CLOUD DETECTION OVER LAND SURFACES IN ATSR-2 IMAGES

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ABSTRACT:

For the effective application of processing techniques used to derive surface information from satellite data, it is first necessary to determine if the image data contains atmospheric artifacts. This paper presents a pilot-processing scheme that has been developed using ATSR-2 image data. This scheme is part of a novel approach that will utilise all of the attributes of the ATSR-2 instrument, i.e. the visible and thermal channels, and the dual look capability. Cloud detection will be performed using a synergy of familiar methods (algorithms, knowledge-based systems and fuzzy set theory) that will be controlled using fuzzy logic operators. The performance of this scheme is evaluated with a simulated data set containing pixels of known classes, to which the processed image is compared, and a single ATSR-2 image scene.

I. INTRODUCTION

There are many applications for low-spatial resolution satellite data. Climate, land and cloud studies all include examples of commercial and scientific uses of such data.

Scientific projects, such as climate modelling, require information on land-atmosphere interaction to improve their predictions. This necessitates the identification of cloud in satellite images over land; land-use studies also require the surface data to be free from contamination by cloud and so again, cloud flagging is required. Kriebel *et al.* [1] state that "there is no algorithm which derives surface products from satellite data which doesn't require the pixel to be completely cloud free", and conversely that "there is no algorithm to derive cloud products which doesn't require the pixel to be fully cloudy".

Poor determination of whether a pixel is cloud filled or not will lead to inaccurate analysis when using the data contained within it. Jones *et al.* [2], [3] discuss the presence of cloud contamination in the ATSR spatially-averaged sea-surface temperature product (ASST), in which use has been made of the cloud clearing tests implemented by the Rutherford Appleton Laboratory (RAL). The presence of this cloud contamination alters the derived sea-surface temperature and, as is obvious, will cause errors in those applications using the data, such as climate modelling.

Many climate monitoring/modelling programs have specified a need for high accuracy ocean, climate and land surface data. The ATSR instrument series is built to take measurements to high accuracy (i.e. sea surface temperature derivations with accuracy better than 0.3K [4]), but without effective cloud detection the accuracy of the derived data sets will be significantly worse than the requirements of the users.

This doctoral research project, based at Cranfield University, aims to fulfil the need for higher accuracy data sets through the development of a robust cloud screening system for ATSR-2 data. Since the initial focus of the ATSR and Advanced Very High Resolution

Radiometer (AVHRR) instruments was for the collection of ocean-atmosphere data, there has been a great deal of research done into the detection of cloud over sea-surfaces. The focus of this project is to develop a system that works effectively over land as well as ocean surfaces.

II. The ATSR Instrument

The ATSR-2 instrument was designed and built by a consortium led by RAL. It operates on-board the second European Remote Sensing satellite (ERS-2) in a polar orbit that enables global imaging with a scene revisit time of 35 days [5].

The first generation Along-Track Scanning Radiometer (ATSR-1) operates with four wavelength bands (1.6µm, 3.7µm, 10.8µm, and 12µm), and two views (a nadir view, and a forward view set at approximately 47^{o} forward of the nadir). This allows for a significant improvement in deriving surface characteristics through the calculation and removal of atmospheric effects. ATSR-1 was designed with seven main applications:

- sea-surface measurements,
- cloud and atmosphere measurements,
- lake measurements,
- sea-ice measurements,
- land-ice measurements,
- de-forestation measurements,
- forest-fire detection.

The addition of the extra visible channels to the second generation instrument, ATSR-2 (0.55µm, 0.67µm, and 0.87µm), expands the ATSR-1 objectives to include [6]:

- quantitative vegetation measurements,
- leaf-moisture measurements,
- vegetation state measurements.

The next version of this instrument (AATSR) will fly on-board the Envisat-1 satellite.

III. ATSR-2 Data Products and Processing

There are eight ATSR-2 data products described by Mutlow [7] and Bailey [8], six of which require cloud detection to be performed: gridded brightness temperature-reflectance product, gridded browse product, gridded sea-surface temperature product, spatially-averaged brightness temperature-reflectance product, spatially-averaged cloud temperature-coverage product, spatially-averaged sea-surface temperature product. Mutlow [7] also states that a future product "possibly a vegetation index product" will be added to this list in the future.

This study uses the gridded brightness temperature/reflectance data products, including the optional pixel latitude/longitude, X/Y coordinate offsets, and cloud-clearing/land-flagging records.

The cloud clearing tests implemented by RAL were designed for the ATSR-1 instrument and for optimum performance in detecting cloud over sea surfaces. The tests, described in Zavody *et al.* [9] and Jones *et al.* [2] are:

- 1.6µm histogram test,
- 11µm spatial coherence test,
- gross cloud test,
- thin cirrus test,
- medium/high level cloud test,
- fog/low stratus test,
- 11/12µm nadir/forward test,
- 11/3.7µm nadir/forward test.

As the list shows, within the formal RAL cloud-clearing scheme, no use is made of the additional visible channels on ATSR-2.

IV. CLOUD DETECTION

(a) Background

Shin *et al.* [10] describe four characteristics of clouds:

- clouds are usually brighter than the underlying surface,
- clouds are usually colder than the underlying surface,
- the presence of clouds increases the spatial variability of apparent temperature,
- the spectral response of clouds are different from that of the surface.

These characteristics are obviously of great use for detecting cloud over a surface such as the oceans, which are usually dark (low reflectivity), warm, of low spatial variability, and have very different spectral responses to clouds. Over land surfaces however these broad features are more difficult to apply. Land surfaces contain many features of higher reflectivity (e.g. sand, rock and at some wavelengths vegetation). Land surfaces also include features at low temperatures (snow and ice at northerly latitudes and high altitudes). Land surfaces contain such a wide variety of materials that they also exhibit high spatial variability, and as has already been mentioned, some land surfaces exhibit similar spectral responses to clouds.

A large problem with cloud detection lies in the fact that no single algorithm can effectively detect cloud for all image scenes. This has lead to the development of algorithm packages that include a suite of algorithms that are used to analyse an image. Kriebel *et al.* [1] describe a method for the detection of cloud in AVHRR data that employs five tests, labelling pixels cloud free, partially cloudy, fully cloudy, and snow/ice. The method has a common feature of many multi-algorithm packages, for surface products, all the tests must declare a pixel cloud free for the scheme to assign it that class. The converse is true if cloud products are required.

The method presented in this paper uses a fuzzy classification algorithm and a knowledge-based system. A pilot scheme is presented that uses only the 0.55 μm channel.

(b) Theory

Fuzzy sets exist as a set of ordered pairs where each member, x, of the set, , has an associated membership value, μ (x), this can be said to denote the degree of truth that a given element is a member of a given set (1). This membership value is given by a defined membership function.

$$= \{(x, \mu\ (x)) \mid x \in X\} \qquad (1)$$

If the membership function is defined such that its range of possible values is between 0 and 1, the degree of membership can be interpreted to be the probability that a given element is a member of a given set.

In this study the sets that have been defined are:

- clouds,
- water,
- urban,
- rural,
- agriculture,
- forest.

These sets then have membership

$$\mu_{\tilde{A}}(x) = e^{-\frac{1}{2}\frac{(x-\omega)^2}{\sigma^2}} \qquad (2)$$

functions defined for them using a simple un-normalised distribution curve (2). The membership value μ (x) is given as a function of ω (the mean of the set) and σ (the standard deviation of the set).

The mean and standard distributions have been defined using spectral reflectance profiles for a variety of surface types detailed by Bowker *et al.* [11]. One hundred and fifty-six profiles were categorised and used to calculate the required values for each of the above sets. Figure 1 shows the calculated membership profiles for the given categories in the 0.55µm channel.

(c) Data Set

The classifier has been tested against two data sets. The first is a simulated data set (see figure 2) produced using Modtran 4. This data set contains twenty-five different simulated targets.

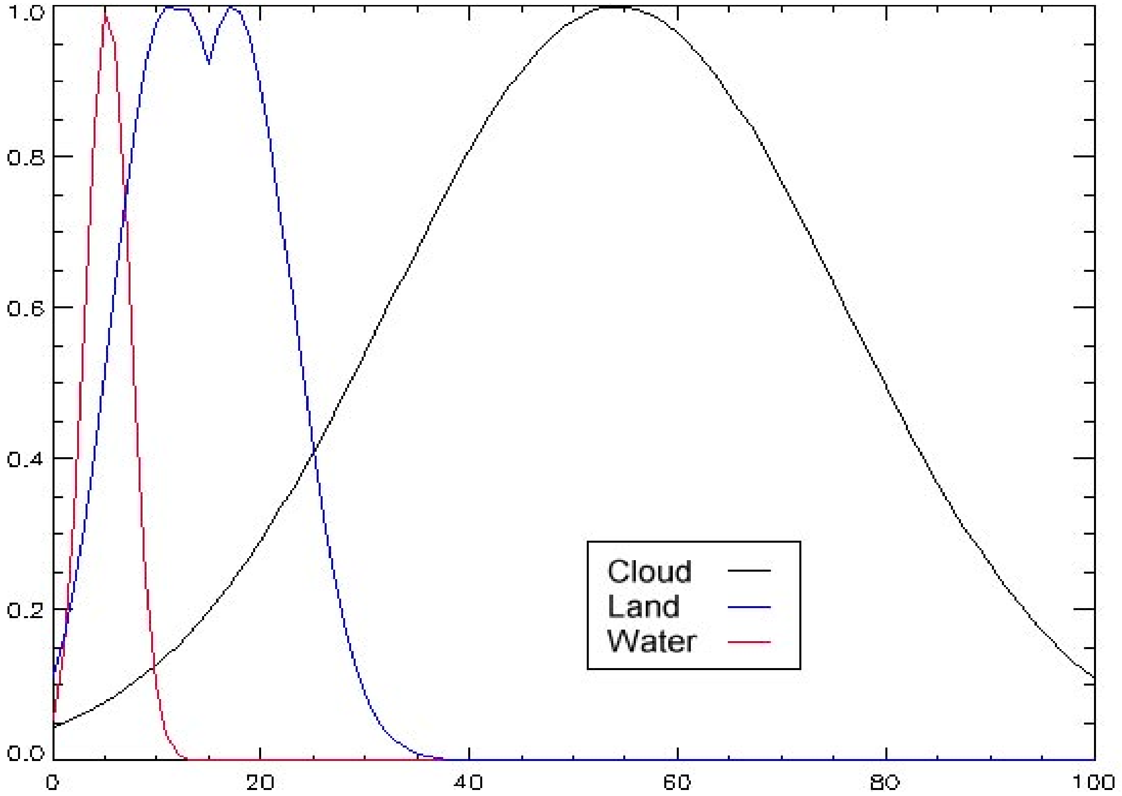

Figure 1
Plot of membership value vs % reflectance

The next stage in processing is to calculate the membership values for each image pixel for each set using (2). A matrix is produced of membership values for each class, each cell corresponding to an image pixel. Using fuzzy sets the mean and standard deviations for each set are now re-calculated using the image pixel reflectances.

The algorithm then re-calculates the membership values using (2) and iterates through the outlined process, until a stable set of means and standard deviations are achieved. Stability is measured using a least-squares approach.

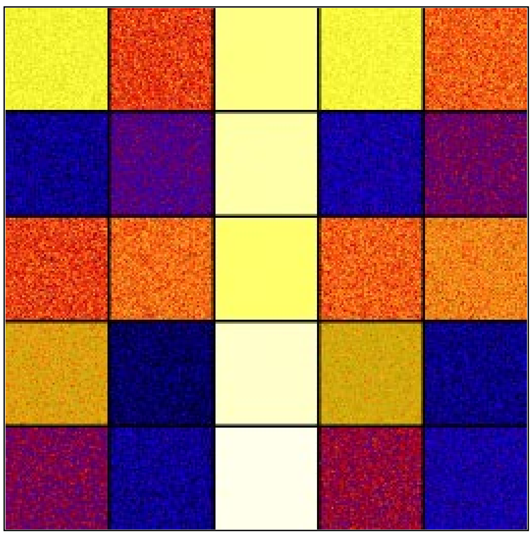

Figure 2a
Simulated 0.55µm channel data set

SAND	URBAN	NIMBO-STRATUS	CIRRUS & SAND	CIRRUS & URBAN
GRASS	RURAL	STRATO-CUMULUS	CIRRUS & GRASS	CIRRUS & RURAL
PINE TREES	ASPHALT	STRATUS	CIRRUS & PINE	CIRRUS & ASPHALT
SYCAMORE TREES	WATER	ALTO-STRATUS	CIRRUS & SYCAMORE	CIRRUS & WATER
WHEAT	SOIL	CUMULUS	CIRRUS & WHEAT	CIRRUS & SOIL

Figure 2b
Simulated 0.55μm channel data set – key

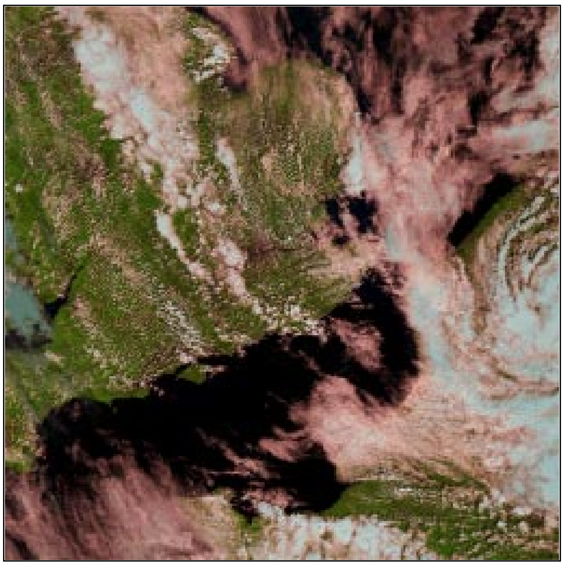

Figure 3
False colour composite ATSR-2 image

The second data set is a real ATSR-2 image, taken of the southern United Kingdom and English Channel on 27th April 1997 at 10.36am UTC (see figure 3).

The image is a gridded brightness temperature-reflectance product, complete with the cloud flags produced by the RAL cloud detection scheme.

(d) Results

The pilot cloud detection scheme has been applied to both data sets and the results are shown as hard classifications (i.e. the pixel has been classified according to its maximum fuzzy set membership value) in figures 4 and 5.

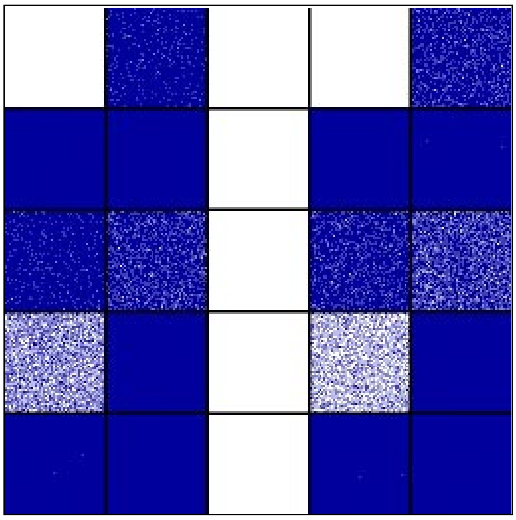

Figure 4
Classified simulated data set:
White = cloudy, Blue = clear

The classified simulated data highlights two of the main problems of cloud detection over land. As can be seen from figure 5 all of the cloud only classes were successfully classified as cloud. Of the clear classes however, the sandy pixels were miss-classified as cloud, highlighting the problem of cloud detection over desert surfaces. The cirrus cases are miss-classified, highlighting the problem of detecting thin cloud over land surfaces.

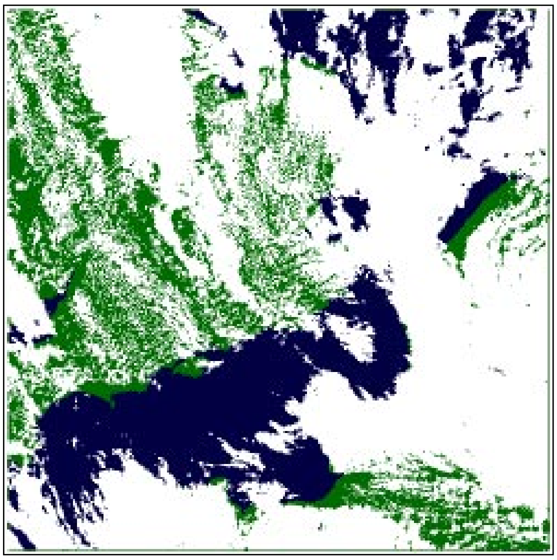

Figure 5
Classified 0.55μm image: White = cloudy, Green = clear land, Blue = clear sea

The real data set appears to give a better classification, especially when viewed against the product cloud flag (see figure 6). The fuzzy system clearly classifies a more realistic quantity of cloud pixels over land, but appears to need improvement over sea surfaces.

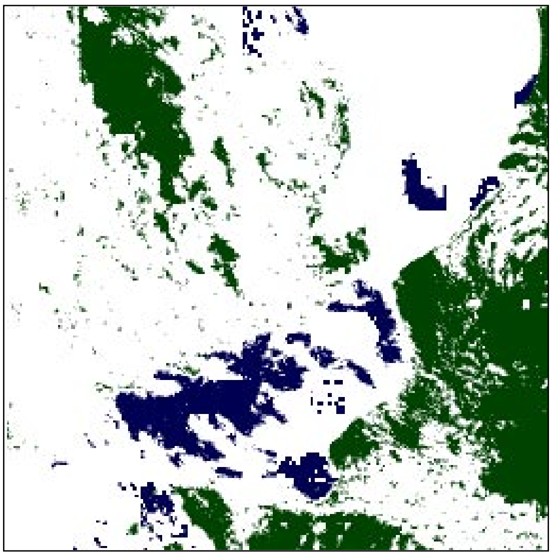

Figure 6
RAL cloud flag: White = cloudy, Green = clear land, Blue = clear sea

V. APPLICATIONS

The direct applications of improved cloud detection over land are obvious, and several have already been mentioned earlier in this paper. The foundation of many models of the atmosphere, the Earth radiation budget, and land-atmosphere interactions is in the data fed into them. With access to improved data sets for land surface regions better models can be developed, and information can be derived with greater confidence in its accuracy.

There are many organisations researching the influences on our environment that would benefit from effective cloud detection. The major organisations such as the Inter-Governmental Panel on Climate Change (IPCC) and World Meteorological Organisation (WMO) clearly stand out as potential users. Smaller projects would also benefit from the detection of atmospheric artifacts, for example AEROCONTRAIL [12], a European project studying the effects of aircraft contrails on the climate. This work is also mirrored by a NASA project [13], and contrail detection in AVHRR images has already been undertaken and shown to be possible by Weiss *et al.* [14].

With greater commercial interest in remotely sensed data at all resolutions from a variety of sectors (e.g. Re-insurance and Stock Market) it is of utmost importance to provide new data sets that meet consumer needs. The development of better products is an essential part of the process towards the self-sustainability of the Earth observation industry, from instrument design and manufacture, to data processing.

VI. CONCLUSIONS

The requirements for and applications of improved cloud detection over land surfaces have been shown. A prototype detection system has been developed using a synergy of fuzzy classification and knowledge-based analysis, with an aim to utilise the benefits of both techniques.

The knowledge-based approach allows an unsupervised analysis to take place based on *a priori* information. The main benefit of fuzzy classification is that the membership values for each pixel in each class can be interpreted as a measure of confidence in the classification. It is therefore beneficial to retain this information in the final output of the detector. For example, it is more useful for a researcher to know that a pixel has been classified with a 92% certainty in its correctness, than simply to be told its classification.

With respect to cloud detection over land surfaces, this prototype fuzzy cloud detector shows some improvement over the existing RAL cloud flagging process. Flaws in the system highlight several of the problems of cloud detection over land, although, as the literature shows, it is unlikely that any one method or algorithm will prove adequate to the task of global cloud detection.

Current work involves the expansion of the detector to include algorithms using additional ATSR-2 wavelengths. Future work on this research project is planned to include the forward view channel data, and spatial analysis techniques. The current knowledge-base of reflectance profiles is planned to be expanded, or superseded by ISCCP data. Modelling of the data set under analysis using Modtran4 will be undertaken and simulated data sets of increasing complexity will be produced, from which quantifiable performance data will be generated.

ACKNOWLEDGEMENTS

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