Training Simple CNN on Synthetic Data for Real Data Applications in CNC Manufacturing

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Abstract

This paper describes the problem formulation, data set generation, and initial testing of image recognition methods for applications in Computer Numerical Control (CNC) machine vision. Synthetic part images are used to train a simple Convolutional Neural Network (CNN) for feature classification. Where potentially infinite parts could be created, but the manufacturing of a great number of different parts is itself expensive, synthetically generated images present an opportunity to train an image classifier on a great span of possible features. This paper contributes a definition of synthetic training data for a simple CNC feature understanding, and explores simple CNN methods on real and synthetic feature data.

1 Introduction

Numerical control machines (NC machines, also commonly referred to as CNC or computer numerical control machines) are designed to operate without any closed-loop feedback. Provided a list of commands, CNCs blindly follow these instructions line-by-line until they reach the end of a program file unless interrupted. While this design has provided automation opportunities across a great number of manufacturing applications such as milling or turning, this simplistic approach neglects the challenges of interacting with real objects in the physical world.

Many human hours must be spent generating tool paths which produce the desired components while accounting for fixture points and load on the tool. Even more hours are required to observe the instructions as executed to safeguard against any mistakes that may cause defects rendering parts useless, or worse, long term damage to high-capital CNC components. Advances in computing technology and artificial intelligence have encouraged investigation into "closing the loop" [1] and developing opportunities to provide the CNC machine knowledge of the work space and the part that is being created. An ideal system would have a knowledge not only of the movements it must take to create a specific part, but of the individual features (holes, pockets, extruded sections) that make up the part. In this way, the machine would be able to make reactive and intelligent decisions about manufacturing, offloading much of the tedious aspects of CNC part production.

Camera and vision systems in manufacturing have become more commonplace for inspection duties. Object recognition and deep learning tasks of computer vision systems see present applications in catching part defects on manufacturing lines, [2, 3]. Computational intelligence often struggles with developing appropriate models for complex systems due to limited data availability. For CNC manufacturing, CNC machine hours and defect example generation could be severely costly on material and tool damage. This paper seeks to investigate the performance of part feature recognition of real part features by systems trained on easily-generated synthetic image data sets. This paper contributes a definition of synthetic training data for CNC feature representation, and evaluates a simple CNN method on real and synthetic feature data.

2 Problem Formulation

In order to focus on a subset of this overall problem of CNC part understanding, CNC vision understanding is explored in terms of feature shape identification. For the applications of industry and manufacturers, desirable methods:

- Locate and identify object features
- Require no or little specialized expertise
- Require no or few tasks for implementation

Convolutional Neural Network classifying solutions are able to perform complex object recognition tasks without the need for specialized image preprocessing tasks. However, neural networks in general require training procedures which may be laborious, especially in sample data generation. Synthetic data generation is proposed to overcome this requirement.

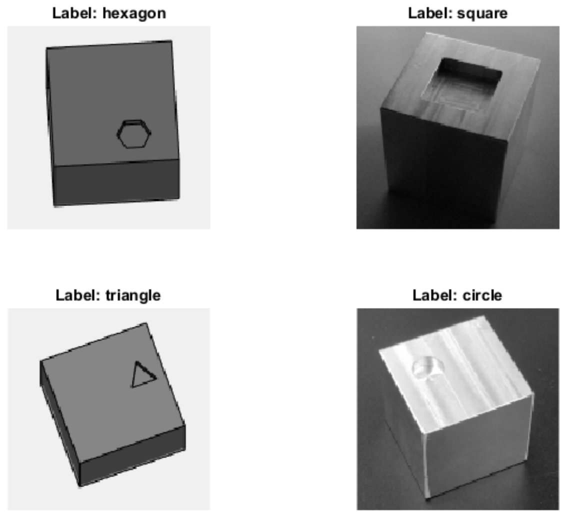

Fig. 1: Sample set of synthetic training images (left) and real training images (right). Images have varying light conditions, and camera angles.

Convolutional Neural Networks Image analysis informs that shape detection is a local image problem. As CNC features imply spatial relationships in images; convolutional models, effective in investigating spatial correlation, [4, 5], are appropriate. Neural network classification techniques are employed to develop a system that is able to model unknown correlations between input and classification. As object and feature recognition models expand, implementing a simple model or employing the use of a well-known machine learning model becomes more accessible to industrial applications. As common for manufacturing problems, [2, 3], this problem assumes a simple CNN architecture described in Section 3.1, with tuneable hyper parameters (e.g. filter size) ReLu activation on the convolutional layers, and softmax activation on the fully connected classification layer [6, 7].

Synthetic Data Training Machine learning networks are typically trained on hundreds or thousands of images in order to produce a generalized model. Since the proposed ML model will be used to identify the location and shape of features on physical machined parts, an appropriate training dataset would typically include photos of hundreds or thousands of different physical machined parts. Unfortunately it is often cost prohibitive for manufacturers and researchers to create such a large dataset due to a combination of time and material costs. Instead, this work investigates the efficacy of training an ML model using synthetic data. Taking this approach requires far fewer physical machined parts, as they will only be used for validation of the network. Data sets are developed as specified in Section 3.2, where an example of produced data can be seen in Figure 1. Real data validation components will be of the same limited composition as the synthetically generated images.

This paper explores whether synthetically generated part images are enough to train a CNN feature recognition system to be employed on real part data.

3 Procedure

This section discusses the simple implementation of a CNN for this image classification problem. The generation of the synthetic data

Table 1: Final Composition Summary of Simple CNN

Layer	Name	Size	Activation	Pooling
1	Input	150x150x1	No	No
2	Convolution 1	150x150x16	ReLu	Yes
3	Convolution 2	75x75x16	ReLu	Yes
4	Convolution 3	37x37x32	ReLu	No
5	Fully Connected	4x43808	Softmax	No
6	Output	1x4	No	No

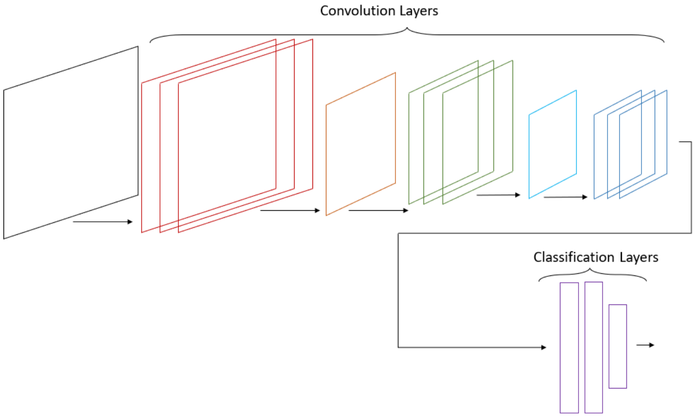

Fig. 2: Diagram of the composition of the simple CNN implemented. Convolutional layers are grouped with normalization and activation layers. Pooling layers are placed after first and second convolutional layers. Classification layers are composed of fully connected layers with softmax activation and cross-entropy loss for classification.

is discussed, and results of synthetic training are explored. Real data testing results of the synthetically trained CNN is explored.

3.1 Model Construction

CNNs are structured by a series of network layers. A set of convolutional layers with associated activation and pooling layers perform image processing tasks. Then, the image as processed is flattened and received as a input vector to a regular neural network which then models the classification, [6, 7].

Examples of simple CNNs were explored [2, 3, 6], and a 3 Convolutional Layer model was chosen according to image and feature size. A diagram of the selected model can be seen in Figure 2. Hyperparameters such as convolution filter size, number of layer nodes, epoch, learning rate, and batch size were trialed and selected for performance. ReLU activation layers were employed with normalization on every convolutional layer. Cross-entropy loss was used for classification. Table 1 describes the developed CNN layer and training parameters, while Table 2 describes the learning performance on the synthetic data.

3.2 Data Generation

Typical examples of machining features include through holes, blind holes, pockets, or shoulders. The distinction between many of these examples may be unclear even to a human machinist; for example, a blind hole could be considered a small pocket, or a pocket may be a hole that has been broached into a non-circular shape. As the focus of this paper is to evaluate the effectiveness of training and testing an ML model using synthetic and real-world images, respectively, a simplified set of "machining features" were created which are more distinct.

A small set of shapes (squares, circles, triangles and hexagons) were selected. For each training sample, a 1 unit x 1 unit cube is embossed with one of these shapes 0.1 units deep into the top face. These shapes are of random size within a predetermined range (as outlined in Table 2), and are placed no closer than 0.05 units from the edge of the cube. Using Matlab, the cube is then rendered with the camera facing between 60° and 90° below the horizontal, and rotated between -22.5° and 22.5°, with the cube in the center of the field of view. Finally, the cube is lit from a random direction in the top hemisphere. An 8-bit greyscale image of the cube is captured

Table 2: Learning Performance of CNN on Synthetic Data Testing and Validation Over Varying Feature Radii

Trial	Epochs	Learning Rate	Train Accuracy (Synth)	Test Accuracy (Synth)	Feature Radii
A	100	0.002	99%	74.9%	0.05-0.3
B	100	0.002	100%	89.8%	0.1-0.3

at a resolution of 300 pixels x 300 pixels, and saved along with the random feature data that was used to produce it.

3.3 Results

Two synthetic data training trials were completed for the generated CNN. These trials are captured in Table 2. Relatively low performance was noticed on the synthetic test accuracy of Trial A. After the minimum feature radius was increased to 0.1 units, test accuracy on synthetic data increased by 14.9%.

Preliminary validation of the model produced in Trial B was conducted with two machined parts. The first machined part was a 48mm cube with a 12.7mm circular blind hole machined to a depth of 4.8mm below the top surface. The second machined part was a 48mm cube with a 24mm x 24mm square hole machined to a depth of 4.8mm. 43 images of both parts were takes (22 images of the circular part and 21 images of the square part). Similar to the synthetic data generated, these images were taken in different lighting conditions and from different angles. Overall, the network was able to identify 19 of the 43 images correctly. A subset of the images were taken in optimal lighting conditions. Of these, the network was able to identify approximately 50% of the samples correctly.

4 Conclusions and Future Work

CNC machine knowledge can provide a myriad of benefits, including pathway correction and adaptation, a real time understanding of machine tolerances, and avoidance of human error that can damage expensive tooling and parts. This research investigated feature identification in CNC part manufacturing as an image recognition problem. This involved constructing a synthetic data set and developing a simple CNN structure. The synthetic data was used to train and validate the CNN, with the aim to use the CNN functionally on real images of parts.

At lower minimum feature radius, the synthetic test accuracy of the network was significantly lower. Fine detail loss over several filtering and pooling operations is likely responsible for poor performance of small feature radii classification.

Based on limited testing of real world images, it is clear that more work needs to be done to improve the classification accuracy of the model. Certain physical features, such as machining marks on the surface of the manufactured parts, were not included in the synthetic training data. Future work may include investigating texture mapping or surface normal reflection mapping to improve the realism of the training data.

To improve accuracy further, it may also be beneficial to train a network with both synthetic and any available real-world images. Synthetic data could be used to produce an initial set of network weights, with real data then used to further tune the network to accommodate aspects of real parts that are difficult to simulate. This technique would still have a reduced real world training image requirement compared to training with only real world images.

Future work may also include the expansion of the feature recognition problem into further image recognition tasks including expanded feature classes, and other prediction output including locating the position of the shape and measuring feature radii within the image.

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