Journal of Engineering and Applied Sciences 12 (20): 5343-5346, 2017
ISSN: 1816-949X

Performance Analysis of Total Variant Techniques for Efficient Segmentation of Medical Images

Ramesh Babu Vallabhaneni and V. Rajesh
Department of Electronics and Communication,
KL University (Konerulakshmia Education Foundation), Vadeswaram, Guntur, India

Abstract: Denoising medical images is often required for efficient diagnosis of the diseases. Total Variance (TV) is employed as a model of partial differential equation to identify the isolated noisy regions in the image. In the due course, the TV has been modified to various versions. In this study, a performance analysis of adaptive TV, median filtering and modified TV is performed, brain MRI of a patient subjected to tumour is considered for denoising process. Later the same is segmented to have a clear vision of the tumour portion. The simulation is carried out in MATLAB using image processing tool box. The evaluation is carried out using performance metrics like PSNR.

Key words: Brain tumour, TV, EADTV, MTV, performance, modified

INTRODUCTION

The concept of evaluating total variation of an image can be considered as an image metrics which involve in calculating total variation of the image. It typically perform this calculation without any consideration to the direction. It is well suited for the cases where there is no possibility of dominance inters of direction. The total variation was applied to denoising along with other algorithm in order to elevate its efficiency in removing conventional noise from natural images. While computing total variation, the normalised gradients are added. In contrast to the conventional total variation which ignores the direction, novel Directional Total Variation (DTV) considers direction. The DTV can be realized as proximal operator (Combettes and Pesquet, 2011). Earlier one parameter family of regularization using the concept of special function (Ayache *et al*., 1996) which can be realized as an inverx problem (Grimson *et al*., 1997).

Image denoising involves in filtering and eliminating noise within the image. The process of denoising is essential as it is always necessary to remove the noise in order to produce a clear image. From a degraded image due to noise it is obvious to note that there is a huge variance between the noise and the surrounding pixel. Hence, the total variance which is based on gradient evaluation strategy is a good technique of separating the noise from pixels. The Adaptive TV (ATV) based denoising model considers that the noise creates falsified edge and degrades the quality considering this.

Accurate segmentation of pathological structures is a crucial step in computer assisted grading and detection of glioma tumours. Several image segmentation algorithms, play a vital role in numerous biomedical imaging applications such as the quantification of tissue volumes (Combettes and Pesquet, 2011), diagnosis (Goldluecke and Cremers, 2011), localization of pathology (Bredies *et al*., 2010), study of anatomical structures (Combettes and Pesquet, 2011), treatment planning (Lawrie and Abukmeil, 1998), partial volume correction of functional imaging data (Taylor, 1995) and computer integrated surgery (Zijdenbos and Dawant, 1994; Khoo *et al*., 1997). Methods for performing segmentations vary widely depending on the specific application, imaging modality and other factors. For example, the segmentation of brain tissue has different requirements from the segmentation of the liver. General imaging artifacts such as noise, partial volume effects and motion can also have significant consequences on the performance of segmentation algorithms.

In this study, the ATV technique is used along with the mean shifting algorithm for efficient denoising of the brain tumour MRI images.

Techniques

Total variance: When an image M(x, y) is adult rated with noise ‘n’ the resultant distorted image D(x, y) is given as:

$$D(x, y) = M(x, y) + 'n' \tag{1}$$

Corresponding Author: Ramesh Babu Vallabhaneni, Department of Electronics and Communication, KL University (Konerulakshmia Education Foundation), Vadeswaram, Guntur, India

For noise with standard deviation 'σ', we can say:

$$\frac{1}{2}\int_{\Omega}(\text{M-D})^2\,dxdy = \sigma^2 \tag{2}$$

According to TV the corresponding denoising model is given as:

$$\arg_t^{\min} E[M] = \frac{\lambda}{2}\int_{\Omega}(\text{M-D})^2\,dxdy + \int_{\Omega}|\Delta M|\,dxdy \tag{3}$$

The basis of this technique adopts the L^2 norm. This significantly contributed to transforming the problem to a simple linear equation model which can be further solved with minimum computation.

It should be referred that the image in its form does not have a continuous and smooth. In such a situation it is not possible to handle discontinuous system as well as the corresponding denoising model. Hence, the L^2 norm emerged as a powerful tool for solving such problems. Moreover, it is experimentally verified that the L^2 norm does have high efficiency in denoising that a L^1 norm.

Adaptive TV: The adaptive TV encaps the merits of both L^2 and L^1 Norms. The respective expression is written:

$$\min E[M] = \frac{\lambda}{2}\int_{\Omega}(\text{M-D})^2\,dxdy + \left(\frac{1}{P(x, y)}\right)\int_{\Omega}|\Delta M|^{P(x,y)}\,dxdy \tag{4}$$

The gradient referred to as $|\Delta M|$ defines the formulation of p(x, y).

Modified TV: The modified TV has the potential to take care of false edges reported by the smoothing function as not in the case of conventional TV. Accordingly, the equation is given as:

$$E = \int_{\Omega}\sqrt{u(x,y)\times n(x,y)d\Omega} + \lambda\int_{\Omega}(\text{u-M})^2\,d\Omega \tag{5}$$

where, n(x, y) is a function of pixel weights though the MTV representation is quite similar to that of TV, it is more efficient than TV.

MATERIALS AND METHODS

The EADTV is used as a basis that defines the objective function. However, the denoising is performed using a nonlinear median filter. The computed gradient acts as a seeking point of the edges of an image. If the gradient compulsory approaches '0' value, it refers to a uniform or flat portion of the image. Similarly, when it projects towards '0', it refers to the boundary. The gradient of a pixel coordinate (x, y) is given as g(x, y). The computation of g(x, y) is performed with respect to its neighbouring pixel values namely (x-1, y-1) (x+1, y+1), (x+1, y), (x, y+1), (x-1, y), (x, y-1). This solves as a window. The window size in this typical case 3×3. However, the window size is adaptive. Over a window the noise points are isolated and excluded from the image. In such situation, the unintended or fraudulent image edges do mislead. But the ATV strategy gets rid of this and adaptively manages with variation.

RESULTS AND DISCUSSION

Results pertaining to the techniques discussed in the previous section referring to an image in terms of its denoising capabilities are presented in this study. The original image is as shown in Fig. 1 to which a considerable noise of $\alpha = 5$ is added.

Figure 2 refers to the denoised image using the EADTV in which the achieved SNR is approximately 74 and the similarity index is around 0.99988. However, after the mean shift spatial filtering the image denoising further improved as shown in Fig. 3.

Finally, the corresponding output denoised image with excellent denoising characteristics using modified TV is as shown in Fig. 4. The tumour is finally segmented and is clearly visible as shown in Fig. 5.

Fig. 1: Original noisy image

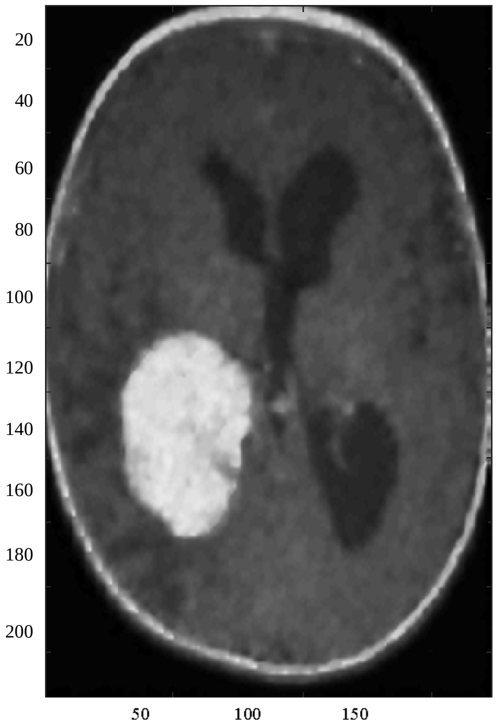

Fig. 2: EADTV denoised image; α = 5; RMSE = 0.051898 EADTVPSNR = 73.8278; MISSIM = 0.99988

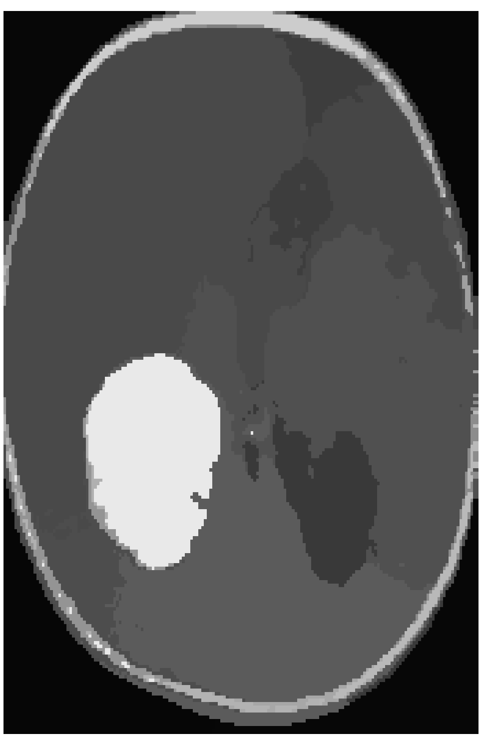

Fig. 3: Mean shift spatial filtering; mean shift+spatial: 25

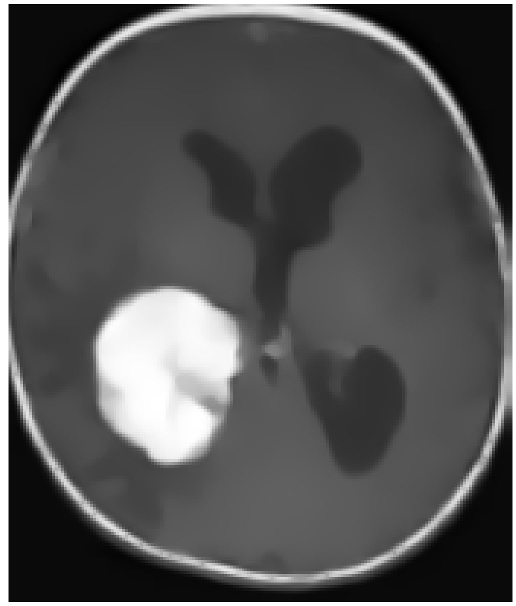

Fig. 4: MTV denoised image; MTV final image lambda (0.010000); dt (0.250000); iter (200); SNR (27.972575)

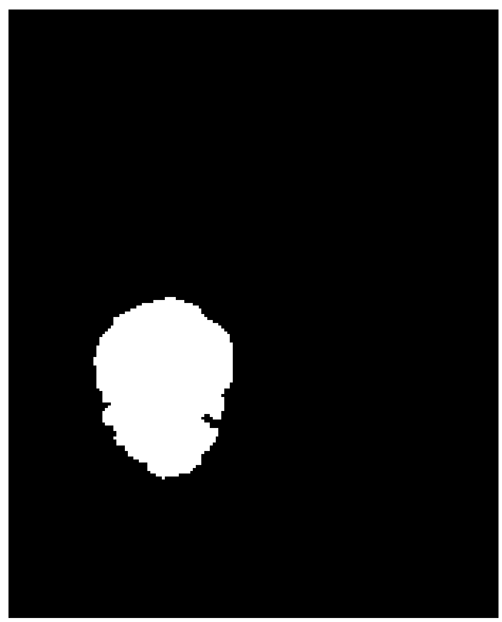

Fig. 5: Segmented image

CONCLUSION

The models pertaining to several methodologies are considered and evaluated. The simulation based experimentation demonstrated the denoising procedure of EADTV, median spatial filtering and modified TV. The

Performance of MTV proposed to be the dominant in terms of efficiency evaluated using the PSNR as well as the minimum complexity involved in implementation. The implementation on fused and further on three dimensional as well as other color image would be a good slope of future work.

REFERENCES

Ayache, N., P. Cinquin, I. Cohen, L. Cohen, F. Leitner and O. Monga, 1996. Segmentation of Complex Three-Dimensional Medical Objects: A Challenge and a Requirement for Computer-Assisted Surgery Planning and Performance. In: Computer-Integrated Surgery: Technology and Clinical Applications, Taylor, R.H. (Ed.). MIT Press, USA., pp: 59-74.

Bredies, K., K. Kunisch and T. Pock, 2010. Total generalized variation. SIAM. J. Imaging Sci., 3: 492-526.

Combettes, P.L. and J.C. Pesquet, 2011. Proximal Splitting Methods in Signal Processing. In: Fixed-Point Algorithms for Inverse Problems in Science and Engineering, Bauschke, H.H., R. Burachik, P.L. Combettes, V. Elser and D.R. Luke *et al.* (Eds.). Springer, Berlin, Germany, ISBN:978-1-4419-9568-1, pp: 185-212.

Goldluecke, B. and D. Cremers, 2011. Introducing total curvature for image processing. Proceedings of the 2011 IEEE International Conference on Computer Vision (ICCV), November 6-13, 2011, IEEE, Barcelona, Spain, ISBN:978-1-4577-1101-5, pp: 1267-1274.

Grimson, W.E.L., G.J. Ettinger, T. Kapur, M.E. Leventon, W.M. Wells III and R. Kikinis, 1997. Utilizing segmented MRI data in image-guided surgery. Int. J. Pattern Recogn. Artif. Intell., 11: 1367-1397.

Khoo, V.S., D.P. Dearnaley, D.J. Finnigan, A. Padhani, S.F. Tanner and M.O. Leach, 1997. Magnetic Resonance Imaging (MRI): Considerations and applications in radiotherapy treatment planning. Radiother. Oncol., 42: 1-15.

Lawrie, S.M. and S.S. Abukmeil, 1998. Brain abnormality in schizophrenia. A systematic and quantitative review of volumetric magnetic resonance imaging studies. Br. J. Psychiatry, 172: 110-120.

Taylor, P., 1995. Computer aids for decision-making in diagnostic radiology-a literature review. Br. J. Radiol., 68: 945-957.

Zijdenbos, A.P. and B.M. Dawant, 1994. Brain segmentation and white matter lesion detection in MR images. Crit. Rev. Biomed. Eng., 22: 401-465.