Application of a Model-free Algorithm for the Packing of Irregular Shaped Objects in Semiconductor Manufacture

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Abstract

A Robotic System is being developed to automate the crucible packing process in the CZ semiconductor wafer production. It requires the delicate manipulation and packing of highly irregular shaped polycrystalline silicon nuggets, into a fragile glass crucible. Here an on-line algorithm is presented to plan the packing. It uses a method called Virtual *Trial and Error*. The on-line algorithm handles large numbers of highly irregularly shaped object of different sizes without requiring the object models. Working with the 3-D range maps of objects, it is computationally fast enough to be applied in real-time to practical industrial applications, such as the CZ wafer manufacture. Simulation results show that it compares well with the human performance. The integrated system is shown to achieve high production rates, required precision and cost effectiveness.

1 Introduction

During the widely used CZ semiconductor production process, highly irregular shaped polycrystalline silicon nuggets are packed into a large quartz crucible (see Figure 1) [7]. Each highly irregularly shaped nugget is unique, with weights ranging from a few grams to over 600 grams, see Figure 2. The small, gravel like, nuggets may be handled in a bulk manner. However, CZ process rules require each of the larger nuggets to be placed individually. Protecting the crucibles from damage, minimizing contamination, and maintaining the required charge density are key constraints of the process [9]. Further, packing rules, that govern both nugget-crucible contact characteristics and variable density packing through the charge, need to be applied. For larger, 36 inch diameter crucibles, manual packing is neither ergonomic nor practical as charging takes about 6 hours per crucible. Clearly, this important task would benefit from automation. Automation addresses these issues with further benefits in the form of eliminating large portions of worker expenses, greater packing consistency, reduction in packing time and less down time while maintaining process flexibility. These translate to higher potential profits. Since each nugget has unique size and shape, a robotic solution is appealing and is being developed [9].

A vision system provides the surface geometries of the nugget at hand and of the nuggets that have already been placed in the crucible [20]. A key component for the automation of CZ crucible charging is an algorithm that uses the measured geometries to determine the optimal packing of the nuggets as they are placed one at a time into the crucible by a robotic manipulator. The packing algorithm has an important impact on the charge density, yield and process cycle time.

Significant research has been done on the problem of bin packing. Work in 2-D and 3-D are generally focussed on structured objects such as rectangles or rectangular solids respectively, thus making the problem mathematically more tractable, but not applicable to arbitrary shaped objects [1, 2, 4, 6, 8, 14, 17, 18]. The algorithms developed are largely either off-line processing or on-line processing [1, 5, 8]. In off-line packing, all the objects to be packed with their bin(s) are considered simultaneously. The packing algorithm then finds an "optimum" packing structure. In on-line packing, each object is considered one at a time by the packing algorithm. The algorithm decides where the next object is to be placed without rearranging the previously packed objects.

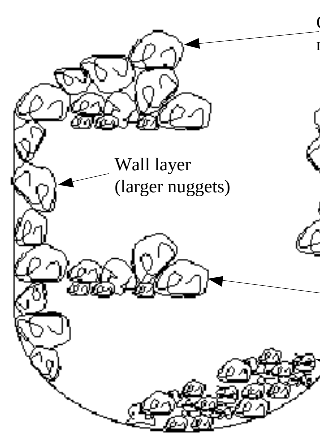

Figure 1. Typical CZ Crucible with Charging Constraints

The off-line bin-packing problem is a classic combinatorial optimization problem that belongs to the class of NP-hard problems [1, 2, 5, 10]. Therefore, the processing time required in finding an optimal solution typically grows exponentially with the number of packing items. To solve these problems, a number of algorithms have been proposed, including dynamic programming, branch and bound, and heuristic search techniques [2, 3, 6, 12, 13, 14, 15]. While they have shown to produce the optimal solutions to these problems, they are at best pseudo-exhaustive in nature, computationally intensive and impractical when the number of objects to be packed is large. In the CZ task, several thousand highly irregular shaped nuggets are used for one crucible. Also limitations of the manipulator require the nuggets to be handled and measured one at a time. Thus, off-line packing optimization is not applicable to this application.

On-line algorithms, such as genetic algorithms, model-based fitting and simulated annealing, have been proposed [11, 14, 19, 21]. Although these have been applied with some success to irregular object packing in 2-D, they are computationally intensive. Several problem-specific approximation optimization algorithms have also been developed to solve packing problems, but such methods are not easily applied to other problems [19]. General methods such as First-Fit decreasing, Harmonic Packing, Level-oriented Packing, with Average-Case and Worst-Case behavior studies, can produce acceptable solutions in reasonable time for a number of applications [5, 15]. These have been applied with success to objects of simple geometries. While effective for a variety of cases, they typically require object models or complete object geometries and hence are not applicable to the CZ crucible charging process where the shape of each nugget is unknown and very irregular. Whelan and Batchelor [22] introduce a useful approach to arbitrary object packing in 2-D based on local optimizations with applications in the material cutting industry. However, extending their principals to 3-D is not simple.

Figure 2. Representative Larger Polycrystalline Nuggets

In this paper, an on-line packing algorithm is presented, packing 3-D irregular object with industrial constraints and limitations. No prior knowledge of the objects is assumed. It utilizes only the raw range image data provided by a 3-D vision system [20]. It does not require feature extraction of range images and construction of models. Using cost functions to determine nugget placement, complex packing rules and constraints of the CZ process can be readily included in the packing algorithm. The result is a computationally simple, effective and practical solution to the nugget placement problem that can be easily extended to other problems of this type with different constraints and limitations.

2 Algorithm Description and Requirements

The automation of the CZ crucible charging process requires a robotic manipulator with a special gripper to handle the nuggets, vision systems to measure the nugget surfaces and the surface of the previously packed nuggets in the crucible, and a packing algorithm to determine nugget placement. The crucible is packed in a stratified manner by alternating between placing large nuggets at the wall and center bulk placement (see Figure 1). Finally, nuggets are placed in a conical form above the crucible rim, to make a crown. To be economically feasible, the charging system must pack the nuggets at a rate comparable to human operators while following a set of packing rules. The packing algorithm must maximize the packing stability, minimize nugget rejection and optimize the charge density profile. Data provided to the packing algorithm consists of the [x,y,z] maps of the nugget surface and the packed surface. To meet the packing rate, processing time of one second on the control computer is established to determine appropriate nugget placement. The smallest packing search step size is 1mm, defined by the resolution of the vision system.

3 Packing Algorithm Description

The nugget and the internal surface of the crucible are represented by an array of height values in the gripper coordinate frame and crucible coordinate frame respectively, see Figures 3 and 4. Surface voids are identified in the crucible map. The nugget map is transformed to a feasible void by a standard transformation matrix:

$$\begin{bmatrix} R_{xyz} & T_{xyz} \\ \vec{0} & 1 \end{bmatrix} = \begin{bmatrix} \cos\beta\cos\alpha & -\sin\gamma\sin\beta\cos\alpha-\cos\gamma\sin\alpha & \sin\gamma\sin\alpha-\cos\gamma\sin\beta\cos\alpha & T_x \\ \cos\beta\sin\alpha & \cos\gamma\cos\alpha-\sin\gamma\sin\beta\sin\alpha & -\sin\gamma\cos\alpha-\cos\gamma\sin\beta\sin\alpha & T_y \\ \sin\beta & \sin\gamma\cos\beta & \cos\gamma\cos\beta & T_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{1}$$

where α, β, γ and T_{xyz} are the roll, pitch, yaw angles and translational vector respectively of the gripper coordinate frame with respect to the crucible coordinate frame. Although the exact nugget center of gravity is not known, an estimate for local static stability is performed at the given nugget location. By varying T_x and T_y, the nugget is sequentially stepped through the feasible surface voids.

At each location α, βand γ are varied to reorient the nugget with respect to the surface. These transformations are evaluated by a cost function. Based on the cost function, the best location for the nugget is determined.

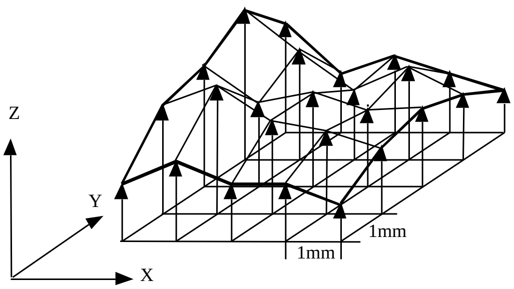

Figure 3. Nugget Surface Representation in Gripper Frame Coordinates

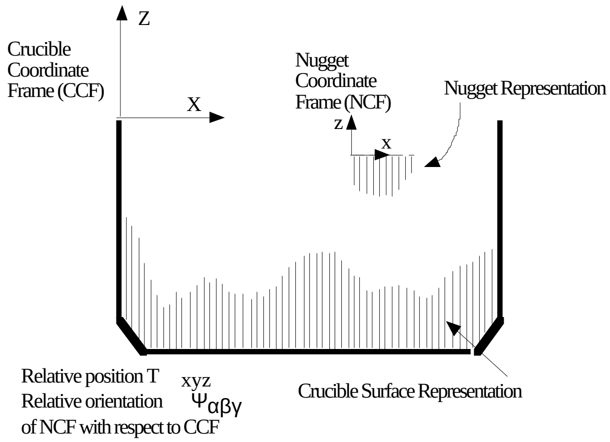

Figure 4. Nugget Approach to Crucible Surface

In Figure 5 the sequence of approach in a two dimensional version of the problem with a virtual nugget and crucible profile is shown. This modeless representation leads to a computationally simple algorithm in which changes to the packing rules can be made by simple by changes in the cost function. A number of global packing rule primitives have been proposed for packing problems, including [15]:

Lowest fit – packing a nugget to lowest position possible.

Minimum Volume fit – packing a nugget into a position with least excess volume.

First fit – packing a nugget to the first location with excess volume less than some predefined value.

Contact fit – packing a nugget into a location with the greatest number of environment to nugget contact points.

A global packing strategy may be one or a combination of several of the above rule primitives. For the CZ packing process, additional packing rules, such as crucible-nugget contact requirements and variable density packing through the charge, can be added directly to the packing strategy. A series of packing strategies were defined and simulations were used to determine the best strategy. Their performance was evaluated based on charge density, the number of nuggets packed successfully out of the number presented and the stability of their placement. It should be noted that acceptable stable positions for some nuggets cannot be found and they must be added to the bulk fill material.

The performance index (P.I.) to evaluate the cost function is defined as:

$$P.I. = \frac{d\ ?N_2}{\sigma\ ?N_1} \qquad (2)$$

where d is the mean charge density, N_1 is the number of nuggets presented and N_2 is the number of nuggets packed. The P.I. formulates a tradeoff between the stability metric, charge density and nugget acceptance ratio of the pack. It penalizes placements that would build a column like structure and rewards those that are more stratified. It further rewards both higher charged packs and higher nugget acceptance ratios. The higher the value of the P.I. the better the expected pack. Note that this definition of the P.I. of a cost function can be changed if other packing criteria become more important [22].

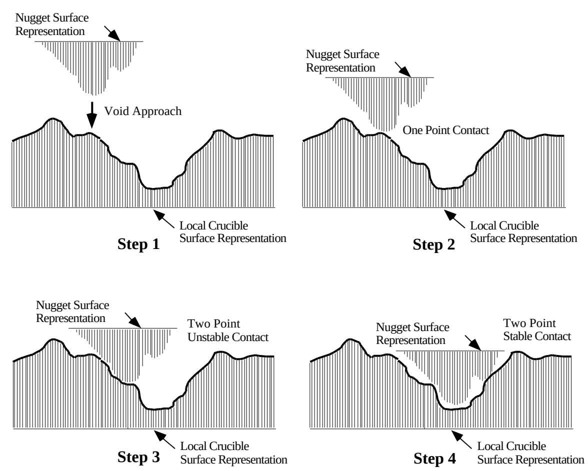

Figure 5. Finding a locally stable configuration

Although each individual nugget may be placed in a locally stable position the global pack may become unstable, much like a house of cards (see Figure 6). To deal with this issue, a stability metric is defined as a measure of how well the algorithm is performing at an arbitrary level in the fill process. Figures 6 and 7 also show the point-wise height distributions of the pack at an arbitrary reference level. It represents the frequency of a given height variation occurring during packing about the current mean height calculated as each nugget is placed. The parameter σ is a measure of the deviation, about the reference level for the pack, obtained from such histograms. A larger deviation value reflects a more column-like pack and a lower deviation reflects a more stable and stratified pack. Hence, histograms narrowly clustered about the zero variations are more stable. To limit σ, a height limiting parameter, δh, is defined as the maximum height above the lowest point on the crucible surface profile to which a nugget can be placed.

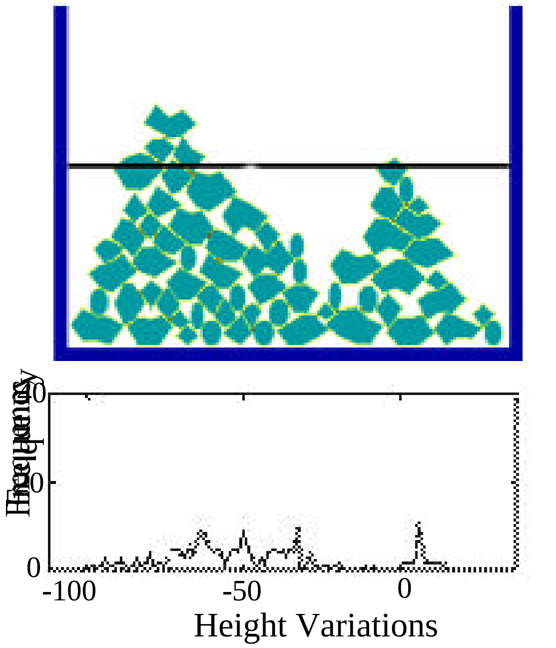

Figure 6: Packing simulation—Local stability without Global stability

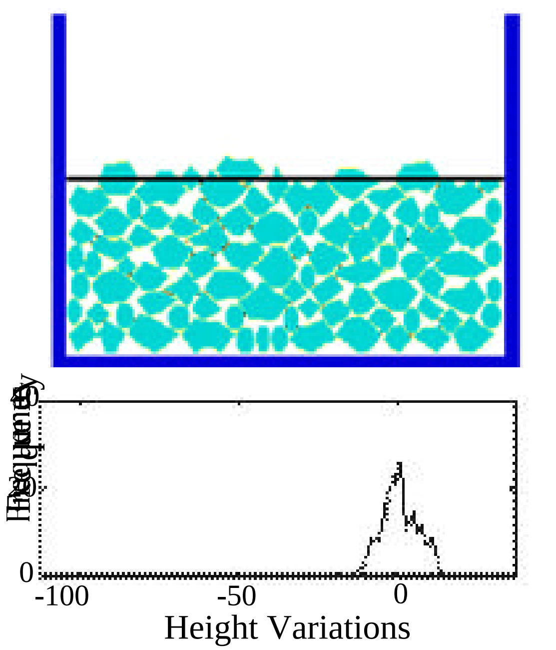

Figure 7: Packing simulation—Local stability with Global stability

4 2-D Packing Results

Defining a cost function requires the identification of the properties that influence the P.I. of the packing rule primitives. In order to enhance or influence these properties combinations of the packing rule primitives are made, thus forming a cost function. Initial simulations were done for the 2-D version of the problem with six cost functions formed from the above packing rule primitives. These include (a) Lowest Fit, (b) Lowest Fit with the minimum excess area, (c) First Fit, (d) Lowest First Fit, (e) Minimized area fit and (f) Minimized area fit weighed by Contact Fit.

The nugget shapes are approximated by random non-convex polygons. The simulations were done where the nugget sizes were randomly selected and where the size distribution was based on measured nugget data [9]. Results for both cases are essentially the same. In addition, for comparison with other methods in the literature, the virtual trial and error algorithm is applied to random 2-D rectangular objects. Benchmark tests for comparison are currently not known. The results for the random distribution of non-convex polygons and for the random rectangles are summarized in Table 1. Table 1 gives the charge densities for the polygon nuggets for the cases where the algorithm is permitted and not permitted to vary the orientation of the nuggets during packing. The results show a consistent three percent increase in density when nugget orientation is varied during packing. This is a significant difference in terms of process productivity. Based on this result, three rotational degrees of freedom (α, β, γin equation 1) were included in the manipulator wrist design [16].

From Table 1, it is seen that the case of lowest fit packing has the best performance index for both the polygonal and rectangular object packing among the cost functions considered. The Lowest-Fit method, unlike the other methods, does not require the explicit use of the height limiting parameter δh, as the function implicitly causes uniform stratified packing. This helps reduce the percentage of rejected objects and provides for a more "natural" packing structure. Further quantitative studies would be required to establish the fundamental influencing parameters for each of the cost functions used.

5 3-D Bin Packing Results

For the 3-D simulation, the general shape used for the nuggets is that of a random polyhedron, with characteristic dimensions limited by the measured sample nugget set [9]. Simulation results for packing the walls and crown of the 18” and 36” diameter crucible yielded an average charge density of 48% and 57.5% respectively (with ±15 degrees wrist rotations in pitch and roll) using the lowest fit packing rule. With bulk filling, the charge density increases to 50% and 60% respectively. It should be noted that there is some evidence that a controlled variable density though the crucible can improve product quality. The use of this robotic system and its automated packing algorithm.

Table 1: Packing algorithm performance description

Packing Scheme	**Mean Charge % w/o rotation (w/ rotation)** **d**	**Number of objects presented** **N_1**	**Number of objects packed** **N_2**	**Stability: Standard deviation about reference (units δh)** σ	**Performance Index** **$(d \cdot N_2/N_1)/\sigma$**
Random Rectangles					
Lowest fit	89.51	131	130	8.0010	11.099
Lowest fit w/ area minimization	89.18	131	130	11.7151	7.553
First fit	90.93	168	132	17.3375	4.120
Lowest First fit	90.46	180	131	22.0667	2.983
Excess Area minimization	87.91	130	117	18.0051	4.394
Excess Area minimization with contact fit	86.9	140	125	28.6165	2.712
Random Polygons					
Lowest fit	75.72 (79.22)	206	204	5.663	13.245
Lowest fit w/ area minimization	75.37 (78.93)	207	203	6.4583	11.442
First fit	66.05 (69.25)	225	175	18.0159	2.851
Lowest First fit	65.78 (68.9)	241	173	16.7	2.827
Excess Area minimization	75.83 (79.26)	232	204	11.3769	5.862
Excess Area minimization with contact fit	73.88 (76.91)	228	200	14.6023	4.439

should provide the consistency to permit this question to be addressed quantitatively.

The computational speeds for placement planning are within the 1.0 second per nugget requirement using a PC with Pentium 166 MHz processor. Further, object shape and geometry are not influencing factors in the performance of the algorithm, which is O (n) (based on n nuggets to be packed as each nugget takes O (1) time).

6 Experimantal Laboratory System Integration

A laboratory system consisting of the robot manipulator and control subsystem, vision/packing subsystem, and wrist/gripper subsystem has been developed (see Figure 8). The packing procedure plays a supervisory role in planning and assigning control to the major subsystems. This includes nugget acquisition, nugget scanning, crucible surface mapping, placement planning, nugget placement and bulk filling.

In order to provide for accurate scheduling, the governing system communicates with the four major subsystems. For inter-computer communication, a series of asynchronous handshaking protocols have been developed for communication. These include:

- Trigger nugget mapping module for nugget scan
- Trigger crucible mapping module for crucible surface profiling
- Trigger packing algorithm for image extraction and placement
- Transfer nugget position and orientation placement coordinates to manipulator for placement

The system was implemented and tested on a 166-MHz Pentium computer, using the C++ programming language. The computer system multitasks between two programs: a slow outer loop (which handles subsystem task scheduling and interaction of the system with the user), and a faster time-critical inner control loop (which processes the encoder information and produces an output control commands for the manipulator/gripper and the vision systems). Information is passed between the two loops via data latching and semaphore.

The system was able to pack nuggets at an average rate of 1 nugget every 10 seconds, reaching a charge density of 50% for the 18” diameter crucibles, allowing the system to meet its performance requirements and stay competitive with human packing.

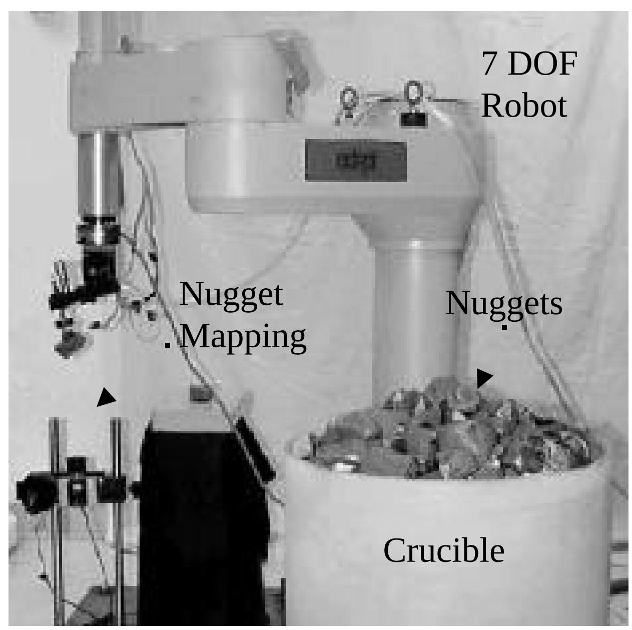

Figure 8: Experimental system

7 Conclusions

An algorithm to automatically determine the placement of polycrystalline silicon nuggets during crucible packing is a key component of a robotic system to automated crucible packing process in CZ semiconductor wafer production. To solve this problem of packing 3-D highly irregular objects with industrial constraints, an on-line model-free packing algorithm has been developed. It is based on a simple, yet effective, approach called Virtual Trial and Error. Simulations show that the Lowest-Fit packing has the best performance for this application. Experimental results also indicate that the algorithm will meet process requirements.

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