AUTO-ALIGNMENT INSIGHTS – PART 2: CASE STUDIES

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PART 2: CASE STUDIES

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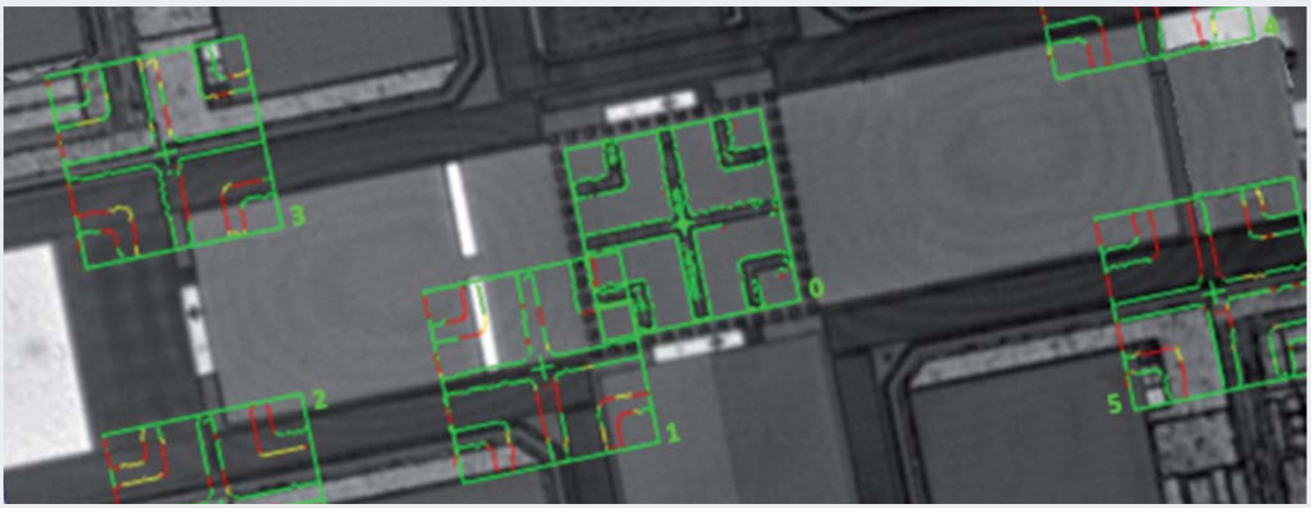

INTRODUCTION

This article is the second part of the short series of articles which started in issue 01/2013 of this magazine. The series focuses on pattern recognition and alignment in SUSS mask aligners. It is meant as a guideline especially for beginners in the field of pattern recognition, but even more experienced users might find one or the other aspect about pattern recognition which is new to him or her. This second part of the series highlights the most common alignment reliability issues using case studies. Based on the analysis of the cases promising measures to improve the alignment reliability in such cases are suggested.

As discussed in the first part of this alignment guide a proper definition of the illumination conditions is one of the most critical steps to achieve a reliable autoalignment. But even under perfect illumination conditions many scenes contain too little significant information or too much disturbing noise. In such cases a smart target design, a clever selection of fields of view and an adept creation of the model can make the difference for you between a stable alignment process and the need of frequent operator intervention.

To quantify the quality of the pattern training and to understand the root causes of alignment errorsit is important to understand the error type causing the alignment mistake.

Leaving unsuccessful alignment due to missing targets out of consideration the two typical statistical error types remain. Errors of type 1, so called false negatives, occur if a target which is present in the current scene is not recognized by the pattern recognition. Errors of type 2, also called false positives, occur if the system detects the trained pattern at positions in the scene where no real target is present. Many parameters of the pattern recognition influence both types of errors – unfortunately inversely. While changing one of these parameters may reduce the errors of type 1, in the same time it will increase the errors of type 2. Typical examples for such parameters are score threshold, contrast threshold, degrees of freedom, score using clutter, scaling and polarity restrictions. To achieve reliable target recognition, careful balancing of the two error types is needed and for an efficient improvement of the alignment stability, it is essential to understand which error type is dominant in the observed errors.

The following paragraphs will highlight typical challenges an engineer will need to confront while setting up alignment processes and will exemplarily sort them into the respective error types. From each case study universally valid recommendations for better alignment stability are derived.

CASE 1: REDUNDANT INFORMATION

The first case is a typical example for error type 2. Figure 1a presents a typical pattern as trained with the standard training method from a life scene and found in a respective life pattern. Almost any life scene contains both relevant and irrelevant pattern information. In Figure 1a additional shadows are visible besides the true target edges (the darker areas around the bright target). These shadows are recognized during pattern training as additional edge information and generate the outer yellow lines in the image. Only the innermost line represents the actual edge information of the real life target. This additional information heavily increases the risk to find the target at wrong positions, especially when further degrees of freedom need to be used, e.g. ignoring polarity. Figure 1b) shows an example of such a wrong detection. Polarity is ignored in this example. All green lines match edges in the life scene. Red lines are pattern features that are not matching to any structure in the life scene. The matching score for such a detection would still be > 0.5. Since the trained pattern contains information that is not part of the real structure on the substrate but is caused by shadow artifacts, matching scores

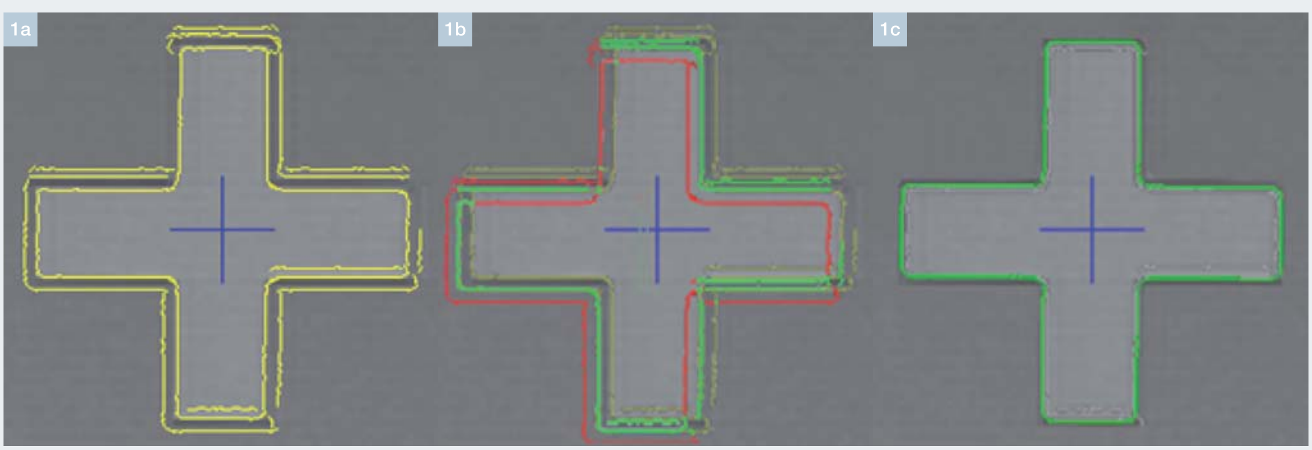

Figure 1 ***a)*** *alignment pattern as trained from a (less than perfect) real scene and* ***b)*** *respective matching information of an error analysis for the same scene. Matching score in b) still would be > 0.50 if polarity is ignored (green lines vs. red lines).* ***c)*** *shows how an improved target would look like: no redundant information is present in the target*

of 0.5 can also occur with perfect matches, if the shadow is not visible in some of the process targets. Therefore the risk of misalignment is significant and must be reduced by optimizing the trained pattern and the setting of recognition parameters.

Already taking the polarity into account would severely improve the situation on this example, but might not always be feasible due to polarity changes of the targets in general due to variations in preceding process steps.

A second, even more promising way to improve would be restriction of the trained pattern on real edges of the target. Figure 1c) shows the match of an accordingly altered pattern in the life scene. Even if polarity is ignored, an offset match of the *model* would result in very low matching scores.

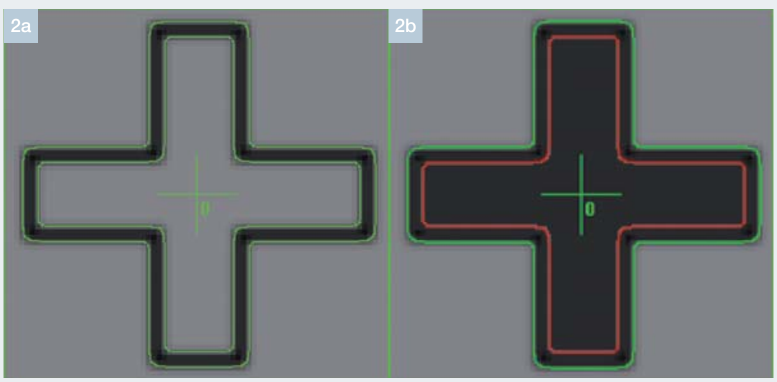

Figure 2 *Example of reduced matching scores due to changes of the target appearance from wafer to wafer. Both targets are real targets from the same production process.*
*While in **a)** the target shows a distinct double edge, which was also trained in the pattern,*
***b)** shows a target with overall darker appearance, that does contains a double edge.*
*Matching score on **b)** is as low as ~0.5*

CASE 2: CONFUSION

A second case of errors of type 2 is confusion of the real target with similar features in the field of view. An example of this can be seen in the title image. The image shows the result of a mistake test, i.e. a test in which the system present all recognized target positions to allow for a quick check about the uniqueness of the alignment feature inside of the field of view. As can be clearly understood of the image in the presented case several additional recognitions occur besides the true pattern recognition in the center of the image. Matching scores for the wrong positives were > 0.7 for some of the recognitions.

In such cases there are basically only two possibilities to improve the alignment.

First and most rigorous would be a redesign of the general layout of the field of view on substrate and mask. Of course, the most straight forward way would be to provide a clearfield around the alignment features which is free of any confusing structures. This would give safety to no longer getting wrong positives. Where this is not possible due to process (or business) restrictions, a redesign of the alignment targets itself is advised. As a general rule targets should always be defined with a geometry that has no resemblance with structures present in the field of view. The predominant structure orientation in the title picture is orthogonal, placed in the image under an angle of about 11 deg. The main features of the alignment pattern are oriented parallel to these predominant structures. Although the human eye does not recognize an obvious similarity, the depicted false positive recognitions prove the high level of confusion risk in this scene. Since the pattern recognition system gives the user full flexibility of the pattern definition, using mainly edges diagonal to the predominant structures or using circular pattern would clearly reduce the risk of confusion.

However, since the scene shown in the title image includes some diagonal structures and even circular noise pattern, such a redesign would most likely not reach the same level of reliability as the design of a clearfield as suggested before.

Where even a redesign of the alignment targets is impossible, e.g. due to customer specifica-

tions, a combination of changed model design and improved parameter setting can still be helpful. However, such approach typically cannot provide the same level of reliability as the strategies described before.
A more thorough analysis of the title image reveals that the adjustment of several parameters could be improved in order to reduce the amount of false positives.

- **Polarity:** when defining the alignment recipe, polarity was switched to "ignore", as can be understood e.g. from match 4, where an edge is recognized along a polarity change. With regarded polarity several of the false positives would drop underneath the defined threshold and not being recognized anymore.
- **Score using clutter:** Also score using clutter was switched to off. This parameter controls, whether information which are additionally contained in the life scene, but not in the trained model are recognized as feature edges. This parameter can be a mighty tool to reduce errors of type 2. All additional matches in the title image present a significant level of additional information, which would reduce their matching score and can push it underneath the threshold. However, this parameter has to be used careful and its influence on the recognition process must be kept in mind when preceding processes introduce a relevant level of noise into the life scenes. When scoring with clutter regarded, this noise can also reduce the matching score of the true target considerably. If noise is present, it should therefore be carefully checked, whether using clutter compels a lower scoring threshold and hence counters the benefit in the exclusion of false positives.

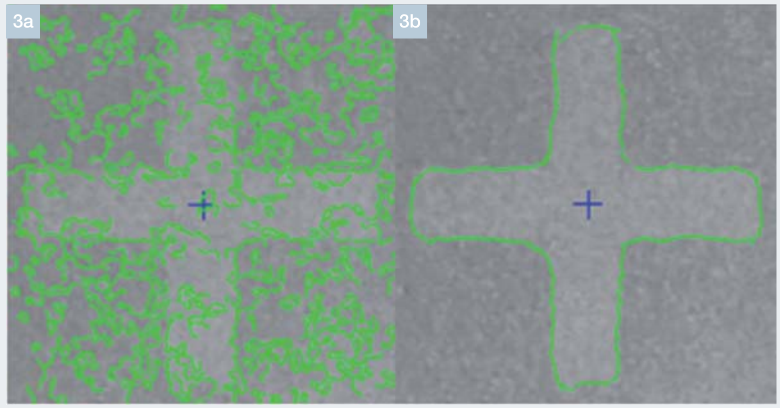

Figure 3 *Alignment models as used in the alignment of wafers with unpolished surfaces.*
a) *shows the original model as created by the customer based on edge recognition from a life target* ***b)*** *an optimized model cleaned off the noise*

CASE 3: NOISY MODEL

Also caused by noise, but causing errors of type 1 instead of type 2 is the case presented in figure 3. Due to the high level of noise in the original model, which the customer created from a life scene, obviously no reliable pattern recognition was possible.
Several methods can be used to improve the model. Using a synthetic target, created from life images in an image editor program or by importing CAD data is the most rigorous and successful approach for images with similar noise level. However, also adjustments of the edge threshold, image processing like contrast and brightness adjustments as well as masking irrelevant structures in the image can be helpful and can be accessed from the advanced alignment editor at the machine. Figure 3b) presents the result of the model training after several of these optimizations were applied to the training image. Using this target model a stable and reliable alignment was possible.

GENERAL RULES

From the presented cases a couple of general rules can be given to support the setup of reliable alignment models and recipes and to speed up the optimization process of the recipes.

As a starting point, the target and its model

- Should be located in a reasonable clearfield
- Should have a different predominant structure orientation than the neighborhood
- Should contain all relevant feature edges of the target
- Should not contain any irrelevant edges of noise or other structures
- Should not contain edges that are in close neighborhood to each other (redundancy)
- Should take the polarity into account
- Should use clutter information for scoring

Since in general errors of type 1 have a smaller impact on the customers product (a pure error type 1 would stop the machine, but would not damage customer material), it is sensible to start the alignment recipe optimization with the strictest parameter set possible, i.e. besides the parameters mentioned in the list above also high matching score thresholds and deactivated degrees of freedom.

If this recipe is producing errors of type 1 too frequently an error analysis similar to the presented case studies will guide the user which parameters have to be relaxed to allow for a stable and reliable pattern recognition.

At this point we would like to remind the reader of the extensive trainings that are offered by the SUSS training department covering this subject. For information on trainings please be referred to the respective SUSS webpage: http://www.suss.com/en/customer-service/training.html and the contact information therein.

Dr. Marc Hennemeyer is Product Manager at SUSS MicroTec Lithography. He is responsible for the automatic mask aligner product group. After his graduation in Physics at University of Munich where he also received his PhD working on micro fluidic systems for biological applications he joined SUSS MicroTec in the Application Department before he proceeded to his current job.

He authored and coauthored several papers on various topics, including micro imprinting and lithography.