DICTIONARY BASED IMAGE ENHANCEMENT FOR INTEGRATED CIRCUIT IMAGING

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ABSTRACT

The rapid decrease in the dimensions of integrated circuits has necessitated corresponding higher-resolution methods for defect imaging. Current state of the art, defect imaging systems are reaching the limits of their resolution. In this work, we are proposing a new overcomplete dictionary based sparse signal imaging framework to improve the resolution and localization in confocal microscopy systems for backside optical integrated circuit defect imaging. The domain of integrated circuit imaging is particularly suitable for the application of overcomplete dictionaries in an image reconstruction framework because the images are highly structured, containing predictable building blocks derivable from the corresponding computer aided design layouts. This structure provides a strong and natural a-priori dictionary for scene reconstruction. This dictionary prior is coupled with a physically-based observation model to create enhanced scene reconstructions. The approach is described and results on simulated data are provided.

***Index Terms*—** backside integrated circuit imaging, sparse signal representation, overcomplete dictionary, image reconstruction, high numerical aperture microscopy

1. INTRODUCTION

Integrated Circuits (ICs) have undergone a continuous and ongoing reduction in size. This reduction in the dimensions of circuit features necessitates the use of higher and higher resolution defect detection and failure analysis techniques, such as Laser Voltage Imaging, Laser Voltage Probing. Optical techniques for defect detection are limited to backside methods because of opaque metal interconnect layers and flip-chip bonding. Backside optical imaging as a non-invasive technique is crucial for lateral registration of coupled failure analysis measurements to the circuit layout. The state of the art technique to achieving the highest resolution in backside IC optical imaging is to use an aplanatic Solid Immersion Lens (aSIL) [1], which increases the numerical aperture (NA) of the optical system and hence improves the resolution. In high NA optical systems, focused light near the dielectric interfaces has properties which cannot be explained by scalar optical theory requiring a full vectorial analysis of the fields [2, 3]. Spatial resolution improvement in selected directions has been shown through the use of linearly polarized light in SIL backside optical imaging systems [4, 5]. Unfortunately, even the resolution of aSIL imaging is being overcome by new, smaller IC manufacturing methods.

In our previous work [6], we proposed a novel image fusion framework that benefits from both polarization diversity of the high numerical aperture (NA) optical systems and prior knowledge about the structures in ICs. The reconstruction framework in [6] incorporated vectorial polarization effects in the system model and accomplished resolution improvement by fusing information from various polarizations and by using currently popular sparse reconstruction priors. While the use of such generic sparsifying priors produces an improvement over conventional methods, more improvement is needed.

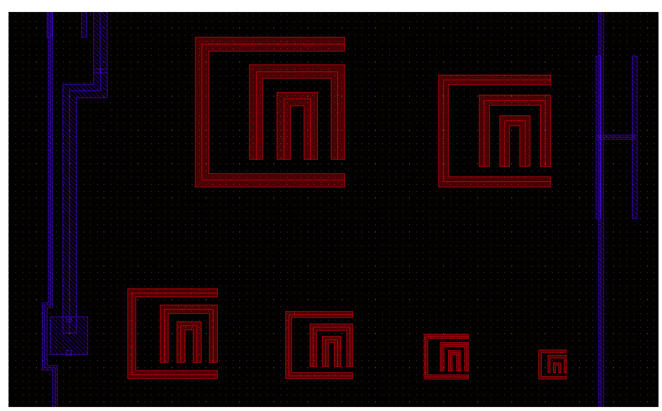


Fig. 1: CAD design example

In this work our goal is to exploit the highly structured nature of this problem and impose stronger structural priors through the use of predefined overcomplete dictionaries in the reconstruction framework. Such a framework is well matched to IC imaging since associated chip CAD layouts contain the information about the building blocks of the ICs. A CAD layout example is shown in Fig. 1. In particular, ICs are mostly composed of horizontal or vertical lines of varying, constrained and known widths and lengths. This suggests that regions we are imaging in ICs can be sparsely represented using a predetermined overcomplete dictionary composed of these building blocks. This sparse representation based on predetermined overcomplete dictionaries will provide increased robustness to model mismatches, noise and resolution limits since they pose strong priors for the structures in ICs. We couple this new IC imaging prior with our previous physics-based aSIL imaging model for enhanced image reconstruction.

Sparse signal representation through overcomlete dictionaries has been well studied in the image reconstruction literature. Dictionary based reconstruction methods differ in how they form the overcomplete dictionary. One set of techniques learns an overcomplete dictionary from a set of training images and then uses this learned dictionary in the image reconstruction by representing the underlying image as a sparse linear combination of the elements of the learned dictionary[7, 8, 9]. Another approach is to use a predetermined overcomplete dictionary to sparsely represent the scene being imaged, such as a wavelet based dictionary [10, 11], a point and region-based dictionary or a shape-based dictionary [12]. In this work, we adapt the shape and region based dictionary approach.

To best of our knowledge there is no prior work that incorporates sparse representations and dictionaries for resolution enhancement in IC imaging. This type of representation is especially useful for this application field because of the information coming from the CAD layouts, which contain all the underlying structures and building blocks in the IC. Unlike general dictionary-based problems, this constraint serves to effectively limit the corresponding problem size and allows the use of global rather than local, patch-based dictionaries.

Our paper is organized as follows. In Section 2, we provide details of the proposed framework. In Section 2.1 we develop the physics-based IC imaging observation model. The sparse representation framework is presented in Section 2.2 while the corresponding construction of the dictionaries is given in Section 2.3. We present experimental results on simulated data in Section 3. In Section 4, we provide summary and conclusions.

2. DICTIONARY-BASED IC IMAGING FRAMEWORK

2.1. Observation model

When linearly polarized light is used as the illuminating source in high NA optical systems, the point spread function (PSF) has an elliptical support resulting in better resolution in a certain direction. The PSF rotates when the polarization direction is changed. Multiple observations can be obtained by changing the polarization direction. Each of the observations provides more detail in the direction aligned with tighter support while under-resolving in other directions. We approximated the nonlinear optical system with a linearized convolutional forward model relating the intensity of the object to the collected image intensity through a PSF, ignoring the coherence and phase effects for now. Such a model can be expressed as follows:

$$g^j(x,y) = h^j(x,y) * f(x,y), \tag{1}$$

where $g^j(x,y)$ is the observed intensity under linearly polarized light corresponding to direction j, $f(x,y)$ is the intensity of the underlying object, $*$ denotes the convolution operation, and $h^j(x,y)$ is the PSF of the optical system having linear polarized light at direction j as input light source. In order to incorporate high NA and dielectric interface effects in our simulation of the theoretical PSF, we used the Angular Spectrum Representation (ASR) [2].

In practice, the data we collect is discretized in spatial coordinates on a uniformly spaced grid and Eq. 1 becomes:

$$\mathbf{g}^j = H^j \mathbf{f}, \tag{2}$$

where $\mathbf{g}^j$ is the vectorized discrete observation data, $\mathbf{f}$ is the discrete vectorized underlying object image, H^j is the Toeplitz matrix that implements convolution as a matrix operation.

2.2. Sparse Representation framework for resolution enhanced IC imaging

The goal of the proposed sparse representation framework is to benefit from underlying knowledge about the structures in ICs to produce a higher resolution image. We also combine the information coming from high-resolution orientation information in each observation by incorporating the multiple observations from Section 2.1 into the sparse representation framework.

If we assume that the unknown underlying scene $\mathbf{f}$ can be represented as:

$$\mathbf{f} = \Phi\alpha, \tag{3}$$

where Φ is the appropriate overcomplete dictionary composed of building blocks of the structures in the IC and α is the vector of representation coefficients. This dictionary allows us to sparsely represent the image of the unknown IC region we are imaging. The dictionary can be predetermined by using our prior knowledge about the structures in ICs under consideration – for example that the structures are lines of specified width and varying length. Combining this sparse representation with the observation model in Eq. 2, the overall model can be rewritten in the presence of noise $\mathbf{w}_j$ as:

$$\mathbf{g}^j = H^j \Phi\alpha + \mathbf{w}_j. \tag{4}$$

We now create an estimate of the underlying IC scene by posing this as a basis pursuit denoising problem [13]; that is, a sparse reconstruction problem with respect to the given circuit dictionary Φ. An equivalent, Lagrangian form of this optimization problem is given by:

$$\hat{\alpha} = \arg\min_{\alpha} J(\alpha) = \sum_{j=1}^{n} \| H^j \Phi\alpha - \mathbf{g}^j \|_2^2 + \lambda \| \alpha \|_1, \quad (5)$$

where n is the total number of observed images at various polarizations and λ is a regularization parameter that determines the overall level of problem sparsity.

The cost function in Eq. 5 is non-quadratic resulting in a challenging nonlinear minimization problem. There are a number of methods that have been developed for its solution in the literature from greedy methods, such as matching pursuit to linear programming methods. Here we adapt the quasi-Newton optimization method developed in [12]. This method solves a sequence of reweighted least squares problems in an iterative context. Each iteration results in a linear problem that is solved using matrix inversion. The outer iterations are terminated when $\|\hat{\alpha}^{(k+1)} - \hat{\alpha}^{(k)}\|_2^2 / \|\hat{\alpha}^{(k)}\|_2^2 < \delta$, where δ is a small positive constant.

2.3. Construction of Dictionaries

The structures in ICs consist of flat regions consisting of horizontal and vertical lines of constrained and varying width and length as can be seen in the CAD layout in Fig. 1. To construct our dictionary we divided the structures into rectangles and included all possible locations of different size rectangles into the dictionary. For example if we want to sparsely represent the design shown in Fig. 2, we would construct the dictionary consisting of the elements shown in Fig. 3. The columns of the dictionary Φ would consists of vectorized versions of all these images shown in Fig. 3, figure shows every third element of the dictionary.

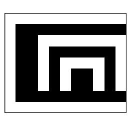


Fig. 2: Design example

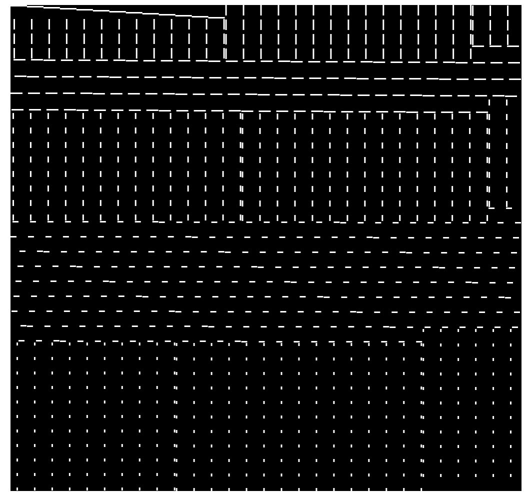


Fig. 3: Dictionary elements for design example

Ideally, we would specify the minimum and maximum width and length of the rectangles, since these are set by design rules of ICs and then we would include all rectangles within these limits to be in the dictionary.

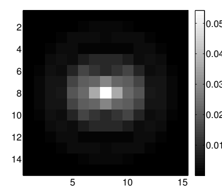


Fig. 4: Simulated theoretical PSF for linearly-polarized input light in x direction

3. EXPERIMENTAL RESULTS

The theoretical PSF of the aSIL optical system for a linearly polarized input light source with polarization in the x direction is shown in Fig. 4. We used ASR ([2]) to simulate this theoretical PSF. For light polarized in the y direction the PSF is the same but rotated by 90 degrees. Motivated by the CAD test example in Fig. 1, we first created the phantom shown in Fig. 5. Using the theoretical PSFs we obtained observation data at multiple polarizations. Then different levels of additive Gaussian noise was added. Noisy observations with 20 dB SNR are shown in Fig. 6. The reconstruction result of the proposed sparse representation framework using the observations shown in Fig. 6 as input, are shown in Fig. 7a. The iterations are terminated when δ, explained in Section 2.2 became smaller than 10^{-4}. The regularization parameters are chosen for best Mean Square Error (MSE) performance. We also performed Tikhonov reconstruction ([14]) using the same observations and the reconstruction is shown in Fig. 7b. The mean square errors obtained for reconstructions with different levels of noise are given in the plot in Fig. 8.

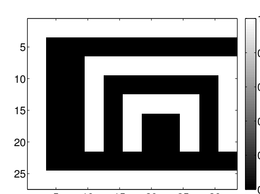
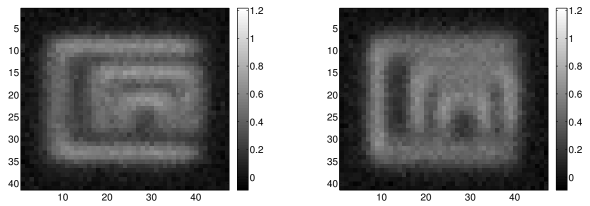
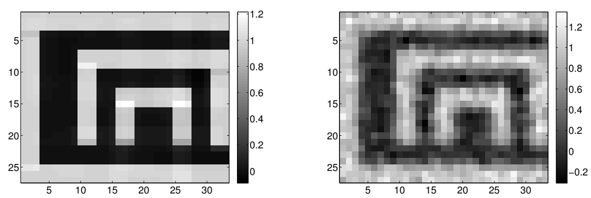


Fig. 5: Phantom



(a) (b)

Fig. 6: Observed images under polarization in (a) x direction and (b) y direction at 20 dB SNR.



(a) (b)

Fig. 7: Reconstructions from observations with 20 dB SNR (a) Sparse representation framework $\lambda = 0.325$, (b) Tikhonov reconstruction $\lambda = 0.01$.

4. CONCLUSIONS

In this work, we proposed a dictionary based reconstruction framework for improvement of backside aSIL imaging of integrated circuits. The predetermined overcomplete dictionary based sparse signal representation framework poses strong priors for underlying IC structures and provides improved resolution in image reconstruction for this problem. The framework incorporates polarization properties of high NA optical systems using vectorial optics for PSF modeling and enables fusion of multiple polarization observations to benefit from improved resolution in each set of observation data. IC imaging is particularly suitable for dictionary based image reconstruction methods. First of all, CAD layouts store the necessary information about the structures in the ICs that we are imaging and these layouts can be used to predetermine the dictionary. Also, the building blocks of structures in ICs come from a limited set, mostly line segments of varying width and length. Hence, these are strong priors for the structures in the underlying image.

5. ACKNOWLEDGEMENTS

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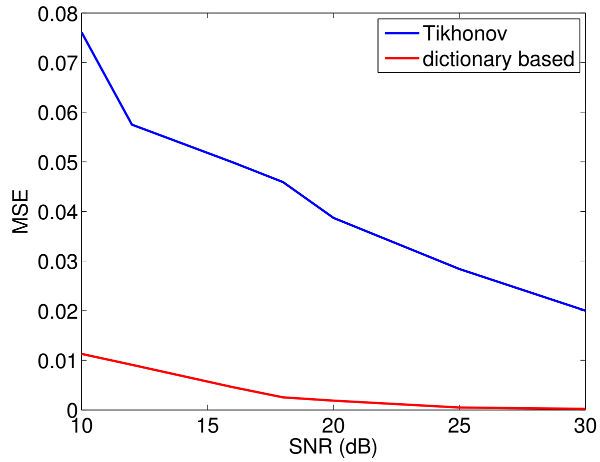

Fig. 8: MSE plot comparing the proposed method with Tikhonov reconstruction over different noise levels

6. REFERENCES

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