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A FAST HIGH QUALITY COMPRESSED HALFTONE IMAGE DESCREENING

Rizwana Fathima.J[1], Balaji.S[2]

PG Scholar[1], Head of the Department[2]
Department of Computer Science and Engineering
SCAD College of Engineering and Technology
Cheranmahadevi. Tirunelveli - 627414.
e-mail:anawzir1311@gmail.com[1]

Abstract: - Conventional electro photographic printers usually yields artefacts while making an attempt to printing a scanned image that has already scanned from some printed material. Using halftone technique, we propose a novel non repetitious, non linear and space variant descreening technique that removes a wide range of screen frequencies from such halftone image while protecting image sharpness and edge detail. Image redundancy based denoising algorithm is initially performed to scale back attenuate distortions. The frequency phase values are spherical coded using arithmetic encryption scheme. The local gradient features obtained from scanned image is employed for adaptive filtering. Finally an edge conserving filter is employed to boost the sharpness of edges. The overall scheme is non redundant which means that the sub band level of pictures is conveyed using equivalent set of variables while not the requirement for any aspect parameters. we compare the performance of proposed algorithm to different descreening solutions and demonstrate that the new algorithm improves quality over existing strategies while reducing computation. The performance is evaluated on the premise of PSNR values.

Keywords: - Descreening, Denoising, Artefacts, Halftone, Adaptive Filtering.

1. Introduction

Most of the available printing technologies cannot produce continuous tones. Instead the images printed with these devices contain a series of dots organized in specific patterns to simulate completely different shades of gray.The process of converting a continuous-tone image into a binary image which will be rendered using a bi-level printing device is named halftoning. Conventional strategies involve either changing the size of printing dots called amplitude modulation (AM), or changing the relative density of dots on page referred to as frequency modulation. To reconstruct high quality contone image from halftone image, a variety of different inverse halftoning strategies are proposed. Even though most of those strategies recover contone images with sharp edges and details from binary halftone images, they cannot be used to descreen scanned halftone images. Some of the strategies are LUT [3], Dot diffusion [4], Error diffusion[5], LMS MMSE [6], training based descreening [8], collaborative filtering [9], Hardware friendly descreening [10], LMS based descreening [11].

In LUT technique [3], the estimated value may be a non linear function of those pixels. In this technique, it is necessary to stay the neighbourhood to be small, which is to be employed in the prediction. The dot diffusion technique tries to retain the nice options of error diffusion, while providing substantial parallelism. But this technique produces halftone images of low PSNR value. Error diffusion technique is single pass, employs a extremely sophisticated multiscale gradient estimator and uses smoothing filter specifically tuned to the characteristics of error subtle halftones. But this technique cannot produce prime quality images. The LMS-MMSE technique [6] is employed within the training of inverse halftone filters, but during this technique halftoning and inverse halftoning are not optimized artificial language to each other. The based primarily based descreening technique [8] effectively removes a wide range of Moiré inflicting screen frequencies and error diffusion halftone noise from a scanned document while maintaining the overall image quality in terms of image sharpness and detail preservation. The collaborative filtering method [9] reveals even the finest details shared by cluster fragments and at the same time .it preserves the essential unique features of every individual fragment. The Hardware friendly descreening method [10]works by extracting a spatial feature vector comprising the intensity gradients computed at totally different pixel locations in a tiny neighbourhood of given pixel. This technique also preserves sharpness and quality of text. The LMS collects all the qualified sub halftone images known as the effective votes for majority voting. If any effective votes are found in a halftone, the majority voting is just applied with these effective votes to yield a better classified result. If all the selected sub halftone images are non effective votes, then the majority voting is applied for all sub halftone images in a test image. But during this technique, usage of FFT will increase overall complexity in spatial domain.

In this paper, we tend to introduced the “Spherical Representation”, that provides a new adaptive framework for modelling and coding the image information in wavelet sub bands.

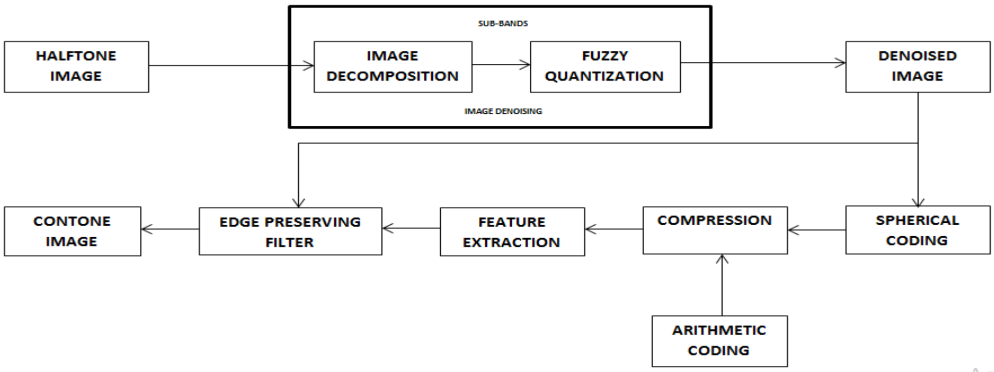
TABLE.1-Comparitive Study

TYPE	FEATURES	DEMERITS
LUT	➢ Employs less computations ➢ Creates samples from particular training set	➢ Suitable only for bilevel halftones,not for scanned halftones
DOT-DIFFUSION	➢ Non iterative ➢ POCS gives higher PSNR value ➢ Embedded multi resolution property	➢ Morw memory requirement ➢ Perceptual quality not optimal
ERROR-DIFFUSION	➢ Produces high quality of images ➢ Efficient for inverse halftoning	➢ Renders inferior quality of images
LMS-MMSE	➢ Low complexity ➢ Excellent reconstructed quality	➢ Halftoning and inverse halftoning are not optimal to each other
TRAINING	➢ Does not require any features for descreening ➢ Also perform deblurring of scabbed images	➢ PSNR not higher than other methods
COLLABORATIVE	➢ Perceptual image quality better than MMSE ➢ Suits high CR images like in medical images	➢ Not suitable to denoise non-gaussian noise ➢ Cannot denoise 1-D signals and videos
HARDWARE FRIENDLY	➢ Robust filtering of scanned halftone ➢ Preserves sharpness of image	➢ Cannot diffuse pixel error in color space
LMS	➢ Low computation complexity ➢ Easy implementation	➢ Usage of FFT increases overall complexity

2. Image Descreening

The proposed technique is to obtain clean smooth edge preserved scanned halftone image. First, the halftone image is denoised to remove the noise patterns within the image. This can be done by decomposition of the image, which implies the image is level splitted to obtain various blocks which can be used for block matching. Then these level values are fuzzified to obtain the optimized values. Finally these values are aggregated to form the denoised image.

FIG.1-Image Descreening

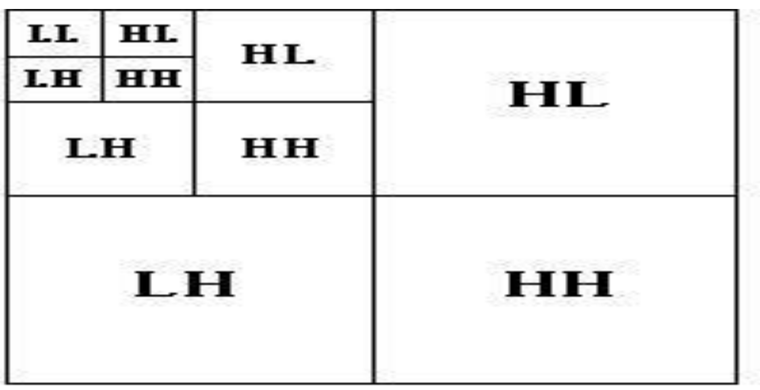


Now, from the denoised image the phase values are spherical coded. The spherically coded values are compressed using arithmetic encoding technique. Using adaptive filtering technique, the image is reconstructed. An edge preserving algorithm is employed to get sharp edges of the reconstructed image.

3. Image Decomposition

An image is represented as a two-dimensional array of coefficients every coefficient representing the brightness level in that point. Once looking from a better perspective, we can't differentiate between coefficients as a most important, and lesser important ones. However thinking additional intuitively, we can. Most natural images have smooth color variations, with the fine details being represented as sharp edges in between the smooth variations. Technically, the smooth variations in color are often termed as low frequency variations and also the sharp variations as high frequency variations. The low frequency components (smooth variations) constitute the base of an image, and also the high frequency components (the edges which offer the detail) add upon them to refine the image, thereby giving a detailed image. Hence, the smooth variations are demanding a lot of importance than the details. Separating the smooth variations and details of the image are often done in many ways.

FIG.2-Pyramidal Decomposition



4. Fuzzy Quantization

Fuzzy logic is a kind of multi-valued logic derived from fuzzy set theory to deal with reasoning that's robust and approximate rather than brittle and exact. Fuzzy logic variables might have a truth value that ranges in degree between zero and one. Fuzzy logic corresponds to degrees of truth. The sub band coding of the image at numerous levels, results a collection of wavelet coefficients. Building the spherical tree using true coefficient values and coding this original tree doesn't result in an optimal answer. Because the coder might end up spending bitrate coding the total energy, not knowing that, this energy comes from an insignificant region of the sub band and hence the resulting codeword can't be optimal one. Ideally spherical coding tree must be constructed using optimally quantized values. Therefore the fuzzification method of the coefficients are performed. The fuzzification method, quantize the wavelet coefficients thus splitting the lower and higher coefficients. the higher coefficients are fuzzified and from the obtained quantized coefficients, the spherical tree is constructed.

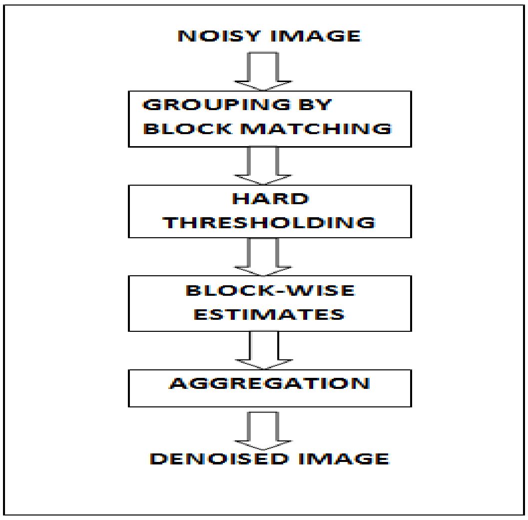
5. Image Denoising

Image redundancy based denoising algorithm consists of four basic steps

1. Partition the input noisy image into overlapped patches.
2. Search for similar patches.
3. Estimate the clean patch supported similar patches.
4. Aggregate the clean patches to generate the output noise-free image.

For each block within the noisy image, perform the grouping process. Grouping process is that; find blocks that are similar to the presently processed one so attach them together in a 3-D array. Then collaborative hard thresholding is performed. Hard thresholding is that, a 3-D transform is applied to the shaped cluster, then the noise is attenuated by hard-thresholding of the transform-coefficients. Then the 3-D transform is inverted to provide estimates of all sorted blocks so all the estimates of the blocks are returned to their original positions. Next to aggregate the obtained blocks, the basic estimate of the true image is computed by weighted averaging all of the obtained block-wise estimates that square measure overlapping. Using the essential estimate, improved grouping and collaborative wiener filtering is performed. For each block, block matching is employed among the essential estimate to search out the locations of the blocks that are same as the presently processed one. Using these locations, two groups are formed, one from the noisy image and one from the essential estimate. Then the collaborative wiener filtering is performed like a 3-D transform is applied on both groups and then a wiener filtering is performed on the noisy image using the energy spectrum of the essential estimate as the true energy spectrum. Then the estimate of all grouped blocks are produced by applying the inverse 3-D transform on the filtered coefficients and also the estimate of the blocks are returned to their original positions. Then the aggregation process is performed. In the aggregation process, a final estimate of the true-image is computed by aggregating all of the obtained local estimates employing a weighted average.

FIG.3-Image Denoising



6. Spherical Representation

The clustering of energy in wavelet sub bands motivates the utilization of spatially varied models in coding the

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wavelet information. Natural images provide several complications in modelling the existing non-homogeneity. Different image regions require totally different characterizations for efficient coding. Due to the wealthy structure of edges and texture, statistical variations need to be recognized within windows of different shapes and sizes, ranging from large chunks of coefficients in smooth regions all the way down to the extent of single isolated locations. it's because of these challenges there's a need for flexible representations that may affect such varied information content.

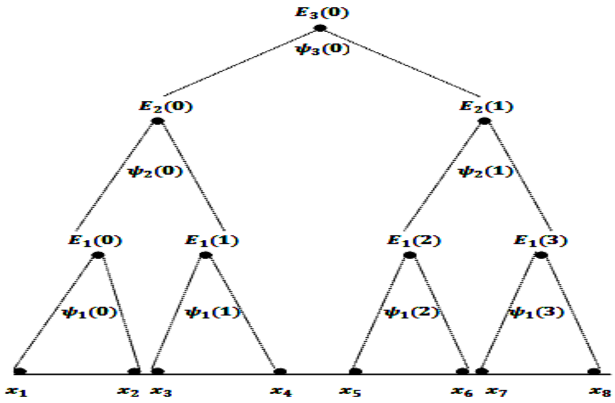
The “spherical representation” may be a flexible representation that deals with the above said varied information contents. The “spherical representation” [4] may be a hierarchical description of how total energy gets distributed inside within each sub band. The non-homogeneity of wavelet sub bands is handled through a non-parametric modelling of this hierarchy. Spherical representation and coding method share a similar philosophy with the equivalent coder in its use of local energy. the problem in equivalent is the obligation to use the causal neighbourhood for variance estimation in order to avoid side information. one way to overcome the problem in equivalent is to represent local energy as a part of wavelet information to be coded, and not as further parameters required for modelling. With that perspective, it's convenient to define local energy hierarchically, ranging from the entire energy of the complete sub band going down to smaller regions, even all the way down to the energy of a single coefficient. Motivated by this reasoning, we propose to use the subsequent hierarchical structure to represent a random process X.

$$E_m(n) = \Sigma_{i=2^n(n+1)}^{2^n(n+1)} x_i^2 \qquad (1)$$

$$\Psi(n) = \arctan\left(\sqrt{\frac{E_{m-1}(2n)}{E_{m-1}(2n+1)}}\right) \qquad (2)$$

The variables Em (n) offers local energy information at totally different resolution levels m.The phase variables ψm (n) indicate how the local energy gets split between two neighbour regions. Going from the highest level (m=k) to the bottom level (m=1) of the hierarchy, the phase values offer a refinement of the obtainable information in every region of the sub band. During this type of representation, we tend to are able to use local energy, not only to differentiate between statistically distinct components of the method however also to provide direct information regarding the coefficient values.

FIG.4-Spherical Representation



The attractiveness of the spherical representation isn't limited by its ability to gather modelling mismatch at the few higher level phases. It also creates a extremely adaptive coding framework, where completely different coding techniques may be developed at different levels of the hierarchy without requiring any facet data.

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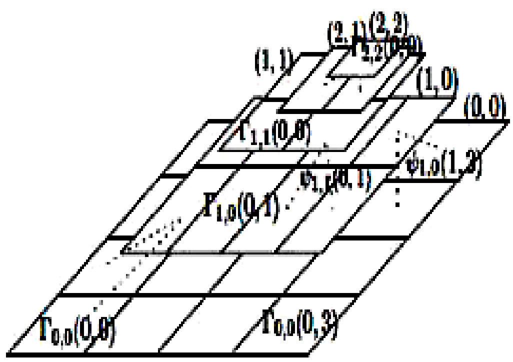
7. Spherical Coder

Spherical representation can be simply extended to 2-D to be utilized in wavelet image coding.In coding the wavelet coefficients, the spherical coder acts on the subsequent assumptions.

- The technique is applied independently at every sub band.
- The phase variables are assumed to be independent random variables.
- Optimal coding of phase depends o the decoded values of corresponding coding energy.

The job of the encoder is to settle on the optimal codeword that is admissible among the spherical coding framework.

FIG.5-Spherical Representation in 2-D



A codeword is admissible if its spherical tree is decoded with zero distortion at the selected bitrate. At a given bitrate, the set of all permissible code words defines the spherical codebook.

The spherical coding algorithmic rule is given (for every wavelet sub band at completely different scales and in several orientations) as follows.

1) Use Soft thresholding to estimate the coefficients.

$$C(m,n) = \begin{cases} c(m,n), if\,|c(m,n)| > T \\ 0 \qquad\qquad else \end{cases}$$

2) Outline the energy and phase values.

$$\Gamma_{u,v}(s,t) = \sum_{m-2^u s}^{2^u(s-1)-1} \sum_{n-2^v t}^{2^v(t+1)-1} c(m,n)^2$$

$$0 \le s < 2^{(j-u)}, 0 < t < 2^{(j-u)}$$

And for,

$$0 \le u < j$$

$$\Psi_{u+1,u+1}(s,t) = \arctan\left(\frac{\sqrt{\Gamma_{u-1,u}(s,2t)}}{\sqrt{\Gamma_{u+1,u}(s,2t+1)}}\right)$$

$$0 \le s, t < 2^{j-u-1}$$

$$\Psi_{u+1,u}(s,t) = \arctan\left(\frac{\sqrt{\Gamma_{u,u}(2s,t)}}{\sqrt{\Gamma_{u,u}(2s+1,t)}}\right)$$

$$0 \le s \le 2^{(j-u-1)}, 0 \le t < 2^{j-u}$$

$$\Gamma_{u,v}(s,t)$$

And,

$$\Psi_{u,v}(s,t)$$

3) Quantize the coefficients by fuzzification.

4) Encode the coefficients using arithmetic encoding.

Arithmetic coding is employed to code the phase variables. The spherical tree provides a natural context for adaptive arithmetic coding. The coding model of every phase value is adapted based on the corresponding range of quantization levels. The performance of the algorithm is extremely much dependent on how the spherical tree is constructed. Since the spherical representation is robust to coding mismatch, the spherical coder with the independence assumption remains very successful.

8. Conclusion

This work was carried through with a creative idea in image descreening. An alternative manner applied to the screening classification is that the crucial part in creating an accurate choice of descreening filter for removal of attenuate distortions. The proposed methodology detects screen frequency of scanned image and takes advantage of the local gradient information to perform adaptive filtering. It will descreen scanned images at different printing and scanning resolutions without standardization parameters manually. In this adaptive manner, an appropriate filter with the chosen arguments not only created the descreening process easier however conjointly rendered the processed images attractive ones with terribly sharp edges and clean smooth regions. Our future research will target denoising scheme to preserve spatial details since in this methodology, denoising works on pixel level reduces quality of images0≤u.

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