# Design of two-dimensional zero reference codes with a genetic algorithm

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In mask-alignment systems a reference signal is needed to align the mask with the silicon wafers. The optical reference signal is the autocorrelation of two two-dimensional (2D) codes with binary transmittance. For a long time, one-dimensional codes have been used in grating-measurement systems to obtain a reference signal. The design of this type of code has needed a great computational effort, which limits the size of the code to about 100 elements. Recently, we have applied genetic algorithms to design codes with arbitrary length. We propose the application of these algorithms to design 2D codes to generate 2D optical signals used in mask-alignment systems. © 2006 Optical Society of America

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The absolute measurement of the position in grating-measurement systems and the detection of a reference position in mask-alignment systems are very similar problems. Both systems need a reference signal to detect a predefined position. They are especially important in precision engineering, nanoscience, and nanotechnology. In 1972 King and Berry[1] were the first to use the moiré technique for mask alignment in optical lithography. The system consisted of a collimated laser beam passing through a pair of gratings. At some positions from the second grating, a pattern of fringes is generated (moiré phenomena). When a lateral displacement between gratings takes place, a variation of light intensity (moiré signal) is registered in a photodiode. The modulation of moiré signals strongly depends on the gap between the gratings. Several authors have used this technique in different configurations.

On the other hand, in grating-measurement systems a zero reference signal is necessary to obtain an absolute measurement. Traditionally, zero reference signals are generated by means of optical correlation of two binary transmittances, named zero reference codes (ZRCs). The ZRC consists of a group of specially coded transparent and opaque slits. A collimated beam propagates through both codes, and the total amount of transmitted light is registered by means of a photodiode. The transmitted light depends on the relative displacement between the ZRCs, and the signal registered in the photodiode is the autocorrelation of the ZRC. The characterization and design of optimum codes to obtain suitable reference signals was addressed by Yang and Yin[2] and Li.[3] They established methods to semiautomatically generate limited-length codes (up to 10–12 elements) but are still lacking a systematic computing method from which arbitrary-length ZRCs could be obtained. In Ref. 4 we have presented a systematic method for the design of ZRCs, which generates optimum reference signals for codes up to 100 elements by means of a direct search algorithm.

Chen *et al.*[5] proposed a two-dimensional (2D) version of the ZRCs for precise mask alignment. The system operation is similar to one used to generate the zero reference signal in grating-measurement systems. The 2D ZRCs are made up of unevenly located, opaque, and transparent pixels. When the movement takes place on the *xy* plane, the signal is obtained as the 2D correlation of the ZRCs. Therefore two-axis alignment can be detected with a simple system. Despite the simplicity of the optical-alignment system, 2D ZRCs are considerably harder to design than the 1D version, as the number of elements in the code (which determines the complexity of the design) squares with the size of the code in 2D ZRCs. In Ref. 6 we presented a systematic method of design for a 2D ZRC based on the DIRECT search algorithm. The algorithm obtains the optimal solutions for codes up to $10\times10$ elements. The design of larger ZRCs shoots up the computer memory requirements and makes the problem unapproachable. Memory requirements can be kept under control by limiting the number of objective function evaluations, but this limitation leads to suboptimal solutions. A complete description of DIRECT can be seen in Ref. 7. In this Letter we show a genetic algorithm (GA) with a restricted search operator, which allows the generation of optimal solutions for larger 2D ZRCs. The parallel processing of binary variables makes of them a powerful tool for handling problems with a great number of variables.

The studied alignment system is shown in Fig. 1. The 2D ZRCs are parallel to each other, and one of them is set in an *xy* mobile stage. A collimated beam passes through them in the perpendicular direction, and the total transmitted flux is registered in a photodiode. The output signal is the 2D autocorrelation of the ZRC, and it is a function of the relative dis-

 

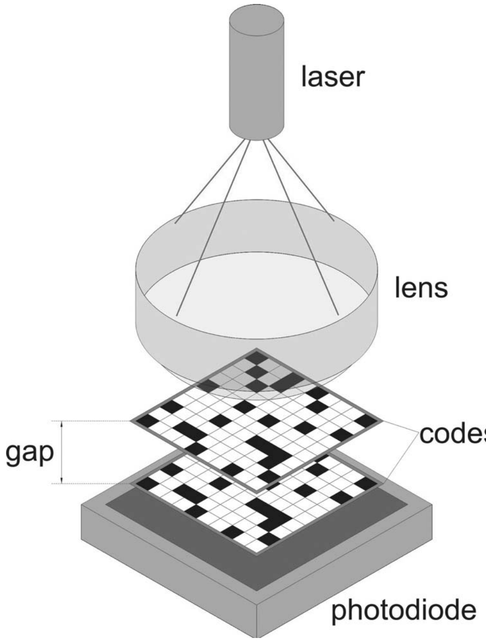


Fig. 1. 2D alignment system based on 2D ZRCs.

placements along the $x$ and $y$ directions of the ZRC.

Mathematically, the structure of the 2D ZRC is represented by the following matrix of binary data:

$$\mathbf{c} = [c_{ij}] = \begin{bmatrix} c_{11} & \cdots & c_{1n} \\ \vdots & \ddots & \vdots \\ c_{n1} & \cdots & c_{nn} \end{bmatrix}, \quad c_{ij} \in \{0,1\}, \tag{1}$$

where $n^2$ is the total number of elements of the ZRC, $c_{ij}=1$ if a transparent pixel is located at the $ij$ position, and $c_{ij}=0$ elsewhere. The number of transparent pixels is $n_1$. The sizes of the transparent and opaque regions in the ZRC are integer multiples of the width of a single pixel.

We will assume that the illuminating light is a parallel ray beam and that diffraction effects are negligible. This approach is valid when the gap between ZRCs is small with regard to the size of the pixels in the code, and this size is greater than the wavelength of the illuminating light.

When the two ZRCs have relative displacements of $k$ and $l$ units in the $x$ and $y$ directions, respectively, the signal registered in the photodiode is proportional to

$$S_{kl} = \sum_{i=1}^{n-k} \sum_{j=1}^{n-l} c_{ij} c_{i+k,j+l}, \tag{2}$$

where $k,l=-n+1,\ldots,n-1$, and the signal $S_{kl}$ is the autocorrelation matrix of the ZRC matrix defined in Eq. (1).

The units of the autocorrelation signal are the number of transparent pixels that coincide in a relative position of the codes. $S_{00}$ is the signal obtained when the relative displacement between ZRCs is zero, and it is equal to the number of transparent pixels, $n_1$

$$S_{00} = \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij}^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} = n_1. \tag{3}$$

The secondary maximum of the signal is $\sigma = \max_{k^2+l^2\neq 0} [S_{kl}]$, where $k^2+l^2\neq 0$ means that $k\neq 0$ and $l \neq 0$ at the same time. A good zero reference signal must be a single and well-distinct peak, and the sensitivity and robustness of the system depend on the difference between the first and the second maximum. In the absence of diffraction the size of the pixels of the ZRC defines the width of the central peak of the reference signal, and this width is the resolution of the alignment system. The diameter of the light beam limits the number of pixels in the ZRC and, in turn, the sensitivity of the photodetection optoelectronics determines the minimum value for the central maximum of the signal, that is, the number of transparent pixels of the ZRC. In accord with these working requirements, we have $n$ and $n_1$ predetermined, and we have to minimize the second maximum of the signal, $\sigma$. In Ref. 6 we presented a study of the properties of the autocorrelation signal, and we have calculated a theoretical lower bound for the second maximum of the signal. The bound is

$$\sigma \geqslant \sigma_1 = \frac{-(2n^2+n-1) - \sqrt{(2n^2+n-1)^2 + 4\left(1+\frac{1}{n}\right) n_1(n_1-1)}}{-2\left(1+\frac{1}{n}\right)}. \tag{4}$$

This bound is conservative, although there are some simple cases in which this bound is reached. GAs are population-based algorithms[8] in which a set of potential solutions to the problem are evolved. The GA we implement starts with a randomly generated initial population of binary strings (individuals) of length $n$. Each individual represents a possible solution to the problem, which must be evaluated in order to obtain an objective function value associated with it. The population is evolved through the successive application of the genetic operators, basically selection, crossover, and mutation. Selection is the process by which individuals are randomly sampled with probabilities proportional to their fitness values. The selected set is subjected to the crossover operation, which consists of first, the binary strings that are coupled at random. Second, for each pair of strings, an integer position along the string is uniformly selected at random. Two new strings are then composed by swapping all bits between the selected position and the end of the string. This operation is applied to the couples with probability $P_c$ (we have used 0.6). The last operator in the standard GA is the mutation operator, which consists of changing every bit of the binary strings from 1 to 0, or vice versa, with a very small probability $P_m$ (we have used 0.01). The GA evolution stops when a given stop criterion is fulfilled, usually the number of generations. Note that the GA described above needs an extra operator in order to fix the number of 1 s in the binary strings to $n_1$. This operator is known as a restricted search operator, and it has been used before in the literature.[9]

We will apply GA to the design of an optimum 2D ZRC. For this application, the objective function is

$$\min_{\mathbf{c}\in \text{binary}} f(\mathbf{c}), \quad f(\mathbf{c}) = \max_{k^2+l^2\neq 0} \{S_{kl}\}, \quad S_{kl} = \sum_{i=1}^{n-k}\sum_{j=1}^{n-l} c_{ij}c_{i+k,j+l}, \tag{5}$$

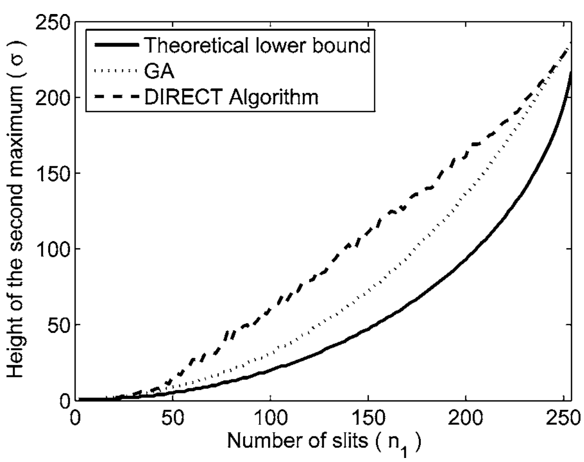


Fig. 2. Height of the second maximum of the autocorrelation with respect to the number of transparent pixels. The codes have $16\times 16$ pixels, and the number of transparent pixels varies from 1 to 255.

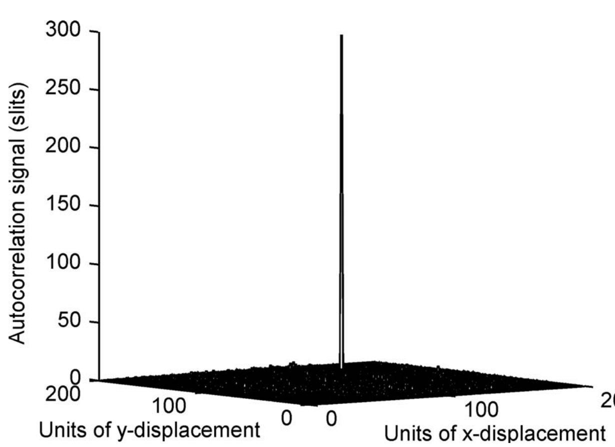


Fig. 3. Autocorrelation signal obtained with a ZRC of $100\times 100$ elements and 300 transparent pixels ($n_1$). The second maximum is 14.

where $f(\mathbf{c})=\sigma$ is the second maximum of the autocorrelation signal, $\mathbf{c}$ is a binary matrix, and the constraint is the maximum of the signal, which is equal to the number of transparent pixels in the ZRC [Eq. (3)].

In Fig. 2 we demonstrate the performance of the method. We calculated the second maximum for a code of $16\times 16$ elements ($n=16$) and a number of transparent pixels ($n_1$) that varies from 1 to 255. The calculations have been made with the GA previously described, with the DIRECT algorithm[6] and evaluating the lower bound [Eq. (4)]. The DIRECT algorithm does not handle this number of variables, and suboptimal solutions can be obtained with a low number of function evaluations. (In this case the number of function evaluations used is $1.2\times 10^5$; normally we need $3\times 10^5$ to guarantee optimal solutions.) It can be seen in Fig. 2 that the solutions of the GA are closest to the theoretical lower bound and therefore they are much better than DIRECT solutions. In Ref. 5 Chen *et al.* show a 2D code of $16\times 16$ elements with 64 transparent pixels. The autocorrelation of this code has a second maximum of 16 pixels. In Fig. 2 the value of the second maximum reached with GA is 13 pixels. Therefore we show that the code used in Ref. 5 is not optimal. The dimension of the code previously analyzed is relatively small but adequate to compare the GA with other techniques. In order to demonstrate the potential of the GA with a large number of variables, we have computed the optimal code for a 2D ZRC with $100\times 100$ elements with 300 transparent pixels. The height of the secondary maximum is 14, so an extremely well-distinct autocorrelation peak is obtained. The 2D autocorrelation signal for this example is shown in Fig. 3.

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