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Towards multiprocessor feature recognition

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The availability of low-cost computational power is enabling the development of increasingly sophisticated CAD software. Automation of design and manufacturing activities poses many difficult computational problems—significant among them is how to develop interactive systems that enable designers to explore and experiment with alternative ideas. As more downstream manufacturing activities are considered during the design phase, computational costs become problematic. Creating working software-based solutions requires a sophisticated allocation of computational resources in order to perform realistic design analyses and generate feedback.

This paper presents our initial efforts to employ multiprocessor algorithms to recognize machining features from solid models of parts with large numbers of features and many geometric and topological entities. Our goal is to outline how improvements in computation time can be obtained by migrating existing software tools to multiprocessor architectures. An implementation of our approach is discussed. Published by Elsevier Science Ltd

Keywords: distributed computing, feature-based modelling, feature recognition, multiprocessor solid modelling

The availability of low-cost computational power is enabling the development of increasingly sophisticated CAD software. Software tools designed to reduce time-consuming build–test–redesign iterations are becoming essential for increasing engineering quality and productivity. Examples include tools for finite element analysis, mechanism analysis, simulation, and rapid prototyping. Such tools have become crucial components for research in collaborative engineering and engineering design.

Automation of the design process and construction of such tools, however, pose many difficult computational problems. To realize the advantages of collaborative engineering, more downstream engineering activities are considered during the design phase. As design is an interactive process, developing techniques to manage computational costs better is critical in systems that enable designers to explore and experiment with alternative ideas during the design stage. Achieving reasonable levels of interactivity between design and downstream activities (such as analysis, process planning, and simulation) requires an increasingly sophisticated allocation of computational resources in order to perform design analyses and generate feedback.

It is becoming increasingly evident that one necessary component of an automated design analysis tool is a subsystem for recognizing manufacturing features directly from a CAD or solid model. This problem has been the focus of extensive research over the last decade. Feature recognition is used for a variety of applications, including the generation of process plans[53,14,15], translation between design and manufacturing features, and generation of redesign suggestions[5,6]. What has also become evident is that feature recognition, for realistic classes of parts with multiple and interacting feature interpretations, requires extensive geometric reasoning and is computationally expensive. Hence, generating the features from a part is a computational bottleneck within an integrated design system.

In this paper we present our initial efforts toward developing a methodology for recognizing a class of machining features using multiprocessor algorithms on a distributed system. Feature recognition has been approached using a variety of techniques, some of which are easier to parallelize than others. In previous work[27], we described serial *trace-based* algorithms for finding feature instances from solid model data. A trace represents the information in the solid model of the part produced by an instance of a feature.

The techniques presented in this paper demonstrate the feasibility of migrating existing serial feature recognition systems to take advantage of multiprocessor computing technologies. We report results indicating that trace-based feature recognition methodologies are particularly well suited for parallelization. The basic steps in our approach are:

(1) *Task initialization.* Initialization is performed at four levels: (1) the types of features to be recognized; (2) the types of trace information used to construct the feature instances; (3) the decomposition of the geometry and topology of the traces; and (4) the simplification of the part geometry to reduce the costs to solid modelling operations.
(2) *Task distribution.* The problem is divided using the task decomposition—isolating independent portions of the recognition problem and identifying a suitable computational resource for solving it.
(3) *Synthesis of results.* The results obtained by each separate processor are combined into a global solution. This solution set can then be passed on to

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the application at hand—in the context of our previous work, this application is a system for automated manufacturability analysis and redesign for machined parts[5,12,13].

The contributions of this research include:

- *Increasing the complexity of parts that are now computationally feasible.* In the feature recognition area, serial approaches have had great success in two types of domains: (1) where the number of feature instances are relatively few; and (2) where the number of interactions among the features are relatively few. In general, most techniques have proven difficult to scale in order to address complex, real-world, parts having thousands of geometric and topological entities and several hundred interacting feature instances.
  One focus of this work was to develop techniques that can handle parts with large numbers of feature instances with moderate numbers of interactions. The results reported in this paper reveal an approach suited for parts in which there might be thousands of interacting feature instances but the individual features themselves are simple in structure. This multiprocessor distributed approach can put a greater number of such components within reach.
- *Enabling of more interactive analysis and feedback.* Recognition of the many alternative features can be done for complex parts in manageable amounts of time. This facilitates faster and more comprehensive analyses of manufacturability for the part at hand.
- *Techniques for reusing existing software and migrating it to a multiprocessor architecture.* We present a top-down approach for modifying existing feature recognition techniques to take advantage of the possibilities presented by new developments in hardware. It makes use of existing commercial solid modelling tools directly, and does not require parallelized versions of common algorithms or the implementation of multithreaded, multiprocessor solid modelling systems.
- *Demonstration of how to exploit the growing ubiquity and power of networked computing facilities to provide a flexible means of utilizing networked computational resources.* Effective utilization of large collections of inexpensive processors enables applications to perform computationally intensive (and enterprise-wide) CAD/CAM activities efficiently and interactively.

The remainder of the paper is organized as follows. The second section gives an overview of related work on multiprocessor solid modelling and recognition of features. A basic approach to feature recognition, on which we will build our distributed algorithms, is outlined in the next section. The fourth section presents our method for dividing the recognition problem to be solved, distributed on multiple machines. The fifth section briefly discusses the implementation and presents an example of the performance improvements. Lastly, concluding remarks and discussion are presented.

RELATED WORK

The bibliography of work on multiprocessor algorithms for solid modelling applications is limited but growing. Currently, most work has focused on parallel operations on CSG trees and other CSG representations of polygonal or polyhedral entities. Ellis *et al.*[8] have developed the RayCasting Engine: a hardware-implemented facility for sampling solids represented in CSG for a variety of purposes, including rendering and mass-property calculations. They outline how this special-case hardware makes possible brute-force solutions to difficult computational problems, such as spatial sweeping and offsetting.

Narayanaswami and Franklin[22] present a parallel multiprocessor method for calculating the mass properties of polygonal CSG objects and outline some extensions for applying the techniques to 3D polyhedra. Banerjee *et al.*[2] have developed parallelized algorithms for evaluating CSG trees that operate with a fixed number of processors with shared memory.

In the domain of boundary representation modelling, Karinthi *et al.*[19] have produced a parallel algorithm for performing Boolean set operations on polygons and polygons with holes. In Almasi *et al.*[17], these techniques are extended to more general loops of edges.

Strip and Karasick[30] present techniques for performing solid modelling operations on a massively parallel SIMD (single instruction multiple data) computer. They provide a data structure for representation of solid models and a variety of parallel algorithms for implementing solid modelling operations. In addition, they present performance comparisons with serial implementations.

Existing work on recognition of features has dealt with exclusively serial computer architectures. These feature technologies are based heavily on the geometric and topological manipulation capabilities of solid modelling systems and deal predominantly with form or machining features. Much has been written on this topic in the literature and we will not attempt to cover all of this work here. We present below some of the more recent and relevant work.

The work of Henderson has continually brought new computational techniques to address the feature recognition problem. His dissertation work[16] was the first to apply expert systems to the feature recognition problem. Gavankar and Henderson[11] presented techniques to identify protrusions and depressions in the boundary model of a part. More recently, Prabhakar and Henderson[25] described the use of neural networks to recognize and classify features. A strength of this approach is that it exploits the trainability of a neural net to incorporate new feature types. Further, neural nets have been demonstrated to be effective in classifying patterns in domains where there is 'noise'. In the context of feature recognition, this noise is in the form of incomplete or missing feature data lost due to feature intersections.

Graph-based algorithms have proven useful for extracting some classes of features. These methods fall into two categories: those based on graph search[7,4] and those based on pattern matching[18,23,28]. A common difficulty for both categories of graph-based approach is that the graph-based representations for solid models of parts are difficult to extend to the complex geometry and topology of interest to us. Secondly, methods based on pattern matching and finding subgraph isomorphisms (a problem known to be NP-hard) are prone to combinatorial difficulties.

Chuang and Henderson[3] explore graph-based pattern matching techniques to classify feature patterns based on geometric and topological information from the part. Efforts at Carnegie Mellon University[23,28] have employed graph grammars for finding features in models of injection moulded parts. Recently, Corney and Clark[4] have employed graph-based algorithms to find general feature classes from $2\frac{1}{2}$-dimensional parts.

Gadh and Prinz[9] were the first to describe techniques for combating the combinatorial costs of handling complex industrial parts (i.e. those with thousands of topological entities). They point out that, in such cases, traditional knowledge-based, decomposition, and pattern-matching techniques are computationally impractical because the fundamental algorithms (i.e. frame-based reasoning or subgraph pattern matching) are inherently exponential. Gadh and Prinz's method is to abstract an approximation of the geometric and topological information in a solid model and find shape features in the approximation. Their approach employs a differential depth filter to reduce the number of topological entities. A second pass maps the topological entities onto structures called 'loops'. In their work, features are defined using the higher-level loops as opposed to being defined as patterns in the boundary representation's geometry and topology. This approach significantly reduces the number of entities that need to be searched to build feature instances. While this kind of approach holds much promise for addressing combinatorial problems, it does not address how to extend the techniques to better handle interacting features and non-linear (non-faceted) solid models.

Fields and Anderson[9] present an approach to feature recognition that overcomes some of the representation and efficiency problems common in previous work. Unlike pattern-based or decomposition-based recognition methodologies, they categorize sets of faces on the surface of the part into classes of general machining features: protrusions, depressions, and passages. The shapes within each class, while sharing many operational similarities, may vary in geometry and topology. For each of their feature classes, they present a linear-time algorithm for identifying features.

Trace-based feature recognition

Most relevant to the work in this paper are the recent trace-based feature recognition methodologies. Fundamentally, a trace-based approach to feature recognition attempts to reconstruct feature instances from the information that they contribute to the final geometric model of the product.

The work of Marefat and Kashyap[2] presented an early trace-based technique. They expanded on the work of Joshi and Chang[18], augmenting it with hypothesis testing techniques. In Marefat and Kashyap's method, information from the solid model is used to generate hypotheses about the existence of features. These hypotheses are tested to see if they give rise to valid feature instances.

Vandenbrande and Requicha[33] were the first to formalize trace-based (or hint-based) techniques for constructing features from information in a solid model. In the work of Vandenbrande, the traces are used to fill 'feature frames' in a frame-based reasoning system. After filling frames with the trace information present in the part, the system classifies the partial frames and attempts to complete information for producing promising frames using a variety of geometric reasoning and computational geometry techniques. This work has recently been enhanced and extended by Han and Requicha[14,15].

Regli *et al.*[27] present an approach for guaranteeing completeness of a recognition algorithm, i.e. it describes how one can define a class of features and verify that a particular approach was capable of producing all features in that class. They present feature recognition as an algorithmic problem in which traces are found by traversing the geometry and topology of the part and then used to construct feature instances. They formally describe the behaviour of their algorithm and calculate a general measure of its complexity. This approach has been employed for automated design analysis[13] and automated redesign[5,6].

Many aspects of the feature recognition problem are still open and active areas of research. Among these are: recognizing and representing interacting features[33], incremental recognition of features during feature-based design[20,14,15], modelling alternative feature interpretations and completeness[21,27], and reasoning about the manufacturability of features[13].

APPROACH TO FEATURE RECOGNITION

In this section we outline a basic trace-based feature

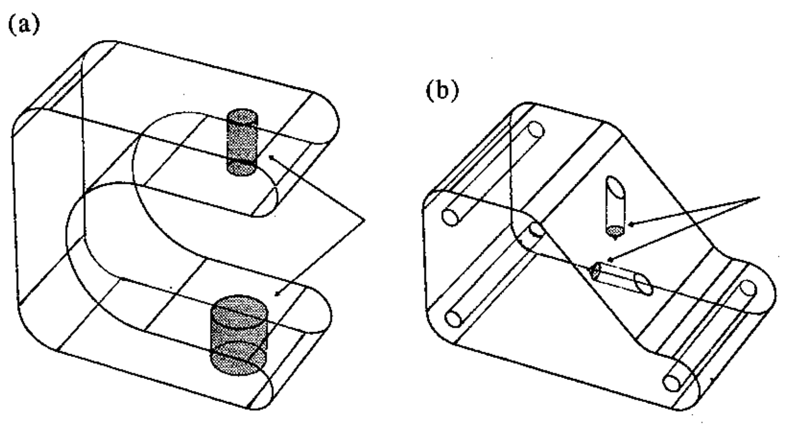


Figure 1 An example of traces left by drilling features: (a) trace 1: cylindrical surface; (b) trace 2: conical surfaces

recognition technique on which we will build our multiprocessor algorithms in the next section.

A *trace* t_M corresponds to the information contributed to the part by an instance of a feature f of type M and provides sufficient information for calculating the parameters of f. For example, a drilling operation on a three-axis machining centre can be used to create cylindrical surfaces on the part, hence these surfaces can be thought of as traces left by a particular feature instance as shown in *Figure 1a*. Traces are similar to the *feature presence* notion of Reference 33.

A trace comprises geometry and topology, design features, tolerances, and other design attributes associated with the CAD model. While the traces addressed in this paper cover only geometry and topology, this approach can be expanded upon with traces based on other forms of design information or enhanced with more domain-specific machining knowledge.

Trace-based approaches have several properties that are just beginning to be exploited by researchers, including the following:

- Feature traces can be derived from a variety of design information such as tolerances, surface finish requirements, and functional information associated with surfaces. Traditional feature recognition methodologies often consider only the part's geometry and topology.
- Feature classes can be customized by users. Recognition routines for new features can be built by introducing traces for the new features and methods for building instances of the new features from these traces.
- Trace-based techniques can be adapted to recognize features from a variety of manufacturing domains and processes. Existing feature recognition literature focuses primarily on machined parts, due in part to the fact that the functionality of solid modelling systems is well suited for manipulating volumes that describe the material to be machined and decompose these volumes into features.

Trace-based techniques also lend themselves well to parallelization, providing several levels at which the problem can be divided. Less evident, however, is that in parallelizing the problem, one can further simplify the independent problem subtasks and thereby reduce overall computational difficulty.

The remainder of this section will specify a simple example domain features for machined parts and trace-based recognition techniques. Using this domain we present a multiprocessor recognition methodology in the next section.

Machining features

In this paper, a *machining feature type M* is a parametrized volumetric template that represents the solid volume removed from a workpiece by a machining operation. An instance f of a machining feature is created by a specific machining operation with a single cutting tool in one tool set-up. In this work, M represents the generalized feature describing a machining operation and f is a particular example of an operation occurring with respect to some part.

To perform a machining operation, one sweeps the tool along some trajectory. Only a portion of this swept volume corresponds to the volume of material that is to be removed by the machining feature. This volume is called *removal volume* of feature f (rem(f)).

Machining features are referred to in terms of the operations used to create them. For example, we say that the hole h in *Figure 2a* is an instance of a *drilling feature*. The pocket m in *Figure 2b* is an instance of an *end-milling feature* and is characterized by the edge profile bounding the area swept by the milling tool cutting at a specific depth.

Note that many types of machining operations cannot be represented with simple volumes (e.g. finishing operations, deburring, etc.). While this paper only discusses volumetric machining features, in practice these other types of features would have their own traces and recognition methods.

Machining feature recognition

The initial workpiece S is represented as a solid model of raw stock material to be acted upon by a set of machining operations. The machined part is a solid object, represented by a solid model of the part P, to be produced as a result of a finite set of machining operations. The *delta volume* is the regularized difference[17] of the initial workpiece and the part: $\Delta = S -^* P$.

In general, there may be several alternative interpretations of the part as a collection of machining features, each interpretation corresponding to a different way

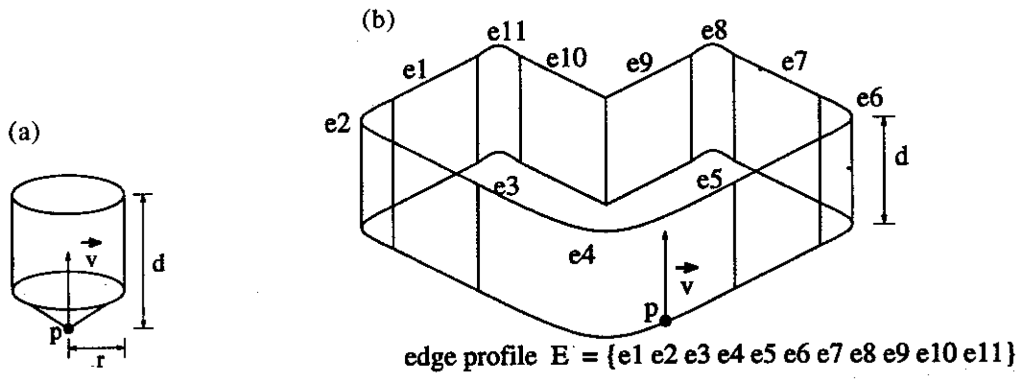


Figure 2 Examples of machining features: (a) hole h, a drilling feature; (b) pocket m, an end-milling feature

of manufacturing it. A *feature-based model* is a set of feature instances that models a single, unique interpretation of the part. The feature recognition problem can be defined as follows: given a collection of machining features $\mathcal{M} = \{M_1, M_2, \ldots, M_j\}$, a part P, and a piece of stock S, find the set $\mathcal{F}$ of instances of feature types from $\mathcal{M}$ recognized from P and S. The feature set $\mathcal{F}$ is a finite set of features the set being composed of the union of the alternative feature-based models for the part[27].

Trace-based recognition of features

A *trace* represents the information in the solid model of the part produced by an instance of a feature. The basic components of a trace-based feature recognizer are the following:

(1) A finite set $\mathcal{M}$ of feature types. In the context of this paper, $\mathcal{M}$ is made up of the simple feature domain defined earlier.
(2) Each feature type M in $\mathcal{M}$ has associated with it a finite set of trace types $t_{M_1}, t_{M_2}, \ldots, t_{M_k}$. Trace types are developed below in this subsection.
(3) For each trace type t_{M_i}, there is a procedure $\mathcal{P}_{t_{M_i}}()$ such that $\mathcal{P}_{t_{M_i}}()$ constructs, from instances of the traces and the solid model of the part and stock material, instances of features of type M capable of producing the trace t_{M_i}.

Note that a feature type M might have several different types of traces associated with it; also a feature instance f might leave several different traces on the model of the part. Conversely, a trace type might produce one or more feature instances (e.g. the cylindrical surface of a through hole can be considered as two different drilling features, one in each direction along the axis of the cylinder). In this work we are focusing on feature traces that can be identified on the boundary of the part (i.e. traces left in $(f) \cap b(P)$ where $b(P)$ is the boundary of P).

An outline for a generic algorithm for trace-based recognition of features can be presented as follows:

(1) Input a collection of feature types $\mathcal{M}$, a solid model for the part P, and a solid model for the initial stock material S.
(2) From P and S, identify the set $\mathcal{T}$ of all potential traces present.

There are several ways in which the traces can be identified (for example, previous research has included hypothesis testing[21] and frame-based reasoning approaches[33]). The traces in this paper can be identified by examining the topology in the boundary representation of Δ.

(3) For each potential trace t in $\mathcal{T}$ do: If t matches a t_{M_i}, call the procedure $\mathcal{P}(t_{M_i})$ and construct (if possible) feature instances, $f_1, f_2, \ldots, f_n$, of type M. Add these to the set $\mathcal{F}$ of all feature instances.

Detailed presentation of trace-to-feature algorithms is beyond the scope of this paper. Interested readers are referred to related work which contains detailed examples of such algorithms[12,14,27,33] for all of the above traces.

Example trace types

For illustrative purposes, the task of recognizing basic drilling and end-milling features can be accomplished using the following traces types:

1. *Drilling features.*

Trace 1. Any convex cylindrical surface s_c in the delta volume created by the side surface of a drill during a drilling operation.
Rationale: This trace type is used to build instances of drilling features when a portion of their side surface remains on the boundary of the delta volume. An example of this trace is illustrated in *Figure 1a.*

Trace 2. A convex conical surface s_f in the delta volume created by the side surface of conical tip of a drilling tool.
Rationale: This trace type is used to build an instance of a drilling feature when only a portion of its ending tip surface remains on the boundary of the delta volume. An example of this trace is illustrated in *Figure 1b.*

2. *End-milling features.*

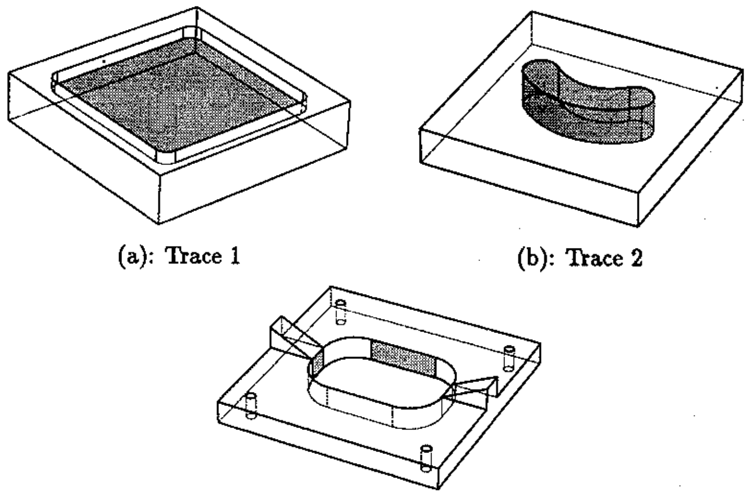
Trace 1. A planar surface s_p in the delta volume created by the cutting tip of an end-mill. This trace is used to build instances of end-milling features when only a portion of their bottom surfaces are present on the boundary of the delta volume.
Rationale: This trace type is used to determine the profile of end-milling features. Given an edge $e_1 = \langle v_1, v_2 \rangle$ of the planar surface s_p, orientations and locations for potential milling features can be obtained from other edges* $e_2 = \langle v_3, v_4 \rangle$ in the delta volume for which the vertices v_1, v_2, v_3, v_4 are coplanar. An example of end-milling trace 1 is given in *Figure 3a.*

The following two traces are used to build instances of end-milling features when only a portion of their side surfaces are present on the boundary of the delta volume. In these cases, the end-milling features may extend completely through the stock material. Examples of such features include through pockets and profiles.

Trace 2. A cylindrical surface in the delta volume as a surface created by the side cutting surface of an end-mill. An example of end-milling trace 2 is given in *Figure 3b.*
Rationale: The profile of a milling feature might comprise curved edges, for example, the corner radii created when a round tool machines a convex corner. This trace type uses these curved surfaces to determine the orientation of potential through features.

Trace 3. A planar surface in the delta volume, considered as a face created by the side cutting surface of an end-mill during the same machining operation. *Figure 3c* shows an example of milling trace 2.
Rationale: For some instances of through milling features, all that may remain are walls. This trace type begins with a single planar wall and, by considering other planar surfaces in the delta volume, obtains orientations for potential through milling features from the normal vectors; i.e. two non-parallel planar surfaces can be used to determine the orientation of

* Note that in the solid model of the delta volume, the edges e_1 and e_2 might be non-linear curves, e.g. they could be elliptical.



(a): Trace 1 (b): Trace 2 (c): Trace 3

Figure 3 Parts illustrating end-milling traces 1, 2 and 3

the through features that might have made them (if any) as the dot product of their normals.

Note that with these trace types there may be multiple ways in which to identify each feature instance. These redundancies are resolved when the final feature set is created, as outlined in the second subsection of 'Approach to parallelization'.

A presentation of the details of the various procedures $\mathscr{P}(t_{M_i})$ for constructing feature instances from instances of these trace types is not central to the focus of this paper. Such algorithms have been developed in previous work, notably: Vandenbrande and Requicha[33] for drilling feature traces 1 and 2 and end-milling feature trace 1; and Regli *et al.*[27] for all of the above traces.

APPROACH TO PARALLELIZATION

In the distributed computing paradigm, collections of autonomous computational resources are interconnected on a network, as illustrated in *Figure 4* from Reference 32. They may share access to common devices such as peripherals, file systems, and output devices. Software systems can use the network and shared peripherals to exchange information among the autonomous resources.

In this section, we will apply distributed algorithms to the example problem domain from the previous section.

Motivations

The feature types and their traces each introduce natural partition lines along which the problem can be divided into independent subproblems to be solved by different processors.

As presented in the subsection 'Machining feature recognition', the final feature set $\mathscr{F}$ contains all those feature instances from $\mathscr{M}$ that are members of feature-based models of the part. $\mathscr{F}$ contains all instances of the feature types in $\mathscr{M}$ present in the given part. Note that for the features in $\mathscr{M}$, the act of recognizing a feature of type M_1 is independent of the recognition of a feature of type M_2—hence the feature instances of type M_1 can be calculated separately from those of type M_2. For instance, in the example domain presented in the previous section, the fact that a particular drilling feature f is a member of some feature-based model does not alter the existence of any end-milling features.

Secondly, the set of traces $\mathscr{T}$ (from the generic algorithm in subsection 'Traced-based recognition of features') introduces an additional level for partitioning the problem. Recall that for each feature type M in $\mathscr{M}$, there is a collection of traces $t_{M_1}, t_{M_2}, \ldots, t_{M_k}$ for building instances of features of type M. One can decompose the problem of finding all features of type M using the traces by handling each trace t_{M_i} on a different processor.

One observation is that this may introduce some redundancy; i.e. it may be possible to find the same

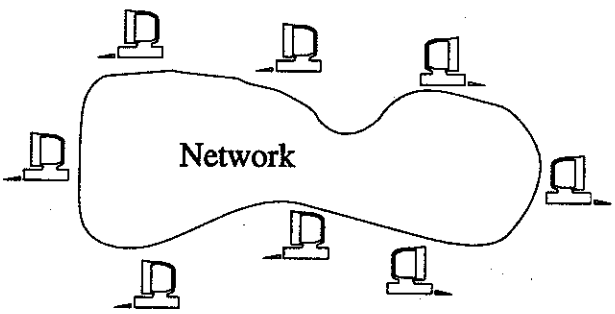


Figure 4 Internetworked computational resources

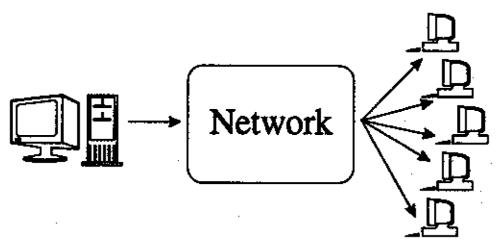


Figure 5 Source machine distributing the tasks to clients

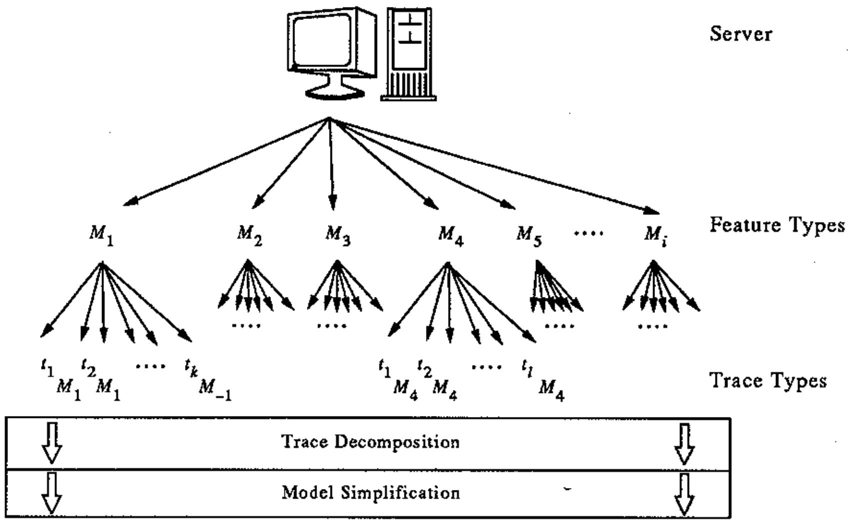


Figure 6 Divide-and-conquer parallelization based on feature types and trace types

feature instance f in different ways using different traces. There are two possible approaches to handling this redundancy. One method is to delete duplicate features while building the final feature set $\mathscr{F}$. A second approach, and the one that we will employ, is to identify the traces capable of producing equivalent feature instances and handle them together on the same processor, removing duplicates as they are found. This introduces another level of parallelization by dividing the set of traces found into independent subsets. In this way redundancies are addressed at the level at which they occur, thus simplifying the task of building the final feature set $\mathscr{F}$.

Parallelizing feature recognition produces other, less obvious benefits. In particular, a large portion of the costs in a feature recognition system are due to the complexity of geometric computations and geometric reasoning. When isolating independent problem subtasks, one can make geometric and topological simplifications that identify the information in the original part needed to build and verify the feature instances. In this way, many of the subproblems may require only a fraction of the information present in the solid models of the original part and stock.

Distributed methodology

For the example domain of the previous section, our approach is to have a central computing resource act as a server to set up the problem and transmit subtasks to client machines distributed on the network, as illustrated in *Figure 5*. Each of the individual client processors is given an independent portion of the particular global feature recognition problem.

A distributed algorithm

Recalling the serial trace-based algorithm of subsection 'Traced-based recognition of features', we present an outline for a multiprocessor trace-based feature recognition algorithm. There are two main components to this system: a parent algorithm and a child algorithm. Note that these algorithms partition the problem at several levels, as shown in *Figure 6*. The parent algorithm is as follows:

Parent algorithm

(1) Input a collection of feature types $\mathscr{M}$, a solid model for the part P, and a solid model for the initial stock material S. Initialize the set $\mathscr{F}$ of recognized features, $\mathscr{F} = \emptyset$.
(2) For each feature type M in $\mathscr{M}$, fork a new process* on a free resource (i.e. a CPU or machine) and do
  (a) For each trace type t_{M_i} for feature type M do
    (i) Find the set $T_{t_{M_i}}$ of traces of type t_{M_i} present in the CAD model of the part P.
    (ii) Use the set $T_{t_{M_i}}$ to divide the problem into independent subtasks, $\tau_1, \tau_2, \ldots, \tau_j$.
    (iii) for each τ_i do
      (A) *Decompose* the part P using the τ_i—result P'. Trace decomposition is discussed in more detail later.
      (B) Fork a new process on a free resource to call the child recognition algorithm on P'.
    (iv) Let $F_{t_{M_i}}$ be the set of features returned by the child.
(3) $\mathscr{F} = \mathscr{F} \cup_{\forall t_{M_i}} F_{t_{M_i}}$.
(4) Return $\mathscr{F}$.

The child algorithm constructs, when possible, feature instances from the traces. It is executed over the available processors as follows:

Child algorithm

(1) Input a feature type M, a trace type t_{M_i}, a set of instances of $T_{t_{M_i}}$ of trace t_{M_i}, and solid models for the part P', and the stock material S.
(2) *Simplify* the solid model of the part P'—result P''. Model simplification is discussed later.
(3) Call $\mathscr{P}(t_{M_i})$ to build feature set $F_{t_{M_i}}$.

*To fork a process is to start a separate task running within a multitasking operating system. In current practice on multiprocessor systems this can also be accomplished by starting a thread[24,31]. A thread can be thought of as an independent subprocess that can be executed on its own separate CPU, if one is available.

(4) Remove duplicate features from $F_{t_{M_i}}$.
(5) Return $F_{t_{M_i}}$.

To implement this client-server algorithm, three technical areas must be addressed.

Task initialization
There are four levels at which initialization occurs, in sequential order:

- *Types of features to be recognized.* Different feature types (in this example drilling and end-milling) are considered by separate computing resources, as discussed earlier.
- *Types of feature traces.* Different traces for each of the feature types are considered by separate computing resources, as discussed earlier.
- *Trace decomposition.* Given a specific feature type and a trace for recognizing it, decompose the set of these traces (occurring in the part P) into independent subsets to subdivide the recognition task. This is discussed below.
- *Part simplification.* Given a specific feature type and a trace for recognizing it, alter the geometric and topological information in the solid model of the part to reduce its complexity. This is discussed later.

In this current work, all of the initialization occurs on the parent. Specific details are given in the next subsection.

Task distribution
Once tasks are initialized, the next phase is to distribute the individual tasks to the available computing resources. This is done by invoking a child feature recognition procedure for each separate task, with each task to be performed on its own processor.

In the example domain in the third section, distributing tasks is straightforward. This becomes more complex when bounds are placed on the number of available computing resources.

Synthesis of results
Each separate child procedure, upon termination of its portion of the recognition task, transmits its results back to the parent machine. The features returned are then integrated into an overall solution. In this domain, recombining results requires building the final feature set as the union of those features returned by each child machine.

However, the fact that this example domain lends itself well to building an overall solution from the separate subtasks may not generalize to other manufacturing domains. For example, one might wish to include additional computations in this phase, such as modelling how geometric interactions among manufacturing features affect operation planning or identifying compound features, feature relationships, and feature groups.

An example of task initialization

The task initialization stage groups feature information and isolates traces to be handled by separate computing resources. There are four levels of task decomposition.

For illustration purposes, we shall assume there is no limit on our computational resources. When there is a bound on the number of processors available, the task decomposition or the distribution of the task may vary to partition the problem more efficiently. In particular, in our current implementation (discussed in the next section), we distribute the tasks evenly over the available processors.

The decomposition by feature type and decomposition by trace, as noted before, are straightforward. In developing techniques for part decomposition and simplication, one is faced with a trade-off between the sophistication of techniques and their computational costs. In choosing the following conditions, we have picked decompositions and simplifications that are computationally inexpensive.

While it is certainly possible to present more complex decomposition criteria, an important consideration is that the conditions themselves cannot be more complex than the original recognition problem. Very sophisticated techniques to maximize the ability of each individual processor might require computational overheads that eliminate any of the speedup benefits we hope to achieve using a multiprocessor approach.

The remainder of this section discusses trace decomposition and techniques for part simplification.

Trace decomposition
A given feature instance might be created from any one of several traces it leaves in the part. The objective of trace decomposition is to collect all of the trace information capable of producing equivalent or identical feature instances. While we will only consider geometric and topological information in this paper, this decomposition can be extended to include other data that might serve as potential feature traces (i.e. tolerances, surface properties, etc.).

We present a four step decomposition for the geometric and topological information in the part—this corresponds to Step A in the *Parent Algorithm* presented earlier. The conditions are based on properties of the traces for constructing feature instances. Note that there may be other conditions that provide an equivalent means of arriving at a task decomposition with the desired properties. Decomposition of the geometry and topology based on feature types and traces proceeds as follows:

(1) *Decomposition for drilling traces 1 and 2.* Group together cylindrical and conical faces with equivalent axes that are convex with respect to the delta volume Δ.
Rationale: This collects all possible drilling traces that might be machined in the same orientation. Drilling features with multiple traces (e.g. several separate cylindrical faces) can be isolated and identified. For the part in *Figure 7a*, this results in the grouping of traces shown in *Figures 7b* and *c*.
(2) *Decomposition for end-milling trace 1.* Group together all coplanar faces. In the example illustrated in *Figure 8b*, six disjoint planar part faces are grouped to be handled together on the same processor. This grouping collects all faces sharing the same underlying surface.
Rationale: This collects all possible end-milling traces that might be machined in the same orientation,

possibly by the same operation. End-milling features with multiple traces (e.g. a bottom surface divided into multiple subfaces) can be isolated and identified. For the part in *Figure 7a*, this results in the grouping of traces shown in *Figure 7d.*

(3) *Decomposition for end-milling trace 2.* Group cylindrical surfaces with equivalent axes.
Rationale: This groups all potential corner radii and curved walls for end-milling features with the same machining orientation. For the part in *Figure 7a*, this results in the grouping of traces shown in *Figure 7e.*

(4) *Decomposition for end-milling trace 3.* Group planar surfaces with normals perpendicular to a common vector; i.e. for each grouping there is a vector **v** such that, for all surfaces s_i and s_j in the grouping, normal $(s_i) \cdot \mathbf{v} = \text{normal}(s_j) \cdot \mathbf{v} = 0$.
Rationale: This groups traces for end-milled features based on machining orientation; hence through features that can be machined in the same orientation are placed in the same group. For the part in *Figure 7a*, this results in the grouping of traces shown in *Figure 7f.*

The above decomposition groups those traces from the part which might produce equivalent feature instances. In this way, redundancies can be eliminated at the subprocess level and later recombination of results can be facilitated.

Part simplification

The objective of part simplification is to reduce the amount of data that must be considered by each processor to a minimum amount sufficient to construct feature instances from the traces it has been given. The goal is to reduce the cost of operations during feature recognition. For example, one can reduce the number of geometric and topological entities while still retaining the information required to construct feature instances from the particular trace. In this way, geometry which does not affect the feature trace under consideration can be eliminated.

This section describes Step 2 of the *Child Algorithm*, in which the solid models of the part and stock are simplified based on the trace information and feature types. In each case, the geometry and topology of the model for the part P is modified to P' as follows:

(1) *Simplification based on drilling trace 1.* Given a cylindrical surface c in the delta volume of radius r, P' contains all the portions of P that lie within r of the axis of c.
Rationale: This simplification retains enough information to check for interference between the cutting tool and the final part. To check for interference between the workpiece and the machine tool, this radius may be enlarged depending on the size of the tool assemblies available in the particular set of manufacturing resources.

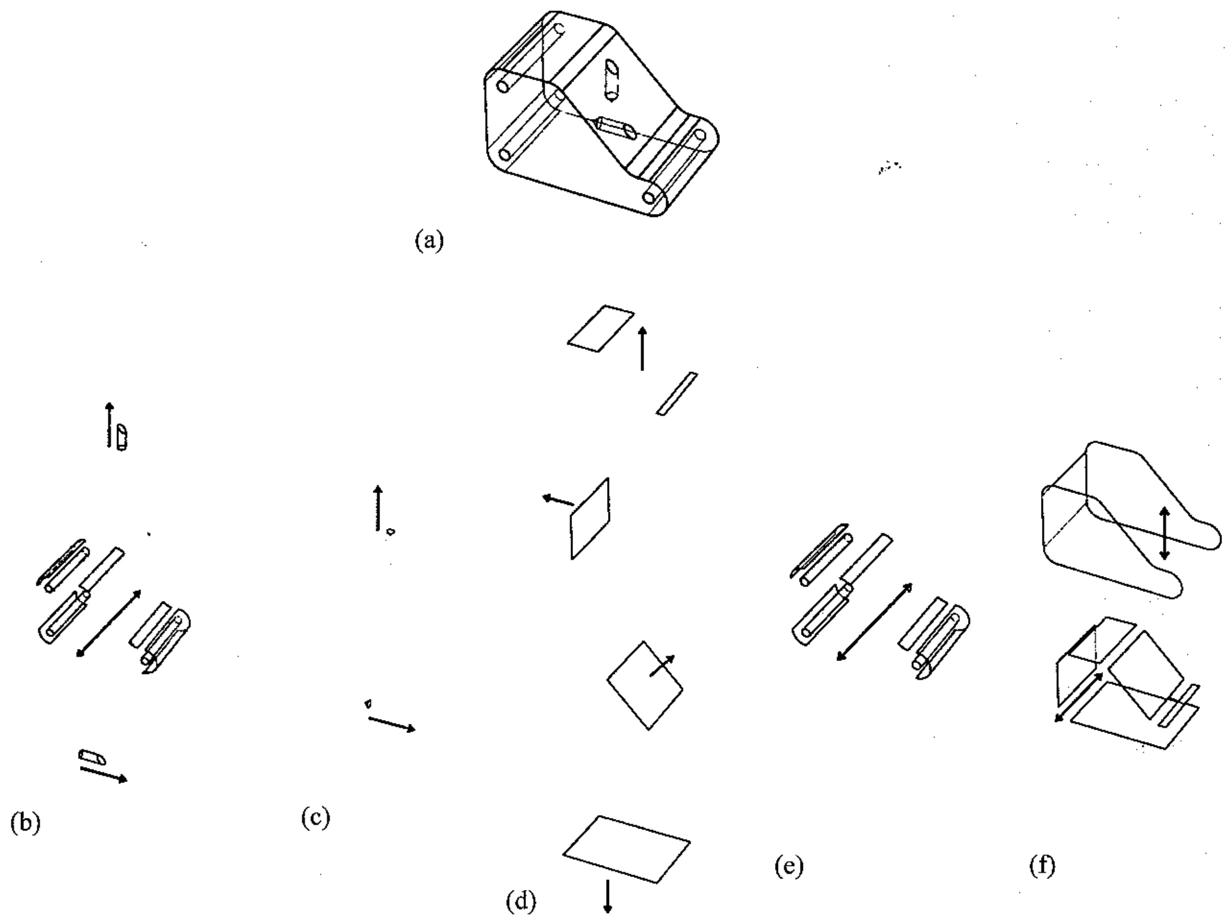


Figure 7 An example part and its trace decomposition. The arrows in each figure denote the orientation vector **v**, for the features that might have created these traces: (a) an example part; (b) drilling trace 1; (c) drilling trace 2; (d) milling trace 1; (e) milling trace 2; (f) milling trace 3

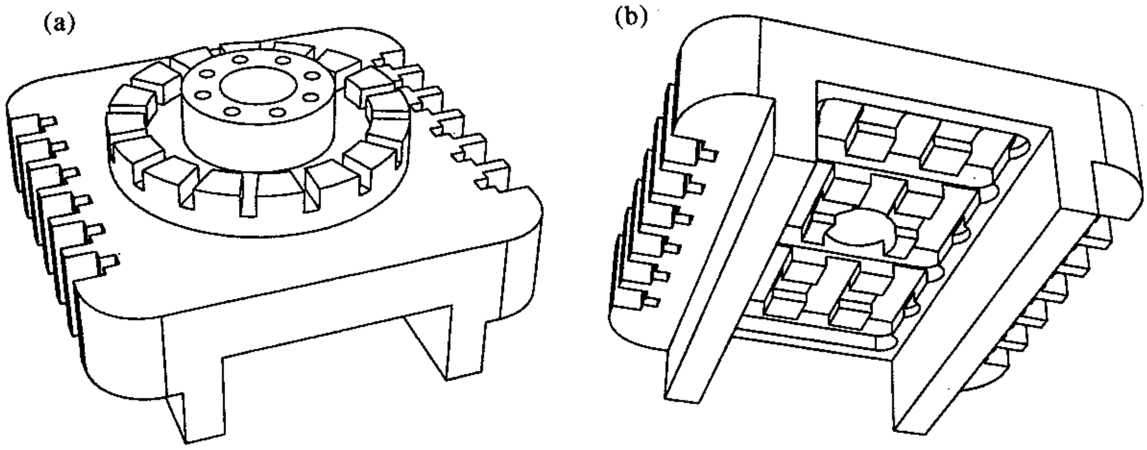


Figure 8 An example part: (a) part (after machining); (b) part (underside view, after machining)

(2) *Simplification based on drilling trace 2.* Given a conical surface c in the delta volume with a maximum radius r and located at point d, P' contains all the portions of P that lie within r of the axis of c and in the half-space above d.
Rationale: This simplification is identical in intent to that for drilling trace 1.

(3) *Simplification based on end-milling trace 1.* Given a planar surface p in the delta volume with a root point d and normal vector $\mathbf{v}$, P' contains all the portions of P that lie in the half-space defined by d and $\mathbf{v}$.
Rationale: This simplification retains all geometric and topological information that lies above the bottom surface of the milling feature and discards all information below it.

(4) *Simplification based on end-milling traces 2 and 3.* No simplifications are made for these traces.
Rationale: Finding these types of end-milling feature instances might require consideration of information

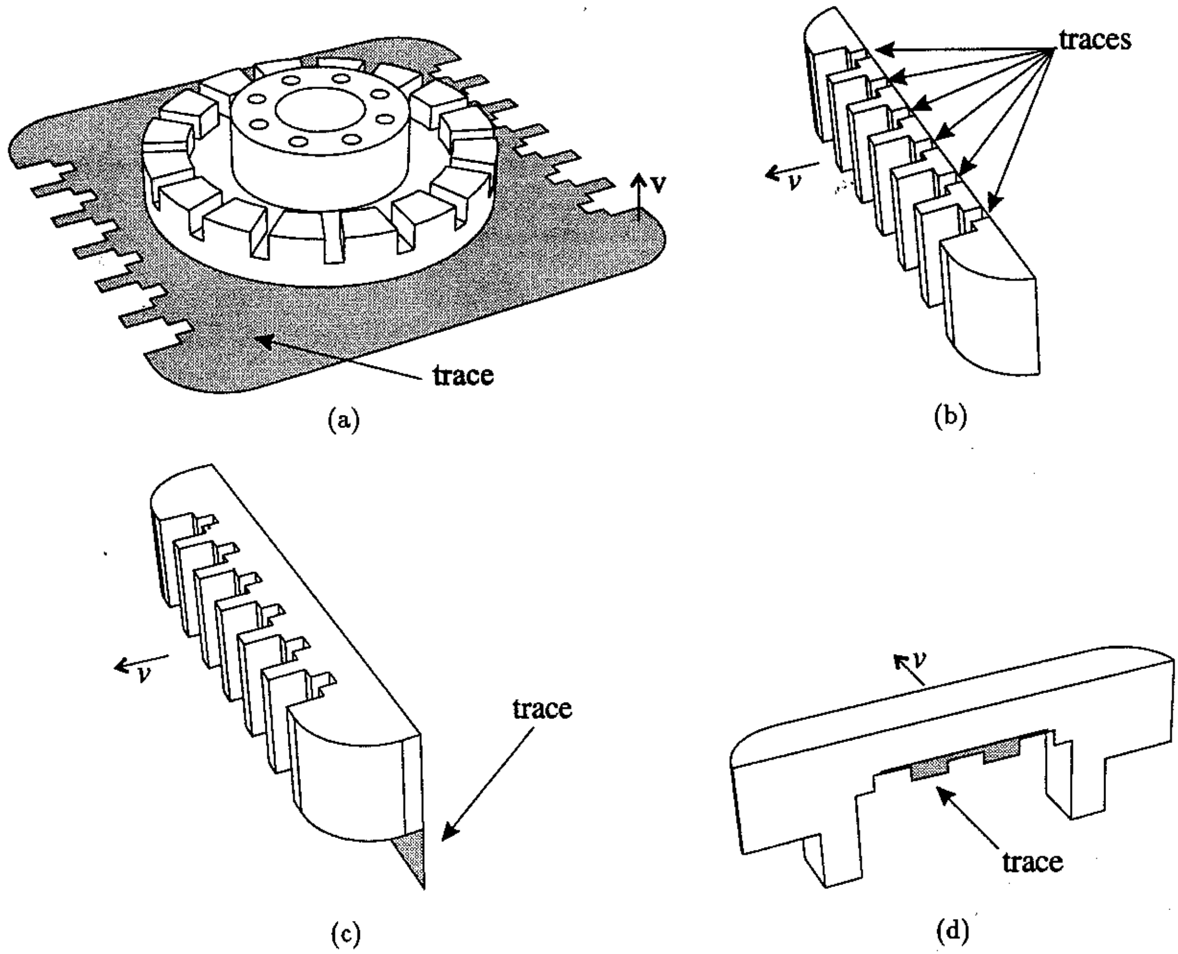


Figure 9 Four end-milling recognition subtasks and their simplified part information for the example in *Figure 8*

from the entire part, and the processing required in this case might be costly.

Figure 9 shows an example part and four illustrations of part simplification for end-milling trace 1. In the figure, the planar faces are being considered as traces indicating potential bottom surfaces of several end-milled features; vector **v** denotes the orientation of the potential feature. In each case, the trace information is used to eliminate the portion of the part lying below the trace (in the direction −**v**)—information that does not get considered when building a feature instance in direction **v**. Note that in making this rudimentary simplification the number of geometric and topological entities to be considered is greatly reduced.

Potential for computational improvement

We can expect the speedup to be no more than a factor of K, where K is the number of processors available. In reality, the task decompositon to set up parallelization incurs some added cost, as does the recombination of results at the end. These additions are negligible, however, when compared with the costs incurred to perform the recognition process on the subproblems.

Within a trace-based methodology, the overall complexity of recognition depends on two factors: the difficulty in generating the set $\mathcal{T}$ of potential traces, and the complexity of the methods for generating feature instances from traces.

A rough upper bound on the size of $\mathcal{T}$ can be computed from the model of the part and the types of traces by counting the number of geometric and topological entities. The complexity of the feature construction routines is more difficult to assess and is where the majority of the computational costs occur. Much of this cost is due to geometric queries and reasoning used to find the parameters of feature instances. While there is no authoritative reference on the general complexity of solid modelling operations such as Booleans, sweeps, and the like, indications are that these operations account for the majority of the computational cost during feature recognition[33]. The complexity of Boolean operations appears to lie between $O(n^2)$ and $O(n^4)$ or $O(n^5)$ time, depending on the particular configuration of geometric entities and many implementation-specific details.

The fact that these basic solid modelling routines are at least quadratic in the size of the model implies that small reductions in the number of entities in the model translate into large reductions in computational cost.

In the next section, we provide rough estimates of both the speedup factor and the reduction in the number of geometric and topological entities achieved by our approach.

IMPLEMENTATION AND RESULTS

A proof-of-concept implementation of this distributed feature recognition methodology, dubbed *F-Rex*, has been done in C++ using version 3.0.1 of the AT&T C++ compiler from SUN Microsystems running on networked SUN SPARC Stations. F-Rex employs version 1.5.1 of Spatial Technologies' ACIS© solid modelling system and version 3.14 of the NIH C++ Class Library developed at the National Institutes of Health. Additional tools include Ithaca Software's HOOPS© Graphics System and the Tcl/Tk embeddable command language and user interface toolkit from the University of California at Berkeley.

F-Rex is the feature recognition subsystem for IMACS, an interactive manufacturability analysis tool under development at the University of Maryland's Institute for Systems Research. One of the fundamental goals of IMACS is to provide interactive feedback and redesign suggestions to the user. Multiprocessor algorithms have provided IMACS with a means of handling computational bottlenecks.

F-Rex runs on a cluster of SUN workstations; processes communicate over the Internet using UNIX-based and TCP/IP-protocol-based network software utilities and shared disk storage. The geometric computations required for task initialization are implemented with direct C++ calls to the ACIS kernel; distributed processes are invoked using UNIX remote shell commands; and the resulting feature set is generated by examining the features produced by each processor and eliminating redundancies.

The data for the examples below have been collected using six processors, one SPARC Station model 10, one model 2, and 4 IPX models. In this version of the implementation, when the number of tasks is greater than 6, the tasks are distributed evenly over the available processors.

These timing results represent the elapsed clock and CPU times and are not absolute measures of the intrinsic difficulty of the feature recognition problem—this example domain is not directly comparable to those of other feature recognition efforts. Further, there are hidden costs in the implementation not directly related to the recognition of feature templates (such as feature accessibility analysis) and these algorithms and their implementation can certainly be improved. The results are intended to provide a rough indication of the time-lag experienced by the user of the system. More significant than any precise calculation of elapsed time is the speedup factor between the serial and parallelized algorithms. Measurements of elapsed CPU time are summarized in *Table 1*.

Example 1

The example part in *Figure 10a*, taken from Reference 33, contains 21 part faces. Vandenbrande and Requicha[33] report identifying 7 features (3 slots, 3 open pockets, and a step) in 2.5 min on a SUN 4/360. The OOFF system[33] handles a wide variety of machining features and process planning constraints; hence it is not directly comparable

Table 1 Estimated elapsed CPU times for each example

Example	Serial (s)	Distributed set-up (s)	Recognition (s)
1	54	0.96	9.8
2	116	3.5	43.1
3	127	1.2	6.4
4	>1800	75	700
5	>1800	19.5	701.5

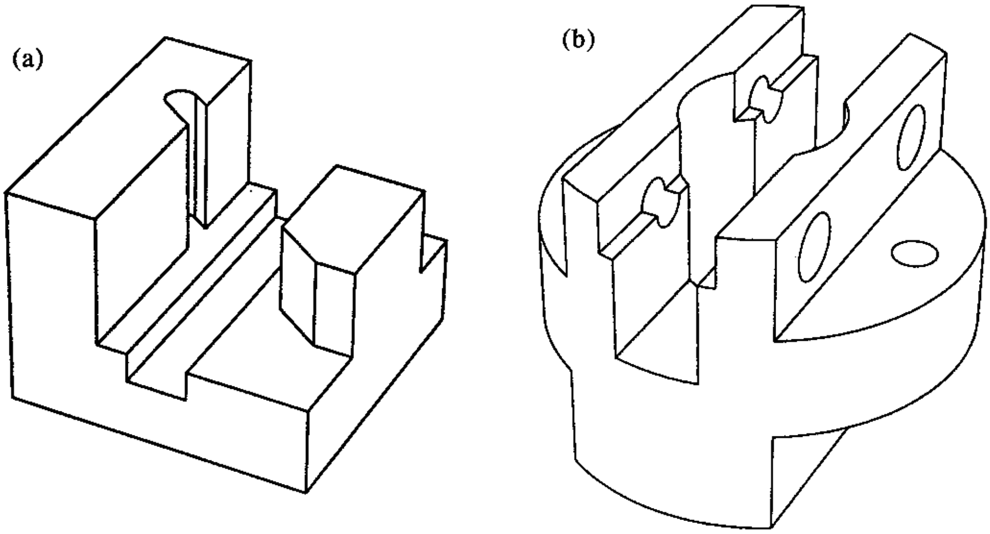


Figure 10 Two example parts addressed in previous literature: (a) example from Reference 1; (b) example from Reference 6

to the approach outlined in this paper. It does, however, provide a general indication of the computational costs required to recognize features in relatively straightforward parts.

Running in serial on the SPARC 10, our system finds 1 drilling and 8 end-milling features in approximately 1 min. In parallel on 6 processors, it takes approximately 3 s to set up the decomposition and 12 s to recognize the features—a speedup of approximately 5× (500%). Using the simplification techniques, the number of geometric and topological entities that had to be considered was reduced by 22%. Note that this example has only a few feature instances with relatively straightforward interactions.

Example 2

The example part in *Figure 7a* has 19 faces. This part, when machined from a rectangular block of stock material, has 37 faces in its delta volume. In serial, F-Rex identifies 10 drilling and 10 milling features in approximately 2 min. In parallel on 6 processors it takes 4 s to set up the decomposition and about 45 s to find the features—a speedup of 2× (200%). In this case, simplification resulted in a 10% reduction in the number of geometric and topological entities that had to be considered. Note that this example has more curved surfaces and several interacting milling features, requiring more geometric computation to identify.

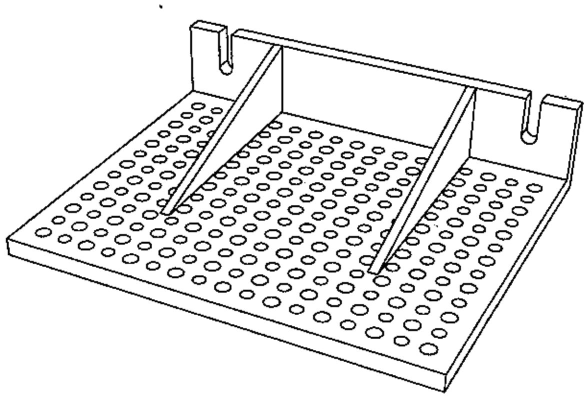


Figure 11 A fixture from ICEM's PART System

Example 3

The example part in *Figure 10b* is a socket taken from Reference 27. This part, when machined from a cylindrical piece of stock material, has 37 faces in the delta volume. There are 12 drilling and 20 end-milling features in its feature-based models that can be produced with the traces given above. In serial running on the SPARC 10, F-Rex identifies these 32 feature instances in approximately 65–70 s. When run distributedly, using 6 processors, F-Rex takes 10 s to set up the decomposition and approximately 12–16 s to identify the features—a speedup of 3× (300%). In this case, simplication resulted in a 35% reduction in the number of geometric and topological entities that had to be considered. Note that this part has several curved surfaces and most of the feature instances interact.

Example 4

The example part in *Figure 11* is a fixture used in Control Data Corporation's* ICEM PART Process Planning System. The solid model for this part contains 245 faces. When running in serial, F-Rex takes over 1 h to find the feature instances. In parallel, F-Rex takes 1.3 min to set up the problem and approximately 12 min to recognize the features—a speedup of approximately 4× (400%). In this case, simplification resulted in a 23% reduction in the number of geometric and topological entities that had to be considered. Note that this example contains

* This part is named 'WINKLE' and is a fixture for use with CDC's and ICEM's PART generative process planning system. This part was used with the permission of CDC and it is available for anonymous ftp from the NIST Process Planning Testbed at ftp.cme.nist.gov or http://www.parts.nist.gov/parts/.

many cylindrical curved surfaces and that few of the feature instances interact; also note that the decomposition techniques handle all of the drilling features on the same processor.

Example 5

The example part in *Figure 9* is a shuttle intended to move along a guideway, with many of the feature instances added to reduce weight. The solid model of this part contains 281 faces. In serial, F-Rex takes over 1 h to find more than 100 feature instances. When running distributedly, F-Rex took 2 min to set up the task decomposition and approximately 32 min to find the features—a speedup of approximately 2× (200%). In this case, simplification resulted in a 43% reduction in the number of geometric and topological entities that had to be considered. Note that in this example nearly every feature interacts with every other feature and that calculation of accessibility volumes for feature instances is rather complex.

Discussion of results

These preliminary results confirm that performance gains can be made through effective parallelization of algorithms. One issue is how to systematically identify *a priori* how to produce effective decompositions (i.e. some classes of features might prove more amenable to this approach). In general, however, it is difficult to assess what a typical decomposition and its speedup factor will be.

We believe that the considerable variation in our experiments between parallel and serial speedup is due to three primary factors. First, the complexity and particular shape of the parts themselves. The example part in *Figure 10a* has only one curved surface, while that in *Figure 9* contains many dozens. A more general analysis of speedup factors would require testing the software against a set of benchmark parts of varying degrees of complexity, e.g. parts with many features, parts with difficult surfaces, parts with both.

The second factor in these variations is the environment for the experiments, which were conducted on a busy network of heterogeneous multiuser machines. The data were collected under everyday operating conditions and is intended as part of our demonstration of the feasibility of the technique. Because it was not feasible to create controlled experimental conditions, the data are only presented as a general indication of the technique's potential.

The third factor contributing to the variability among examples (and among feature recognition systems in general) is the treatment of feature accessibility for machining. In the system used as a basis for the approach in this paper[27], each machining feature has associated with it an *accessibility volume* which approximates the non-cutting portion of the cutting tool and tool assembly (an example from Reference 26 is shown in *Figure 12*). Testing each feature to ensure that the accessibility volume does not interfere with the final part requires a considerable amount of geometric computation—computation which varies greatly depending on the shape of the individual part.

We believe that parallelized trace-based feature recognition is highly suitable for parts in which the feature instances themselves are relatively simple, but numerous. It is not as well suited to problems where the feature instances themselves have very complex geometric configurations.

CONCLUSIONS

The focus of this research was to demonstrate the feasibility of using multiprocessor architectures to enable large increases in computational power for geometrically intensive CAD problems. As collaborative engineering pushes more downstream manufacturing issues into the design phase, the need to build effective and interactive CAD software systems requires an increasingly sophisticated allocation of computational resources.

The contributions described in this paper include our initial work toward an approach for performing trace-based feature recognition using a multiprocessor architecture. We present a commonly addressed collection of features and illustrate how to identify a task

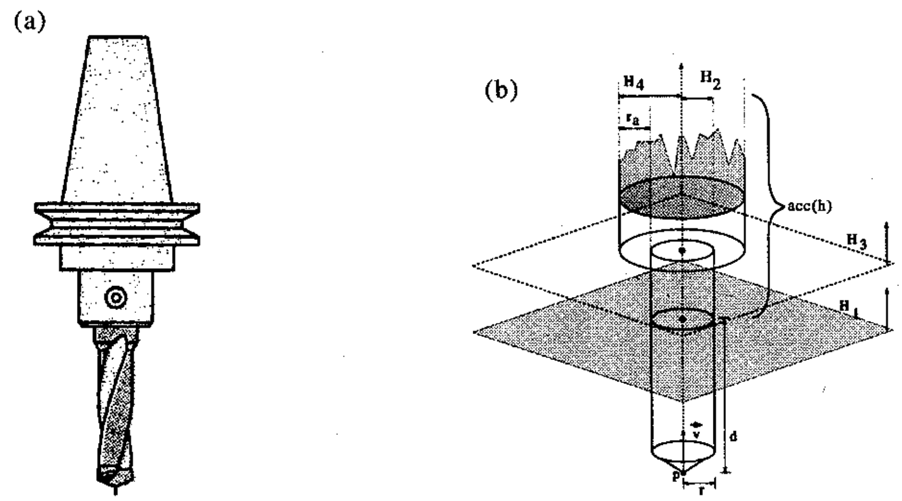


Figure 12 An illustration of a tool assembly and accessibility volume for drilling features. Testing accessibility conditions adds significantly to the cost of recognizing features for certain types of parts: (a) a drilling tool assembly, from Reference 29; (b) drilling feature *h* and accessibility volume acc(*h*)

decomposition of the recognition problem. The task decomposition is used then to divide the work among several distributed computing resources whose individual results are integrated into a unified solution for the part at hand.

We have demonstrated that this parallelized approach holds promise for domains of complex parts containing, possibly, thousands of features instances, but for which the structures of the feature instances themselves are relatively simple and their interactions well defined. This implies that multiprocessor algorithms can increase in the complexity of feasible mechanical designs and the ability to produce real-time feature data for complex parts. In addition, the techniques for simplification and complexity reduction presented are directly applicable to existing approaches to the feature recognition problem.

More generally we show that the application of multiprocessor algorithms to problems in solid modelling and engineering analysis holds immediate promise for enhancing existing CAD tools. As distributed and multiprocessor computing technologies become more accessible, algorithms that coordinate efforts between autonomous and geographically diverse computing resources will be commonplace in the modern manufacturing enterprise. Making this transition will require changes to the underlying architecture of solid modelling and CAD systems, their data structures, and algorithms to exploit multiprocessor computing. It is clear that further research will be needed on how to effectively migrate current solid modelling applications toward a multiprocessor computing framework. In addition, as engineering software applications built on top of solid modelling systems continue to grow in complexity, obtaining performance improvements will increasingly involve distributed and multiprocessor algorithms.

We anticipate that this novel multiprocessor feature recognition technology will increase the complexity of mechanical parts within the reach of traditional feature recognition systems and will reduce the computational bottlenecks they pose. This will enable more sophisticated design analyses and, in turn, aid in building an environment that will allow designers to create high-quality products that can be manufactured more economically—thus reducing the need for redesign, lowering product cost, and shortening lead times.

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ACIS .sat, Bentley MicroStation .dgn, and STEP AP203 format solid models for the example parts in this paper can be obtained through the World Wide Web through the NIST Process Planning Testbed Repository—please see URL http://www.parts.nist.gov/parts.html for more details.

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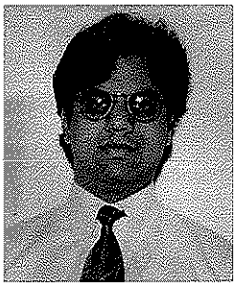

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