the N -th power magnitude of the result is

$$K[n, m] = e^{j \cdot \phi[n, m]}$$

To compress the image, the nonlinear phase profile $\phi[n, m]$ should be chosen such that DAST applies a spatial warp to the image with a particular profile described below. To describe the applied warp, we define the DAST Local Frequency (LF) profile as the 2D spatial gradient (derivative) of the DAST Kernel phase function. LF is the equivalent of time domain instantaneous frequency but in 2D spatial domain. For better understanding on selection of $\phi[n, m]$ or the DAST Kernel, we introduce a mathematical tool to describe the image bandwidth and the resulting image spatial size after it is subjected to the transformation. To this end, we define discrete-domain Stretched Modulation (Sm) Distribution as follows:

$$S_M[n, m, p, q] = \sum_{k_1, k_2} \bar{B}[k_1, k_2] \cdot \bar{B}^*[p + K_1, q + K_2]$$

$$K[k_1, k_2] \cdot K^*[p + k_1, q + k_2] \cdot e^{j \cdot (n \cdot k_1 + m \cdot k_2)}$$

where the symbol $*$ represents complex conjugation. S_M or Anamorphic Distribution provides a tool for engineering the image brightness space-bandwidth product through proper choice of $\phi[n, m]$.

The distribution can be described as the cross-correlation of the complex output image spectrum with its spatially shifted version. It shows spatial and spectral distributions of image intensity after diffractive propagation through a dispersive medium that imparts a nonlinear phase operation described by the Kernel. To show use of the Distribution to design the DAST Kernel $K[n, m]$, we have plotted it for the Lena image. For simplicity, we consider one randomly chosen line scan of the image.

At $n=0$ (i.e. spatial shift of zero) the Distribution becomes the autocorrelation of the brightness spectrum and its width gives the output intensity bandwidth. Also the maximum absolute amount of spatial shift that complex cross-correlation has non-zero values is image spatial size. The S_M Distribution provides a powerful and intuitive tool for identifying the general shape of the Kernel those results in image compression.

However, the image size is proportionally stretched. This offers no compression. Similarly, if the Distribution is warped in the manner in Fig. 2.2(d), corresponding to sub linear LF profile shown in (a), the space-bandwidth product is expanded and the data size is increased. However, if we cause a nonlinear tilt (i.e. a warp) having the shape shown in Fig. 2.2(e), corresponding to super linear LF profile shown in (a), the bandwidth is reduced but the size is not stretched proportionally. In this case, one achieves image compression. In Fig. 2.2(f), we have plotted the Sm Distribution corresponding to another randomly chosen lines can in the Lena image confirming the generality of operation on randomly chosen lines can. As suggested by Sm Distribution plots, super linear LF profile in DAST Kernel results in image compression. One of the simplest (e.g. least number of parameters) yet effective such profiles is the tangent function:

$$LF[n, m] = a_1 \cdot \tan(b_1 \cdot n) + a_2 \cdot \tan(b_2 \cdot m)$$

Where a_1, b_1, a_2 and b_2 are real-valued numbers? This LF profile results in the following DAST Kernel phase profile:

$$\Phi[n, m] = \frac{a_1}{b_1} \cdot \ln \cos(b_1 \cdot n) + \frac{a_2}{b_2} \cdot \ln \cos(b_2 \cdot m)$$

After the anamorphic transform with proper phase profile the brightness bandwidth is compressed (the coherence increased). The transformed image can now be re-sampled at a lower rate without losing information given by the amount of brightness bandwidth compression after DAST. The compressed image including the re-sampled transformed image and its filtered one using the discriminator kernel (described below) along with the metadata a_1, a_2, b_1, b_2 and re-sampling factor is sent to the transmission channel or storage device. We note that only five parameters (real numbers) are required for reconstruction, resulting in negligible data overhead. The algorithm can also be combined with vector quantization and entropy encoding to further reduce the image data size. Also, the re-sampled image can be compressed further by a secondary compression, e.g. JPEG. For application to color images the DAST image compression is applied to each of the constituent color components.

Figure shows that only the case with superlinear LF profile results in image compression. (f) Distribution corresponding to another randomly selected linescan in Lena image, for the case of superlinear LF profile confirming the generality of operation on randomly chosen linescan. The decoding algorithm consists of up-sampling followed by inverse propagation through the DAST which incorporates 2D local frequency measurement. A number of techniques such as phase discrimination or iterative methods can be used for this purpose [12]–[14]. These phase discrimination techniques are based on measuring two instances of the signal’s scalar amplitude (one filtered and one unfiltered). The phase is then recovered from these quantities. Although different discriminator kernels can be used, in this paper we have used a simple filter with linear frequency response (Ramp filter) for discrimination.

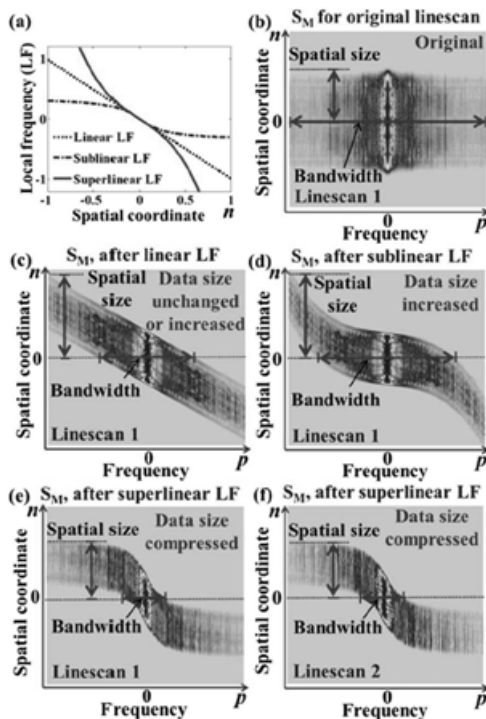


Fig. 2.2. Stretched Modulation () Distribution is a new density function used to design the Kernel of Discrete Anamorphic Stretch Transform (DAST). It shows the dependence of the image brightness on spatial and frequency variables. (a) Three different DAST Kernel Local Frequency (LF) profiles, (b) S_M Distribution of a randomly selected linescan in Lena image without the DAST, (c)-(e) S_M Distribution of the linescan after it is subjected to DAST with LF profiles in (a).

An anamorphic stretch transform (AST) also referred to as warped stretch transform is a physics-inspired signal transform that emerged from photonic time stretch and dispersive Fourier transform. The transform can be applied to analog temporal signals such as communication signals, or to digital spatial data such as images. The transform reshapes the data in such a way that its output has properties conducive for data compression and analytics. The reshaping consists of warped stretching in Fourier domain. The name “Anamorphic” is used because of the metaphoric analogy between the warped stretch operation and warping of images in anamorphosis and surrealist artworks.

III. DAST + JPEG FOR VIDEO COMPRESSION:

Video clips are made up of sequences of individual images, or “frames.” Therefore, video compression algorithms share many concepts and techniques with still image compression algorithms, such as JPEG. In fact, one way to compress video is to ignore the similarities between consecutive video frames, and simply compress each frame independently of other frames. For example, some products employ this approach to compress video streams using the JPEG still-image compression standard.

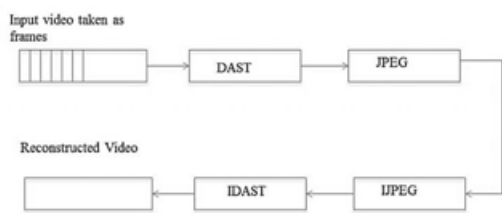


Fig. 3.1: DAST+JPEG for video compression

In this method for video compression, input video taken as of individual images, or “frames and Discrete Anamorphic Stretch Transform (DAST) is operated on the the images one by one followed by secondary compression such as JPEG image compression algorithms. To recover the original video as frames, the inverse operation is performed on the compressed video.

IV.EXPERIMENTAL RESULTS

4.1 DAST + JPEG for image compression result:

In this section, we study an example to show the effect of DAST on images. We also examine the proposed image compression method and compare it to JPEG image compression format. As it can be seen, the autocorrelation is broadened leading to increased spatial coherence and reduced spatial intensity bandwidth. This is done without an image spatial size increase, i.e. the original and transformed images have the same pixels with 8 bits/pixel accuracy. The reduced spatial bandwidth (increased coherence) allows one to re-sample the transformed image at the lower rate, to achieve compression. However, it should be noted that compression is not merely obtained from the re-sampling, but rather from the increase in correlation caused by the reshaping.

We prove this experimentally in the following example. To study the performance of DAST for image compression, in the first example we show that DAST pre-compression can improve the performance of JPEG for a given image quality. The original image is Lena colour image with pixels in TIF format. The compression factor (original over compressed image file sizes) in this case is 2.3 times. In the case of using DAST pre-compression we achieved a compression factor of 5.1. Thus, both cases provide the same PSNR but the case with DAST pre-compression has more than twice compression factor. For this example, we have not used any down sampling,

however since the spatial coherence of the image is increased, we achieved more than twice better compression factor. In the next example, we show how DAST pre-compression can improve the performance of JPEG for a same high compression factor. Results are shown in Fig. 4.1 to 4.5.



Figure 4.1 Standard Image



Figure 4.2 Medical Image

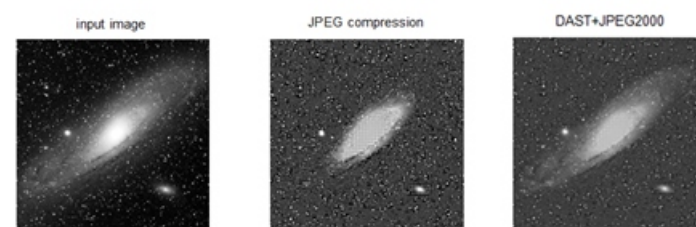


Figure 4.3 Astronomy Image



Figure 4.4 Satellite Image



Figure 4.5 Security and Survivalace Image

Table 4.1 Comparatives of Quantitative Measurements

Method	Image	PSNR	Compression Ration
JPEG	Standard	16.9288	2.3510
DAST + JPEG	Standard	18.0301	5.7822
JPEG	Medical	18.7176	4.1723
DAST + JPEG	Medical	20.6329	6.0873
JPEG	Astronomy	16.3797	1.5545
DAST + JPEG	Astronomy	17.1856	1.5819
JPEG	Satellite	20.2138	1.9807
DAST + JPEG	Satellite	39.6926	2.3406
JPEG	Security and Survivalace	16.1245	2.4050
DAST + JPEG	Security and Survivalace	17.4026	2.7120

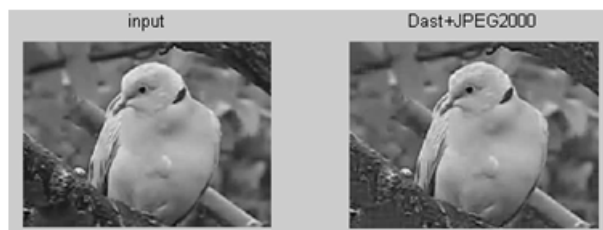


Fig: 4.6 DAST + JPEG video compression frames

Table 4.2 Quantitative Measurements

Method	Frames	PSNR	Compression Ration
DAST+JPEG	Frame1	30.4775	2.1683
DAST+JPEG	Frame5	30.0563	2.0754
DAST+JPEG	Frame50	30.7512	2.1897
DAST+JPEG	Frame100	31.5567	2.3459

4.2 DAST + JPEG for video compression result



V.APPLICATIONS:

Text Here we study some emerging Big Data applications in which DAST can prove to be advantageous. The observed improvements are not unique to the specific images used here, but rather illustrate the general property of the Anamorphic Stretch Transform. The DAST Kernel Phase Derivative (PD) profile normalized to the image size used for image compression.

5.1. Medical Image Compression:

Here, we compare JPEG compression alone with the case of DAST pre-compression followed by post-compression using JPEG for digital pathology image compression. To numerically compare the performance, we calculate the Peak Signal to Noise Ratio (PSNR) for the two cases. PSNR for the case of JPEG alone is 18.7 dB versus 20.6 dB for the case of using DAST pre-compression. This shows that the case with DAST pre-compression has a higher quality than JPEG alone.

5.2 Astronomy Image Compression:

Here we show improvement of JPEG compression enabled by DAST.As an example we use the image of astronomy kind. Here we compare two cases, JPEG compression alone and the case with DAST pre-compression followed by JPEG.

The DAST improves the performance of JPEG as well as application of DAST to astronomy image compression. Shown in experimental results.

5.3 Security and Surveillance:

Here, we present an example to study the performance of DAST compression combined with JPEG for security and surveillance applications. JPEG compression alone and the case with DAST pre compression followed by JPEG. Shown in experimental results.

5.4 Satellite Image Compression:

In the experimental results, we compare the performance of our image compression method when combined with JPEG format for applications in satellite image compression. Our method clearly shows superior performance when combined with JPEG over JPEG alone while having the same total compression factor.

VI. CONCLUSION:

In this project, it is shown that how DAST pre-compression can improve the performance of JPEG for high compression factor and high PSNR. And also shown how video compression is done using DAST pre-compression followed by JPEG. The DAST method can be to extend to digital compression for Big Data as Big Data can present big problems, especially in fields where the events being studied happen at rates that are too fast to be sampled and converted into digital data in real time. For instance, in order to detect rare cancer cells in blood, researchers must screen millions of cells in a high-speed flow stream. And other existing image compression algorithms such as EZW.

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