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A failure feature identification method for adaptive remanufacturing

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ABSTRACT

Accurate and efficient identification of failure features of returned used mechanical components/parts is the prerequisite for adaptive remanufacturing. However, due to part-to-part variation, it is error-prone and ad-hoc to manual inspect each part with various defects. This paper proposes a failure feature identification method for adaptive remanufacturing. An innovative identification algorithm is developed to quickly identify the failure features which integrates point-clouds generation, fine-registration and Boolean calculation. For the identified features, hybrid tool path for adaptive remanufacturing can be generated automatically. A turbine blade is taken as an example to demonstrate the efficiency and reliability of the proposed method.

1. Introduction

Remanufacturing is regarded as a promising eco-friendly industry that returns End-of-Life (EOL) products to a “like new” functional state with a warranty to match (Jones et al., 2012). It is a sustainable manufacturing industry with great benefits subject to environmental, social and economic gains (Feng et al., 2016; Sundin and Bras, 2005).

However, remanufacturing is usually a complex procedure including disassembly, cleaning, inspection, repair, test, and reassembly. Among these processes, the inspection of the returned used mechanical components/parts to identify failures is the prerequisite for adaptive remanufacturing (Errington and Childe, 2013; Ridley and Ijomah, 2015). It is because that the identified failure features not only influence the subsequent decision-making of remanufacturing strategy and process planning but also lay a foundation for the subsequent implementation of adaptive remanufacturing technologies including Additive Manufacturing (AM) to deposit material and Subtractive Manufacturing (SM) to remove material. Fig. 1 shows some failure features and their influences on remanufacturing. For example, failure volume will influence the selection of remanufacturing strategy as well as the remanufacturing cost and time. In addition, the failure features of each returned defective part, which is the raw material for remanufacturing, exhibits great uncertainties subject to failure location, failure mode, failure volume, failure degree, etc. It is caused by different service operation environment, service life, and maintenance measures (Kin et al., 2014). Thus, due to part-to-part failure variation, each remanufacturing part needs manual treatment separately and requires customized remanufacturing strategy and process planning which mainly depends on the skill level of the operators and their experience. The failure feature identification is still an error-prone and ad-hoc work which greatly limits the remanufacturing efficiency, quality and success rate. There is a lack of deep understanding of failure features and an intelligent method for failure feature inspection, especially the quantitative analysis. This paper aims to develop an efficient method to identify failure features of returned used parts for adaptive remanufacturing.

Due to the vital significance of failure feature identification for remanufacturing, it has received increasing attention in recent years. Du et al. (2017) proposed a failure mode analysis-based methodology for remanufactured machine tools. Wang et al. (2017) employed the Fault Tree Analysis (FTA) model to identify fault features of used parts, based on which alternative remanufacturing process plans can be obtained. However, these studies only analyzed failure mode for used parts at the qualitative level. Failure features of failure location, failure volume and failure degree of the used parts arriving in the remanufacturing system have not been discussed.

To facilitate a quick and accurate acquisition of failure location and failure volume of returned used parts, Reverse Engi-

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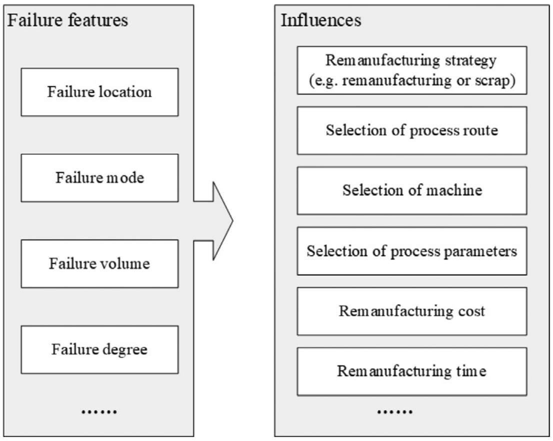

Fig. 1. Failure features and influences on remanufacturing.

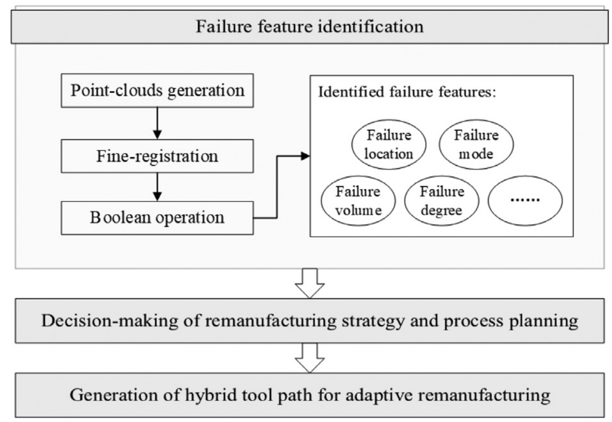

Fig. 2. The framework of the proposed failure feature identification method.

neering (RE) technologies are employed widely in recent years. The three-dimensional (3D) model of the defective part is reconstructed in the form of 3D data. The identification of failure location and extraction of failure volume can be achieved through registration and Boolean calculation by comparing the original Computer Aided Design (CAD) model with the 3D model of the defective part (Santamaría et al., 2011). Gao et al. (2006) presented a RE based adaptive restoration approach, namely polygonal modelling, to recreate worn parts and extract repair geometry for the build-up process and machining process to remove weld bead. Wilson et al. (2014) developed a semi-automated geometric algorithm based on Prominent Cross Sections (PCS) for repairing defective voids that appear on gas turbine airfoils after extensive use. Hou et al. (2018) proposed an adaptive repair surface modelling method for worn blades. It integrates restructuring welded surface and machining surface which can be utilized in Computer Aided Manufacture (CAM) system for the welding process and machining process. Zheng et al. (2018) developed an algorithm for remanufacturing of damaged parts where Non-uniform Rational B-splines (NURBS) are employed to reconstruct the surface of the defective part to extract failure volume. Feng et al. (2018) proposed a repair volume extraction approach for damaged parts in the field of remanufacturing repair. These studies provided approaches for identifying failure locations and extracting the geometry representation of failure volume, however, little research is explored to quantitative analysis of failure volume and failure degree. To effectively generate advisable decision-making of remanufacturing strategy and process planning and thereby generate a hybrid tool path for adaptive remanufacturing, basic problems like quantitative identification for failure features of returned used parts need to be solved.

In addition, these methods above are mostly based on the reconstruction of NURBS surface or polygonal model which is a complex and time-consuming process. Comparing the point-clouds between the original part and defective part directly provides a feasible and more efficient approach to identify failure features instead of reconstructing NURBS surface and polygonal model. With the comparison results, failure volume and failure degree of various defects can be qualified accurately. Little studies have been reported for failure features identification using point-clouds to the best known of authors. With the purpose of identifying failure features accurately and efficiently, this paper proposes a failure feature identification method for adaptive remanufacturing, which combines point-clouds generation, fine-registration, and Boolean calculation. For the identified failure features, the hybrid tool path of AM and SM for adaptive remanufacturing can be generated automatically.

2. Framework of failure feature identification method

Fig. 2 shows the framework of the proposed failure feature identification method for adaptive remanufacturing. Point-clouds of the original model and defective model are generated and used to quickly identify failure features including failure mode, failure location, failure volume and failure degree. According to the identified failure features, operators can make advisable decisions on remanufacturing strategy and process planning quickly. For the identified defects, hybrid tool path of AM and SM can be generated to remanufacturing the defective part back to a like-new status. The procedure of the proposed remanufacturing method is detailed in the following sections.

2.1. Point-clouds generation

With the rapid development of RE technology, it is easy to obtain the point-clouds to represent the geometry of the defective part. Common point-clouds generation technologies include laser scanning, coordinate measurement machine, stereo scanning, structured light scanning. In this study, the point-clouds model is generated using structured light scanning and used directly for the identifications of failure features. Thus, there is no need to reconstruct the surface or polygonal model which saves a lot of time and labour.

The CAD model of the original part is usually available and the point-clouds of the original model can be generated from the CAD model quickly. Firstly, the CAD model is converted to Stereo Lithographic (STL) format, a mesh model with numbers of quadratic elements can be generated to represent the geometry with a mesh operation. As an important property of the mesh model, a number of elements nodes can be obtained and converted to point-clouds of the geometry model. It is noted that a finer mesh has more elements as well as more nodes but costs more time and computer resources. The degree of refinement of the mesh can be controlled in MATLAB programming by setting different ‘Hmax’, ‘Hmin’ and ‘MeshGradation’ which mean maximum mesh edge length, minimum mesh edge length, and rate of mesh growth. For example, the smaller the ‘Hmax’, the higher the degree of refinement and more points. After the initial point-clouds generation, outliers whose distance to the center of mass of the point-clouds are more than three times the standard deviation are removed to form a filtered and more accurate point-clouds.

2.2. Fine registration of the point-clouds

Once the filtered point-clouds have been generated successfully, two point-clouds of the original model and defective model need

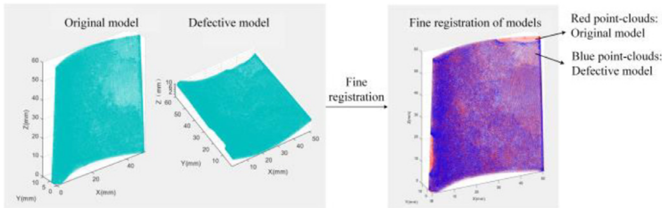

Fig. 3. Fine-registration of point-clouds of two models.

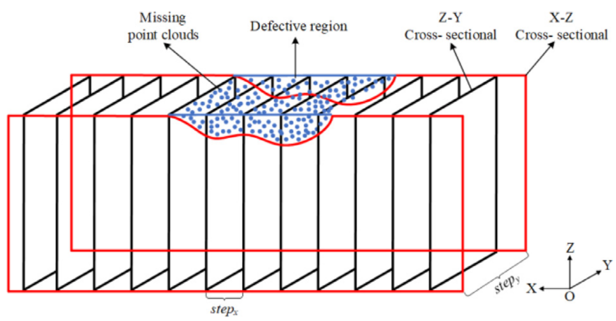

Fig. 4. Slices of the point-clouds to identify failure location and volume.

to be aligned for subsequent failure feature identification. In this study, the Iterative Closest Point (ICP) algorithm which is a classic point-clouds matching algorithm is introduced to achieve fine registration for the point-clouds of the original model and defective model (Kersten et al., 2016; Marani et al., 2016). Let $P_r = (x_1, x_2, ..., x_{n1})$ and $P_n = (y_1, y_2, ..., y_{n2})$ be the point-clouds of original part and defective part respectively. Through calculating the nearest Euclidean distance, a corresponding point y_i in P_n can be searched for a point x_i in P_r so that a point pair (x_i, y_i) can be determined. Based on the matching point pairs, fine registration for the two point-clouds above can be achieved through the following four steps:

- *Step1*: Search the nearest point in the set of P_n for each point in the set of P_r;
- *Step2*: Calculate a transformation matrix $M_{rn} = [R_{rn}\ T_{rn}]$ to minimize Eq. (2), where R_{rn} is the rotation matrix and T_{rn} is the translation matrix, and k denotes the number of successfully searched matching point pairs.
- *Step3*: Apply the M_{rn} to the point set P_n to obtain a new point set P_n'.
- *Step4*: Estimate the registration error between P_r to P_n'. If the registration error is greater than the user-set threshold, replace P_n with P_n', and repeat step1 to step3 until complete.

As can be seen in Fig. 3, point-clouds of the original and defective models are aligned after multiple iterations using the ICP algorithm, which lays the foundation to compare these two point-clouds for failure feature identification. The red point-clouds represents the original model and the blue point-clouds represents the defective model respectively.

2.3. Identification of failure features

Once the fine registration of point-clouds has been achieved, failure regions can be identified quickly and thereby to analyze failure location, failure mode, failure volume, failure degree, etc. using the developed failure feature identification algorithm.

The boolean calculation is employed to identify the failure regions of the defects where are represented by the point-clouds located in the defective regions, namely missing point-clouds as shown in Fig. 4. Since the defective turbine blade is a 3D object, two cross-sectional integration analysis is carried out to analyze the missing point-clouds for failure features. One cross-sectional analysis is for the X-Z cross-sectional to identify where is the failure area and the other cross-sectional analysis is carried out along Y-axis to identify the depth of the failure region. Before generating the cross-sectionals along X and Y axis, users need to determine the interval between two cross-sectionals, namely $step_x$ and $step_y$ (e.g. 1mm), firstly. The number of cross-sectionals along X and Y axis, namely $Slice_x$ and $Slice_y$, can be obtained using Eq. (1) and Eq. (2), where $length_x$ and $length_y$ are the length and width of the turbine blade respectively. The smaller the interval, the more slices will be generated, which in turn leads to more accurate calculation of failure features. With the extracted missing-points and generated cross-sectionals, the coordinate value of the point-clouds can be obtained to analyze the following failure features.

- The most common failure locations are located at the tip, edge, and surface of the turbine blade. It is easy to identify failure location using the relative position between missing points with original point-clouds.
- Wear and crack are typical failure modes in turbine blades. Currently, in this study, the failure mode can be identified as "Wear" if the failure length and width are larger than the depth simultaneously, otherwise, the failure mode can be identified as "Crack".
- As for the identification of failure volume, the defective area in the X-Z cross-section is firstly calculated by Eq. (3) and then the failure volume can be calculated by Eq. (4), where x_{max} and x_{min} means maximum and minimum x coordinates of the missing points respectively, similarly, y_{max} and y_{min} means maximum and minimum y coordinates of the missing points. $Z_{original}$ and $Z_{defective}$ means the maximum and minimum value of z coordinates of original point-clouds and missing points respectively in each intersection line of the X-Z cross-sectional and the Z-Y cross-sectionals.

$$Slice_x = \frac{length_x}{step_x} \tag{1}$$

$$Slice_y = \frac{length_y}{step_y} \tag{2}$$

$$Slice_x = \int_{x\min}^{x\max} \left(Z_{original} - Z_{defective}\right) dx \tag{3}$$

$$Volume = \int_{y\min}^{y\max} Area\, dy \tag{4}$$

- Base on the failure mode and failure volume, the failure degree can be quantified and scored like Table 1 shows according to Wang et al. (Ridley and Ijomah, 2015).

2.4. Decision-making and tool path generation

After the failure features of the defects are obtained, operators can make advisable decisions on whether to remanufacture the part or not. It is because that the remanufacturability of used parts is associated with technical feasibility, economic feasibility and environmental benefits which are influenced by the identified failure location and failure volume. Based on the identified failure features, an optimal remanufacturing process planning can be generated quickly. In addition, a reference case can be retrieved and reused using the identified failure features as key attributes if there exists a remanufacturing case base, which in turn brings great savings in terms of time and labour.

For the identified failure volume, hybrid tool path of adaptive AM and SM can be generated to repair the defects. SM tool path

Table 1
Quantified score of failure degree of wear and crack.

Failure mode	Volume of damage (mm^3)	Quantified score equation	Quantified score interval [0,10]
Wear	0	–	0
	$0 < x < 50.0$	$q = \frac{x-0}{50.0-0} \times 5$	(0, 5)
	$50.0 \leq x < 100.0$	$q = \frac{x-50.0}{100.0-50.0} \times 5+5$	[5,10)
	$x \geq 100.0$	10	10
Crack	0	–	0
	$0 < x < 10.0$	$q = \frac{x-0}{10.0-0} \times 5$	(0, 5)
	$10.0 \leq x < 20.0$	$q = \frac{x-10.0}{20.0-10.0} \times 5$	[5,10)
	$x \geq 20.0$	10	10

Table 2
Specific identified failure features of defects.

Number of defects	Failure location	Failure mode	Failure volume	Failure degree
1	Blade tip	Wear	31.7672	3.2
2	Blade surface	Wear	65.0302	6.5
3	Blade edge	Wear	131.0857	10

(such as milling tool path) is first generated to remove excess material around the defects to form a regular and smooth surface. It can be done with the aid of a CAM system, e.g. HyperMill, which can not only simulate the repair process but also generate G-code to drive CNC machine for actual material removal. Once the pre-processed surface is obtained, AM tool path (such as laser direct metal deposition tool path) can be generated to deposit material in the defective region layer by layer so as to bring the defective part back to the original geometry. Finally, SM operation (such as grinding) is carried out again to finish the part surface so as to meet the geometry size and accuracy requirement.

3. Implementation and discussion

3.1. Implementation and example

The failure feature identification method for adaptive remanufacturing presented above is implemented by employing the software tool MATLAB R2018a and the used laptop for development runs on Windows 10 operating system with 12GB RAM. A software prototype for failure feature identification has been developed, in which the CAD model of the original part is input and then compared with the point-clouds of the defective part after a serious of processes of point-clouds generation, fine-registration and Boolean calculation. Failure features including failure location, failure mode, failure volume and failure degree can be calculated quickly.

A turbine blade is a kind of typical aero-engine part with complex geometry. It is susceptible to wear or damage because of high-temperature and high-pressure working environment. A defective turbine blade with multi-defects is taken as an example to validate the proposed method.

Fig. 5 demonstrate the identified results of failure features of the turbine blade. Three defects located in the blade tip, blade surface and the blade edge respectively are identified accurately which are represented with red point-clouds in the picture. Table 2 shows specific identified failure features of these three defects.

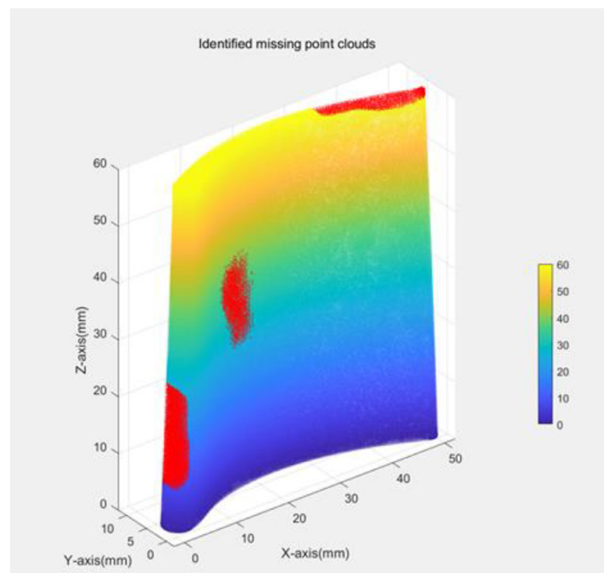

Fig. 5. Identified results of failure features of the defective turbine blade.

3.2. Discussion

Considering the relatively small geometry size of the blade, the parameters of 'Hmax' and 'Hmin' is set to 0.5mm and 0.1mm respectively and 'MeshGradation' is set to 1.5 after several times of trial to obtain higher accuracy and cost less time at the same time. The whole mesh operation is very quick which only takes 24.56 seconds in current laptop configuration. The whole failure feature identification process for the illustrated turbine blade takes less than 3 minutes which not only increases the traditional manual inspection accuracy but also decreases the cost and labour at the same time using the proposed method. Accurate identification of failure features facilitates operators to make strategy and process planning for adaptive remanufacturing. The remanufacturing quality will be influenced by the uncertainty of RE technology, CNC machining, and additive manufacturing. How to generate optimal material removal tool path to form the regular surfaces considering material-saving and workability for AM operation simultaneously has not been discussed so far. The automatic generation of the hybrid tool path for adaptive remanufacturing will also be an important part of future work.

4. Conclusion

Failure feature identification is a significant process for remanufacturing. However, the failure feature identification is still an error-prone and ad-hoc work due to part-to-part variation. An efficient method for failure feature identification is required to ensure the remanufacturing efficiency, quality and success rate. This paper proposed a novel failure feature identification method for adaptive remanufacturing. The failure features such as failure location, failure location, failure volume and failure degree of multi-defects are identified quickly through processes of point-clouds generation, fine registration, and Boolean calculation. The identified results facilitate the decision-making of remanufacturing strategy and process planning as well as generation of the hybrid tool path for adaptive remanufacturing. A defective turbine blade is taken as an example to validate the effectiveness of the proposed method.

The proposed method can be extended to the real application of remanufacturing, enhancing existing remanufacturing technologies and thereby creating more economic and environmental benefits.

CRediT authorship contribution statement

Yan He: Conceptualization, Methodology, Writing - original draft. **Chuanpeng Hao:** Software, Validation, Resources, Data curation. **Yufeng Li:** Formal analysis, Investigation. **Ming K. Lim:** Writing - review & editing, Visualization. **Yan Wang:** Supervision, Project administration, Funding acquisition.

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