Machine Learning Method Applied in Readout System of Superheated Droplet Detector

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***Abstract*—As one of most important applications in homeland security, radiation portal monitors (RPM) rely on ^{3}He neutron detector for revealing special nuclear materials (SNM). New neutron detection technology is required in RPMs because of the ^{3}He supply crisis. Superheated droplet detector (SDD) has potential to be an alternative neutron detection technology since it can be absolute insensitive to gamma rays. In this research, image analysis methods based on machine learning techniques were applied in the readout system of SDDs. Compared with generally used image analysis algorithms, these new machine learning methods showed a better performance in recognizing circular gas bubbles.**

I. Introduction

Radiation portal monitor (RPM) system is crucial for stopping illegal transportation of special nuclear materials (SNM) at international borders [1], [2]. Since the RPM system relies on neutron detection technologies (traditionally the ^{3}He detector) for revealing SNMs, ^{3}He supply crisis has triggered a lot of research on alternative neutron detection technologies [3].

Superheated droplet detectors (SDD) have the potential to be used in RPM systems since they have advantages of zero sensitivity to gamma-rays [4]. To be applied in RPM system, thermal neutron sensitivity of SDDs must be improved through doping boron or lithium into the detector [5]. Also, an accurate readout system for quantitatively measurement is required [6]. Research in this paper focus on the readout system of SDDs.

One simple and effective readout method of SDD is to set up a back-light illumination imaging system [7]. Through analysis images taken by such system, the bubble number can be accurately counted for quantitatively measurement of incident neutrons. Several imaging analysis methods have been developed for such image analysis purpose, but seldom one utilize machine learning techniques [8], [9], [10], [11]. Here in this paper, new machine learning methods were proposed and compared with other generally used algorithms.

II. Superheated Droplet Detectors

Superheated droplet detectors (SDDs) were made through uniformly dispersing superheated droplets into another insoluble liquid which is called host gel (as shown in Fig. 1) [12]. Each superheated droplet works as a tiny bubble chamber [13]. For an incident neutron, it first interacts inside the detector through scatter or capture reaction. The secondary charged particles produced in the interactions can deposit energy inside these tiny superheated droplets. If the deposited energy is high enough, the superheated droplet will vaporize into a visible gas bubble. The number of gas bubbles indicates neutron doses.

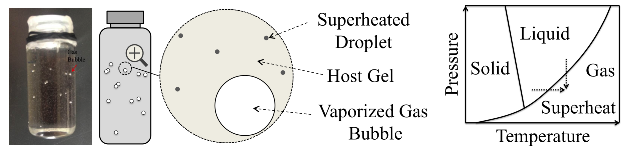


Fig. 1: Superheated droplet detector

III. Readout System

Since the number of gas bubbles inside the detector indicates number of incident neutrons, purpose of a readout system of SDDs is to accurately count the gas bubbles. The back-light illumination imaging system is used here as a readout system. As shown in Fig. 2, a detector is put between a camera and a LED light source for imaging. Images taken by the camera is transmitted to a computer and analyzed by different algorithms for bubble count.

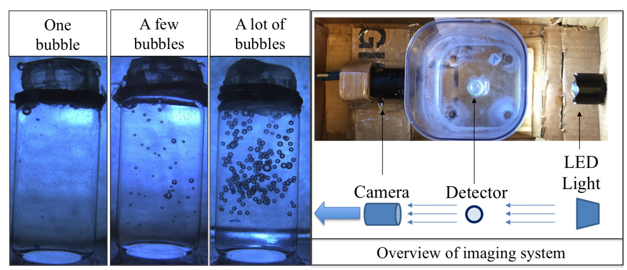


Fig. 2: Back-light illumination imaging system

IV. Image Analysis Method

As shown in Fig. 2, purpose of image analysis is to count the circular gas bubbles in the image. It is essentially a circular object recognition problem. Difficulty of accurate count is how to separate overlapped bubbles.

In this research, two generally used methods and two new machine learning methods are implemented and compared. [14].

A. Hough Transform

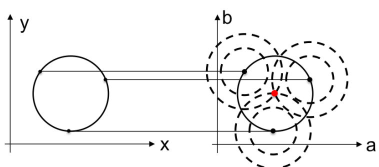
Hough transform is generally used for shape detection [15]. Circular or elliptical shape recognition can be done with this method. Algorithm based on Hough transform first convert image into binary data through edge detection. Then all positive pixels vote for possible circle parameters (center position and radius). With the vote result, algorithm output possible circles.

As shown in Fig. 3, a circle with radius R and center (a, b) can be described with the parametric equations

$$x = a + R\cos(\theta)$$

$$y = a + R\sin(\theta)$$

If an image contains many points, some of which fall on perimeters of circles, then the job of the search program is to find parameter triplets (a, b, R) to describe each circle. Denote (x, y) as geometric space and (a, b, R) as the parameter space, then each point in geometric space vote for all possible circles that contain the point (infinity number of circles) in parameter space. If there are several points falls on the same circle in geometric space, then there should be a local maxima of vote in parameter space that corresponding to the circle in geometric space. All the circles can be detected according to this vote procedure.



Each point in geometric space (left) generates vote for possible circle center and radius in parameter space (right). The point in parameter space with most vote is the center in geometric space.

Fig. 3: Hough transform

B. Curvature Analysis

Ref [8] reported a robust ellipse recognition method based on analysis of curvature information. This method uses perimeter information of an object. After edge detection, perimeters of segments are used for curvature calculation. Because the curvature usually changes rapidly in connection points of two overlapped ellipses, the algorithm try to detect the connection points through identify extreme of derivatives of curvature. The detected connection points will separate one perimeter into several perimeters. All these perimeters are then regrouped according to if they might belong to same ellipse. The final stage is ellipse fitting.

The algorithms of the curvature method can be described as following [9].

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Data: t_i, i = 1,...,N_s initial segments produced by the
contour segmentation

Result: SE = {s_i, i = 1,...,K} , where SE is the set of
      final K groups of segments.
        BUBBLE = {B_i, i = 1,...,N_b} , where BUBBLE is
      the set of detected N_b bubbles

Distance function d(si, sj) between two groups of
      segments s_i, s_j ∈ SE.

Parameter D: maximum distance between two groups of
      segments.

Algorithm:
1. Initialization: SE = {s_i, i = 1,...,N_s}.
2. Search for s_i, s_j which d(s_i, s_j) is minimized, i ≠ j.
3. if d(si, sj) < D then
      begin
         Delete s_i, s_j from SE.
         Add s_i ∪ s_j to SE.
         Skip to step 2.
      end.
   else end
4. BUBBLE = ∅
   Do ellipse fitting for s_i in SE = {si, i = 1,...,K}.
      if fitting result (ellipse b) satisfy criteria
        BUBBLE = BUBBLE ∪ b
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C. Support Vector Machine

In machine learning, support vector machines (SVM) are supervised learning models that can recognize pattern and classify data [16].

To use this method for bubble recognition, image is divided into 10 pixels $\times$ 10 pixels $\times$ 3 colors patches. For training data, each patches is labeled as positive (+1) or negative (-1). Positive means the corresponding image patch is part of a bubble and negative means opposite.

Assume each image patch is a vector $(\mathbf{x}_i)$ with 300 dimensions, SVM is solving the following problem

$$\underset{\mathbf{w},b,\xi_i}{\operatorname{argmin}} \frac{1}{2}\mathbf{w}\cdot\mathbf{w} + C\sum_{i=1}^{n}\xi_i$$

$$\text{subject to} \quad \xi_i \geq 0 \quad \text{and} \quad y_i(\mathbf{w}x_i + b) \geq (1 - \xi_i) \quad \forall i$$

where y_i is the label (+1 or -1) of the vector $(\mathbf{x}_i)$; $\mathbf{w}$ and ξ_i are parameters for classifying new image patches.

With SVM method, all the bubble region in the image will be labeled as positive. The number of small image patches can indicate number of gas bubbles.

D. Neutral Network

For training neutral network, image is also divided into small patches. Different from SVM method, each small image patch is labeled as probability of being part of the bubble image. With such probability labels, sum of probabilities of all patches would be a good estimation of number of gas bubbles.

The python neutral network package TensorFlow is used for programming.

V. Results Comparison

The bubble recognition result of hough transform is shown in Fig. 4. The method successfully detected bubbles in bright region but failed in the dark region. Reason is that the edge detection before doing hough transform works not good for dark region. The perimeters of bubbles in dark region is lost in the edge detection.

The curvature method works more robust than hough transform. As shown in Fig. 5, through calculation of derivatives of curvature, connection points of two bubbles can be successfully detected. Then with adaptive segmentation and edge detection method, curvature method achieved a very good result as shown in Fig. 6. Almost all the bubbles are successfully detected. There are still some false positives resulted from perimeters of non-bubble objects

The result in Fig. 7 shows that the SVM method works much better. This is because, instead of using only perimeter information, the SVM use information from every pixels for

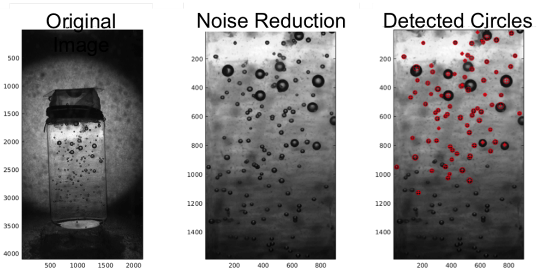

Fig. 4: Bubble recognition result of Hough transform

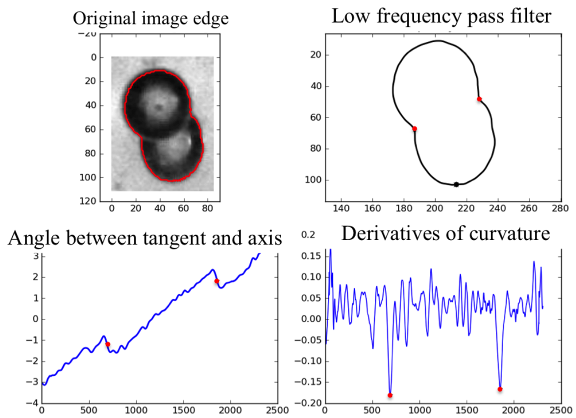

Fig. 5: Connection points detection with derivatives of curvature

bubble identification. The accuracy is expected to be better with more information.

The neutral network performs similar to SVM (as shown in Fig. 8) since it also use information from every pixels. One advantage of using neural network is that it could give more accurate counts of bubbles. The SVM method only labels each image patch as positive or negative. It will be not very accurate to estimate number of bubbles with number of positive patches. In contrary, neural network labels each image patch as probability of being a bubble. As a result, sum of probability of all image patches can estimate number of bubbles more accurately.

For accurate comparison of algorithm performance, algorithms are tested on 41 different cases. In all 41 cases, the detector has different number of gas bubbles. Also, three images was taken in each case. As a result, algorithms were performed on 123 images for evaluation. Fig. 9 shows the test result of algorithms. The Hough transform and curvature methods showed a decent linearity in bubble recognition. The curvature methods performs a little better since the edge detection in Hough transform is more sensitive to noises.

VI. Conclusion

Applying machine learning methods in the readout system of superheated droplet detector, the gas bubble count becomes more accurate. The reason is that generally used image analysis method only utilize the perimeter information. The

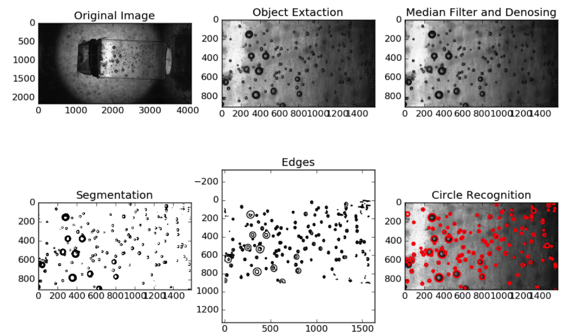

Fig. 6: Bubble recognition result of curvature analysis

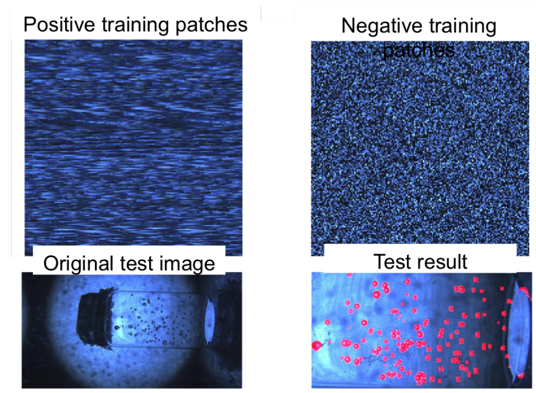

Fig. 7: Bubble recognition result of SVM method

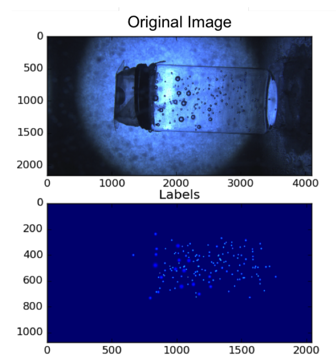

Fig. 8: Bubble recognition result of neural network method

machine learning method use information of every pixels for bubble recognition. Therefore, research in this paper improved performance of back-light illumination imaging system of superheated droplet detector. And this improvement is important for applying SDD in RPM system as an alternative neutron detection technology in further research.

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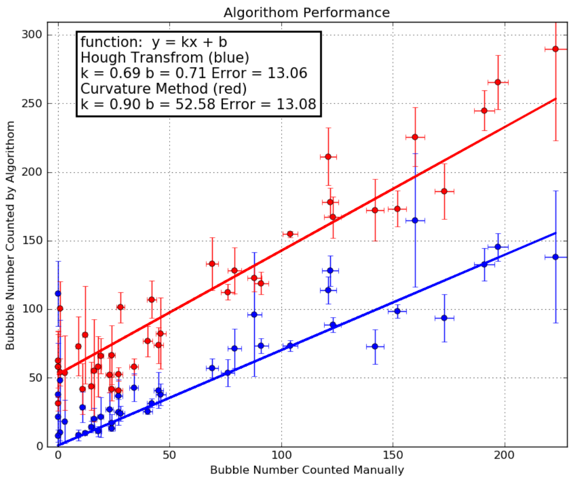

Fig. 9: Linearity comparison of Hough transform and curvature method

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