ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

Reduction of Noise Based on Partial-Reference, Dual-Treewavelet Transform Compressing

Manisha Vidyasagar Gawai
ME Final Year,VLSI Design and Embedded System
E&TC Engineering Dept,
S.V.I.T Nasik.

Prof. R.R.Bhambare
Associate Professor,
E&TC Engineering Dept,
S.V.I.T Nasik.

ABSTRACT:

This paper actually developed to decrease noiseintroduced or exacerbated by image enhancement methods in the system, this algorithms is based on the random spray samplingtechnique. According to the nature of sprays and output images of spray-based methods tend to exhibit noisewith unknown statistical distribution in this process.hense to avoid inappropriateassumptions on the statistical characteristics of noise in the system, a differentone is made here the non-enhanced image is considered to beeither free of noise or affected by non-perceivable levels of noise in the system. Here, taking advantage of the higher sensitivity of the human visualsystem to changes in brightness and the analysis can be limited tothe luma channel of both the non-enhanced and enhanced image process.

Also, given the importance of directional content in human vision in the system.thenthe analysis is performed through the dual-tree complex wavelettransform (DTWCT) in this method.it unlike the discrete wavelet transform method. herethe DTWCT allows for distinction of data directionality in thetransform space in this method. For each level of the transform. Actually, the standarddeviation of the non-enhanced image coefficients is computedacross the six orientations of the DTWCT and then it is normalized in this method.

The result is a map of the directional structures present inthe non-enhanced image in this method. Said map is then used to shrink thecoefficients of the enhanced image in this method. In this paper, the shrunk coefficients andthe coefficients from the non-enhanced image are then mixed. Finally, a noise-reduced versionof the enhanced image is computed via the inverse transforms of the given data.In this paper, the numerical analysis of the results has been performedin order to confirm the validity of the proposed approach in the system.

So, this paper presents details of some significant work in the area of image denoising of the data. Then, some famous approaches are classified into different groups and an overview of various algorithms and analysis is provided for this process.

Index Terms:

Dual-tree complex wavelet transform(DTWCT), image enhancement, random sprays, shrinkage,wavelets, image denoising.

I. Introduction:

Although the field of image enhancement has beenactive since before digital imagery achieved a consumerstatus, it has never stopped evolving. In this process, the recent work introducesa novel multi-resolution denoising method tailored toaddress a specific image quality problem that arises whenusing image enhancement algorithms based on random spraysampling in this system.it is inspired by the peculiar problem of suchmethods, the proposed approach also works for other imageenhancement methods that either introduce or exacerbatenoise of this process.

In this method the work builds and expands on a previous article [1]. At this stage, among image denoisingalgorithms the multi-resolution methodshave a long history of the system. In this, a particular branch is that of transformspace. Among this, someof the most commonly used transforms for shrinkage-basedreduction of noise are the Wavelet Transform (WT) [5]–[7] and the Steerable Pyramid Transform [8]–[10] of this system.In this paper the ContourletTransform [11]–[12]. According to the subject over-completeness is animportant characteristic as it is usually associated with theability to differentiate data directionality in the transform space of the system.

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

Generally, independently of the specific transform used and the generalassumption in multi-resolution shrinkage is that imagedata gives rise to sparse coefficients in the transform space.so, denoising can be achieved by compressing (shrinking)those coefficients that compromise data sparsity of the process. Suchprocess is usually improved by an elaborate statistical analysisof the dependencies between coefficients at differentscales. Here the traditional multi-resolution methodsare designed to only remove one particular type of noise. In this process anddue to the unknown statistical propertiesof the noise introduced by the use of sprays then traditionalapproaches do not find the expected conditions of the process, and thus theiraction becomes much less effective process. In this technique, the proposed approach still performs noise reduction viacoefficient shrinkage and yet an element of novelty is introduced in the form of partial reference images of the noise reduction method.Actually, having a referenceallows the shrinkage process to be data-driven system. A strongsource of inspiration were the works on the Dual-tree ComplexWavelet Transform by Kingsbury. the work on theSteerable Pyramid Transform by Simoncelliet al. [8] and thework on Wavelet Coefficient Shrinkage by Donoho and Johnstoneof this paper. Fig. 1shows the differences between traditionalnoise-reduction methods.

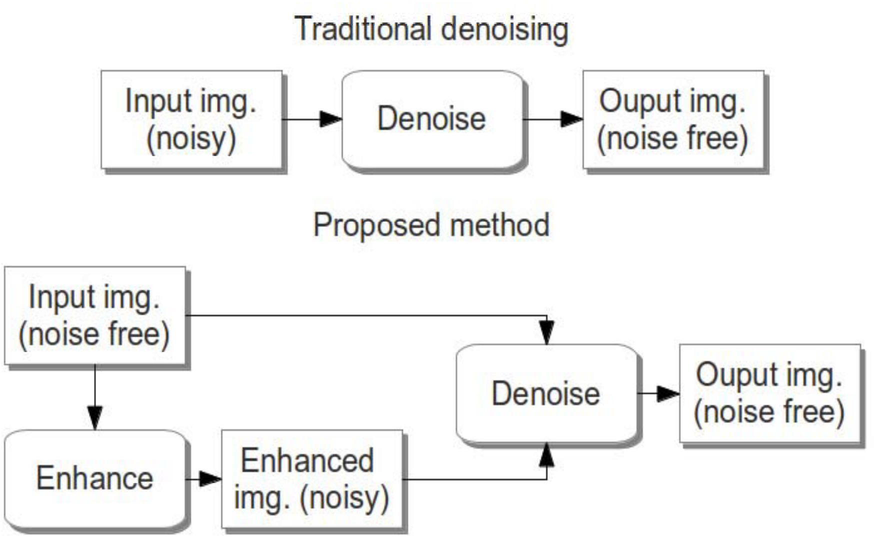

Figure 1.High-level flow charts for traditional noise-reduction methods and the proposed one. It is evident that the scope of application is different, although the goal is the same.

II. System Description:

A. RSR and RACE:

This Section, describes the process of random spray sampling,then introduces Random Spray Retinex (RSR) andRACE. The two algorithms that utilize said sampling method.RACE (crasis of RSR and ACE) is the fusion of RSR and anadapted version of Automatic Color Equalization (ACE) of the system.Random spray sampling was first introduced by Provenziet al. [2] as an elaboration over the physical scanning structuresused by Land and McCann in the original Retinex work of the system.

B.Proposed System:

The main idea behind this work can be explained asfollows: directional content is what conveys information tothe Human Visual System. thstatement given is backed up by past

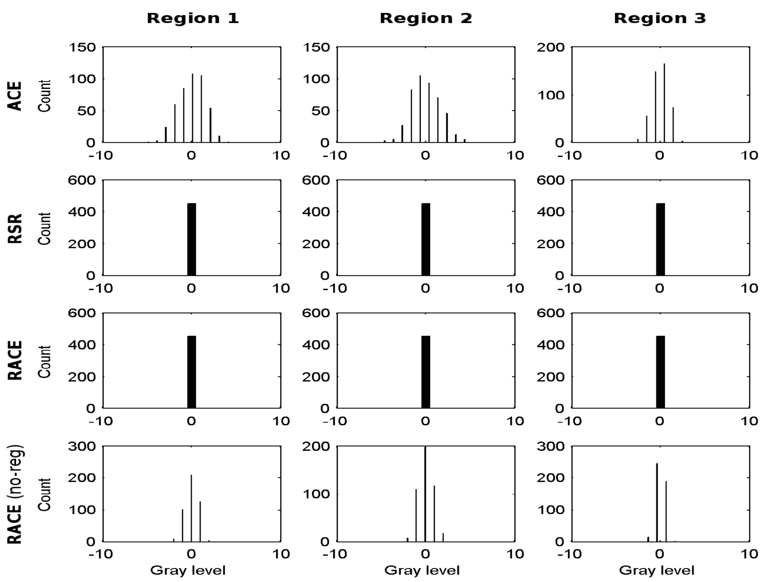

Figure 2. "Multiple shapes" test image. Histograms for the different areas after enhancement with four different algorithms. Plots have been centered around the mean for sake of comparison.

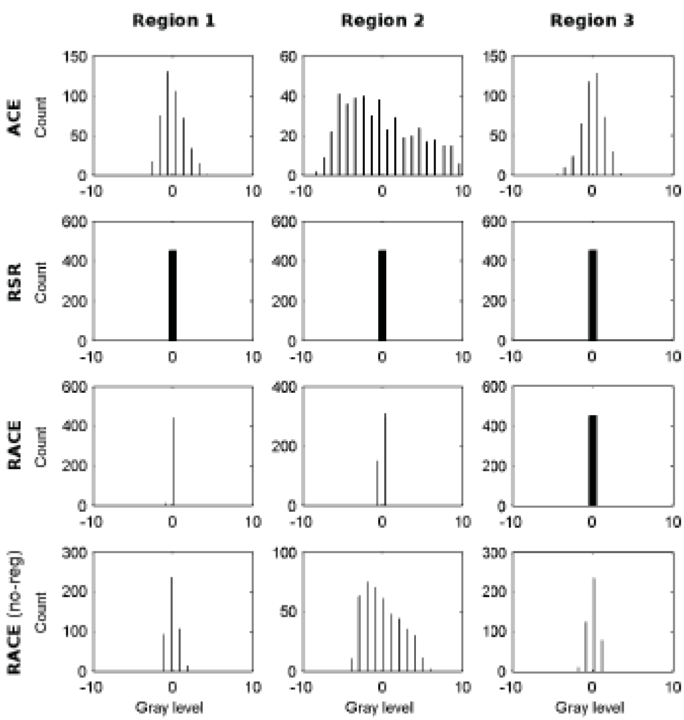

Figure 3.. "Big square" test image. Histograms for the different areas after enhancement with four different algorithms. Plots have been centered around the mean for sake of comparison.

researchsuch as the Retinex theory as well as the high-ordergray-world assumption. So, in particular the local white patch effect described by Retinex comes intoplay when, for a given channel. In this process, the scanning structure samplesa positive intensity change. In this process the geometrical reasons and intensity changes of a directional nature are more easilycrossed than point-like structures such as noise.

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

Algorithm 1 Algorithm for Proposed Noise-Reduction Method

$E_{RGB} \leftarrow \text{enhance}(I_{RGB})$
$I_{YCbCr} \leftarrow \text{rgb2ycbcr}(I_{RGB})$
$E_{YCbCr} \leftarrow \text{rgb2ycbcr}(E_{RGB})$
$Y_I \leftarrow$ Y channel of I_{YCbCr}
$(b^I, c^I) \leftarrow \text{dtcwt}(Y_I)$
$Y_E \leftarrow$ Y channel of E_{YCbCr}
repeat
  $(b^E, c^E) \leftarrow \text{dtcwt}(Y_E)$ ▹ Y_E is iteration dependent
  for $j = 1 \to J$ **do**
    for $k = 1 \to 6$ **do**
      $e_{j,k} \leftarrow (b^I_{j,k})^2 + (c^I_{j,k})^2$
    end for
    $w_j \leftarrow \text{mm}(\text{stddev}_k(e_{j,k}), \text{median}_k(e_{j,k}), \gamma_j)$
    for $k = 1 \to 6$ **do**
      $\tilde{b}^E_{j,k} \leftarrow w_j \cdot b^E_{j,k} + (1 - w_j) \cdot b^I_{j,k}$
      $\tilde{c}^E_{j,k} \leftarrow w_j \cdot c^E_{j,k} + (1 - w_j) \cdot c^I_{j,k}$
      $i^I_{j,k} \leftarrow \text{ord}(b^I_{j,k})$ ▹ Rank of $b^I_{j,k}$
      if $i^I_{j,k} \in \{1, 2\}$ **then**
        $b^O_{j,k} \leftarrow \tilde{b}^E_{j,k}$ ▹ Shrunk coefficients from Y_E
        $c^O_{j,k} \leftarrow \tilde{c}^E_{j,k}$
      else
        $b^O_{j,k} \leftarrow b^I_{j,k}$ ▹ Coefficients from Y_I
        $c^O_{j,k} \leftarrow c^I_{j,k}$
      end if
    end for
  end for
  $Y_E \leftarrow \text{idtcwt}(b^O, c^O)$ ▹ Inverse DTCWT
until $\text{ssim}(Y_I, Y_E) < 0.001$
$O_{YCbCr} = \text{concat}(Y_E, E_{CbCr})$ ▹ Y_E as in last iteration
$O_{RGB} = \text{ycbcr2rgb}(O_{YCbCr})$

Figure 4. Algorithm for noise reduction method

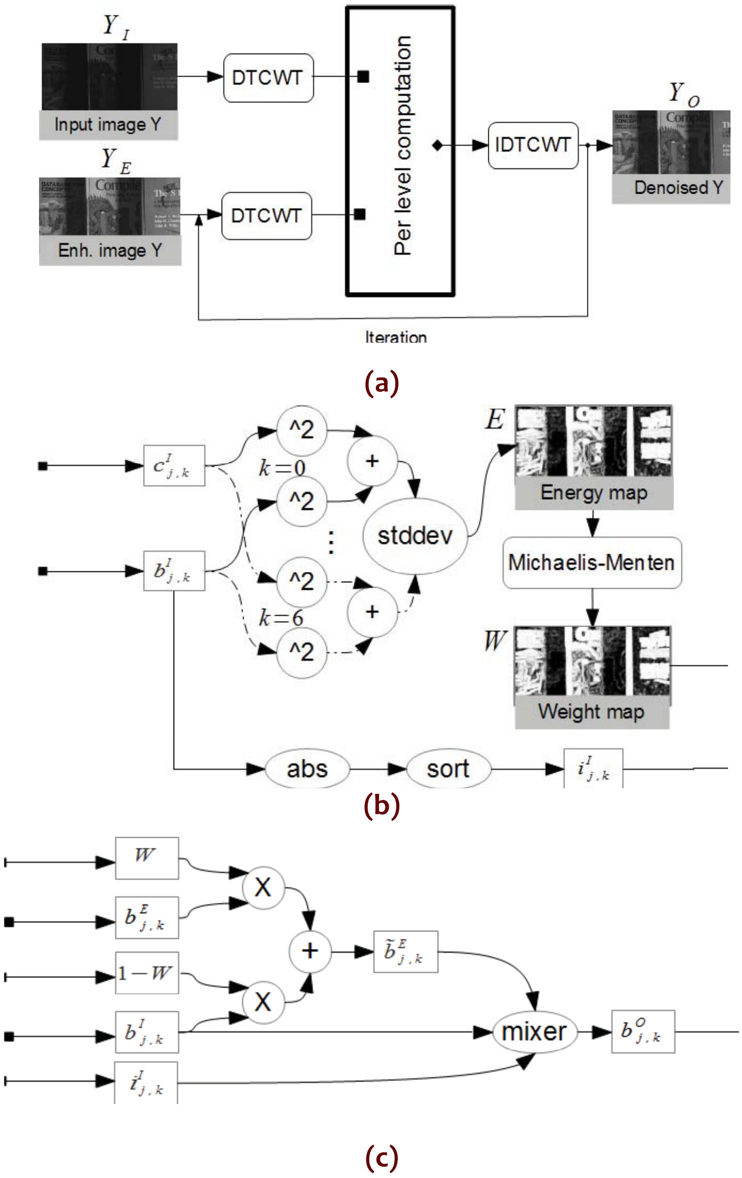

Figure 5. Proposed method flowchart(a) is performed per level of the decomposition. (b) Directional energy map is first computed as the standard deviation of sum-of-squares of the coefficients. A weight map is then obtained by using the Michaelis–Menten function for normalization (c) Weight map is used to scale the coefficients of theenhanced image.

Theproposed method revolves aroundthe shrinkage data directionality and wavelet coefficients generated by the Dual Tree Complex WaveletTransform. The DTCWT is chosen for the ability to distinguishdata orientation in transform space, its relative simplicity andother useful properties. Finally, a fundamental assumption is made: the input imageis considered to be either free of noise, or contaminated byno perceivable noise. In this process, if such an assumption holds then inputimage contains the information needed for successful noisereduction.The algorithm for the proposed method is given asAlgorithm 1. For ease of reference, a visual description is alsogiven in Figure 5. The following subsections explain the detailsof the shrinkage process and the tests performed to optimizethe algorithm parameters of the system.

IIIResult analysis:

The proposed method of this paper, wedevised a set of five different tests and performance assessmentincludes scanline analysis then quality metrics comparison and subjectiveevaluation and panel tests in the system.

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

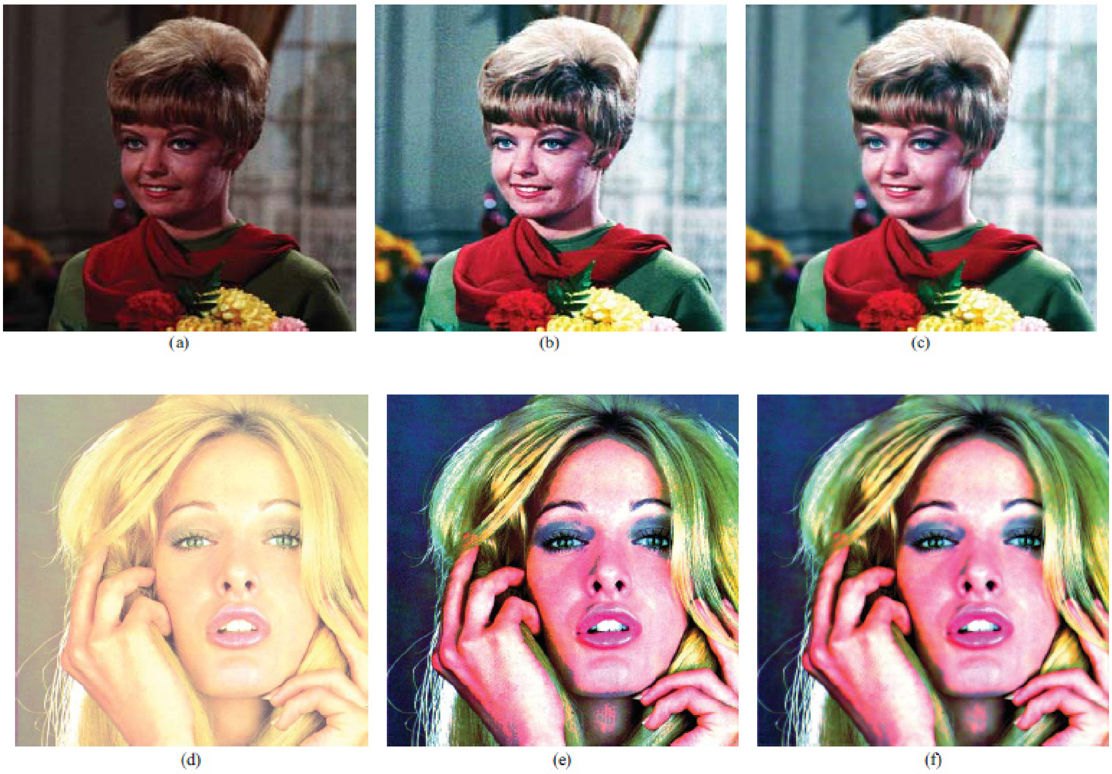

Figure 6. Proposed denoising method applied to histogram equalized images. In this case, either grain or compression noise is already present in the nonenhanced images and exposed by histogram equalization. The proposed method effectively reduces both, while still maintaining sharp edges. (a) Girl, original.(b) Girl, histogram equalized. (c) Girl, denoised with J = 2. . (d) Tiffany, original. (e) Tiffany, histogram equalized. (f) Tiffany, denoised with J = 2.

1) Required Test on Difficult Images for RSR: here, we first used theproposed method on two images taken from the work onRSR [2] which happened to trigger the appearance of noise in the data.

The images, their enhanced versions and the noise reducedresults are shown in Figure 5. Scanline data is also given inFigure 6.(a)–(b).here, the proposed denoising method respects thedesired behaviour and shows good performance of the system.

Acknowledgement:

We especially thanks to our department and our institute for the great support regarding paper and their all views. I really thankful to my all staffs and my guide Mr. who showed me the way of successful journey of publishing paper and project.

Conclusion:

According to the paper, the given work presents a noise reduction method based onDual Tree Complex Wavelet Transform coefficients shrinkage method. here, theproposed method produces good quality output and removingnoise without altering the underlying directional structures inthe image process. It is designed to tackle a quality problemspecific to spray-based image enhancement methods and theproposed approach also proved effective on compression andlatent noise brought to the surface by histogram equalization of the system.

References:

[1] M. Fierro, W.-J.Kyung, and Y.-H. Ha, "Dual-tree complex wavelettransform based denoising for random spray image enahcementmethods,"inProc. 6th Eur. Conf. Colour Graph., Imag. Vis., 2012,pp. 194–199.

ISSN No: 2348-4845
International Journal & Magazine of Engineering, Technology, Management and Research
A Peer Reviewed Open Access International Journal

[2] E. Provenzi, M. Fierro, A. Rizzi, L. De Carli, D. Gadia, and D. Marini,"Random spray retinex: A new retinex implementation to investigate thelocal properties of the model," vol. 16, no. 1, pp. 162–171, Jan. 2007.

[3] E. Provenzi, C. Gatta, M. Fierro, and A. Rizzi, "A spatially variant whitepatchand gray-world method for color image enhancement driven bylocal contrast," vol. 30, no. 10, pp. 1757–1770, 2008.

[4] Ø. Kolås, I. Farup, and A. Rizzi, "Spatio-temporal retinex-inspiredenvelope with stochastic sampling: A framework for spatial coloralgorithms," J. Imag. Sci. Technol., vol. 55, no. 4, pp. 1–10, 2011.

[5] H. A. Chipman, E. D. Kolaczyk, and R. E. McCulloch, "Adaptivebayesian wavelet shrinkage," J. Amer. Stat. Assoc., vol. 92, no. 440,pp. 1413–1421, 1997.

[6] A. Chambolle, R. De Vore, N.-Y. Lee, and B. Lucier, "Nonlinear waveletimage Processing: Variational problems, compression, and noise removalthrough wavelet shrinkage," IEEE Trans. Image Process., vol. 7, no. 3,pp. 319–335, Mar. 1998.

[7] D. Cho, T. D. Bui, and G. Chen, "Image denoising based on waveletshrinkage using neighbor and level dependency," Int. J. Wavelets, MultiresolutionInf. Process., vol. 7, no. 3, pp. 299–311, May 2009.

[8] E. P. Simoncelli and W. T. Freeman, "The steerable pyramid: A flexiblearchitecture for multi-scale derivative computation," in Proc. 2nd Annu.Int. Conf. Image Process., Oct. 1995, pp. 444–447.

[9] F. Rooms, W. Philips, and P. Van Oostveldt, "Integrated approach forestimation and restoration of photon-limited images based on steerablepyramids," in Proc. 4th EURASIP Conf. Focused Video/Image Process. MultimediaCommun., vol. 1. Jul. 2003, pp. 131–136.

[10] H. Rabbani, "Image denoising in steerable pyramid domain based on alocallaplace prior," Pattern Recognit., vol. 42, no. 9, pp. 2181–2193,Sep. 2009.

[11] S. Foucher, G. Farage, and G. Benie, "Sar image filtering based onthe stationary contourlet transform," in Proc. IEEE Int. Geosci. RemoteSens. Symp., Jul.–Aug. 2006, pp. 4021–4024.

[12] W. Ni, B. Guo, Y. Yan, and L. Yang, "Speckle suppression for sar imagesbased on adaptive shrinkage in contourlet domain," in Proc. 8th WorldCongr. Intell. Control Autom., vol. 2. 2006, pp. 10017–10021.