Image Reconstruction using Compressive Sensing Architecture for Application in Surveillance Systems

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ABSTRACT

As far as present day situations are concerned key area of security issues are largely related to cctv cameras and their image information, so picture or data enhancement plays a crucial role for development of security issues. Keeping as major issue we have been working on image reconstruction for surveillance system for compressive sensed data by back projection algorithm. Image enhancement have been implemented so far using least squares, and fast in painting algorithmand various other algorithms in the fields of medicine and various other applications so far. Now we have tried to apply back projection algorithm to enhance the surveillance video .we have used wiener filter for noise removal which is the best alternative for inverse filtering which is very sensitive to additive noise, more over the approach of reducing one degradation for a time allows us to develop a restoration algorithm for each type of degradation and simply combine them. The application of this field of image reconstruction is a fast booming research field which finds its application in a vast spectrum of today's world surveillance, medical science, geography, and media and so on.

1. INTRODUCTION

Through our work regarding image reconstruction we aim to reconstruct a better quality video from the given video, taking surveillance system as a source video. Our work involve digital image processing using the latest compression sensing (cs) technique involving back projection algorithm. While comparing with other techniques (motion & texture based) cs is better in terms of response, time, robustness & noise reduction .It allow signal sampling at sub nyquist rate and get recovered as the size of the input increases sampling memory requirement and computational burden on the reconstruction increases to solve this problem we use blocks/frames of the input which in turn causes block artefacts which degrade quality of reconstruction image for compensating this it's coupled with smoothed projected land wiener filter is used for smoothening and better output with a slight decrease in detailing of the image.

In our work we have managed to include edge detection & improved signal to noise ratio within a decent amount of time. We have used mat lab 2015 for our work since it's a scientific programming language and provide strong mathematical and numerical support for advanced literal algorithms.

2. LITERATURE REVIEW

Though back projection is a heuristic algorithm, it provides comparable and sometimes most accurate results inreconstructing the noiseless input. In the noisy signal reconstruction case, reconstruction by both least squares and KNN contains errors that, though small, may not be acceptable. Features selection is very important in deciding the accuracy[7]. Here is an attempt is made to present CS fundamentals and the implementation of CS reconstruction by Back projection algorithm.

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3.   PROBLEM STATEMENT

1. The objective of our work is to consider the pixels in the rendered image to be independent from each other. An interesting extension would be to consider sub-pixel samples.

2. A benefit of our CS framework is that, for all results proposed approach can be utilized directly since only the input data for training and reconstruction is changed.

4.   BACK PROJECTIONALGORITHM IN DETAIL

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Coming to algorithm, The most common used approach for image reconstruction from dense projection data is filtered back projection (FBP).it was mainly implemented for medical purposes, but for the first time we are trying it on surveillance systems to recover videoas a substitute of other algorithms which are slightly less efficient in terms of run time and recovering efficiency.

A CT surveillance system uses an array of equally spaced unidirectional sources of frames which are of division. Spatial variation of the frame division in the two-dimensional plane can be expressed by the attenuation coefficient say $\mu(x, y)$. The logarithm of the measured radiation intensity is proportional to the integral of the attenuation coefficient along the straight line traversed by the surveillance system.

If the set of values given by all detectors in the array constituting one dimensional projection of the attenuation coefficient, $P(t, \theta)$, let t be the detector distance from the origin of the array, and θ be the angle at which the measurement is made. These combined projections for different angles over 180° can be viewed in the form of an image in which one axis is considered on position t and other as angle θ. This is called a sinogram or Radon signature of the two-dimensional function μ, containing information needed for the enhancement of an image $\mu(x, y)$. The Radon transform can be formulated as

$$\text{Log } (I0/I_D) = \iint \mu(x, y)\, \delta\, (x\cos\theta + y\sin\theta - t)dxdy\ = p\, (t,\theta) \tag{1}$$

Where I_o is the source intensity, I_d is the detected intensity, and $\delta\,(\cdot)$ is the Dirac delta function. Equation (1) is actually a line integral along the path surveillance projected data, which is perpendicular to the t axis. At $t = x\cos\theta + y\sin\theta$. The Radon transform represents maps an image $\mu(x, y)$ to a sinogram $P(t, \theta)$. Therefore inverse mapping and the inverse Radon transform together combined when applied to a sinogram results in an enhanced image. The filtered back projection (FBP) algorithm performs this mapping [1].
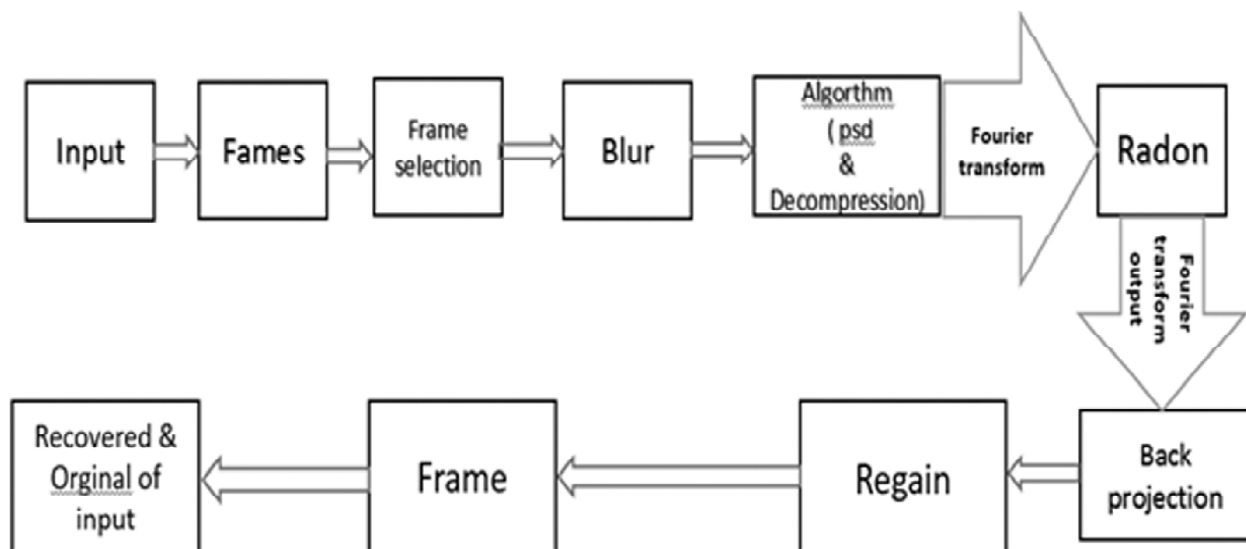
Block diagram for our entire procedure

Back projection algorithm is started by high-pass filtering ofall projections before they take video as input data, whose response is $|W|$. The discrete formulation of back projection is

$$\mu(x,y) = \pi/k\left(\sum_{i=0}^{k}\pi(t)(x\cos\theta + y\sin\theta)\right) \tag{2}$$

Where $\prod(t)$ is a filtered projection at angle θ, and K is the number of projections scanned at angles θ_i over a 180° range. The number of values in $\prod(t)$ depends on size of image. In the case of $n \times n$ pixel images, $N = 2nD$ detectors are required. The ratio $D = d/\tau$, where d is the distance between adjacent pixels and τ is the detector spacing, which is a important factor for quality of the reconstructed image and it should satisfy $D > 1$. In our implementation, we utilize values of $D \approx 1.4$ and $N = 1024$, which are general values for real systems. Higher values do not increase the image quality as significantly.

Algorithmically, Eq. (2) is implemented as a triple nested "for" loop. The outermost loop is over projection angle θ. For each θ, updation of every pixel in the image is done. Thus, from (2), the pixel at location (r; c) increased by the value of $\prod(t)$ where r and c *are functions of t, but* there is issue here connecting reconstructed pixel value, in general, intersects the array between detectors. This can be solved by linear interpolation. The point of intersection can be calculated as an address regarding the numbers from 0 to 1023. The fractional part is defined by interpolation factor. The equation for linear interpolation is given by

$$(i) = \pi(i+1) - \pi(i).IF + \pi(I) \tag{3}$$

Where *IF* is interpolation factor, $\prod(t)$ is the 1024 element array which contains filtered projection data at angle θ, and i is the integer part of the address calculated. The interpolation can be done before hand, or it can be a part of the back projection hardware itself. We implement interpolation in hardware because it reduces the amount of data. The key to an efficient implementation of Equation (2) is shown in Figure 1b. It shows how a distance d between squared adjacent areas concerning to adjacent pixels can be converted to a distance columns.

5. BACK PROJECTION FORMULAE MATHEMATICAL PROBABLISTICS

For parallel beam tomography the projections can be expressed as the Radon transform of the reconstructed object. The Radon transform is defined as:

$$g(s,\theta) = R(f)\int\int_{-x}^{x} f(x,y)\delta(x\cos\theta + y\sin\theta - s)dxdy$$
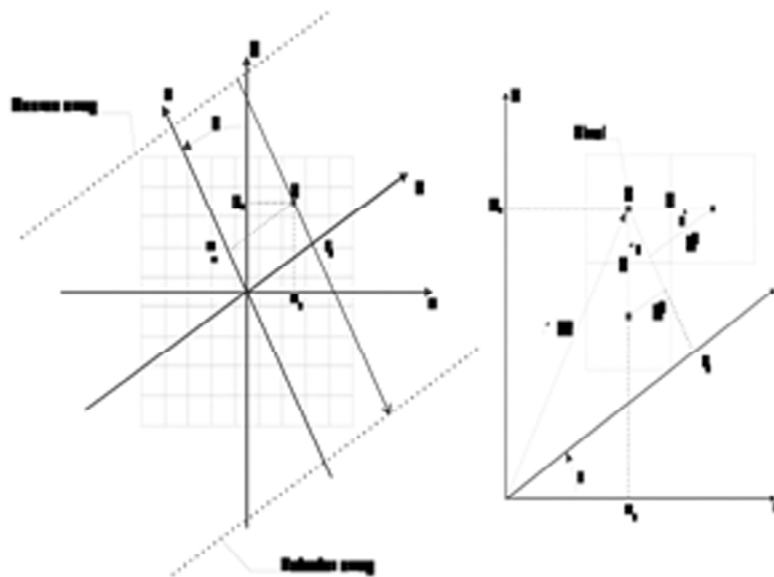

Figure 1: a) Illustration of the coordinate system used in parallel-beam back projection
b) Geometric explanation of the incremental spatial address calculation

i.e., the line integral along a line (a tomography beam) at an angle θ from the y-axis and at a distance |s| from the origin. Rotating coordinate axissystem, we have

Orcan be expressed as,

$$g(s,\theta) = \int_{-x}^{x} f(s\cos\theta - u\sin\theta * s\sin\theta + u\cos\theta)\,du \qquad (3)$$

$L(x, y, \sigma)$ at the keypoint's scale σ is taken so that all computations are performed in a scale-invariant manner. For an image sample $L(x, y)$ at scale σ, the magnitude gradient $m(x, y)$, and orientation $\theta(x, y)$, are precomputed using pixel differences:

$$M(x, y) = \sqrt{(L(x + 1, y) - L(x - 1, y)^2 + L(x, y + 1) - L((x, y - 1))^2}$$
$$\theta(x, y) = a * tan\ 2\ L(x, y + 1) - L((x, y - 1), L(x +) - L(x - 1, y))$$

5.1. Results and Discussion

Table 1below shows the parameters for improved video compared to various other algorithms.

The values are the random values taken from internet as source Figure (3)

Various outputs have been included along with source image and filtered output image.

Table 1
Comparisions of results

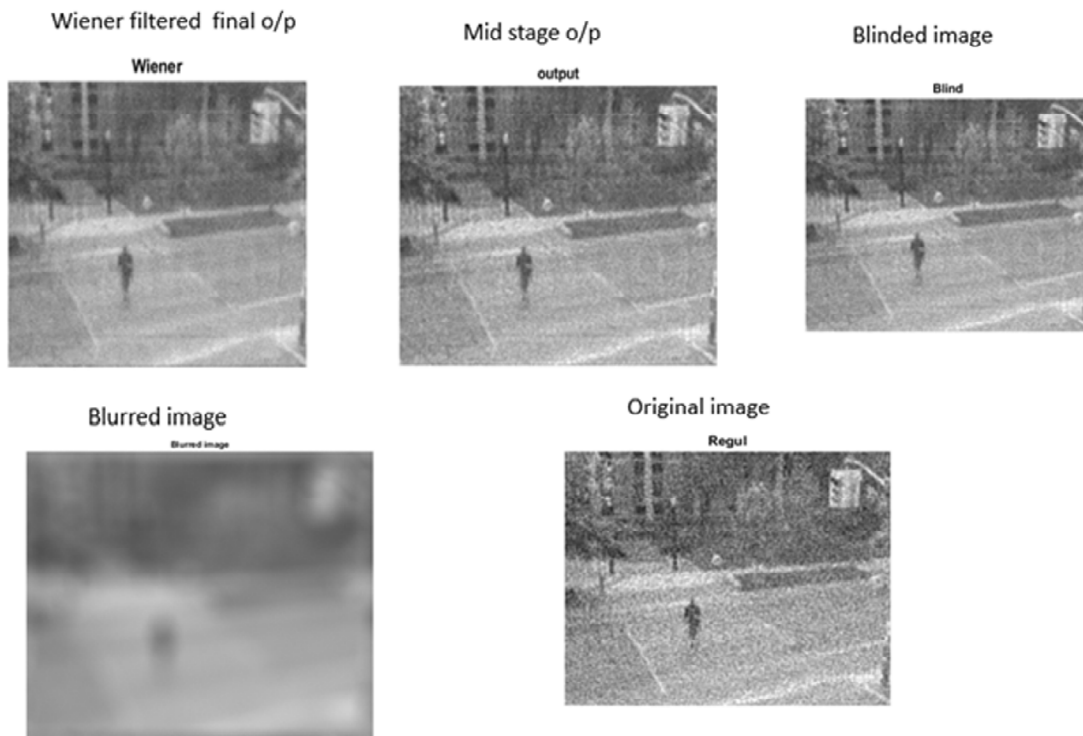| Parameters	Previous algorithms (least squares and knn)	Back projection algorithm
NSR	0.891	0.961
Running time	3.813 min	1.72 min
Mean variance	0.86	0.981
Comp ratio	0.901	0.921

Figure 2: Simulated outputs

6. CONCLUSIONS

As far as results are concerned this is best algorithm in terms of efficiency and speed i.e. run time .moreover use wiener filter executes an optimal tradeoff between inverse filtering and noise smoothing. It makes blur inversion simultaneous. The Wiener filtering is optimal in terms of the mean square error. This procedure can be applied to any source video not only to surveillance video but also to others. Through comparing the quality of different kinds of images, it shows that it works best in infrared images, and when dealing with texture images, the performance of reconstruction is reducing. Other popular CS algorithms are also tested in this paper, results show that the proposed method reconstruction is promoting not only sparsity but also Smoothness. The proposed method encourages superior image quality, particularly at infrared images.

REFERENCES

[1] Chen, S.S. 1995. Basis pursuit. Ph.D. thesis. Department of statistics, Stanford university, Monterey, ca, USA, November.

[2] Supatana auethavekiat "introduction to the implementation of compressive sensing" pp. 39-46, July 2010.

[3] Naveen Kulkarni "compressive sensing for computer vision and image processing" (thesis).

[4] Aaron M., Elda M., Buckstein a.: k-svd: an algorithm for designing overcomplete dictionaries for sparse representation. ieee transactions on signal processing.

[5] Baraniuk Caver wakin m. lowdimensional models for dimensionality reduction and signal recovery:

[6] A geometric perspective. Proceedings of the ideas djan coric, Miriam leeser, Eric miller, and marc trepanier, "parallel-beam back projection: an fpga implementation optimized for medical imaging" *tenth acm international symposium on field-programmable gate arrays (fpga02),* February, 2002, pp. 217-226.

[7] S. Dhanalakshmi, C. Venkatesh, "Classification of Ultrasound Carotid Artery Images Using Texture Features", International review on software and computers, Vol. 8, No. 4 (2013)