International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 1 Issue 7, September - 2012

An Innovative Approach for Aurora Recognition

Prof. Chandrakanth. Biradar, Pratiksha.S.B

Abstract — ***Digital image processing techniques with the help of the available data set will lead us to perform the existing complex task much easier and efficient. The gathered knowledge and data will allow us to understand the nature of aurora. The aurora provides us with a powerful tool for studying the near-Earth space. Processes in the magnetosphere and the ionosphere shape the visual appearance of the aurora, which itself is caused by precipitating particles colliding with atmospheric atoms and molecules. Millions of auroral images are captured every year by ground-based imagers. The occurrence of auroral system in different part of the earth signifies the different meaning which may suggest the temporal changes in the environment of the trees or it may indicate the feature changes in the environment. Image Segmentation refers to partitioning of an image into meaningful regions. In order to resolve the problem incurred by low efficient manual classification of tremendous aurora images, an automatic aurora images classification system for huge dataset application is proposed The boundary based image segmentation and representation system takes a thinned edge image and produces a unique hierarchical representation using nearest mean classifier. In the proposed work segmentation using K-means clustering of feature vectors and denoising techniques such as Gaussian noise method, Weiner filter methods are used to improve the resolution of the images. The experimental results which prove that the hierarchical representation supports the fast and reliable computation of several geometric features which recognizes the aurora images are presented.***

Keywords — Aurora, K-mean clustering, Gaussian noise, Weiner filter, Segmentation.

I. INTRODUCTION

Aurora is also known as the Northern Lights, often occurs in the polar regions of Earth. It appears as colorful clouds and rays of green and red (and sometimes blue) light that dance across the sky [1]. The aurora is formed when charged particles (electrons and protons) are guided by the Earth's magnetic field into the atmosphere near the poles. When these particles collide with atoms and molecules of the upper atmosphere, primarily oxygen and nitrogen, some of the energy in these collisions is transformed into the visible light that characterizes the aurora.

There are three distinct categories of aurora appearance in the all-sky images.

- Arcs: one or more aurora arcs;
- Patchy auroras: irregular patches of aurora intensity visible in the whole field-of-view;
- Omega-bands: brighter shapes that resemble those seen when an Omega-band is visible in the field-of-view.

The emergence of digital imaging technology makes it possible for researchers to acquire more and more aurora data. However, the wide application of aurora imaging systems results in mass data which is difficult to manually process. Therefore automatic analysis and retrieval of aurora images in the huge dataset has evolved and become essential. The research of content-based image retrieval has been very active in recent years, yet only a few applications for auroral image retrieval are developed. But our goal is to retrieve the diurnal patchy auroras with extremely complicated shape which is difficult to describe. Through the observation of the aurora images, was found that different kinds of aurora have different texture, shapes.

In this work, we propose a region and color based image classification and recognition for aurora. Digital image processing technique will help us to perform the task of acquiring, processing, storing and analyzing of the auroral captured images. The main features which are considered like color, region of interest, boundary extraction are used to achieve the task.

The main steps in digital image processing are (i) preprocessing, which is a data preparation step for contrast enhancement, noise reduction or filtering, (ii) feature extraction, for retrieving non-redundant and significant information from an image.

II. RELATED WORK

Auroral images are captured every year by ground-based imagers. Even though the auroral appearance or “type” yields relevant information about the physical processes in the ionosphere and the magnetosphere, qualitative descriptions of auroras are typically used [2]. In order to numerically compare auroral objects, we can either describe individual auroral shapes such as arcs or use statistical appearance models (texture).

The aurora provides us with a powerful tool for studying the near-Earth space [3]. Processes in the magnetosphere and the ionosphere shape the visual appearance of the aurora, which itself is caused by precipitating particles colliding with atmospheric atoms and molecules. In this proposed method we use K-nearest-neighbor classifier that agrees with a human expert with an accuracy of about 90%.Can successfully track auroral arcs.

The proportion of aurora region to the field of view is an important index to measure the range and scale of aurora. A crucial step to obtain the index is to segment aurora region from background [4]. Image classification is a complex process that may be affected by many factors. Focusing on image classification has long attracted the attention of the remote-sensing community because classification results are the basis for many environmental and socioeconomic applications [5]. The major steps of image classification may include selection of training samples, image preprocessing, and feature extraction, selection of suitable classification approaches, post-classification processing, and accuracy assessment.

Color image preprocessing and segmentation are classical examples of multichannel information processing. Out of the existing image enhancement procedures, filtering techniques have become very popular over the years for addressing the problem of noise removal and edge enhancement [6].

Image Segmentation refers to partitioning of an image into meaningful regions. The objective of this paper is to implement Segmentation Techniques through various clustering algorithms. k - Means clustering, segmentation using clustering of feature vectors and normalized cut method [7]. K-means clustering is an image segmentation technique based on color features (unsupervised algorithm). It partitions the input dataset into k clusters. Each cluster is represented by an adaptively changing center (also called cluster center), starting from some initial values named seed points. K-means computes the distances between the inputs (also called input data points) and centers and assigns inputs to the nearest center.

III. PROPOSED WORK

Aurora Images acquired are increasingly important, not only as an essential support to scientific knowledge and technical applications, but also as an important component of graphic communication in the media. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it. Image processing usually refers to digital image processing, but optical and analog image processing are also possible. Identification and Classification of aurora images aims to be a forum in which innovative methods are presented and applied to cases of study in different fields.

The objective of this work is to improve the understanding of magnetosphere processes and the interaction between the solar wind, magnetosphere and ionosphere. One signature of this interaction is the occurrence of the aurora. This work includes the modules as follows:

- Image acquisition
- Feature extraction
- Image classification
- Auroral recognition

The overall view of the system for classification of auroral image is as follows

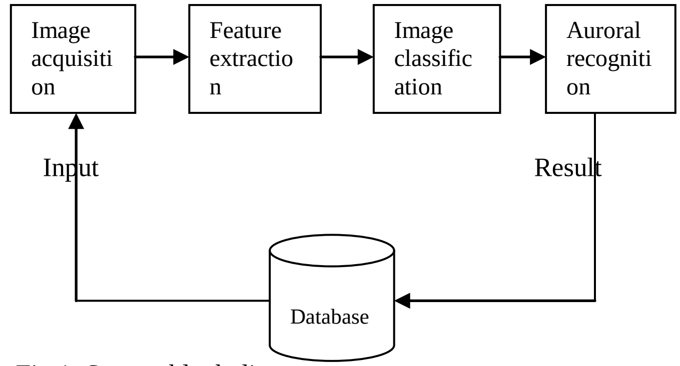

Fig 1: System block diagram

Image processing usually refers to digital image processing, but optical and analog image processing are also possible. The *acquisition* of images (producing the input image in the first place) is referred to as imaging.

When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (e.g. the same measurement in both feet and meters) then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called *feature extraction*. It is important to identify what features are unique for the case of images. Some common image features are

- Color
- Texture
- Shape
- Edge
- Shadows
- Region etc.

In this work color, region, boundary and texture are considered for aurora recognition.

1. **Color:** Images are identified by the different colors and textures specifically shade of pink (rusty rose) and black. Hence the picture elements can be compared to these spectra.

2. **Texture:** Texture is defined as a neighborhood feature – as a region or a block. The variation of each pixel with respect to its neighboring pixels defines texture. Hence the textural details of similar regions can be compared with a texture template.

3. **Edge:** Edge is simply a large change in frequency. This is particularly important here, as the distinction between the dark and the lighter shades of the aurora image can be considered as an edge.

Edge-based segmentation relies on discontinuities in the image data to locate the *boundaries* of the segments before assessing the enclosed region. Edge detection is a well-developed field on its own within image processing. Region boundaries and edges are closely related, since there is often a sharp adjustment in intensity at the region boundaries. Edge detection techniques have therefore been used as the base of another segmentation technique.

The human visual system can distinguish hundreds of thousands of different color shades and intensities, but only around 100 shades of grey. Therefore, in an image, a great deal of extra information may be contained in the color, and this extra information can then be used to simplify image analysis, e.g. object identification and extraction based on color. Color depends primarily on the reflectance properties of an object. The tristimulus theory of color perception seems to imply that any color can be obtained from a mix of the three primaries, red, green and blue.

Texture depicts the structure of the object's surface. Different kinds of textural features have been proposed, such as multi-channel filtering features, fractal based features and co-occurrence features. In our work, textural features suit because when different types of aurora images are used, each gives its own texture on its top surface.

An important feature in the image is the edges of objects. It is possible to extract image contours from the detected edges. From the object contour the shape information is derived. We extract and store a set of shape features from the contour image and for each individual contour.

Segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. The simplest method of image segmentation is called the thresholding method. This method is based on a clip-level (or a threshold value) to turn a gray-scale image into a binary image.

A. Image Segmentation by Clustering Pixels

Clustering is a process whereby a data set is replaced by clusters, which are collections of data points that "belong together". It is natural to think of image segmentation as clustering; we would like to represent an image in terms of clusters of pixels that "belong together". The specific criterion to be used depends on the application. Pixels may belong together because they have the same color and/or they have the same texture and/or they are nearby, etc. It is relatively easy to take a clustering method and build an image segmenter from it. The distance used depends entirely on the application, but measures of color difference and of texture are commonly used as clustering distances. It is often desirable to have clusters that are "blobby"; this can be achieved by using difference in position in the clustering distance.

B. K - MEANS CLUSTERING

Simple clustering methods use greedy interactions with existing clusters to come up with a good overall representation. For example, in agglomerative clustering we repeatedly make the best available merge. However, the methods are not explicit about the objective function that the methods are attempting to optimize. An alternative approach is to write down an objective function that expresses how good a representation is, and then build an algorithm for obtaining the best representation. A natural objective function can be obtained by assuming that we know there are k clusters, where k is known. Each cluster is assumed to have a center; we write the center of the i'th cluster as ci. The j'th element to be clustered is described by a feature vector xj . For example, if we were segmenting scattered points, then x would be the coordinates of the points; if we were segmenting an intensity image, x might be the intensity at a pixel. We now assume that elements are close to the center of their cluster, yielding the objective function.

$$\Phi(\text{clusters}, \text{data}) = \sum_{i \in \text{clusters}} \left\{ \sum_{j \in i\text{'th cluster}} (\boldsymbol{x}_j - \boldsymbol{c}_i)^T (\boldsymbol{x}_j - \boldsymbol{c}_i) \right\}$$

- Assume the cluster centers are known, and allocate each point to the closest cluster center.
- Assume the allocation is known, and choose a new set of cluster centers. Each center is the mean of the points allocated to that cluster. We then choose a start point by randomly choosing cluster centers, and then iterate these stages alternately. This algorithm is usually referred to as k-means. It is possible to search for an appropriate number of clusters by applying k-means for different values of k.

After sementation of images,the resultant image will be denoised.The noise removal algorithm for gray scale images corrupted by adaptive Gaussian noise by wiener filter is used. First, an additive Gaussian noise detector using mathematical residues is to identify pixels that are contaminated by the additive Gaussian noise. Then the image is restored using specialized open-close sequence algorithms that apply only to the noisy pixels

Digital image classification procedures are differentiated as being either supervised or unsupervised (clustering).

The first is to find a map of a feature space (which is typically a multi-dimensional vector space) to a set of labels. This is equivalent to partitioning the feature space into regions, then assigning a label to each region. Such algorithms (e.g., the nearest neighbor algorithm) typically do not yield confidence or class probabilities, unless post-processing is applied. Another set of algorithms to solve this problem first apply unsupervised clustering to the feature space, then attempt to label each of the clusters or regions.

The most widely used classifiers are the Neural Network (Multi-layer Perceptron), Support Vector Machines, k-Nearest Neighbors, Gaussian Mixture Model, Gaussian, Naive Bayes, Decision Tree and RBF classifiers and Nearest Mean classifier. The system is trained by giving a set of images, and an input/test image. It extracts features (histogram) from the images (both, from the training sets and the test set). Each class is represented by it's mean vector and the classifier uses the mean values for each of the classes calculated from the training areas. Each distribution of the color within the test image is then examined to determine the mean value that it is closest to based on distance classifier. This is detected as the class to which the input would belong to.

The Nearest Mean Classifier is used to classify unknown image data to classes which minimize the distance between the image data and the class in multi-feature space which uses Mahalanobis Distance. The distance is defined as an index of similarity so that the minimum distance is identical to the maximum similarity. Classification can be used in thematic maps or can be further incorporated into digital analysis. It can be performed on single or multiple image channels to separate areas according to their different scattering or spectral characteristics. Grouping image pixels into categories or classes to produce a thematic representation.

Pattern recognition aims to classify data (patterns) based on either a priori knowledge or on statistical information extracted from the patterns. Patterns to be classified are usually groups of measurements/observations, defining points in an appropriate multidimensional space.

In statistical pattern recognition a set of features values (constituting a feature vector) are extracted from the segment(s) identified in the image and a statistical or a neural network classifiers is then used to automatically find the best match in a database of objects.

IV. CONCLUSION

In the proposed work, the successful auroral image classification technique group images of aurora caused by some common underlying physical process is presented. By using the minimum dataset available and resources we are able to successfully perform the understanding of magnetosphere processes and the interaction between the solar wind, magnetosphere and ionosphere and the concept of segmentation based on the color, boundary and region features of an image is taken into account. The aurora recognition, classification will lead us to future work as deployment in weather forecasting, automation of aurora system, future prediction based on the results available. The storing and retrieving the results will help us to get the knowledge and most needed results in the field of the aurora.

REFERENCES

[1]M. T. Syrjasuo, E. F. Donovan, X. Qin, and Y.-H. Yang, "Automatic classification of auroral images in substorm studies (2006)".

[2]M. T. Syrjasuo, E. F. Donovan, X. Qin, and Y.-H. Yang, "Automatic classification of auroral images in substorm studies (2006)".

[3] M.T. Syrjäsuo and E.F. Donovan, " Analysis of Auroral Images: Detection and Tracking" University of Calgary, Canada (October 2001).

[4] Rong Fu, Xinbo Gao, Yongjun Jian,"Patchy Aurora Image Segmentation Based on ALBP and Block Threshold",Xidian University, International Conference on Pattern Recognition,2010.

[5] D.LU,Q.WENG,"Image classification methods and techniques for improving classification performance" ,International Journal of Remote Sensing,Vol. 28, No. 5, 10 March 2007, 823–870.

[6]Siddhartha Bhattacharyya, "Color Image Preprocessing and Segmentation Techniques" ,Journal of Pattern Recognition Research 120-129February 5, 2011.

[7] B.Naga Jyothi, Dr.G.R.Babu and Dr.I.V.Murali Krishna,"Color Image Segmentation Using Clustering Techniques" International Journal of Computer, Electronics & Electrical Engineering(ISSN: 2249 - 9997)Volume 2– Issue1.

[8]Shenmiao Han,Zhensen Wu,Guangli Wu and Jun Tan, "Automatic classification of Ultraviolet Aurora Images Based On Texture And Shape Features,"International Conference on Images and Graphics",2011.

[9] Xinbo Gao , Rong Fu , Xuelong Li ., Dacheng Tao , Beichen Zhang and Huigen Yang, "Aurora image segmentation by combining patch and texture thresholding"Xidian University,November 2010.

[10]Http://www.mathworks.in/products/matlab/