Infrared Satellite Image Segmentation

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Abstract—**Satellite images are difficult to segment due to the complexity of phenomena captured within. Based on a rarely employed technique presented by Ahuja, we proposed a method for satellite infrared image segmentation. The previously introduced transform is extracting a pixel cohesion force field based on their similarities. We have found that the forces convergence points forms median lines of uniform regions. Combining the features provided by the transform with an adapted segmentation method, a successful region extraction is performed.**

***Keywords-** infrared satellite image; segmentation; Ahuja transform; cloud detection*

I. INTRODUCTION

The complexity of phenomena implied in satellite imagery creates difficulties to any segmentation method from the two main categories of techniques employed: supervised or unsupervised. Several classical or state-of-the-art techniques are failing to extract uniform regions from this type of images. Multi-stratification, equal temperature and flue contours are some of the causes of nonsuccess.

Segmentation methods can be classified as based on pixel analysis, on region analysis or contextual analysis [1], [2]. From the category of segmentation techniques based on region properties, we have noticed the one of active contours [3] or deformable models [4], [8] or watershed [5]. Unfortunately, all of them require a-priori knowledge on the geometry of the regions needed to be identified. They cannot be applied to satellite images, due to three main causes: the need to initialize the process, the minimizing energy function and the difficulty related to the modification of topology.

The splitting and fusion phenomena of different regions (in the case of clouds) cannot be taken into account, regardless of the used method. In the same context of segmentation, some authors have tried to apply different techniques based on texture [6], [10], [11] or wavelet [7], but also in these cases, the concern was to determine the contour between the area of dominant texture and different regions.

Punctual analysis methods based on thresholding or on pixels classification through neural techniques [9] are adapted to segmentation when data are naturally organized around some distinct centers. In addition, the discreet Karhunen-Loeve transform was used in the classification process of pixels [12], or Markovian models in a scheme of low altitude cloud detection [13]. Depending on the purpose, some authors have used stereo images to estimate low altitude clouds [14].

In this context, we proposed to apply and adapt the transform mentioned by Ahuja [15] to the specific case of satellite images. The first problem regarded the irregular forms, the small dimensions and the flue contours presented by clouds. As a result of the mentioned image characteristics areas, in order to avoid over-segmentation, a pre-processing step was considered. Also, after a series of tests, we have determined that for the homogeneity factor σ_g = 20, the segmentation process classifies the pixels in one of the following classes: low altitude, medium altitude, high altitude clouds, ground and, eventually, sea areas. Chapter II introduces the transform and the proposed framework is presented in chapter III.

II. THE AHUJA TRANSFORM

The following region segmentation method has its background in physics, where the homogeneity of physical properties of molecules or particles creates compact formations of similar elements [16]. Molecules are grouping together in a region based on their position and common property. This property will characterize the region.

The segmentation process has correspondence to the phenomena exposed before. It determinates an image partition, based on pixel homogeneity, such as luminance level. The grouping process can be achieved using the Ahuja transform, which converts the pixel characteristics in a cohesion force [15], [16] attracting similar pixels.

The general form of the transform applied to an image $I(x,y)$ creates a family of cohesion forces $\mathbf{F}(x, y; \sigma_g(x,y), \sigma_s(x,y))$:

$$\mathbf{F}(x,y;\sigma_g(x,y),\sigma_s(x,y)) = \iint_R d_g(\Delta I,\sigma_g(x,y)) \cdot d_s(\vec{r},\sigma_s(x,y)) \frac{\vec{r}}{\|\vec{r}\|} dwdv \qquad (1)$$

where R = domain $(I(u,v))\backslash\{(x,y)\}$ and $\vec{r} = (v-x)\vec{i} + (w-y)\vec{j}$.

For each pixel in the image, the transform produces a force vector based on surrounding pixel properties. A scale homogeneity factor σ_g is associated to each pixel, reflecting the homogeneity of the region to which the pixel belongs and consequently a spatial scale factor σ_s defining the neighborhood in which the force is computed.

Hence, the transform establishes for every pixel a vector sum of affinity pairs between the pixel and neighboring pixels. The resulting vector defines the direction and the magnitude of attraction to the rest of the image pixels. The affinity between a pair of pixels is determined by the scale factors. The space factor σ_s controls the spatial distance function $d_s(.)$, and the homogeneity parameter σ_g, the homogeneous distance function $d_g(.)$. For a grey level image, the homogeneity between two pixels, ΔI is given by:

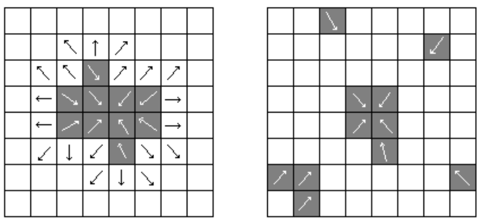
$$\Delta I = \left| I(x,y) - I(v,w) \right| \qquad (2)$$

Using this definition of the **F** force field, the pixels are grouped in regions with contours corresponding to divergent vectors and interiors corresponding to convergent vectors. In addition, one can deduce that for greater σ_g values, less homogeneous structures will be coded and greater σ_s values will ensure the coding of larger structures.

It has been shown that if the value σ_g for which a pixel is belonging to a structure is known, the σ_s value could be determined. This fact simplifies the forces fields' expression:

$$\mathbf{F}(x,y;\sigma_g(x,y),\sigma_s(x,y)) = \mathbf{F}_{\sigma_g}(x,y) \qquad (3)$$

If the homogeneity factor is invariant in space, the image will be transformed in a family of attraction fields relying on one parameter $\mathbf{F}_{\sigma_g}$. These fields will contain all image structures at different spatial scales.



a) b)

Figure 1. Force field. a) the right choice of σ_s transforms the region into a zone of attraction consisting of a single area of convergent flow; b) σ_s has been chosen too large and attractive area contain several regions of convergent flow [16]

The selection of σ_s for a pixel having σ_g given corresponds with the inclusion of the pixel in a region of convergent forces in which the pixels are homogenous. This area is called attraction region and the contour of the region is the flux origin (see figure 1). The term of attraction region is used for nominate a convergent field space, even if this space is formed by one or more regions.

For a certain value of σ_g corresponding to the pixel of coordinates (x_0, y_0) located in region R, the value of $\sigma_s(x_0, y_0)$ must be chosen as the pixel belongs to a region of convergent **F**. Generally, an interval of values of $\sigma_s(x_0, y_0)$, noted $\left[\sigma_s^-, \sigma_s^+\right]$, determines a convergent flux. This interval is obtained by examining the behavior of $\mathbf{F}\sigma_g(x_0, y_0)$ while $\sigma_s(x_0, y_0)$ is varied. For each σ_g, a pixel (x_0, y_0) belongs to one region of attraction. If $\sigma_s(x_0, y_0)$ is small enough as $d_s(.)$ is not exceeding the region, then $\| \mathbf{F}_{\sigma_g}(x_0, y_0) \|$ will be very small and the vector direction will be sensitive to noise. If $\sigma_s(x_0, y_0)$ is increased so that $d_s(.)$ will exceed the region in cause, $\| \mathbf{F}_{\sigma_g}(x_0, y_0) \|$ will increase too and the vector direction will become stable and approximately orthogonal on the region contour. In this case, the incidence of the pixel is determined.

One can define the lower limit of the interval:

$$\sigma_s^- = \min(\sigma_s) \text{ so that } \| \mathbf{F}_{\sigma_g}(x_0, y_0) \| \geq T(\sigma_\gamma, \sigma_\sigma) \qquad (4)$$

where T establish the size of the smallest form which can be included in this region. Practically, the value $T = 4$ allows regions with arbitrary sizes and forms to be identified, excepting those regions containing a few pixels.

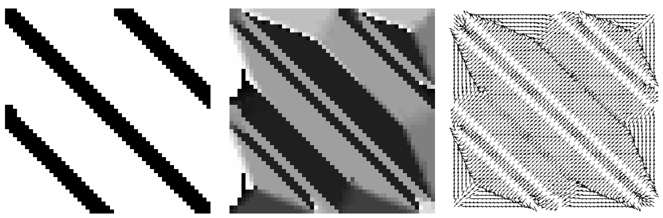
The value of σ_s^+ corresponds to the biggest value of $\sigma_s(x_0, y_0)$ for which the pixel is not attracted by other attraction zone. This value can be found by increasing the σ_s value over the minimum and observing the direction of the force vector. First, the direction will change very slowly, then a transition will appear and then the pixel will belong to another attraction zone. The values of $\sigma_s(x_0, y_0)$ for which the vector direction does not change are called points of spatial stability.

If $\theta(\sigma_s)$ is the angle in radians between $\mathbf{F}_{\sigma_g}(x_0, y_0)$ and a reference direction, we can define the upper limit of the interval as the value of the first point of spatial stability:

$$\sigma_s^+ = \min(\sigma_s) \text{ when } \frac{d}{d\sigma_s}\left| \frac{d}{d\sigma_s}\theta(\sigma_s) \right| \geq 0 \qquad (5)$$

for $\sigma_s \geq \sigma_s^-$. Choosing $\sigma_s(x_0, y_0) \in \left[\sigma_s^-, \sigma_s^+\right]$ for each pixel, we can obtain an **F** field with each vector belonging to an attraction region.

Along each contour, the force vectors are divergent, thus the segmentation of image structures can be fulfilled by searching divergences in **F**.



a) b) c)

Figure 2. a) The original image; b) force directions represented as grayscale for σg=30; c) vector field F.

III. A NEW METHOD FOR THE SEGMENTATION OF CLOUD IMAGES

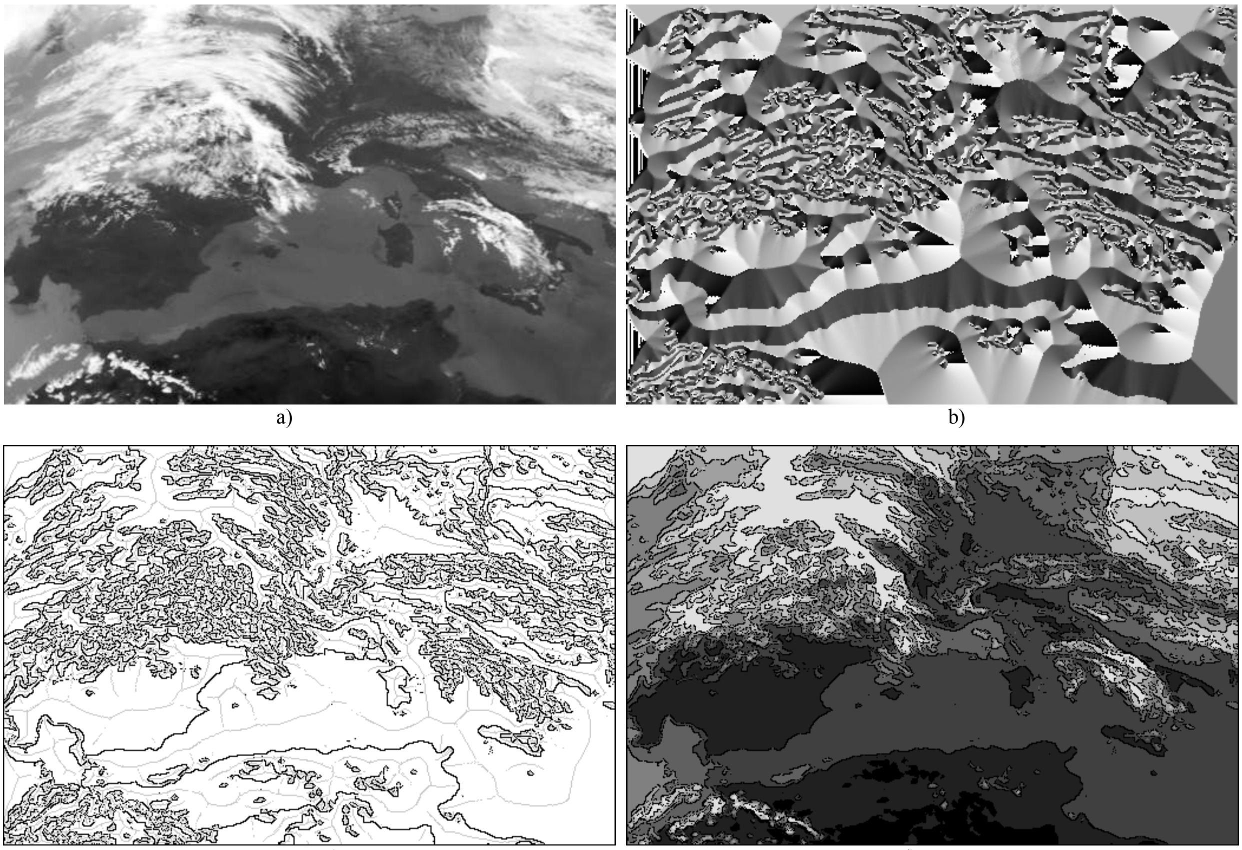
As we have presented and verified through experiments in the previous section, the Ahuja transform can detect borders between different homogeneous regions. In our bibliographic search, applications of the transform have been developed for image compression or segmentation of non-deformable objects. Satellite image features, due to their complexity, make difficult to apply any segmentation method. In this context, we have proposed to apply and adapt the transformed already mentioned at the specific situation for satellite images. The transform is applied to determine the direction of the force, taking into account the homogeneity factor and varying the scale factor. The scale factor is chosen at the value of stability of the force for a pre-established value of homogeneity σ_g, for every pixel from the image.

After a smoothing process, the proposed algorithm continues to compute the cohesion force using the adapted Ahuja transform. A multi-level segmentation, as presented in [16] and [17], is not interesting in the case of satellite images due to the specific content and the presence of flue contours. This is why, we have proposed to calculate first the optimal value of the homogeneity factor in order to successful identify all regions of interest. The value was experimentally found around the value of 20, using calibration data provided [18].

For each pixel of the image, the transform is applied, successively increasing the spatial neighborhood. In the evolution of the force, there are two interesting moments. The first one refers to the situation in which the force gains stability, which means that it points to the region center for which the pixel is belonging. The second moment is the situation when the force changes its direction, the pixel being attracted by another region.

This, increasing σ_s, the value of the cohesion force is determined. According to the two scale factors the minimum level of stability is established σ_s^- according to (4). Then, the maximum threshold σ_s^+ is determined, according to eq. (5). The force angle is computed for the middle of the $[\sigma_s^-, \sigma_s^+]$ interval.

The result of this process is a table containing the force angles in the interval [0, 2π]. Then, for each pixel, the value is compared with its 8 connected neighbors in order to determine the divergence of forces, and so if it is a contour pixel. In a situation of force convergence pixels are belonging to the median line and marked consequently.



a) b) c) d)

Figure 3. The segmentation of a satellite image through the proposed algorithm; a) infrared image METOSAT from June the 2nd, 12:00 GMT; b) the force angles represented in grey levels; c) the contours and median lines detected; d) segmented image using the proposed algorithm.

Even if for some test images, the detected edges are continuous, in the majority of real life images, the original algorithm does not correctly detect contour lines. The explanation is that there is a gradient of intensity variation between two regions and for the border pixels their region belonging could not be decided by the transform. That is why we proposed to use complementary information, the one of force convergence to determine the median lines (always in the interior of a region). The pixels found on the lines will be considered seeds for an adapted region-growing algorithm.

In essence, the original method presents two disadvantages: the first one consists in finding the seeds inside of each region, and the second one, in establishing the homogeneity criterion for each region. These two inconveniences can be surpassed if we start from the premise that the pixels found on the median lines are found at equal distance from the region contour and represent the best the homogeneity in grey levels of the respective region.

From all the pixels found on median lines of the image, a seed pixel is chosen, and then the region is „enlarged", marking all neighbor pixels. The process is stopped when marked pixels belonging to the contour are met, or when the homogeneity factor σ_g is exceeded. The algorithm stops when there are no pixels from median lines unallocated to a region.

The results obtained through this method naturally correspond to the borders between the regions and surpass the situations in which the contours are not perfectly closed.

IV. RESULTS

Figure 3 presents images extracted from the processing chain of the previously described method. The original image (fig.3.a) was captured by METEOSAT-7 satellite in infrared, and received by the Dundee University Satellite Receiving Station, on June 2nd at 12:00 GMT. From the "full disk" image, the sector D2 targeting Central and Eastern Europe was considered.

After applying a gaussian smoothing, the cohesion force angles were computed using the Ahuja transform. In figure 3.b one can observe their coded values represented as grey levels, for the homogeneity factor of 20. The determination of contours and median lines is the next step, which is depicted in figure 3.c. Here, the borders of the regions are represented in black, and the points belonging to the median lines in a light grey. Starting from this representation, in correlation with the original image, the proposed algorithm accomplishes the final and complete segmentation, as in figure 3.d. The five different grey levels found in the segmented image are corresponding to high, medium and low altitude clouds, ocean and ground surface respectively.

For meteorological reasons, the features of interest are the low altitude clouds, stratus or cumulus type. They are responsible for rain, snow or fog. Their higher temperature, found in the interval of [0, 15] Celsius, combined with air masses, ground or relief of low temperature, produces meteorological phenomena. In certain conditions, the lifting effect of air masses can determine storms or tornadoes. Unfortunately, because of a relatively similar temperature with ground and due to a multi-stratification of clouds this type of is difficult to identify. We managed to segment clouds closer to the altitude of 2 kilometers and having temperatures around to 0° C.

The data obtained after the segmentation process will have to be corroborated with information supplied by the terrestrial meteorological networks (isobar maps, temperature maps, radar and visual observations) in order to forecast with a higher degree of confidence. For further information concerning the fusion of information from satellite images and meteorological data, we recommend the website of Zentralanstalt für Meteorologie und Geodynamik, Wien.

In fig. 4 it has been shown the result of image sequence segmentation captured at 06.00, 08.00, 09.00 and 12.00 GMT. In the first image we can notice, in the early morning, the presence of fog above the Hiberic Peninsula, detected by our segmentation algorithm in class of low altitude clouds. One can observe two spring season phenomena; the low temperature of ground during the night, as well as the higher temperature and relatively constant of the Mediterranean Sea. These phenomena can lead to classification errors of pixels belonging to ground surfaces, maritime surfaces and low-altitude clouds. In the following daylight sequence, it can be noticed the rightness of the segmentation, as well as the possibility of pursuing the evolution of clouds.

V. CONCLUSIONS

The segmentation of infrared cloud images appears to be a difficult task. We have proposed a new segmentation method employing the Ahuja Transform combined with an adapted region growing algorithm. We have found that the point of cohesion force convergence correspond to the median axis of the homogenous regions. Using the contour points determinate by the transform, together with median points as seeds, the segmentation is successfully accomplished. By means of periodical calibration data provided by Meteosat, we have found that the homogeneity factor of can be established, simplifying the transform application.

In order to extract the optical flow of a satellite images sequence, we use the results of the segmentation stage for a novel block matching algorithm, as presented in [19].

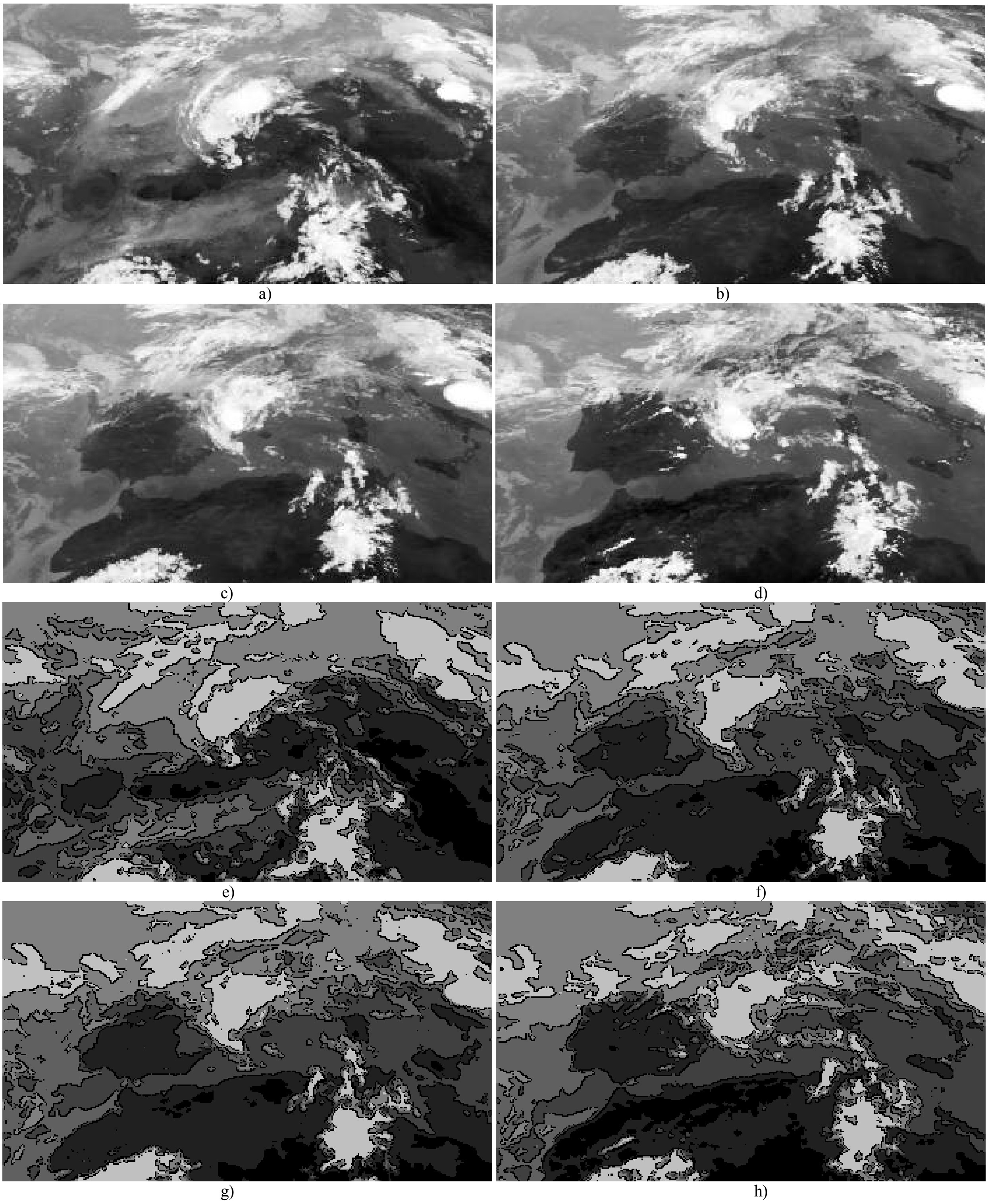


Figure 4. The segmentation of an infrared sequence image of METEOSAT satellite captured in March the 16th, 2008; a) at 06.00 GMT; b) 08.00 GMT; c) 09.00 GMT and d) 12.00 GMT; The results of the segmentation are presented in e), f), g) and, respectively, h).

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