I J C T A, 10(20), 2017, pp. 231-241
ISSN: 0974-5572

An Efficient Feature Extraction Based Segmentation and Classification of Antarctic Peninsula ICE Shelf

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ABSTRACT

Monitoring ice-shelves snowmelt is fundamental to understanding global climate change. A simple and automated snowmelt detection is crucial to the establishment of an ice-shelves snowmelt monitoring system. These monitoring system uses image processing techniques to detect the snow melt. In the last decades, glaciologists have studied and observed steady decrease in ice shelf extent through melt, and absolute disintegration of some ice shelves. Global warming could cause increased melting of Antarctic ice shelves. In this paper, to detect the snow melt of multichannel Wilkins ice shelf disintegration we propose automatic method consisting of three phases such as pre-processing, segmentation and classification. Initially, Wiener filter is applied to reduce the noise and to preserve the edges. Secondly, Fuzzy K Means (FKM) segmentation is used to obtain the melting surface. In FKM segmentation, the region and Gray Level Covariance Matrix (GLCM) based features are extracted , and segmentation in all the seven spectral bands collected by Moderate Resolution Imaging Spectroradiometer (MODIS). Finally, the SVM classification is processed to detect melting and not melting snow parts. The proposed method has been tested in MODIS Wilkins Ice Shelf image and effectively classified but is also more accurate.

Keywords: Antarctic Peninsula ice shelf, Fuzzy K Means, Multispectral image, Image segmentation, feature extraction, classification.

1. INTRODUCTION

Portions of ice shelves annually experience surface melting. Snowmelt on ice shelves plays an important role in the strength of global vapour flow, global heat balance and climate change. Huybrechts [1] reported that the Antarctic ice shelve accounts for 90% of all the ice on Earth. In this process, if the Antarctic ice sheet were to melt completely means, it would cause a rise in sea level of about 60 m. Multispectral image processing techniques has been extended newly in varied fields like vegetation monitoring, geological mapping and medical images. The optical remote sensing is depending on the number of spectral bands images and it can be classified as panchromatic image, multispectral image, super spectral image and hyper spectral image. Normally, panchromatic image are those images without any spectral information whereas in multispectral contains both brightness and color information. Multispectral images consist of several bands of data. For a visual point on view, each band of image can be displayed one band at a time or in combination of three bands as a grey scale image or color composite image . However, knowledge of spectral signature plays a vital role for the interpretation of multispectral glacier image.

Tracking of the dimensions and thickness of the ice and ice bergs is needed so that it will decide the mass of the sparkling water that could be released into the Southern Oceans. Synthetic Aperture Radars (SAR) are the only imaging radars which might be able to penetrating heavy cloud cover across the planet, day or night time however the imagery is constrained to lower resolutions. SAR software is now connected

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to almost each earth environment tracking satellite. Sounding radar makes use of low-frequency ground-penetrating radars which can be used to retrieve data from the sub-surface of earth. Their low working frequency allows them to penetrate hundreds of metre beneath the ground at the same time as synthetic aperture radar is generally decreased to the surface layer. This is because of the low working frequency and small allowable antenna measurement, for this reason the beam could be very huge and much less effective. Envisat mapped the most properly recognize extreme Antarctic ice calving occasion of 2002 - The crumble of Larsen B - in mild MODIS imagery and contained progressed versions of many of the units on-board ESR. Larsen B ice shelf(https://en.wikipedia.org/wiki/Larsen_Ice_Shelf) changed into the most speedy collapse seen of an ice shelf and confirmed that that ice shelves are incredibly dynamic with this event releasing 3250km^2 220m height of ice bergs into the Southern Ocean.

Melting and freezing of snow/ice affects the exchange of heat between the land and atmosphere [4]. Melt over Antarctica, particularly the trend over ice shelves is of great importance because it is sensitive to the changes in air and ocean circulation near Antarctica. Excessive melting results in ice shelf collapse. Although breaking of ice shelf does not lead to rise in sea water level, collapse of ice shelf speed up the flow of glaciers feeding the shelf. Since the glaciers rest on land, their flow on sea contributes to sea level rise. The melt and freeze status is highly dynamic, hence it is necessary to monitor it at regular interval. A large number of studies have been carried out to detect the surface melt of Antarctic Peninsula ice shelves. Large uncertainties remain in the present and future contribution to sea level rise from Antarctica.

Segmentation is an important part in analysis of multispectral imagery. During the segmentation [2] the images are divided into regions. A set of segments to facilitate collectively cover the entire image, otherwise a set of contours extracted from the image is obtained as image segmentation results. Each of the pixels in a region is parallel with distinguish to a number of characteristic or computed property, probably intensity color, or texture. Then the classification is used to exact detection of affected or melted area. Multispectral image classification [3] can be analyses as a combined mission of both image processing and classification techniques. In general, image classification process, in the field of remote sensing is the process of allocating pixels/basic units of an image to classes. This method is possible to collect groups of identical pixels found in remotely sensed data into classes that suit the informational classes of user curiosity by comparing pixels to one another and to these of recognized identity.

The paper is organized as follows. Section 2 explains the background information about Antarctic Peninsula ice shelves disintegration and Wilkins ice shelf. Section 3 describes the methodology. In Section 4 the method is evaluated using MODIS Wilkins Images. Section 5 concludes the paper.

2. BACKGROUND LITERATURE SURVEY

Wilkins ice shelf is the biggest ice shelf in West antarctica currently undergoing speedy reduction in size. Recession has occurred through a series of speedy partition events, wherever it calved a number of large, tabular icebergs [5]. Important break-ups occurred in 1998 and March and July 2008, and at last again in Apr 2009. The overall area was reduced to 5434 km^2, which are around two thirds of its original size.

Wilkins ice shelf melts gradually melts , at around 30-90 metres per year (the close Wordie flows at 200-2000 metres per year). It's a catchment area of 16, 900 km^2, which may be a small area of grounded ice to nourish an ice shelf, and it's sustained largely by in place accumulation [5]. Melting on the Wilkins ice shelf is essentially by basal melting and some surface melting in the summer [6]. Per year (1992-2008), the Wilkins ice shelf is retreating at a rate of 0.8 metres, which is driven by a basal melt rate of 1.3 ± 0.4 metre annually [7].

Jansa et al., [9] presented MA31 manages various water supply catchments in a Karstic region of sequence of masses some 80km south west of Vienna, during a considerable part of the year where the springs are fed by snow melt water. MA31 initiated a research, to predict the space-time patterns of melt water. Here, a hydrological snow accumulation setup and melt model based on the 20m grid of the DTM that simulates the energy balance elements at the snow surface and the coupled heat and mass flow within the snowpack for every grid component. By meteorological observations at an hourly time step the snow model is driven. It is very complex in SAR images and also adequate accuracy depends on many parameters but these are not available in this technique.

Tekelia et al., [10] introduced a modeling of snow-covered area in the mountainous regions of eastern and it has significant importance inorder to forecast snowmelt discharge particularly for flood control, irrigation, energy production and reservoir operation optimization. A pilot basin, positioned on the upper euphrates river, it is choose where five automated meteorological and snow stations are put in for real time operations. From Moderate Resolution Imaging Spectroradiometer (MODIS) the everyday snow cover maps are obtained at 500m resolution are evaluated with ground info for the winter of 2002–2003 both throughout accretion and ablation and at accretion period for the winter of 2003–2004 but it has presented only for small areas and estimated based on other satellite data.

Liu et al., [11] provided the active and passive microwave satellite remote sensing information to evaluate effects for defining snow regions .With a high-resolution radarsat synthetic Aperture Radar (SAR) image mosaic, percolation zones, dry snow zones, blue ice patches and wet snow zones for the antarctic continent have been successfully represented.This method not reliably detect melt in smaller snow zones.

Tarabalka et al., [12] proposed a new temporal segmentation technique for multitemporal segmentation of multiyear ice floes. The microwave radiometer is employed to trace the position of an ice mass. After that, a time series of MODIS images are created with the floe in the image center. It is performed to segment these images into ice mass and Background. The two-region map is post-filtered by applying morphological operators. However it has weak contrast segmentation between the multiyear ice and the neighbouring young ice floes.

Lato et al., [13] studied Snow avalanches in mountainous areas create a significant threat to infrastructure (roads, railways, and energy transmission corridors), personal property (homes) and recreational areas additionally as for lives of individuals living and moving in alpine terrain. The authors have used an object–oriented image interpretation approach that employs segmentation and classification methodologies, to detect recent snow avalanche deposits within very High Resolution (VHR) panchromatic optical remote sensing imaging. This produces avalanche deposit maps, which has been integrated with other spatial mapping and environment information. But masking layers and terrain information is not focused in that model, so it reduce the accuracy and reliability of snow melt segmentation.

Price et al., [14] proposed a unique approach for segmentation a multiyear floe from statistic of satellite images using form analysis and graph-based improvement in satellite images segmentation. The performance of this proposed approach has been validated on a group of MODIS and AMSR-E images and assessed the area of a sea floe as a function of time. The drawback of this approach is energy consumption and computation time is high.

Liang et al., [15] proposed an automated melt signal detection methodology developed using melt signals derived from the wavelet transformation-based snowmelt recognition technique over antarctica and the cross-gradient polarization ratio snow melt recognition technique over greenland. Primary results specify that this methodology not only increases computational potency, usefulness and operability however is also more accurate.

Steiner and Tedesco [16] presented a melt detection method over antarctica by a new melt recognition algorithm based on wavelets. In this method, wavelet-based estimations of melt spatial area and duration are evaluated with those gained with means of threshold-based detection methods, where melting is perceived when the calculated backscattering is 3 db below the preceding winter mean. However the accuracy of melt detection is less and the efficiency and reliability of this method is not very good.

In this paper, SVM based classification is presented for Wilkins Ice shelf, which experienced multiple disintegration events in 2008. First step, Wiener filter applied to remove the noise present in the spectral bands of Wilkins ice shelf image. Secondly, region and GLCM based feature extraction process takes place. The extracted pixel based features are then segmented into groups using Fuzzy K means algorithm. Then, extracted regions of each band are analyzed and Wilkins ice shelf disintegration is segmented.Finally, the SVM classification is processed to detect melting and not melting snow parts.

3. METHODOLOGY

In this section, pre-processing and segmentation of Multispectral Wilkins Ice Shelf MODIS image by means of FKM is presented including the SVM classifier.

3.1. System overview

The overall architecture of proposed system is illustrated in Fig 1. It contains the following steps:

Step 1. Wiener filter applied to remove the noise present in image.

Step 2. Region and GLCM based features are extracted to improve the classification accuracy.

Step 3. The extracted pixel based features are then segmented into groups using FKM.

Step 4. Extracted regions of each band are analyzed and Wilkins ice shelf disintegration is segmented.

Step 5. The SVM classification is processed to detect melting and not melting snow parts.

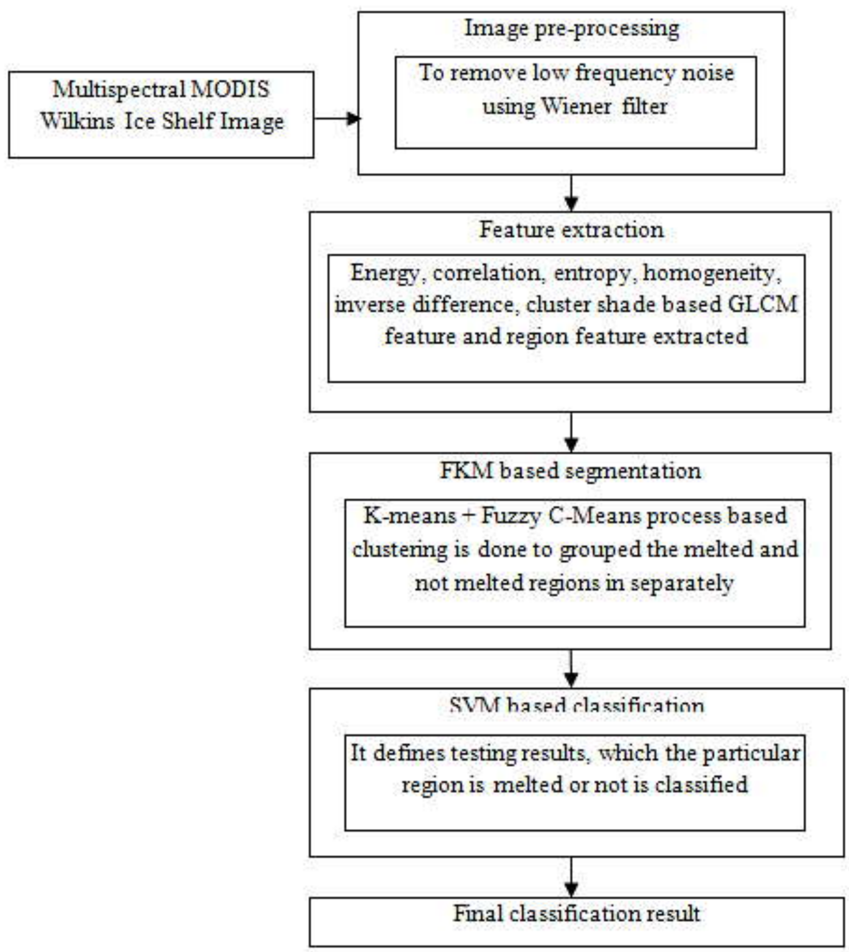

Figure 1: overall architecture diagram of proposed system

3.2. Pre-processing using Wiener filter

Pre-processing of images usually involves in removing low frequency noise, and normalizing the intensity for enhancing information images prior to computational process.Wiener filter tries to make an optimum estimate of the initial image by implementing a minimum Mean Square Error (MSE) constraint between estimate and original image. In proposed method, the noisy image is modelled as,

$$M\left(i,j\right)=x\left(i,j\right)+y\left(i,j\right) \tag{1}$$

Where $M(i, j) \rightarrow$ the noisy image, $x(i, j) \rightarrow$ is the noise free image and $y(i, j) \rightarrow$ is additive Gaussian noise. The goal is to remove noise, or denoise $M(i, j)$, and to obtain a linear estimate $\hat{x}\left(i,j\right)$ of $x(i, j)$ which minimizes the mean squared error

$$MSE\left(\hat{x}\right)=\frac{1}{N}\sum_{i,j=1}^{N}\left(\hat{x}\left(i,j\right)-x\left(i,j\right)\right)^{2} \tag{2}$$

Where $N \rightarrow$ number of elements in $x(i, j)$.

Specifically, when $x(i, j)$ a Gaussian process is the proposed wiener filter has a very simple scalar form

$$\hat{x}\left(i,j\right)=\frac{\sigma_x^2\left(i,j\right)}{\sigma_x^2\left(i,j\right)+\sigma_y^2\left(i,j\right)}\left[M\left(i,j\right)-\mu_x\left(i,j\right)\right]+\mu_x\left(i,j\right) \tag{3}$$

Where $\sigma_x^2\left(i,j\right)$ is the variance of ice image and $\mu \rightarrow \mu_x(i, j)$ is the mean, and where normally assume the mean of the noise to be zero.

3.3. Feature extraction using GLCM

Grey-level co-occurrence matrix (GLCM) defines the spatial association among each intensity tone with considering changes between grey levels *i* and *j* at a particular displacement distance *d* and at an exacting angle θ. In this all 28 features are extracted in which the following 7 bfeatures from GLCM are considered for FKM algorithm for clustering

1. Energy measuring uniformity of local grey scale distribution;
2. Correlation measuring the joint probability of occurrence;
3. Inertia measuring the local variations;
4. Entropy measuring randomness;
5. Cluster shade measuring a group of pixels that have parallel grey level values;
6. Homogeneity measuring the closeness of the distribution
7. Inverse difference moment measuring local minimal changes. .

3.4. Fuzzy k-means based segmentation

The proposed FKM is specifically design to incorporate both conventional K-means and the conventional Fuzzy C-means (FCM). In FKM, consider a digital image with $M \times N$ pixels (i.e., M represents number of columns and N represents number of rows) to be clustered into n_c regions or clusters. Considered $p(x, y)$ be pixel and c_i is i-th centre, where $x = 1, 2, ..., M,\ y = 1, 2, ..., N$ and $i = 1, 2, ..., n_c$. Based on the aforementioned concern, for the conventional K-Means, based on Euclidean distance all data will be allocated to the nearby centre. The new position for each centre is calculated using [18]

$$c_i = \frac{1}{n_{c_i}} \sum_{x \in c_i} \sum_{y \in c_i} p(x, y) \tag{4}$$

For the traditional FCM, allocation process of each data member to be allotted concurrently to different class is based on the following membership function [18]

$$MS^{in} ip(x, y) = \frac{1}{\sum_{k=1}^{n_c} \left(\frac{d_{ip(x,y)}}{d_{kp(x,y)}} \right)^{2/(m-1)}} ; if \ d_{kp(x,y)}$$

$$\begin{cases} > 0, \forall_i, p(x, y) \\ MS^{in} kp(x, y) = 1 \\ MS^{in} ip(x, y) = 0; for \ p(x, y) \neq k, ifd_{kp(x,y)} = 0 \end{cases} \tag{5}$$

where $d_{ip(x,y)} \rightarrow$ distance from point (x, y) to the current cluster centre i, and $d_{kp(x,y)} \rightarrow$ distance from point (x, y) to other k cluster centres, $n_c \rightarrow$ is number of centres and in is an integer, $in > 1$ which determine the degree of fuzziness. For the proposed FKM, all centres are firstly initialized to a certain value. To ensure a better clustering process using (4) fuzziness and belongingness concepts are introduced in the proposed FKM algorithm. The concept of fuzzy partitioning concept is applied to allow each data to be assigned different class concurrently by different degrees of membership $MS^{in}ip(x, y)$. To achieve a good clustering development, the modification proposed that each cluster must have a significant value of belongingness which measures the association potency between the cluster centre and its members. So, in the proposed FKM, after specifying the membership for each data, the degree of belongingness, B_i for each cluster is computed. A stronger relationship between the centre and its members is shows higher degree of belongingness, which will establish a better data clustering. B_i – The degree of belongingness is calculated based on

$$B_i = \frac{C_i}{MS^{in} ip(x, y)} \tag{6}$$

Based on the degree of belongingness, the degree of membership is optimized according to

$$\left(MS^{in} ip(x, y)\right)' = MS^{in} ip(x, y) + \Delta MS^{in} ip(x, y) \tag{7}$$

Where $\left(MS^{in} ip(x, y)\right)'$ is new membership. $\Delta MS^{in} ip(x, y)$ is defined as

$$\Delta MS^{in} ip(x, y) = \alpha (c_i)(e_i) \tag{8}$$

Where $\alpha \rightarrow$ a designed constant with value between 0 and 1 and the proposed set it is to 0.1. Then, the value of e_i is calculated according to

$$e_i = B_i - \hat{B}_l \tag{9}$$

Where $\hat{B} \rightarrow$ the normalized value for degree of belongingness.

After all the new centre positions of the all previous clusters are calculated based on the new (optimized) membership function according to

$$c_i = \frac{\sum_{x\in c_i}\sum_{y\in c_i}\left(MS^{in}ip(x,y)\right)' p(x,y)}{\sum_{x\in c_i}\sum_{y\in c_i}\left(MS^{in}ip(x,y)\right)'} \tag{10}$$

These processes are repeated until the values of all centres are no longer change. The given input image is clustered to segment icy region and non icy regions.

3.5. SVM based classification

SVM is a learning algoritrhm based on statistical learning theory and is illustrated in Fig. 2. In case of classification problems, the major intention of SVM is to discover an Optimal Separating Hyper-plane (OSH) that appropriately classifies data points to the extent that is possible and separates the points of two classes to the extent that is possible, by minimizing the risk of misclassifying the training samples and hidden test samples.

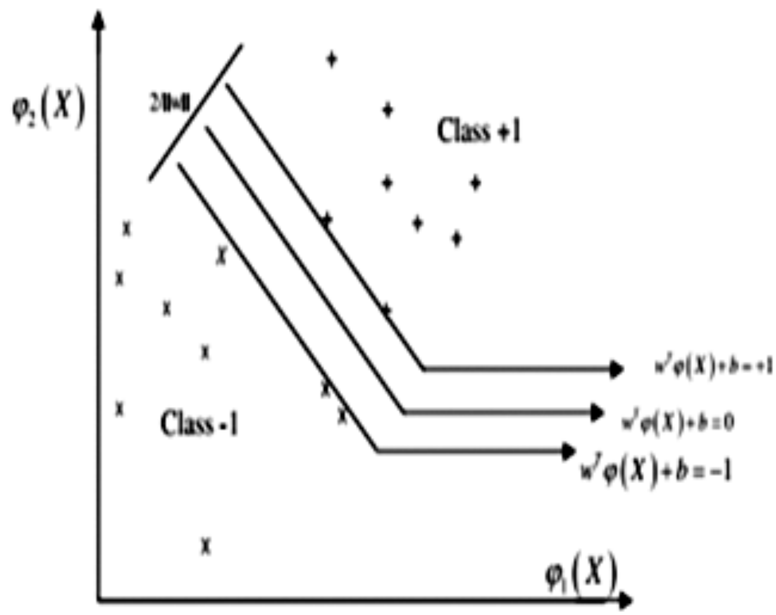

Figure 2: Illustration of SVM optimization of the margin in the feature space

In this work, the SVM is considered for classification problem of snow melt detection. Initially, the GLCM features are used to train the SVM learning process. Considered a selected set of features b ∈ with i = 1, ..., N each feature x_i is based on to either of two classes (melted or non-melted) with the label $y_i \in \{-1, +1\}$. The optimization problem for the SVM can be defined as:

$$\min \rho(w,b) = \frac{1}{2}(w,w)$$

$$\textit{subject to } \forall_i y_i\left(w.x_i + b\right) \geq 1 \tag{11}$$

The constraint given in (11) is also regarded as hard margin, where no space is provided for errors. It is observed that most of the time it is linearly non separable. Hence slack variable is introduced to allow error and the optimization function takes the form of (12) as given below

$$\min \rho(w,b) = \frac{1}{2}(w,w) + C\sum_{i=1}^{1}\xi_i$$

$$\textit{subject to } \forall_i y_i \left(w.x_i + b \right) \geq 1 \tag{12}$$

The optimal hyper plane separating binary decision classes is defined as

$$f\left(x\right) = \sum_{i=1}^{1} y_i \alpha_i K\left(x_i, x\right) + b \tag{13}$$

C, K represents constants.

Nonlinear separable problems can be solved using Non-linear SVM defined as

$$\min \rho\left(w, b\right) = \frac{1}{2}\left(w, w\right) + c\sum_{i=1}^{1} \xi_i$$

$$\textit{subject to } \forall_i y_i \left(w.\varphi\left(x\right) + b \right) \geq 1 \tag{14}$$

Where $K\left(x_i, x\right) = \varphi\left(x_i\right)^T + \varphi\left(x\right)$ is taken with a semi positive kernel meeting the mercer theorem [19]

For kernel function $K\left(x_i, x\right) = \left(x_i^T.x\right)$.

Based on the optimized value the segmented region are classified melted or not.

4. RESULTS AND DISCUSSION

In this section, the proposed SVM classification method performance is evaluated. MATLAB tool is used to simulate proposed algorithm. The performance of proposed methodology for MODIS Wilkins Ice Shelf Image using SVM is illustrated from Fig 3.

4.1. Dataset description

Research of MODIS images gathered as part a U.S. National Snow and Ice Data Center (NSIDC) program to frequently check Antarctic Wilkins ice shelves and the images are downloaded from http://www.nsidc.org/data/iceshelves_images/.The ice-melt event was first noticed on 28 February, 2008. The break-up occurred on the western WIS ice facade among Charcot and Latady islands. The WIS disintegration began with the calving of a 2.5 by 41 km in March 2008 tabular iceberg (or a series of adjacent calving) totalling 77 km^2 and spanning the north-western WIS ice front. The entire area of disintegrated and calved ice shelf was 431 km^2. In March 2008 the ice debris and ice block mass extended to 1200 km^2 then it is drifted out of the embayment and had dispersed seaward by early April.

The step by step process of proposed SVM is illustrated from fig 3.

4.2. Performance Evaluation Metrices

The performance of snow melt classification is analyzed with the following parameters:

Sensitivity =TP/ (TP+FN))
Specificity =TN/ (TN+FP))

Accuracy = (TP+TN)/ (TP+FN+TN+FP)

Precision measure is calculated based on the formula

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall is calculated based on the formula

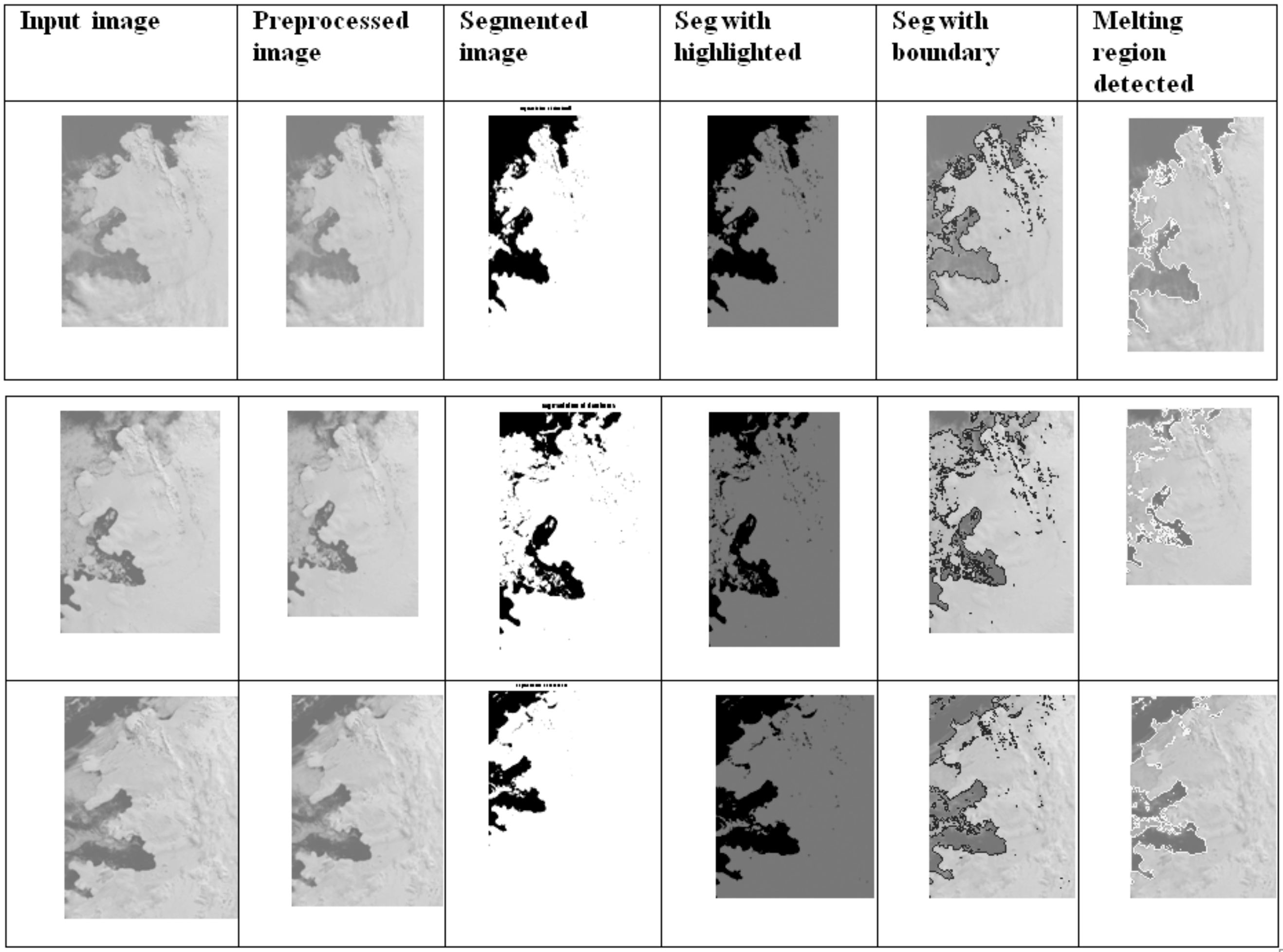

Figure 3: Multispectral MODIS Wilkins Ice Shelf Melt extraction by means of FKM and classified by SVM. The first column explains the multispectral images of test regions #1,#2,#3 respectively. The second column represents the result of pre-processed image. Third column shows the result of segmented image and forth column highlights the segmented regions. Column 5 and 6 explains segmentation with boundary and detected melting regions.

$$\text{Recall} = \frac{T_P}{T_P + F_P}$$

F-Score is calculated using given below equation

$$\text{F - Score} = 2.\frac{\text{precision.recall}}{\text{prrecision} + \text{recall}}$$

Where, $TP \rightarrow$ true positive, $FP \rightarrow$ false positive, $FN \rightarrow$ false negative and $TN \rightarrow$ true negative. True Positive refers to the correctly identified melt detection, True Negative refers to the wrongly identified melt, False Positive refers to the correctly identified not melted and False Negative refers to the wrongly identified not melted regions.

The simulation results for the evaluation of the proposed approach against various performance measures like Precision, Recall, Accuracy and F-Measure.

The proposed SVM produces better accuracy rate, sensitivity rate, specificity rate, precision, recall, and f-score shown in Fig.4. When the number of images increases the accuracy rate, sensitivity rate, specificity rate, precision, recall, and f-score of the result is increased in SVMbecause the prediction accuracy is better.

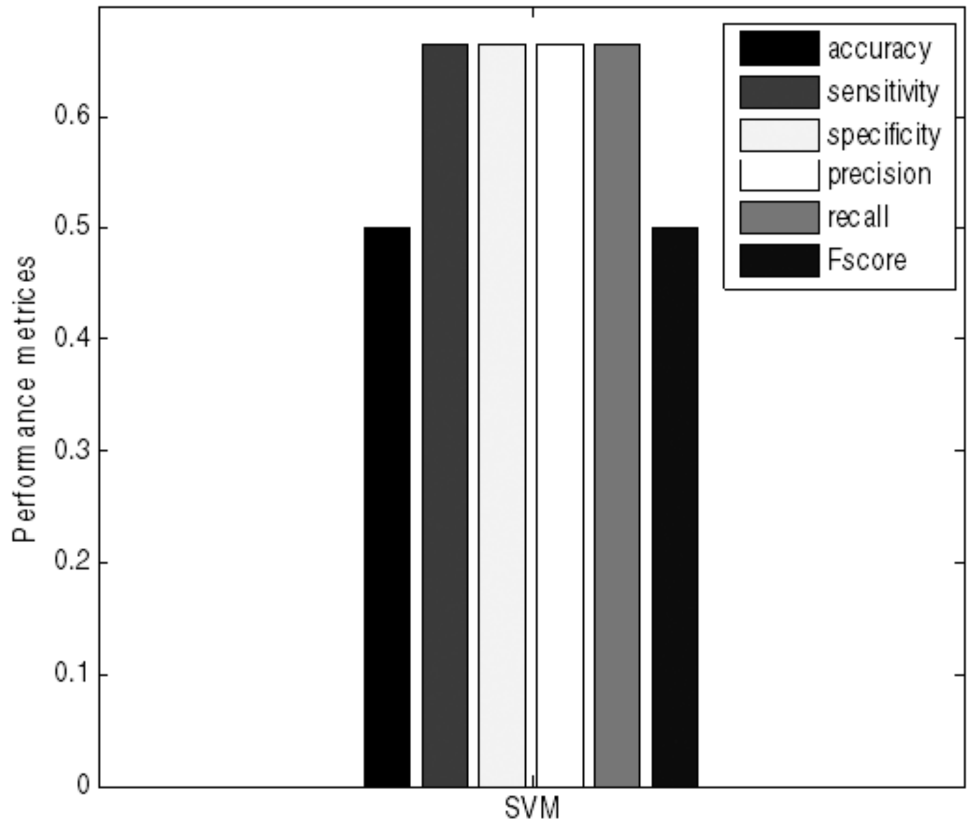

Figure 4: performance evaluation

5. CONCLUSION

This paper has presented a methodology using FKM and SVM classification for snow melt detection in Wilkins ice shelves of MODIS images. Initially, Wiener filtering is applied as pre-processing technique to remove the noise. Secondly, GLCM features are used for FKM based segmentation of icy and non icy regions. Experimental results show that the proposed system is highly effective in terms of identifying melt regions.

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