A SIMILARITY MEASURE FOR PCB GROUPING USING ENTROPY METHOD

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ABSTRACT

Group setup strategy exploits the PCB similarity in forming the families of boards to minimize makespan that is composed of two attributes, the setup time and the placement time. The component similarity of boards in families reduces the setup time between families meanwhile, the geometric similarity reduces the placement time of boards within families. As each similarity has different importance in reducing makespan, combining attributes by giving appropriate weights is essential to solve the optimization problem. Current group setup strategy considers the component similarity and the geometric similarity by giving equal weights or by considering each similarity sequentially. In this paper, we propose an improved group setup strategy which combines component similarity and geometric similarity simultaneously. The entropy method is used to determine the weight of each similarity by capturing the importance of each similarity in different production environments. Test results show that the entropy based group setup strategy outperforms existing group setup strategies.

KEYWORDS: PCB, group setup, entropy,

INTRODUCTION

In an automated PCB assembly processes, one of the most important operational issues is how to setup the Surface Mount Technology (SMT) machine for a set of boards grouped together for processing under a common setup. Another issue is how to determine the boards of groups to implement such setups. If every board is grouped as a single family, the setup will occur only once minimizing setup time. However, PCB assembly operations clearly exhibited a tradeoff between setup time and placement time. That is, the single family solution will increase the total placement time since the common setup is not prepared for individual boards. On the other hand, if every board forms a unique family of its own, the placement time reduction will be surpassed by setup time. Hence, boards must be grouped such that within the family, boards share as many common component types as possible (i.e., component similarity) in order to reduce setup time between families. Also the placement locations of boards within the family must be similar to each others (i.e., geometric similarity) in order to reduce placement time. Therefore a good clustering of boards would be possible by carefully considering the resemblance of boards in terms of the component similarity and the geometric similarity in order to reduce total processing time (i.e., makespan). Several numerical coefficients have been proposed to measure the component similarity and the geometric similarity of different boards (see section 2 for more details).

Existing group setup strategies

case (1): considers component similarity only (Leon and Peter, 1998)or

case (2): forms families of boards based on geometric similarity and select the cluster of boards based on component similarity in sequential manner (Leon and Jeong, 2004)or

case (3): considers an overall board's similarity coefficient which combines component similarity and geometric measure by assigning equal weights(Quintana and Leon, 1999).

Leon and Jeong (2004) reported that the performance of group setup strategy of case (2) performs better than other cases.

The motivation of this paper was the belief that the determining appropriate weights of case (3) could achieve a further reduction of makespan. Combining different criteria into a synthesized criterion falls into a well known research area, Multiple Criteria Decision Making (MCDM). In this paper, we use the entropy method for calibrating the weights assigned to the component similarity and the geometric similarity. The entropy concept suggests that if the component similarity or the geometric similarity of boards is the same, the similarity can be eliminated from further considerations in forming the families of boards. Alternately, the weight assigned to a similarity is small if all boards have the similar value of corresponding similarity coefficient.

PROBLEM DESCRIPTION

This paper considers a group setup problem in a single SMT machine producing multiple types of boards. The placement process begins from the movement of placement head. The head starts from a given home position, moves to feeder carriage on the machine to pick up the component. After picking up the component, the head moves to the placement location on the PCB for this component. Then the component is placed on the board and the head travel back to the feeder carriage to pick up the next component. The pick-and-place process continues until all components required for the board have been completed.

Leon and Peters (1996) proposed the following conceptual formulation of the group setup problem:

Minimize: Makespan

Subject to: Feeder capacity constraints
Component-feeder constraints
Component placement constraints

The objective is to minimize the makespan for producing multiple types of boards. The first constraints represent the feeder capacity constraints. Total number of different component types in any family can not exceed the feeder capacity since only one component type can reside in one feeder slot..

The second constraints, component-feeder constraints means that each component needed for boards in a family must be assigned to a feeder. The third constraints, component placement constraints are equivalent to traveling salesman problem (TSP)'s constraints.

That is, the placement head must visit all the placement locations on a board. The distance between two placement locations is the time for the head to move from the first placement location to the feeder slot containing component for the second placement then to the second placement location.

BACKGROUNDS

In this section, we briefly review existing group setup strategies with different board's similarity coefficient for PCB assembly.

Generic group setup procedure for PCB assembly

Traditional group setup procedure has two main phases. In phase 1, similar boards are grouped into families using a hierarchical clustering algorithm. In phase 2, component-feeder assignment and placement sequences are generated by treating each family, determined in phase 1, as a single composite-board. The traditional group setup procedure is summarized in the following steps.

Phase 1. Clustering

- Step 1: Put each board-type in a single-member family
- Step 2: Compute similarity coefficient, s_{ij} for all pairs of family i and j
- Step 3: Set $T = \max(s_{ij})$
- Step 4: Merge the pair of board i^* and j^*, if $s_{i^*j^*} = T$. Repeat until no more pairs can be merged at similarity level T.
- Step 5: Compute clustering objective value for the solution obtained in the previous step. Save the families of boards if an improvement is achieved.
- Step 6: Repeat Step 2 through 6 while merging is possible.
- Step 7: Pass the best families of boards to Phase 2.

Phase 2. Component-feeder assignment and placement sequence

- Step 8: Form a composite-board H_f for all families f, this board consists of the superposition of all the placement locations with their corresponding components of the boards in family f.
- Step 9: Determine a feasible component-feeder assignment $C(H_f)$
- Step 10: For all $i \in N_f$ where N_f, is the set of board types in family f. Find a placement sequence $P(i)$, given $C(H_f)$
- Step 11: For all $i \in N_f$, Find a component-feeder assignment $C(H_f)$ given $P(i)$
- Step 12: Repeat Step 10 and Step 11 for a predetermined number of iterations.

In phase 1, the hierarchical clustering algorithm merges similar boards into a family. The clustering procedure continues until all boards form a single family. To form good families of boards, it is essential to develop a similarity coefficient which considers both the component similarity and the geometric similarity of any two boards. If boards in a family share many common component types, the setup time between families will be reduced. However, even if boards require exactly the same components in a family, the placement time for the family will be increased if the component layout of boards is totally different (Leon and Peters, 1998).

Another issue in hierarchical clustering is the development of clustering objective in order to evaluate the quality of board clustering. The clustering objective might be a minimization of the similarity coefficient between families or maximization of the similarity coefficient within families.

Component-feeder assignment and placement sequences are generated by treating each family as a single composite-board as shown in Phase 2. Component-feeder assignment and placement sequences are determined by solving iterative Linear Assignment Problem (LAP) and TSP proposed by Drezner and Nof (1984). For a given component-feeder assignment, $C(H_f)$, the placement sequencing problem can be solved as TSP problems. The placement locations are represented as cities, the placement head is the salesman and the distance from one location to the next is the time required by the head to pick up components from the appropriate feeder slot and place them on the board. In this paper, we use the nearest-neighbor heuristic to solve the TSP. For a given placement sequences, $P(i)$, the component-feeder assignment problem is a LAP. The cost matrix of assignment is the component delivery time from feeder slots to placement locations. In this implementation, the LAP is solved using the shortest augmenting path algorithm proposed by Jonker and Vogenant (1987). The LAP/TSP heuristic terminates when it reaches the predetermined number of iteration. Leon and Peters (1996) argued that LAP/TSP converged to a local optima within 3 iterations in their pilot tests for group setup procedure.

<u>Existing group setup strategies</u>

Leon and Peters (1998) proposed the component similarity based similarity coefficient of board i and j, s_{ij}^{NCC} as follows

$x^{i \cap j}$: Number of Common Component (NCC) types between board i and j
$x^{i \cup j}$: total number of different component types required by board i and j

$$s_{ij}^{NCC} = \frac{x^{i \cap j}}{x^{i \cup j}} \tag{1}$$

Suppose that board i and j have the same number of placement locations of component type c. Then the Euclidean distance matrix from locations in board i to board j can be constructed. The problem is to find the best assignment of from-to locations which minimize the total sum of Euclidean distance namely, Minimum Metamorphic Distance (MMD). The solution can be easily found using LAP method (see Jonker and Vogenant. for more details). When boards with different number of locations are used, all the locations on the board with more locations are assigned to the locations on the board with less number of locations. In MMD based setup, a new geometric similarity has been proposed as follows:
MMD_{ij}^{c} : minimum metamorphic distance of board i and board j for component type c.
p : placement locations of board i.
q : placement locations of board j.

d_{pq}^{c} : Euclidean distance between location p and q with component type c.

$$s_{ij}^{MMD} = 1 - \frac{\sum_{\forall c} MMD_{ij}^{c}}{\sum_{\forall c}\sum_{\forall p} \max_{\forall q} d_{pq}^{c}} \qquad (2)$$

The nominator of the coefficient in equation (2) is the total sum of MMD for all types of components and the denominator is the normalizing factor. As shown in equation (2), when MMD increases, the geometric similarity decreases. The authors suggested a group setup strategy considering the component similarity (i.e., s_{ij}^{NCC} in equation (1)) and the MMD based geometric similarity (i.e., s_{ij}^{MMD} in equation (2)) sequentially. In hierarchical clustering, the proposed procedure merges two boards with the largest MMD similarity. Then the clustering objective is the maximization of average MMD similarity within families per unit feeder change between families. Therefore, the clustering objective is maximized when all boards in families are geometrically similar (i.e., placement time is minimized) and the number of feeder change is minimized (i.e., setup time is minimized). The limitation of the MMD based group setup is that the component similarity and the geometric similarity are not considered simultaneously. Forming the families of boards considering only geometric similarity may reduce the possibility of generating solutions which is favorable in reducing setup time. However the authors reported that MMD based group setup outperformed the Placement Location Matrix (PLM) based group setup which gives equal weights for component similarity and geometric similarity. In section 4, we propose a new group setup strategy which combines s_{ij}^{NCC} and s_{ij}^{MMD} using the entropy method.

ENTROPY BASED GROUP SETUP STRATEGY

In the past two decades, there has been of enormous growth in the area of multi-attributes optimization. One of the most important issues in this research area is the development of appropriate weights for different attributes. As each attribute has different scale, synthesizing attributes by giving appropriate weights to each attribute is essential to solve the optimization problem (Zeleny). The entropy method suggests that the weight assigned to a criterion must be small if all alternatives have similar value for the criterion. On the other hand, when the difference between a criterion's values is great, the criterion must be considered as important by giving large weight. The same reasoning can be applied to the PCB grouping problem under consideration in this paper.

Let

$NCC_{ij} = x^{i \cap j}, \forall i, \forall j, i \neq j, i, j = 1,2,\ldots,N$

$MMD_{ij} = \sum_{\forall c} MMD_{ij}^{c}, \forall i, \forall j, i \neq j, i, j = 1,2,\ldots,N$

Then the entropy measures of the criteria for NCC and MMD are as follows:

$$e(NCC) = -\sum_{i=1}^{N}\sum_{j \neq i}^{N} \frac{NCC_{ij}}{S_{NCC}} \ln \frac{NCC_{ij}}{S_{NCC}} \qquad (3)$$

$$e(MMD) = -\sum_{i=1}^{N}\sum_{j\neq i}^{N}\frac{MMD_{ij}}{S_{MMD}}\ln\frac{MMD_{ij}}{S_{MMD}} \tag{4}$$

where $S_{NCC} = \sum_{i=1}^{N}\sum_{j\neq i}^{N} NCC_{ij}$, $S_{MMD} = \sum_{i=1}^{N}\sum_{j\neq i}^{N} MMD_{ij}$ When all NCC_{ij} are equal, then $\frac{NCC_{ij}}{S_{NCC}} = \frac{2}{N(N-1)}$ and the maximum of $e(NCC)$ is achieved which is $e_{\max}(NCC) = \ln\left(\frac{N(N-1)}{2}\right)$. This implies that if the value of a criterion is evenly distributed, then the entropy of the criterion is maximized and the entropy is minimized when the criterion value is biased.

By setting a normalization factor, $K = \frac{1}{e_{\max}(NCC)} = \frac{1}{\ln\left(\frac{N(N-1)}{2}\right)}$, $0 \le e(NCC) \le 1$.

Therefore the normalized entropy measures of equation (3) and (4) are

$$e(NCC) = -K\sum_{i=1}^{N}\sum_{j\neq i}^{N}\frac{NCC_{ij}}{S_{NCC}}\ln\frac{NCC_{ij}}{S_{NCC}} \tag{5}$$

$$e(MMD) = -K\sum_{i=1}^{N}\sum_{j\neq i}^{N}\frac{MMD_{ij}}{S_{MMD}}\ln\frac{MMD_{ij}}{S_{MMD}} \tag{6}$$

We impose a large weight for a criterion when the corresponding entropy measure is small since the information transmitted by the criterion is great (i.e., there exists great difference between the values of the criterion). The weights are calculated as follows:

$$W_{NCC} = \frac{1-e(NCC)}{2-(e(NCC)+e(MMD))} \tag{7}$$

$$W_{MMD} = \frac{1-e(MMD)}{2-(e(NCC)+e(MMD))} \tag{8}$$

Using the entropy method, we propose a board's similarity coefficient of board *i* and *j* as follows;

$$s_{ij} = W_{NCC}s_{ij}^{NCC} + W_{MMD}s_{ij}^{MMD} \tag{9}$$

where s_{ij}^{NCC} is the component similarity as shown in equation (1) and s_{ij}^{MMD} is the MMD based geometric similarity as shown in equation (2). It is important to note that the entropy method can easily be extended to the development of board's similarity coefficient with more than two criteria.

EXPERIMENTS

Leon and Jeong (2004) considered a generic machine that has 70 feeder slots with 20mm between the slots. The board dimensions are maximum 320mm × 245mm and the coordinates for each board were randomly generated from uniform distributions as follows: X=635+U(0,245), Y=254+U(0,320). The home position coordinate is (0,0) and the first feeder slot location is (457,0). The number of component types required per board were generated from U(6,20) from 70 different component types. We considered the time to install or remove feeder, 30(sec). The head velocity was tested for 100(mm/sec). The batch size of boards were generated from U[50,100]. Also the total number of boards were generated from U[5,15].

The placement locations and the corresponding component types were generated from a seed board. A seed board is created with location ($L_{sx}(i)$, $L_{sy}(i)$)and corresponding component type $C_s(i)$ for ith placement location. We fixed the number of placement location to 50 for the seed board. Then based on the seed board, another board (i.e., a child board) is created using the following formula;

$$L_{cx}(i)= L_{sx}(i)+ 0.5\times 245\times \mathrm{U}(-1,1) \tag{10}$$

$$L_{cy}(i)= L_{sy}(i)+ 0.5\times 320\times \mathrm{U}(-1,1) \tag{11}$$

$$C_c(i)= \begin{cases} C_s(i) & \text{with probability } C \\ U(1, NC_c) & \text{otherwise} \end{cases} \tag{12}$$

Where $L_{cx}(i)$ is the x-coordinate of ith placement location for child board and $L_{cy}(i)$ is the y-coordinate. $C_c(i)$ is the component types of ith placement location for the child board. NC_c is the number of component type of the child board c.

We generated 20 random problems and for each random problem, we applied 6 different levels of the feeder capacity 20, 30, 40, 50, 60, 70. In this test, we compare NCC considering only component similarity, MMD considering only geometric similarity, PLM giving equal weight for component similarity and geometric similarity and ENT combining component similarity and geometric similarity using entropy method.

<u>Analysis of test results</u>

Figure 1, 2, 3 shows the average setup time, placement time and makespan of NCC, PLM, MMD and ENT. Figure 1 shows that NCC and PLM tend to perform better as the feeder capacity increases in terms of setup time. However, MMD and ENT do not reduce the setup time much even if the feeder capacity does not restrict the solution space. This is because MMD and ENT achieve an improvement in the reduction of the placement time instead of setup time as shown in Figure 2. The figure indicates that the placement time of NCC, PLM and MMD increases as the feeder capacity increases. However, the placement time of ENT does not increase regardless of the feeder capacity. This implies that ENT assigns the larger weight for the geometric similarity of boards under consideration. As a result, ENT dominates NCC, PLM and MMD by reducing 11.5%, 7.9% and 4.1% of makespan relatively as shown in Figure 3. This result implies that ENT balances the tradeoff between the setup time and the placement time and finds the solution that minimizes the makespan.

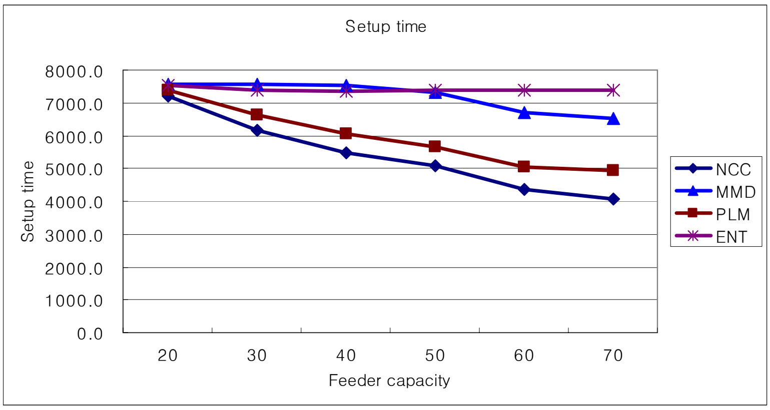

Figure 1. Result of setup time

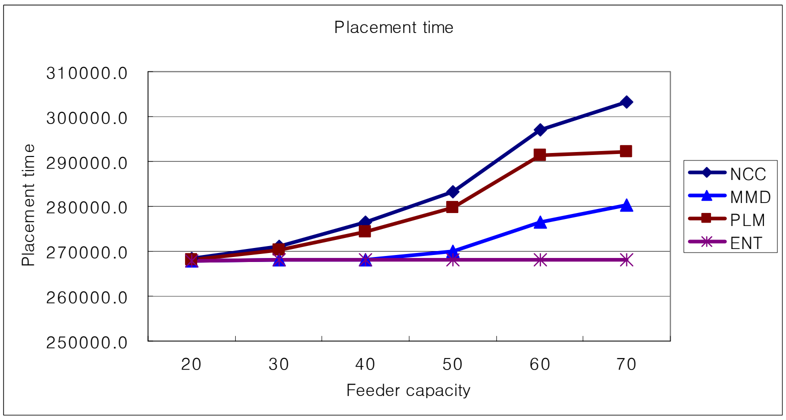

Figure 2. Result of placement time

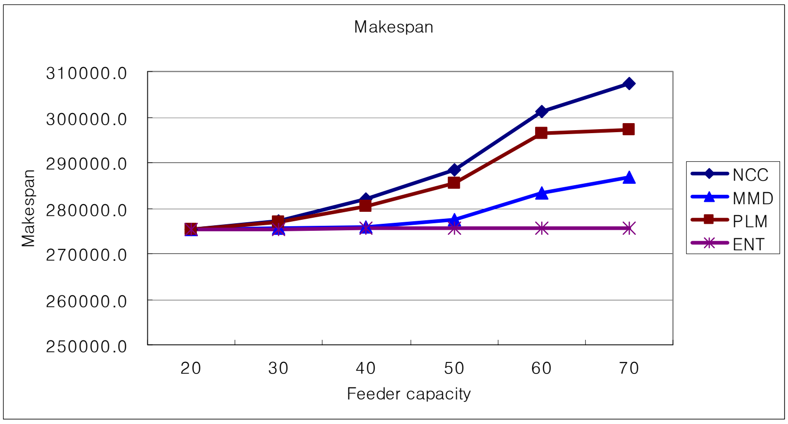

Figure 3. Result of makespan

CONCLUSION

This paper has presented an improved group setup strategy based on entropy method considering both component similarity and geometric similarity. It has demonstrated how the entropy method determines weights for different criteria to adapt to a variety of production conditions. The entropy based group setup strategy dominated NCC, PLM and MMD based group strategy under the condition that the feeder capacity constraints are not binding constraint. Future research includes the extension of the experiments to a variety of production conditions and the consideration of multiple criteria in grouping PCBs (e.g., due dates).

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