IC Microscopic Image Stitching Based on Improved Line Matching

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Abstract. Integrated Circuit (IC) microscopic image stitching is an important process in IC reverse engineering. However, IC is highly integrated and miniaturized, with many similar structures and dense distribution, and the overlapping region of some IC microimages may be the low-texture region. As a result, the traditional image stitching method is prone to mismatch, and the stitching effect is poor. This paper proposes an IC microscopic image stitching method based on improved line matching. The method first extract line segments from two IC microscopic images to be stitched by using Edline algorithm. Secondly, the intersection of line segments is generated by using the position relation of line segments in a certain strategy. Then, combined with the 2D capture method of the IC microscopic image, we limit the matching region. Finally, image registration is completed by combining points and lines, and a transformation matrix is obtained to stitch IC microimages. Experimental results demonstrate that the proposed method reduces the possibility of mismatching in the stitching process while using the stable line features and the position constraints between line segments in IC microscopic images. Moreover, the image stitching guided by line features can also achieve good stitching results in low-texture IC micrograph.

1. Introduction

IC design is the key to promoting IC industrial development. IC reverse is a tool to learn design skills, improve design experience, cooperate with and improve forward design. The pre-chip processing is the basic link of IC reverse, the chip image data that contains chip layout information is obtained by acquire chip images and do image processing. Due to the complexity, high integration and miniaturization of the chip, optical microscopes are required for image capture. However, due to the limitation of the field of view of the lens, to obtain a complete chip image, it is necessary to sequentially acquire different positions of the same chip, and then through image stitching to get the overall microscopic image of the chip. The quality of image stitching directly affects the subsequent related work, so image stitching is crucial step to IC reverse.

Image stitching is a technique for generating large-size panoramic images from multiple small-size images with overlapping areas. Image stitching has been widely used in many task in virtual reality, medical image analysis and remote sensing. Image registration is the first and most crucial step in image stitching. The methods of image registration can be classified into two categories: the region-based registration approach and the feature-based registration approach. Region-based registration is simple to implement and has high registration accuracy. However, it brings large computation costs, and the matching effect is not ideal, when the overlapped area is small. Moreover, it is strongly disturbed by light. The feature-based matching is fast and has good adaptability to translation, rotation, scale scaling, and uneven illumination. Different methods are suitable for different occasions.
Although various image registration methods have emerged, there is a major difficulty in the IC microscopic image registration process, there are many similar structures in the IC micrograph, and these similar structures are often densely distributed, which is easy to cause misalignment. Meanwhile, the overlapping area of some IC microscopic images may be a low-texture area, it is difficult to achieve good alignment of images due to insufficient and unreliable point correspondences.

In this paper, we propose an IC microscopic image stitching method based on improved line matching. There are rich line structures in IC microscopic images, line features have good robustness, and line features can be well used for geometric description and scene constraints. It can be used to accurately guide image registration. Meanwhile, we improve the line matching method based on the 2D capture method of the IC microscopic image.

The remainder of this paper is organized as follows. Section 2 gives a brief review of the related works. Section 3 describes the proposed method in detail. The experimental results and analyses are reported in Section 4. Finally, we draw the conclusion in the last section.

2. Related works
The traditional microscopic image stitching based on hardware, [1,2] realize automatic stitch of PCB images through sophisticated hardware facilities. This method has a fast stitching speed, but it has high requirements on hardware equipment, and difficult to guarantee the accuracy of stitched images. In recent years, image processing has been mainly used to achieve image stitching. The core of image stitching is image registration. Image registration is mainly divided into two categories: the region-based registration approach and the feature-based registration approach.

Most region-based image registration methods [3,4] use the gray information of the image to establish the similarity measure between the two images, then achieve the purpose of registering the image. In some scenes, region-based image registration has high accuracy. However, it also has limitations, such as poor anti-interference ability, high time complexity. Feature-based image registration uses only part of the image information, such as points and lines. The feature-based registration is strong in anti-interference, and has strong adaptability to gray-scale changes, deformation and occlusion. This makes feature-based image registration widely used in image registration, among which point feature matching is the most common. In the literatures [5,6,7,8] proposed different feature point extraction methods, which can extract stable point features for image registration. In most cases, microscopic image stitching based on feature point [9,10] have achieved good stitching effect. But there are many similar structures in the IC microscopic image, resulting in a small feature descriptor distance of the point features. The small difference between point features will result in a large number of mismatches.

As an important feature in images, image registration based on line features become the focus of scholars' research. The existing line matching methods can generally be classified into two categories: (1) construct descriptors for individual lines and match lines by computing the similarity of their descriptors and (2) utilize the geometric or topological relationship between lines and match groups of lines. Some methods matching line segments in individuals exploit the image information associated with line segments, such as gradient [11,12], and color [13] in the local regions around line segments. However, these methods will leads to the failure due to the overlapping area of the IC micrograph is small where corresponding line segments share insufficient corresponding parts. Matching line segments by utilizing the geometric or topological relationship between lines is more complex, but more constraints are available for disambigation. Most of these methods [14,15,16] to utilize the geometric or topological relationship between lines to intersect line segments to form junction points and then utilize features associated with the generated junction points for line segments matching. However, how to effectively form junction points and utilize them to assist line segments matching is still a problem. In [17], two types of line matching methods are combined. Adjacent line segments form connection points, and construct an LJI descriptor. Line segments are matched first in groups and then in individuals. LJI uses structure descriptors to match line segments and has achieved good matching results. However, this method has high complexity and low matching efficiency.
3. The proposed approach

3.1. Edlines line segment extraction

EDLines [18] is a fast, parameterless line segment detector, that produces robust and accurate results. EDLines is comprised of three steps: edge detection, line segment extraction, and line validation.

1. Edge detection. Given a grayscale image, use ED (Edge Drawing) algorithm for edge detection. Firstly, the image is first passed through a filter, e.g., Gauss, to suppress noise and smooth out the image. The next step is to compute the gradient magnitude and direction at each pixel of the smoothed image. Going over the gradient map and eliminating pixels with gradient values less than $\rho = 5.22$. In the third step, compute a set of pixels, called the anchors, which are pixels with a very high probability of being edge elements (edgels). The anchors correspond to pixels where the gradient operator produces maximal values, i.e., the peaks of the gradient map. Finally, connect the anchors computed in the third step by drawing edges between them.

2. Line segment extraction. Given an edge segment comprised of a contiguous chain of edge pixels, the goal of this step is to split this chain into one or more straight line segments. The basic idea is to walk over the pixels in sequence, and fit lines to the pixels using the Least Squares Line Fitting Method until the error exceeds a certain threshold. When the error exceeds this threshold, generate a new line segment. The algorithm then recursively processes the remaining pixels of the chain until all pixels are processed. There are two parameters associated with line fitting to a chain of pixels: (1) minimum line length and (2) maximum mean square line fit error. We refer to [18] for more details.

3. Line validation. Use Helmholtz's law to remove the wrong line segment from the extracted line segment.

3.2. Line description

Describe the characteristics of the line segments by the Line Band Descriptor (LBD) [11]. Given a line segment, the descriptor will be computed from the line support region (LSR) which is a local rectangular region centered at the line as shown in figure 1.

![Figure 1. Illustration of the band representation](image)

This support region is divided into a set of bands $\{B_1, B_2, \ldots, B_m\}$ where each band is a sub-region of the LSR and parallel with the line. The number of bands in the LSR is $m$, and the width of each band is $w$. Two directions which form a local 2D coordinate frame are introduced to distinguish parallel lines with opposite gradient directions. According to the line direction $d_L$, the orthogonal direction $d_\perp$ is defined as the clockwise orthogonal direction of $d_L$. The gradient of each pixel in the LSR is projected into this local frame $g' = (g^T \cdot d_\perp, g^T \cdot d_L)^T = (g'_d, g'_a)$, where $g$ and $g'$ are the pixel gradients in the image frame and the local frame respectively. A global weighting coefficient is assigned to give less emphasis to gradients that are far from the line mitigating the sensitivity to small changes in the position of the LSR along the direction $d_\perp$. And a local Gaussian window is assigned to reduce boundary effects. It avoids that the descriptor changes abruptly as pixels move from one band to the next.
For a band \( B_j \) in the LSR, the band descriptor \( BD_j \) is computed from rows of \( B_j \) and its nearest two neighbor bands \( B_{j-1}, B_{j+1} \). After computing \( \{BD_j\} \), the Line Band Descriptor LBD is simply generated by concatenating them, \( LBD = (BD_1^T, BD_2^T, \ldots, BD_n^T)^T \).

For the \( k \)th row in the band \( B_j \) or its neighbors, accumulate the gradients of pixels within this row as:

\[
\begin{align*}
 v1_j^k &= \lambda \sum_{d_i \leq 0} g'_d, \\
v2_j^k &= \lambda \sum_{d_i > 0} -g'_d, \\
v3_j^k &= \lambda \sum_{d_i \leq 0} g'_d, \\
v4_j^k &= \lambda \sum_{d_i < 0} -g'_d
\end{align*}
\]

where \( k \) is the \( k \)th row of \( B_j \), the Gaussian coefficient \( \lambda = f_j(k) f_j(k) \). Then each row of the band has a gradient in four directions. By stacking these four accumulated gradients of all rows associated with the band \( B_j \), the band description matrix \( (BDM_j) \) is constructed. Now \( BD_j \) is simply constructed using the mean vector \( M_j \) and the standard deviation vector \( S_j \) of the matrix \( BDM_j \), \( BD_j = (M_j^T, S_j^T)^T \). The mean part and the standard and deviation part of LBD are normalized separately. Finally, renormalize the restrained vector to get a unit LBD.

\[
LBD = (M_1^T, S_1^T, M_2^T, S_2^T, \ldots, M_m^T, S_m^T)^T
\]  

3.3 Line Matching

In the process of IC microscopic image collection, the IC is fixed on the worktable, and the translational movement of the platform produces the translational transformation of the image. Affected by the accuracy of the instrument itself and external factors, it will cause certain displacement errors, rotations and scale changes between the collected images and the preset images, but these errors are small. In this paper, we only consider the translational transformation of the image. For the translation transformation between the IC microscopic images, we propose an improved line segment matching method.

Given reference image \( I_r \) and query image \( I_q \). We first apply the EDLines algorithm to detect line segments in the reference and query images. Define \( L_r, L_q \) as the line segment set of images \( I_r \) and \( I_q \), respectively. Then use the positional relationship of the extracted line segments to generate line junction points. The formation of the line junction points as shown in figure 2(a). For the line segment \( l_i \) in the image, we extend it to determine its intersection with other line segments. The junction point of line segment \( l_i \) and other line segments is divided into two types. One is the direct intersection with other line segments, as shown in the figure 2, \( l_i \leftrightarrow l_j \). The second is to intersect with the extension lines of other line segments, as shown in the figure 2, \( l_i \leftrightarrow l_2 \) and \( l_i \leftrightarrow l_4 \). We keep the first kind of junction point, such as point \( p_2 \). For the second type of intersection, we only take the closest intersection with \( l_i \), which is point \( p_i \) in the figure. As shown in figure 2(b), line junction point is defined as \( p = (l_1, l_2, x, y) \), which \( l_1, l_2 \) are the line segments forming point \( p \), and \( x, y \) are the coordinates of point \( p \). Therefore, each line segment junction point contains the information of the line segment forming the point and the geometric position relationship between the line segments. Define \( P_r, P_q \) as the set of line junction point of images \( I_r \) and \( I_q \), respectively. Then we use the combination of points and lines to match the line segments.
Figure 2. Line segments intersecting with each other

Take the stitching of horizontal IC microscopic images as an example. Based on the fact that there is only a translation transformation between the two images to be stitched, for a line segment intersection point \( p_{qi} \in P_Q \) in \( I_Q \), when searching for the matching line segment intersection point \( p_{qi} \in P_R \) in \( I_R \), there is no need to traverse all intersection points. It only needs to search within a small narrow band. As shown in figure 3, \( p \) is a line intersection in \( I_Q \), and \( p' \) is the line intersection in \( I_R \) that match \( p \). When searching for \( p' \), it is only necessary to search within the rectangular area \( S \), which reduces both the matching time and the probability of mismatching.

Figure 3. Line segment intersection matching region

For any line intersection \( p_{qi} \) in \( I_Q \), the process of finding its matching point in \( I_R \) is as follows:

step 1: According to the point \( p_{qi} \) coordinates to determined the query area \( S \) in \( I_R \).

step 2: Compare the slopes of the line \( l_{q_1} \), \( l_{q_2} \) forming the point \( p_{qi} \) and the line \( l_{j_1} \), \( l_{j_2} \) at an intersection \( p_{j} \) in the area \( S \). If approximately satisfied \( l_{q_1} \parallel l_{j_1} \) and \( l_{q_2} \parallel l_{j_2} \) (or \( l_{q_1} \parallel l_{j_2}, l_{q_2} \parallel l_{j_1} \)), that the angle of the corresponding line segment is less than thresholds \( \theta \), go to the next step.

step 3: Take \( p_{qi} \) and \( p_{j} \) as the center, respectively, to generate patches, use SSIM (Structural Similarity) to compare the similarity of two patchs. If the similarity satisfies formula (3), enter the next step.

\[
E_{patch}(p_{qi}) = \frac{1 - SSIM(p_{qi})}{2} < \gamma \quad (3)
\]

step 4: According to the \( p_{qi} \) and \( p_{j} \) coordinates, to determine the overlapping area \( \Omega \) of \( I_Q, I_R \).

step 5: For the line segments that form point \( p_{qi} \) and point \( p_{j} \), intercept the part located in the overlapping region \( \Omega \), and the line feature descriptor is constructed using the LBD descriptor. Then calculate the line feature descriptor distance \( d \) and the proportion of inline points.

step 6: Repeat steps 2 to 5 to traverse other intersections in area \( S \). Suppose that in the region \( S \), the distance \( d \) between the line feature descriptors of points \( p_{r1} \) and \( p_{qi} \) is \( d < t_d \) and the proportion of inline points is the largest, then record \( p_{qi} \leftrightarrow p_{r1} \) as the candidate matching pair.

For the intersection of line segments in \( I_Q, I_R \), follow the above steps to establish a matching relationship. Finally, we use the RANSAC algorithm to eliminate mismatch points and calculate the transformation matrix.
In summary, our method is comprised of three steps: (1) Line segment extracted by EDLines. (2) Next, we match lines by using line junction points and LBD. (3) Finally, image stitching are performed by transformation matrix.

4. Experimental results and analysis
The platform used for the experiment in this paper is a Windows 10 PC with a CPU frequency of 2.3GHz. Visual Studio 2013 was used to complete the experiment. In the experimental part, we use the improved line segment matching method proposed in this paper and other image registration algorithms to stitch IC microscopic images, set the parameters \( t_\theta = 2^\circ, \gamma = 0.3, t_\rho = 0.3 \).

Figure 4(a) shows two IC micrographs to be stitched. In the overlapping area, there are many line segments with similar structures. Figure 4(b) illustrates the performance of LBD+S&G [11] for images registration and stitch, LBD+S&G has a wrong match. This is because there are many line segments in the overlapping region of the input image, but these line features are similar. And these two images have a feature, a complete line, partly in the overlapping area, partly in the non-overlapping area. So the line feature descriptor cannot accurately describe the line features of the overlapping area. The method in this paper uses point-line combination to first determine the overlap area by points matching. Then only construct line feature descriptors for the line segments located in the overlapping region, avoiding the construction of line feature descriptors in non-overlapping regions. Ours method makes full use of the constraints between line segments in the image, and constructs effective line segment descriptors correctly, reducing the possibility of mismatching.

Figure 4. Comparison with LBD+S&G. (a) Input images. (b) LBD+S&G matching and stitching results. (c) Our result

Figure 5(a) is the input images. There are many pads with similar structure in the overlapping area of the two IC microscopic images. Figure 5(b) show the result of using SURF [8] algorithm for image stitching, the threshold of Heiser matrix is set to 2000, and the threshold of nearest neighbor ratio for feature point matching is set to 0.6. There was a mismatch using the SURF algorithm. This is because the feature points, which extracted by the SURF algorithm, are concentrated around the pads that have similar structure. Although there are many feature points detected, due to the similar structure, the difference between the feature descriptors of each feature point is extremely small, resulting in a small number of matching points and mismatches. Figure 5(c) use the line matching method proposed in this paper, which has achieved satisfaction stitching result.

Figure 5(d) are two low-texture images. When the threshold of the Hessian matrix of the SURF algorithm is set to 2000, the feature points extracted from the two images are 1 and 13, respectively, and no matching pair can be obtained. Then, lower the threshold of the Heiser matrix to 1500. At this time, the number of obtained feature points is 5 and 20. Although the threshold is lowered, the number of obtained feature points is still small. The result of stitching using the SURF algorithm is shown in figure 5(e). In the low-texture area, it is difficult to obtain sufficient feature points, and the image registration performed by a small number of feature points results in poor stitching results. The image registration based on line features in this paper is still applicable in this low-texture area, and the image stitching are completed correctly.
5. Conclusion
IC microscopic images have the nature of dense local distribution and many similar structures, and the overlapping areas of some IC microscopic images are low texture areas. This makes the existing image stitching methods prone to mismatches, which can not accomplish the task of IC microscopic image stitching well. The IC microscopic images stitching method based on improved line matching proposed in this paper utilizes line features that are more stable than point features. Although IC microimages are densely packed with similar structures, line features are much better than point features. We improve line matching method in this article. Compared with other line segment matching methods, we combines the special acquisition method of IC microscopic images, limiting the matching area, reducing false matching and improve matching efficiency. At the same time, the method of combining points and lines is used to make full use of the geometric constraints between the line segments in the image, and the constructed line feature descriptors have higher credibility, reducing the possibility of mismatching. Moreover, the image stitching guided by line features can also achieve good stitching results in low-texture IC micrograph.

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