Research on Tolerance Redistribution Method Based on Measurement Data

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Abstract. As the performance requirements of aircrafts increase, the mechanical structure of the product is more complicated and the requirements for assembly are getting higher and higher. Due to the accumulation of errors in the processing and assembly process, assembly may not meet the product design requirements. It is necessary to repair some of the processed parts before performing the assembly process. This paper proposes an assembly simulation analysis and a tolerance redistribution approach based on measurement data that is making decisions on which part should be repaired. Firstly, the processed parts and assembly fixture are measured by measuring devices and fitted into the digital model with measurement data. Secondly, the assembled digital simulation is performed to verify whether the processed parts can be assembled successfully. Finally, if the parts cannot be assembled successfully, an improved genetic algorithm is used to optimize the tolerance to form a repair scheme.

Keywords: Measurement data; Assembly simulation; Iterative optimization; Assembly repair

1. Introduction

Aircraft products are more complicated compared to general mechanical products. The number of parts is more, the assembly execution is more difficult, and the control process of assembly is more complicated. Meanwhile, since the aerodynamic performance and structural strength of the aircraft are related to the error in the manufacture and assembly of the aircraft components and products, the error in manufacturing and assembly may lead to a decrease in the quality of the assembly, thereby loss the performance of the aircraft. Consequently, assembly results may not satisfy the process requirements. Therefore, the analysis and optimization of assembly error during aircraft assembly is an urgent problem to be solved.

With the development of computer technology, Computer Aided Tolerancing (CAT) has been widely used in the current processing and assembly process. It can solve the problems that the occurrence of assembly errors leading to unsatisfactory process requirements to some extent. With the development of CAT technology, many experts and scholars have focused on the relationship between assembly...
tolerance and assembly performance. Zhang established the relationship between the assembly performance and tolerance based on traditional assembly dimension chain with the consideration of the assembly performance [1]. Oureshi proposed a mathematical formula for tolerance analysis that verifies that the assembly requirements of the product are met within acceptable tolerances and acceptable tolerances using the Monte Carlo method [2]. Ghali employed CAT methods to study and analyze the effects of tolerance values on post-production and assembly early in the design process [3]. Tang disassembled the large-scale nonlinear problem into a series of sub-problems by analyzing the nonlinear relational view of the weighted graph tree model, and the complexity of the overall tolerance distribution solution by solving the sub-problems were reduced [4]. Those scholars analyzed the tolerance distribution of the aircraft model where the theoretical model is used, but in practice many random error may occur, resulting in the tolerance of the actual parts or assembly process may not meet the actual assembly needs.

The theoretical model cannot establish the information transmission mechanism in the design, manufacture and assembly process of the product completely. In order to solve these problems, scholars were no longer satisfied with the analysis on the theoretical model, but paid more attention to simulating the real assembly situation and solving practical problems. Some research worked on the error accumulation in the process of dimensional chain transfer. Based on the minimum region constraint degree of freedom associated with geometric error, Guo combined the three-dimensional convex hull to construct the minimum region. A geometric error evaluation method was proposed based on the minimum region method [5]. Liu studied the error in the manufacturing and assembly process, and dealt with the difficulty to express and error transmission of parts manufacturing error information [6]. Zhang predicted the assembly accuracy by assembly positioning of parts, and proposed an assembly simulation positioning method based on surface constraint matching algorithm [7]. According to multi-color set theory, Li combined the joint surface and error relation contour matrix (JSS) which described the assembly relationship, joint surface type and error transfer characteristics, the error transfer characteristics of the surface of common assembly joints were then analyzed [8]. Zhao established a method for calculating the error bound by establishing a planar single-ring mechanism assembly uncertainty analysis model. In this work, the randomness of the assembly joint gap was solved for the purpose of satisfying the product design requirements [9]. Chen proposed the statistical analysis method of assembly error for geometric error and material error of coupled parts by using first-order perturbation theory and finite element method [10]. Cai and Qiao proposed a rigid-flexible mixed variable model, which applied the transformation relationship between different coordinate systems to represent the spatial relationship between the theory and error of the assembly unit [11]. The research of above mainly focus on mathematical modeling analysis at a certain point in the assembly process, and lack analysis of the overall assembly performance, which is difficult to practically apply in actual product processing and assembly processes.

This paper combines traditional tolerance technology and actual assembly error analysis, using measurement technology and model reconstruction technology to analyze the error of real product assembly. On the basis of obtaining the actual measured point cloud data of the actual machined parts, the part reconstruction technology is used to re-fit the measured point cloud data to form the model of measurement data. The model with measurement data is used to replace the theoretical model for assembly error analysis, in order to find the suitable parts being repaired. Using the model with measurement data analysis, on the one side, the actual assembly situation of the product can be predicted more accurately. On the other side, by analyzing the assembly simulation results of the product, the problems in the assembly can be found as well as in manufacture, process and design phases. Hence, the product design can be then optimized and the process methods can be improved. In the meantime, the information transmission in the whole product development phases could be enhanced, the product development cycle could be shortened, and the development cost is reduced. The overall process of assembly simulation based on the model with measurement data is shown in Fig. 1.
2. Error analysis during assembly modeling
The error types from the establishment of the part processing model to the assembly model establishment mainly include positioning error, measurement error, machining error, fitting reconstruction error, assembly constraint error between different parts and random error at the assembly site. The measurement error, machining error and fitting error constitute the feature error of the part in the digital space. The part error positioning error, assembly constraint error and assembly site random error together constitute the assembly error of the assembly simulation, as shown in Fig. 2.

Fig. 2 Assembly error analysis

In this paper, the model reconstruction is based on the feature unit, and the measured point cloud is re-fitted into the measured feature to form the measured data part model. In order to enhance the accuracy of the assembly simulation, it is necessary to minimize the error generated during the measurement and fitting process in the simulation. Selecting the appropriate measuring equipment and making a reasonable measurement plan during the measurement process can reduce the measurement error.

This paper applies the three-coordinate measuring instrument as the data acquisition device for the actual processed parts, and the measurement data point cloud is generated according to the measurement plan set in the process stage. In the fitting stage, the point cloud obtained by the coordinate measuring instrument is used for noise reduction and data simplified. Then the point cloud is divided into regions
according to the features on the part, and consequently the features are fitted. Finally the new part model based on measurement data is formed.

In addition to the machining error of the parts, deviations are also generated during the assembly process. The constraint error is between the two features and the theoretical position of the actual phase matching. Due to the geometric error of the surface of the matching feature, there are peaks and valleys on the surface, which directly affects the position and posture of the two parts when they are assembled, and deviates from the ideal assembly position.

Combining the errors of the above analysis with the traditional tolerance analysis, the actual manufacturing and assembly errors are added on the basis of the theoretical dimension chain, so that the tolerance analysis can reflect the assembly of the product more accurately, as shown in Fig. 3.

![Fig. 3 Tolerance analysis and optimization based on model of measurement data](image)

Through the analysis of the dimensional chain, the unreasonable part of the dimensional chain is found and the tolerance is re-assigned. The tolerance distribution no longer refers to the amount of error allowed on the theoretical model, but the amount of parts that need to be repaired in the model with measurement data.

3. Assembly simulation tolerance analysis based on measurement data

As described above, this paper works on the error analysis based on the traditional tolerance analysis. The theoretical model used for the assembly simulation is replaced by the model with measurement data. The tolerance analysis is then performed under the measurement data model. Tolerance analysis based on measurement data mainly includes tolerance in modeling and assembly simulation calculation, as shown in Fig. 4.

![Fig. 4 Tolerance analysis and optimization based on model of measurement data](image)

3.1. Tolerance modeling based on measurement data

First, according to the assembly process, the assembly sequence and positioning reference of the product are determined. The assembly relationship between the parts is defined to form the assembly process model of the product. The dimensional chain is searched based on the model to form an assembly
dimension chain. The assembly deviations are added, as mentioned in the previous chapter, to the corresponding features to simulate the real assembly environment.

Fig. 4 Tolerance redistribution based on measured data

Consequently, it is necessary to define a closed loop. The closed loop is a natural part (indirectly obtained) of the product assembly. It is a ring that needs to be guaranteed in the dimensional chain and is also an important factor of verifying the assembly quality of the product. Closed rings are mostly judged by measuring the critical dimensions of the product, such as the gap or step between two part planes. The closed loop is formed by the transfer of individual parts through the dimensional chain. The key factor affecting the size of the closed loop measurement is the accumulation of the deviations in individual constituent loops. The measurement of the closed loop is mainly divided into distance measurement and angle measurement. The distance measurement mainly includes plane gap measurement, plane step difference measurement, and axis position measurement.

The calculation for tolerance analysis in this paper is based on the analysis of 3DCS (Dimensional Control Systems), a commercial size analysis software that examines whether the product assembly meets the design requirements by analyzing the assembly dimension chain. In this paper, 3DCS is used as the computational solver for tolerance distribution. It is verified whether the tolerance value of the model redistribution can make the assembly of the product meet the required satisfaction. Therefore, it is necessary to convert the dimensional chain in the model into a 3DCS identifiable size chain, wherein the closed loop is an important one. The requirement of the closed loop needs to be converted into the measurement in the 3DCS. In order to reduce the complexity of assembly simulation, it is often necessary to convert feature measurements into measurements for discrete points.

For example, for two plane gap measurements, the points belonging to three different lines on the plane can be used instead of the related plane, and the corresponding three points can be found on the other plane that cooperates with it. Thus, the gap measurement between the two planes is converted into the distance measurement between the three pairs of points. Similarly, the axial position measurement is the comparison between the actual axial position of the product and the theoretical position. The theoretical position is mostly calibrated in the fixture, while the actual position is located on the part. By comparing the theoretical position and the actual position of the axis, it can be determined whether the axial position meets the design requirements of the product.
Based on the steps described above, the tolerance analysis model is established. Next, the assembly simulation needs to be performed.

3.2. Assembly simulation calculation
The Monte Carlo method has been widely used in the assembly simulation process. It is a method for simulating probability and statistics by computer. As the assembly simulation is run repeatedly, the statistical data can be obtained in order to acquire the credible results of the simulation. Afterwards, a list consisting of the contribution of every feature or point is calculated for each closed loop measurement. If the measurement does not meet the requirements, it can be appropriately adjusted according to the contribution value.

The contribution of the statistical situation is calculated as follows.

\[
\text{contrib}_i = \left( \frac{\partial U}{\partial x_i} \times \sigma_{x_i} \right)^2 \times \frac{100}{\sigma_U}
\]

where \( x_i \) is the ith variable representing each feature, \( U \) is the measurement object, \( \sigma_{x_i} \) is the standard error of \( x_i \), and \( \sigma_U \) is the standard error of \( U \).

If the results of the assembly simulation using real measurement data cannot meet the design or process requirements, it needs to find out the very part or parts in the dimension chain that affects the assembly. Then, the contribution values of the constituent loops to the closed loops in the dimensional chain, which leads to the unsatisfactory results, are calculated. The constituent loops are sorted according to the contribution values. Finally, according to the difference of contribution in the simulation results, the ring size is adjusted iteratively, in order that the size range which satisfies the assembly requirements can be found.

4. Iterative adjustment of tolerance based on measured data
Through the simulation calculation of the above process, the overshoot of all closed loop measurements can be obtained from the simulation results. If the tolerance is within an acceptable range (the proportion of the simulated 2000 assembly simulations that meets the requirements is higher than the specified percentage, eg ±3σ), then it is expected that the currently processed parts can be assembled under the current assembly process plan, while the design and process requirements can be achieved.

Conversely, if the out-of-tolerance rate is within an unacceptable range, then tolerance-based redistribution using the current measurement data is required to be performed. In other words, without changing the assembly process plan, through the analysis of the assembly dimension chain, the component ring that affects the assembly success rate needs to be found and the scope of the repair processing needs to be decided. Furthermore, the repair position and the repair size needs to be determined.

Before the assembly repair scheme performs, the size chain relationship needs to be converted into a relationship that the 3DCS solver can recognize. In 3DCS, the direction and length of the constituent loops and closed loops in the dimensional chain are converted into directions and distances between corresponding points in space. As shown in the Fig. 5, the closed loop represents the measurement point pair of the part where the two part features match in assembly. The constituent loop represents the distance between every two assembly control points, which are formed by the assembly constraint relationship.
Then, the closed loop which does not meet the assembly requirements needs to be found. The size chain is analyzed where the closed loop is located. The constituent loops which have a large influence on the closed loop is then determined. This process is performed with the contribution analysis as described above. With the experimental practice, it is found that the selection set of features with the contribution value greater than 10% can generally solve the problem of closed loop. These features that may be repaired are used as an alternative feature of tolerance redistribution.

Since the features have been converted into discrete points, i.e., using three points to represent the plane feature. The feature points on the constituent loops can be used as the input variables in the calculation. The measurement of the closed loop also replaces the gap or step of the plane with 3 pairs of points as described above, which converts the distance measurement between the corresponding point pairs and uses the measured value as the output. Here, the difference between the measured distance and the theoretical distance of the point pairs is smaller, the performance is better. In that case, the tolerance allocation problem is transformed into a multivariate and multi-objective optimization problem.

Because there may be conflicts and competition among the various objectives, the outcome of this optimization problem is usually a solution set. The traditional genetic algorithm cannot solve the problem appropriately. Therefore, this paper proposes a combined genetic algorithm to seek for optimal or near optimal solutions.

The factors in combined genetic algorithm GA are represented as the following seven-dimensional vector form.

$$GA = (N_{pop}, N_{gen}, \Omega, \omega, \text{fitness}, \text{fitness}, \text{selection rule})$$

where $N_{pop}$ is the population size, $N_{gen}$ is the iterative times, $\Omega$ is the genetic operator (crossover and mutation) and their probability set, $\text{fitness}$ is the fitness function of the subpopulation, $\omega$ is the selection rule of the subpopulation, $\text{fitness}$ is the fitness function of the recombined population, and $\text{selection rule}$ is the selection rule of the recombined population.

In the combined genetic algorithm, the multi-objective optimization problem is divided into several independent single objective optimization problems before performing the selection operation. According to the number of optimization objectives, all individual chromosomes in the initial population are divided into corresponding number of subpopulation groups, and a selection operation based on the fitness function is performed for each subpopulation group.

Consequently, the selected subpopulation individuals with relatively high fitness value are recombined into new large populations, and the squares of the single objective function are summed up to form a new objective function, which is employed in the selection, crossover, mutation operations for the recombined population. After several iterations, a solution that satisfies all the closed loop measurement objectives can be obtained, shown as Fig. 6. The specific steps of the combined GA approach are described as follows:
The feature points with the greater contribution values than 10% in the 3DCS assembly simulation report are selected, and the number of feature points is obtained thereafter. Then, the range of acceptable repair values of the feature points is determined according to the assembly process procedure.

According to the product assembly process procedure and the CAD model, the assembly requirements that the closed loops need to be guaranteed, are determined as the objectives of the optimization problem. Here the number of objective is recorded.

A form of the solution to the optimization problem is converted into a representation of a chromosome individual consisting of several genes. The genes in the chromosome represent the repair values of control points for each of the constituent loops. The number of iterations and the number of populations are set, and an initial population is generated.

![Genetic algorithm optimization](image)

**Fig. 6 Genetic algorithm optimization**

The populations are grouped equally according to the number of objectives, and each group corresponds to an optimization objective.

Each individual chromosome, representing a solution consisting of repair values of the control points, is set to be the input of 3DCS solver for simulation and calculation. For each subpopulation, the chromosomes with higher fitness values, corresponding to each respective objective, are selected. Here, the fitness function is calculated as shown in Eq. (3). The greater the function value is, the higher the fitness of the individual is in the corresponding subpopulation, and the easier this chromosome is to be selected.

\[
fitness = \frac{1}{mean - Normal}
\]  

Where fitness is the contribution value of each measurement area, mean is the statistical median value of the corresponding measurement area, and Normal is the theoretical value of the measurement.

The Roulette Wheel selection method is employed as the subpopulation selection rule \( f_s \). The possibility of each chromosome being selected as a parent is the proportional to its fitness value. Parents selected from subpopulations are recombined into a new population group.
In the newly recombinated population, the simulation and calculation result of the solver is used again, where the contribution values represented by chromosome fitness functions. The function here is calculated as shown in Eq. (4). The descendant selection rule $F_{sel}$ of large populations is the roulette method, and the individuals with higher fitness are more likely to be selected.

$$FITNESS = \frac{1}{\sum_{i=1}^{N} (mean_i - Normal)}$$

where $FITNESS$ is the total fitness value of all measurements; mean is the statistical median of the corresponding measurement area; Normal is the theoretical value of the measurement, $n$ is the number of measurements.

The Roulette Wheel is adopted again and newly formed group of parent chromosomes are then generated.

Parent chromosomes produce offsprings, based on single-cutoff-point crossover. The probability of crossover execution is set to be $\Omega_c$. When the crossover probability values of two parents are greater than $\Omega_c$, the crossover is executed. Fig. 7 shows an example of the crossover operation.

|        | Before crossover | After crossover |
|--------|------------------|-----------------|
| $H_1^*$ | $a_1a_2\cdots a_n$ | $a_1a_2\cdots a_n$ |
| $H_2^*$ | $b_1b_2\cdots b_n$ | $b_1b_2\cdots b_n$ |

**Fig. 7** Crossover operation

In order to increase the diversity of the population, the mutation operation is performed after the crossover. The mutation probability is set to be $\Omega_v$. When the mutation probability of a certain gene in a certain chromosome is greater than $\Omega_v$, the gene value is changed to complete the mutation operation. For example, if the gene $a_i$ is mutated, the new gene becomes $(a_i + u)$, where $u$ is a random number in a fixed range such as $[-0.2, 0.2]$.

Determine whether the pre-defined number of iterations is reached. If not, return to step (3).

After a certain iterations finish, or the individuals in the population stop changing, the chromosomes are converged to one or several solutions which are able to satisfy the assembly requirements. The mechanism ends. These optimal or near optimal solutions can be adopted before the assembly execution. Thus which processed parts needs to be repaired and the repair values are then determined.

5. Example analysis of typical assembly

In this paper, a typical frame-like component is used as an example for analyzing the approach described above, as shown in Fig. 8. The assembly procedure is performed as follow. First, the skin (part1) is positioned on the basis of the frame. Then the rib (part3) is assembled onto the skin. Finally, the stringer (part2) is assembled onto the skin. There is a gap between the stringer and the rib, and the required gap size is $6 \pm 0.5$ mm.
5.1. Assembly simulation based on measured data
Using the tolerance analysis software 3DCS, the assembly simulation analysis model of the assembly is established according to the actual assembly process plan, and the gap requirements of the assembly are converted into the measurement scheme recognized by 3DCS.

The specific method is taking four measurements of the four vertices on the measurement gap surface of Part 3 and Part 2, respectively named up_1, up_2, down_1, down_2. The gap measurement between Part 2 and Part 3 is replaced by the measurement between these four pairs of point. Then, the error in the assembly process is added for all the assembly joints. The deviation value is determined according to the assembly process procedure and the error analysis calculation. The measurement and assembly error here is assigned to be 0.1mm. The measurement points are shown in Fig. 9. The inside of the frame is the gap between the stringer and the rib.

5.2. Simulation analysis based on measured data
As shown in Fig. 8, the point cloud measured by the three coordinates is simplified. The assembly simulation has been run for 2000 times, and the results are shown in Fig. 10.
Fig. 10 Analysis of measured data

It can be found from the simulation assembly results that the points with the maximum contribution values are red_b1 and red_b2 of Part3, yellow_b1 and yellow_b2 of Part2, red_b1 and red_b2, yellow_b1 and yellow_b2 of Part1. Consequently, these points with greater contribution values are mainly located on the connection between Part3 and Part1, as well as on the connection between Part2 and Part1. From the analysis of the measurement data, it can be found that there are certain processing errors on the plane belonging to Part1, where the Part3’s corresponding plane is matched during assembling. In that case, we can estimate that the results of the simulation analysis were credible. Moreover, through the analysis of the contribution value for each point, we can also find other solutions to meet the gap assembly requirements, so the 3DCS contribution analysis can find out where the assembly problems.

5.3. 3DCS-based tolerance redistribution with measurement data

By analyzing the computational results of 3DCS simulation, the measurement data points with a contribution greater than 10% are selected. These points will be used as variable inputs for tolerance distribution. Next, the tolerance variable is initialized, and the tolerance variable value is assigned to be the input for the 3DCS.

The Monte Carlo method is used for 2000 assembly simulation, and the results are statistically analyzed. The median of the statistical measurements was compared with the theoretical median, and individuals with a small median difference were retained.

In the GA steps as described in the last chapter, the offspring need to be selected twice. The first selection is for each measurement objective, and the individuals whose statistical median values deviate from the median of the measurement theory are selected thereafter. After chromosomes recombination, the reciprocal of the square sum for all the measured statistical median values and the theoretical median values are selected. The individual chromosome with the larger value is more likely to be selected. Then, after crossover and mutation, a new child chromosome is generated. Its corresponding solution is assigned as the new input to the 3DCS solver for the next iteration. After 500 times iteration, we can find the optimal individual with the smallest square sum. The iteration results are shown in Fig. 11.
The variable with the largest FITNESS value is input to the solver for verification, and the result is shown in Fig. 12.

As can be seen from the results of the iterative process, all the measurements are within the allowable tolerance. The statistical median value of the errors in the maximum closed loop measurement is 6.27, and the difference from the theoretical measurement value is 0.27. The difference between the measurement value and the theoretical value is small, resulting in assembly requirements satisfaction. The feasibility of using the combined genetic algorithm to iteratively optimize the amount of repair scheme is verified.

6. Summary and outlook
This paper proposes a tolerance redistribution method based on measurement data. The dimensional analysis software 3DCS is applied for acquiring the assembly simulation results, while the combined genetic algorithm is used to adjust the size of the processed parts. The tolerance adjustment amount is then calculated to achieve the optimal assembly quality. Since the types of assembly features currently established are relatively simple, in future the approach described in this paper will be applied with enriched assembly feature types and with the consideration of more complex surfaces. Moreover, in order to increase the authenticity of the assembly simulation, finite element analysis could be involved to solve the problems of clamping deformation, loose clip rebound and other force deformation during the assembly process of flexible parts.
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