COMPARATIVE EVALUATION OF FILTERS FOR SMOOTHING THE GLACIER SURFACE VELOCITY ESTIMATES

KAVITA V. MITKARI[1], REET K. TIWARI[2], MANOJ K. ARORA[1,3]

[1] PEC University of Technology, Chandigarh 160012, India

[2] Indian Institute of Technology Ropar, Punjab 140001, India

[3] Indian Institute of Technology Roorkee, Uttarakhand 247667, India

KEY WORDS: COSI-Corr, Filtering, Glacier ice, Ice velocity

ABSTRACT: The surface velocity of glaciers is important for the estimation of ice discharge, to understand glacier dynamics and its response to climate change, etc. However, the glacier surface velocity data collected using conventional field measurements is insufficient. Therefore, remote sensing based techniques are being used extensively in glaciological studies as it offers the comprehensive and repetitive monitoring in a cost effective manner. Recently, Co-registration of Optically Sensed Images and Correlation (COSI-Corr) tool (Leprince et al., 2007) which is based on image matching method of optical images has gained popularity for the estimation of glacier surface velocity and has proved to be robust and effective. For denoising the glacier surface velocity estimates, Non-Local Means (NLM) filter has been incorporated in COSI-Corr. However, to discard/replace erroneous values, user has to manually define the threshold to discard/replace erroneous values. Although the NLM filter in COSI-Corr gives smooth estimates, but it has been observed that the filtered values deviate from the original ones. Therefore, the main purpose of this study has been to find an optimal filter for obtaining smooth estimates while preserving the original. Various spatial domain filters such as mean filter, low-pass filter, adaptive filter and statistical filters have been applied and evaluated in this study to obtain smooth glacier surface velocity estimates. The comparative evaluation of these filters showed that the application of statistical filter with multipliers 1, 2 and 4 in sequential order followed by 3 x 3 mean filter provided close match with the original estimates.

INTRODUCTION

Digital image processing is being used extensively for extracting and representing the information in an efficient manner. Digital images acquired by satellites are known as remotely sensed images. Digital image processing plays an important role in processing the remotely sensed digital images. In recent times, remote sensing images are being widely used in glaciological studies. The estimation of glacier surface motion is important for estimation of ice discharge, to understand glacier dynamics, its response to climate change etc. The conventional field surveys on glaciers are laborious, time consuming, expensive and can be risky in high mountainous regions. However, extracting information from remotely sensed images using digital image processing techniques offers the most pragmatic tool for their extensive, cost-effective, and repetitive study while retaining sufficient accuracy and precision (Tiwari et al., 2012).

Glacier surface velocities are being estimated using optical image matching and correlation techniques and the Co-registration of Optically Sensed Images and Correlation (COSI-Corr) tool developed by Leprince et al. (2007) is being used widely to measure the glacier surface velocity. There are several processing steps in COSI-Corr to derive glacier surface velocities which include selecting tie points to co-register the image pair, orthorectification, correlation and post-processing of the result for obtaining smooth surface velocity estimates. For removing the erroneous values, COSI-Corr has Non-Local Means (NLM) filter implemented in the post-processing tool. NLM has an ability to preserve fine detail while reducing additive white Gaussian noise. It exploits the repetitive character of structures in an image, unlike conventional denoising algorithms, which typically operate in a local neighbourhood (Buades et al., 2006; Goossens et al., 2008). Though the implementation of NLM provided in COSI-Corr extends the method to denoising of scientific data sets in general, user has to manually define the threshold to discard/replace erroneous values in the NLM filter. Processing of large number of image pairs to cover extensive glaciated regions at many time-steps will require automated method for filtering of results with minimal user interaction. There are different opportunities, such as mean filter, low-pass filter, and adaptive filter and very suitable is applying a statistical filter. The spatial domain filters modify the pixel values based on the values of surrounding pixels.

SPATIAL DOMAIN FILTERS

The various spatial domain filters that have been explored in this study are as described below:

Mean Filter

Mean filter smoothes the local variations in an image, and the noise is removed as a result of blurring. The idea of mean filtering is simply to replace each pixel value in an image with the mean value of its neighbours, including itself. This has the effect of eliminating pixel values which are unrepresentative of their surroundings.

Low Pass Filter

Low pass filter is equivalent to mean filter in as sense that it corresponds to low-pass filtering in the spatial frequency domain, by which the high-frequency components are removed.

Adaptive Filter

Adaptive filter is commonly used to enhance or restore data by removing noise without significantly blurring the features in an image. The behaviour of adaptive filter changes depending on the statistical characteristics of the image inside the filter window. The standard formulation of adaptive filter exhibits low pass characteristics. Statistical measures include mean and variance.

Statistical Filter

It improves pixel values that fall outside a user defined statistical range. In this, the moving window is set in such a way that it is large enough to provide meaningful statistics and small enough to minimize blurring. The center pixel is replaced by the average of all pixels within the moving window that fall within a defined range about the center pixel, that is, [center pixel DN] = DN/sigma. Sigma is statistically one standard deviation and defines coefficient of variation as given by equation (1).

$$\text{Sigma} = \text{coefficient of variation} = \frac{\sqrt{Variance}}{Mean} \tag{1}$$

This value can be modified by using the multipliers. The range of values within the moving window used to calculate the average can be increased or decreased by using the multipliers. The filter can be used sequentially with increasing multipliers. This preserves fine detail, yet result in a very smooth final image.

Because so much focus has been put into developing, improving, and automating the spatial domain filters, it is now possible to compare and evaluate the spatial domain filters for providing the best performing spatial domain filter to obtain smooth glacier surface velocities estimates while maintaining the original values. All the above spatial domain filters implemented in ERDAS Imagine 2014, are used in this study to smoothen the glacier surface velocity estimates obtained from COSI-Corr tool.

STUDY AREA

For the present study, Gangotri glacier (shown as blue outline in Figure 1) which is situated in the Uttarkashi district of Uttarakhand State, India has been considered as a study area. It is a valley-type glacier and one of the largest glaciers in the Indian Himalayas. It extends between latitudes 30°43'20"N to 31°01'07"N and longitudes 78°59'42"E to 79°17'10"E. It is a debris-covered glacier with a series of glacial lakes and EIFs in the ablation zone. The glacier originates from Chaukhamba group of peaks at the elevation of 7138 m above msl. The accumulation and ablation zones lie around 6200 m and 4800 m above msl, respectively (Srivastava, 2012). It has four major tributaries (Kirti glacier, Ghanohim glacier, Maiandi glacier and Swachhand glacier). The snout area in general and the ice cave in particular are popularly known as ′Gaumukh′ from where the glacier melt channel originates. Western disturbances cause heavy snowfall from December to March (Thayyen and Gergan, 2010) and seasonal melting occurs from May to October (Dobhal et al., 2008). The period of satellite data acquisition corresponds to the melting season because during this period the temporary snow cover is at its minimum and the entire glacier area can be clearly demarcated.

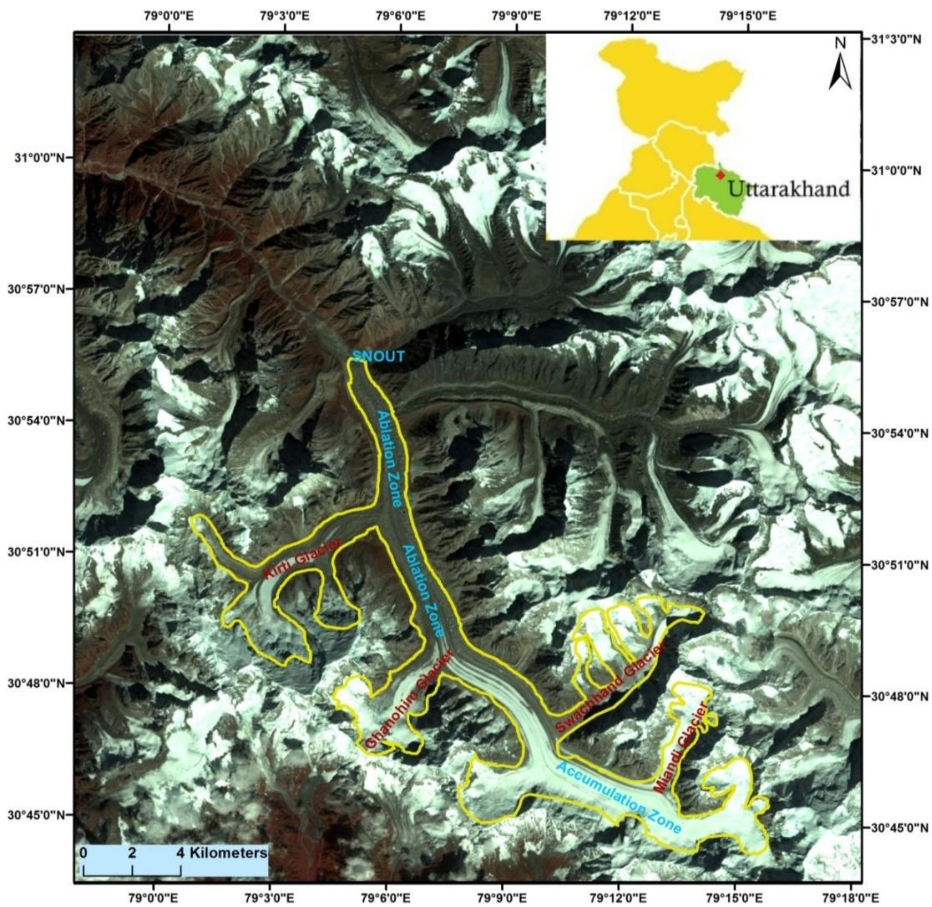

Figure 1. Standard FCC (R: Band 4, G: Band 3, B: Band 2) of Landsat Thematic Mapper Image showing Gangotri glacier (yellow), its major tributaries (Red) and zones (Blue).

RESULTS AND DISCUSSION

The surface velocity maps obtained as a result of applying filters such as mean filter, low pass filter, adaptive filter, statistical filter and NLM filter are shown in Figure 2. The performance evaluation of these filters is quantified by Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE). The MSE and PSNR values obtained for each of the filters compared in this study are given in Table 1.

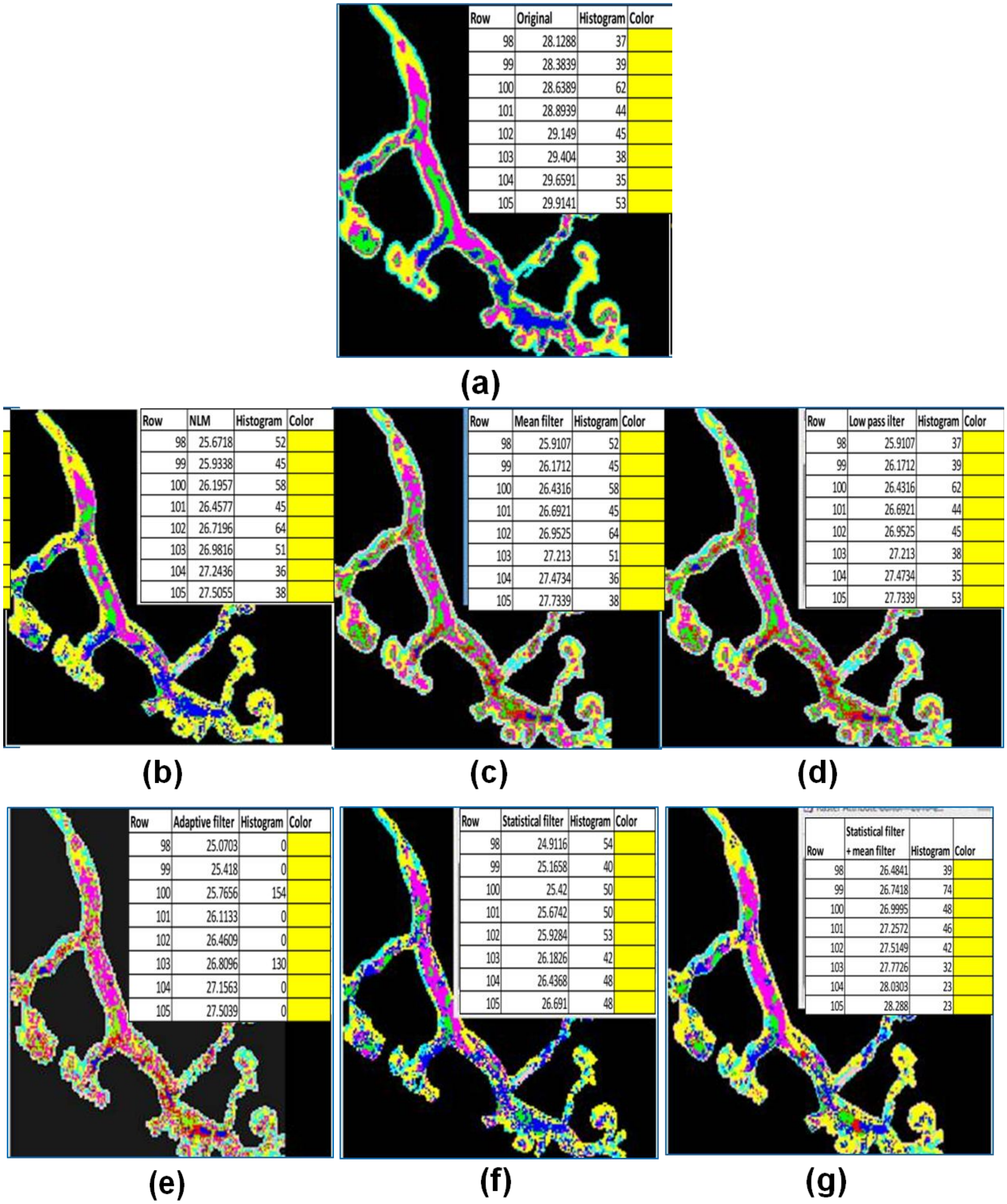

Figure 2. Glacier velocity estimates obtained as results of applying different filters (b) NLM, (c) mean, (d) low pass, (e) adaptive, (f) statistical, (g) statistical + mean and their comparison with (a) original estimates.

A comparative study of the spatial domain filters such as mean filter, low pass filter, adaptive filter and statistical filter against NLM filter has been carried out so as to choose the best method for removal of noise and to smooth the surface glacier velocity estimates. The performance evaluation of these filters is quantified by Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE) calculated using equations (2) and (3) respectively.

$$\text{PSNR} = 10log_{10}\left(\frac{MAX(g)^2}{MSE}\right) \tag{2}$$

Where

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{i=1}^{N}[g(i,j) - f(i,j)]^2 \tag{3}$$

Where, M and N are the total number of pixels in the horizontal and the vertical dimensions of image respectively; g denotes the noise image and f denotes the filtered image. The MSE and PSNR values obtained for each of the filters compared in this study are given in Table 1.

Table 1. MSE and PSNR values of the NLM filter and spatial domain filters

Filtering method	MSE	PSNR
NLM	28.51	-16.66
Mean filter	52.54	-19.56
Low pass filter	55.16	-17.42
Adaptive filter	50.61	-15.41
Statistical filter	46.33	-14.55
Statistical filter + mean filter	18.26	-12.62

NLM has an ability to preserve fine detail while reducing additive white Gaussian noise (Buades et al., 2006; Goossens et al., 2008). Though the implementation of NLM provided in COSI-Corr extends the method to denoising of scientific data sets in general, user has to manually define the threshold to discard/replace erroneous values in the NLM filter. Processing of large number of image pairs to cover extensive glaciated regions at many time-steps will require automated method for filtering of results with minimal user interaction. There are different opportunities, such as mean filter, low-pass filter, and adaptive filter and very suitable is applying a statistical filter. The comparative evaluation of the filters applied in this study showed that the best filter to obtain smooth glacier surface velocity estimates is application of statistical filter with multipliers 1, 2 and 4 in sequential order followed by 3 x 3 mean filter. Figure 2 shows that it gives closer match with the original estimates compared to all other filters evaluated in this study. The comparative study explained with the help of PSNR and MSE also illustrates the same.

CONCLUSION

In this paper, the comparative study of NLM, mean filter, low pass filter, adaptive filter and statistical filter has been carried out. The comparative evaluation of these filters showed that the best filter to obtain smooth glacier surface velocity estimates is application of statistical filter with multipliers 1, 2 and 4 in sequential order followed by 3 x 3 mean filter. It gives closer match with the original estimates compared to all other filters evaluated in this study. The comparative study explained with help of PSNR and MSE also illustrates the same.

ACKNOWLEDGEMENT

This work was supported by the Department of Science & Technology, Government of India under Grant SB/DGH/59/2013.

REFERENCES

R. K. Tiwari, R. P. Gupta, R. Gens and A. Prakash, “Use of optical, thermal and microwave imagery for debris characterization in Bara-Shigri glacier, Himalayas, India”, IEEE International Geoscience and Remote Sensing Symposium Proceedings 22-27 July, 2012, Munich, Germany, pp. 4422 to 4425, 2012.

S. Leprince, S. Barbot, F. Ayoub and J.P. Avouac, “Automatic and Precise Ortho-rectification, Coregistration, and Subpixel Correlation of Satellite Images, Application to Ground Deformation Measurements”, IEEE Trans. Geosci. Remote Sensing, vol. 45, no. 6, pp 1529-1558, 2007

A. Buades, B. Coll and J.M. Morel, “The staircasing effect in neighborhood filters and its solution”, IEEE transactions on Image Processing, vol. 15, no. 6, pp. 1499 to 1505, 2006.

B. Goossens, H. Luong, A. Pizurica and W. Philips, “An Improved Non-Local Denoising Algorithm”, Proceedings of the 2008 International Workshop on Local and Non-Local Approximation in Image Processing, Lausanne, Switzerland, 2008.

D. Srivastava, “Status report on Gangotri Glacier”, Science and Engineering Research Board, Department of Science and Technology, New Delhi, Himalayan Glaciology Technical Report No. 3, 102, 2012.

R. J. Thayyen and J. T. Gergan, “Role of glaciers in watershed hydrology: a preliminary study of a ‘Himalayan Catchment’ ”, The Cryosphere, vol. 4, pp. 115 to 128, 2010.

D. P. Dobhal, J. T. Gergan and R. J. Thayyen, “Mass Balance Studies of Dokriani Glacier from 2000, Garhwal Himalaya, India”, Bulletin of Glaciological Research, vol. 25, pp. 9 to 17, 2008.