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Deviation Modeling and Shape transformation in Design for Additive Manufacturing

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Abstract

Additive Manufacturing (AM) technologies have gained extensive applications due to their capability to manufacture parts with complex shape, architected materials and multiple structure. However, the dimensional and geometrical accuracy of the resulting product remain a bottleneck for AM regarding quality assurance and control. Design for Additive Manufacturing (DfAM) aims at using different methodologies to help designer take into account the technological or geometrical specificities of AM, to maximize product performance during the design stage. As a main concern in DfAM, the consistency between the digital product and the final outcome should be effectively assessed. Therefore, the geometric deviations between designed model and real product should be modeled, in order to derive correction and compensation plans to increase geometrical accuracy, or to predict product performance more precisely. In this paper, a new deviation modeling method based on the STL file is proposed. A new shape transformation method is developed based on contour point displacement. In each slice, systematic deviations are represented by polar and radial functions and random deviations are modeled by translating the contour points with a given distance derived from the random field theory. The proposed method makes a good prediction of both repeatable and unexpected deviations of product shape, thus providing the designer with meaningful information for design improvement.

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Keywords: Digital thread; Geometric Modeling; Shape Transformation; Design for Additive Manufacturing

1. Introduction

Additive Manufacturing (AM), also known as 3D printing, has gained extraordinary popularity and research interest in the past decades, due to its capability to manufacture parts with complex shape, multiple structures and a wide variety of materials. New AM processes and machines have continuously being developed and refined to extend their application to a wider spectrum such as automotive, aerospace, engineering, medicine and biological systems [1].

The layer-wise additive characteristics distinguish AM from traditional manufacturing processes, therefore, the design issues regarding to design knowledge, tools, rules, processes and methodologies, are substantially different [1]. In this context, the concept of Design for Additive Manufacturing (DfAM) is proposed aiming at using different methodologies to help designer take into account the technological or geometrical specificities of AM, to maximize product performance during

the design stage [2]. As one of the main aspects of DfAM, the geometrical validation is to effectively assess the consistency between the digital product and the final outcome [3]. Therefore, the modeling of geometric deviations between designed model and manufactured product becomes more important, based on which corresponding correction and compensation plans can be made on the designed model to increase geometrical accuracy, or to predict product performance more precisely.

As indicated in [4], the AM process consists of a digital dataflow and a subsequent physical workflow. In the former dataflow, first the digital volume or facet models are created based on input 2D images, CAD models, or point clouds obtained from reverse engineering. The models are then repaired to remove errors, and sliced to provide layer information that instructs the machine in the building process. Support structures are also generated if necessary, to ensure the quality and stability of the final product. In the physical workflow, the AM machine fabricates the product from raw

material according to the instructions, after which post-processing procedures like support removal, cleaning, heat treatment and NC machining are executed to ensure the final product quality.

Geometric deviations may arise in both of the abovementioned stages. The facet model, which is commonly represented by the Stereolithography (STL) file, is transformed from the CAD model through triangular approximation, thus chordal deviations are introduced as the Euclidean distance between the STL facet and the CAD surface. In the layer-by-layer building process, additional deviations are introduced due to the “staircase effect”. Moreover, machine errors, process parameter settings and material shrinkage will also bring about deviations that affect the geometric consistency between nominal model and final product. Effective modeling and control of these deviations is obviously critical for an optimal design for AM.

In this paper, a new deviation modeling method based on the STL file is proposed. A shape transformation method is developed based on contour point displacement. The proposed method makes a good prediction of both repeatable and unexpected deviations of product shape, thus providing the designer with meaningful information for design improvement. The paper is structured as follows: in Section 2, existing literature regarding DfAM and shape deviation modeling are reviewed. Different deviation models for AM are explained and compared; in Section 3, the new deviation modeling and shape transformation method is proposed and a case study is given in Section 4; conclusion and future research focus are drawn in Section 5.

2. Literature review

In this section, existing researches on DfAM and shape deviation modeling will be reviewed. A comprehensive overview of current shape deviation modeling approaches for AM will be presented.

2.1. Design for Additive Manufacturing

In spite of the short history of AM technologies, DfAM has gained much research attention and methodological maturity. An early definition of DfAM can be found in [5], based on the concept of Design for Manufacturing and the specificities of AM, DfAM is defined as “Synthesis of shapes, sizes, geometric mesostructures, and material compositions and microstructures to best utilize manufacturing process capabilities to achieve desired performance and other lifecycle objectives”.

In both [2] and [3], a taxonomy is proposed that classifies the current DfAM methods into DfAM for design marketing and DfAM for design assessment. DfAM for design marketing is aimed at guiding designers in the design process by developing intermediate representations (IRs) that consist in guidelines or design features. While DfAM for design assessment focuses on employing acceptability criteria, such as cost, time and manufacturability, to evaluate IRs in the design stage. DfAM for design assessment is further classified into opportunistic DfAM, restrictive DfAM and dual DfAM according to their different ways to assist designers [2], among

which restrictive DfAM methods aim to reach a consistency between the nominal geometric model and the skin model [6] that includes geometric deviations introduced in manufacturing processes, by taking into account the limitations of AM. The focus of this paper right belongs to the restrictive DfAM, since deviation modeling can effectively assist design optimization to ensure the geometric consistency.

2.2. Shape deviation modeling

The modeling of geometric deviations in traditional manufacturing processes has been extensively investigated in researches on geometric dimensioning and tolerancing (GD&T), and especially Computer Aided Tolerancing (CAT). Multiple models have been proposed and some of them are already adopted in commercial CAT tools. However, these models tend to represent deviations as rotational and translational feature defects of the nominal model, while ignoring the predictable and observable form deviations of the product shape that may reflect the influence of actual working condition and environment. With this regard, the concept of Skin Model Shapes (SMS) has emerged as a computational model for geometrical variations management [7]. It considers geometric deviations that are expected, predicted or already observed in real manufacturing processes, and incorporates the deviations directly in the shape model based on a discrete geometry framework. The main contributions of the SMS have been highlighted recently in different applications, such as assembly, contact modeling, tolerance analysis, and motion tolerancing [8]. The promising application of SMS in shape deviation modeling of the AM has also been envisioned [9].

While in the context of AM, deviation models have been proposed mainly to discover the effects of process parameters, input file quality or thermal shrinkage on the geometrical accuracy of the final product, thus correction or compensation plans can be made to ensure the surface quality. Main approaches can be classified into two categories. One category focuses on the modification of input files for AM machines. In [10] and [11], Vertex Translation Algorithm and Surface-based Modification Algorithm are proposed to modify the STL facets locally based on criteria like chordal error, cusp height and form error, so as to decrease the approximation deviation introduced in translation from CAD model to STL file. A variety of adaptive slicing approaches are proposed to minimize the deviation induced by staircase effect, and at the same time to reduce build time [12,13]. These approaches are applicable in the early design stage when the AM process hasn't been executed yet and only digital models are available. Later, Sushmit et al. [14] propose an Artificial Neural Network based method that learns from the deviations in measured surface data and uses the trained network to modify STL file to compensate for the deviations. However, these methods cannot provide a quantitative formulation of geometric deviations and an adaptive criterion for modification can hardly be reached. The other category aims at deriving closed-form parametric expression of deviations caused by shape shrinkage in certain AM processes and accordingly making optimal compensation of the design model to neutralize the deviations. Since AM is a layer-wise building process, the shrinkage deviations occur

both in each 2D layer and also the build direction. So it is reasonable to consider both the in-plane and out-of-plane deviations respectively. In a series of works [15,16,17], Huang et al. develop a predictive model of shrinkage deviations that is able to learn from the deviation information obtained from a certain number of tested product shapes and to derive compensation plans for new and untested products. The model is represented as a parametric function based on the Polar Coordinate System (PCS), in which the parameters can be estimated by statistical learning of the deviations. The model has been refined to represent both in-plane and out-of-plane deviations in Stereolithography (SLA) and Fused Deposition Modeling (FDM) processes. The repeatable in-plane shrinkage deviations of cylindrical, regular polygon and freeform shapes have been effectively predicted by this model. To improve model generality, in a recent study, they develop a new approach based on effect equivalence and modular deformation features to incorporate all available data for deviation model construction, so that the model can be extended across different process conditions and shapes [18]. Similarly, Kai Xu et al. [19] propose another reverse compensation framework, which models deviations in 3D space with multi-order polynomials. To conclude, existing studies consolidate the possibility in quantification of repeatable geometric deviations in AM and provide the context for the methodology in this paper.

3. New Deviation modeling and shape transformation method for AM

In this section, a new deviation modeling and shape transformation method will be proposed. This method aims at assisting the DfAM process in evaluation of geometric conformance between the design model and the actual product.

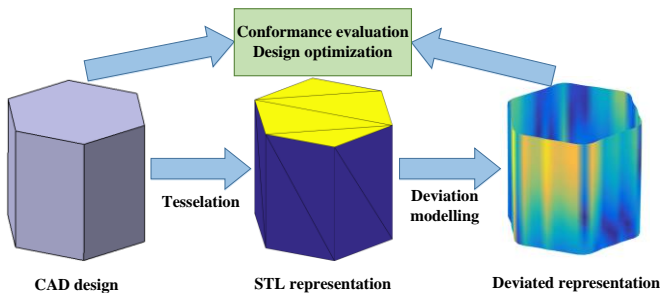


Fig. 1. Principle of the proposed method.

The design stage deals with the CAD product model, whereas the manufacturing process is normally based on the STL file, which is a tessellated representation of the design model. Starting with the nominal STL representation, this method derives a deviated representation of product shape by predicting the deviations brought in by the AM process. The deviations are provided to the designer as an important feedback for optimization of product design. Fig. 1 is provided to illustrate the principle of this method.

As mentioned above, shape shrinkage occurs during the layer-wise printing process due to the thermal effect, and is closely related to the characteristics of the AM process. Therefore, deviations caused by shape shrinkage are repeatable,

thus can be seen as systematic deviations, and be predicted through observation of the measurement data. Meanwhile, there are deviations caused by inevitable fluctuations of material and environmental conditions. Such deviations are unpredictable and can be seen as random deviations. In this method, the in-plane systematic and out-of-plane random geometric deviations in the SLA process are modeled. The out-of-plane systematic deviations caused by “sink-in” of layers are not discussed in this paper, but remain an important issue to be addressed. A shape transformation method will be proposed to model these deviations by displacement of contour points based on the STL file. The methodology aims at a good prediction of both repeatable and unexpected deviations of manufactured product shape to facilitate DfAM.

3.1. The framework

The procedure of the method is stated as follows. First, the CAD product model is tessellated to obtain its discrete representation as stored in a STL file. The STL file is sliced and the contour points in each slice are clockwisely connected to form a nominal slice contour. Based on a parametric function of shape shrinkage, the in-plane systematic deviations can be derived and the nominal contour points are deviated according to the function to incorporate the systematic deviations. Thereafter, the deviated points in each slice are connected layer by layer in a geometric way to form a new triangular facet model. Then, the random deviations are generated based on the random field theory and incorporated in the triangular facet model by translating each triangle vertex in its normal direction.

3.2. Modeling of systematic deviations

The in-plane systematic deviations are the deviations between the actual printed shape and the nominal shape of a 2D layer. These deviations have been validated to be repeatable for tested shapes in SLA [15], thus can be predicted using a parametric function whose parameters are estimated based on measurement.

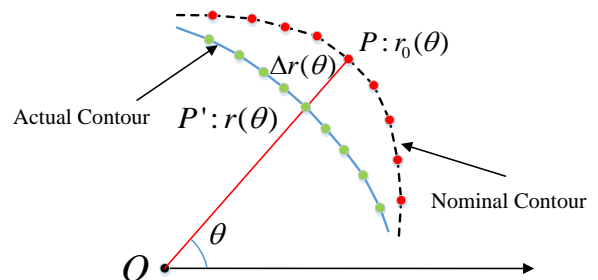


Fig. 2. In-plane deviation represented in PCS.

The nominal shape of a layer can be obtained by slicing the STL file at the layer height and connecting the points to form a nominal contour. The actual printed shape are obtained in a similar fashion, where the points are gathered from measurement to form an actual contour. In order to facilitate deviation representation, we propose to adopt the PCS, in which the deviations between the actual contour and nominal

contour can be distinguished as their radial difference at each polar angle, as shown in Fig. 2 and represented as Eq. (1).

$$\Delta r(\theta) = r(\theta) - r_0(\theta) \quad (1)$$

Since $r_0(\theta)$ is known, the problem is how to parameterize $r(\theta)$ to represent the actual contour. Here we make a truncated Fourier expansion of $r(\theta)$ as Eq. (2).

$$r(\theta) = a_0 + \sum_{k=1}^M [a_k \cos(k\theta) + b_k \sin(k\theta)] \quad (2)$$

In Eq. (2), $a_0, \omega, \{a_k, b_k, k=1, \dots, M\}$ are parameters that control the shape of the actual contour with deviations. With a reasonable value of M , the representation can reach an acceptable approximation accuracy. By combining Eq. (1) and Eq. (2), and using the polar form of Eq. (2), $\Delta r(\theta)$ can be represented as Eq. (3).

$$\Delta r(\theta) = a_0 + \sum_{k=1}^M A_k \cos(k\theta - \alpha_k) - r_0(\theta) + \varepsilon_\theta \quad (3)$$

$$A_k = \sqrt{a_k^2 + b_k^2}, \alpha_k = \arctan(b_k / a_k)$$

An extra component ε_θ is added in Eq. (3) as the noise term to represent unexpected randomness of the data. This function provides a continuous parameterization of the in-plane shape deviations in the PCS. The parameters can be obtained from empirical data or be estimated from measured contour points of the manufactured part, and used to predict the in-plane deviations of parts under the same or similar AM process. Based on this deviation function, we can displace each point P_i on the nominal contour to a new point P_i^s accordingly and obtain a new contour with systematic deviations.

3.3. Modeling of random deviations

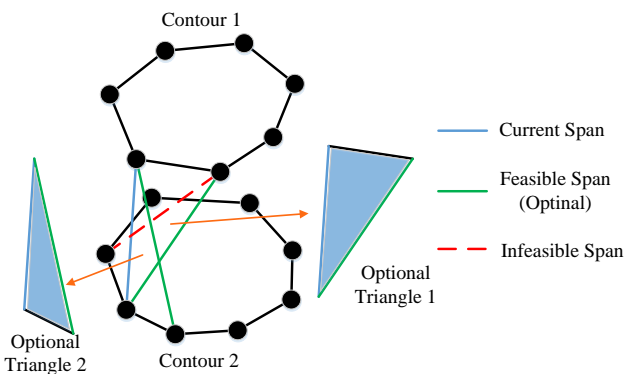


Fig. 3. Layer connection based on the span tour method.

The next step is to connect the deviated points in each layer to form a new triangular facet model. This is done with a “span tour” based method as inspired by the work of Park et al. [20].

First the points in each layer are connected in a consecutive way as a close contour, each segment of the contour serves as an edge of a triangle. Then each pair of contours in adjacent layers are connected with “spans” that link two corresponding

points in both contours, which is called a “span tour”. It should be ensured that the spans do not cross each other, thus non-intersecting triangles can be constructed with two spans and one segment of either contour. In this way, multiple possible span tours are resulted, among which the one with the least total span length is defined as the best solution and adopted to connect the contours. Fig. 3 illustrates how the span tour based method works for two closed contours.

After the new triangular facet model is established, the random deviations can be modelled. Based on our previous research on the Skin Model Shapes [7], we propose to use the random field method. The random field method offers a framework to express spatial random processes, and has shown effectiveness in modeling random deviations of spatially correlated variables. Since our purpose is to have the random deviations of 3D spatial points, a discretized form of random field using the series expansion method is adopted in this paper, which approximates the random field as a truncated series involving random variables and deterministic spatial functions. The random filed function is shown as Eq. (4).

$$f(t) = \mu(t) + \sigma(t)A\zeta \quad (4)$$

In Eq.(4), $\mu(t)$ is the mean vector of the random field, which is usually set as a zero vector, since the mean deviation is zero for every point; $\sigma(t)$ is the matrix of standard deviations; ζ is a vector of independent random variables with zero mean and unit variance; and A is the so-called transformation matrix $A = VD^{1/2}$, where D is a diagonal matrix with the M largest eigenvalues of the correlation matrix ρ of the random variables on the principal diagonal, $D = \text{diag}(\lambda_1, \dots, \lambda_M)$, and V is a matrix with corresponding eigenvectors.

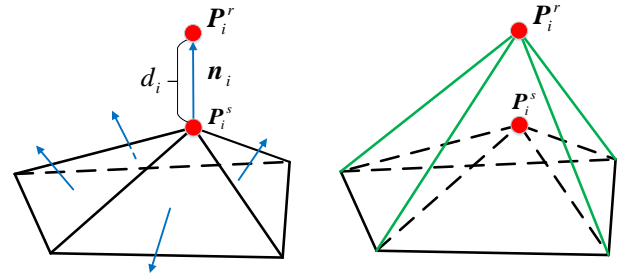


Fig. 4. Modification of STL file to model random deviations.

The coordinate of each point P_i^s on the triangular facet model is seen as a random variable in the random field. Thus the generation of random deviations is done in the following procedures:

- The vertex normal n_i of each point P_i^s is calculated based on the average of the facet normal of its neighboring triangle facets.
- A correlation matrix ρ is calculated using an assumed correlation function $\rho(\cdot)$ and correlation length l_ρ , which is a parameter that varies the impact one random variable has on the neighboring random variables.
- Eigen values D and corresponding eigenvectors V of ρ are calculated and thus A is obtained.

- The vector of random deviations at all points is then given by $d = \mu(t) + \sigma(t)A\zeta$.
- The corresponding random deviation d_i is added on each point of P_i^s in the triangular facet model in its vertex normal and new points $P_i^r = P_i^s + n_i d_i$ are obtained, as shown in Fig. 4.
- The triangular facet model is reconstructed using the new point coordinates.

Compared with the nominal triangular facet model in the STL file, the new triangular facet model comprises both systematic and random deviations. Note that the parameters in the random field method can also be estimated from measurement data of the manufactured parts.

4. Case study

In this section, a case study will be presented to validate the proposed method. The input is the CAD design of a cone model, with the height as 15mm, and the radius of bottom circle and upper circle as 10mm and 5mm respectively. The CAD model is discretized to obtain its STL representation, based on which the proposed deviation modeling and shape transformation method is conducted to derive deviations of product surface for evaluation of geometric conformance. The CAD model and its STL representation are shown in Fig. 5.

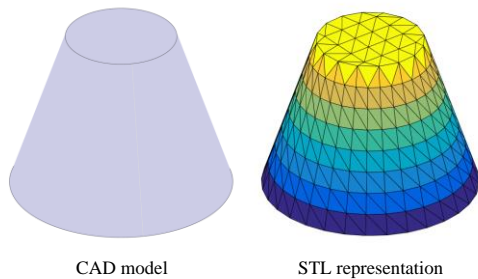


Fig. 5. CAD model and STL representation of the cone.

The STL representation is sliced with a thickness of 1mm, and the contour points in each slice are linked consecutively to form the nominal contour and transformed into PCS. For systematic deviations, empirical parameter values from our previous simulation results are used to establish the deviation function. Based on this deviation function, the in-plane systematic deviation of each nominal contour point is derived and the point is accordingly deviated to form a new contour. As an example, we demonstrate this process on the 6th slice (height = 5mm). In the deviation function, 8 components of the Fourier Series are used, with $a_0 = 8.833$ and other coefficients given in Table 1 and Table 2. The noise is independently considered at each angle θ as $\varepsilon_\theta \sim N(0, \sigma_\varepsilon^2)$. An assumed value of ε_θ is given as 0.002mm.

Table 1. Coefficients of the Fourier Series – Part 1.

| k | 1 | 2 | 3 | 4 |
|-------|----------|---------|----------|---------|
| a_k | -5.55e-5 | 0.0663 | -5.47e-5 | 1.20e-4 |
| b_k | 2.20e-4 | 2.17e-5 | -3.09e-4 | 3.54e-4 |

Table 2. Coefficients of the Fourier Series – Part 2.

| k | 5 | 6 | 7 | 8 |
|-------|----------|---------|----------|---------|
| a_k | -5.77e-4 | 7.48e-4 | -7.87e-4 | 5.74e-4 |
| b_k | -2.94e-4 | 2.93e-5 | -5.95e-5 | 5.06e-4 |

As a result, nominal contour and deviated contour of the slice are depicted in Fig. 6 in PCS, together with the corresponding contour points. Two zoom images are also provided to better visualize the deviations.

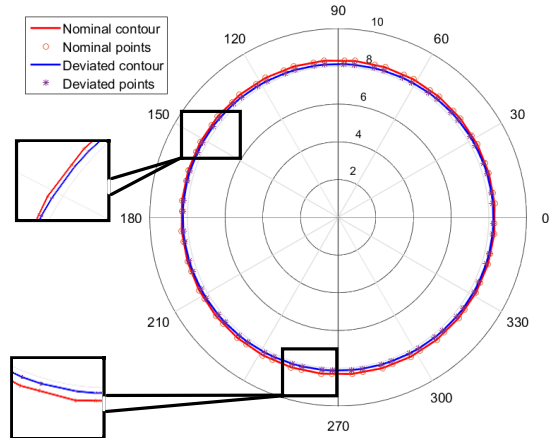


Fig. 6. Comparison between the nominal contour and deviated contour.

The deviated contour points in each slice are connected using the method as explained in Section 3.3 to form a new triangular facet model. Based on this model, the vertex normal of each point is calculated. Then the random field method is used to calculate random deviations. Here we make an assumption of the random field parameters, and set the correlation function as $\rho(\cdot) = \exp(\zeta_{ij} / l_\rho)$, in which ζ_{ij} is the distance between two arbitrary points. Other parameters are set as $l_\rho = 25mm$, $\mu = 0mm$ and $\sigma = 0.01mm$ for all points. The points are translated in their normal direction according to the random deviations and their new coordinates are updated in the triangular facet model. An illustration of systematic, random and total deviations modeled in the whole process is provided in Fig.7, in which deviations are visualized with varying colors to distinguish their values. The resulting model incorporates geometric deviations that are either repeatable or unexpected, and reflects the possible condition of manufactured part, thus can be used for validating the geometric conformance between designed model and manufactured product to assist DfAM.

5. Conclusion and outlook

Modeling of geometric deviations is an important concern in DfAM in order to evaluate the geometric consistency between designed model and final product. Current demand for AM parts in complex and dimensionally critical assemblies adds to the significance of deviation control of the AM process. In this paper, a new deviation modeling approach is proposed. With the CAD product model as input, this method models the possible deviations in AM processes based on its STL

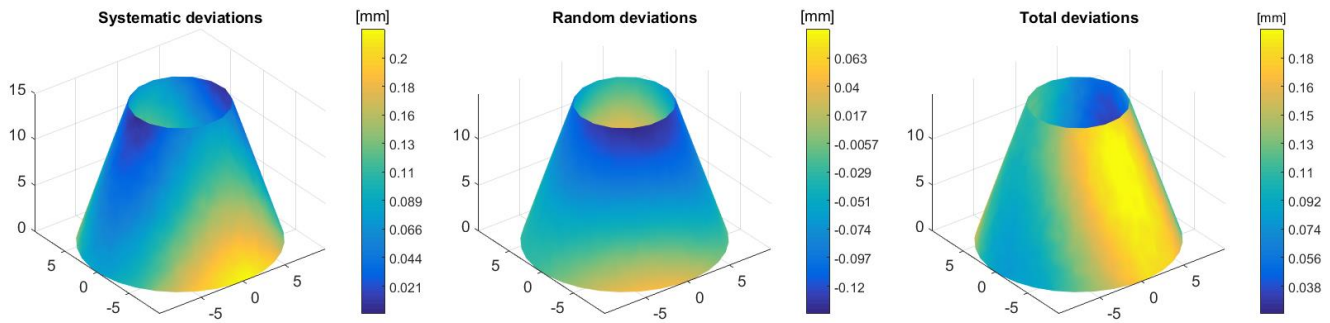


Fig. 7. Visualization of systematic, random and total deviations

representation. The in-plane systematic deviations and spatial random deviations are considered, and as a result, a triangular facet model is obtained that comprises both repeatable and unexpected deviations on product surface. Through evaluation of this model and the CAD model, important information can be gained for optimization of product geometry in the DfAM process. Future work will be focused on calibration of the proposed model with measurement data of real printed product, and comparison with existing AM simulation tools will be made to validate. The out-of-plane systematic deviations that occur in the build direction will also be considered.

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