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Efficient parameterized characterization of manufacturing strategies for automated copied driving

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Abstract

A knowledge-based automation concept, called automated copied driving, has been introduced for a special driving process. Thereby, a database of tool paths for component shapes is employed. New components are produced through the composition of appropriately transformed parts of the data pool. Up to now, building the database has been the main issue due to the complex cataloging of tool paths.

This paper presents an automated approach for cataloging that is fast and universally applicable. Therefore, tool paths are parameterized by probabilistic density functions, which, subsequently, are used for tool path derivation. For the computation, a bivariate kernel density estimation is applied.

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Keywords: Automation; Flexible manufacturing system (FMS); Incremental sheet forming; Knowledge-based system; Tool path

1. Introduction

These days, businesses face a highly challenging backdrop driven by, increasing competition in the course of a progressive globalization and, the customers' requests for more individualization [1]. In consideration of the altering conditions, the sheet metal forming industry quarries for efficient manufacturing systems that enable the production of individualized components. Precisely for that reason, incremental sheet forming (ISF) has been the subject of many studies and investigations. Particularly, asymmetric ISF methods allow for the production of almost any desired sheet component geometry. In this context, two-point incremental forming (TPIF) and single-point incremental forming (SPIF) are of primary interest for research, as these allow for the production of arbitrary asymmetric sheet metal shapes [2]. However, up to now, these processes have still struggled with open issues, e.g. the restricted geometric spectrum of the produced sheet parts, excessive material thinning and poor shape accuracy.

Numerical approaches can enhance a better understanding and, thus, an improvement of the processes. Regrettably, the enormous number of forming steps and grave fluctuations in material and tool parameters during the process boost modelling effort and computation time. Therefore, such approaches cannot be applied adequately to asymmetric ISF [3]. Hence, typical research on TPIF and SPIF tries to deepen the fundamental understanding of the processes [4,5], whereas other results can be used to assist decision-making in the early stages of production, e.g. where and when is SPIF an appropriate technology for part manufacturing [6]. Furthermore, diverse tool path strategies are developed and applied to reduce occurring shape inaccuracies [7-10]. Alternative approaches locally differentiate material properties to improve the performance and accuracy of the process, e.g. through dynamic local heating [11]. These procedures are often supplemented by multi-stage strategies in order to overcome geometric restrictions of TPIF and SPIF [12-14]. The latest research makes use of feature-based approaches to increase geometric accuracy appreciably [15]. Further improvements and modifications lead to even better results in deviation reduction [16]. However, TPIF and SPIF still do not meet strict industry standards. In particular, for straightening usages, these processes are hardly applicable.

Within this paper, we consider a specific type of driving process that is capable of remedying the geometric limitations

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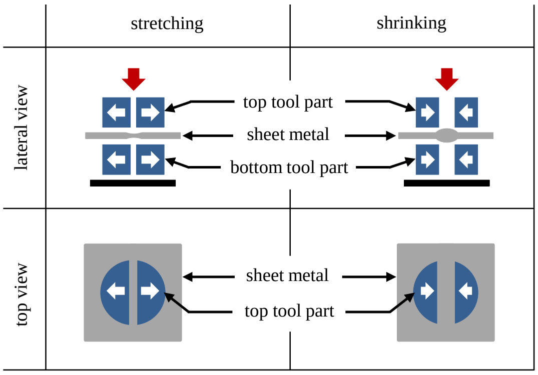

Fig. 1. Principles of local material stretching and shrinking for the utilized tool sets of the considered driving process

of TPIF and SPIF. The process is carried out on simple C-frame presses in combination with cost-effective universal tool sets, whereas each tool set consists of a top and a bottom tool. For the investigations, we focus on the two most interesting tool sets, which are often used in practical applications: the stretching and the shrinking sets. Fig. 1 shows a schematic draft of the principles of stretching and the unique feature of shrinking, which also can be found in a more general context in [17,18].

In any case, the considered driving process involves one important issue that cannot be neglected. Because of the free forming character of the process, the degree of freedom is increased in comparison to TPIF and SPIF implementations. Actually, except for handling reasons, the sheet blank is not fixed in space while strokes are performed on it. Furthermore, the stroke impact, with respect to deformation, is highly dependent on the tool orientation when impinging upon the sheet surface. Hence, tool path generation turns out to be rather difficult. In general, the component shape is in no way connected to manufacturing strategies for the part production and, thus, cannot be derived from CAD data, what makes path generation a challenging task.

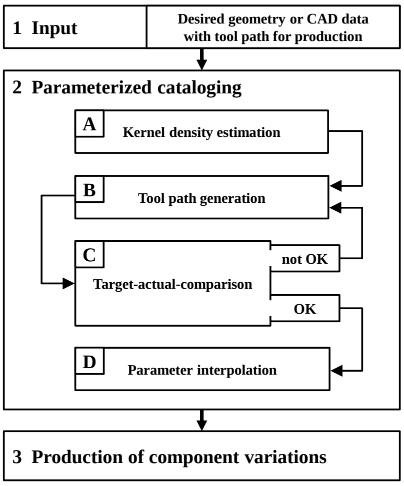

Fig. 2. Flow chart for an enhanced variation of components by automated driving with focus on efficient cataloging procedures

So far, there exists no strategy for tool path generation. In practice, part manufacturing rests upon worker experience and knowledge. In consideration of the facts, a knowledge-based automation concept utilizing a database of tool paths for component geometries is proposed. Based on this information, new geometries can be produced by composition of appropriately transformed parts of the database [19]. However, the main deficiency of the concept is the compilation process of the structured database. Currently, the cataloging of component geometries is done in a manual step, which proves to be highly complex, and has to be performed separately for every specific part to be added to the data pool [20].

This research presents an efficient approach for completely automated parameterized cataloging that further enhances the proposed knowledge-based automated driving concept. Thereby, the component shape is characterized by an analysis of the manufacturing strategy. The specific tool path is mapped onto a stroke distribution function on a blank that can be utilized for further geometric shape modeling and variation, which are needed for the cataloging routines.

2. Automated driving concept and problem formulation

In general, driving is a highly complex and strongly interactive manual process. Changing material parameters and process conditions make it very difficult to model the complete procedure. Thus, a model-free idea is proposed that allows fully automated manufacturing of new parts by composing geometric variants of known components stored in a data pool. The fundamentals of such an automated copied driving approach are fast processing and user-independent routines, which allow for an efficient database preparation in terms of cataloging parameterized sheet metal part geometries.

In [20], the component variation by such an automated database concept succeeded. Nevertheless, the parameterized characterization of components, the essential cataloging step, is user-dependent and very inefficient. Thus, the main objective of this paper is to present an efficient automated cataloging procedure. For validation and verification purposes, we embed the procedure in a framework for an enhanced variation of components by automated driving. Exemplifying, we will pick out a scaling application to demonstrate the approach. The associated flow chart for reaching this target is shown in Fig. 2.

The desired part geometry is given as well as an associated tool path, respectively. Utilizing this input, the component geometry has to be cataloged in a parameterized way, so as to be able to produce different geometric variations of the sample part. As we focus on the cataloging, the input step (1) will not be considered within our studies as this represents the available knowledge we assume to be given. Thus, we use a known sample sheet metal component with an appropriate tool path for production. The used part is depicted in Fig. 3.

At the core, we focus on the parameterized cataloging module (2) with its sub-modules. We will start by mapping the given discrete tool path onto a stroke density function using the

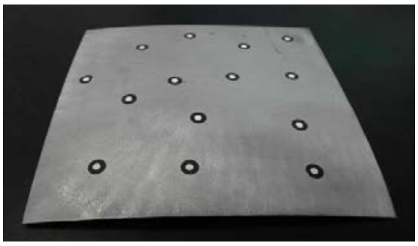

Fig. 3. Sample component used for the investigations; the associated tool path for the production is already available and can be utilized for the research

theory of kernel density estimation (A). Afterwards, we will take a look at the tool path generation sub-module (B), which will be followed by a brief introduction of the parameter interpolation principle (D). The target-actual-comparison sub-module (C) is not considered in particular. However, relevant results, e.g. the analysis of error tolerances of digitized parts, are integrated into the section dealing with sub-module (D). The production of component variants (3) is considered in terms of a conceptual evaluation.

Consequently, the main objective is the development of an automated user-independent cataloging concept for the proposed automated copied driving process. For this purpose, the focus of this paper is the representation of discrete tool paths by analytic stroke density functions. Furthermore, the transformation back is of central importance, i.e. the derivation of discrete tool paths out of probabilistic density functions.

3. Parameterized characterization

The automated driving process is strongly based on an analytical description of tool paths in order to apply component variations. The main goal is to find a general approach for including parameterized characterizations of standard elements into the part catalog.

3.1. Stroke density function

Manufacturing strategies for the considered driving process are described by tool paths, which are the discrete positions of the strokes performed during part production. This empirical data set is a reasonable base when cataloging comes into play, as the tool path is the central process influencing parameter for a specific component geometry. One option for handling empirical data is by deploying models of probability calculus.

A probabilistic density function (pdf) contributes to the treatment of continuous probability distributions. Let P be a probability measure and let X be a d-dimensional continuous random variable with the associated pdf $f\colon \mathbb{R}^d \to \mathbb{R}_0^+$. Furthermore, assume the addressed problem is limited to a finite dimensional real vector space. According to [21], for $a_1 < b_1,\ \ldots,\ a_d < b_d$ the pdf on the d-dimensional interval $I = [a_1, b_1] \times \ldots \times [a_d, b_d]$ is given as

$$P(X \in I) = \int_{a_1}^{b_1} \ldots \int_{a_d}^{b_d} f(x_1,\ldots,x_d)\,dx_d \ldots dx_1 \,. \tag{1}$$

A sheet metal part can be regarded as a regular 2-manifold in $\mathbb{R}^3$. For the tool path analysis, the discrete stroke positions are referred to the plane sheet blank as suggested in [20]. We define two continuous random variables X_1 and X_2, which represent the stroke coordinates on the plate for generating the predetermined standard part and are combined in the vector X. X_1 and X_2 are independent and restricted by the dimensions of the blank geometry $I = [a_1, b_1] \times [a_2, b_2]$. This is determined by the length $l = |b_1 - a_1|$ and the width $w = |b_2 - a_2|$ of the sheet blank. Applying (1), the corresponding pdf f, a stroke density function (sdf), can be written as follows

$$P(X \in I) = \int_{a_1}^{b_1} \int_{a_2}^{b_2} f(x_1, x_2)\,dx_2 dx_1 \,. \tag{2}$$

Such a description of discrete tool paths by sdfs is independent from the complexity of the considered tool path. Hence, this approach enables an automated procedure for any kind of stroke pattern.

For deriving sdfs for stroke positions on the sheet metal, we utilize bivariate kernel density estimation. In general, for a statistical analysis we assume that discrete data are subject to a certain probability distribution. Kernel density estimation is a nonparametric statistical method, which approximates the underlying distribution in form of a pdf. It relies exclusively on the underlying data and no further assumptions are required [22].

Let $n \in \mathbb{N}$ be a number of d-dimensional random variables $X_i \in \mathbb{R}^d$, $H \in \mathbb{R}^{d \times d}$ a symmetric, positive definite, banded matrix and $K\colon \mathbb{R}^d \to \mathbb{R}_0^+$ the d-dimensional Gauss kernel

$$K(x) := \frac{1}{2\pi} e^{-\frac{1}{2}x^T x} \,. \tag{3}$$

A function $\tilde{f}\colon \mathbb{R}^d \to \mathbb{R}_0^+$ is a kernel density estimator of the random variables X_i if the following representation holds

$$\tilde{f}(x) = \frac{1}{n} |H|^{-\frac{1}{2}} \sum_{i=1}^{n} K(H^{-\frac{1}{2}}(x - X_i)) \,. \tag{4}$$

For the 2-dimensional sheet metal blank, the coordinates of the n stroke positions are given by random variables $X_i \in \mathbb{R}^2$, $i = \{1, \ldots, n\}$. Thus, the sdf of a stroke pattern on the blank can be expressed as given in (3) with $H \in \mathbb{R}^{2 \times 2}$ and the two-dimensional Gauss kernel. Note that H is the essential parameter in estimating the pdf when it comes to accuracy.

In this research, for the bivariate kernel density estimation of pdfs, the robust formulation based on the heat equation was utilized [22]. Consequently, now we are able to derive analytic characterizations of arbitrary tool paths in an efficient way. As an example, in Fig. 4, the derived sdf from the discrete tool path of the sample component presented in Fig. 3 is illustrated as in surface design.

Up to now, we offered an automated possibility for an analytic description of sheet parts in terms of the underlying

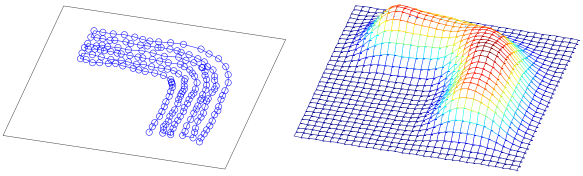

Fig. 4. 2D-projection in the sheet metal part coordinate system of the tool path for crafting the sample component (left), where circles indicate stroke positions on the sheet blank with the shrinking tool set, and the derived sdf for this tool path (right)

production tool path. In the next step, a concept has to be developed to generate tool paths utilizing the sdf of stroke patterns.

3.2. Tool path generation

As an alternative to the introduction of pdfs following (1), a pdf can be defined as the derivation of an underlying probability distribution function. From this point of view, we can easily observe that information gets lost in the process of the characterization. Due to the loss of information concerning discrete stroke position and order, a reproduction of the initial tool path is impossible. However, a predetermined number of strokes can be distributed onto the sheet blank according to the estimated pdf $\tilde{f}$.

For robot control, the 6-dimensional series of coordinates is mandatory, which consists of the three translational coordinates for positioning and the three Euler angles for orientation. Following [20], the complete series is computed from the distributed strokes on the blank through a coordinate interpolation approach, utilizing a functional dependency of the coordinates.

Let $\tilde{f}$ be the given sdf for a specific component shape and $X_i = [x_i, y_i]$, $i = \{1, \ldots, N\}$, are the desired N stroke positions for the tool path on the sheet blank with sdf $\hat{f}(X_i)$. Assuming that equal distributions lead to equal components, we call for the following condition to hold

$$\tilde{f} = \hat{f}(X_i)\,. \tag{5}$$

For that reason, a predefined number $h \in \mathbb{N}$ of sdf contour lines are chosen and projected onto the blank. These projections partition the sheet blank into $(h+1)$ sections. Hence, the surface is divided into disjoint areas A_j, $j = \{0, \ldots, h\}$, of different densities, allowing for the distribution of the N striking points according to the following correlation

$$N_j = N\frac{(h+1)p_j}{\sum_{j=0}^{h} f_j p_j}\,. \tag{6}$$

Thereby, p_j is the quotient of the area A_j to the total area A of the sheet and N_j represents the number of points allocated in A_j. A scaling is realized by the weighting factor $f_j = \{1, \ldots, h+1\}$.

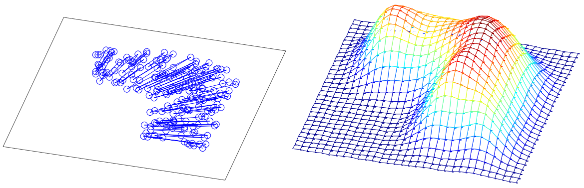

Fig. 5. 2D-projection in the sheet metal part coordinate system of a generated tool path computed according to the sdf of the sample component for crafting the sample component (left), where circles indicate stroke positions on the sheet blank with the shrinking tool set, and the derived sdf for this tool path (right); the strong similarity between the sdf derived from the original tool path (Fig. 4) and the generated one show the validity of the path generation concept

Based on the calculated number of points for each area A_j, the distribution within A_j is performed randomly. Fig. 5 shows a generated tool path for the sample component depicted in Fig. 3.

For allocating higher numbers of strokes, Monte Carlo methods can be applied, e.g. implementations of the acceptance rejection method.

3.3. Sheet metal part production

Up to now, we have introduced an automated possibility for handling tool paths for sheet components in the sense of an analytic description by sdfs and the derivation of new tool paths from these representations. Before we are able to produce sheet metal part variations of components in the database, one more step is necessary for cataloging. We need to set up a parameterization of the part geometry to be cataloged. As mentioned before, we depict the procedure for part scaling with varying scaling factor λ.

Therefore, we follow the procedure presented in [20]. First, we have to clone the sample part within given tolerances by a generated strategy to prove the validity of the approach. If we are able to recreate the component successfully, it is replaced by the new one wrought with the generated strategy.

Utilizing the representation of manufacturing strategies by sdfs and the generation of new tool paths from these analytic equivalents, a recreation of the sample sheet succeeded within a tolerable accuracy with a standard deviation of 0.22 mm. This deviation level is completely feasible since some influencing factors cannot be neglected: the positioning accuracy of the handling robot, tribological effects during the process, uncertainty of measurement results when digitizing the sheet metal parts, etc. In Fig. 6, the deviation analysis for ten parts produced with a generated tool path for sample part recreation is compiled, where the recreated sample part corresponds to scaling factor $\lambda = 1$.

Afterwards, we recreate digitally scaled variations of the sample shape the same way, where some process parameter variation and manufacturing steps are required.

For this study, digitally scaled components were reproduced for factors $\lambda = \{0.90, 1.50\}$ employing generated tool paths of varying stroke numbers. For a scaling factor of $\lambda = 0.9$, a recreation with a standard deviation of 0.22 mm is successfully

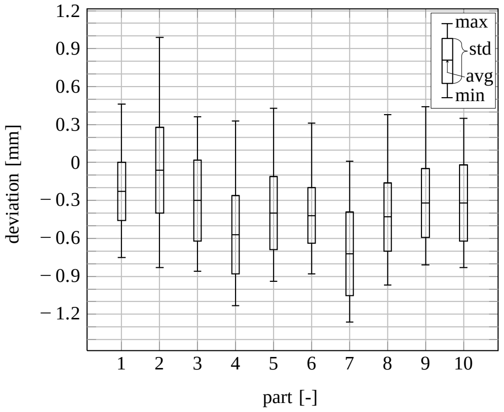

Fig. 6. Deviation analysis for the recreation of the original sample component size (λ = 1); alongside the illustration of the maximal (max), the minimal (min) and the average distances (avg) between the compared parts, the standard deviation (std) is displayed

achieved and for λ = 1.50 a standard deviation of 0.50 mm succeeded. All in all, considering the enlarged surface of the component the obtained deviation level appears to be feasible for λ = 1.50.

These recreated shape variations with their associated parameter configurations are applied as supporting points for a process parameter interpolation (see Fig. 7). As the only process parameter is the number of strokes, the search for properly generated strategies for the recreation of part variations is straightforward. After interpolation, the user is able to generate tool paths for the sample component of arbitrary scaling by demand.

In conclusion, the presented approach is a strong enhancement for the automated driving concept as it allows for fully automating the complex cataloging step. For clarity, it should be stated that the concept enables variance even for big scaling factors and no further error analysis is required since the interpolation ensures high geometric conformance assuming sufficient supporting points are provided [20].

4. Conclusion

A knowledge-based automation approach allows for the automation of the driving process. Utilizing a database of tool paths for component shapes, new geometries can be produced by composing appropriately transformed elements of the data pool. Therefore, the ability to produce geometric variations of the database elements is mandatory. To achieve this ambition, the preparation of the database is of outstanding importance, as tool paths and components need to be cataloged in a parameterized form. Up to now, the cataloging step has turned out to be highly complex and is done manually. This has impeded an effective realization of the automation concept.

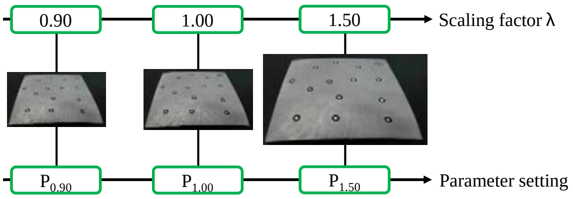

Fig. 7. Process parameter interpolation principle: reproduced variations of the sample component with their associated parameter settings are utilized as supporting points for an interpolation; the interpolation enables generating tool paths for arbitrary scaling factors

In this paper, we presented a technique for the efficient implementation of a cataloging routine. For this purpose, a parametric representation of tool paths based on probabilistic density functions is derived. A bivariate kernel density estimation is applied to compute a specific stroke density function (sdf) on the sheet blank, which is stored in the database. Following these sdfs for the database elements with respect to the required component shape, variations of the part shapes are produced by generating suitable tool paths with matching stroke numbers.

In particular, the presented method makes the previous obligatory analytical replication of manual tool paths obsolete, which had to be performed explicitly for every sheet metal part geometry. The concept of sdfs is fast and universally applicable, as it is not dependent upon any specific component features, but on the strokes, which enables a simple control of process parameters. Thus, a comprehensive application and a significant increase in the degree of automation are achieved.

Further research will turn focus toward an improved modeling of the stroke order, as it is not considered in detail for the presented cataloging concept by sdfs. Nevertheless, it will strongly improve the accuracy of the produced parts or highly simplify the recreation steps for supporting point generation, respectively.

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