Computer-Vision Algorithm for Advanced Feature Extraction from Images of EUV Lithography System Tin Targets

2021-2022 UCSB Senior Year Capstone Project with ASML

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Background: ASML, a multinational company with over 28,000 employees in 16 countries, produces the Extreme Ultraviolet (EUV) lithography systems that all of the world's major chipmakers (Intel, TSMC, Apple, Samsung, etc) use to fabricate their state-of-the-art silicon IC's (see FIG. 1). Lithography systems work by projecting light through a mask onto a photoresist (PR) layer on a semiconductor wafer to define a pattern in the PR, which is then used to form features of the IC (see FIG. 2). The minimum size of the features (current state-of-the-art IC's use ~5 nm technology) is largely determined by the wavelength of the light, and also how well parameters of the light (e.g., the dose) and overall system efficiency can be controlled.

FIG. 1: ASML EUV Source

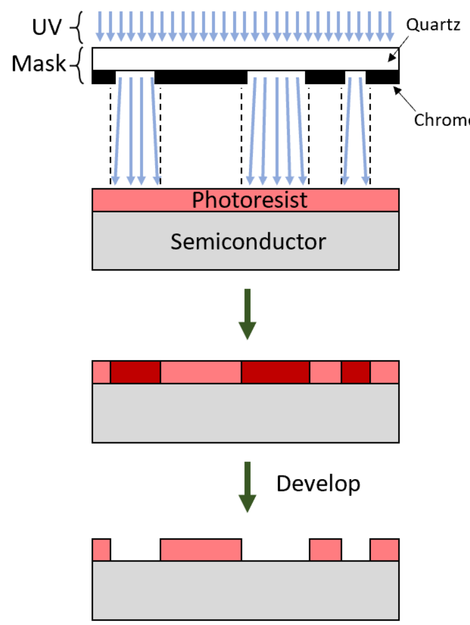

FIG. 2: Optical Lithography

ASML San Diego, CA, develops the EUV light sources (13.6 nm radiation) for these systems. EUV production takes place inside a large vacuum chamber as follows. As seen in FIG. 3, a ~30 micron diameter tin (Sn) droplet (referred to as a target) is produced and directed into the chamber. The droplet is first hit by a laser pre-pulse, which causes its shape to become more elongated (resulting shape is termed a "pancake"), and the pancake target is then vaporized by a second, more powerful (tens of kW) pulse from a CO_2 laser. The plasma that results from vaporizing the tin pancake target produces the 13.6 nm EUV light, which is then directed by a set of reflective surfaces to the mask. This operation occurs at a rate of 50 kHz (i.e., 50k droplets are generated/vaporized every second).

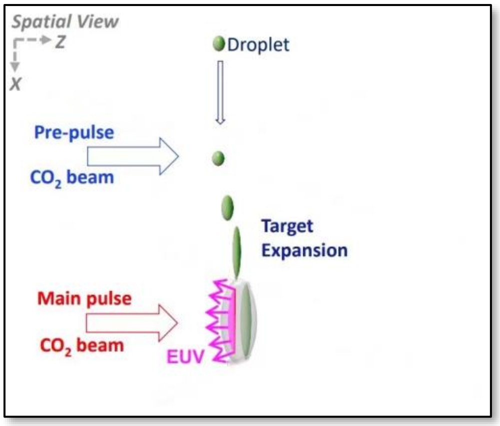

FIG. 3: EUV light generation

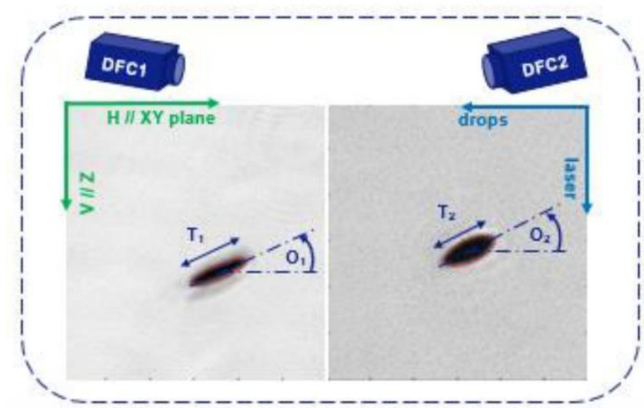

FIG. 4: Stereoscopic shadowgraph of a Sn pancake

The EUV source uses conditions for droplet generation and for the pre-pulse and main pulse that ensure consistently high conversion efficiency (i.e., that maximizes the amount of EUV light produced per droplet) to maintain EUV power output. Some of the parameters having the largest effect on the conversion efficiency are the tin pancake metrics (length T and angle O, shown in FIG. 4), which are determined by the droplet generation and laser pulse conditions. These metrics are derived/measured from shadowgraph measurements of the tin targets with two droplet formation cameras (DFCs, see FIG. 5). In the EUV source vessel the cameras are located at 90 degrees with respect to each other and 90 degrees to the CO_2 laser beam. DFCs are back-illuminated by the near infrared (NIR) back-light modules (BLM). Achieving the tin target metrics necessary for optimal conversion efficiency with required accuracy is challenging in practice due to limitations of detection optics and assumptions of ASML's existing computer vision (CV) algorithms.

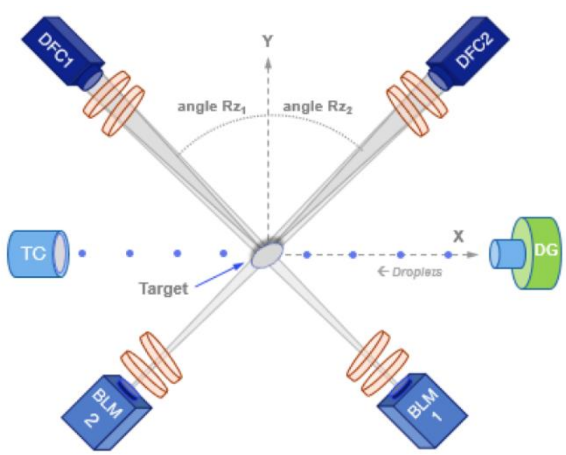

FIG. 5: Layout of shadowgraph metrology

Problem Statement / Project Description: ASML's current CV algorithm for characterizing the metrics of the tin pancake targets (target size and orientation) rely on a priori assumption of an ellipsoid object. Inspection of the raw images of the targets (FIGS. 5-6) suggest that a spheroid model is more descriptive of the pancake; however, the computation of the parametrization for a spheroid from its projected images is not straightforward. The problems are, thus, to develop methods for computing the parameters, and additionally, to develop a testing methodology by which different methods, as well as different tin object models, may be assessed.

The goals of this project are as follows:

- Design, implement, and test robust computer vision (CV) algorithms for estimating the parameters of the tin targets based on images of the projections onto the two DFCs assuming a spheroid object. The algorithms should be sufficiently fast that they could be substituted for ASML's existing algorithm (~100ms or less per pair of images). If possible, multiple methods should be explored. Different approaches may include, but are not limited to:
    - Posing the parametrization as an optimization problem which minimizes the mismatch between predicted and actual images;
    - Developing and extracting image features which allow the direct calculation of the spheroid parameters;
    - Machine learning methods.
- Develop a test suite with which the error between the images predicted by a model and the actual images can be computed, thereby providing a methodology to compare performance of different models. This entails projection of the modeled object onto the image planes of the two cameras, and then translating each projection to overlap the tin objects on the original images.[1]
- Compare the performance of the spheroid estimation algorithms with ASML's existing ellipsoid estimation algorithm as well as with the optimal spheroid estimate obtained from the full-dimensional parameter search currently used.
- Survey the literature and explore extensions of the models, e.g. new image features which improve the estimation of the spheroid model parametrization or models which describe dispersed Sn particles (micro-droplets).

[1] The error calculation should use the pixel intensity of the grayscale image, as opposed to binarizing the original image first. Some thought should be given to how such an error is calculated given that the modeled projections typically have binary pixel values.