Cloud Tracking Using Ordinal Measures and Relaxation Labelling

Adrian N. Evans
University of Bath
Department of Electronic and Electrical Engineering
Claverton Down, Bath, BA2 7AY, United Kingdom
Tel: +44 1225 826833, Fax: +44 1225 826305, Email: A.N.Evans@bath.ac.uk

ABSTRACT

Ordinal measures, based on the relative order of intensity values within window, provide a robust method for finding correspondences between non-ideal images. However, for medium sized windows their discriminatory power is low. To overcome this problem, they can be applied within a correlation-relaxation labelling framework. The advantages of this approach are demonstrated in application to cloud tracking in a sequence of Meteosat infrared images.

INTRODUCTION

The problem of tracking clouds over time is of much interest to meteorological agencies, who use cloud motion vectors as input parameters to weather models, and for studying the dynamic behaviour of weather systems. However, the semi-fluid behaviour of cloud structures presents major difficulties to image processing-based motion estimation techniques. Widely used algorithms based on template matching and a similarity metric, such as the cross-correlation coefficient (CCC), do not perform well in the presence of image noise and deformation. The matching problem for satellite cloud images can be further compounded depth discontinuities and occlusions.

These difficulties have motivated the development of a wide variety of techniques for cloud tracking, including Hopfield neural networks [1] and image warping [2]. One promising approach is correlation-relaxation labelling [3], which uses relaxation labelling to refine multiple candidate matches found by template matching. This method is attractive as it overcomes the problems posed by the multi-modal correlation surface, producing a locally smooth motion field. The quality of the initial matches affects the overall performance of the correlation-relaxation scheme and it has been shown that, in the presence of high level distortion, the CCC requires less relaxation iterations and produces better results than less computationally efficient metrics, such as the sum of absolute value of differences (SAVD) [4].

A new correlation coefficient for template matching, based on ordinal measures, has recently been proposed [5]. The metric has been demonstrated to be robust to noise and distortion. Ordinal measures gauge the degree of similarity between two windows by measuring the distance between rank permutations and are therefore independent of the absolute intensity values. Although very robust, replacing the intensity values with their relative ranks inevitably results in a loss of information and this adversely affects the metric's discriminatory power, making mismatches (false positives) more likely.

Within the context of a correlation-relaxation framework, ordinal measures can be used to robustly generate candidate matches in the presence of noise and distortion, providing a set of high quality candidate matches. The relaxation routine selects the most appropriate of these candidates using information from the local neighbourhood and therefore rejects the false positives and other local maxima caused by poor discrimination and image noise.

Results, obtained by application to a sequence of 800×800 pixels infrared Meteosat images show the advantages conferred by this approach to the problem of cloud tracking.

ORDINAL MEASURES

A core component of window-based matching methods is the choice of similarity metric. The CCC, SAVD and sum of squared difference (SSD) are all based on the absolute intensity data and, as such, are sensitive to noise and distortion. Ordinal measures are based on the relative rank of the intensity values and offer a more robust alternative. Their operation is briefly described below.

If I_1 and I_2 are windows on the two images to be matched, following [5], let π_1^i and π_2^i be the ranks of the I_1 and I_2 data in the set of window intensity values $\left(I_1^i, I_2^i\right)_{i=1}^n$. The ranking of I_2 with respect to I_1 is given by the composition permutation s, such that

$$s^i = \pi_2^k, \quad k = \left(\pi_1^{-1}\right)^i \qquad (1)$$

where π_1^{-1} is the inverse permutation of π_1. When π_1 and π_2 are identical s is equal to the identity permutation $u=(1,2,...n)$. The distance between u and s provides a basis for measuring the difference between π_1 and π_2 and is given by the distance metric

$$d^i = i - \sum_{j=1}^{i} \mathrm{B}\left(s^j \le i\right) \tag{2}$$

where *B(x)* is a Boolean operator that is either true (1) or false (0). Each element of *d* estimates the number of previous elements of *s* that are out of position and is bounded 0 and $\lfloor n/2 \rfloor$. A correlation coefficient κ with a range of ±1 can now be defined as

$$\kappa\left(I_1, I_2\right) = 1 - \frac{2\max\sum_{i=1}^{n} d^i}{\lfloor n/2 \rfloor}. \tag{3}$$

This metric has been shown to be robust to noise and rank distortion. However, the price paid for this robustness is poor discriminatory power, especially with small windows. Even with medium sized windows (9-11 pixels) multiple peaks in the correlation surface often result. Therefore, though the best match may be one of the peaks, additional information must be used to separate it from the other candidate matches. This is precisely the role of the relaxation labelling routine.

CORRELATION-RELAXATION LABELLING

Application of the correlation coefficient of (3) finds a predetermined number of candidate matches, with the highest coefficient values, for templates from the first of an image pair. To select template positions, a local operator can be used to determine image positions likely to produce good matches. Alternatively, regularly spaced points can be chosen and a post filter applied to eliminate and/or replace inconsistent matches [6].

A probabilistic relaxation algorithm then selects the most appropriate of the candidate matches, according to the initial match probabilities and the candidate matches within the local neighbourhood. The support for each candidate velocity vector *Q(J→j)* is gauged by measuring the compatibility between the vector *J→j* and the candidate vectors within the local neighbourhood G_j, given by

$$Q(J \to j) = \prod_{I \in G_j} \sum_{i \in \Omega_{2J}} P^{(n)}(I \to i) R(I,J,i,j) \tag{4}$$

where *R(I,J,i,j)* is a mutual information measure, based on the vectors horizontal and vertical components and their separation. At each iteration, the probability of each velocity vector is updated, producing a smoothed motion field. To accommodate the possibility that no suitable vector exists within the set of candidates, a post filter is applied to the relaxation results, deleting inconsistent vectors and replacing them with ones indicative of those in the local neighbourhood. Full details of the relaxation algorithm and the post filter can be found in [6].

RESULTS

Results are presented in application to two successive 800×800 pixels Meteosat infrared images, taken at a time interval of 30 minutes on 7th December 1998. Matches for 11×11 templates centred on a regularly spaced grid at a spacing of 25 pixels were found by applying the ordinal measure of (3) over a search area of ±11 pixels and recording the nine highest match positions. Fig. 1 shows the velocity vectors associated with the highest value of κ. Many of the templates have more than one vector as a result of the correlation surface having multiple peaks; this demonstrates the inappropriateness of the direct application of ordinal measures to this problem.

The relaxation scheme was then applied to select the most appropriate of the candidate velocity vectors. After six iterations the smoothed motion field of Fig. 2 was produced. All multiple maxima have been eliminated and at the majority of locations a suitable vector has been chosen. The only exceptions occur where none of the original candidates was consistent with the local flow or no cloud was present, resulting in a vector of zero magnitude

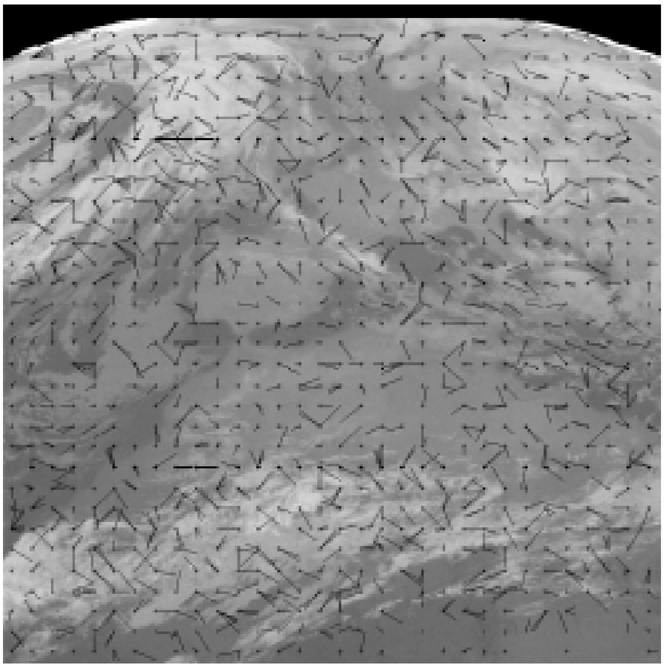

Fig. 1. Velocity vectors for maximum correlation positions.

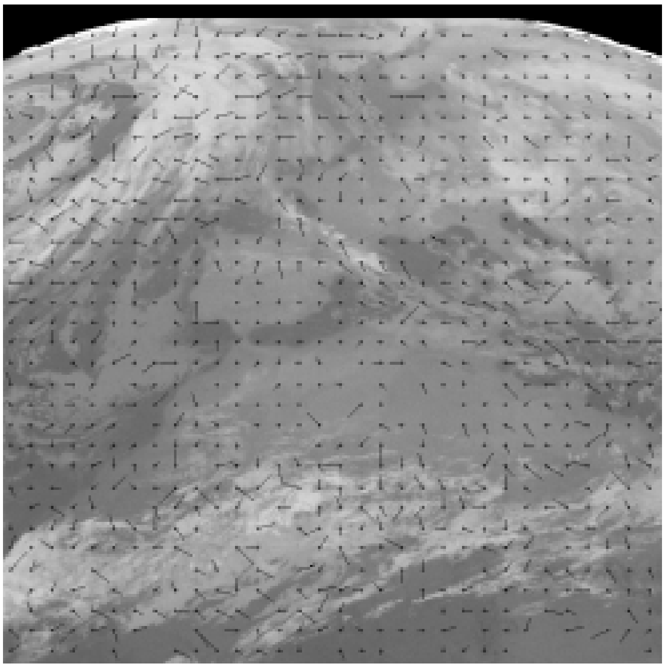

Fig. 2. Velocity vectors of Fig.1 after application relaxation labelling.

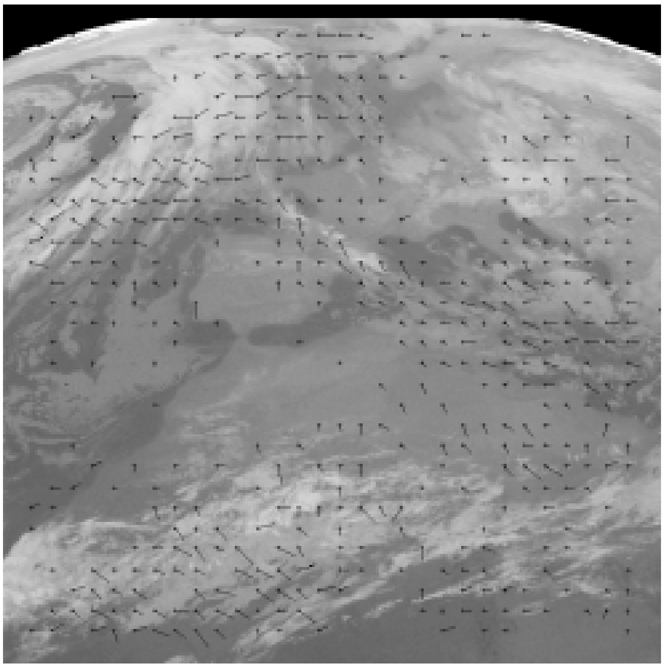

Fig. 3. Post filtered velocity vectors from Fig. 2, using a 5×5 mask.

To further improve the relaxation result, the post filer was applied with a 5×5 window, producing the result shown in Fig. 3. Fifteen percent of the vectors have been changed, further smoothing the motion field, and all the zero magnitude vectors have been removed. The final result is a clear and consistent flow that is suitable for further interpretation.

CONCLUSIONS

The use of ordinal measures for cloud tracking has been investigated. Although robust, their direct application produces a multi-modal correlation surface that needs a further processing stage to determine the best vector. This is achieved by a relaxation labelling routine and, finally, a post filter.

Results from a sequence of Meteosat infrared images show that this approach produces a clear picture of the velocity flow field, allowing the motion of the clouds formations to be readily identified and quantified.

ACKNOWLEDGMENTS

The support of this work in part by The Nuffield Foundation, grant NF-NAL is gratefully acknowledged.

REFERENCES

[1] S Coté and A.R.L Tatnall, “The Hopfield neural network as a tool for feature tracking and recognition from satellite sensor images”, Int. Journal of Remote Sensing, 18(4) pp. 871-885, 1997.

[2] K. Palaniappan, C Kambhamettu, A.F. Haslar and D.G. Goldgof, “Structure and semi-fluid motion analysis of stereoscopic satellite images for cloud tracking”, in Proc. IEEE Int. Conf. On Computer Vision, pp. 659-665, 1995.

[3] Q.X. Wu, "A correlation-relaxation-labeling framework for computing optical flow - template matching from a new perspective", IEEE Trans. on Pattern Analysis and Machine Intelligence, 17(8) pp. 843-853, 1995.

[4] Q.X. Wu, S.J. McNeill and D. Pairman, “Correlation and relaxation labelling: an experimental investigation on fast algorithms”, Int. Journal of Remote Sensing, 18(3) pp. 651-662, 1997.

[5] D.N. Bhat and S.K. Nayar, “Ordinal measures for image correspondence”, IEEE Trans. on Pattern Analysis and Machine Intelligence, 20(4) pp. 415-423, 1998.

[6] A.N. Evans, “Glacier surface motion computation from digital image sequences”, unpublished.