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An automated approach to reuse machining knowledge through 3D – CNN based classification of voxelized geometric features

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Abstract

The enhanced digitalization in the manufacturing sector is claimed to facilitate the generation or the use of the existing process data incorporating the production variations and offers a significant increase in the productivity and efficiency of a system. Moreover, manufacturing companies possess substantial knowledge while designing a product and manufacturing procedures. The primary requirement is to link and organize all the information sources related to the operation design and production. This research is concerned with the reuse of machining knowledge for existing and new parts having similarities in geometric features and operational conditions. The proposed methodology starts by extracting each machining operation's geometric information and cutting parameters using industrial part programs in the numerical control (NC) simulator VERICUT. The removed material between two consecutive operations is obtained through mesh comparison in the simulator to analyze the feature interactions. A deep learning approach based on 3D convolutional neural networks (CNN) is applied to classify similar geometries to reuse the process design knowledge by creating a library of operations. The proposed approach is implemented on actual machining data, and the results demonstrate the effectiveness of the proposed solution. The obtained knowledge clusters in the operations library assist in making propositions related to operational parameters for similar geometric features during the process planning phase reducing the planning and designing time of operations.

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Keywords: Reuse Machining Knowledge; Operational Parameters; Classification of geometric features; Knowledge clusters

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1. Introduction

The development of the concept of industry 4.0 and smart manufacturing is revolutionizing the manufacturing landscape by offering state-of-the-art technologies and innovating their software infrastructure through high-level automation and digitalization. Manufacturing activities in the era of mass production were categorized by the repetition of the same machining tasks for identical parts and products. However, in some instances the invariability in product design and monotony in planning tasks still exists, characterizing the existing processes of contemporary industries. Hence, in this globalized and data-driven economic situation, reusing embedded manufacturing knowledge in process design draws a load of attention [1]. Manufacturing process information is the core component of intelligent process design as it determines the level of intelligence of the decision-making systems for processes [2]. The foremost key to modernizing the manufacturing process is enabling a secure and reliable system to transfer the process data back and forth between the process planning and the execution phase in order to produce goods more effectively and productively across the value chain. Therefore, including shopfloor and machining information in operations management offers opportunities to enhance product quality and process capability while saving time and cost [3]. Process knowledge connects product design and manufacturing in the advanced manufacturing industry[4]. Therefore, the existing machining knowledge is becoming a valuable asset for the manufacturers, which is available in the company's NC part programs. In most cases, NC programs are unidirectionally transferred to the Computer Numerical Control (CNC) machines without capturing the changes and fine-tuning adjustments provided by machinists, resulting in a massive reliance on human experience and the lack of shopfloor knowledge feedback [5]. Consequently, machining knowledge remains an implicit concept that can be misplaced, misdirected or simply remain unused for potential process optimization [6]. The unavailability of formalized data induces terrible impacts on the process and system due to the recreation of the same knowledge in case of re-manufacturing. Therefore, reusing the existing information resources is broadly acknowledged for preserving the process knowledge and promoting liable process planning[3]. Acquiring and reusing functionalities of processes are some of the crucial problems to be solved in reusing the information and supporting the standardization of machining operations design [7]. To deal with this challenge, there is a need to create an equitable connection between the digital environment of Computer-Aided Design (CAD) and Computer-Aided Manufacturing (CAM) models and their physical fabrication [8]. This can be achieved by extracting and systematizing the scattered information across different knowledge sources of a company. This kind of knowledge extraction is far from trivial; however, if done appropriately and efficiently, it assists in managing its reuse instances [9,10].

Modern manufacturing industries encounter numerous challenges due to the competitive manufacturing environment and enlarged product variety. Product design changes can often be predicted; however, sometimes it goes beyond the available design range. This necessitates the accessibility of innovative enablers and adaptable mechanisms to minimize the consequences of these variations in manufacturing . For this reason, industries need to be responsive in order to accommodate the production of parts either new or variants [5]. Moreover, whenever there is a need to re-manufacture, the unavailability of standardized information delays in process planning time and has a terrible impact on the process and system level. Reusing process knowledge is incredibly critical in manufacturing, specifically for complex structural parts. The rules of process design are an essential part of process design information, and if these are recovered, their efficient reuse can help save time in process planning for the next generation of the same part as well as machining similar parts [10] . In literature, different approaches are suggested to provide tentative solutions to this problem. The first set of approaches follows the conventional way of reusing data, i.e., similarity amongst the CAD geometries of existing parts. Nevertheless, this way of capturing and reusing manufacturing knowledge is unreliable since the amount of the identical parts is often limited [10,11]. To effectively capture machining process information, various feature-based approaches were presented in the literature. Although the parts are vastly different, they can be viewed as a collection of multiple machining features with geometric and operational similarities, reducing the preparation cycle of NC machining and improving NC programming efficiency [12]. Krahe et al.[13] suggested an approach for automated decision-making by extracting machining knowledge using the artificial intelligence technique. In this work, the implicit knowledge of common design patterns between CAD models is obtained and validated using machine learning for the development of new product generations and variants. A technique of obtaining thinking process procedures for process design is suggested by Zhaou et al [14] to recognise the reuse of process knowledge, consequently increasing the quality as well as efficiency of process design. Liu et al [15] presented a strategy to reuse the process information for similar machining features to manage the dynamic variations in machining conditions and uncertainties in the availability of manufacturing resources. Huang et al. [4] suggested a general framework for similar subparts combining 3D CAD model retrieval and data mining for the NC procedure and its reuse. A quality-based factor-driven model is created to validate the links between knowledge embedded in the machining aspect and the factors of cutting tools, geometries, and machining schemes. The retrieval of machining features or the reuse of machining knowledge through feature recognition of CAD model dependence has received enormous attention in the past few years, especially with the advent of deep learning and machine learning technologies. One of the approaches in the literature is based on reconstructing machining features using geometrical and process information of existing pocket features through an unsupervised clustering algorithm to avoid human interferences [10]. Zhang et al. [8] proposed a framework that can recognize features utilizing 3D CNNs characterized FeatureNet to understand machining features from low-level geometric information such as voxels with high accuracy for improved visualization. A voxel-based convolutional neural network (CNN) intended for 3D object recognition. The network utilizes normal object surface vectors as input, demonstrating more significant discrimination potential as compared to binary voxels [16] . Recently, Asghar et al. [17] proposed an approach for extracting the process data to recover the functional and useful information to obtain self-contained structures. The process knowledge is attained from NC part programs run in VERICUT, and removed volumes are generated for each operation along with the operational parameters and cutting tool conditions.

Summarizing the literature, although various approaches have been developed for manufacturing knowledge reuse, there is a scarcity of integrated knowledge frameworks to support design and planning processes. The main reason for the restricted application of data reuse is the partial manufacturability due to the lack of connectivity amongst knowledge sources and the interdependency of processes. Therefore, there is a requirement to capture, standardize and reuse the information enclosed in a process plan. Despite the noticeable advances in the methods of reusing machining knowledge, there is still room for a practical and automated approach to handling and reusing the available process information. To the best of the author's knowledge, no approach is presented in the literature to generate the knowledge clusters considering geometrical features as the primary knowledge component. This research work aims to reuse extracted machining information by creating a library of operations consisting of 3D geometric features and associated machining attributes. This method can be used as the basis for growth of the process information; it can stimulate the application and development of the intelligent process planning. A case study is also illustrated to show the implementation and potential of the presented work. The structure of the paper is as follows: a brief analysis of the existing methodologies is presented in this section 1. The proposed methodology is described in section 2. The case study is presented in section 3 and the results are analyzed and discussed in the subsequent subsection. In the end, section 4 concludes the work along with some future recommendations.

2. Proposed Methodology

The processes are the combination of instructions available in the company's NC part programs and on the shop floor, and it remains an implicit knowledge that can be misplaced or misdirected due to oblivions. One of the possible solutions is formalizing the information and using it for current and new parts considering each operation as an independent object. This machining data includes spindle speed, feed-rates, cutting tool and workpiece material and geometric information of processes. The knowledge is extracted using a commercial NC simulator (VERICUT) from the industrial NC part programs which is carried out in the previous work [17]. The conversion of solid CAD models into an STL model provides information about the external surface and shape of the model part. The reason behind this conversion is that STL file is simpler and has sequential access. The objective of this ongoing work is to propose micro-process plans for new parts for which the interactions between the consecutive machining operations must be analyzed. To investigate the machining interactions between the geometric features, the raw solid stock in VERICUT was converted into an STL model file. Subsequently, the geometry of the removed material was obtained by mesh comparison of two consecutive operations. The extracted geometries of the removed volumes are voxelized for better visualization of interacting surfaces. Since this is ongoing research, the analysis for interacting geomteries is under process and will be discussed in another article.

The extracted theoretical and geometric information are saved separately, however, linked together through a parser developed in MATLAB. The proposed approach suggests organizing the process data based on the shapes and size of the geometric features. Since artificial intelligence (AI) and machine learning (ML) allows to take full advantage of the information generated across operation design, process planning and factory floor through classifying and clustering the information considering a set of criteria. Thus, there is a need for a classifier which could automatically categorize the new or unseen geometries extracted from real part programs in the most suitable category. This is accomplished by applying 3D CNN to the generated dataset of geometric features. The classified geometries and the operational parameters are characterized as the data-base of operations. The proposed methodology is illustrated in Fig.1.

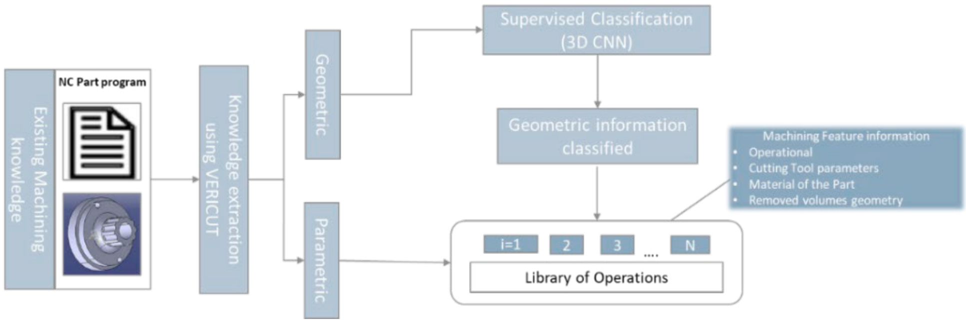


Fig.1. Proposed methodology to formulate library of operations for machining knowledge reuse

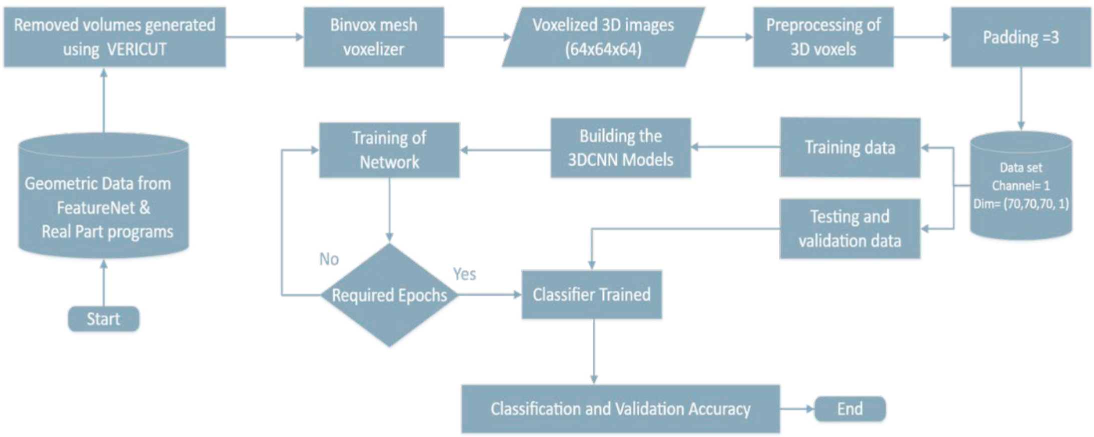


Fig.2. Voxelization and 3D CNN classification of geometric features

The overall working and insight of a deep learning classifier and the data creation is shown in Fig 2. To classify these geometric features, a large dataset is required to train a classifier. For this purpose, adequate samples of the renowned dataset '3D FeatureNet' are used after creating the removed volumes of its machining features. Combining two datasets (i) extracted from NC part programs and (ii) FeatureNet makes the training data dynamic and effectual. Once the geometric data is classified, it is connected with the parametric data to form the directory or the library of operations. 3D CNN is implemented on the voxelized 3D models for the required geometric features classification. The proposed CNN architecture consists of multiple convolutional layers and a dynamic dataset to learn 3D models accurately. The dataset contains voxelized geometries across six machining feature categories: o-ring, drills, round, mills, chamfer, and slots as shown in Fig 3.

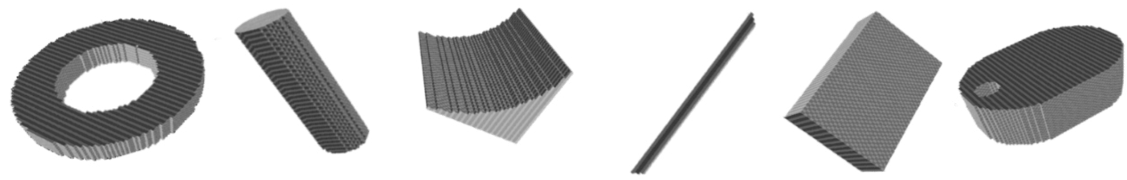


Fig.3. Voxelized removed volumes of 6 classes - machining features obtained through VERICUT and 3D Binvox mesh voxelizer

3. Case Study

The proposed approach has been used to connect the knowledge sources having the information about geometry, operational parameters, and cutting tool inserts. The significance of the presented approach is tested and validated by performing an industrial case study in which geometric features of an industrial part named 'shimming locking support' made of carbon steel C60 is used. The NC part program has been delivered by an Italian startup company- Tech.Kno S.r.l. which provides services in technology planning and knowledge exploitation. The results obtained from 3D CNN classification and operations library are discussed in the subsequent section.

3.1 Results and discussions

As mentioned in the previous section, the interactions between operations must be analyzed to consider the machining constraints while suggesting micro-process plans. This is why the voxelization is carried out to geometric features of removed volumes using the 3D mesh voxelizer library 'binvox' in which each 3D object is signified as binary indicators corresponding to a 3D voxel grid centered on the shape. Here, '1' represents that the corresponding 3D voxel is inside and occupied by the object, and '0' indicates that it is outside. It is worth mentioning here that the credibility and reliability of the operations library hugely depend upon the efficiency of the classification model trained on the geometric features. A robust deep learning algorithm require an adequate and large dataset. Therefore, a large dataset of various classes with different shapes, dimensions, and orientations is generated. In a CNN, convolutional layers are usually arranged so that they slowly decrease the spatial resolution of the representations, whilst expanding the number of channels. The proposed 3D CNN architecture consists of multiple convolutional layers connected layers to learn 3D models accurately. The performance of 3D CNN hugely depends on (i) the type of dataset used, and (ii) multiple convolution layers. In the proposed 3D CNN architecture, the 3450 samples are divided into 80% for training and 20% for testing and cross-validation of 0.2. While applying convolutional layers there is a possibility of losing pixels on the edges of an image, and this issue is rectified by adding extra pixels across the boundary of an input image, thus enhancing the adequate size of the image [18]. Hence, the 3D shape is represented by a binary three-dimensional tensor having a grid size of 70x70x70. In this work, this size is normalized such that the size of the object is 64x64x64, and the remaining voxels help with padding in all directions. Multiple class labelled data containing actual industrial machining features are used to train the 6-way classification through a 3D convolutional neural network. TensorFlow library is used to implement 3D CNN. In the presented 3D CNN architecture, four convolutional layers, one input, and one fully connected layer are used with ReLU as an activation function. The first layer has16 filters of size 6 and stride of 2, the second layer consists of 32 filters of size 5 and stride of 2, the third layer with 64 filters, size 5 and stride 2, and the fourth and final convolutional layer is of 64 filters of size 4 and stride 2, and the network ends with a Softmax layer having hidden units which depend on the number of classes. The classifier was run for 30 epochs, training time of 130 min with a batch size of 40 during training. This batch size is based on results obtained through the iterative running of this network. Adam optimizer was selected because of its ability to converge quickly, and the learning rate was set to 0.001 [19]. Since the classes are imbalanced, the average per-class accuracy metric is used as a standard. Categorical cross-entropy is used as the loss function for training the model as it is a multiclass classification.

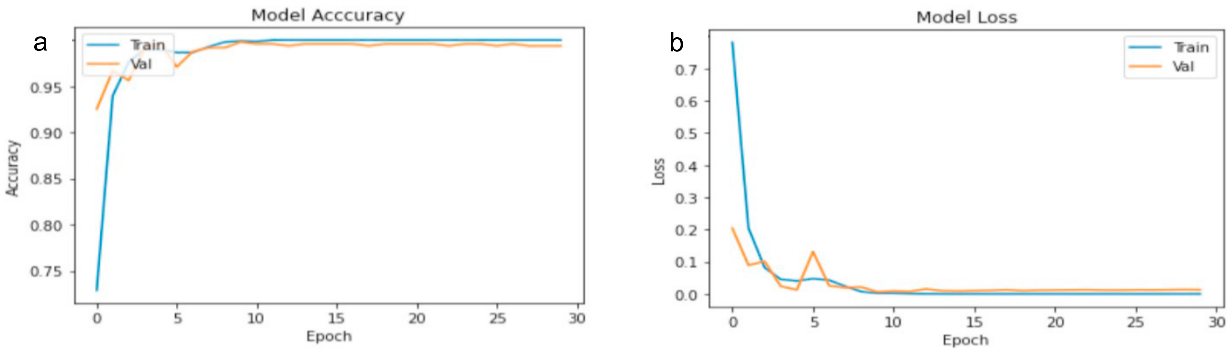


Fig.4. (a) Model accuracy of proposed 3D CNN (b) Model Loss of proposed 3D CNN

Fig.4 (a) shows the model accuracy for training and validation data, and the curves illustrate that the proposed architecture performs well for the considered case as the model is not underfitting or overfitting as the validation accuracy gets better with the number of epochs. The model losses are shown in Fig.4(b), where validation losses decrease with the increasing epochs. The optimizer and loss function was set correctly as for the learning rate of 0.001 the maximum accuracy achieved was 99.58%, test accuracy of 89.9%, and the average-per-class accuracy of 90.6%. The classification accuracy can be improved by improving voxel resolution, however, at the expense of an increase in the training time and the RAM usage. The performance estimate of the classifier is elaborated in a cross-validation confusion matrix shown in Fig.5. This matrix illustrates the true and predicted labels of classification results of 6 classes of geometric data for convenient visualization. The performance of deep learning networks hugely relies on the data and the architecture of the model. It can be seen that the matrix is close to diagonal, showing the effectiveness and accuracy of the model. However, class 'cham' (chamfer) shows more inaccuracies than others because of the lack of diverse 3D voxels in this class.

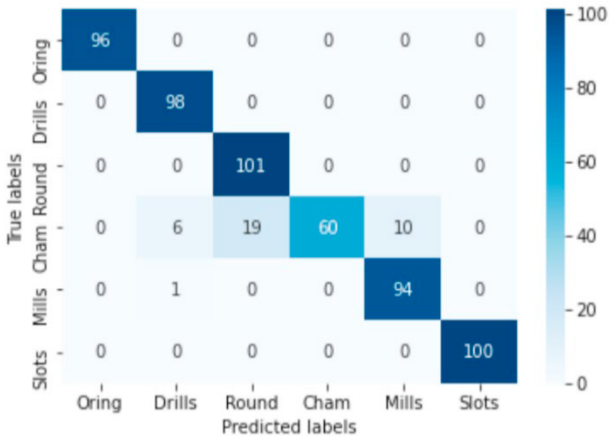
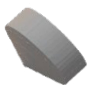


Fig.5. Confusion matrix showing the predictions for 6-way classification

The proposed CNN model is effective and reliable as it classifies majority of the geometric features correctly because the model is trained on the removed volumes of two data types: geometric features from real part programs and machining features from FeatureNet dataset. Therefore, when an unseen geometric features is given for the prediction in order to have a class assigned to it, the model classifies it on the basis of shape as per the training criteria. Geometric feature classification plays a significant role in the presented knowledge reuse methodology as it determines the categorization of the 3D voxelized removed volumes. The effectiveness, reliability and efficiency depends on the amount of process information exploited for systematizing and developing the knowledge database.

Once the model is trained, it has the tendency to accurately classify and categorize the features. The existing geometries of operations and the corresponding parameters are logically mapped together and available as the library of operations. Therefore, when a new part geometry is to be machined, rather than recreating the same knowledge of operational design and shopfloor, the part is decomposed into its operational geometries following the procedure mentioned in previous section. The removed volumes of these new geometries are assigned a class through 3D CNN. Later, the similarity amongst the features belonging to the same class are identified and the most suitable operational parameters are suggested to machine various mechanical components. Table.1 contains the geometric information associated with the operational parameters, including the spindle speed, feedrate, and tool insert, along with the particular class assigned to this feature by the classifier. More process information can be embedded with the geometric data to have accurate and reliable propositions for knowledge reuse phase. The proposed method is the basis for the accumulation of process information as it can stimulate the application and development micro process planning reducing process planning time.

Table 1. Library of Operations

Geometry of Part	Spindle Speed (rev/min)	Feed-rate (mm/rev)	Operation	Tool Insert	Class 1.. N
	3500	700	Round	Face Mill	0 0 1 0 0 0
	3500	530	Drilling	Twist Drill	0 1 0 0 0 0
	590	2350	Chamfering	Face Mill	0 0 0 1 0 0
	1500	1000	Milling	Face Mill	0 0 0 0 1 0
	2800	350	Drilling	Twist Drill	0 1 0 0 0 0

4. Conclusion

Manufacturing companies have collected a significant quantity of information while designing a product and the processes of manufacturing. Although the manufacturing landscape is drastically transformed, various new products share numerous commonalities with the past cases not only in respect of the processes and operations design but also in views of the planning and resources. Thus, data interoperability is becoming important and yet it is a challenge to implement in smart manufacturing. One of the main reasons of the limited application of knowledge reuse systems is the absence of sufficient factory floor data as well as the lack of a framework to resourcefully reuse the information. Thus, in order to effectively reuse the machining information, there is a need to generate a data-base of operations consisting of case-base level of details. This directory must have enriched operational knowledge which could be integrated with the existing processes to automatically support operation design and planning activities of modern manufacturing. Hence, the objective of this work is to reuse the significant existing machining knowledge and standardize the operation design using the combined operation design and shopfloor data. In this instance, a library of operations is created by mapping geometric and parametric information to offer machining suggestions based on the similarity amongst 3D geometric features. The proposed approach starts by systematic capturing and retrieval of machining knowledge which enables it’s reuse in process planning and design phase. The geometrical similarity is obtained through the application of a deep learning classifier 3D CNN which instinctively characterize the geometries and associates corresponding operational parameters. The obtained results validate the applicability of the proposed framework as 3D CNN shows decent efficiency-per-class accuracy. An industrial case study has been employed to highlight the benefits of reusing the process knowledge. The advantage of this approach is that less information is required for machining any part, thus saving time in the process planning phase. This is an ongoing research, hence the knowledge clusters amongst each class and the similarity criteria adopted for the clustering will be discussed in another article. In the future, this approach will be improved to predict complex geometric features by collecting more intuitive data to deliver improved and flexible recommendations for process planning to make better decisions.

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