Manufacturing Processes Recognition of Machined Mechanical Parts using SVMs

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Introduction

This research studied using curvature and support vector machines (SVMs) to identify manufacturing processes of mechanical parts. Prior developments in computer vision and graphics has been able to recognize shapes of 2D and 3D models. This work contributes a technique for recognizing manufacturing processes from CAD models. Prismatic machined and cast-then-machined are two typical processes for making mechanical parts; being able to recognize them respectively assists in manufacturing cost estimation. This work integrates surface curvature estimation (from computer graphics) and machine learning to perform manufacturing recognition of artifacts. Surface curvature is used as the discriminating feature; SVMs learn the separation in between the two manufacturing processes.

Prismatic Machined and Cast-then-machined

Machining is a high precision and time consuming process. Process plans route tools for material removal operations. The application of casting procedure loosely constructs the shape of parts to reduce the need for machining. Cast-then-machined reducing costs by decreasing the complexity of process plans and in turn manufacturing time. Figure 1 shows a sample of models classified by process.







(a) Prismatic Machined (b) Cast-then-Machined

Figure 1: Manufacturing Classification Examples

Process Classification with Shape Matching

Current research (Osada *et al.* 2002; Bespalov *et al.* 2003; Hilaga *et al.* 2001; Novotni & Klein 2004) on shape matching recognizes the shape and appearance of models successfully, but they alone do not adequately distinguish different manufacturing processes. Table 1 shows nearest neigh-

bor classification accuracies for some shape matching techniques when classifying the manufacturing process classified dataset.

Shape Matching Techniques	Accuracy
Shape Distributions (Osada et al. 2002)	57%
Scalespace (Bespalov et al. 2003)	54%
Reeb Graph (Hilaga et al. 2001)	55%
Zernike Moments (Novotni & Klein 2004)	53%

Table 1: Classification accuracies of shape descriptors

Curvature Statistics Classification

This research used surface curvature and SVMs to recognize prismatic machined and cast-then-machined models. Surface curvature is relevant for distinguishing between the two processes. While the casting process produces a larger variety of surfaces, due to limited tooling directions, material removal machining operations only construct a finite set of surfaces. The challenge for recognizing these two processes is that they share a common set of surfaces.

Estimating Curvature from Mesh Models

The curvature of a point on a planar curve is defined as the reciprocal of the the radius of the osculating circle at that point. Extending this to regular surfaces, normal curvature is the curvature of the intersection on the smooth surface with a plane in a certain direction. Principal curvatures, κ_1 and κ_2 , are the largest and smallest normal curvature at a point in all directions.

Curvatures are estimated from the mesh representation of CAD models. Following (Rusinkiewicz 2004), per vertex curvature can be computed by weighting the curvature of triangle faces adjacent to the vertex.

Figure 2 shows colored sample models according to κ_1 and κ_2 , zero curvature regions are colored in white, non-zero regions are colored according to curvature values. The following observations can be made:

- The cast-then-machined process produces artifacts with a higher portion of curved (shaded) surfaces.
- The minimum curvature, κ₂, of machining features, holes, slots, and pockets, surfaces are zero (white).

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• The cast-then-machined parts possess a higher variation of curvature values (more colors).

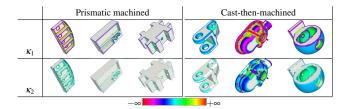


Figure 2: CAD models colored by curvature values (Please refer to the URL for larger figures)

Curvature based Shape Descriptor

Statistics on per vertex curvature are used to construct shape descriptors for process recognition. Each of the curvature values, c, is mapped from $[-\infty,\infty]$ to [-1,1].

$$c' = \frac{c}{||c||} \left(1 - \frac{1}{1 + ||c||} \right)$$

Equal width bins divide the range [-1,1] to record the frequencies of different curvature c' values. Frequencies of curvature values are then normalized. Curvature bins are aligned to produce meaningful comparisons. (e.g. Planar surfaces (c = 0) always align to the same bin.) Figure 3 shows a sample of CAD models and the corresponding descriptors.

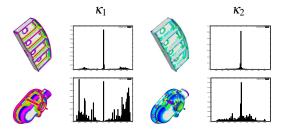


Figure 3: Curvature Descriptors (Please refer to the URL for larger figures)

Support Vector Machines Classification

Recognition of prismatic machined and cast-then-machined processes is learned by radial basis function (RBF) SVMs. Support vector machines were proposed by Vapnik (Cortes & Vapnik 1995) for finding an optimal margin (hyperplane) that separates the target classifications from a set of labeled training examples. The RBF kernel function non-linearly projects the curvature descriptors into a high dimensional feature space for the algorithm to find a separating margin. This allows SVMs to find linear or non-linear separating margins in the input space.

Experimental Results

To validate our approach, the proposed technique is applied to learn and recognize manufacturing processes from

a dataset of 100 hand classified prismatic machined or cast-then-machined CAD models, available from http://designrepository.org/dataset/. Implementation of the curvature estimation and SVMs were provided by Trimesh2 and libsvm.

Table 2 shows a summary of our results. κ_1 , κ_2 , mean curvature, H, and Gaussian curvature, K, histograms of 100 bins were computed for this evaluation. Half of the dataset was used as training examples. This experiment was performed for 40 times to confirm the robustness.

	κ_1	κ_2	$H = \frac{\kappa_1 + \kappa_2}{2}$	$K = \kappa_1 \kappa_2$
Maximum	84%	86%	80%	80%
Average	71.5%	75.33%	67.5%	65.94%

Table 2: Curvature Statistics Classification Accuracy

Minimum curvature, κ_2 , produced the highest classification rate of 86% with an average of 75%. This is a 20%-30% increase over the existing shape matching algorithms (Table 1, accuracy $\approx 50\%$). κ_2 performed the best in this classification because most curved surfaces generated by volume removal operations, such as holes, slots, and pockets, have zero minimum curvature. The remaining variation in curvature signifies surfaces produced by the casting process.

Conclusions

This research demonstrated a new approach to recognize the manufacturing processes of machined parts. The contribution of this research is the use of surface curvature and SVMs to enable manufacturing process recognition from CAD models. This approach relates automatic mesh model recognition to manufacturing costs estimation. This application of new relevant features and classifiers further the development in the challenging domain of CAD model databases.

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