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Dynamic aurora sequence recognition using Volume Local Directional Pattern with local and global features

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ABSTRACT

Aurora event consists of the spatial structure and temporal evolution of aurora luminosity, which attributes to the effects of the solar wind-magnetosphere interaction and the physics of the magnetosphere-ionosphere interaction. Dynamic aurora event provides a meaningful projection of effects from plasma processes of outer space and also reveals some certain physical phenomenon and principle. Aurora sequence recognition is one of the key procedure in the analysis of dynamic aurora event. Lots of effective features for static aurora image classification are proposed. If these features for static image classification are utilized to recognize the dynamic aurora sequence, it will result in higher computational complexity. The dynamic features of aurora sequence are seldom proposed due to its complexity. To this end, this paper proposes an efficient aurora sequence descriptor which combines local and global spatial information with temporal location information, which is called as Volume Local Directional Patterns. The ring-section spatial pyramid partition structure is used in the VLDP code image which is coded by Volume Local Directional Patterns to obtain the local spatial feature. After combining the global feature of VLDP code image, the final RSPLDP feature is obtained. Finally, the STSC (self-tuning spectral clustering) method is used to classify the aurora sequence. The experimental results on the dataset which is captured from All-sky Imager (ASI) at the Chinese Yellow River Station demonstrate the effectiveness of the proposed classification scheme.

1. Introduction

An aurora is a beautiful and mysterious natural splendor, which occurs at the polar regions and arises humans infinite reverie and exploration for thousands of years. As we know, it is a light emission phenomenon caused by the complex coupling of ionized stream of charged particles, interplanetary magnetic field and earths magnetosphere [1]. Since an aurora is the most intuitive trace of the ionosphere in the coupling process between the space energy and various magnetospheric motions [2,3] which can affect our lives, the research on aurora can help us to learn these magnetosphere events.

Undoubtedly, different morphology characteristics of aurora sequences yield relevant information about space physics, such as IMF, solar wind speed, electron density and energy. As we know, arc aurora is a typical form of auroras whose occurrence and development are correlated to magnetospheric pulsation of geomagnetic activity [4].

The traditional data analysis in aurora studies usually uses a statistic method and actual measurements of physical properties. Now we are facing the big data problem: large imaging networks, such as NORSTAR, capturing millions of all sky images annually. With the development of polar research in different countries, more and more scientific research stations have been built in recent years, which will produce over 100 million or more images per year.

With the development of image processing, computer vision and machine learning, lots of techniques and methods have been widely utilized in statistical image classifications from large database, and the satisfied results have been obtained. Further, it is possible to extract useful information, retrieve significant events, recognize meaningful patterns, and detect the occurrence of aurora by these automatic methods. However, there are still some challenges to analyze aurora images. Firstly, interferences such as cosmic ray tracks, bright stars, clouds, day glow contamination [5], and system noise caused by equipment can lead to mistakes on labeling the aurora types. Then, the aurora images are usually low in contrast, which makes it difficult to distinguish the types from the background with intense emission at 427.8 nm, 557.7 nm and 630.0 nm. Finally, the shapes are very complex and sometimes are

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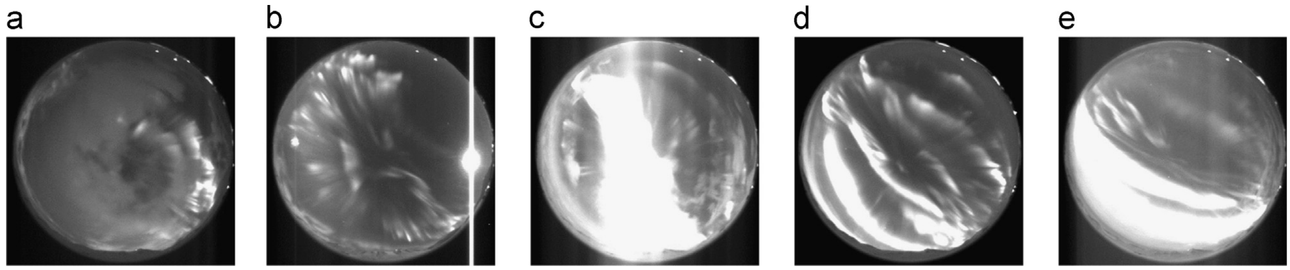

Fig. 1. Challenging images for aurora image classification (a) images with clouds; (b) images with a lamp or stars; (c) images with overexposure; (d) arc aurora images with radiation structure; (e) arc aurora images with complex shapes.

combined with different morphologies that ought to be represented by different features. Consequently, it is difficult to represent and analyze aurora image using the features obtained from existing feature extraction methods. Fig. 1 shows some examples, which are captured by All Sky Imager at the Chinese Yellow River Station and reported under the aforementioned conditions.

Since Syrjasuo [6] firstly introduced a method using computer vision technique into static aurora image classification in 2004, several effective methods have been proposed to classify static aurora images [7–9]. Wang [10] put forward X-GLAMs based method to extract the texture feature of image. Han et al. [11] adopted SIFTS feature and fuzzy C-means to classify aurora images. Yang et al.[12] proposed an algorithm based on the hierarchical wavelet model to represent the feature of aurora image. In addition, Han [13] developed the image classification method by combining saliency information and LDA model in 2013.

For the automatic analysis of aurora sequences, the method based on Hidden Markov Model (HMM) had already been proposed by Yang [14]. However, the statistic features of each image are employed in this work, so that the recognition results are not be satisfied by using these static features because these static features cannot represent the aurora event efficiently. As a result, the main research on aurora sequence focuses on the extraction of more effective descriptors which can represent the dynamic characteristics of aurora event.

LBP was proposed by Ojala et al. [15] which provided an illumination invariant description of an image in 1996. LBP operator, a gray-scale invariant texture primitive, has gained significant popularity for describing texture. However, the strategy is not able to extract more details contained in the local variance. Moreover, it suffers much from non-monotonic illumination variation and random noise. Uniform LBP presents multiresolution approach to gray-scale and rotation invariant texture classification based on uniform LBP model. Uniform patterns are recognized to be a fundamental property of texture as they provide a vast majority of local texture patterns [16]. Complete LBP [17,18] analyzes the local information according to local difference “sigh-magnitude transform”. Sobel LBP [19] combines Sobel operator with LBP methods. The algorithm represents the edge response in two directions because Sobel operator contain two 3×3 kernels, named horizontal and vertical kernel. These feature descriptors obtained from different LBP methods can not represent image sequences effectively. Afterwards, the spatial-temporal poleward volume local binary patterns (ST-PVLBP) have been proposed to discriminate the movement trend of arc aurora in aurora sequences [20]. Since the ST-PVLBP is a dynamic feature, it can represent aurora sequences effectively. The variants of LBP mentioned above are still sensitive to random noise and non-monotonic illumination variation, and there is less directional information in LBP methods.

Local Derivative Pattern encodes the high order derivative information of an image, while the final Local Derivative Pattern code is defined as the concatenations of the four 8 -bit directional LDPs [21]. Local Derivative Pattern contains more detailed discriminative features. However, the problem of the non-monotonic illumination variation is still being in Local Derivative Pattern models.

The Local Directional Patterns (LDP) was proposed by Jabid et al in 2010 [22]. “This method computes” the edge response values in eight different directions by Kirsch masks. LDP provides more consistency in the presence of noise, since the magnitude of edge response is more stable than pixel intensity, which has been already proved to be a robust feature in face recognition and other applications.

As mentioned and discussed above, we adopt LDP features and extend these LDP code to spatial-temporal LDP descriptor, called Volume Local Directional Patterns in this paper. Texture features are extracted from three consecutive frames by constructing operator based on LDP information of neighborhood. In addition, we preserve the location information by a particular partition which is conforming to the characteristic of aurora image. The proposed method can detect arc aurora sequences from mass aurora videos accurately by STSC method, which is effective to classify the complicated data.

The reminder of this paper is organized as follows: LBP and LDP operators are illustrated in Section 2. Section 3 details the VLDP and ring-sector spatial pyramid features based LDP method. While, Section 4 shows experiment results, and Section 5 makes a conclusion and also gives the future work.

2. LBP and LDP operators

2.1. Local Binary Pattern (LBP)

Local Binary Pattern (LBP) [15] and its variants [16,19,21] have been considered as the most effective feature description for image representation. In order to calculate LBP easily, LBP operator is usually defined in 3×3 neighborhood. As shown in Fig. 2, the derivation of LBP starts from comparing the gray value of adjacent eight pixels with the center pixel. If the value of adjacent point is greater than that of the center pixel, the sign of this center point will be marked as 1, otherwise it will be marked as 0. Thus, eight contiguous points in 3×3 neighborhood can produce an 8 bit binary number which is usually converted to a decimal number. Then we set this decimal number as the LBP code of the center pixel in the certain window. As the example shown in Fig. 2, the LBP code of center pixel is $(01111100)_{10}=124$. LBP code contains rich texture information of the local region and has been widely used in the feature extraction and image recognition [18,19,23].

2.2. Local directional pattern (LDP).

A more robust descriptor, named Local Directional Pattern (LDP) was proposed by Jabid et al. [22,24]. The LDP feature is an eight bit binary code assigned to each pixel in an input image. It