Design Classification and Hybrid Variant-Generative Process Planning

Dana S. Nau
University of Maryland

Jeffrey W. Herrmann
University of Maryland

William C. Regli
Drexel University

Abstract: We are developing a new hybrid process planning approach that uses a generative procedure to select processes and a variant fixture planning procedure to complete the process plan. This paper describes components of this approach and related work on indexing mechanical designs and estimating manufacturing cycle time during product design. Specifically, we have created data structures that represent features and developed techniques that intelligently retrieve solid models. We have used a neural network to create specialized design similarity measures for fixture planning. We have implemented an algorithm to solve the maximal cutter finding problem for general 2-D milling processes. In addition, we have identified a set of manufacturing system models that can be used to estimate the manufacturing cycle time of a new product.

Introduction: Developing successful generative process planners for complex machined parts is a difficult challenge. Although researchers have developed generative techniques for process selection, they have been less successful developing generative techniques for completing the process plan. To address this problem, we are developing a new hybrid approach to process planning. We believe that, in most cases, a generative planner is a better approach for creating a preliminary process plan. A variant approach is a very useful technique, however, for completing the process plan and adding the necessary details, like fixturing.

This research is developing a new hybrid approach that uses a successful generative process planning approach and adds a variant fixture planning approach. The following sections describe components of this approach and related work on indexing mechanical designs and estimating manufacturing cycle time during product design. More complete details appear in our papers [1-9].

Indexing and Retrieving Mechanical Designs: CAD databases and knowledge-bases are at the core of the modern engineering enterprise. These emerging digital libraries store all information relevant over a product's life-cycle (geometry, topology, features, revisions, etc.). Given this database, a designer or engineer may need to determine if a given design is contained in this database or to find a similar part that can be used to create a process plan for a new part. The goal of this research is to develop algorithmic techniques to manage databases of CAD and solid models. To accomplish this goal, we have developed techniques that intelligently retrieve solid models and data structures that represent features [1-3].

Features, whether they are design features or manufacturing features, represent structural properties of the solid model. A representation of feature data is a representation of the structure of the model. If two solid models have similar features and feature interactions, then in some way the two solid models are similar. This work attempts to be independent of the class of features in question. That is, the representation discussed may be applied to design features obtained from the design feature history for a given model and alternatively the representation may be applied to manufacturing features that may be obtained by running a feature recognizer over a collection of CAD models. It may also be desirable to represent both the design features and the manufacturing features and have multiple views of the data in the given CAD knowledge-base.

Nearly all major commercial computer-aided design systems have adopted a feature-based design approach to solid modeling. Thus design feature data is easily obtained from the CAD system in use. In order to efficiently store and retrieve solid models from a CAD knowledge-base, one requires a more uniform representation for the feature information used to describe the artifact.

This work has developed geometric reasoning techniques that generate an abstraction of a CAD model's design feature history. This abstraction removes the ambiguity and non-uniqueness inherent in the ordering of the design feature history. These same techniques may also be applied to manufacturing features to result in an alternative view of the CAD knowledge-base. The representation described is called the Model Dependency Graph (MDG) and alternatively the Undirected Model Dependency Graph (UMDG). These schemes represent features as nodes and feature interactions as edges between the nodes representing the features of the interaction. Based on the MDG and UMDG, we have created algorithms that can assess the similarity of solid models based on features; index models for database storage; and identify meaningful part families from large sets of designs, such as engineering databases. The algorithms include an inexact solution to the subgraph isomorphism and graph isomorphism problems using a gradient descent approach that allows for a measure of similarity. Finally, we have developed a fast A* algorithm for the subgraph isomorphism problem that we call the A* Subgraph Isomorphism Checker (ASIC).

Hybrid Variant-Generative Process Planning: In this project we have developed a hybrid process planning approach that extends an existing generative approach. We began by proposing a hybrid process planner that first decomposed a design into independent collections of features and then searched for partial process plans that would create each collection [4, 10]. After this variant procedure, the approach then used a generative procedure that would combine and modify the partial plans to create a final plan. Since then, our work has proceeded and we have revised various aspects of this approach. The current hybrid approach begins by using a generative approach for process selection and then employing a variant procedure to select fixtures, which completes the process plan. For more complete details, see Balasubramanian *et al.* [7].

In a machining operation, a cutting tool sweeps along a trajectory, and the motion of the tool relative to the current workpiece removes material. A machining feature is the volume resulting from a machining operation. A machining feature corresponds to a single machining operation made on one machine setup. Each machining feature has a single approach direction (or orientation) for the tool.

Features are parameterized solids that correspond to various types of machining operations on a 3-axis machining center: side-milling, face-milling, end-milling, and drilling.

A design is represented as a collection of machining features. Given this feature-based representation, there may be several alternative representations of the design as different collections of machinable features, corresponding to different ways to machine the part. The approach proceeds as follows:

Repeat the following steps until every promising feature-based model (FBM) has been examined:

- Generate a promising FBM from the feature set. An FBM is a set of machining features that contains no redundant features and is sufficient to create the part. An FBM is unpromising if it is not expected to result in any operation plans better than the ones that have already been examined.
- Do the following steps repeatedly, until every promising operation plan resulting from the particular FBM has been examined:
  - Generate a promising operation plan for the FBM. This operation plan represents a partially ordered set of machining operations. We consider an operation plan to be unpromising if it violates any common machining practices.
  - Estimate the achievable machining accuracy of the operation plan. If the operation plan cannot produce the required design tolerances and surface finishes, then discard it. Otherwise, estimate the production time and cost associated with operation plan.
  - For each setup in the operation plan, design a fixture in the following way: Search a database of existing designs, process plans, and fixtures, for fixtures that that could be used for the new design. Modify the retrieved fixture as necessary and verify its feasibility.
- If no promising operation plans were found, then exit with failure. Otherwise exit with success, returning the operation plan that represents the best tradeoff among quality, cost, and time.

Variant Fixture Planning: The above hybrid process planning approach includes a variant fixture planning step. The goal is to retrieve, for a new product design, a useful fixture from a given set (or database) of existing designs and their fixtures. The variant approach thus exploits this existing knowledge. However, since calculating each fixture's feasibility and then determining the necessary modifications for infeasible fixtures would require too much effort, the approach searches quickly for the most promising fixtures. The approach uses a design similarity measure to find existing designs that are likely to have useful fixtures. Then, it modifies the retrieved fixtures as necessary and identifies the best one for the new design.

In order to demonstrate our approach, we have studied a particular class of products and modular components. One face of the part rests on the supporting plane (a baseplate) and the fixture elements constrain all motion of the part in the supporting plane. Thus, only the 2D projection of any given design onto the supporting plane is needed for fixture planning. Only polygonal shapes are considered. In this setting, a fixture is a set of three locators (pins) and one clamp, which provides form closure. Because generative fixture planning approaches are available, this domain is a convenient environment for testing our approach. Future work will extend the variant fixture planning approach to a broader class of products and fixtures.

For a new product design, an existing fixture's usefulness is defined as its ability to provide form closure and its maximum contact reaction force under a unit torque. The reciprocal of this reaction force is the torque resistance metric. If the maximum contact reaction force is smaller, the metric is larger. Large contact reaction forces are undesirable since they may deform the part. Moreover, in the presence of large machining forces, large contact reaction forces can make large clamping forces necessary. Unfortunately, calculating this measure requires some effort, so checking each existing fixture against a new design is impractical if the database is large. Thus, the approach requires a specialized design similarity measure. The following steps describe the variant fixture planning approach.

Let D denote the new design. Let **D** be the set of existing designs and fixtures. Let A be the similarity threshold.

0. **S** = {}.
1. For each D' in **D**, calculate h(D',D). If h(D',D) > A, add F' (the fixture for D') to **S**.
2. For each F' in **S**:
    - 2a. Determine all feasible configurations of D in the locator triplet of F'.
    - 2b. For each feasible configuration, find the clamp positions that achieve form closure
    - 2c. For each feasible clamp position (and configuration) C, evaluate the torque resistance metric r(C,D).
    - 2d. Let t(F',D) = max r(C,D).
3. Select the fixture F' that maximizes t(F',D).

The specialized design similarity measure is h(D',D). This measure reflects fixture usefulness and was developed using the neural network approach described below.

Defining Specialized Design Similarity Measures: Our research has developed some novel techniques for defining specialized design similarity measures for problems such as variant fixture planning [5-8]. Balasubramanian and Herrmann [8] present an approach that uses an artificial neural network. The existing designs and information are used to train the neural network, which learns the specialized design similarity measure. We have applied this approach to the domain of variant fixture planning. However, the approach is also appropriate for variant process planning and variant manufacturability evaluation.

The decision-maker has a set **W** of product designs and relevant information about those product designs. Let (Di, Li) be a product design and the relevant information (e.g., fixture). The decision-maker has a new product design D0 and needs to create some information L0 about that product design. The decision-maker wants to identify a design Dk in **W** and use the associated information Lk to create L0. One can say that L0 solves the decision-maker's problem.

To do this, the decision-maker needs a design similarity measure S(D0, Dj) that quantifies how well the information Lj can be used to create information about D0. The decision-maker can then search **W** for the existing design Dk in **W** that is most similar to the new product D0. We will assume that S(D0,Dj) ranges from zero to one. If S(D0, Dj) is close to 0, then Lj is not very useful. If S(D0, Dj) is close to 1, then Lj is very useful.

The proper design similarity measure is important since it can help the decision-maker construct a superior solution quickly. An improper design similarity measure will lead the decision-maker to an inferior solution or will cause delays as the decision-maker searches **W** exhaustively to find a better source of information.

Defining a specialized design similarity measure requires some effort. Once done, it yields a more appropriate measure that is quick and easy to use. The key is to use the knowledge that exists in **W**, the set of existing product designs and information. The approach proceeds as follows:

Step 1. Define a function F(Di, Li, Dj, Lj) that quantifies whether the information Lj is appropriate for Di. The function should range from 0 to 1, with F = 0 signaling that Lj is completely inappropriate for Di, and F = 1 signaling that Lj is perfect for Di. F(Di, Li, Di, Li) should equal 1. Note that F(Di, Li, Dj, Lj) does not necessarily equal F(Dj, Lj, Di, Li). For example, if Lj is the fixture for Dj, F describes how well the fixture holds Di.

Step 2. For all pairs i, j in **W**x**W**, calculate Uij = F(Di, Li, Dj, Lj). (Note Uii = 1.)
Create a set **X** = {(Di, Dj, Uij): for all i, j in **W**x**W** }.

Step 3. Construct a neural network that has one output node. Its input nodes correspond to the key design attributes of two designs. Initialize the weights with randomly selected values.

Step 4. Partition **X** into two sets: a training set and a testing set. Use these sets to train the neural network. The input signals to the neural network are the attributes of the designs Di and Dj, and the desired output is Uij. The resulting neural network is the specialized design similarity measure S(Di, Dj).

When applied to the variant fixture planning problem, the neural network generates a design similarity measure that finds more appropriate existing designs that design similarity measures based on individual product attributes. The better design similarity measure leads to better fixtures.

Cutter Size Selection: NC machining is being used to create increasingly complex shapes. These complex shapes are used in a variety of defense, aerospace, and automotive applications to (1) provide performance improvements, and (2) create high performance tooling (e.g., molds for injection molding). The importance of the machining process is increasing due to latest advances in high speed machining that allows machining to create even more complex shapes. Complex machined parts require several rouging and finishing passes. Selection of the right sets of tools and the right type of cutter trajectories is extremely important in ensuring high production rate and meeting the required quality level. It is extremely difficult for human planners to select the optimal or near optimal machining strategies due to complex interactions among tools size, part shapes, and tool trajectories. This work has implemented an algorithm to solve the maximal cutter finding problem for general 2-D milling processes. This is addressed in terms of a target profile and an obstruction profile. Three different approaches of cutting feasibility have been defined. By using the area covering idea, we can find the largest cutter that can cover the target profile without interfering with the obstruction profile. Based on our definition and approach, we can prove the correctness of our algorithms. For further details see [11].

Estimating Manufacturing Cycle Time during Product Design: Much effort is spent to reduce manufacturing cycle time by improving manufacturing planning and control systems and developing more sophisticated scheduling procedures, and these efforts have shown success. However, it is clear that the product design, which requires a specific set of manufacturing operations, has a huge impact on the manufacturing cycle time. Product development teams need methods that can estimate the manufacturing cycle time of a given product design. If the predicted manufacturing cycle time is too large, the team can reduce the time by redesigning the product or modifying the production system Estimating the manufacturing cycle time early in the product development process helps reduce the total product development time (and time-to-market) by avoiding redesigns later in the process. Thus, the product development team should include this activity in their concurrent engineering approach as they address other life cycle concerns, including testing, service, and disposal.

This project is studying methods for estimating manufacturing cycle time early in the product development process. Design classification and process planning are important issues in this domain. One can estimate the manufacturing cycle time of a new product by using the manufacturing cycle time of a similar product. Classifying product designs and defining similarity measures appropriately will be a key step. In addition, one can determine the process plan of the new product design and use that in the estimating process.

At this point our research has examined existing approaches and classified these methods. In addition, we have identified a set of manufacturing system models that can be used to estimate the manufacturing cycle time of a new product [9]. We have focused on products that follow a simple routing and are produced in one facility. The basic types of models available include fixed lead times, conveyor models, queueing system models and approximations, production scheduling models, and discrete event simulation models. Their data requirements, computational effort, descriptive power, approximation accuracy, and ability to do sensitivity analysis vary widely.

Identifying these models is the first step towards a more systematic and rational methodology for estimating manufacturing cycle time during product design in a variety of production systems. The ultimate goal is a decision support tool that can help a designer make tradeoffs between different designs or redesign suggestions and select the one that best meets the requirements of performance, manufacturing cost, and time.

Conclusions: The technologies that we are developing will impact design and manufacturing research and practice in several ways. First, they will reduce the effort of product design and process planning by automating tedious and time-consuming details, such as design retrieval, fixture selection, and cutting tool selection. Second, they will help designers and manufacturing engineers develop better products by providing feedback about manufacturability concerns such as the manufacturing processes to be used and the manufacturing cycle times.

References

[1] Regli, W.C., and V. Cicirello, "Managing Digital Libraries for Computer-Aided Design," to appear in the *Journal of Computer Aided Design*, July 1999.

[2] Regli, W.C., and V. Cicirello, "Resolving Non-Uniqueness in Design Feature Histories," Proceedings, Fifth ACM/SIGGRAPH Symposium on Solid Modeling and Applications, David Anderson and Wim Bronsvoort, editors, Ann Arbor, Michigan, June 8-11, 1999.

[3] Cicirello, V., *Intelligent Retrieval of Solid Models,* M.S. Thesis, Computer Science, Drexel University, June 1999.

[4] Elinson, A., J.W. Herrmann, I. Minis, D. S. Nau, and G. Singh, "Toward Hybrid Variant/Generative Process Planning," Design for Manufacturing

Symposium, ASME Design Engineering Technical Conference, Sacramento, California, September 14-17, 1997.

[5] Herrmann, J.W., and G. Singh, “Design similarity measures for process planning and design evaluation,” Technical Report 97-74, Institute for Systems Research, University of Maryland, College Park, 1997.

[6] Herrmann, J.W., and G. Singh, “Defining similarity measures for process planning and manufacturability evaluation,” submitted to *Journal of Manufacturing Systems*.

[7] Balasubramanian, S., A. Elinson, J.W. Herrmann, and D. Nau, “Fixture-based usefulness measures for hybrid process planning,” Proceedings, 1998 ASME Design for Manufacturing Conference, Atlanta, Georgia, September 13-16, 1998.

[8] Balasubramanian, S., J.W. Herrmann, “Using Neural Networks to Generate Design Similarity Measures,” Technical Report 99-38, Institute for Systems Research, University of Maryland, College Park, 1999.

[9] Herrmann, J.W., and M. Chincholkar, “Models for Estimating Manufacturing Cycle Time during Product Design,” submitted to International Conference of Flexible Automation and Intelligent Manufacturing, June, 2000.

[10] Elinson, A., D. S. Nau and W. C. Regli, “Feature-Based Similarity Assessment of Solid Models,” In *Proc. ACM Solid Modeling Conference*, May, 1997.

[11] Gupta, S.K., D. S. Nau, W. Qui, and Z. Yao, “A Geometric Algorithm for Finding Maximal Cutters for 2-*D* Milling Operations,” in preparation.

Acknowledgments: This work has been supported in part by NSF grant DMI 97-13718, ONR grant N00014-96-10888, and NSF grant EEC 94-02384.