Unsupervised morphological segmentation of objects in contact

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RÉSUMÉ

Dans cet article nous proposons un nouvel algorithme pour la segmentation automatique d'objects et formes fermées sur un fond irrégulier. Notre intérêt se portera en particulier sur le problème d'attibuer des marqueurs pour identifier les objects differents, même ceux qui se touchent. La méthode est utile non seulement aux images statiques mais fournit aussi de bons resultats sur des sequences d'images. Une fois le marqueur a été attribué, nous determinons le contour des objects avec un procés de decision basé sur l'application locale de l'algorithme de watershed. Cette procedure a besoin d'un temps de calcul inférieur à rendement égal, par rapport aux resultats obtenus dans nos travaux précedents [1][2].

ABSTRACT

This paper proposes an algorithm based on morphological transformations for the automatic segmentation of objects over an irregular background. The main emphasis of this work is to present a method to find objects' markers even if the objects are touching or overlapping. We show how our markers extraction algorithm can also be used to detect occlusion situation when we analyse moving objects in a sequence of images. Once the markers have been extracted, the objects' contours have to be located. We propose a decision step based on a local application of the watershed algorithm. It reduces the calculations and keeps the quality of the results we had achieved in previous works [1][2].

1 Introduction

In this work we present the last results we have achieved in unsupervised segmentation of images over an irregular background. This paper would be the third in a series devoted to morphological analysis of images for identification of closed objects. Previous works deal with non linear segmentation of breast cancer images [1], and the analysis of cells' nucleous in breast tissue for a classification of the sample [2]. We present the advances in the method to segment any type of closed objects even if they are in a cluster. Lets call this kind of objects particles. We propose an automatic system for particles segmentation over an irregular background based on mathematical morphology [3][4][5]. The main emphasis of this paper is to show the power of morphological transformations for location of particles in the context of segmentation. We present an algorithm to find markers of touching and even overlapping particles that can be used as inputs to the watershed algorithm. The method gives good results with images so different as biopsies and sparkling wine scenes.

The proposed system is able to detect clusters and to recognize the different particles in them. This way it is able to evaluate the features of each particle in the image. Generally, the goal of the particles' analysis is to supply parameters for a further classification of the sample. It is necessary to identify the clusters, find the number of particles in them, and evaluate their features independently.

The analysis of particles has many applications; we can find a wide range of them in biomedicine, examples are the identification of lung diseases, the automated classification of white blood cells, the detection of cancerous cells' nucleous and the quantitative cytology. The system can also be used in other fields such as the analysis of seeds or the measure of the sparkling wines' quality by the analysis of the bubbles when it is droped in a glass.

2 Morphological segmentation vs other segmentation techniques

The difficulty of the segmentation of particles lies on the presence of an irregular background and the possibility of overlapping situations. Many image segmentation techniques have been proposed in traditional image segmentation literature [6][7][8]. Most of the existing algorithms are either based on the concept of similarity (eg. clustering algorithms) or discontinuity (eg. edge detection algorithms). Both criteria are not suitable when trying to individually identify touching or overlapping particles. In that cases some additional information of form has to be supplied to achieve the right identification. Classical segmentation algorithms either do not segment the touching particles or lead to an oversegmentation. They do not take into account parameters such as size or form of the region. Moreover, so far, image segmentation techniques are strongly application dependant.

We propose a non linear segmentation process based on mathematical morphology. Morphological transformations are a very attractive tool for segmentation purposes because they deal with geometric features, such as size, shape, contrast or connectivity. Thus morphological transformations can be considered as object-oriented, and therefore segmentation oriented.

The approach we present mimics, to some extend, the human recognition process ; however, it does not only ease the analysis work but also quantify parameters that give significant information of the particles. These parameters (particle area, perimeter, uniformity, texture,...) would not be easily measurable by human inspection.

Morphological processing provides great advantages when trying to make an object oriented segmentation. Mathematical morphology provides a set of non linear tools that are very suitable for treatment of images as images are non linear signals. On the other side, morphological transformations are based on size, form and connectivity criteria which are the visible features in an image. The morphological segmentation is usually divided in three steps: simplification, features or markers extraction and decision. This sequence is followed in different works [3][4]. Simplification has been discussed in several papers [9][10]. And the watershed algorithm [11][12] has proven to be a powerful tool for the decision step as it precisely locate contours once the particle has been detected. It provides a systematic method to achieve accurate segmentations from markers. However, few references can be found dealing with a generic algorithm to achieve the markers extraction. In our work we present a systematic method for markers extraction, useful not only for static images but also for image sequences.

2.1 A systematic process to simplify the image

The simplification step preprocesses the original image in order to eliminate the non interesting components, these are noise and regions not suposed to contain any particle. Morphological tools make it possible to remove these components while preserving the structure of the interesting regions [9][10]. Knowing the approximated minimum and maximum size of the particles that we want to analyse, we can follow a systematic sequence in order to remove the non interesting components. First of all we use an alternate sequential filter (ASF) based on the composition of the families of openings and closings both with reconstruction. For more information about these morphological operators refer to [3][4]. The effect of this transformation is to progressively reduce noise, either inside the particles or in the background, while preserving the remaining particles. The first iteration starts with an structuring element (SE) of unitary size. The SE size increases every iteration. We stop the process when the SE size reaches the size of the smallest particle we want to preserve.

After the application of an ASF it is necessary to remove components greater than the particles. It is achieved by means of a tophat transformation of the particle's maximum size. It does not only remove all components greater than the particles, but also achives an uniformity of the background. In this point, most of the images are simplified enough to be binarized with a non critical threshold. Fig. 1 correspond to a biopsy image, and Fig. 2 shows the result of the simplification step. The binarization result is not the particles themselves but the regions in which they are located.

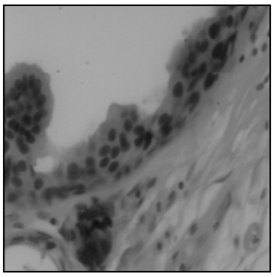

Fig. 1 Original image

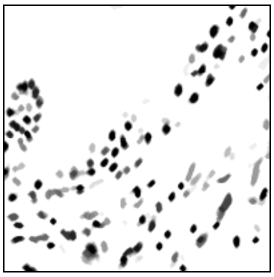

Fig. 2 Simplified image

Next step consists in the evaluation of these regions in order to calculate the number of particles that are situated in each region. We will indicate the presence of an object by a marker. So we will have one marker for each particle. This is the aim of the markers extraction step.

2.2 Finding object oriented regions : the markers extraction step

After simplification, we have achieved a binary image of the regions with particles. In this image, clustered particles are still in the same region. We can achieve an object oriented segmentation if we find significant markers in the image and afterwards they are used as inputs to the watershed algorithm. A marker is a binary signal which indicates the presence of an object. The key point in morphological segmentation, is then, the markers extraction. The aim of this process is to assign a marker to each particle. We present an algorithm to find markers of particles even if they are touching or overlapping. We face the marker extraction problem as one of individual identification of the objects of interest regardless of its geometrical form and size; in this step we are only interested in locating each particle even if it forms a cluster. Markers extraction is not concerned with contours location, which will be the decision step aim.

Classically, a last symmetrical erosion [3][4] is applied to the binary result of the simplification to mark each isolated object. However, not all clusters are divided correctly with this method; some of them still have only one marker. In Fig. 3 we show two different clusters of particles, and the result of its last erosion. In Fig. 3a we can see a cluster with a weak union region and the correct result from the last symmetrical erosion. Fig. 3b shows two particles with an strong union; in that case, last symmetrical erosion results in a single marker, which will lead the counting and the analysis process to error.

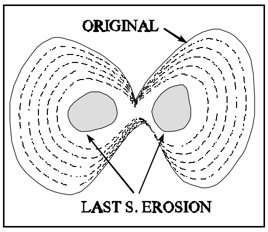

Fig. 3a Last symmetrical erosion of a weak union

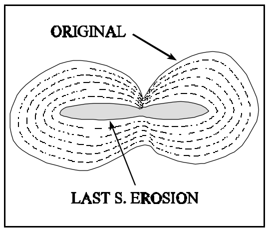

Fig. 3b Last symmetrical erosion of an strong union

However, we can distinguish the right markers, which have circular and small form, from the wrong ones, that have elongated forms. Morphological transformations makes it possible to identify objects with a particular shape, so we can identify the erroneous regions by an opening with a linear SE. We use a bank of four opening filters, one in each possible direction in the digital grid, in order to detect the wrong markers. Once they have been identified they are reconstructed and reprocessed by means of a directional last erosion [1], that achieves the clusters' separation as we show in Fig. 4. We use the information of the reconstruction process to know the cluster's orientation. This orientation determines the directional structuring element we will use in the directional last erosion. We add the new markers to the ones that were well found in the first last erosion; the result is the set of particles' markers.

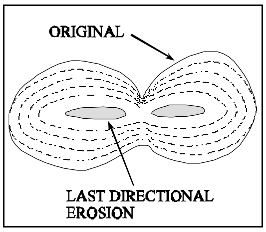

Fig. 4 Last directional erosio of an strong union

It is also necessary to take into account the dual information that provides the background. We need to determine a background marker to guide the decision algorithm. Within this framework, watershed is applied to the union of two kinds of markers: the set of particles' markers, determined as mentioned above, and a background marker which should correspond to the partition associated with the dual of the particles' markers; it means, the influence zone squeleton or SKIZ of the background region [4]. We find the background marker as the dividing line of the watershed over the binary image obtained after the simplification. The result is a single connected marker that identify all regions between particles. We add the information of both marker images and pass the result to the decision step. Fig. 5 shows a portion of a biopsy image with clusters of cells nucleous. Fig. 6 shows the markers obtained for the portion of image in Fig. 5.

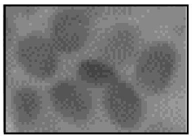

Fig. 5 Cells image

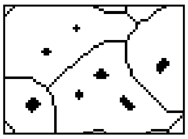

Fig. 6 Markers

2.3 Locating the contours: A local application of the watershed algorithm

Once the markers have been extracted, the decision step leads to an image where each particle is identified as an isolated element, it means, the algorithm assigns a different uniform grey level to each particle and defines a single pixel width contour for each particle. The markers are passed to the watershed algorithm which achieves the right contours location for each marked object. Thus, the decision step is the system mechanical part. However, results depend on the images chosen as inputs. Good results are achived working with the gradient image and starting the flooding process by the marked regions.

Unlike other works, we do not apply the watershed to the whole image at once; instead of this, we make successive local applications over the regions in which we know the particles are. This way we reduce the calculation time, it can be largely reduced when particles occupies an small area of the total image. We propose a local application of the watershed in order to avoid the consideration of background pixels that are not decisive for the particles' contour location.

For each one of the regions obtained in the simplification process, we apply a local watershed. We calculate it limited to a squared window centered in each region. The side window's dimension is *(2n+3)* where *n* is the iteration in which the last symmetrical erosion of the region has been found. This dimension assures that the window encloses the object region and a minimum portion of the background. The iteration in which we obtain the last symmetrical erosion let us know the size of the particle being marked. Taking into account this last iteration, we can define the external marker as the frame of the window that describes the local region in which the watershed will be applied. We join this marker to the particles' markers and start the flood.

Bounding the watershed to the local regions surrounding each object or cluster of objects, we avoid the evaluation of all pixels in the image. We only evaluate an small set of pixels that makes it possible to find the contours of each particle. On the other hand, using a local watershed, we do not need to calculate a global background marker, as we take the frame of each local window as background marker. Fig. 7 shows the resultant segmentation of the image in Fig.5. We can observe that each particle is identified with a different grey level. In Fig. 8 we can see the resultant contours. Notice how the obtained contours correctly separate the different particles in the clusters.

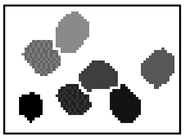

Fig. 7 Segmentation

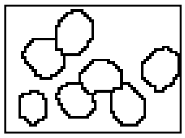

Fig. 8 Contours

3 Morphological segmentation for the analysis of sequences

The method described above is also useful when dealing with image sequences in which moving particles have to be analysed. Markers for image in time *t* can be obtained from the difference between the image in time *t* and a reference image. The difference image do not directly give us the markers we are looking for, but it needs to be processed. Processing of the difference image to obtain the markers can also be made with morphological tools. We take the difference image as the input to the morphological segmentation described above. The simplification of the difference image will preserve only the regions likely to come from particles' movements. It will remove small variations between the image in time *t* and the reference image. On the other hand it can also compensate other effects, such as illumination variations, which affect the whole image and that appear in the difference image as a non uniform background. Once the difference image has been simplified, we proceed to the markers extraction as we made for static images.

One of the main problems in the analysis of image sequences is the crossing situations. The markers extraction algorithm described above proves to be also efficient for the detection of crossings or occlusions. The occlusion starts with an overlapping situation, that can be detected by the algorithm proposed above, and ends with the same configuration. The proposed markers extraction algorithm solves the crossing situations in image sequences, as it does with overlapping situations in static images.

The described method is useful when we are interested in the analysis of the particles' features in an image sequence. It is suitable for applications in which the particle can vary its features over time. An example of this kind of applications is the measure of bubbles features when an sparkling wine is dropped in a glass. This analysis gives a measure of the quality of the wine. In Fig. 9 we show an image of champagne and the detected bubbles.

As we have seen in section 2.3, we can associate a window to each particle or cluster. Thus we can modify the well known block matching algorithm [13] in order to study the trajectory of the particles over time. It makes it possible to work with an adaptive block matching in which the number of blocks, its size and position are automatically defined depending on the particles present in the image.

4 Conclusions

Mathematical morphology proves to be a powerful tool to achieve object oriented segmentations. In this context, morphological segmentation presents clear advantages over other segmentation schemes. We have proposed an algorithm for the automatic segmentation of particles over an irregular background. It is able to distinguish different particles even if they are in a cluster.

We follow the traditional sequence for the morphological segmentation but we present new trends for what concerns to markers extraction and decision steps. We have presented a method to find markers of particles either if they are isolated or overlapping. Moreover, it is shown how the proposed algorithm is also useful for the analysis of moving particles in a sequence. Unlike other works, we do not apply the watershed to the whole image at once; instead of this, we make successive local applications over the regions in which we have detected particles. This way we reduce the calculation time.

The method gives good results with images so different as biopsies (Fig. 10) and sparkling wine scenes (Fig. 9).

5 References

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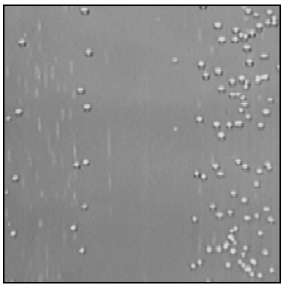

Fig. 9a Image of champagne bubbles

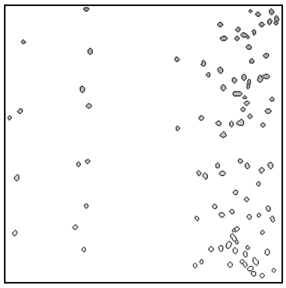

Fig. 9b Detected

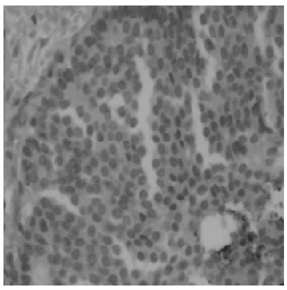

Fig. 10a Image of biopsy

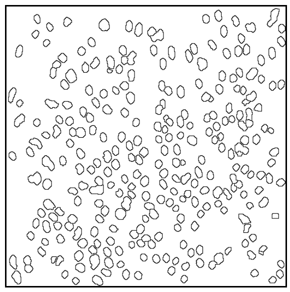

Fig. 10b Detected nucleous