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Parts Classification Based on Solid Model and Neural Networks

G. Nawara

Faculty of Engineering, Zagazig University, Egypt

M. A. ELBaz

Faculty of Engineering, Zagazig University, Egypt

A. M. Attia*

Faculty of Engineering, Zagazig University, Egypt
*Corresponding author: am_attia@yahoo.com

Abstract

The main problem in developing a parts classification system is the obtaining of geometric information about machining features from the solid model. Therefore, this paper presents a methodology of 3D prismatic parts classification based on the geometry of their machining features. The methodology works in three main phases. The first phase takes a neutral file in STEP-AP203 format as input, restructures it and extracts the geometric information of the machining features. The second phase recognizes the machining features through training neural network (NN) with a large set of feature patterns. The third phase classifies parts based on the variation in geometry of their machining features using self organized map (SOM) NN. Finally, the validity of the proposed methodology has been discussed through examples.

Keywords: Parts classification; GT; STEP; Feature recognition; NN

1. INTRODUCTION

Parts classification in group technology (GT) is a manufacturing philosophy in which similar parts are grouped together to take advantage of their similarities in design and manufacturing. Similar parts are grouped into families, where each family possesses similar design and/or manufacturing characteristics [1-4]. The recognition of machining features is considered as the bottleneck of the classification problem. An overview of syntactic pattern recognition, graph based methods and expert system is presented by [5]. The state of the art in feature recognition research is discussed by [6]. They focused on the three major approaches: graph-based algorithms, volumetric decomposition techniques and hint-based geometric reasoning.

Graph-based feature recognition for injection molding based on a mid-surface approach is presented by [7]. Their feature recognizer can be applied to face features (fin, hole and boss), junction features (T and X junctions) and stiffener features (rib and buttress). There have been several attempts to combine some characteristics of existing approaches of feature recognition. Attributed adjacency graph (AAG) was proposed by [8] as input to their system and the AAG is then decomposed to make a set of SGs for each machining features. A hybrid approach for recognizing non-interacting 3D features from CAD database is proposed by [9], which is partially mathematically iterative and partly based on heuristic rules. While [10] proposed a hybrid hint-based and graph-based framework for recognition of interacting milling features.

Various solid modeling protocols are used by many researchers [11]. They proposed a methodology consists of three main phases, includes the converting a CAD data in IGES/B-rep format into an object oriented data structure, classifying geometric features obtained from the converter into different feature groups and mapping the extracted features to process planning point of view. The learning capabilities of NNs with multi layer perceptron (MLP) architecture and BP procedure for training and feature recognition is employed by [12-14]. To speed up the convergence speed of training NNs, [15] proposed a unique 12-node vector scheme to represent machining feature families having variations in topology and shape. While the adaptive resonance theory (ART2) NN for features classification is presented by [16].

One of the early attempts for parts classification based on machining features was [2]. They assumed that there are well defined part families as initial part-families and the subsequent parts will be classified into one of these families after training NN. While 3D prismatic parts can be classified base on global shape information [3]. An attempt to integrate both fuzzy theory and NNs for grouping the parts into several families based on the image captured from the vision sensor is proposed by [17]. The proposed methodology can recognize features of symmetrical parts and symmetrical interacting features. The idea of applying SOM NN as a grouping tool in GT is presented by [18, 19]. Where, SOM serves as a clustering tool that can group parts into appropriate categories based on the similarities in the characteristics of a given set of parts.

The proposed methodology presented in this paper consists of three main phases: (1) STEP file conversion and geometric information extraction, (2) machining features recognition and (3) parts classification, as shown in fig. 1. The details are given in the following sections.

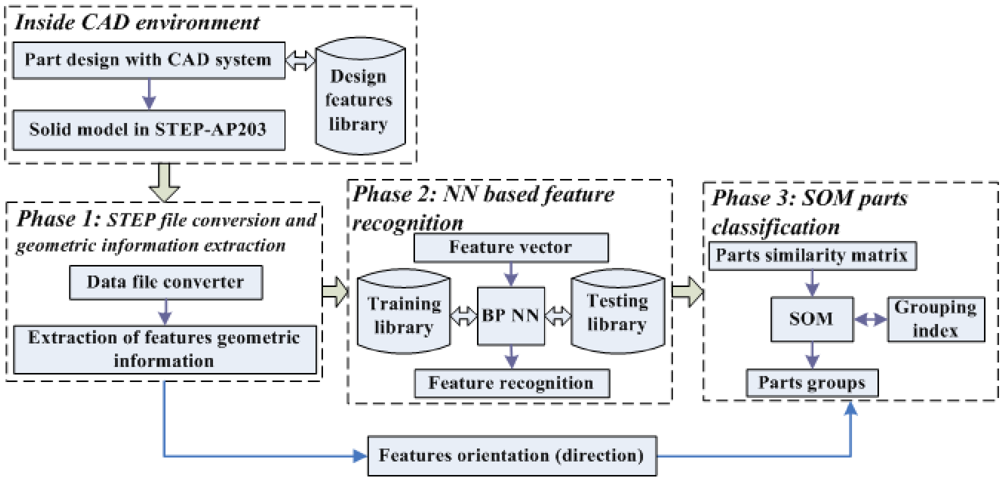


Fig. 1: The architecture of the proposed methodology

3. PHASE 1: STEP FILE CONVERSION AND FEATURES GEOMETRIC INFORMATION EXTRACTION

3.1 Machining features

A number of attempts have been made to define and classify machining features [11, 12, 15]. Some are based on geometrical properties and other based on the machining method associated with the features. Although there are differences among these approaches, many of them share important similarity; a machining feature usually corresponds to the volume of material that can be removed by a machining operation. In this work features classification proposed by [15] is used (fig. 2).

3.2 STEP file conversion

STEP represents parts as a set of faces; each face is bounded by edges and each edge is bounded by vertices [20]. A face is represented by advanced face (AF) entity; AF is described in terms of face outer bound (FOB) entity which points to edge loop bounded the face, face bound (FB) entity which points to inner edge loop and plane entity which points to the direction (D) of the normal to the planar face. Hierarchical data structure of AF76 of a sample part in fig. 3(a) is shown in fig. 3(b).

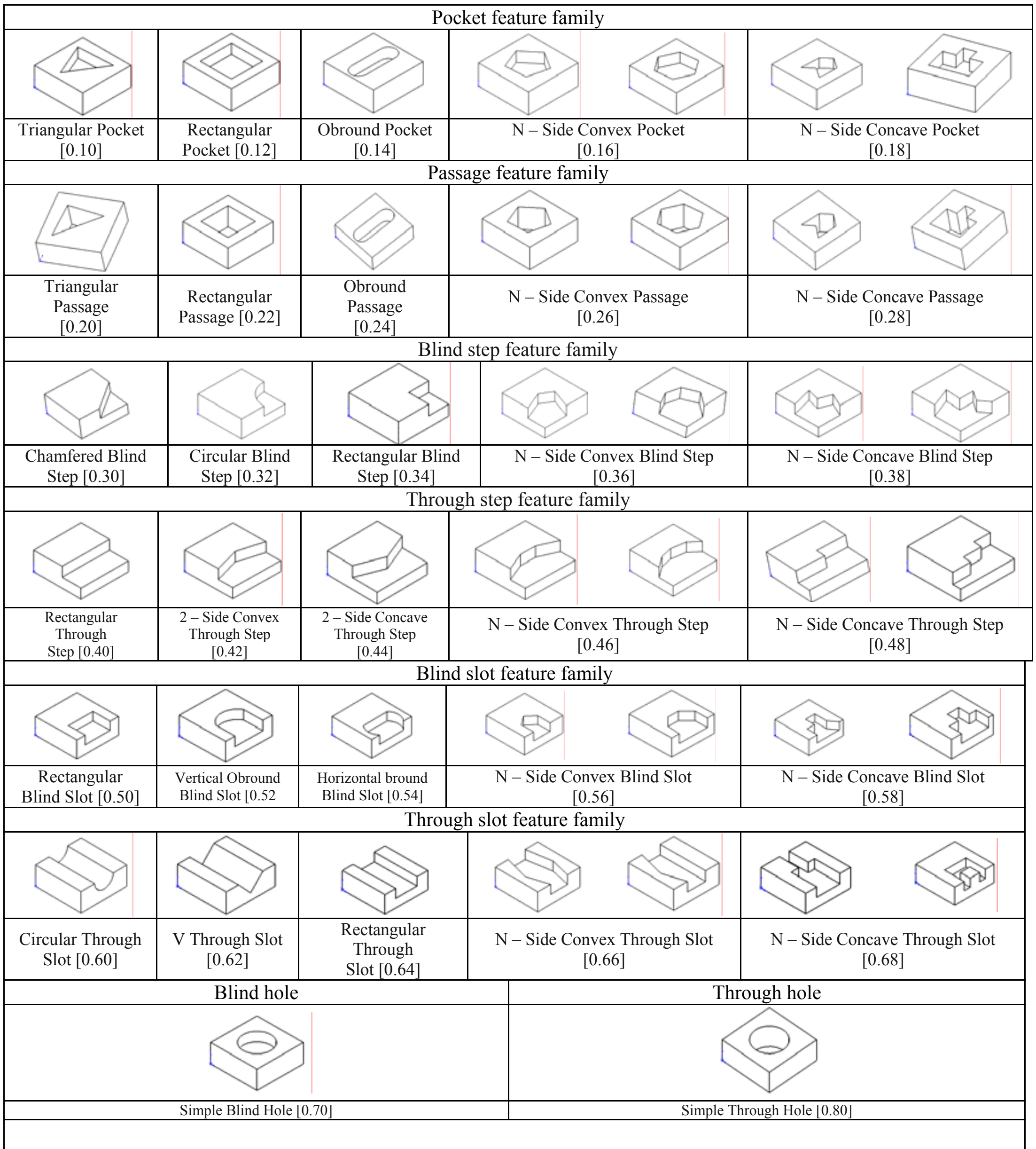
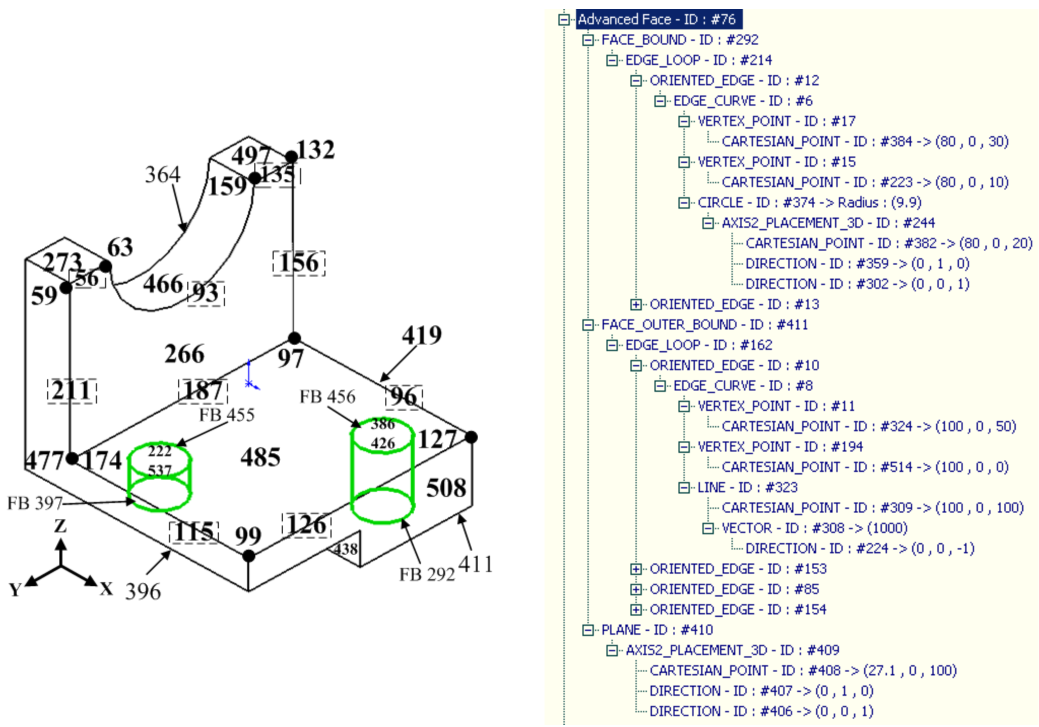


Fig. 2: Features taxonomy (NN output target value shown in brackets)



(a) Part drawing (b) Hierarchy of STEP file

Fig. 3: Face representation in STEP format

3.3 Geometric information extraction

Features are sub-classified into either interior (pocket and hole families) or exterior (step and slot families). The proposed methodology for geometric information extraction works as a filtering system; in which solid model faces does not all examined at a time. Where, STEP leaves FBs as traces for interior features and exterior features information are extracted based on the edge type between faces. Edges are classified as convex or concave according to the angle between the connected two faces. Edges are classified as concave if the material included angle is greater than 180° or convex if it is less than or equal 180°; the proposed algorithm is described as a flowchart in fig. 4. The proposed algorithm for extracting the geometric information of interior and exterior features is described below.

Extracting geometric information of interior features:

1. Find all FBs: if many FBs exist, rank them as follows:

1.1 Rank faces parallel to XY plane in descending order according to Z coordinate.

1.2 Rank faces parallel to XZ plane in descending order according to Y coordinate.

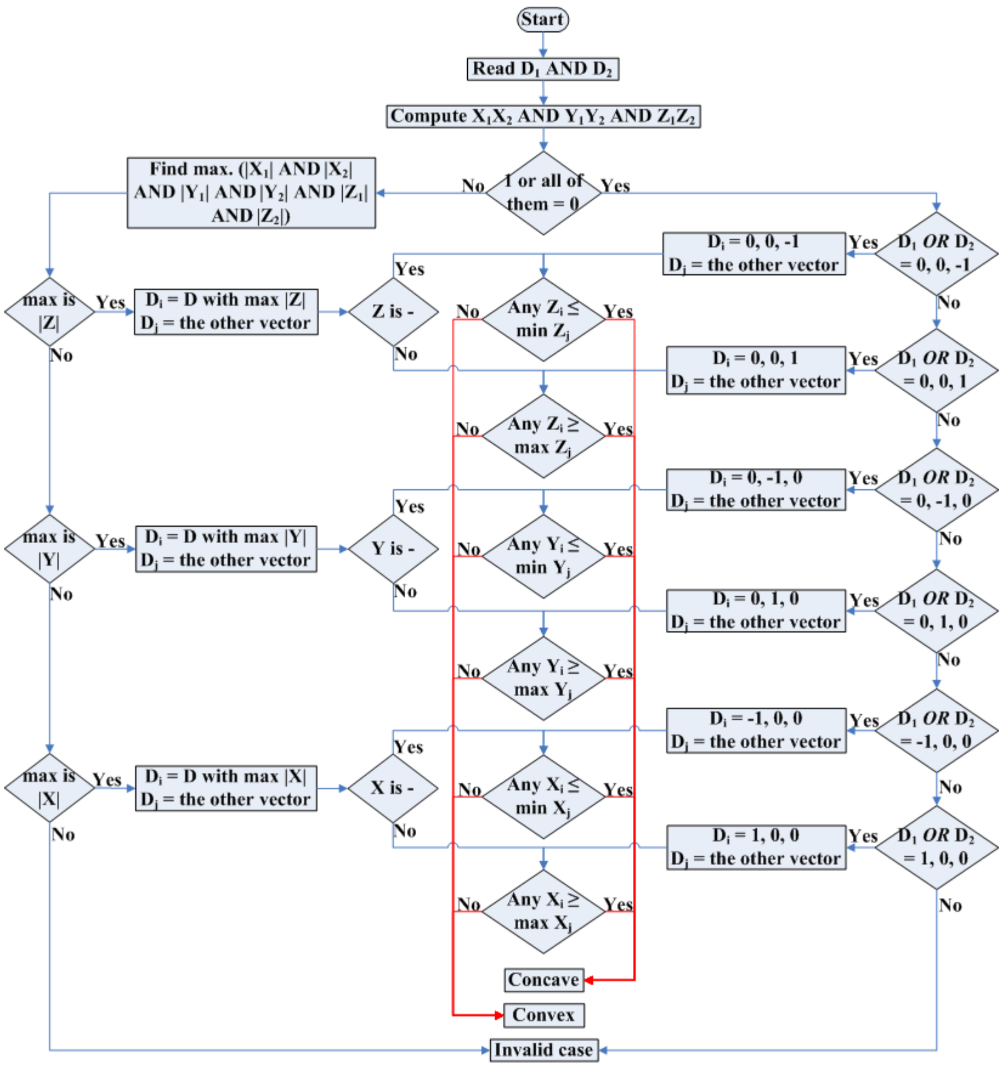


Fig. 4: Flowchart for edge classification

1.3 Rank faces parallel to ZY plane in descending order according to X coordinate.

2. Select the first FB:

2.1 Find all FOBs connected to that FB, which represents the wall faces (WFs).

2.2 Find all FOBs connected to WFs by concave edges. Where these FOBS represents the base faces (BFs) for cavities. Then stop and examine another FB.

3. Post processing for merging cylindrical faces:

If there are two or more cylindrical faces connected to each other, having the same radius and direction

Then connect them to form one cylindrical face

Extracting geometric information of exterior features:

1. Ignore all faces making only convex connections.
2. Rank FOBs in descending order according to the number of concave connections.
3. If many FOBs exist equal in concave connections, rank them as follows:

3.1 Rank faces parallel to XY plane in descending order according to Z coordinate.

3.2 Rank faces parallel to XZ plane in descending order according to Y coordinate.

3.3 Rank faces parallel to ZY plane in descending order according to X coordinate.

4. Select first FOB as BF and FOBs connected to it with concave connections as WFs.
5. Return back to examine the next face and delete faces selected in step 3.3.

The algorithm starts with finding all edges, vertices for each edge, its connecting faces and directions of these faces for specifying the edge type. Table 1 summarizes all edges and edge type for the sample part shown in fig. 3. Where edge 83 connects FOB364 with D (100) and FOB477 with D (0-10), then X_1X_2 = 0 AND Y_1Y_2 = 0 AND Z_1Z_2 = 0. Therefore, N_i = (0,-1,0) *AND* N_j = (100) and since Y coordinate of cartesian point of plane i <= minimum Y coordinate of any cartesian points of face j is not a true condition, the edge is convex.

Table 2 shows the extracted features information of the part, where FBs are ranked based on their orientation for interior feature information. All FBs are parallel to XY plane but according to Z coordinate FB456&455 is considered first then FB397&292. FB456 represents the top face for the first interior feature, FOBs386&426 connected to it represent the WFs and FB397 represent the BF. FB455 represents the top face for the second interior feature, FOBs222&537 connected to it represent the WFs and FB397 represent the BF. In post processing FOBs386&426 is considered as one face and also FOBs222&537, as shown in table 2.

For exterior feature information, FOBs477, 273, 497, 364, 419, 508, &411 are ignored because they all make convex connections. FOBs266, 485, 396, &438 all make 1 concave connection, but FOBs485&396 parallel to XY plane, FOB438 parallel to XZ plane and FOBs266 parallel to ZY plane. Therefore, FOBs396 is considered the BF and FOB438 as WF for the first exterior feature, and FOBs485 is considered the BF and FOB266 as WF for the second exterior feature. Finally the FOBs466 is a cylindrical face and make convex connection with other faces, but it is not ignored because it forms a half cylinder cavity.

Table 1: Edges list and their type for part shown in fig. 3

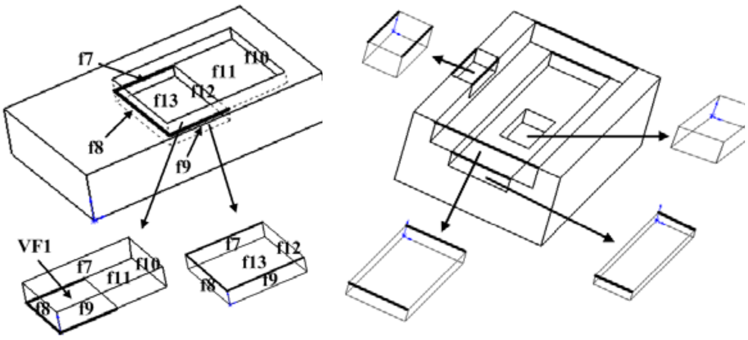
Edge_id	:Face 1	Face 2	Direction 1	Direction 2	Vertex 1	Vertex 2	Edge type
20	222	397	010	001	35	37	Convex
27	222	537	010	010	35	38	-
31	222	455	010	00-1	38	29	Convex
26	222	537	010	010	37	29	-
16	386	292	010	001	15	17	Convex
32	386	426	010	010	15	19	-
5	386	456	010	00-1	19	34	Convex
25	386	426	010	010	17	34	-
68	364	466	100	0-10	43	65	Convex
23	364	497	100	00-1	65	64	Convex
2	364	419	100	010	7	64	Convex
192	364	411	100	001	196	7	Convex
9	364	438	100	0-10	196	119	Convex
113	364	396	100	001	119	176	Convex
83	364	477	100	0-10	176	72	Convex
69	364	273	100	00-1	72	43	Convex
60	273	466	00-1	0-10	43	63	Convex
58	273	477	00-1	0-10	72	59	Convex
56	273	266	00-1	-100	59	63	Convex
6	292	426	001	010	17	15	-
8	411	508	001	-100	11	194	Convex
84	411	438	001	0-10	196	11	Convex
155	411	419	001	010	7	194	Convex
135	266	497	-100	00-1	159	132	Convex
93	266	466	-100	0-10	63	159	Convex
211	266	477	-100	0-10	174	59	Convex
187	266	485	-100	00-1	174	97	Concave
156	266	419	-100	010	97	132	Convex
138	397	537	001	010	37	35	-
195	396	508	001	-100	110	74	Convex
131	396	477	001	0-10	176	74	Convex
180	396	438	001	0-10	119	110	Concave
190	455	537	00-1	010	29	38	Convex
189	456	426	00-1	010	34	19	Convex
96	485	419	00-1	010	97	127	Convex
115	485	477	00-1	0-10	174	99	Convex
126	485	508	00-1	-100	99	127	Convex
121	419	497	010	00-1	64	132	Convex
80	419	508	010	-100	194	127	Convex
77	438	508	0-10	-100	11	110	Convex
213	466	497	0-10	00-1	65	159	Convex
177	508	477	-100	0-10	74	99	Convex

3.4 The interacting features decomposer

This research proposes decomposing rules of interaction between features works on two steps. The first step slices the part into vertical layers and the second decomposes the horizontal interaction within each vertical layer.

Step 1: If a BF in a feature has a convex edge with a WF of another feature, it could be extended along this edge as FB by virtual edges (VEs). In fig. 5(a) f11 is a BF of a feature and has a convex edge with f12 which is a WF of another feature, therefore f11 extended along faces F7, f8 and f9 by VEs as FB. Then f11 and the FB are merged to form one face, this process is called face merging. Fig. 5(b) illustrates the basic idea about vertical slicing.

Step 2: If WFs in the same layer have the same D and can be connected together without being intersected by other faces in the layer, they could be merged as a single WF. Fig. 6 shows through slots 1 and 2 interacts and two faces of the slot 1 are separated as FOB1&FOB2. Since FOB1 & FOB 2 satisfy the above conditions they can be combined as one face.



(a) Interior features (b) Idea of vertical interaction

Fig. 5: Illustrative examples of virtual faces and edges

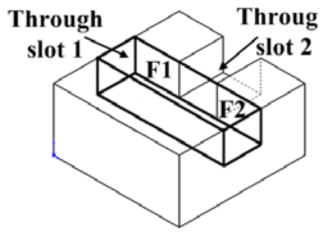


Fig. 6: Part with combinable faces

4. PHASE 2: NN BASED FEATURE RECOGNITION

NN is determined by four elements: input representation, output format, architecture and learning algorithm.

4.1 Input representation

The extracted geometric information in tables 1 and 2 is translated into a unique 12-node vector scheme [15]. Where *Nodes 1 to 7* represents values based on the face geometry, edge geometry and edge-vertex connectivity. For edges and face geometry: convex edge (+0.5), concave edge (-0.5), plane face (0) and cylindrical face (-2). The vertex score $V_s=E_{s1}+E_{s2}+E_{s3}$, where E_{s1}, E_{s2} & E_{s3} are the score for the three edges that are incident to the vertex. The face score is given by:

$$F_s = \sum_{j=1}^{n} \frac{V_{sj}}{n} + F_g \qquad (1)$$

In nodes 1 to 6 only F_s values are stored in ascending order. If the number of F_s values is less than 6, the remaining elements are given 1.5. Using the above scheme to represent the feature Ext_2 using data from table 1 and 2, as shown in fig. 3, the vertex scores of V127, V99, V132, V159, V63, and V59 is 1.5 and V97, and V174 is 0.5. The face scores for face FOB485 = 1 and for face FOB266 = 1.17. So the nodes 1 to 7 for that feature will be given the values as [0.5, 1.17, 1.5, 1.5, 1.5, 1.5, 1.36].

Node 8 stores topological attributes of different feature families by V+E-5F, where V, E and F are the number of vertices, edges and faces. *Node 9* stores information on the number of 'Zero transition faces'. Number of transition is defined as the sum of all transitions from convex to concave edge or vice versa during a traversal along the boundary of a face. *Node 10* stores the number of 'Four transition faces'. *Node 11* stores the total number of faces in the set of connected candidate faces that can for a feature. *Node 12* stores the number of external faces attached to the set of connected candidate faces.

The input vectors is then normalized in the range of 0.05 to 0.95 to get good convergence. Where the input vector nodes n_1 to n_{12}, node values n_1 to n_7 are real numbers and node values n_8 to n_{12} are integers. Table 2 summarizes the 12-node normalized input vector representing the features of sample part in fig. 3.

Let,

Min = minimum value in the set of all input vector nodes n_1 to n_7

Max = minimum value in the set of all input vector nodes n_1 to n_7

Normalized value $= \left(\frac{n_i - \min}{\max - \min}\right) \times 0.9 + 0.05$, for $1 \leq i \leq 7$

$$= \left(\frac{\frac{n_i}{5} + 1}{2}\right) \times 0.9 + 0.05, \text{ for } i = 8$$

$$= \left\{\begin{matrix} 0.05 \text{ if } ni = 0 \\ 0.95 \text{ if } ni = 1 \\ 0.50 \text{ if } ni > 1 \end{matrix}\right\}, \text{ for } i = 9, 10$$

$$= \left\{\begin{matrix} 0.05 \text{ if } ni = 1 \\ 0.25 \text{ if } ni = 2 \\ 0.45 \text{ if } ni = 3 \\ 0.65 \text{ if } ni = 4 \\ 0.85 \text{ if } ni = 5 \\ 0.95 \text{ if } ni \geq 6 \end{matrix}\right\}, \text{ for } i = 11$$

$$= \left\{\begin{matrix} 0.05 \text{ if } ni \neq 4 \\ 0.95 \text{ if } ni = 4 \end{matrix}\right\}, \text{ for } i = 12$$

4.2 Architecture and learning algorithm

NN architecture used in this research is the MLP with BP procedure for training. Architecture parameters are determined by trial and error approach with different initial weights, number of hidden layers and number of neurons in hidden layers [13, 14, 15]. The architecture is specified by training the network with MATLAB NN toolbox [21], considering the feature classifications and target values in fig. 2. Table 3 summarizes the parameters considered for training and testing of the network and the final network configuration that proved to be most appropriate.

Table 2: Geometric information and normalized features vectors

Feature_id	Face_id	Face value	Edges	Edge value	Connected faces	Vertices	Vertex value	Feature vector (normalized)											
								1	2	3	4	5	6	7	8	9	10	11	12
Int_1	386 & 426	-2	31 & 190	0.5	455	38	0.5	-1.50 0.05	1.50 0.95	1.50 0.95	1.50 0.95	1.50 0.95	1.50 0.95	1.00 0.80	1.00 0.59	0.00 0.05	0.00 0.05	1.00 0.05	2.00 0.05
						38	0.5												
			26	-0.5		38	0.5												
						35	0.5												
			20 & 138	0.5	397	35	0.5												
						35	0.5												
			26	-0.5		35	0.5												
						38	0.5												
Int_2	222 & 537	-2	5&189	0.5	456	19	0.5	-1.50 0.05	1.50 0.95	1.50 0.95	1.50 0.95	1.50 0.95	1.50 0.95	1.00 0.80	1.00 0.59	0.00 0.05	0.00 0.05	1.00 0.05	2.00 0.05
						19	0.5												
			32	-0.5		19	0.5												
						15	0.5												
			6&16	0.5	292	15	0.5												
						15	0.5												
			32	-0.5		15	0.5												
						19	0.5												
Ext_1	396	0	195	0.5	508	110	0.5	1.00 0.05	1.00 0.05	1.50 0.95	1.50 0.95	1.50 0.95	1.50 0.95	1.33 0.65	3.00 0.77	0.00 0.05	0.00 0.05	2.00 0.25	4.00 0.95
						74	1.5												
			131	0.5	477	74	1.5												
						176	1.5												
			113	0.5	364	176	1.5												
						119	1.5												
			180	-0.5	438	119	1.5												
						110	0.5												
	438	0	77	0.5	508	11	1.5												
						110	0.5												
			180	-0.5	396	110	0.5												
						119	0.5												
			9	0.5	364	119	0.5												

						196	1.5												
			84	0.5	411	196	1.5												
						11	1.5												
Ext_2	485	0	96	0.5	419	127	1.5	1.00 0.05	1.17 0.36	1.50 0.95	1.50 0.95	1.50 0.95	1.50 0.95	1.36 0.70	7.00 1.13	0.00 0.05	0.00 0.05	2.00 0.25	6.00 0.05
						97	0.5												
			187	-0.5	266	97	0.5												
						174	0.5												
			115	0.5	477	174	0.5												
						99	1.5												
			126	0.5	508	99	1.5												
						127	1.5												
	266	0	135	0.5	497	132	1.5												
						159	1.5												
			93	0.5	466	159	1.5												
						63	1.5												
			56	0.5	273	63	1.5												
						59	1.5												
			211	0.5	477	59	1.5												
						174	0.5												
			187	-0.5	485	174	0.5												
						97	0.5												
			156	0.5	419	97	0.5												
						132	1.5												
Ext_3	466	-2	93	0.5	266	63	1.5	-0.50 0.05	1.50 0.95	1.50 0.95	1.50 0.95	1.50 0.95	1.50 0.95	1.17 0.80	3.00 0.77	1.00 0.95	0.00 0.05	1.00 0.05	4.00 0.95
						159	1.5												
			213	0.5	497	159	1.5												
						65	1.5												
			68	0.5	364	65	1.5												
						43	1.5												
			60	0.5	273	43	1.5												
						63	1.5												

Table 3: Parameters considered for training and testing of the network

Dataset	
Training set	60x10 normalized input-target pairs
Testing set	12 normalized input-target pairs
Network architecture and network parameters	
Network architecture	12-16-1, 12-24-1, 12-30-1, 12-24-16-1, 12-24-24-1
Transfer function per layer	Log Sigmoid, Tan sigmoid
BP algorithm	Gradient descent
Training function	Traingd
Training parameters	
Learning rate	0.1, 0.6
Number of epochs	60000, 120000, 180000
Performance measure	
Training error	Max. training error(Number of training set features not recognized)
Testing error	Max. testing error(Number of testing set features not recognized)

5. PHASE 3: NN BASED PARTS CLASSIFICATION

SOM is an unsupervised network that useful in analyzing data without having the desired outputs. The learning process of this network is based on the competitive learning, or winner-take-all effect algorithm. Typically, SOM consists of two layers, an input layer connected to Kohonen layer by a weight vector [18]. The learning algorithm concept is to make individual neurons in the Kohonen layer compete with one another to represent one of the cluster subgroups of similar input data. Where SOM algorithm consists of the following steps:

<u>*Step 1:*</u> Initialization phase:
1.1 Input the part/features matrix, with the following assumptions:
1.1.1 Each part does not have more than two features of the same class.
1.1.2 The feature orientation (direction of the BF) is taken into account such that:
If D = 1,0,0 OR -1,0,0 OR 0,1,0 OR 0,-1,0 *Then* D = 0.5
Else if D = 0,0,-1 *Then* D = 1
Else if D = 0,0,1 *Then* D = -1
Else invalid BF D
1.2 Normalize part-feature matrix by calculating similarity coefficient between parts:
$F(d_n,d_c) = W_n d_n + W_c(1-d_c)$ (2)
Where
d_n: Levenshtein's distance measure [22], the smallest number of transformations required to derive the feature vector of one part from that of the other part.
d_c: the number of common features between the parts divided by their total number of distinct features.
W_n, W_c: the weights attached to d_n and d_c ; $W_n + W_c = 1$ and $W_n, W_c \geq 0$
1.3 Specify the number of Kohonen layer nodes C (number of groups).
1.4 Randomly assign weight values to the connections
<u>*Step 2:*</u> Input the first similarity coefficient vector from similarity matrix

Step 3: Recognition phase:

3.1 Measure the distance between the weight vector (w) and the similarity coefficient vector (S) of the first part for node i in Kohonen layer

$$D_i = \sqrt{(s_1 - w_{i1})^2 + (s_2 - w_{i2})^2 + \ldots + (s_m - w_{im})^2} \qquad (3)$$

3.2 Bias the distance measure

$$B_i = \gamma\left(\frac{1}{N} - F_i\right) \qquad (4)$$

Where

γ : Starts at a large value and then decrease over time.

F_i: Winning frequency of node i and it is updated constantly during the training cycle and is assigned the value 1/N at initialization.

N: Number of nodes in Kohonen layer

For the wining node i at a time t+1: $F_{i,t+1} = F_{i,t} + \beta\,(1.0 - F_{i,t})$ (5)

For all other Kohonen nodes: $F_{i,t+1} = F_{i,t} + \beta\,(0.0 - F_{i,t})$ (6)

3.3 The modified distance

$$D_i' = D_i - B_i \qquad (7)$$

Kiang et al [19] stated that based on the above frequency function, if a node has higher winning frequency than average its distance will be adjusted to a higher value to prevent it from winning again.

Step 4: Comparison phase:

Use the winner take all effect response to find the node with the minimum D_i value

Step 5: Learning phase (weights updating):

$$W_{ij,t+1} = W_{ij,t} + \alpha\,(X_j - W_{ij,t}) \qquad (8)$$

Where

α: learning coefficient, is a slowly decreasing function of time to guarantee convergence.

Step 6: Performance evaluation:

6.1 Similarity measure:

$$C_i = \sum_{x \neq y} S_{xy} \Big/ \binom{n_i}{2} \quad (X, Y \in \text{group } i) \qquad C = \frac{(n_i - 1)\,C_i}{n - k} \qquad (9)$$

Where

C_i: cohesion measure, the mean similarity between a pair of parts in the group i

S_{xy}: similarity coefficient between a pair of parts P_x and P_y belonging to group i

$\binom{n_i}{2}$: the number of pairs inside each group

C: overall cohesion, the lower the value of C the better the similarity

K: number of Group's n: total number of parts n_i: number of parts of cluster i

6.2 Measure of central tendency:

$$S_i^2 = \sum_{X \neq Y} \frac{(C_i - S_{xy})^2}{\binom{n_i}{2} - 1} \qquad V = \sum_{i=1}^{k} \left(\frac{n_i - 1}{n - k} \right)^2 S_i^2 \tag{10}$$

Where

S_i: variance of group i V: overall variance

6.3 Grouping index:

$$\gamma = \frac{1 - \alpha}{1 + \alpha} \qquad \alpha = \frac{q\, e_v + (1 - q)(e_o - A)}{B} \tag{11}$$

Where

γ: grouping index, proposed by Nair and Narendran [22]

e_v: number of voids in the diagonal blocks

e_o: number of ones in the off diagonal blocks

B: block diagonal space q: weighting factor, $0 \le q \le 1$

$A = 0$ for $e_o \le B$; $A = e_o - B$ for $e_o > B$

6. TESTING AND IMPLEMENTATION

The proposed approach has been implemented using the 16 parts from [1]. The solid models of the parts are created and saved as STEP-AP203. Phases 1 and 2 are performed as descried in details in sections 3 and 4, the results are summarized in table 4. Part/features matrix (see table 5) is then normalized by constructing similarity coefficient matrix (see table 6). The SOM algorithm is then applied using 2, 3, 4 and 5 groups. Results are evaluated and the 4 groups in give the best results according to the grouping index (see tables 7, 8 and fig. 7). As the number of groups increased the similarity increased and variance decreased.

Table 4: Normalized features vectors

		Feature vector												Feature Value
		1	2	3	4	5	6	7	8	9	10	11	12	
P1	F1	0.05	0.95	0.95	0.95	0.95	0.95	0.80	0.59	0.05	0.05	0.05	0.05	0.80
	F2	0.05	0.95	0.95	0.95	0.95	0.95	0.80	0.59	0.05	0.05	0.05	0.05	0.80
	F3	0.05	0.36	0.95	0.95	0.95	0.95	0.70	1.13	0.05	0.05	0.25	0.05	0.40
	F4	0.05	0.05	0.95	0.95	0.95	0.95	0.65	0.77	0.05	0.05	0.25	0.95	0.40
	F5	0.05	0.95	0.95	0.95	0.95	0.95	0.80	0.77	0.95	0.05	0.05	0.95	0.60
P2	F1	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F2	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F3	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F4	0.05	0.95	0.95	0.95	0.95	0.95	0.80	0.77	0.95	0.05	0.05	0.95	0.60
P3	F1	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F2	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F3	0.05	0.05	0.33	0.95	0.95	0.95	0.55	1.13	0.05	0.05	0.45	0.05	0.48
P4	F1	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F2	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F3	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F4	0.05	0.05	0.95	0.95	0.95	0.95	0.65	0.77	0.05	0.05	0.25	0.95	0.40
	F5	0.05	0.05	0.95	0.95	0.95	0.95	0.65	0.77	0.05	0.05	0.25	0.95	0.40
P5	F1	0.05	0.05	0.65	0.65	0.95	0.95	0.55	0.50	0.05	0.50	0.65	0.05	0.24
	F2	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F3	0.05	0.05	0.95	0.95	0.95	0.95	0.65	0.77	0.05	0.05	0.25	0.95	0.40
P6	F1	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F2	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F3	0.05	0.59	0.77	0.95	0.95	0.95	0.71	0.77	0.05	0.95	0.45	0.05	0.68

P7	F1	0.05	0.05	0.65	0.65	0.95	0.95	0.55	0.50	0.05	0.50	0.65	0.05	0.24
	F2	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F3	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F4	0.05	0.05	0.95	0.95	0.95	0.95	0.65	0.77	0.05	0.95	0.45	0.95	0.64
	F5	0.05	0.05	0.95	0.95	0.95	0.95	0.65	0.77	0.05	0.05	0.25	0.95	0.40
P8	F1	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F2	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F3	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F4	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F5	0.05	0.95	0.95	0.95	0.95	0.95	0.80	0.77	0.95	0.05	0.05	0.95	0.60
	F6	0.05	0.23	0.35	0.55	0.95	0.95	0.51	1.85	0.05	0.05	0.95	0.05	0.48
P9	F1	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F2	0.05	0.50	0.73	0.73	0.95	0.95	0.65	0.50	0.95	0.95	0.65	0.05	0.28
	F3	0.05	0.59	0.95	0.95	0.95	0.95	0.74	0.77	0.05	0.05	0.25	0.95	0.32
P10	F1	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F2	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F3	0.05	0.05	0.95	0.95	0.95	0.95	0.65	0.77	0.05	0.05	0.25	0.95	0.40
	F4	0.05	0.05	0.95	0.95	0.95	0.95	0.65	0.77	0.05	0.05	0.25	0.95	0.40
	F5	0.05	0.95	0.95	0.95	0.95	0.95	0.80	0.77	0.95	0.05	0.05	0.95	0.60
P11	F1	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F2	0.05	0.05	0.28	0.50	0.50	0.95	0.39	0.05	0.95	0.05	0.85	0.05	0.14
	F3	0.05	0.05	0.65	0.65	0.95	0.95	0.55	0.50	0.05	0.50	0.65	0.05	0.24
	F4	0.05	0.05	0.95	0.95	0.95	0.95	0.65	0.77	0.05	0.95	0.45	0.95	0.64
	F5	0.05	0.59	0.95	0.95	0.95	0.95	0.74	0.77	0.05	0.05	0.25	0.95	0.32
P12	F1	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F2	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F3	0.05	0.65	0.95	0.95	0.95	0.95	0.75	1.13	0.05	0.05	0.25	0.05	0.40
	F4	0.05	0.65	0.95	0.95	0.95	0.95	0.75	1.13	0.05	0.05	0.25	0.05	0.40
	F5	0.05	0.65	0.95	0.95	0.95	0.95	0.75	1.49	0.05	0.95	0.45	0.05	0.64
	F6	0.05	0.95	0.95	0.95	0.95	0.95	0.80	0.77	0.95	0.05	0.05	0.95	0.60
P13	F1	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F2	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F3	0.05	0.05	0.95	0.95	0.95	0.95	0.65	0.77	0.05	0.05	0.25	0.95	0.40
	F4	0.05	0.05	0.95	0.95	0.95	0.95	0.65	0.77	0.05	0.05	0.25	0.95	0.40
	F5	0.05	0.59	0.77	0.95	0.95	0.95	0.71	0.77	0.05	0.95	0.45	0.05	0.68
P14	F1	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F2	0.05	0.05	0.95	0.95	0.95	0.95	0.65	0.77	0.05	0.95	0.45	0.95	0.64
	F3	0.05	0.59	0.95	0.95	0.95	0.95	0.74	1.94	0.05	0.95	0.45	0.05	0.68
P15	F1	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F2	0.05	0.05	0.65	0.65	0.95	0.95	0.55	0.50	0.05	0.50	0.65	0.05	0.24
	F3	0.05	0.05	0.95	0.95	0.95	0.95	0.65	0.77	0.05	0.95	0.45	0.95	0.64
	F4	0.05	0.59	0.77	0.95	0.95	0.95	0.71	0.77	0.05	0.95	0.45	0.05	0.68
P16	F1	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F2	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F3	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F4	0.05	0.28	0.95	0.95	0.95	0.95	0.69	0.05	0.95	0.05	0.25	0.05	0.80
	F5	0.05	0.95	0.95	0.95	0.95	0.95	0.80	0.77	0.95	0.05	0.05	0.95	0.60
	F6	0.05	0.65	0.67	0.95	0.95	0.95	0.70	0.77	0.05	0.05	0.65	0.05	0.48

Table 5: Part/Feature matrix

	Blind pocket				Through pocket				Blind step				Through step			
	F1	D1	F2	D2	F3	D3	F4	D4	F5	D5	F6	D6	F7	D7	F8	D8
P1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	1.00	0.40	-1.00
P2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
P3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.48	1.00	0.00	0.00
P4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	1.00	0.40	1.00
P5	0.00	0.00	0.00	0.00	0.24	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	1.00	0.00	0.00
P6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
P7	0.00	0.00	0.00	0.00	0.24	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	1.00	0.00	0.00
P8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.48	1.00	0.00	0.00
P9	0.00	0.00	0.00	0.00	0.28	1.00	0.00	0.00	0.32	1.00	0.00	0.00	0.00	0.00	0.00	0.00
P10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	1.00	0.40	1.00
P11	0.14	1.00	0.00	0.00	0.24	1.00	0.00	0.00	0.32	1.00	0.00	0.00	0.00	0.00	0.00	0.00
P12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	1.00	0.40	1.00
P13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.40	0.50	0.40	0.50
P14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
P15	0.00	0.00	0.00	0.00	0.24	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
P16	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.48	11.00	0.00	0.00

	Blind slot				Through slot				Blind hole				Through hole			
	F9	D9	F10	D10	F11	D11	F12	D12	F13	D13	F14	D14	F15	D15	F16	D16
P1	0.00	0.00	0.00	0.00	0.60	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	1.00	0.80	1.00
P2	0.00	0.00	0.00	0.00	0.60	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.80	1.00	0.80	1.00
P3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	1.00	0.80	0.50
P4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	1.00	0.80	0.50
P5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.50	0.00	0.00
P6	0.00	0.00	0.00	0.00	0.68	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	1.00	0.80	0.50
P7	0.00	0.00	0.00	0.00	0.64	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.50	0.80	0.50
P8	0.00	0.00	0.00	0.00	0.60	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	1.00	0.80	0.50
P9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	1.00	0.00	0.00
P10	0.00	0.00	0.00	0.00	0.60	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	1.00	0.80	1.00
P11	0.00	0.00	0.00	0.00	0.64	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	1.00	0.00	0.00
P12	0.00	0.00	0.00	0.00	0.60	1.00	0.60	1.00	0.00	0.00	0.00	0.00	0.80	1.00	0.80	1.00
P13	0.00	0.00	0.00	0.00	0.68	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	1.00	0.80	0.50
P14	0.00	0.00	0.00	0.00	0.64	1.00	0.68	1.00	0.00	0.00	0.00	0.00	0.80	1.00	0.00	0.00
P15	0.00	0.00	0.00	0.00	0.64	0.50	0.68	1.00	0.00	0.00	0.00	0.00	0.80	1.00	0.00	0.00
P16	0.00	0.00	0.00	0.00	0.60	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.80	1.00	0.80	0.50

Table 6: Similarity coefficient matrix with $W_n = 0.5$, $W_c = 0.5$

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14	P15	P16
P1	0.000	0.500	0.500	0.400	0.725	0.500	0.500	0.300	0.829	0.100	0.675	0.275	0.300	0.600	0.725	0.400
P2	0.500	0.000	0.463	0.600	0.700	0.267	0.700	0.450	0.600	0.500	0.743	0.642	0.600	0.463	0.500	0.338
P3	0.500	0.463	0.000	0.225	0.463	0.267	0.500	0.225	0.600	0.300	0.829	0.642	0.500	0.600	0.717	0.225
P4	0.400	0.600	0.225	0.000	0.600	0.600	0.542	0.300	0.717	0.300	0.838	0.458	0.400	0.717	0.729	0.300
P5	0.725	0.700	0.463	0.600	0.000	0.700	0.400	0.600	0.463	0.725	0.725	0.843	0.817	0.700	0.700	0.600
P6	0.500	0.267	0.267	0.600	0.700	0.000	0.500	0.225	0.600	0.500	0.633	0.642	0.400	0.350	0.600	0.338
P7	0.500	0.700	0.500	0.542	0.400	0.500	0.000	0.300	0.725	0.450	0.571	0.586	0.450	0.725	0.725	0.400
P8	0.300	0.450	0.225	0.300	0.600	0.225	0.300	0.000	0.717	0.300	0.657	0.458	0.300	0.500	0.625	0.113
P9	0.829	0.600	0.600	0.717	0.463	0.600	0.725	0.717	0.000	0.829	0.400	0.938	0.829	0.600	0.600	0.717
P10	0.100	0.500	0.300	0.300	0.725	0.500	0.450	0.300	0.829	0.000	0.675	0.183	0.300	0.633	0.743	0.400
P11	0.675	0.743	0.829	0.838	0.725	0.633	0.571	0.657	0.400	0.675	0.000	0.789	0.675	0.633	0.633	0.700
P12	0.275	0.642	0.642	0.458	0.843	0.642	0.586	0.458	0.938	0.183	0.789	0.000	0.580	0.550	0.671	0.550
P13	0.300	0.600	0.500	0.400	0.817	0.400	0.450	0.300	0.829	0.300	0.675	0.580	0.000	0.633	0.730	0.400
P14	0.600	0.463	0.600	0.717	0.700	0.350	0.725	0.500	0.600	0.633	0.633	0.550	0.633	0.000	0.338	0.600
P15	0.725	0.500	0.717	0.729	0.700	0.600	0.725	0.625	0.600	0.743	0.633	0.671	0.730	0.338	0.000	0.533
P16	0.400	0.338	0.225	0.300	0.600	0.338	0.400	0.113	0.717	-0.400	0.700	0.550	0.400	0.600	0.533	0.000

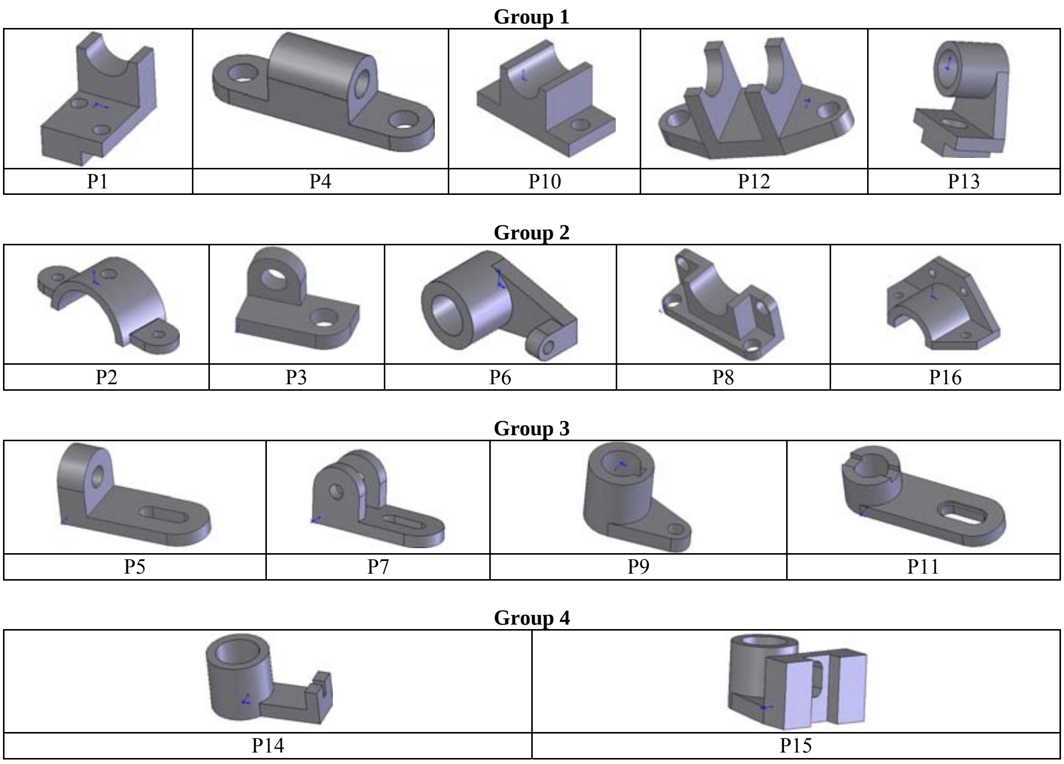


Fig. 7: Classification results for 4 groups

Table 7: part/feature matrix and final grouping results with grouping index = 90.14%

	Through step				Through slot				Through hole				Blind pocket		Through pocket		Blind step	
	F13	F14	F15	F16	F21	F22	F23	F24	F29	F30	F31	F32	F1	F2	F5	F6	F9	F10
P1	0.40	-1.00	0.40	1.00	0.60	-1.00	0.00	0.00	0.80	-1.00	0.80	-1.00	0.00	0.00	0.00	0.00	0.00	0.00
P4	0.40	-1.00	0.40	-1.00	0.00	0.00	0.00	0.00	0.80	-1.00	0.80	0.50	0.00	0.00	0.00	0.00	0.00	0.00
P10	0.40	-1.00	0.40	-1.00	0.60	-1.00	0.00	0.00	0.80	-1.00	0.80	-1.00	0.00	0.00	0.00	0.00	0.00	0.00
P12	0.40	-1.00	0.40	-1.00	0.60	-1.00	0.60	-1.00	0.80	-1.00	0.80	-1.00	0.00	0.00	0.00	0.00	0.00	0.00
P13	0.40	0.50	0.40	0.50	0.68	-1.00	0.00	0.00	0.80	-1.00	0.80	0.50	0.00	0.00	0.00	0.00	0.00	0.00
P2	0.00	0.00	0.00	0.00	0.60	0.50	0.00	0.00	0.80	-1.00	0.80	-1.00	0.00	0.00	0.00	0.00	0.00	0.00
P3	0.48	-1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	-1.00	0.80	0.50	0.00	0.00	0.00	0.00	0.00	0.00
P6	0.00	0.00	0.00	0.00	0.68	-1.00	0.00	0.00	0.80	-1.00	0.80	0.50	0.00	0.00	0.00	0.00	0.00	0.00
P8	0.48	-1.00	0.00	0.00	0.60	-1.00	0.00	0.00	0.80	-1.00	0.80	0.50	0.00	0.00	0.00	0.00	0.00	0.00
P16	0.48	-1.00	0.00	0.00	0.60	0.50	0.00	0.00	0.80	-1.00	0.80	0.50	0.00	0.00	0.00	0.00	0.00	0.00
P5	0.40	-1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.50	0.00	0.00	0.00	0.00	0.24	-1.00	0.00	0.00
P7	0.40	-1.00	0.00	0.00	0.64	-1.00	0.00	0.00	0.80	0.50	0.80	0.50	0.00	0.00	0.24	-1.00	0.00	0.00
P9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	-1.00	0.00	0.00	0.00	0.00	0.28	-1.00	0.32	-1.00
P11	0.00	0.00	0.00	0.00	0.64	-1.00	0.00	0.00	0.80	-1.00	0.00	0.00	0.14	-1.00	0.24	-1.00	0.32	-1.00
P14	0.00	0.00	0.00	0.00	0.64	-1.00	0.68	-1.00	0.80	-1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
P15	0.00	0.00	0.00	0.00	0.64	0.50	0.68	-1.00	0.80	-1.00	0.00	0.00	0.00	0.00	0.24	0.50	0.00	0.00

Table 8: Similarity, variance and grouping index for different number of groups

Number of groups	Parts	Similarity (C)	Variance (V)	Grouping index (q = 0.2)
2	1, 2, 3, 4, 6, 8, 10, 12, 13, 16	0.509	0.147	82.59%
	5, 7, 9, 11, 14, 15			
3	1, 4, 10, 12, 13	0.443	0.130	83.67%
	2, 3, 6, 16, 8			
	5, 7, 9, 11, 14, 15			
3*	3, 4, 5, 7, 12	0.561	0.186	70.53%
	1, 2, 8, 10, 12, 16			
	6, 9, 11, 13, 14, 15			
4	1, 4, 10, 12, 13	0.401	0.125	90.14%
	2, 3, 6, 8, 16			
	5, 7, 9, 11			
	14, 15			
5	1, 4, 10, 12, 13	0.380	0.105	90.14%
	12, 13			
	2, 3, 6, 8, 16			
	5, 7, 9, 11			
	14, 15			

3* groups used by Moon and Roy [1]

7. CONCLUSIONS AND FUTURE WORK

The proposed system is effective because it has the following aspects:

- The methodology for geometric information extraction does not examine all faces at a time, but it works like a filtering system. At the first stage, it searches for the traces of interior features, finds all faces constitutes these features and ignoring them from further examinations. At the second stage, it deletes all faces that makeonly convex connections. At the final stage, the remained faces are examined to form exterior features.
- Interacting features are restored to their primitive forms by applying a set of rules works on two steps. First step slices the part into vertical layers to facilitate the accessibility to the lower layers features. Second step decomposes the horizontal interaction inside each vertical layer.
- Parts are classified based on geometry of their machining features considering variations in shape, topology and orientation between features using SOM NN.
- Part/feature matrix is normalized to help SOM in learning process. Then the performance is evaluated based on the similarity inside groups, mean similarity between groups, variance between groups and grouping index.

Possible extensions can be considered in the following directions. First, more surface types can be considered by specifying their geometric parameters. Second, enhance the capability of decomposing interaction between features through considering wider variety of topology and geometry variations .Third, global shape information should be extended in parts classification.

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