Image Enhancement In Spatial Domain With Expedient Optimized Framework

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Abstract- *Image enhancement is a process, rather a preprocessing step through which an original image is made suitable for a particular application. To enhance an image with auxiliary information we have proposed a framework using FGT for Bilateral Filtering and Nystrom Approximation to perform spectral analysis. The optimization scheme is more feasible for large input images and is more robust to obtain the effective refinement than conventional algorithms. Of the many existing fast algorithms for Gaussian bilateral filtering, we employed the Fast Gauss Transform(FGT).The Fast Gauss Transform(FGT) has successfully accelerated the kernel density estimation to linear running time for low dimensional problems. However for high resolution images, it is impractical to directly evaluate the eigen-vectors of the affinity matrix owing to the high computational requirements. The Nystrom method provides an efficient way to approximate the large-scale affinity matrix by low-rank approximation.*

Keywords- Terms-Fast Gauss Transform (FGT), Nystrom Approximation, Spectral Analysis.

I. INTRODUCTION

The bilateral filter can be also considered as a very powerful modification of the Yaroslavsky filter [1] in which the spatial convolution with a box function is changed to the spatial convolution with a Gaussian. Because of its edge preserving ability and conceptual simplicity, the bilateral filter has become a popular and powerful image and shape processing tool. It has been extended and generalized in several ways for video enhancement [2, 3], mesh denoising [4], high dynamic- range (HDR) image compression [5] purposes, and many other image processing and computer graphics applications. In this paper, we propose a fast version of the bilateral filter. Fast Gauss Transform (FGT), a technique for fast and error-controlled computation of a weighted sum of Gaussians. FGT belongs to the family of fast multipole methods that combine clustering and manipulations with truncated series expansions to achieve computationally efficient and accurate approximations of sums of radial basis functions. First we apply the dimension elevation trick of [6] and convert the discrete bilateral filter to a normalized weighted sum of Gaussians in a spatial-tonal domain. To demonstrate the computational power of our approach we consider a number of applications including image denoising and HDR image tone mapping. It has linear computational complexity with respect to image elements, such as pixels, voxels, etc. It can be applied to non-uniformly sampled data leading to an extremely fast implementation of a version of the Yaroslavsky filter with a spatially constant kernel. It turns out to be very efficient for volumetric filtering and HDR image tone mapping tasks.

Since the original work of Greengard and Strain [7], the fast Gauss transform has proven to be a very efficient algorithm for solving many problems in applied mathematics and physics. . Direct evaluation of the sum at M target points due to N sources requires O (MN) operations, which makes the computation of large scale problems prohibitively expensive. To break through this computational barrier, Greengard and Strain developed the fast Gauss transform, which requires O (M + N) operations, with a constant factor depending on the dimensionality d and the desired precision. The fast Gauss transform is an “analysis based” fast algorithm in the sense that it speeds up the computation by approximation of the Gaussian function to achieve a desired precision. The sources and targets can be placed on general positions. In contrast the most popular fast Fourier transform requires the point to be on a regular mesh which is in general not available in the application of statistics and pattern recognition. An implementation in two dimensions demonstrated the efficiency and effectiveness of the fast Gauss transform [8]. When implementing FGT we used the Taylor series to expand the exponential function, as described in [9], instead of the Hermite function, to reduce the coefficients required in computation. The intermediate structure clusters pixels in a group, where the cluster range is determined by the spatial parameter. The computational complexity of FGT is O(pn), given number of groups p and image size n.

The FGT algorithm is based on subdividing source B into smaller box-s with sides of length $r\sqrt{2\lambda}$ parallel to the axes, with a fixed r < 1/2. We can then assign each source s_j to the box B in which it lies and each target t, to the box C where it lies. For the sake of clarity, we maintain a notational distinction between source boxes B and target boxes C even though they may be the same. For each target box C, we need to evaluate the total field due to sources in all boxes B, at each target in C.Thus, there are four possible ways in which B can influence C,in centre of all N_B gaussians (1)N_B Gaussians - directly evaluated. (2) N_B Gaussians - accumulated in Taylor series. (3) Hermite series - directly evaluated (4) Hermite series - accumulated in Taylor series.

The Nystrom method is a low-rank matrix approximation technique that samples only a small subset of pixels, and then, extends the solution of the subset to the entire image. This method can effectively reduce the computation and memory requirements, thereby facilitating the computation for a large-scale image. The investigation by Zhang et al. [10] showed that k-means clustering is an effective sampling method because it can result in a smaller error upper bound. For an image of N pixels, each pixel is embedded into a 5-D space (R,G,B,X,Y), and then, all the pixels can be divided into K clusters with K centers. For Nystrom approximation, these K centers can be used to choose the sampling points (s_k). s_k = arg min_i |Z_i – μ_k|, where Z_i is the 5-D data of pixel i and μ_k is the center of cluster k. After all the sampling points S (S = {s_1, s_2, ..., s_n}) are fully defined, the affinity matrix A can be calculated, and then, the Nystrom approximation can be applied.

II. IMPLEMENTATION

Here an image with auxiliary information for instant in this paper a Dehazed image with foggy content is to be enhanced and the refined image has to be obtained.

HazyImage RoughDepth RefinedDepth DehazedImage

Fig 1: Image Dehazing Process through a refinement process for removal of haze.

For the dehazing process we apply FGT as bilateral filter to the rough depth and we apply nystrom approximation using k-means clustering to extract the segment required to produce a Dehazed image. The pre-processing procedure, which selects the sampling points, may have a significant effect on the performance of the approximation. High repeatability does not guarantee that the error resulting from approximation is small.K-mean clustering is an effective sampling method because it can result in a small error upper bound. The bilateral filter is popularly used as a denoising tool.FGT based bilateral filtering is a faster approach for image denoising in an iterative approach. First the rough depth and refined depth of the given input Dehazed image is obtained. The refined depth is subjected to a bilateral filter using FGT and with the image received the required pixels for the enhanced image are obtained using k-means clustering. The architecture flow of the implementation is given in Fig 2.

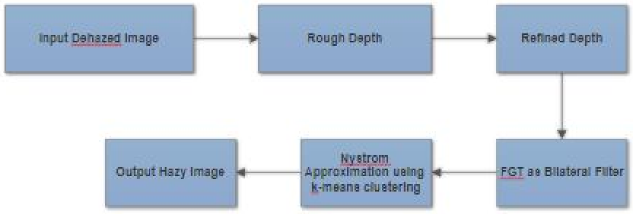


Fig2: Architecture diagram for the image dehaze process.

FGT as BILATERAL FILTER

Consider two point sets: targets (t_1, t_2,…….,t_N} and sources (s_1,s_2,…………….,s_M) in R^{n+1}.Assume that each source point s_j is equipped with a positive scalar weight α_j where α=(α_1,α_2,. . .,α_M).The discrete Gauss transform of target points t_i with respect to all source points is defined by

$$G(\alpha, t_i, s, M) = \sum_{j=1}^{M} \alpha_j \, G(t_i - s_j). \quad (1)$$

The Fast Gauss Transform (FGT) method we employ is derived from a more general fast multipole method [11] adapted for dealing with Gaussian kernels. The Fast Multipole Method strategy for evaluating the sum of Gaussians (1) includes using far-field and near-field asymptotic expansions for G (t − s). For the sake of simplicity, we consider the 1D case because multi-index notations allow for treating the multidimensional case in a very similar way. A far-field expansion centered at s_0 for 1D Gaussian G(t − s) has the form

$$\sum_{i=0}^{\infty}\left[\frac{1}{k!}\left(\frac{s-s_0}{\sigma}\right)\right]^k h_k\left(\frac{t-s_0}{\sigma}\right) = \sum_{k=0}^{\infty} A_k \, h_k\left(\frac{t-s_0}{\sigma}\right) \quad (2)$$

where $h_k(x) = (-1^k)\frac{d^k}{dx^k}\exp(-x^2)$ are Hermite functions. Interchanging target t and source s treats this formula as the Taylor series expansion centered at a nearby target t_0 (near-field expansion).

$$G(t-s)=\sum_{l=0}^{\infty}\left[\frac{1}{l!}h_l\left(\frac{s-t_0}{\sigma}\right)\right]\left(\frac{t-t_0}{\sigma}\right)^l=\sum_{l=0}^{\infty}B^l\,\frac{(t-t_0)^l}{\sigma} \quad (3)$$

$$B_l=\frac{(-1)^l}{l!}\sum_{k=0}^{\infty}A_k h_{k+l}\left(\frac{s_0-t_0}{\sigma}\right) \quad (4)$$

Since the Gaussian falls off quickly, only a limited number of terms, say first p terms, in the above expansions are needed for evaluating the sum of Gaussians (3) with a given precision ε. The original FGT method starts from constructing a space partition consisting of regular boxes parallel to the coordinate axes in R^n. Then the targets and sources are assigned to these boxes. For each source box, it requires O (p^nN) operations to compute the coefficients $A_k$corresponding to p-truncated expansions. For each target box, all the Hermite expansions in the source boxes within an interaction region are transformed into a Taylor series expansion to be used inside the target box. The sources within $(2r+1)^n$ nearest boxes are sufficient to obtain single (r=4) and double (r = 6) precisions [GS98]. Computing B_l involves O (np^{n+1}) operations. This leads to O$((2r+1^n)np^{n+1})$complexity per each target box if$(2r+1^n)$ interaction regions are involved. Finally, for each target, evaluating the Taylor series expansion takes O (p^nM) operations.

K-Means Clustering

K-means clustering partitions the dataset into k clusters, where each instance is allocated to one cluster. Each cluster is represented by the cluster's center, also known as the centroid. The procedure works iteratively by relocating the K centroids and re-classifying data points[12].

Step 1: Initialize K centroids .
Step 2: For each data point, find the nearest centroid and classify the sample into the respective clusters.
Step 3: Recalculate centroids as the arithmetic mean of all instances assigned to it.
Step 4: Repeat steps 2-3 till convergence. The K final clusters are then obtained.

Convergence is achieved when no further improvement can be made[13]. That is, until there is no more change of the centroids or their memberships. It is a heuristic algorithm, which means that results will depend on the initial clusters. In initializing centroids for a foggy image we randomly choose among the data points. The optimization criterion for k-means clustering:

$$min_{c_j}\sum_{j=1}^{K}\sum_{x_i\epsilon c_j}\|x_i-c_j\|^2 \quad (5)$$

Where cluster j has centroid c_j.This algorithm basically uses Euclidean distance.

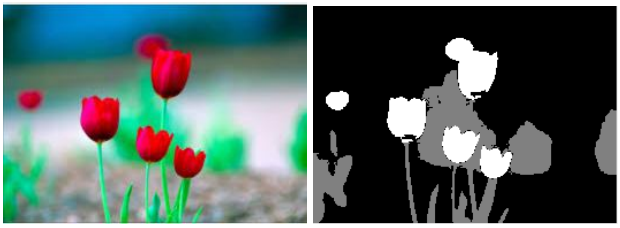


Fig 2:Original Image Clustered Image

III .EXPERIMENTAL RESULTS

An input hazy image is first subjected to a bilateral filtering using FGT and the image is subjected to k-means clustering and the needed image segments are clustered. Finally the Dehazed image is produced.

Original Hazy Image Filtered Image

Clustered Image Dehazed Image

Fig 3: Results for Sweden Image through our method.

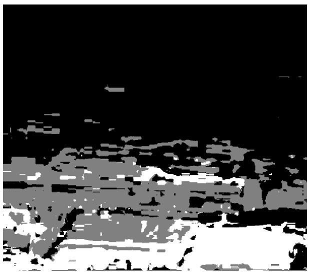
Original Hazy Image Filtered Image

Clustered Image Dehazed output

Fig 4: Results for pumpkin image through our method.

Original Hazy Image

Filtered Image

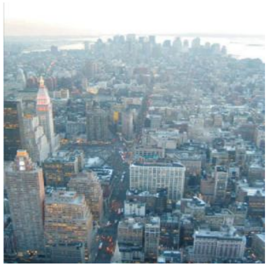


Clustered Image

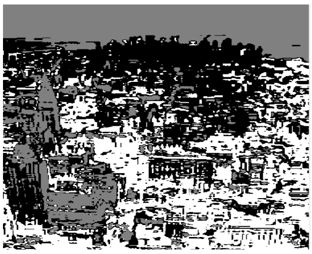
Dehazed Image

Fig 5: Results of Canon image through our method

Original Hazy Image



Filtered Image



Clustered Image

Dehazed Output

Fig 6: Results Of Tower Image through our method

The features of the Dehazed image are extracted using GLCM (Gray Level Cooccurence Matrix)[15] which is used to extract second order statistical features. Feature Extraction is done mainly to describe a large set of data more accurately. A number of texture features may be extracted from GLCM,,we have extracted energy, correlation and entropy for the above images.

ENERGY

Energy is also known as Uniformity or Angular Second Moment. It is the sum of squares of entries in the GLCM.Energy measures the image homogeneity. Energy is high when image has very good homogeneity or when pixels are very similar.

$$\text{Energy}=\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} P_{ij}^2 \quad (6)$$

Where i,j are the spatial coordinates of the function p(i,j),N_g is the gray tone.

ENTROPY

Entropy shows the amount of information of the image that is needed for the image compression. Entropy measures the loss of information or message in a transmitted signal and also measures the image information.

$$\text{Entropy}=\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} -P_{ij} * \log P_{ij} \quad (7)$$

CORRELATION

Correlation measures the linear dependency of grey levels of neighboring pixels.Digital Image Correlation is an optical method that employs tracking & image registration techniques for accurate 2D and 3D measurements of changes in images.

$$\text{Correlation}=\frac{\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}(i,j)p(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y} \quad (8)$$

The following table gives the features extracted for the above datasets.

Image	Energy	Entropy	Correlation
Sweden	382	12	32
Pumpkin	32	10	7
Canon	2.429147	1	379
Tower	32	14	9

The above features extracted reveal that the filtering used in this paper using FGT and K-means clustering produce an enhanced image in an optimized manner when the image has pixels to be enhanced in a very close affinity.

IV. CONCLUSION

In this paper we have developed an optimized framework using a fast and accurate FGT-based approach of bilateral filtering to enhance a hazed image.We also use Nystrom approximation based k-means clustering to extract the image needed by applying FGT based bilateral filtering to remove auxiliary information(removal of haze). The success in acceleration of the FGT comes from two innovations: the use of the farthest-point algorithm to adaptively subdivide the high dimensional space, and the use of a new multivariate Taylor expansion we developed to dramatically reduce the computational and storag cost of the fast Gauss transform. The recursive computation of the multivariate Taylor expansion further reduces the computational cost and necessary storage.

V. FUTURE WORK

The optimization scheme used in this paper involves FGT as the bilateral filtering ,it is mainly used for low dimensionality image and to avoid truncation errors due to Hermite expansions.But the major drawback of FGT is the exponential growth of complexity with dimensionality.The use of box structures in the FMM is inefficient in higher dimensions.To overcome this in future work we may apply Improved Fast Gauss Transform(IFGT) which has been applied to the mean shift algorithm achieving linear computational complexity.K-means clustering based on nystrom method is used but we can achieve different sampling methods to provide efficient nystrom approximation. The Nystom method is used in a variety of large-scalelearning applications, in particular in dimensionality reduction and image segmentation.

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