NEUROFUZZY EXTRACTION OF WIND DATA FROM REMOTELY SENSED IMAGES

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ABSTRACT

Object- and feature-based neurofuzzy techniques for processing METEOSAT images have been developed for generation of height assigned wind data. Three basic types of cloud object motion have been identified, and a fuzzy system has been used to determine the degree of each motion type within image regions. Preliminary results are given for a series of METEOSAT infrared images. Parameters suitable for quantifying each motion type have been implemented. Previous work has successfully applied a neural network approach to matching one of the parameter sets over time, for generating cloud motion wind vectors. A neurofuzzy approach to generation and combination of wind vectors from all the motion parameter sets defined has been considered. In addition to the increase in generated wind vector data, the proposed system has the advantage of a core 'fuzzy rule base' which allows for easier wind vector quality control, as the network's decision processes can be more easily visualised and interpreted within the context of cloud motion analysis. It also offers a more flexible interface with which to adapt the object matching criteria for tracking features, for example to incorporate new object motion types or motion analysis parameters, and could be used to incorporate expert knowledge of specific meteorological phenomena.

1. INTRODUCTION

A 'bottom-up' pixel-based approach to image processing requires pixel information to be joined together to determine object change. Current statistical approaches to cloud motion analysis can be thought of in this context: cross-correlation techniques find matching regions of pixels independent of the information depicted by those pixels. Knowledge about the motion of the cloud is derived from the pixel change. Object-based approaches offer a fundamentally different starting point: they impose knowledge about the image at an early stage of processing, thus allowing subsequent analysis to use that knowledge (e.g. GOUGE, J. O. & GOUGE, S. B., (1996)). They are relevant to cloud motion wind generation in that much of the image information related to wind is present in the changes in structure, texture and other time development of the cloud content (the cloud object motion), and these phenomena are all correlated to some degree with cloud type. A cloud motion wind generation technique that has some awareness of the cloud regions under analysis is able to utilise parameter sets appropriate to the different cloud motion types considered, to generate suitable motion vectors. The vectors are then able to be combined from all the relevant motion parameters to obtain a complete description of the evolution of the given cloud object. Awareness of cloud evolution allows underlying wind data to be generated. This approach should aid the identification of poor cloud wind tracers, and could potentially be used to remove some of the clouds' influence on generated winds. In this paper, three basic motion types have been analysed. Section two outlines the parameter sets used for motion identification and analysis of cloud objects.

Fuzzy logic provides a means of handling vagueness in the presence of mixed-class data, where it is not able to be segmented into discrete regions. MASCARILLA, L., (1994) and WANG, Y., (1990) describe applications of fuzzy logic for handling mixed-class data within a remote sensing context. ZADEH, L. A., (1995) outlines many of the fundamental elements of fuzzy logic, and its differences compared to probabilistic approaches of analysis. Analysis of the motion characteristics of cloud objects is an appropriate application of fuzzy logic in that most real cloud objects display more than one motion type. By quantifying the degree to which any cloud object displays the characteristics of a given motion, subsequent analysis can be targeted at quantifying the recognised motion types, and combining them based on the degree to which they are recognised within the object. Section three details the fuzzy system used to generate cloud objects, and gives preliminary results.

Neural networks have long been applied to problems of determining unknown input-output space connectivity by the use of training data. They have been shown to offer improved efficiency of processing compared to statistical approaches, both in terms of speed and computational power requirements (e.g. HAYKIN, S., (1994) and MASTERS, T., (1994)). They have also been successfully applied to optimisation problems based on given goals and constraints. Object motion analysis can be considered as an optimum parameter matching problem: by matching object parameters over a timestep, the change in location and nature of the parameters can be used to generate object motion vectors. Neural network optimisation techniques can be applied to the generation of wind vector data by applying suitable goals and constraints for matching identified object and feature parameters over imagery time-series. Section four details such a parameter matching technique applied to one of the object motion parameters identified in this paper. It has been used to generate cloud motion wind data (CÔTÉ, S. & TATNALL A. R. L., (1995)), and compares favourably with MCC methods.

Neurofuzzy systems offer greater transparency of network functionality over standard neural networks: the parameter space of the network itself is able to be interpreted within the context of the input and output data, by use of a fuzzy rule base. This aids both with network initialisation and performance interpretation and analysis. In wind vector generation, a neurofuzzy approach to feature matching enables the network's match performance to be analysed from the fuzzy rule base of goals and constraints that define the match: the degree of reliance on the given goals and constraints can be used to determine the quality of the match, and corresponding wind vectors. In addition, the fuzzy rule base can be readily adapted to incorporate new cloud features or expert knowledge related to the method of matching, by adding or adapting rules. Section five discusses a proposed implementation of a neurofuzzy optimiser for cloud motion wind generation.

2. OBJECT AND FEATURE PARAMETER SPACE

The choice of parameters for an object-based image interpretation is an important issue (PANKIEWICZ, G., (1995), LEWIS, H. G., CÔTÉ, S. & TATNALL A. R. L., (1995)), as they must represent sufficient and appropriate information to describe the chosen objects. There are two components to the determination of cloud object motion that have been studied, namely the identification of standard object motion types within the imagery, and analysis of the cloud motion within the constraints of those standard types. The approach considered in this paper involves identification of 'frontal flow' (motion of an entire cloud region), 'textural flow' (motion within the identified cloud region, but with no significant boundary motion), 'small object motion' and background. Figure 1 shows a segmentation applied to a METEOSAT IR image. Pixel regions are assigned to more than one standard motion type according to the degree of relevance of each type. The identified types are suggested as suitable object motion descriptors, and are used to prove the concepts involved in an object-based wind analysis. Further analysis and consultation within the meteorological community may lead to a more appropriate set of motion types, however. The parameters used to generate this initial motion type assignment are as follows:

- THRESHOLDED RAW IMAGE DATA:

The image is high-level thresholded at a raw grey scale of 135 over land, and 135-(land pixel mean - sea pixel mean) over sea, each region defined using a suitable mask for METEOSAT D2 data.

- TIME GREY-LEVEL DIFFERENCE:

$$\frac{\sum_{t=-24}^{-1}\sum_{i=-10}^{9}\sum_{j=-10}^{9}\sum_{k=0}^{255} k f_{\delta\theta}(k)}{24 * 400 * 256} \tag{1}$$

where: i, j are pixel co-ordinates relative to the pixel concerned
k is the greyscale
t is the timestep in hours
$f_{\delta\theta}(k)$ is the probability distribution of the difference in greyscales across one timestep, within the 20*20 pixel region surrounding the pixel concerned, at spatial separation δ=0 and thus zero angular separation

- SPATIAL GREY-LEVEL DIFFERENCE:

$$\frac{\sum_{i=-10}^{9}\sum_{j=-10}^{9}\sum_{k=0}^{255} k f_{\delta\theta}(k)}{400 * 256} \tag{2}$$

where all parameters are defined as per the time grey level difference except:
$f_{\delta\theta}(k)$ is the probability distribution of the difference in greyscales within the 20*20 pixel region surrounding the pixel concerned, at spatial separation δ=1 and angular separations of θ=0°, 45°, 90°, and 135°

As can be seen from figure 2, the chosen parameters are able to discriminate between the four desired region types. The thresholded image is a crude measure for removing land and sea pixels from an image selection. The time grey-level difference parameter shows clearly the time homogeneity of the lower region of cloud, compared to the moving frontal cloud. The spatial grey-level difference parameter enhances regions of strong texture, which are indicative of areas containing many small clouds in close formation.

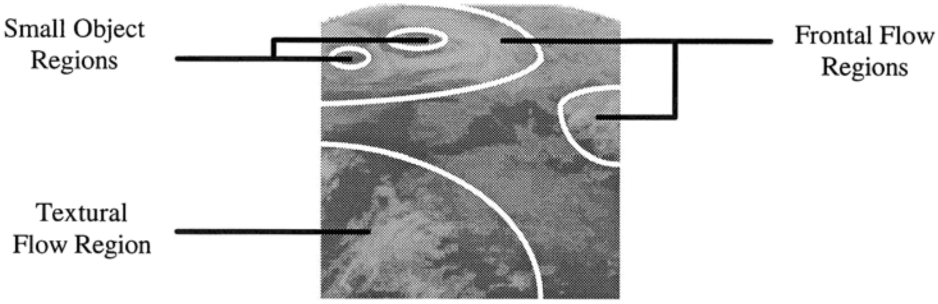


FIGURE 1: Initial Image and Desired Flowfield Segmentation for METEOSAT IR D2 data from February 18th 1996 at 0030h

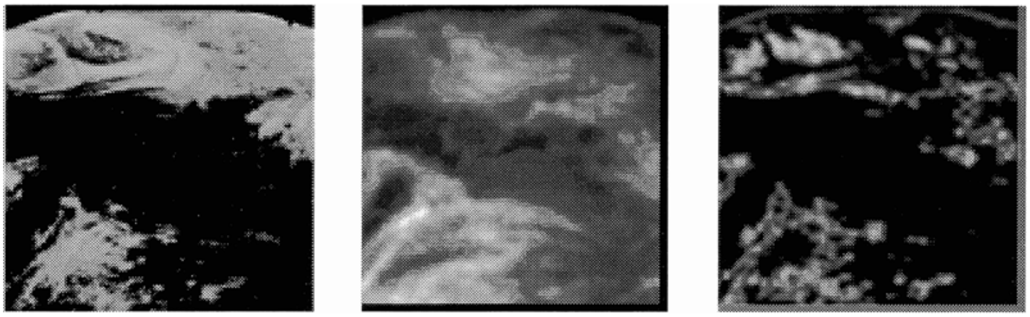


FIGURE 2: Thresholded Raw Image Data, Time Grey-level Difference and Spatial Grey-level Difference parameter sets.

Individual objects are generated within each motion region presently using multi-level thresholding techniques (CÔTÉ, S. & TATNALL A. R. L., (1995)). Quantification of object motion within each region has been considered using four parameter types. Each is most applicable to one particular type of object motion, but any real object may display any combination of these motions. The four types of cloud motion quantified are: curved extended body motion, discrete small body motion, significant growth/shrinkage and standard texture motion. Again the identification of more suitable parameter sets for motion analysis will form a key aspect of future work on this approach. Of particular interest for future object motion analysis are parameters that offer improved frontal motion measures. Some work to date has suggested the potential for wavelet and fourier techniques for such analysis (GAMAGE, N. & BLUMEN, W., (1993)). The parameters defined for the types of flow region identified in this paper are as follows:

- **Object mathematical curve descriptor:** the best fit quadratic to three points on the body defined as the mean pixel positions in the upper third, the mid third and the lower third of the body. The orientation is decided from the best fit bounding box, and the location of the object's centre of gravity within that bounding box. The edge closest to the centre of gravity is defined as the leading edge (figure 3(a)).

- **Object centre of gravity:** suitable for analysis of smll bodies (figure 3(b))

- **Object shape parameter set,** defined as Area, Perimeter, Eccentricity (Major axis / Minor axis: figure 3(c)) and Compactness (Perimeter^2/Area). For more information on Shape and Growth

Parameters, see (LEWIS, H. G., CÔTÉ, S. & TATNALL A. R. L., (1995)).

- **Object texture measures:** Time and Spatial Grey-level Difference Vector data

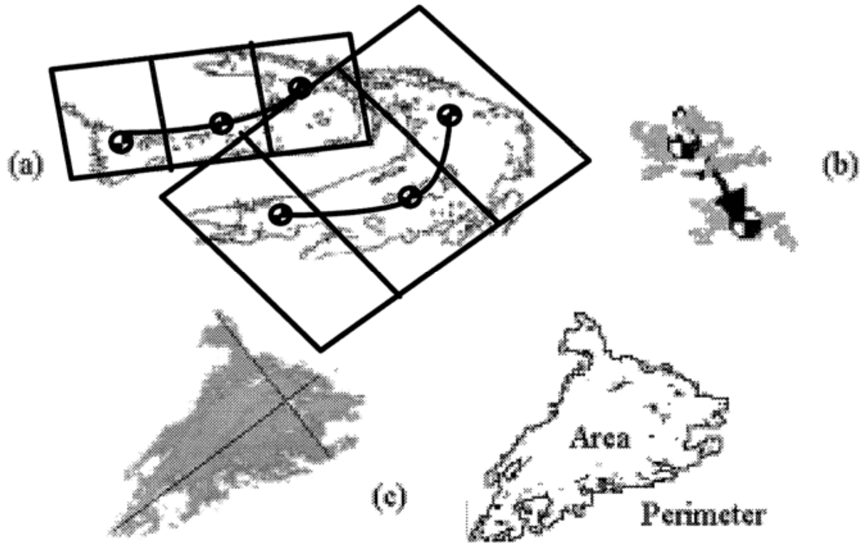


FIGURE 3: (a) Curve Descriptor, (b) Object centre of gravity and (c) Object growth parameter set

3. FUZZY FLOWFIELD ANALYSIS

The fuzzy systems for associating pixel regions with object motion types consist of sets of if-then rules relating the input parameters to degrees of membership of the motion types. Each rule has a 'confidence', which defines its significance compared to other rules relating to the same output. The output of such a system consists of degrees of appropriateness of the chosen output labels to the data applied. Four fuzzy systems were used, one each for each flow type (frontal, textural, small object and background). To illustrate the function of the system, the generation of frontal motion membership for pixel regions will now be analysed more closely. The frontal motion identification system used the time grey-level difference parameter and threshold parameter. Five labels were defined for each parameter, as shown in figure 4.

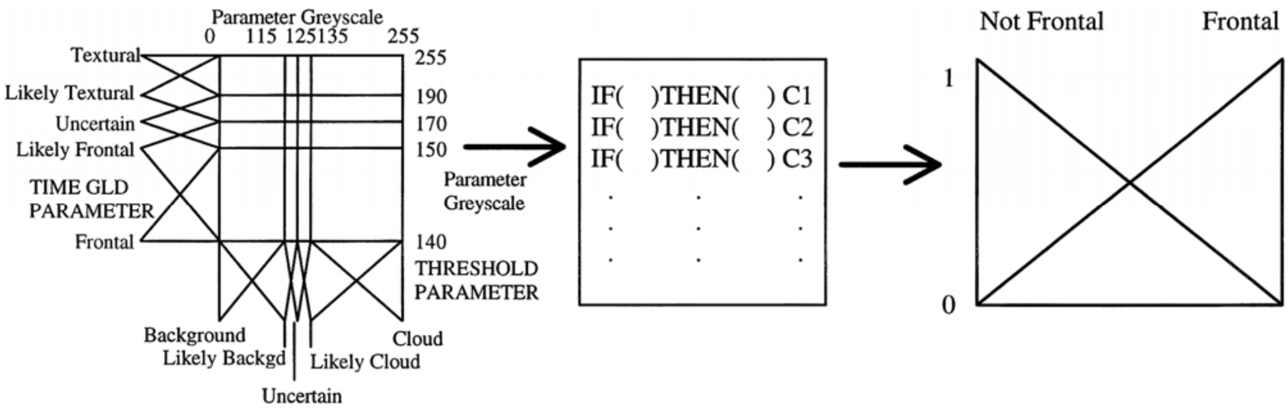


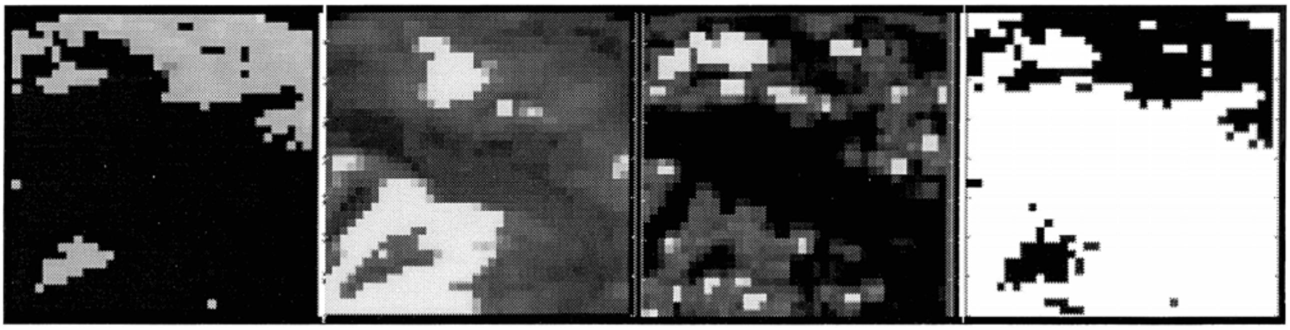
FIGURE 4: Frontal feature identification fuzzy system

Having assigned any given data point to one or two labels for each parameter, the rules relating to those labels were applied, and the association to output membership was made. The output was generated from a combination of the 'active' rules, based on the degree of membership of the input labels in those rules and the associated rule confidences.

The rules in the rule base for the frontal system include:

IF(Threshold Parameter is Background)
    THEN(Frontal Output Parameter is Not Frontal) 1.0 (100% confidence)
IF(Threshold Parameter is Cloud)AND(Time GLD is Frontal)
    THEN(Frontal Output Parameter is Frontal) 1.0
IF(Threshold Parameter is Cloud)AND(Time GLD is Textural)
    THEN(Frontal Output Parameter is Frontal) 0.1
IF(Threshold Parameter is Cloud)AND(Time GLD is Textural)
    THEN(Frontal Output Parameter is Not Frontal) 0.9
IF(Threshold Parameter is Likely Cloud)AND(Time GLD is Uncertain)
    THEN(Frontal Output Parameter is Frontal) 0.55
IF(Threshold Parameter is Likely Cloud)AND(Time GLD is Uncertain)
    THEN (Frontal Output Parameter is Not Frontal) 0.45

Figure 5 shows the identified motion type applicability for the data, as generated by the fuzzy systems. The lighter pixels depict greater relevance of that motion type to the region. This data was obtained using the NeuFrame[1] software package. It is necessary for pixel regions to be associated with more than one motion type as real objects tend to display more than one type of motion. The data in figure 5 is used to identify the most relevant motion parameter sets for each object. The degree of membership of each output set will be used in combining the various wind vectors generated from each motion parameter.



(a) (b) (c) (d)

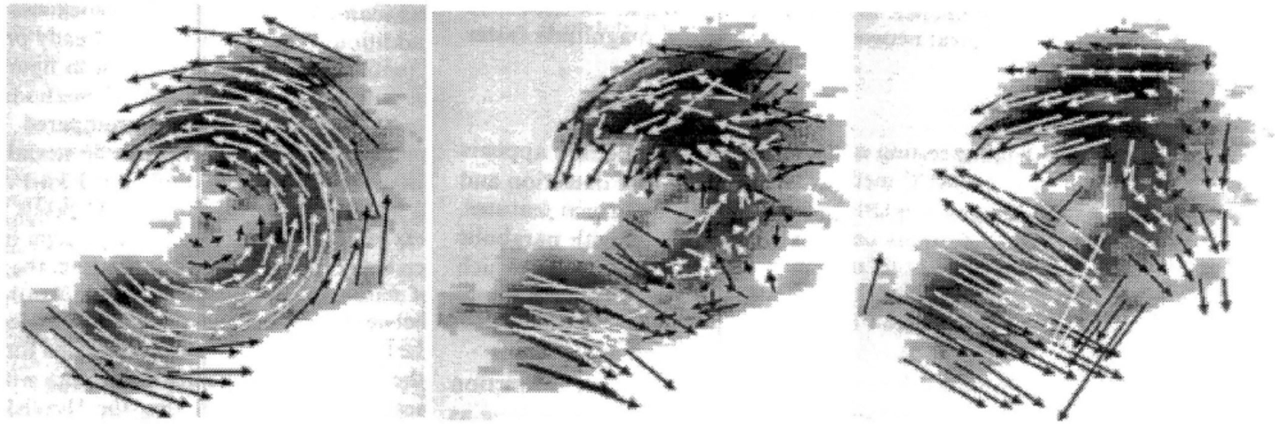
FIGURE 5: Fuzzy Region Memberships for the image: (a) Frontal, (b) Textural, (c) Small Objects and (d) Background

4. NEURAL NETWORK FOR IMAGE FEATURE TRACKING

CÔTÉ, S. & TATNALL, A. R. L., (1995) have applied a hopfield neural network to tracking image features similar to the mathematical curvature set outlined in section two. The identified features are matched in order, based on a 'cost function' of constraints and goals including feature shape and location, and local smoothing of neighbouring vectors. Wind vectors were generated for a cloud object that was allowed to evolve over 30 minutes, and was also manually rotated through 30 degrees.

[1] Neural Computer Sciences: http://www.demon.co.uk/skylake/

The resulting vectors were compared to a standard MCC approach (figure 6). The mean error in vector head location was improved by almost 40% in the network case, compared to the MCC technique, with a corresponding variance improvement of around 80%.



(a) (b) (c)

FIGURE 6: (a) True Vectors, (b) Network Vectors, (c) MCC Vectors
(adapted from CÔTÉ, S. & TATNALL, A. R. L., (1995))

This work is now quite mature, and its ability to generate motion vectors from cloud object parameters has been sufficiently successful to validate the general approach of identifying and matching object-based parameters for generation of cloud motion wind data.

5. FUTURE WORK

The constraints and goals used to match features in the hopfield network approach to wind vector generation are defined in a fairly rigid cost function. At present the technique does not report the relative contribution of constraint and goal terms in the cost function, thus giving no intrinsic measure of the quality of the network's match. By modelling the cost function in a fuzzy rule base, these issues of adaptability, interpretability and network function visibility can be addressed. Rules would fall into three fundamental categories, namely those related to the goals for matching parameters, the constraints for local consistency and the modelling of expert knowledge not contained within the data. Three such possible rules are:

IF (some object a's centr of gravity at time t is near to some object b's centre of gravity at time t+ 1)
THEN (match is good)
IF (some motion vector a is similar to some motion vector b) AND (vector a is close to vector b)
THEN (match is good)
IF (vector a is over the alps) THEN (vector should be longer)

The network functionality would adapt the confidence in each active rule in the rule base until the output match parameter was optimised. By analysing these rule confidences for a match, the quality of the corresponding wind vectors could be assessed: a match dependant on constraints alone would be less reliable than one based on data-driven goals, for example. Having matched object parameters and generated cloud motion vectors from the matched data, vectors from different parameter sources would be combined according to the appropriateness of the parameter for modelling the object's motion as identified in the initial fuzzy motion region memberships. In addition to developing the above neurofuzzy wind generation system, analysis of more suitable motion types and parameters for modelling them will be investigated. Where possible, expert knowledge relating to the relationship between cloud motion and the underlying windfield will also be incorporated.

CONCLUSIONS

An object-based analysis of cloud motion has been considered, and a potential parameter set for performing such analysis has been generated. An image was segmented into regions defined by fuzzy memberships using a fuzzy rule base defined on the object generation parameter set. An approach to tracking features defined on objects using a neural network was discussed, and the benefits of incorporating a fuzzy rule base into this wind vector generation component were highlighted, with particular regard to quality control improvements and the ability to incorporate scenario-specific expert knowledge in an easily interpretable and adaptable format.

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