Available online at www.sciencedirect.com
ScienceDirect
Comput. Methods Appl. Mech. Engrg. 285 (2015) 621–638
Computer methods in applied mechanics and engineering
www.elsevier.com/locate/cma

A manifold learning-based reduced order model for springback shape characterization and optimization in sheet metal forming

Guenhael Le Quilliec[a], Balaji Raghavan[b,*], Piotr Breitkopf[c]

[a] *Laboratoire de Mecanique et Rheologie EA 2640, Universite Francois Rabelais de Tours, 7 avenue Marcel Dassault, 37200 Tours, France*
[b] *Laboratoire de Genie Civil et Genie Mecanique EA 3913, INSA de Rennes, 20 Avenue des Buttes de Coesmes, 35708 Rennes cedex, France*
[c] *Laboratoire Roberval UMR 7337 CNRS - Universite de Technologie de Compiegne, Centre de Recherches de Royallieu BP 20529 - 60205 Compiegne cedex, France*

Received 20 June 2014; received in revised form 19 October 2014; accepted 18 November 2014
Available online 9 December 2014

Abstract

The parameters of a stamping process include the geometry of the tools, the shape of the initial sheet blank, the material constitutive law and the process parameters. When designing the overall process, one has to also take into account the springback effect that appears when the tools are removed and additional surfaces are cut-off. The goal then is to obtain a final shape *as close as possible* to the desired shape, while satisfying the admissibility constraints on the variable parameters as well as the feasibility constraints frequently expressed in the form of forming limit diagrams. In the present paper we represent the post-springback shape by a level set function. Then, rather than rely on arbitrarily selected case-dependent measurement locations as in the NUMISHEET benchmark problems, we build a reduced order "shape space" where this level set evolves, by extending our recent shape manifold approach to the problem of springback assessment for 3D shapes. Next, we propose an optimization algorithm designed to minimize the gap between the post-springback and the desired final shapes. The required level set functions are generated from a corresponding set of springback shapes predicted by Finite Element simulations. Using our approach, we determine the *minimal* number of parameters needed in order to uniquely characterize the final formed shape regardless of complexity. Finally, we demonstrate the approach using an industrial test-case: springback assessment of the deep drawing operation of an automotive strut tower.

Keywords: Model reduction; Springback; Shape optimization; Characterization; Level set; Manifold learning; Proper orthogonal decomposition; Eulerian

1. Introduction

From the view of manufacturing of structural parts, high strength steels and aluminum are very attractive materials due to their good formability, high strength characteristics, price, or quality [1]. They are commonly used for complex

* Corresponding author. Tel.: +33 0 620 975 226.
E-mail address: balaji.raghavan@insa-rennes.fr (B. Raghavan).

http://dx.doi.org/10.1016/j.cma.2014.11.029

sheet metal parts. One of the most important problems however with these and similar materials (*i.e.* high ratio σ_y/E) is that of springback, which is severe during the unloading phase of a sheet metal forming operation and greatly affects the dimensional accuracy of the parts. High strain steels are vulnerable due to the high yield stress while aluminum alloys due to their low Young's modulus [2]. Springback is related to forming conditions, tool and blank geometry, other material properties such as yield stress, work hardening, strain rate sensitivity, Young's modulus *etc.* [3,4].

Corrections for springback are essential during die design in order to obtain specified final shapes. When dealing with the springback effect in an optimization context, we face a high dimensional problem. Post-springback shapes are typically represented by *deformed* FE meshes, although meshless representations with a set of nodes may be used as well [5]. The initial shapes are defined by up to a few hundred CAD parameters (that are not necessarily independent), but this is not the case with deformed meshes. The dimensionality in this case depends on the number of elements and/or nodes in the mesh and may thus be prohibitively high (e.g. the parameterization in [6]) and not directly concordant when remeshing is used. An obvious, but inefficient, way is to define *a posteriori* a set of geometric parameters to describe the complex 3D post-springback shape.

For example, even in the 2D draw bending of a simple U-channel, three parameters are used to measure the amount of springback [7] as was proposed in the benchmark of the NUMISHEET 93 conference. First of all, these are not easy to measure (*e.g.* optical scanning [8]), and moreover they are essentially decided on an ad-hoc basis, and either redundant or insufficient to *fully quantify* the final shapes obtained [9,10]. Furthermore, it is significantly more difficult to apply this simplistic approach to complex 3D test cases.

Secondly, when performing a set of numerical experiments, one obtains a family of post-springback shapes corresponding to different values of design parameters. The inverse problem [11] then consists of finding the values of parameters that yield a final shape as close as possible to the desired one. This requires predicting a new shape from a set of already computed ones by defining a proper space in which we are able to measure the distances and to interpolate between shapes.

Working directly with finite element meshes is not realistic due to potentially high numbers nodes/elements involved, as has already been mentioned.

We may define a set of CAD-like parameters (NURBS, *etc.*) spanning the variety of deformed shapes (including the desired shape), but this approach is tedious, arbitrary, and most importantly, difficult to automate.

Thus, since the springback shape is not easy to characterize, and given that the form obtained after springback frequently differs from the *desired* final shape, it is difficult to predict a unique set of process parameters (tool/punch geometry, blank holding force, *etc.*) in order to obtain a final shape as close to the manufacturer-desired shape as possible.

In order to numerically evaluate the springback and to be able to characterize complex shapes, we need a universal and case-*independent* technique to find the smallest number of parameters needed to fully describe the final shape obtained regardless of complexity, and easily compare it with the desired geometry. The first effort was made by the authors in [12] using their previously introduced "shape manifold" concept [13,14] for the simple NUMISHEET 93 benchmark problem of 2-D draw bending. Here, the concept of an "admissible shape" for a forming process was introduced for the first time to distinguish between *realizable/attainable* post-springback shapes and idealized shapes for a given drawing process, and the notion of interpolation between admissible shapes was introduced. The concept of interpolating level set functions has also been studied by [15] and [16] both of whom used radial basis functions (RBFs) and in conjunction with the level set equation.

The goal now is to parameterize a general complex 3D post-springback shape (in *level set* form, *i.e.* a signed distance function φ from the shape's surface), and interpolate between level set functions in a way that implicitly satisfies all the admissibility constraints, *i.e.* by developing the "shape space" *locally*. Using this we determine the intrinsic dimensionality of the drawing problem and thus the minimum number of parameters that control the final shape obtained at the end of the drawing process, and to express the final shape as a function of the geometric parameters $G_1, G_2, \ldots$, material parameters $M_1, M_2, \ldots$, and process parameters $Pr_1, Pr_2, \ldots$ (*e.g.* blank holding force, speed, friction, *etc.*) *i.e.* $\varphi = \varphi(G_1, G_2, \ldots, M_1, M_2, \ldots, Pr_1, Pr_2, \ldots)$. By calculating the distance between two admissible shapes *i.e.* $dist(\varphi_1, \varphi_2)$ or the distance of an inadmissible shape from the surface of the manifold of admissible shapes (*i.e.* realistic post-springback shapes), we can characterize the amount of springback and express it in terms of the set of design variables. A vital component here is the meta-model used to "reduce" the level set functions representing the shapes. Meta-modeling has been widely used to approximate the physical fields associated with the design problem using a lower order meta-model *i.e.* output space [17–19], using the methods of Proper