Irregular Packing Based on Principal Component Analysis Methodology

Baosu Guo1, Zhuo Liang1, Qingjin Peng2, Yongxin Li1, Fenghe Wu1

1 College of Mechanical Engineering, Yanshan University, Qinhuangdao 066004, China
2 Department of Mechanical Engineering, University of Manitoba, Winnipeg, MB R3T 5V6, Canada

Corresponding author: Fenghe Wu (e-mail: risingwu@ysu.edu.cn).

This work was supported in part by the National Natural Science Foundation of China under Grant 51605422, in part by the Natural Science Foundation of Hebei Province under Grant E2017203156, in part by the Science and Technology Projects of Universities in Hebei Province under Grant QN2017152, in part by Beijing-Tianjin-Hebei Cooperation Project of Hebei Province Natural Science Foundation under Grant E2017203372, in part by the Postdoctoral Science Foundation of Hebei Province B2016003021.

ABSTRACT Irregular packing problems exist widely in industrial applications. To obtain better packing results, packing shapes are rotated freely during the packing process. However, equal angle-intervals are commonly used in the existing packing algorithms without considering the shape contour features, which may miss the best packing positions with the reduced packing quality. To solve this problem, an irregular packing algorithm is proposed based on a principal component analysis methodology in this paper. The principal components of convex features on the shapes are calculated. The rotation angles are then searched according to the first principal components. Finally, the shapes are rotated and packed based on the rotation angles. Experimental results show that the packing time is reduced and the material utilization is improved by the proposed algorithm.

INDEX TERMS layout, principal component analysis, Computer graphics, optimization method, shape, forward line, irregular packing

I. INTRODUCTION

The irregular packing problems, also known as nesting problems, occur when a given resource, raw material or motherboard must be cut into smaller non-overlapping shapes in irregular shapes with the minimal material waste [1]. The irregular packing problem is widely used in the garment, luggage, footwear, tools manufacturing, shipbuilding and aerospace industries. Each application has its specific issues related to the shape and cutting method of the motherboard and shapes.

The approach involves two phases to solve the irregular packing problem: optimization phase and placement phase. The optimization phase searches for the packing sequence that leads to a minimized waste of the motherboard, and the placement phase determines the final solution of the shape [2]. The diversity of the shape sequence and rotation angles leads to multiple packing result. Thus, the irregular packing problem has been proven to be a non-deterministic polynomial problem [3].

Researchers have used heuristic algorithms in the optimization phase, such as the genetic algorithm, mixed-integer linear programming (MIP) model, particle swarm optimization algorithm, and Sequential Quadratic Programming Optimization Method [4-7]. Some traditional algorithms are used in the placement phase such as the BL strategy [8], lower step strategy [9], and BLF strategy [10]. Methods used in the placement phase can be classified into three major classes. One is the polygon enveloping method, which envelops the irregular shape with a rectangle and then places the rectangle enveloping contours instead of the irregular shape [11-14]. This method produces a waste area when enveloping irregular shape with the rectangle, which reduces the material utilization. The second method is the no-fit polygon (NFP) method [15-18]. The NFP is a popular method to calculate an area where any two shapes will not overlap [19]. The NFP is a powerful and effective tool for handling the geometric requirements of irregular cutting and packing problems [20]. The paper [21] presents a hybrid heuristic optimization algorithm reduced computation complexity and improved adaptability according using trace line segments. But the computation time increased and it also used the equal angle-intervals method. However, the NFP method increases the processing time when shapes are rotated in a free rotation. If the method reduces the rotation times, it may miss the best packing position to affect the quality of packing. The third method is the pixel method...
determine the direction of convex features. This is the first time that the contour feature of the shapes is used to determine the rotation angle of shapes which can be rotated continuously. We also propose a placement strategy based on the forward line and judgment distance between shapes. Experimental results show that the packing time is reduced and the material utilization is improved by the proposed algorithm.

This paper is organized as follows. The proposed approach is introduced in Section 2. Section 3 describes the PCA method to determine the rotation angle. Section 4 introduces the collision algorithm based on a forward line. Experimental results and discussions are given in Section 5. Section 6 presents conclusions and further work.

II. PROPOSED APPROACH

The proposed packing algorithm abbreviated as PCA is based on PCA and forward line collision methods. The paper [31] used the PCA algorithm to analyze the internal structure of existing packing problem but it doesn’t propose one algorithm to solve packing problem. This paper uses PCA to determine rotation angles of shapes for convex features. The collision distance is calculated between the forward line and shapes. If the distance is negative, the shape contour must be moved to the opposite direction to avoid the overlap between the shapes. The forward line is the top counter of all the packed shapes. Fig 2 shows the main processes of this algorithm.
III. DETERMINATION OF ROTATION ANGLE BASED ON PCA

To obtain a better packing solution, rotation angles of shapes must be determined. The proposed method uses shapes’ convex features and PCA to determine rotation angles for reducing the number of shape rotations, which ensures that the shapes will not miss the optimal rotation angle and packing position.

A. CONVEX FEATURES EXTRACTION OF SHAPES

Common methods to decide the convexity and concavity of shapes are the angle method, control points method, and Simpson area method. [32] These methods can be simplified into a vector product method that is the most concise and easy to realize. Therefore, this paper adopts the vector product method to extract convex features.

The algorithm uses counterclockwise order data points \( \{ P_i \}, i = 0, 1, 2, \ldots, n \). The vector product formula for the convex vertexes is as follows.

\[
P_{i-1} \times P_{i+1} \times P_i = 
\begin{vmatrix}
    x_{i-1} & y_{i-1} \\
    x_{i+1} & y_{i+1} \\
    x_i & y_i
\end{vmatrix}
\]

(1)

If the result of the calculation is a positive value, the vertex \( P_i \) is the convex vertex of the shape. The vertex \( P_i \) is the concave point if the result is a negative value. The shape contour is a straight line when the value is 0. When a continuous convex vertexes occurs, these vertexes will form a convex feature. The minimum convex feature can be controlled by controlling the number of continuous convex vertexes.

As shapes have different numbers of contours vertexes, the number of continuous convex vertexes requires a dynamic setup to select convex features. The distance of interval contour points is a reference to determine the number of continuous convex vertexes when the number of shapes vertexes is small. When the number of convex features can be ensured, the number of rotation angles can be limited to a suitable level. Thus, this method accurately expresses the convex features of shapes to limit the packing time.

The interval distance of contour vertexes is as follows.

\[
L_i = \sqrt{(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2}, i = 0, 1, 2 \cdots n
\]

(2)

The number of contour vertexes:

\[
N = n + 1
\]

(3)

The perimeter of the contour:

\[
L = \sum_{i=0}^{n} L_i + \sqrt{(x_n - x_0)^2 + (y_n - y_0)^2}
\]

(4)

The density of the contour vertexes:

\[
\rho = \frac{N}{L}
\]

(5)

The control parameter of continuous vertexes:

\[
\mu
\]

(6)

The number of consecutive vertices is as follows.

\[
V = \rho \mu
\]

(7)

Through the experiment, continuous vertex parameters \( \mu \), and the number of continuous vertices can be obtained using the above formula. The appropriate number of convex features...
features can then be obtained. Fig. 3 shows the result of obtaining convex features in two examples.

![Convex feature diagram](image)

**FIGURE 3. Examples for obtaining convex features**

**B. DETERMINATION OF ROTATION ANGLE USING PCA**

In this paper, protruding direction of convex features need to be determined. So, feature extraction (dimensionality reduction) is required. There are many methods for data dimensionality reduction, for example PCA, LDA (Linear Discriminant Analysis), LLE (Locally Linear Embedding) and Laplacian Eigenmaps method.

PCA is the most commonly used data dimensionality reduction method and the most commonly used feature extraction method. By calculating the maximum variance in data, PCA method can capture the dominant features in an N-dimensional dataset which is in descending order through an orthogonal transformation [33]. PCA can retain more features of the original data and minimize the loss of original data. LDA makes the data points easy to classify. LLE is a nonlinear dimensionality reduction algorithm that enables the dimensionality-reduced data to maintain a streamline structure. Laplacian Eigenmaps can reflect the inherent streamline structure of data.

In order to obtain the protruding direction of convex features we need to retain more features of the original data points and the streamline structure is not need. In addition, data points do not need to be distinguished. So the PCA will be the best choice to obtain the protruding direction and we will use this method in this paper.

1) INTRODUCTION OF PRINCIPAL COMPONENT ANALYSIS

The principal component analysis (PCA) is a statistical procedure that uses an orthogonal transformation to regroup the numerous original indexes that has certain correlations into a new set of comprehensive indexes. [34] These indexes are independent of each other instead of the original index. In order to interpret the datasets methods are required to drastically reduce their dimension in an interpretable way, such that most of the information on the data is preserved. Many techniques have been developed for this purpose, but PCA is one of the oldest and most widely used. [35]

The basis of PCA is to transform several original indexes into a few representatives and comprehensive indexes. The few indexes have most information about the original index (85%) to remain independent avoiding overlapping of the information. PCA reduces data dimensions and simplifies the data structure.

The PCA can be described in a mathematical model as follows. For n samples and p indexes observed in each sample, p indexes as p random variables are denoted as $X_1, X_2, \cdots, X_p$, the data matrix is:

$$X = \begin{bmatrix}
    x_{11} & x_{12} & \cdots & x_{1p} \\
    x_{21} & x_{22} & \cdots & x_{2p} \\
    \vdots & \vdots & \ddots & \vdots \\
    x_{n1} & x_{n2} & \cdots & x_{np}
\end{bmatrix} = \begin{bmatrix} X_1, X_2, \cdots, X_p \end{bmatrix}$$ (8)

where

$$X_i = (x_{i1}, x_{i2}, \cdots, x_{ip})^T, i = 1, 2, \cdots, p.$$ (10)

The PCA aggregates p observation variables into p new variables (aggregate variable) as follows.

$$F_1 = a_{11}X_1 + a_{12}X_2 + \cdots + a_{1p}X_p$$
$$F_2 = a_{21}X_1 + a_{22}X_2 + \cdots + a_{2p}X_p$$
$$\cdots$$
$$F_p = a_{p1}X_1 + a_{p2}X_2 + \cdots + a_{pp}X_p$$ (9)

They are aliased as:

$$F_i = a_{i1}X_1 + a_{i2}X_2 + \cdots + a_{ip}X_p, i = 1, 2, \cdots, p$$ (10)

It meets following conditions:
(1) The PCA are independent of each other:
\[ \text{Cov}(F_i, F_j) = 0, i \neq j, i, j = 1, 2, \ldots, p \]

(2) The variance of the PCA decreases successively, and the importance decreases in turn:
\[ \text{Var}(F_1) \geq \text{Var}(F_2) \geq \cdots \geq \text{Var}(F_p) \]

(3) The sum of coefficients of each principal component is 1:
\[ a^2_{11} + a^2_{22} + \cdots + a^2_{pp} = 1 \]

Above all, the key to obtain the first PCA is to find a suitable unit vector \((a_{11}, a_{21}, \ldots, a_{p1})\) and the maximize variance of PCA \(F_1\). For the current solution, it only needs to identify the unit vector \((a_{11}, a_{21}, \ldots, a_{p1})\) that corresponds to the largest characteristic root \(\lambda_1\) of X’s covariance matrix S, where \(\lambda_1\) is the variance of \(F_1\).

Similarly, the unit vector that corresponds to the characteristic root \(\lambda_2 \cdots \lambda_p\) of X’s covariance matrix S is \((a_{12}, a_{22}, \ldots, a_{p2}) \cdots (a_{1p}, a_{2p}, \ldots, a_{pp})\). \(\lambda_1 \cdots \lambda_p\) is the variance of \(F_1 \cdots F_p\) and decreases in order.

2) USING PRINCIPAL COMPONENT ANALYSIS TO DETERMINE THE ROTATION ANGLE

After determining shapes’ convex features, the protruding direction of convex features need to be determined. From the point of view of geometry, PCA method rotates the original coordinate axis to get the orthogonal coordinate axis, so that the direction of one coordinating axis is the direction with the greatest degree of dispersion of all data points. The eigenvector of the first principal component represents the direction with the greatest degree of data dispersion. The direction of the maximum discretization degree of convex feature data points also represents the protruding direction of convex feature. So, the eigenvector of the first principal component can be used to calculate the protruding direction of convex features.

Using the PCA to analysis the convex feature data. The eigenvector of the first principal component can be obtained. The direction of eigenvector will be used to represent the protruding direction of convex features. The angle between the eigenvector and direction of gravity is the rotation angle of shapes.

For irregular packing problems, data points are two-dimensional. There are only two principal components: the first principal component \(F_1\), and the second principal component \(F_2\).

Data points for the convex feature are coming from the bottom of the example one of Fig. 3:
\[ (X, Y) = [393 \ 387 \ 378 \ 363 \ 351 \ 339 \ 324 \ 315 \ 309] \begin{bmatrix} 552 & 585 & 600 & 609 & 612 & 609 & 600 & 585 & 552 \end{bmatrix}^T \]

(11)

The mean value of the data points is first calculated, that is, the sample data centralization:
\[ \overline{X} = \frac{1}{n} \sum_{i=1}^{n} X_i \]

(12)

According to Equations (11)-(16), the covariance matrix of the data matrix can be determined as follows:
\[ \text{cov}(X, Y) = \begin{bmatrix} 983.250 & 0 \\ 0 & 542.5 \end{bmatrix} \]

(17)

From the eigen-decomposition of the Equation (17), we can get
The eigenvalues:
\[ \lambda_1 = 983.25, \lambda_2 = 542.5 \]

The eigenvectors:
\[ a = (a_1 \cdots a_p)^T \]

(19)

Then eigenvalues \(\lambda_1\) and \(\lambda_2\) will be listed in a descending order. Based on the eigen-decomposition of equation (17), the equation (18) and equation (19) are acquired as follows.
\[ \lambda_1 = 983.25, a_1 = (0, 1)^T \]
\[ \lambda_2 = 542.5, a_2 = (1, 0)^T \]

According to Fig. 4, the first principal component represents the primary data, and the \(a_1\) (1st PCA’s eigenvector) represents the protruding direction of convex features. Two examples of Fig. 5 show convex features and protruding directions of the convex features.

**FIGURE 4. Result of calculating PCA for one convex feature**
IV. ALGORITHM FOR COLLISION USING JUDGMENT OF DISTANCE BASED ON THE LOWEST-GRAVITY-CENTER

The existing algorithm is based on the BL algorithm and the lowest-gravity-center [36] algorithm. The main idea of BL algorithm are placing shapes of the most left then lower most of the motherboard. And the main idea of lowest-gravity-center algorithm is placing shapes of the lower most then most left of the motherboard. The algorithm cannot create a uniform distribution, and BL algorithm also causes holes. It can be seen in Fig. 6. Using the lowest-gravity-center method, the problem of holes can be avoided. A method is proposed based on the forward line and lowest-gravity-center. The forward line of finished shapes is first calculated. The location in the lowest center of gravity of shapes is then chosen. After then, the distance between the shapes and forward line is calculated. The collision can be detected based on the distance. This method ensures that shapes are packed in the lowest of motherboard, which maintains uniformity to avoid the problem of holes in packing.

FIGURE 6. Optimized layout of the lowest-gravity-center approach
In the lowest-gravity-center method, the center of the gravity position and polygons’ area are required. As irregular shapes have the same density, the center of a gravity position is its geometric center. Vertices of the irregular polygons are known, \( \{P_i\}, i=0,1,2,\ldots,n \). Thus, a center of the gravity position of irregular shapes is as follows.

\[
\begin{align*}
    x &= \frac{1}{N} \sum_{i=0}^{N} x_i \\
    y &= \frac{1}{N} \sum_{i=0}^{N} y_i
\end{align*}
\]  

(20)

If counterclockwise data points are given as \( \{P_i\}, i=0,1,2,\ldots,n \), and vertex coordinates are \((x_0, y_0), (x_1, y_1), \ldots, (x_n, y_n)\), the area of irregular polygons can be written as follows.

\[
S = \frac{1}{2} \left( x_0 \begin{vmatrix} x_1 & y_1 \end{vmatrix} + x_1 \begin{vmatrix} x_2 & y_2 \end{vmatrix} + \cdots + x_{n-1} \begin{vmatrix} x_n & y_n \end{vmatrix} + x_n \begin{vmatrix} x_0 & y_0 \end{vmatrix} \right)
\]  

(21)

A. CALCULATION OF THE COLLISIONAL DISTANCE
The collision detection of shapes is the most important step in the packing problem. It ensures the shapes are as close to each other as possible without overlapping. There are two common methods of the shape collision detection. One method determines whether shapes overlap to move the shapes. The other uses the distance judgment. The first method allows shapes to move a certain distance and then determines whether the shapes are intersected. If the contours
are intersected, a shape contour will move back. Otherwise, the shape contour will move forward, until a non-overlapping and closest position is found. The second method determines the distance between shapes to move the shapes using this distance.

The second method reduces the computation time and avoids overlapping the shapes. In this paper, we apply an improved method to calculate the collision distance based on the second method. The method is based on the forward line of the judgment on distance. The main steps are as follows. Shapes are first discretized into a required precision of pixels so that the distance between the shapes can be converted into the distance between pixels and pixels, and pixel positions of the shapes are represented in a matrix. The collision distance is then calculated between shapes using the same x-direction (or y-direction) matrix to perform the subtraction operation. This method is not only suitable for irregular polygons but also is adaptable to complex curve graphs. Additionally, a direction of the collision is converted to the collision in directions of x and y.

If irregular shapes with the order M, Q, R, S, and T as shown in Fig 7, the coordinate system is right for the x-axis positive direction and down for the y-axis positive direction, the main steps of the method in the x direction are shown in Fig 8.

When shape M is on the left and bottom of the motherboard and shape Q on the bottom of the motherboard, the distance between pixels of shape M and Q should be calculated as shown in Fig 9. The minimum distance between shapes M and Q can then be obtained. The final position of shape Q can be found by subtracting the minimum distance from the pixel position of shape Q in the x direction. The collision will be detected.

Just like the collision detection for shapes M and Q in the x direction, the collision detection between shapes M and T in the y direction is shown in Fig 10.
B. CALCULATION OF THE FORWARD LINE

The algorithm based on the PCA and lowest-gravity-center method must calculate the lowest-gravity-center of shapes. To calculate the lowest-gravity-center of shapes quickly, the collision distance between shapes is required. Therefore, the forward line is calculated as a series of pixels of the minimum y-coordinate in the same x-coordinate of the shapes as shown in Fig 7. Steps for calculating the forward line are as follows.

Step 1: Taking the rectangular motherboard as an example, the first tier of the motherboard is packed first. The step is as same as the collision detection between shapes M and Q. The gap between the first tier should be as small as possible to avoid holes by changing the order for shapes. For example, M, Q, R, and S are put in the first tier as shown in Fig 7.

Step 2: Extracting the forward line of packed shapes. Pixels of the minimum y-coordinate are extracted from the same x-coordinate in packed shapes. The forward line is then obtained by connecting all the points in sequence as shown in Fig 7.

Step 3: Similar to the M and T collision in the x-direction, the forward line is taken as packed shapes. The minimum distance of the pixel between shape T and the forward line of y direction is then calculated to determine the collision distance.

Step 4: When shape T is completed packing, the new forward line is calculated to continue the pack of the next shape.

V. EXPERIMENT AND DISCUSSION

The proposed method, or PCA, is compared with the equal angle-interval method and the method MGA proposed in [37]. MGA method is a contour packing approach using a material grid approximation and the lowest-gravity-center methods. The experiment is conducted in a computer with a core i5 CPU, 8 GB of memory using Python programming. In these experiments we use the data of a series of cross-section data from a 3D printing complex model and the prosthodontics models provided by literature [37] including base crowns, full crowns, bridges and inlays. In experiment one, a series of cross-section data from a 3D printing complex model were collected. In the same sequence of shapes given, 30°, 45°, 60°, and 90° equal angle-intervals were compared with the proposed method. In experiment one, the motherboard size was 100 mm × 100 mm; the x-direction moving step was 2 mm; and the collision accuracy was 0.1 mm. In experiment two, prosthodontics models were selected including base crowns, full crowns, bridges and inlays. In the same sequence given, the proposed method was compared with the method MGA. The motherboard size was 45 mm×45 mm; the x-direction moving step was 0.5 mm; and the collision accuracy was 0.1 mm. Results of experiments are shown in Tables 1 and 2, respectively.

It can be seen from Table 1 that the proposed method obtains the highest motherboard filling rate of 69.86% with

---

**FIGURE 9.** Collision detection between shapes M and Q in direction X

**FIGURE 10.** Collision detection between shapes M and T in direction Y
the highest packing number of 31. Compared to a 30° dividing rotation angle, the filling rate is improved from 62.90% to 69.86%. The packing time is decreased from 204.125s to 124.819s. When the equal angle-interval is 45°, the filling rate is as same as the proposed approach. The packing time is decreased from 175.192s to 124.819s. Additionally, it can be seen from Table 1 that the rotation angle of the shapes significantly influences the final result of the packing.

In experiment two, two sets of prosthodontics data were used to compare the proposed method with the method MGA. From Table 2, in example one, the filling rate is improved from 74% to 79.09%. The packing time is decreased from 168.360s to 46.650s. The packing number is increased from 21 to 30. In example two, the filling rate is improved from 75.27s to 81.37s and the packing time is decreased from 108.170s to 39.254s. The packing number is increased from 19 to 28.

### A. EXPERIMENT ONE

#### TABLE 1. Comparison of packing results of experiment one

<table>
<thead>
<tr>
<th>Packing models</th>
<th>Packing result</th>
<th>Packing time (s)</th>
<th>Filling rate (%)</th>
<th>Packing number</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCA</td>
<td>Fig. 10</td>
<td>124.819</td>
<td>69.86</td>
<td>31</td>
</tr>
<tr>
<td>30°</td>
<td>Fig. 11</td>
<td>204.125</td>
<td>62.90</td>
<td>25</td>
</tr>
<tr>
<td>45°</td>
<td>Fig. 12</td>
<td>175.192</td>
<td>69.86</td>
<td>31</td>
</tr>
<tr>
<td>60°</td>
<td>Fig. 13</td>
<td>113.222</td>
<td>65.26</td>
<td>26</td>
</tr>
<tr>
<td>90°</td>
<td>Fig. 14</td>
<td>74.008</td>
<td>67.23</td>
<td>28</td>
</tr>
</tbody>
</table>

**FIGURE 11.** Packing result using the PCA method

**FIGURE 12.** Packing result using a 30° equal angle-interval

**FIGURE 13.** Packing result of a 45° equal angle-interval

**FIGURE 14.** Packing result using a 60° equal angle-interval
B. EXPERIMENT TWO

TABLE 2. Comparison of packing results of experiment two

<table>
<thead>
<tr>
<th>Packing models</th>
<th>Packing result</th>
<th>Packing time (s)</th>
<th>Filling rate (%)</th>
<th>Packing number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Example one</td>
<td>PCA</td>
<td>46.650</td>
<td>79.09</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>MGA</td>
<td>168.360</td>
<td>74.00</td>
<td>21</td>
</tr>
<tr>
<td>Example two</td>
<td>PCA</td>
<td>39.254</td>
<td>81.37</td>
<td>28</td>
</tr>
<tr>
<td></td>
<td>MGA</td>
<td>108.170</td>
<td>75.27</td>
<td>19</td>
</tr>
</tbody>
</table>

VI. CONCLUSION AND FURTHER WORK

In this paper, an effective algorithm was introduced using the principal component analysis for irregular packing problems with the free rotation. Principal components of convex features on shapes were calculated to determine rotation.
angles of shapes. The shapes were then rotated and packed with these rotation angles. This paper also proposed a forward line collision method that uses the pixel and lowest-gravity-center methods to determine the packed position and final rotation angle of shapes. Experimental results show that the material utilization is improved efficiently, and the time is reduced using the proposed algorithm.

This paper uses the PCA and contour features to solve the rotation problem of free rotation shapes, instead of using the equal angle-interval in the present study. The method compensates for the problem of missing the best packing positions by using an equal angle-interval to rotate shapes. Additionally, convex features of the shapes are used as the rotation reference to make each rotation angle of the shapes more objective so that the number of rotation angles is reduced under the premise of guaranteeing the packing position. As a result, the packing effectiveness and material utilization are improved.

In this paper, the proposed algorithm possesses several advantages compared to other packing algorithms. First, the proposed algorithm reduces the number of rotation angles and packing time based on the PCA and shape contour features to determine the rotation angles instead of using equal angle-interval. Second, the proposed algorithm improves the material utilization with respect to shape contour feature matching. Third, the collision detection based on the forward line and pixel method improves the effectiveness and makes the shapes more uniform.

The proposed algorithm also has limitations. The algorithm depends on the sequence of shapes. The results are not stable in different sequences. Additionally, the method efficiency of traversing pixel locations is to be improved.

To improve the filling rate and efficiency, the future research will focus on following three aspects. First, contour features of the irregular motherboard will be considered in the packing, the concave and convex features combination will be used in the packing. Second, in the collision strategy, the collision speed will be optimized to reduce the packing time. Finally, an intelligent algorithm will be introduced to optimizing the sequence of shapes to improve the efficiency of packing.

REFERENCES


Qingjin Peng received his B.S. and M.S. degree in mechanical and manufacturing engineering from Xian Jiaotong University, Xian, China, in 1982 and 1988, and a Ph.D. degree in Mechanical and Manufacturing Engineering from Birmingham University, Birmingham, UK, in 1998. He is currently a Professor in the Department of Mechanical Engineering, University of Manitoba, Canada. His research interests include virtual manufacturing, product design, and image-based methods in reverse engineering.

Yongxin Li received her B.S. degree and PhD in mechanical engineering from Harbin Engineering University, Harbin, China in 2007, and 2012, respectively. She is currently an associate professor with the School of Mechanical Engineering, Yanshan University. Her research mainly focuses on structure optimization and bionic lightweight design.

Fenghe Wu received his B.S. degree and M.S. degree in mechanical engineering from Yanshan University, Qinhuangdao, in 1991 and 1998, respectively, and his Ph.D. degree in aerospace manufacturing engineering from Beihang University, Beijing, China, in 2006. He is currently a Professor with the School of Mechanical Engineering, Yanshan University. His research interests include digital manufacturing, intelligent manufacturing, bionic design and optimized design.

Baosu Guo received his B.S. degree in mechanical engineering from Naval Aeronautical and Astronautical University, Qingdao, in 2009, and his Ph.D. degree in aerospace manufacturing engineering from Nanjing University of Aeronautical and Astronautics, Nanjing, China, in 2015. He is currently a lecturer with the School of Mechanical Engineering, Yanshan University. His research interests include intelligent manufacturing, big data, and image processing.

Zhuo Liang was born in Baoding City, Hebei Province, China in 1993. He received his B.S. degree in mechanical engineering from Shanghai Dianji University, Shanghai, in 2016. He is currently pursuing an M.S. degree in mechanical engineering at Yanshan University, Qinhuangdao China. His research interests include irregular packing and image processing.