COMPUTING CLOUD MOTION USING A CORRELATION RELAXATION ALGORITHM — Improving Estimation by Exploiting Problem Knowledge

Q. X. WU

Image Processing Group, Landcare Research New Zealand
P.O. Box 38491, Wellington Mail Centre, New Zealand

ABSTRACT

A Correlation Relaxation (C-R) algorithm for computing wind velocities from satellite images was recently developed by the author (Wu 1993). Unlike the traditional maximum cross correlation (MCC) method in which only the MCC position (MCCP) in a correlation coefficient matrix is used to derive a displacement, the new method considers many positions associated with high correlations in the matrix, including the MCCP, as candidates for the displacement. It selects an estimate from all candidates using a relaxation labeling technique which iteratively updates the likelihood of each candidate according to a few constraints expressing relevant problem knowledge. The C-R method is shown in this paper to have the potential to exploit a wide range of problem knowledge for improving cloud motion estimation from sequential satellite images. Further developing the C-R method is also justified on the need for more automated estimation of wind vectors in order to reduce or even eliminate manual editing work. In addition, the C-R method can create denser wind vector field than the MCC method.

1. INTRODUCTION

To date, passive tracer pattern tracking using the maximum cross correlation (MCC) method has been the main approach for operationally deriving wind velocity field from sequential images of geostationary meteorological satellites (Proc. 1st Wind Workshop, 1991). The method, because of its stronge needs for final manual editing relying on experts' subjective knowledge, is also inefficient in terms of processing speed. This inefficiency will be further enhanced when future generation satellites provide shorter interval image sequences. More automated approaches are sought for more efficient and objective cloud motion vector production (Szejwash 1991).

Another deficiency of the MCC method is that many suspicious estimates are removed when quality control and manual editing procedures are performed, which necessarily means that some regions will end up without wind estimates and useful information may be lost during these procedures. More estimates are useful for improving numeric weather prediction (NWP) models.

In most existing quality control procedures, knowledge of some kind, for example, wind field continuity (sometimes termed symmetry), comparisons with radiosonde or even NWP data such as those from ECMWF, is employed to determine the quality of each estimate. Subsequently, some estimates will be either labelled as unreliable or simply removed. This kind of quality control is, in fact, *the validation of estimation results*. The subject of the use of problem knowledge for improving the quality of estimation has not been well investigated previously.

This paper attempts to address the above problems by investigating the potential of the newly-developed correlation relaxation (C-R) technique (Wu 1993). The C-R method, which is still in its early development, differs from existing wind estimation procedures in that it exploits problem knowledge for improving the quality of wind estimation. Since the exploration of problem knowledge is fully integrated within the estimation procedure the C-R method by its nature is an attempt towards more automatic wind estimation. Previously, Wu (1993) reported encouraging results achieved by the C-R method using only the knowledge of flow continuity.

2. THE CORRELATION-RELAXATION (C-R) METHOD

2.1 Argument For Developing C-R Method

The C-R method comprises two parts: 1) cross correlation (CC) matching, which is the same as that used in the conventional MCC method; and 2) relaxation labeling. Relaxation labeling is a mathematical technique developed in the area of image processing (Rosenfeld and Kak 1982).

The CC matching focuses on the translational motion cloud tracers which are assumed to be invariant in any two time-lapsed images. Conventionally the first of the two images is subdivided into contiguous rectangles, termed variably segments or templates. Each template is then matched against a larger searching area in the second image. This matching process results in a matrix of correlation coefficients. For the MCC method, a displacement vector is then derived from the position of the maximum correlation in the matrix.

The MCC method has been shown by Ryan (1981), based on the argument in (Whalen 1971), to be a maximum likelihood (ML) approach. The method is purely statistical, and a ML estimate is obtained by considering only the image data statistics. Furthermore, the ML estimate always exists even if the image data is severely corrupted. In the analysis of cloud motion, which is non-rigid or evolving in nature, tracer deformation and image noise resulting, for example, from sensor noise or errors in image calibration, can make ML estimates less reliable.

Given the assumption that a tracer is translated within the scope of the search area between the two time-lapsed images it is natural to reason that any position in the correlation coefficient matrix is a possible candidate for the tracer's displacement even if its likelihood is lower than the ML from statistical calculation. Furthermore, if information in addition to data statistics is available, a candidate may be found to be a better estimate than the ML one. A correlation coefficient, thus, should be taken as only a relative measure of the 'initial' likelihood of a candidate. The above argument establishes the background for the development of the new C-R method.

2.2 The Relaxation Methodology

With reference to (Wu 1993), each tracer template may be associated to a feature point (FP) at its centre. Feature points have been generated at either regular grid or non-regular grid positions within the first of an image pair based on image data variance measures. In future development, feature selection should be based on tracer quality identifications (Holmlund 1991).

Following the rationale in Subsection 2.1, all positions in a correlation coefficient matrix are candidates for the displacement estimate of the corresponding FP. However, it is neither economical nor necessary to use all positions in the matrix. In practice, a small number, typically 10 to 20 in previous work, of positions in the matrix are used. These positions correspond to the highest correlation coefficients in the matrix.

The relaxation labelling part of the C-R method consists of two maior stem: an initial label assignment and an iterative labeling process. In the initial label assignment, a set of labels, i.e. candidates for an estimate, are assigned to each FP. Each label is also given an initial probability derived from its likelihood..

The candidate vector set of a FP is therefore taken to be its label set. A no-match label for the no-solution case is also assigned to each FP to accommodate the situation where image distortion totally dominates signals (equivalently, the assumption of invariant tracer is completely invalid because of some complicated physical process). The initial likelihood of the no-match label is estimated as the difference between 1 and the MCC. This is reasonable because a correlation of 1, which is an extremely rare occurrence, in practice indicates a perfect solution.

To obtain the initial probability measure for each label we normalise its likelihood over the entire set of candidates, including the no-match label, of the corresponding FP.

The second major step of the relaxation labeling process modifies the probability of each label iteratively. The goal of the operation is to achieve a set of labels, one for each FP, which are most consistent with one another according to certain constraints expressing relevant problem knowledge. Within each iteration, the following three steps are performed:

- Check the consistency between each label of a FP and each of the labels of all neighbouring FPs, and calculate a compatibility coefficient according to all constraints used;

- Compute a support for each label from all of its associated compatibility coefficients and the probabilities of all neighbouring FPs' labels;

- Update each label's probability using its support and the supports for other labels within the same label set of the corresponding FP.

Wu (1993) derived the compatibility coefficients according to constraints expressing only the knowledge of flow continuity. The mathematical formulas for computing supports and updating probabilities are also detailed in (Wu 1993). The entire process can be summarised as follows. If a label, amongst other labels of the same FP, has relatively more support from neighbouring FPs under whatever constraints used then its probability will increase, i.e its chance of being selected as the estimate of the FP's displacement is enhanced. The probability will decrease if the label has relatively less support. After a number of iterations the system converges to a state where the probabilities of all labels have only small changes from one iteration to the next. The maximum probability label of each FP is then taken to be the estimate of the displacement if the label is not the no-match one.

As an example of using flow continuity constraints to improve the quality of wind vector field estimation, Fig. *1a* and *lb* compare the result of the MCC method and that of the C-R method.

2.3 Consideration On Template Size

It is well known that the result of MCC pattern matching is sensitive to the size of template. The problem is three-folded. Firstly, when the size is large compared to that of the tracer it is a case of pattern deformation, and subsequently will degrade the displacement estimate. Secondly, when the size is smaller then the tracer there will be a great uncertainty in detecting the peak in the correlation surface as needed in the MCC method. This is the well known *aperture problem.* Thirdly, when the size is relatively small compared to the search area in the second image, non-unimodality (multiple peaks) correlation surface will occur even when the size is compatible to the tracer.

For the C-R method, while template size larger then the tracer will still degrade the estimate the situation is different for smaller template sizes. This is because the C-R method is inherently an uncertainty-reduction process. It is straightforward to see that the C-R can also cope with non-unimodality. Therefore, it is preferable to use relatively smaller template size in the C-R method, which, in turn, can result in denser vector fields. In addition, the use of reduced template increases the processing speed significantly.

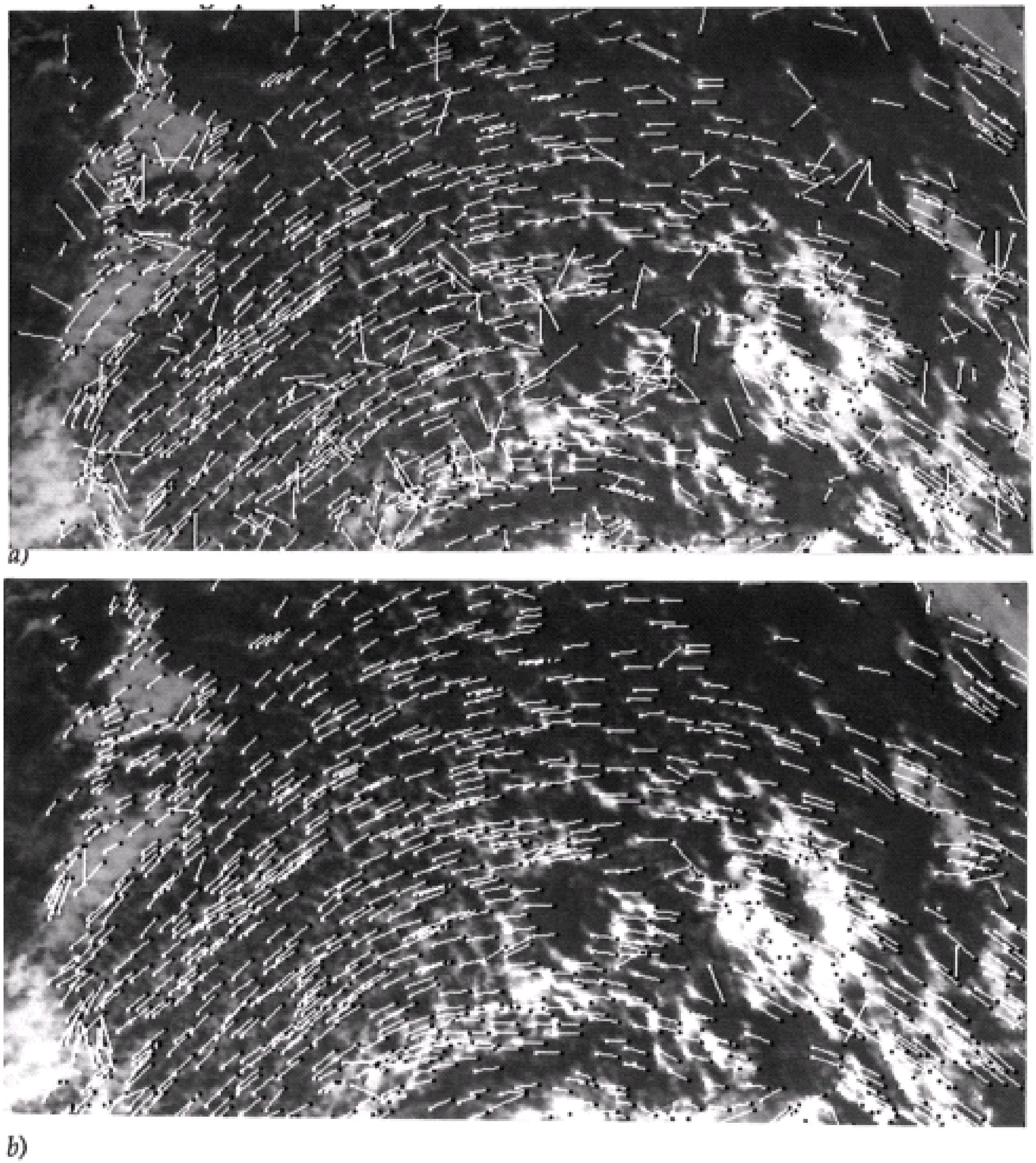

Figure 1. Cloud motion vectors estimated by *a)* the MCC method; and ***b)*** the C-R method from two GMS images.

3. EXPLOITING PROBLEM KNOWLEDGE UNDER THE C-R FRAMEWORK

This section attempts to generalize the C-R algorithm developed in (Wu 1993) to enable it to exploit more problem knowledge for improving the estimation of velocity fields. The objective of this task is two-folded: 1) to reduce as much as possible and eventually remove completely the need for manual editing quality control; and 2) to preserve valuable information which tends to get lost during the MCC processing and following quality control procedures.

Three aspects of generalisation are considered, as described in the following three subsections.

3.1 The Use Of Information On Tracer's And Vector's Quality

The correlation coefficients may be seen as a special kind of knowledge on the quality of a tracer's displacement. A tracer quality measure can in future be used to locate FPs. There may also be information available which can be used to modify a label's initial probability obtained from cross correlation. For example, some search areas can cover clouds from two different layers. In this case, the labels selected corresponding to correlation between two different cloud layers should be given lower probability. This will depend on accurate height assignment to tracers.

3.2 The Use Of Knowledge On Relations Between Vectors And Feature Points

Following (Wu 1993), we see that the compatibility coefficient for flow continuity is the product of three factors:

$$C = Cf\ C_2'\ C_3$$

where, Q expresses the compatibility between two neighbouring labels' directions, C_2 expresses the compatibility between the two labels' magnitudes, and C_3, the weighting factor related to the distance between the two FPs.

This compatibility product can be extended to more than 3 factors when incorporating additional problem knowledge. For example, when tracer height information is available each FP is also attributed with a height value. The total compatibility between two FPs should then be weighted by an factor which is a function of the two FPs' heights. In the simplest case, the factor has only two values, i.e. 1 and 0, indicating whether the two FPs are within the same cloud layer or not.

The existing algorithm exploited only 'spatial' flow continuity constraints. Temporal flow continuity constraints, which corresponds to validating MCC results using the symmetry check (Schmetz 1991, Bueche et. al 1991) between two vector fields, can also be used in the similar manner as the spatial flow continuity constraints.

Information from different spectral channels, i.e, the visible, water vapour and IR channels, can also be used together for achieving quality cloud motion field. Laurent (91) recently showed that each spectral channel can be more advantageous than the others in estimating cloud motion at a specific cloud layer. One would then attempt to combine the use of all three channels to produce an unified and improved wind field.

A possible processing scheme would be to take all spectral channel images as input to the C-R algorithm and generate motion vector candidates from each of them. In determining best estimates compatibility coefficients should modified according to a label's spectral and height information. Knowledge on the relation between tracers from two different spectral channels would also be valuable if available.

Images from two satellites have been employed for accurately determining cloud height using stereoscopic method (Fujita 91). I expect that such data can also be used in combination under the C-R framework for improved wind estimation.

3.3 The Use Of Wind Measurement From Other Sources

Another important way of improving wind estimation is to make use of wind measurement from other sources, for examples, radiosonde data and NWP data, from, say ECMWF. These wind data are more sparsely located than cloud motion vectors. However, they can be used to tune the C-R processmg.

The existing C-R algorithm has already the structure to exploit wind measurements from other sources, but has not been put into use because these data are not available to the author. Within the C-R aleorithm. wind measurements from other sources, if available, are treated as special labels.

Each of these labels will be given a probability according to an expert's confidence on the measurement. These special labels are then used in the same way as other labels to compute supports for neighbouring candidates. However, the probabilities of these special labels will not be modified throughout the process.

4. CONCLUSIONS

It is shown in this paper that the C-R algorithm has the potential to exploit a wide range of problem knowledge for improving cloud motion estimation from sequential satellite images. Further developing the C-R method is also justified on the need for more automated techniques of wind estimation. Finally, the C-R method can create denser wind estimates than the MCC method. Denser wind estimates are needed for improved NWP.

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