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Hybrid K -Means Clustering and Support Vector Machine Method for Via and Metal Line Detections in Delayered IC Images

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Abstract—This paper proposes a hybrid K -means clustering and support vector machine (HKCSVM) method to detect the positions of vias and metal lines from delayered IC images for subsequent netlist extraction. The main contributions of the proposed method include: 1) fully automated detection of via and metal line positions without any need of human interventions; and 2) novel hybrid methodology to embody K -means clustering and support vector machine for retrieving precise positions of vias and metal lines in contrast to the individual techniques which can only provide a region for the detected elements. From experiments on 50 SEM images of 1536×2048 pixels taken from fabricated IC chips (@TSMC 130nm CMOS process), our proposed HKCSVM method achieves an F-score of 99.82% for via detection, and mean intersection over union (IoU) of 94.44% and mean pixel accuracy of 95.83% for metal line detection, which are both superior to the reported approaches.

Index Terms— IC image analysis, via and metal line detections, K -means clustering, support vector machine, hybrid machine learning method.

I. INTRODUCTION

MANUFACTURED IC analysis plays an important role in intellectual property protection, counterfeits detection and hardware security assurance. In recent years, IC analysis has encountered more challenges due to the growing IC complexity. The analysis of a manufactured IC can be typically done in several different forms and one of them is circuit extraction. Conventional circuit extraction process requires several steps: package removal, delayering, imaging, annotation, schematic read-back and organization, and final analysis [1]. Current image annotation process requires an experienced engineer to locate all the circuit components and define the interconnections between different components, which is extremely time-consuming. Thus, many research works have been conducted to automate the labor-intensive

Fig. 1: Sample of a Scanning Electron Microscope (SEM) IC image taken at the metal layer of a delayed IC @130nm process

image annotation process.

Machine learning techniques have recently enjoyed great success in many fields [2], [3], [4], [5], [6] thanks to the availability of large amount of data and the accompanying computing power. Some of these techniques have also been applied in IC image analysis for automated circuit component annotation. In [7], Pearson correlation was adopted to compare the similarity between possible logic gate instances and a standard pattern. In [8], images taken from the backside of poorly resolved ICs were used for transistor detection through pattern matching. However, besides logic gates and transistors, metal layer interconnections are also essential for retrieving the netlist of a circuit design. To the best of the authors' knowledge, no previous work was reported on detecting the interconnections in IC metal layer fully automatically.

Fig. 1 shows a sample of the Scanning Electron Microscope (SEM) image taken at the metal layer of a delayed IC @130nm process. The grey areas are metal lines while the bright and circular-shaped objects are vias (i.e. circuit

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connection points to other layers). The previously reported methods for circuit component detection (for logic gates and transistors) only provide a coarse location for the circuit components of interest. However, to obtain the interconnections in metal layer, it is imperative to know the exact locations of metal lines and vias for which the reported methods were insufficient. These form the two main objectives of this paper: 1) to detect and locate the exact positions of vias, and 2) to detect and precisely segment the metal lines.

Popular machine learning approaches for object detection and segmentation, such as convolutional neural networks (CNN) [9] require large amount of computing power and labeled training data to learn a model from the scratch. This may not be permitted in IC image analysis when only a limited number of samples is available. If pretrained models are to be used for transfer learning [17], plentiful data collection and finetuning need to be performed for the model to accommodate various noises in our IC images. On the other hand, conventional image processing approaches such as circular Hough transform [10], thresholding [11] or clustering [12] have relatively low tolerance to changing image conditions and noises (see our comparison results in Section IV).

In this paper, instead, we leverage on two commonly used machine learning techniques: *K*-means clustering [12] and Support Vector Machine (SVM) [13] and propose a hybrid method termed HKCSVM to detect the exact positions of vias and metal lines. The proposed hybrid method requires much less labeled training data and computing power compared to the more complex CNN models, and is very robust at rejecting noises. With our proposed hybrid *K*-means clustering and support vector machine method, we achieve an F-score of 99.82% for via detection, and mean intersection over union (IoU) of 94.44% and mean pixel accuracy of 95.83% for metal line detection, which are both superior to the reported approaches.

The rest of the paper is organized as follows: Section II provides a brief background on the adopted *K*-means clustering and support vector machine methods. Section III presents our proposed HKCSVM method for via and metal line detections. Section IV presents the experiment results. Finally, conclusions are drawn in Section V.

II. BACKGROUND

A. *K*-Means Clustering

K-means clustering [12] groups all data samples into different clusters based on the similarity between each data sample and the cluster centers. Random samples are first chosen as the initial cluster centers. The remaining samples are then grouped into each cluster which they have most similarity with the cluster center. After grouping is done for every data sample, cluster centers will be updated to the average value of all the elements in that cluster. The grouping and center updating process are iterated until the cluster centers do not change. In our IC images, there are only 3 regions of interest, namely: via, metal line and background. The *K*-means clustering is able to segment the entire image into these 3 regions based on the

intensity similarity between different pixels. However, certain noises (such as chemical residuals and dusts) in the image may appear as bright pixels, which have high similarity to those of via pixels. On the other hand, the shadow areas near vias (caused by the SEM imaging process) are typically dark and are very similar to those of background pixels. Since the *K*-means clustering algorithm depends only on the distance metric where the clustering function is learnt in an unsupervised manner without considering the boundary between the categorical samples, its segmentation accuracy is likely to be degraded by such noises as well as shadow areas in the image.

B. Support Vector Machine (SVM)

SVM [13] maps each data sample into a feature space through a kernel function and the data samples are then separated into different classes in the feature space. The training objective of an SVM is to fit a hyperplane to separate samples into different classes with maximized margin. A soft margin SVM has a cost function as follows:

$$J = \frac{1}{n} \sum_{i=1}^n \max(0, 1 - y_i(\vec{w} \times \vec{x}_i - b)) + \lambda \|\vec{w}\|^2 \quad (1)$$

where J is the cost or error function for the SVM. n is the number of samples. $[\vec{x}_i, y_i]$ are the feature and label for a data sample respectively. b is a bias term and λ is known as the penalty parameter which controls a trade-off between the size of the margin and the penalty applied to samples lying in-between the margin.

The SVM is often trained and assessed utilizing the validation data before applying it to classify unseen data samples based on the distance between the new data sample and the class boundary in the feature space. In the case of our IC images, a trained SVM is tasked to classify a small image region into different classes, such as a via or a non-via. The SVM classification is robust at rejecting image noises. Particularly, it can distinguish between small image regions which contain both vias and dusts because it takes the image features (shape, edge, etc.) of the examined region into account. However, a region-based SVM classifier provides the same classification label to all pixels in the image region being examined. Such image region may contain pixels of other classes (e.g., a small region classified as containing a via by the SVM is likely to also contain pixels from the underlying metal line).

In view of the strengths and limitations of the *K*-means clustering and the SVM, in this paper, we propose a hybrid method to leverage on both techniques for a reliable and precise detection of vias and metal lines in the IC images.

III. PROPOSED HYBRID *K*-MEANS CLUSTERING AND SUPPORT VECTOR MACHINE METHOD

A. Overall System Design

Fig. 2 depicts the block diagram of our proposed hybrid *K*-means clustering and support vector machine (HKCSVM) method. The *K*-means clustering is employed to provide candidate regions for via and background based on the intensity similarities between individual pixels. Circularity filtering is

Fig. 2: Block diagram of proposed Hybrid *K*-means Clustering and SVM (HKCSVM) method for via and metal line detections in delayed IC images.

applied to candidate via regions, which removes non/less-circular regions. An SVM trained for via classification is then applied to the remaining candidate via regions to obtain the final via position. The background region is obtained through an intersection between the segmented regions from the *K*-means clustering and the detected regions by the cascaded SVM. The metal line position is indirectly obtained by subtracting the background region from the SEM image. We will now delineate each step of our proposed hybrid method in turn.

B. Region Segmentation by *K*-means Clustering

There are mainly 3 image regions of interest in the metal layer of delayed IC images, namely via, metal line and background regions, which have different gray levels (i.e., intensities). The *K*-means clustering is first applied to segment the entire image into these 3 regions based on the different gray level ranges. For large images (in our case, 1536×2048 pixels), to speed up the clustering process for fast convergence, we choose the initial cluster centers based on the histogram of the entire image, which depicts the gray level value distribution of all the pixels.

C. Via Detection

For via detection, a total of 1,000 labeled image samples, each with 30×30 pixels, are collected from the metal layer images to train a SVM classifier. Among these images, 500 are positive samples (vias) and 500 are negative samples (non-vias). The gray level values of the 900 pixels in each image sample are used as the raw features, which are standardized to zero mean with unit variance and fed into the classifier as input vectors. The training process is based on a 5-fold cross validation [14] and the tuning of the hyperparameters (for SVM with RBF kernel) is described below:

- Kernel size $\gamma = 2^i$ where i ranges from -15 to 3 with step size of 2;
- Penalty parameter $\lambda = 2^j$ where j ranges from -5 to 15 with step size of 2.

We use the sliding-window approach (window size = 30×30 pixels) for via detection. As shown in Fig. 2, the *K*-means clustering is firstly applied to segment candidate via regions. For each candidate via region, a circular Hough transform [10] is applied to evaluate its circularity. Candidate via regions with low possibility of being circular is removed. The trained SVM classifier for via classification is then applied to the remaining

candidate regions to obtain the final via positions. A bounding box is generated at each detected via region. The step size of the sliding window for both horizontal and vertical direction is set at 2 pixels to ensure a fine scanning resolution.

D. Metal Line Detection

Compared to the background region, i.e., the dark region in between the metal lines (see Fig. 1 earlier), the metal lines have more variations in terms of gray level values, shapes, sizes, and orientations. Thus, it is easier to detect background region, and regions complement to the background are identified as metal lines.

As the shortest distance between two metal lines in our SEM images is around 10 pixels, a 10×10 pixels' scanning window is used as the primary classifier for background region detection. However, a small window size is susceptible to noise. Noise in background region, such as small chemical residuals and dusts, may be misclassified as metal lines by the 10×10 pixels classifier.

To solve this misclassification problem, we propose a two-stage cascaded SVM approach to detect the background region. The entire detection process begins with a classifier with large scanning window size of 30×30 pixels. This classifier is relatively robust to noise and is aimed to detect large area of background regions. Then a classifier with 10×10 pixels' scanning window is applied to detect the background regions of small dimensions. The cascaded classification process is able to detect the background region more accurately and efficiently than each of the two classification stages. Both the SVM classifiers are trained in the same way as the training of via classifier. The detected background regions by the cascaded SVMs are then intersected with the segmented background regions from the *K*-means clustering to obtain the final background regions. With all the background regions obtained, the metal line region can then be obtained through subtracting the background region from the original image.

IV. EXPERIMENTAL RESULTS

A. Via Detection Results

As mentioned in Section III earlier, the SVM classifier for via detection are trained with 1,000 training samples based on 5-fold cross validation. The trained SVM classifier is applied to new IC images for via detection. Fig. 3 depicts the via detection process on a sample IC image using our proposed HKCSVM method. The *K*-means clustering first proposes candidate

Fig. 3: Via detection process for a sample IC image using our proposed HKCSVM method including: (a) the original IC image for via detection, (b) the segmented via region by K -means clustering, (c) the detected via region by SVM on remaining candidate via regions after circularity filtering, and (d) the final pixel-wise via positions in (c).

regions on via positions based on the intensity of via pixels (see Fig. 3(b)), this is followed by a circularity filtering to remove candidate regions which are not in circular shape. The SVM classifier is then applied to classify the remaining candidate regions (see Fig. 3(c)). For benchmarking, we also implemented the reported circular Hough transform method [10] (a popular image processing method for circular shape detection) for via detection. To improve the accuracy of circular Hough transform, we preprocess the IC images using K -means clustering so as to highlight the via regions for easier circle detection. For circular Hough transform, the sensitivity will greatly affect its accuracy. Higher sensitivity means more circles will be detected, yielding higher recall but lower precision. We use two sensitivity values, 0.935 and 0.94 (chosen by iterative experiments), to ensure best performance of the circular Hough transform for comparison. The experiment was performed on 50 IC images of dimension 1536×2048 pixels, which contain over 18,000 vias in total. Table I tabulates the via detection results using the circular Hough transform (with K -means clustering preprocessing) and our proposed HKCSVM method in terms of mean precision, mean recall, mean F-score and variation of F-scores among 50 images. Our proposed HKCSVM method achieves higher accuracy and lower F-score variation than the compared methods indicating its robustness across different testing images. Note that the accuracy of the circular Hough transform

TABLE I
VIA DETECTION RESULTS USING CIRCULAR HOUGH TRANSFORM (WITH K -MEANS CLUSTERING PREPROCESSING) AND OUR PROPOSED HKCSVM METHOD

	Circular Hough Transform [10]		Proposed HKCSVM
	Sensitivity = 0.935	Sensitivity = 0.94	
Mean Precision	98.12%	97.42%	100%
Mean Recall	98.50%	99.64%	99.65%
Mean F-score	98.30%	98.50%	99.82%
F-score Variation	0.00014	0.00023	0.000011

Fig. 4: Via detection results on other IC images by applying our proposed HKCSVM showing: (a) the original IC images, and (b) the detected via positions (in green color).

varies with different images since no optimal sensitivity exists for all images. Fig. 4 depicts via detection results on other IC images by applying our proposed HKCSVM method.

B. Metal Line Detection Results

For metal line detection, we compare the results of our proposed HKCSVM method with two popular reported methods, namely thresholding [11] and K -means clustering [12] for segmenting/detecting objects. The same post processing procedures in our proposed HKCSVM, including noise removal and morphological operations [15], are applied to the thresholding and K -means clustering as well to ensure a fair comparison. Two well-known metrics are used to evaluate the performance of metal line segmentation: mean IoU and mean pixel accuracy [16].

Table II tabulates the metal line detection results using the thresholding, the K -means clustering and our proposed HKCSVM method. Our proposed HKCSVM is able to achieve significantly higher accuracy on both mean IoU (94.44%) and

TABLE II
METAL LINE DETECTION RESULTS USING THRESHOLDING, K -MEANS CLUSTERING AND OUR PROPOSED HKCSVM METHOD

	Thresholding [11]	K -means Clustering [12]	Proposed HKCSVM
Mean IoU	80.42%	79.87%	94.44%
Mean Pixel Accuracy	82.25%	81.66%	95.83%

mean pixel accuracy (95.83%) than the compared methods. Fig. 5 depicts the metal line detection results for a sample image using the thresholding, the K -means clustering and our proposed HKCSVM method respectively.

From the metal line detection results of thresholding (see Fig. 5(b)) and K -means clustering (see Fig. 5(c)), we can see that there are undesirable open holes in the detected metal line regions, which may cause false open circuits problems. This error is due to the shadow areas near vias in the IC image as mentioned earlier in Section II. Thresholding and K -means clustering are not able to distinguish between these shadow areas from the background regions due to the high similarity between their pixel intensities. On the other hand, our proposed

Fig. 5: Metal line detection results on a sample IC image using thresholding, K -means clustering and our proposed HKCSVM method, including: (a) the original IC image for metal line detection, (b) the detected metal line regions using thresholding [11], (c) the detected metal line regions using K -means clustering [12], and (d) the detected metal line regions using our proposed HKCSVM.

Fig. 6: Metal detection results on other IC images by applying our proposed HKCSVM showing: (a) the original IC images, and (b) the detected metal line positions (in white color).

HKCSVM (see results in Fig. 5(d)) is able to overcome this issue thanks to its region-based classification method using SVM. Fig. 6 depicts metal line detection results on other IC images by applying our proposed HKCSVM method.

V. CONCLUSIONS

We propose a hybrid K -means clustering and support vector machine (HKCSVM) method in this paper to retrieve the interconnections (vias and metal lines) of ICs from their metal layer SEM images. The K -means clustering and the SVM are combined in a complementary way to locate vias and metal lines. By using our proposed method, we achieve an F-score of 99.82% for via detection. For metal line detection, we achieve a mean IoU and a mean pixel accuracy of 94.44% and 95.83% respectively. Our results on both via and metal line detections are superior to the two existing methods in the literature. We achieved full automation of via and metal line detections in delayed IC images by using the proposed hybrid method.

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