Cloud Motion Detection from Infrared Satellite Images

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ABSTRACT

The estimation of cloud motion from a sequence of satellite images can be considered a challenging task due to the complexity of phenomena implied. Being a non-rigid motion and implying non-linear events, most motion models are not suitable and new algorithms have to be developed. We propose a novel technique, combining a Block Matching Algorithm (BMA) and a best candidate block search along with a vector median regularisation.

Keywords: Motion detection, block matching algorithm, cloud motion, infrared satellite images

1. INTRODUCTION

Satellite imagery all ready became a common tool for both meteorologists and scientists. A single frame image even if provided in multi-spectral, offers a limited information concerning the evolution of implied phenomena. Furthermore, visible images are available only during daylight, restraining the possibility of a 24-hour analysis. Thus, infrared and water vapour channels are take into account. Due to the dynamical nature of meteorological aspects, an image time sequence analysis is more appropriate. Most of the satellites placed on geostationary orbit are offering half-hourly images in all three spectral channels [1]. The sequence resulting by collecting successive images could be used for cloud motion detection.

As we previously discussed, the infrared image is the only one employed for continuous cloud motion tracking. However, as presented by various authors [2 3], infrared images could contain artifacts due to the integration effect of imaging sensors. The response of the elementary pixel is the average temperature of all objects present on the corresponding elementary surface. This could be the cause of misclassification errors for different type of clouds. Furthermore, in infrared imagery, objects of different nature but with same temperature could appear as one.

Segmentation and cloud classification is an essential issue, as well before the computation of motion vectors, as for the identification of different types of meteorological phenomena. The classification methods vary, starting from the use of neural networks, such as Self-Organizing Maps tuned by the Learning Vector Quantization and capable of unsupervised tasks [4] or the Hopfield neural networks [5]. The Discrete Karhunen-Loeve transformation or Hotteling transformation is performing classification as well as characterization of cloud elevations in [6] and a Markovian model is used in a labelling scheme for the detection of low height clouds by [2]. Focused on extracting specific features, some authors are employing stereo images in estimation of cloud-top height [7] or convection phenomena [8].

The estimation of cloud motion field is a straightforward objective in the context of image sequence analysis and highly valuable for meteorological and climate applications. However, the automatic extraction of motion is a difficult problem due to the non-linear phenomena of cloud formation and the specific nature of cloud fluid motion. Nearly all-previous work in motion analysis is based on the rigidity assumption, that objects do not change their shape form a frame to another. Generally, this is not the case of many real world examples such as clouds. Consequently, an affine motion model [9] or a non-rigid motion model is defined and fitted using a least-square method [10] in order to retrieve cloud-top heights and winds of hurricane sequences. Other approaches are using a polynomial displacement function to model the local deformation of cloud surface [11] or a vortex type model [3].

Widely used algorithms based on template matching and other similarity metric do not overcome the semi-fluid behavior of clouds and could not be utilized without adaptation. One approach uses the relaxation labelling to refine multiple candidate matches found by template matching [12]. The method presented in this paper is focused on cloud motion detection using Block Matching Algorithm (BMA) combined with a best candidate block search. The rest of the paper is organized as follows: in section 2 the BMA and some speed-up observation are presented. In section 3, we describe the best candidate search algorithm and the results are shown in section 4.

2. IMPROVED BLOCK MATCHING ALGORITHM

BMAs are the most common motion estimation methods and widely adopted by image compression and codification standards (MPEG, CCIT H261/262/263). BMA are assuming the fact that a block of pixels has the same translation motion from one frame to another [13]. This is usually applied to a rectangular region of a fixed size. One can define a searching region for the motion vector, such as:

$$|u| \leq \Delta_h \text{ and } |v| \leq \Delta_v \tag{1}$$

If the block size is K lines and L columns, the searching space is $(K + 2\Delta_h)(L + 2\Delta_v)$ and the number of possible directions is $(2\Delta_h + 1)(2\Delta_v + 1)$. Usually, the matching criterion to be optimized is the absolute mean difference of displaced frames:

$$(\hat{u}, \hat{v}) = \underset{\substack{(u,v) \in Z^2 \\ |u| \leq \Delta_h, |v| \leq \Delta_v}}{\arg\min} \sum_{i=0}^{K-1} \sum_{j=0}^{L-1} \left| I_{DFD}(i, j; u, v) \right| \tag{2}$$

where the frame difference is:

$$I_{DFD}(i, j; u, v) = I(i, j; t) - I(i - u, j - v; t - 1) \tag{3}$$

The current window is divided in several rectangular blocks. For each block in the current frame, a displacement vector is obtained. Its coordinates are the best matching block in the search window of the next frame. The Full Search (FS) algorithm is the most common BMA. It requires $(2d+1)^2$ operations and it finds the optimal motion vector among all candidates. Thus, computing complexity makes it useless for real time applications. The aim of reducing the search complexity is achieved by several FS derivations such as: Three Steps Search, 2D Logarithmic Search [14], Cross Search, Orthogonal Search, Four Steps Search [15], Gradient Descend Search.

In our previous work [16], we have derived an improved BMA, by making some comments on the matching process. We have observed the possibility of improving the convergence, using a series of additional tests and a smoothing effect employing an intrinsic optical flow regularization method. Although robust in most cases, for satellite images, the motion vectors retrieved by the mentioned method are not acceptable, as shown in the results section. Due to semi-fluid behavior of cloud motion, the matching process needs to be improved. We have extended the search for the best match candidate over all images in the sequence and proposed a new criterion.

3. BEST CANDIDATE BLOCK SEARCH

The Full Search BMA finds the best match between the two blocks of successive frames without any regard to the future evolution of the block or of the block neighborhood. It also offers at the end of the matching process, a list of candidates with their corresponding scores, S_c. We have restricted the list to a predefined number of candidates, usually three or four.

Considering all N images in the sequence, the BMA is applied to the first N-1 images. For each search window in the nth image, a list of first c candidates is saved along with their scores computed with (3). For each start block, a tree is set up. A tree node is storing the following items: - links to child nodes; - candidates list; - candidates score; - vector distance list.

Due to the motion similarity of the neighborhood, we have considered the distance [17] between the block and candidates motion vectors, defined based on the L_2-norm:

$$\left\| \hat{V} - V_i \right\|_{L_2} = \sqrt{(\hat{u} - u_i)^2 + (\hat{v} - v_i)^2} \tag{4}$$

The distance list is consisting of values computed using (4). For each candidate block, the difference between the two vectors C_c is saved and employed in the search process. The tree arches are assigned a cost based on the resemblance of considered blocks but also on their motion. Therefore, we have considered a weighted sum defined as

$$Cost = p \cdot S_c + (1 - p)C_c \tag{5}$$

where the weight p is balancing the two factors significance.

The best candidate search algorithm starts with blocks on the first image partition. For each block, a list of path costs is build based on all possible paths starting from it and summing arch costs. Minimizing the path costs will lead to the best block match

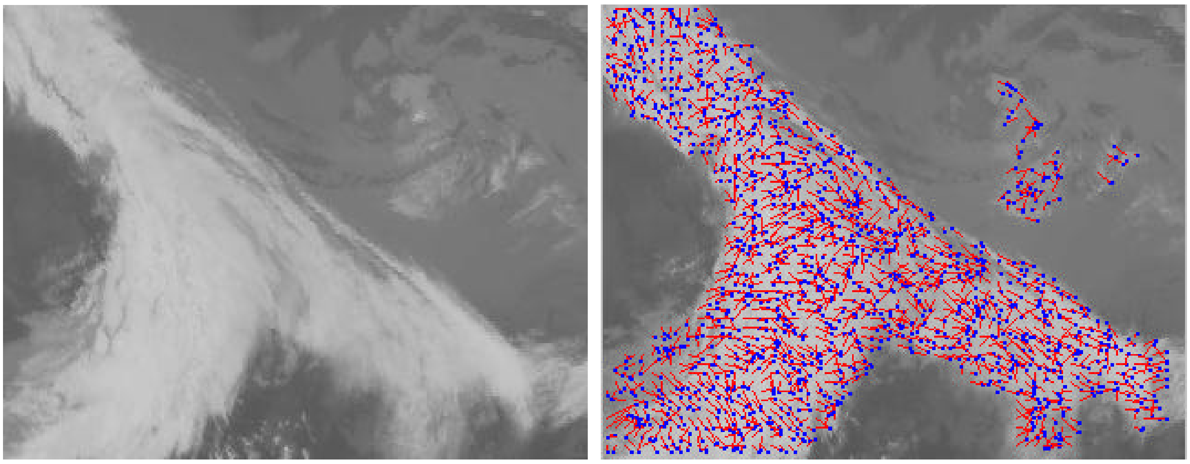
$$Match = \min_{allcandidates} \sum_{n=1}^{N-1} Cost_{n,c} \tag{5}$$

In the aim of smoothing, a motion vector regularisation method is required. We have chosen to apply the vector median filtering [17]. In other cases, each motion vector is replaced by the vector median of the set given by the vector itself and its eight neighbor vectors. Based on observations, we have adapted the above rule for the candidate search process. In our algorithm, each block has a match candidate and further, each of his eight neighbors has their own candidates. We apply the above-mentioned rule to the block candidate and neighbor candidates, choosing the candidate most similar to the median vector. The resulted motion field is smoothed as shown in the following section.

4. RESULTS

Results are presented using infrared images of NOAA satellite, take on 17th of June 2001, over the Western Coast of United States. The sequence is composed of four 320x250 images, take at 30 minutes time interval. The block size was 8x8 and the search displacement ±8. The number of candidates was limited to 3 and weight p was chosen 0.8, in the favor of block resemblance.

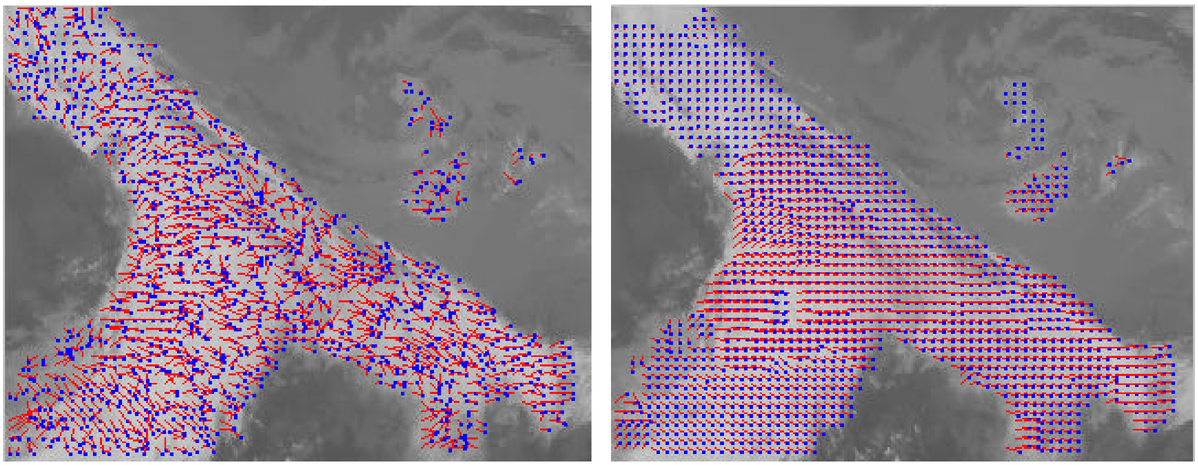
Figure 1 shows the motion vectors corresponding to the BMA without the best candidate search. A threshold was used to eliminate the vectors of static or low motion blocks. Most of the flow is correct, but matching errors also occurs.



a) b)

Figure 1: Results of the BMA without any improvements. a) The first image, taken on 17th of July 2001 0000Z; b) motion vectors recovered from the sequence.

The best candidate search method was then applied and the recovered motion is shown in figure 2a). The vectors are still rough and the median vector regularisation is then used in the algorithm creating the smoothed motion field in figure 2b).



a) b)

Figure 2: Results of the best candidate search method. a) without median vector regularisation and b) with vector regularisation

The final result is a smoothed and distinct motion field suitable for further processing. The image segmentation is straightforward and may be used for meteorological purposes.

5. CONCLUSIONS

We have proposed an improved BMA for cloud motion detection. Although speculative, the beast candidate search method combined with the vector median regularisation can provide very encouraging results. On infrared satellite images, our approach produces a clear and smoothed motion field, allowing the recovery of cloud motion and the identification of cloud formations.

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