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Nuclear Track and Background Dent Discrimination by Parametric Class Definition and Membership Calculation in Nuclear Tracks Images

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ABSTRACT

Background: There are several methods based on image processing algorithms which can be used for track and non-track discriminating in Alpha track images. The methods can be divided into two main categories: geometric-based methods and context-based methods. **Objective:** In this paper, physical parameters of particle type, particle energy and particle-detector collision angle are used to define the fuzzy classes of nuclear tracks of interest. Physical parameters are mapped to the tracks structural parameters as diameter, shape, depth, etc. Due to the uncertainty in the track counting problems, variables are transferred into fuzzy domain and the classes are modeled with Gaussian functions. A detected object is to be determined whether it is a nuclear track or a background dent via calculating its membership to the predefined track classes. If the membership value is higher than a threshold, it will be counted as a track, otherwise it will be rejected. **Results:** The proposed algorithmic manner is tested on 100 Alpha track images of the CR-39 detector sheets. The efficiency of the algorithm is finally validated by the results. **Conclusion:** Noise removal and non-track analysis of nuclear track images can significantly improve the accuracy and efficiency of track measurements algorithms.

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INTRODUCTION

Numerous automatic or semiautomatic methods for track counting of Solid State Nuclear Track Detectors (SSNTDs) including LR-115, CR-39 and polycarbonate detectors have been developed. Some of them are complicated and expensive. Some methods are conceptually simplified and are actually thresholding based methods [1]. There is an extensive literature attempting to overcome an existing drawback and/or providing a solution for the problems in track counting field. Accuracy, precision, wide range linearity and comprehensibility are the main features all methods would have sought [1-3]. Although the software is often developed exclusively for the track counting system used in each laboratory and it is designed according to the output of the imager tool (camera or scanner), there should exist software usable generally for this purpose without any dependency to the particular conditions of a particular system. There is not any sureness and warranty the software designed for a system can work as well for other systems. A track counting method should be developed that can be used for analysis the images of any track counting system. There are several problems which are commonly encountered in the track detection and counting systems and applications. For instance, counting the highly overlapping nuclear tracks, counting the ultra high density nuclear tracks, discriminating between nuclear tracks and non-track dents on the detector surface and counting the tracks with desired parameters as energy, incident angle, penetration depth, etc, may be concerned. In these cases, there should be present such the application based methods appropriate for the desired task. Unfortunately, there has not been used a benchmark track image dataset for evaluation of track counting methods as a comparison tool; hence, manual measurements can only be performed for the assessment procedure. One purpose of this paper is

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introducing a benchmark dataset of chemically etched tracks on the website: http://wdl.persiangig.com/pages/download/?dl=http://khayat.persiangig.com/Nuclear%20Track%20Images/Nuclear%20Track%20Image%20Part%281%29.rar . The main novelty of this paper is defining nuclear track classes of interest to the user according to a mapping from the measuring parameters to the physical parameters of particles-detector incidents.

Khayat et. al. [4] presented a review work on offline track counting methods and the application of Softcomputing methods in the field of nuclear track counting. In another work Khayat et. al. [5] developed a technique to improve the low resolution nuclear track images for which accurate track measurement is not applicable. Khayat and Afarideh [6] defined 12 textual and shape based candidate features among which the most effective ones are selected for track detection and counting. The selected features may vary from one dataset to another due to the difference in the images characteristics. Khayat et. al. [7] developed a code named ATMS code that is able to detect track overlapping and also the orientation of particle collision to the detector surface working based on fuzzy Hough transform. In a later work of the author, Nejad et al. [8] presented a semi-automated algorithm consisting of three phases of preprocessing phase, feature extraction phase and track counting phase. In the preprocessing phase, an automated contrast enhancement method [9] was employed to expand the gray scale range in the nuclear track images. Two main features named Topological feature and contextual feature were defined and extracted in the second phase. In the third phase, the tracks are detected and counted based on the extracted features. As a complementary to those works, the authors intend to develop a method to discriminate the Alpha tracks of interest and the background dents. The main focus in this work is on the geometrical aspect of the nuclear tracks with any shape of interest to be discerned from any non-track objects. The necessity of using such a method is made apparent in the cases where the dents and hollows on the surface of a CR-39 are similar to Alpha tracks in shape. Another case where such a track-dent discriminating method is of concern is for the track images with a lot of overlapping tracks or non-orthogonal (oblique) penetrations.

MATERIALS AND METHODS

Track Counting System:

The track detectors CR-39 available from Intercast Europe SpA via Natta 10/a 43100 Parma Italy (curing time 32 h, thickness 0.7 to 1.5 mm) were used. The small detector sheets were cut by 2 × 4 cm each. Track densities were observed using an optical microscope model Leitz Wetzlar (Germany) fitted with an objective lens of 40 times magnification and the total magnification of 400. The microscope image was viewed with a DCM 35 350Kpixel USB camera, which is connected to a PC-based image viewer. Track images are segmented in 10 different fields randomly taken around the center of the detector.

Track-Dent Discriminating:

There are several methods based on image processing algorithms which can be used for track and non-track discriminating in Alpha track images. The methods can be divided into two main categories: geometric-based methods and context-based methods. The later one refers to the pixel color intensities and gradients. A multi-layer perceptron is employed in this paper to model a nuclear track based on its geometrical and contextual features. Multi-Layer Perceptron (MLP) is one of the most common discriminating tools used for template matching and pattern classification [10, 11]. Artificial Neural Networks originally inspired from biological nervous systems and composed of simple elements as nodes and links. These elements take the advantage of parallel processing [11]. The MLP used in this paper has one hidden layer with N_n hidden neurons with hyperbolic tangent sigmoid transfer function. The output neuron has the linear transfer function.

The MLP as a modelling tool and classifier models the detected objects according to their features as $\{\theta, E, D, d \mid p\}$ in which θ, E, D, d and p refer to the angle, energy, major axis, minor axis and the particle type. Any detected object will be a nuclear track if it belongs to one of the predefined nuclear track classes with a membership value higher than the threshold T, otherwise, it will be rejected as a non-track dent. It should be noted that the discrimination between two different groups of nuclear tracks may be concerned and the rejected objects are not necessarily non-track objects. In this paper, the track detection and counting method of Nejad et al. [8] is used for object detection in the nuclear track images captured from the surface of the CR-39 detectors.

Class Definition:

Let variable O be a detected object of size M×N as

$$O = \{o_{ij}\}\ i = 1{:}M\ \&\ j = 1{:}N \tag{1}$$

which has been detected in the track image I by the method of Nejad et al. [8]. The dimension M×N is assumed to be the reference dimension for the saved templates and the detected objects. Suppose that the desired collision angles are in the range $\Theta = [\Theta_{min}, \Theta_{max}]$ while the tracks major and minor diameters are in the range $D = [D_{min}, D_{max}]$ and $d = [d_{min}, d_{max}]$. Suppose also the energy range of the incidental particles of interest is in $E = [E_{min}, E_{max}]$ interval. Incident particles can be one or more individuals of the set $P = \{Alpha\ particle, Fast\ neutron, Fission\ fragment\}$. Classes of nuclear tracks are defined as

Definition 1: A class of nuclear tracks is a set of one or more nuclear tracks formed by the collision of particles of type $p \in P$ *to the detector surface with the angles* $\theta \in \Theta$ *and the incident energy of* $\widehat{\mathrm{E}} \in \mathrm{E}$ *while a quasi-conical-shape cavity with an aperture of the major axis* $\widehat{\mathrm{D}} \in \mathrm{D}$ *and minor axis* $\hat{\mathrm{d}} \in \mathrm{d}$ *is configured.*

The nuclear track class defined above comprises a set of tracks with a predefined crisp parameter values. Because of the uncertainty in the track parameters values, the crisp values are preferred to be converted into fuzzy sets. Therefore, the nuclear track classes are redefined using the fuzzy variables as

Definition 2: A class of nuclear tracks with the index, i, in fuzzy domain is a set of one or more nuclear tracks formed by the collision of particles of type $p \in P$ *to the detector surface with the angles* $\bar{\theta} \in [\Theta_{\mathrm{i}}, \Theta_{\mathrm{i}} + \Delta\Theta]$ *and the incident energy of* $\overline{\mathrm{E}} \in [\mathrm{E_i}, \mathrm{E_i} + \Delta \mathrm{E}]$ *while a quasi-conical-shape cavity with an aperture of the major axis* $\overline{\mathrm{D}} \in [\mathrm{D_i}, \mathrm{D_i} + \Delta\mathrm{D}]$ *and minor axis* $\bar{\mathrm{d}} \in [\mathrm{d_i}, \mathrm{d_i} + \Delta\mathrm{d}]$ *is configured.*

Mathematically, a class can be formulated as:

$$\Gamma^{\mathrm{i}} = \left\{\psi_{1:\mathrm{N_i}}\left(\mathrm{p}: \bar{\theta}, \bar{E}, \bar{D}, \bar{d}\right) \middle| p \in P \wedge \bar{\theta} \in [\Theta_{\mathrm{i}}, \Theta_{\mathrm{i}} + \Delta\Theta] \wedge \overline{\mathrm{E}} \in [\mathrm{E_i}, \mathrm{E_i} + \Delta\mathrm{E}] \wedge \overline{\mathrm{D}} \in [\mathrm{D_i}, \mathrm{D_i} + \Delta\mathrm{D}] \wedge \bar{\mathrm{d}} \in [\mathrm{d_i}, \mathrm{d_i} + \Delta\mathrm{d}]\right\} \quad (2)$$

where $\mathrm{N_i}$ *denotes the number of tracks in i*th *class,* $\psi(:)$ *is a one-to-one function.*

Now, after the classes of nuclear tracks and non-tracks are defined and the borders of the classes are determined, the detected object *O* is invested to find its membership to any class. The object *O* defined in Eq. (1) can be represented as

$$O = \left(\mathrm{p_o}: \bar{\theta}_o, \bar{E}_o, \bar{D}_o, \bar{d}_o\right) \quad (3)$$

in which, the parameters are calculated from two sets of information:

$$\begin{cases} \{o_{ij}\}_{i=1:M\ \&\ j=1:N} \\ \{Knowledge\} \end{cases} \longrightarrow \left(\mathrm{p_o}: \bar{\theta}_o, \bar{E}_o, \bar{D}_o, \bar{d}_o\right) \quad (4)$$

That means physical parametric information of the object *O* are made “known” either via calculating them based on the object’s pixel arrays or the user’s knowledge. The particle’s type of interest and the energy range are commonly known by the user while the incidental physical parameters are often measured from the structure of the particle’s track.

Assumption 1:
Fuzzy variables $\{\bar{\theta}, \bar{E}, \bar{D}, \bar{d} \mid p\}$ *have Gaussian type fuzzy sets as*

$$V_{variable}^{i,j} = Exp\left(-\frac{\left(v_i - C_j^i\right)^2}{2{\delta_j^i}^2}\right) \quad (5)$$

Where $V \in \{\bar{\theta}, \bar{E}, \bar{D}, \bar{d}\}$, $V_{set}^{i,j}$ *corresponds to the j*th *fuzzy set of variable V in the i*th *class and* C_j^i *and* δ_j^i *are respectively mean and standard deviation of the Gaussian function corresponding to the variable* $V_{set}^{i,j}$. *Standard deviation* δ_j^i *is set as* $\delta_j^i \leq (\frac{1}{2\times\vartheta}) \times \Delta$ *which means for a distance* $\vartheta \times \delta_j^i$ *from the mean value* C_j^i, *the variable* $V_{set}^{i,j}$ *has a value of* $Exp(-\vartheta^2/2)$. *If* $\vartheta = 3$ *then* $V_{set}^{i,j} < 0.01$ *(on borders of the classes).*

The membership value of the object *O* to the ith class is computed as

$$\mu_{O\to\Gamma^{\mathrm{i}}} = \sum_j (\mathrm{p_o} == \mathrm{p}) \times V_{\bar{\theta}}^{i,j}(\bar{\theta}_o) \times V_{\bar{E}}^{i,j}(\bar{E}_o) \times V_{\bar{D}}^{i,j}(\bar{D}_o) \times V_{\bar{d}}^{i,j}(\bar{d}_o) \quad (6)$$

where $V_{variable}^{i,j}(var)$ is the value of Gaussian function for variable *var* according to Eq. (5) and

$$(\mathrm{p_o} == \mathrm{p}) = \begin{cases} 1 & \text{if true} \\ 0 & \text{if false} \end{cases} \quad (7)$$

The classes are defined according to the whole range of variables, resolution of the variations as requested and the possible separability of the variables in the measurement process. After the classes are bounded, a calibration process is required to map the variables to the measuring parameters. For instance, a mapping should be done from the spatial pixel-based distances in the nuclear track image to the metric scale. Another mapping should be performed from gray-scale differences between the central area and border of the track to the particle’s penetration into the bulk detector material and then the relation between the particle’s energy and penetration range is utilized to directly map the gray-scale difference to the particle’s energy.

Experiments:

In the experiments, the MLP with one hidden layer and $\mathrm{N_n}$ neurons in the hidden layer with hyperbolic tangent sigmoid transfer function is used for classification purpose and membership value calculation. The output neuron of the MLP network has the linear transfer function. Implementations were performed by MATLAB software installed on 2.2GHz CPU personal laptop.

Totally, 100 environmental Alpha track images captures from the surface of multiple sheets of CR-39 detector were used in our experiments. The images were initially analyzed by the method of Nejad et al. [8] and the ratio of non-track detected objects to the tracks was found in the range 12% to 48%.

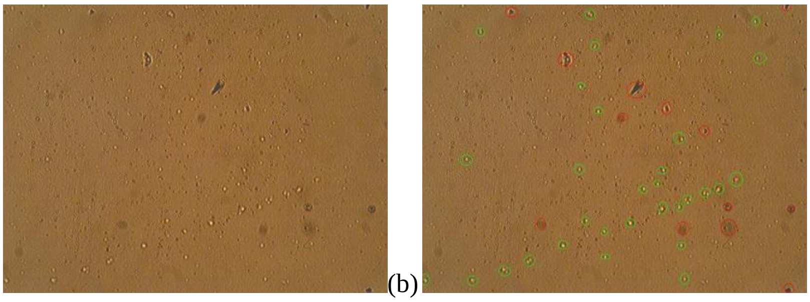
(a)  (b)

Fig. 1: (a) A nuclear track image, (b) detected tracks (green circles) and detected dents (red circles) by visually detection.

Table 1: Discriminating rate (Σ) of track and dent detection averaged over 100 nuclear track images.

				Fuzzy variables ($\vartheta = 3$)				
Feature(s)	Variables	Nn	Visual counting	Th=0.5	Th=0.6	Th=0.7	Th=0.8	Th=0.9
Geometric	D, d, Θ	5	30%±18%	$\bar{\Sigma}$=54%	$\bar{\Sigma}$=59%	$\bar{\Sigma}$=67%	$\bar{\Sigma}$=71%	$\bar{\Sigma}$=72%
Context	Θ, E	5	30%±18%	$\bar{\Sigma}$=47%	$\bar{\Sigma}$=51%	$\bar{\Sigma}$=64%	$\bar{\Sigma}$=69%	$\bar{\Sigma}$=69%
Geometric & Context	D, d, Θ, E	5	30%±18%	$\bar{\Sigma}$=62%	$\bar{\Sigma}$=65%	$\bar{\Sigma}$=73%	$\bar{\Sigma}$=82%	$\bar{\Sigma}$=83%
Geometric	D, d, Θ	10	30%±18%	$\bar{\Sigma}$=57%	$\bar{\Sigma}$=61%	$\bar{\Sigma}$=68%	$\bar{\Sigma}$=73%	$\bar{\Sigma}$=72%
Context	Θ, E	10	30%±18%	$\bar{\Sigma}$=48%	$\bar{\Sigma}$=52%	$\bar{\Sigma}$=66%	$\bar{\Sigma}$=70%	$\bar{\Sigma}$=69%
Geometric & Context	D, d, Θ, E	10	30%±18%	$\bar{\Sigma}$=63%	$\bar{\Sigma}$=66%	$\bar{\Sigma}$=74%	$\bar{\Sigma}$=83%	$\bar{\Sigma}$=83%
Geometric	D, d, Θ	15	30%±18%	$\bar{\Sigma}$=57%	$\bar{\Sigma}$=61%	$\bar{\Sigma}$=68%	$\bar{\Sigma}$=73%	$\bar{\Sigma}$=72%
Context	Θ, E	15	30%±18%	$\bar{\Sigma}$=48%	$\bar{\Sigma}$=52%	$\bar{\Sigma}$=66%	$\bar{\Sigma}$=70%	$\bar{\Sigma}$=69%
Geometric & Context	D, d, Θ, E	15	30%±18%	$\bar{\Sigma}$=63%	$\bar{\Sigma}$=66%	$\bar{\Sigma}$=74%	$\bar{\Sigma}$=83%	$\bar{\Sigma}$=83%

Track-dent discriminations were done visually by an expert user. Energy range, collision angle range, diameter range and the type of particle were categorized into at least two groups and no more that 5 groups. Parameters impacts, fuzziness effect and threshold value were analyzed in our implementations and the target was defined as the discriminating rate as

$$\Sigma = \frac{T_T + T_D}{T_O} \qquad (8)$$

In which Σ is the discriminating rate in percent, T_T, T_D and T_O are the numbers of true detected tracks, true detected dents and true detected objects, respectively.

According to the results given in Table 1, for the fuzziness level $\vartheta = 3$ (which was found optimum) and five threshold values Th={0.5,0.6,0.7,0.8,0.9}, three feature sets of Geometric based features, Context based features and the integration of all features (track physical parameters) were considered for three different N_n values. Parameter N_n indicates the complexity of the classifier used. Since no significant improvement was observed in the classification of the detected objects, it can be inferred that 5 neurons in the hidden layer is sufficient. It is apparent that for higher values of threshold (Th), the larger number of track assignments to the predefined classes is attained but it should be noted that only the true assignments are taken into account. Therefore, as the threshold value reaches about 0.8 the largest discriminating rate is obtained which is $\bar{\Sigma}$=83% (averaged over 100 images) using both Geometrical & Contextual features (all variables D, d, Θ, E).

Conclusion:

In this paper, an algorithmic and analytic method was presented to specify whether a detected object is a nuclear track of interest or not. A non-interested object may be a background dent or a track formed by a particle with a characteristic out of the desired range. For instance, it may be interested to discriminate between the tracks formed by the recoil reactions of a fast neutron and the fission fragments of 237Np where both reactions are applicable in the AEOI NeutrIran Albedo personnel neutron dosimeter [12]. Variables were transferred into fuzzy domain and consequently the classes were defined by fuzzy sets of Gaussian function shape. The membership value of the detected object to the predefined classes determined how much it may be a track with desired parameters. The experiments showed that the threshold value about 0.8 yields the best results and for higher threshold values, though the number of track assignments increases, no significant improvement is reachable.

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