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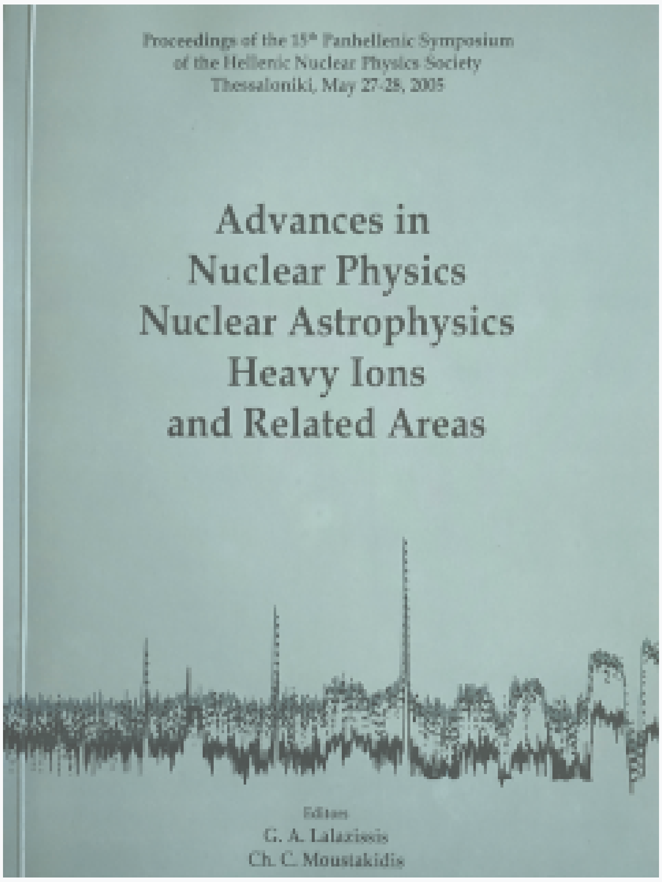

A MATLAB code for recognition and counting of track images

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A MATLAB code for recognition and counting of track images

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Abstract

A computer program named TRIAC written in MATLAB has been developed for track recognition and track parameters measurements from images of Solid State Nuclear Track Detectors CR39. The program using image analysis tools counts the number of tracks and classifies the tracks according to their radii. Comparison of manual scanning counts with those output by the automatic system are presented for detectors exposed to a radon rich environment. The system was also tested to differentiate tracks recorded by alpha particles of different energies.

1 Introduction

Following the passage of a charged particle through a Solid State Nuclear Track Detector (SSNTD) a damage region is created usually named latent track. Latent tracks can be etched using a suitable etchant , which sufficiently enlarges them to become visible under an optical microscope. Using the appropriate apparatus one can take images of the SSNTD's surface and count the number of the tracks. The manual counting of many detectors' images is a tedious and time-consuming task, so an automatic system is needed to speed up the process. A number of automatic track counting systems are currently available [1,3], that recognize tracks on the basis of their grey level.
The code presented here, TRIAC for Track Image Analysis, is

based on a segmentation method that groups image pixels in a number of grey level groups chosen by the user. After the segmentation of pixels, TRIAC counts the tracks that were recorded, even those tracks which overlap and finally classifies them according to their diameters. As an application, the system was used to measure activities of radon and its daughters for dosimetry purposes.

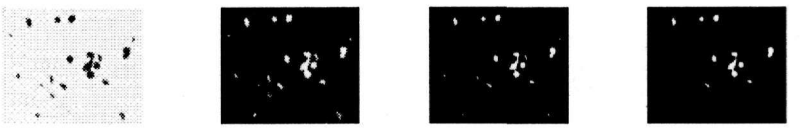
2 Experimental set-up

The track measurements were carried out with CR-39 SSNTDs. To test the performance of the program two trial experiments were performed. In the first trial, the counting capacity of the code was tested. A number of CR-39 detectors were exposed in a radon chamber containing a 2000 Bq source of ^{226}Ra for 1 to 7 days. Due to the different exposure times, different numbers of tracks per optical field were produced (in the order of 10 to 10^3). The second experiment aimed to test if TRIAC could differentiate tracks recorded by alpha particles of different energies. For this trial, plates of CR-39 were exposed to alpha particles from a ^{241}Am source in vacuum. Polyethylene absorbers were used to reduce the energy of the alpha particles and a collimator was placed in front of the source.

3 The algorithms used for the automatic detection of tracks

Code TRIAC was written in the high level language MATLAB.The algorithm performs image segmentation, the process that groups image pixels together, based on attributes such as their intensity, location, texture features etc. A variety of methods have been proposed for image segmentation, such as edge-based or region-based methods [4]. Amongst them, histogram-based clustering methods have been proved very effective, since they basically correspond to clustering approaches. A well known clustering

method is the K-means algorithm [5], which tries to appropriately adjust the K cluster centers in order to minimize the distance from each data point to its nearest center. In the available track data, the resulting images contain, apart from the background (light pixels) and the track regions (dark pixels), pixel regions with a middle level of brightness (grey pixels). To capture the grey level pixels into the image model used for subsequent analysis, we have used K=3 or 4 as the number of clusters for the clustering procedure.
Following image segmentation, pixels are labelled according to the cluster they belong to. Since we are mainly interested in the pixels related to the track regions, we produce a binary image from the segmented image.Furthermore, a morphological operator is performed to remove small objects whose number of interconnected pixels is less than a threshold value P. Figure 1 provides an example of the above image analysis steps.



(a) Original track image (b) Segmentation result (c) Binary image (d) Morphological correction

Fig. 1. The three main steps of track image analysis.

In this stage, the problem is reduced to counting of the number of tracks in the isolated objects in the binary image. The discovered objects may represent one or more overlapping tracks. For each one of them, the edges are found using the Canny edge detection algorithm [6].As the tracks are almost circular, the Hough transform is then applied [7], a technique to automatically detect the number of circles contained in each object.

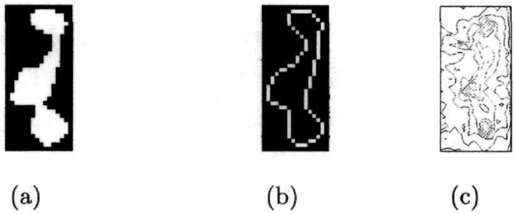


Fig. 2. (a) For an object first we obtain the edges image (b) using the Canny edge detection algorithm. The application of the Hough transform detects 3 tracks, since the accumulator function in the Hough space (c) has 3 major peaks.

4 Results and discussion

The images of tracks taken in the first experiment, were measured first using the computer program TRACKA [8] to "manually" count the number of tracks and second with TRIAC. In the case of manual counting, the reliability of the results is strongly dependent on the user's experience. When counting with TRIAC, the user has only to enter the number of clusters and to adjust (if it is needed) the threshold value of the morphological operator. All following procedure is fully automated, the overlapping tracks are also counted in a systematic way. The geometry of the track

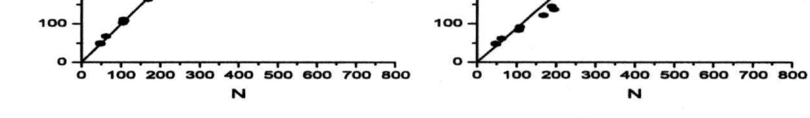


Fig. 3. The counting results, choosing of 3 and 4 as the number of the clusters

development has been considered by a number of authors [9,19]. Generally, the shapes of the tracks are elliptical. In the special case of normal incidence, the shapes of the tracks are circular and their radii are strongly dependent on etching times and energy of particles. As the duration of chemical etching increases,

the thickness of the removed layer and the openings of the tracks also increase. Moreover, the dependence of the tracks' diameters on the energy of alpha particles is not linearly correlated with the thickness of the removed layers according to theoretical models [10,13,18,19].
CR39 plates were exposed to four beams of different alpha particle energies. For a number of different chemical etching times, the distribution of the tracks' radii was measured using TRIAC and an average value was calculated. The experimental results are shown in figure 4 together with the predictions of theoretical model described by D. Nikezic and K. N. Yu [18], while the theoretical results of other models [10], [13] and [19] are also similar for normal incidence. From the comparison of the theoretical and experimental data it is seen that the use of TRIAC straightforwardly verified the prediction of the models on the growth of tracks.

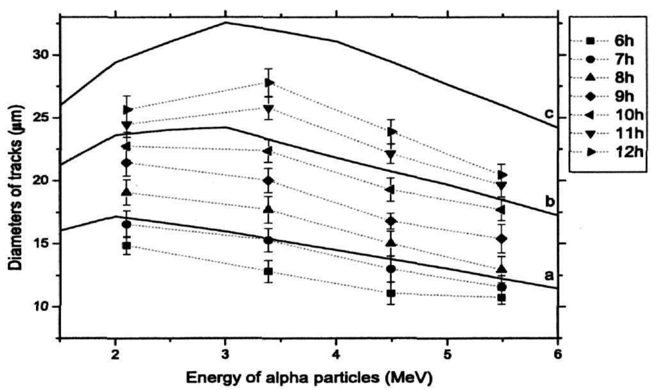


Fig. 4. The comparison between the results for different CE times (6 -12 hours) and the theoretical predictions

5 Conclusions

The computer code described here provides reproducible results at a scanning time of less than 3 minutes per image analyzed. It is easy to operate and provides reliable counting results, even when overlapping tracks exist. Unlike other codes, it does not require the definition of a brightness threshold.

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