Journal of Theoretical and Applied Information Technology
31st August 2014. Vol. 66 No.3

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

# MAPPING OF LAKE SURFACE COVERS USING PIXEL INTENSITIES FOR MONITORING SEASONAL ICE DEVELOPMENT

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**ABSTRACT**

Due to the dramatic change of air temperature, the ice layer expands significantly in the lake region. To monitor and to predict the ice conditions occurred in Ice Lake over seasonal basis, the pixel based classification method is evaluated and experimented. Research in classification of lake ice concurrently takes the history of ice information and structure of the ice cover. In this paper, based on the fundamental information, a methodology is proposed to classify ice from other surfaces based on pixel intensities. By applying Color based segmentation using K-Mean Cluster the intensity of different classes are extracted according to the respective ranges. The pixel intensity ranges are taken as a feature value for the KNN Classification. With that pixel intensity range three classes are identified as ice, water and sand. Experimental results show that the growth rate of the ice is estimated with the classified ice region in the lake area .The accuracy rate of ice classification from other classes in an image is high using KNN. This examination explores and proves the expansion of the ice cover according to the seasonal duration using image analysis methodology.
**Keywords:** *Lake Ice, Image analysis, pixel intensity, K-Mean Cluster, KNN classification*

## 1. INTRODUCTION

The importance of the development of algorithms to monitor ice cover on the Lakes is drastically increasing. Lake ice cover is important to be monitored for many reasons. Its seasonal change has a profound impact on regional environment, ecology, economics, navigation, and public safety. The ice cover in the lake is also a susceptible indicator of regional climate change. By observing changes in ice, it is profound to find the ice cover according to the seasons. The environment of the ice cover problem in lakes and in wide waterways demands the use of satellite SAR data to satisfy the required high spatial resolution. The ice is subject to temperature changes, compressive and shearing forces, surface currents, and wind shear [9]. Lake ice forms in some crystal measures. Different classification systems have been developed for mapping of surface to identify ice formation. When mapping snow cover there are some feasible features of the imagery which must be considered in order to prevent misidentification of ice or no-ice areas. The possibilities of misinterpretation are 1.Clouds- It shows the bright reflectance which is difficult to distinguish from the ice cover [10], [11]. 2. Forest cover- The reflectance from these areas will be darker which is not easily detectable.3.Shadows- As the sun angles are low in case of winter it is highly difficult to distinguish from shadow of rocks and soil. 4. Rocks- the highly reflecting rock will be difficult to map during the melt of ice. In this paper, a methodology is proposed for lake surface classification using satellite SAR data. SAR has the potential to penetrate below the surface and shallow water. But still interpretation of images from ERS-2 and RADARSAT2 is highly complex, since it operates at one frequency and one polarization for sending and receiving [1],[2] .Though there exist conventional methods suitable for class problems , it is found that only less approach is done based on seasonal images. The main goal is to develop a method that classifies ice cover from other region using pixel intensities which is a challenging task in computer vision. As the characteristics of each

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

image and the circumstances for each study [3] differs in its own way, the suitable classifier is identified according to the experimentation and on the evaluation metrics. The organization of the paper is as follows. Section 1 explains the preface of the theme carried out in this work. Section 2 explains the study on the lake data and a short analysis on the experimental data. Section 3 describes the methodology in which the framework is derived for remote sensing data analysis. The image segmentation and the context of classification with the visual assessment of the images will be explained briefly. Section 4 illustrates the experimentation and the findings for the conclusion. Section 5 concludes the research work carried out based on the experimental analysis.

## 2. LAKE ICE DATA

Mapping of surface provides necessary and significant inputs for environmental guard and management. Studies conclude that seasonal observation is very much in need for finding their distribution, drift during the winter and ice break up. Investigations by various researchers were conducted to classify and categorize ice types and features [4], [5] to map ice distribution [6], [7], and to monitor and attempt to forecast ice movement with remotely sensed data. As the Great Lakes is the world's largest freshwater surface, ice cover on the lakes is inherently a large-scale seasonal transformation (http://www.iaglr.org).By examining the changes in ice seasons; researchers have found the drift in recent years of less ice covers and also the seasonal difference. Though there are many categories of algorithms available to map surface covers the significance of accuracy in segmenting the regions is always in demand research. This paper results with algorithm development using SAR data to track the seasonal development of ice cover on the eastern Great Lakes. The images for experimentation have been accessed from the Naval Research Laboratory (NRL), MODIS today and NOAA Coast Watch. Table 1 illustrates the MODIS images taken for experimentation from NRL.

## 3. PROPOSED METHODOLOGY

In radar images, it is often difficult to see low frequency variations because of high frequency features from small scale topography . Pixel intensities is used as the subtle scale features in classifier to identify the regions. The mapping function is obtained simply by rescaling the cumulative histogram so that its values lie in the range 0-255. The RGB color space is achieved by the transformation as eqn (1) on each pixel.

$$\begin{Bmatrix} R' \\ G' \\ B' \end{Bmatrix} = \frac{\max\{R,G,B\}}{\max\{R,G,B\} - \min\{R,G,B\}} \begin{Bmatrix} R - \min\{R,G,B\} \\ G - \min\{R,G,B\} \\ B - \min\{R,G,B\} \end{Bmatrix} (1)$$

### 3.1 Color Based Segmentation using K-Means Clustering

Segmentation can be used to separate class according to pixel ranges or region[14]. Clustering based method attempts to cluster the data set into classes which has same behavior of the observed feature vector. It can work automatically, exhibits faster processing speed, and does not involve the specification of ground truth information which may not be readily available for remote sensing data.K-means is the clustering algorithm used to determine the groupings present in a data set that classifies the pixels with same characteristics into one cluster, thus forming different clusters according to coherence between pixels in a cluster [12]. This algorithm has been used for many remotely sensed images and has given fairly satisfactory results. Here, three classes are separated as ice ,land and sand which estimates the cluster center using distance metrics. Among the distance metrics used in the experimentation, squared Euclidean distance has given better visual output for the segmentation results.

This K means is fast iterative and leads to a local minimum which looks for unusual reduction in variance. This iterative algorithm has two steps:
Assignment step: Each observation to the cluster with the closest mean is assigned as shown in eqn (1)

$$S_i^{(t)} = \{ X_j : \| X_j - m_i^{(t)} \| \le \| x_j - m^{(t)} \| \quad \ldots(1)$$

Update step: The new means to be centroid of the observations in the cluster is calculated as eqn (2)

$$m_i^{(t+1)} = \frac{1}{|S_i^{(t)}|} \sum_{x_j \varepsilon S^{(t)}_i} X_j \quad \ldots (2)$$

The RGB image is cconverted into L*a*b* Color Space and CIE lab color histogram is generated. Based on the colors in 'a*b*' Space it is classified using K-Means Clustering and the results are

**Journal of Theoretical and Applied Information Technology**
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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

displayed by labeling concept. Observations from figure 1 on the performances of segmentation not only confirms superiority of colour pixelwise method, but also states that more refined segmentation leads to better recognition rates.

### 3.2 Classification using KNN Classifier

The k-Nearest Neighbor classifier is a supervised learning algorithm where the result of a new instance query is classified based on the majority of k-nearest neighbor category [13]. The purpose of this algorithm is to classify a new object based on attributes and training samples. The training samples are described by n-dimensional numeric attributes. Each sample represents a point in an n-dimensional pattern space. More robust model is achieved by locating $k$, where $k > 1$, neighbours and letting the majority vote decide the outcome of the class labelling. A higher value of $k$ results in a smoother, less locally sensitive function. The data for KNN algorithm consists of several multivariate attributes namely $X_i$ that is used to classify the object Y. The data of KNN has measurement scale from ordinal, nominal, to quantitative scale. This study deals only with quantitative $X_i$ and binary (nominal) Y. All training samples are included as nearest neighbors if the distance of the training sample to the query is less than or equal to the $k^{th}$ smallest distance. In other words, the distances are sorted of all training samples to the query and determine the $k^{th}$ minimum distance. The unknown sample is assigned the most common class among its k-Nearest Neighbors. These K training samples are the closest k-nearest neighbors for the unknown sample. Closeness is defined in terms of Euclidean distance, where the Euclidean between two points, $X = (x_1, x_2, . x_n)$ and $Y = (y_1, y_2, \ldots y_n)$ is as eqn (3)

$$d(X,Y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \quad (3)$$

The drawback of increasing the value of $k$ is when $k$ approaches $n$, where $n$ is the size of the instance base, the performance of the classifier approach that of the most straightforward statistical baseline. The assumption is that all unknown instances belong to the class most frequently represented in the training data. Pixel values are taken as training and testing samples which is used to classify the region efficiently [15].

## 4. RESULTS AND FINDINGS

Classifier always tries to improve the classification rate by pushing them into an optimised structure. In each image, a measure of range based on the pixel intensity red, blue and green are taken; the classifier then uses these range to determine the different classes available in an image. They estimate the probability of a class object that belongs to each of the target classes that is fixed. The impact of such study may reflect the exploration for using algorithms in remote sensing applications. The proposed method is carried out in three-steps namely:-

i) Training the classifiers with the feature vector (pixel intensities).
ii) To classify the objects to the desired output label.
iii) Performing multiple runs for improvisation of classifier accuracy.

Figure 2 depicts the visual results of the segmentation based on the improvisation of training dataset in KNN Classifier. The classification percentage of the class objects such as sand ,ice, water and others are classified based on the random change of the pixel range values in the training dataset. Below table 2 represents the percentage of mapping between the classes available in each image.

$$\text{Sand accuracy} = \frac{\text{No of green pixel in Sand Image}}{\text{Total no of green pixel in segmented image}} \times 100 \quad .(4)$$

$$\text{Water accuracy} = \frac{\text{No of blue pixel in water Image}}{\text{Total no of blue pixel in segmented image}} \times 100 \quad .(5)$$

$$\text{Ice accuracy} = \frac{\text{No of dark blue pixel in the ice Image}}{\text{Total no of dark blue pixel in segmented image}} \times 100 \quad ..(6)$$

Table 3 represents the classifier accuracy on each class. Eqn 4 ,5 and 6 are used to calculate the Classifiers accuracy for the respective class. Here, the intensity ranges are divided into RGB values and they are Sand -0 255 128, Water-0 128 191 and Ice -0 0 255. To improve the accuracy level of the different regions ,the neighborhood pixel ranges are also taken . As per the experimental study, the classification emerge to be most valid on mapping the regions. In future, the validation can be done by acquiring the measurement period. However, this research work demonstrates a capable methodology to classify the various regions in an image based on the pixel intensities range values.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

## 5. CONCLUSION

In this paper, the objective qualities intrinsic in computer processing is made well suited for mapping the lake surface to identify the ice covers. The classification technique used indicates the different regions in the lake cover image in which each class is identified and mapped. It is also proven that determining the suitable classifiers will optimized training set to give enhanced classification results. The color based segmentation method adds additional benefits of flexibility to explore important pixel intensity range of the class in an image. The advantage of using a KNN classifier with pixel based classification concept states that it can be easily trained iteratively and the performance is high in remote sensing data. This is specifically important in situations where the mapping of boundaries is very much crucial. The future enhancement of this research work could be optimizing the training set that allows the classifier to map the ice covers more efficiently and can also increase more classes of data.Another important future scope is to optimize the classifier accuracy value by tuning the classifier parameters.

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

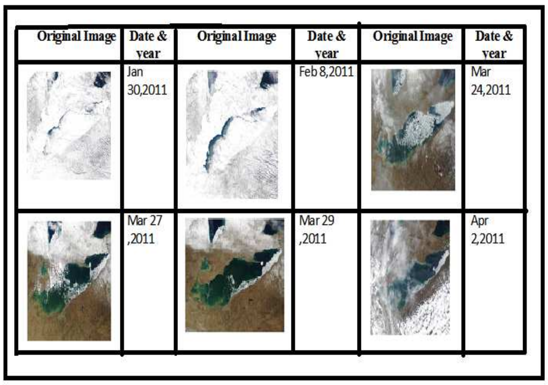
*Table 1. Images taken for experimentation*

| Images | Sand (%) | Ice (%) | Water (%) | Other (%) |
|---|---|---|---|---|
| Image1 | 19 | 79 | 2 | |
| Image2 | 24 | 68 | 2 | 8 |
| Image3 | 34 | 53 | 13 | |
| Image4 | 45 | 38 | 13 | 4 |
| Image5 | 52 | 29 | 19 | |
| Image6 | 38 | 50 | 12 | |

*Table 2 : Percentage of mapping between the classes*

| Images | Sand (%) | Ice (%) | Water (%) |
|---|---|---|---|
| Image1 | 58 | 69 | 90 |
| Image2 | 59 | 67 | 76 |
| Image3 | 71 | 73 | 88 |
| Image4 | 71 | 72 | 78 |
| Image5 | 58 | 56 | 60 |
| Image6 | 70 | 68 | 96 |
| Total | 65% | 68% | 79% |

*Table 3: Accuracy Calculation*



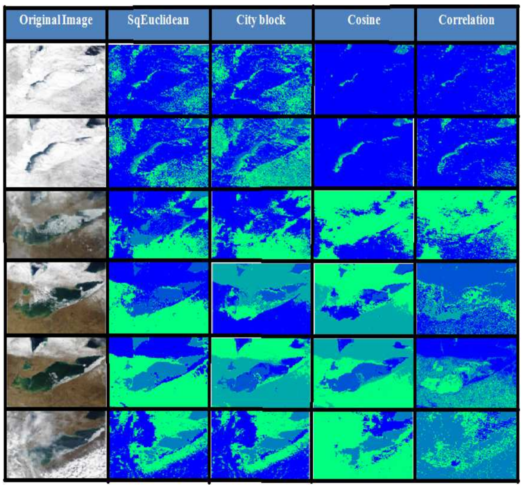




*Figure 1: Segmentation Results Based On Distance Metrics*

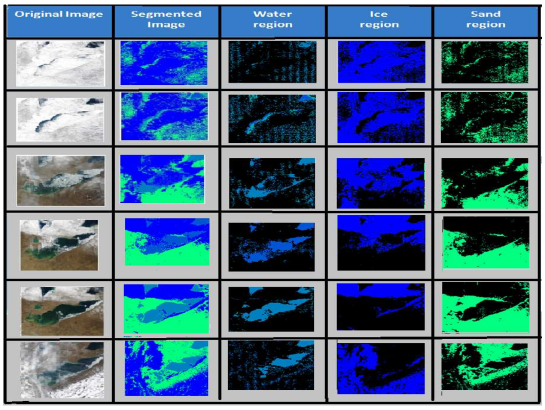



*Figure 2: The Visual Results Of The Images Based On KNN Classifier*