

Title:

**A Visual-cognition-inspired Model for Machining Feature Recognition**

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Introduction:

Artificial neural network (ANN) is a successful implementation of imitating biological neural network. Feature recognition is a key technology in CAD/CAM. Using ANN to identify machining features is a significant interdisciplinary research direction of feature recognition, and has received considerable results. The method mainly performs pre-processing and assigns features based on B-rep information or voxel representation, and then inputs them into the ANN for calculation. Several popular ANN structures are employed, including Convolutional Neural Network (CNN) [1-2] [8], Back Propagation (BP) Neural Network [3-5] and Self-organizing Feature Map (SOFM) [7]. The advantages of the ANN recognition method are that ANNs have the ability to learn and generalize, and process faster. However, the recognition process of ANNs is opaque. Moreover, ANNs can only process numerical input and perform arithmetic operations, not logical operations, which restricts the application of ANNs in the field of CAD machining feature recognition. Therefore, it is essential to research and establish a new and more practical network structure.

The contribution of this paper is that a new Visual-cognition-inspired Model (VCIM) for machining feature recognition especially in aircraft structural parts is established by imitating the visual cognition process of the human brain and related neural mechanisms. The VCIM uses a 3D CAD model as a direct input, and the recognition process of each layer has a clear cognitive meaning. The new network structure also has three new activation functions that can perform logical operations and have their own characteristics and meanings.

Main Idea:

Fig. 1 is a biological model of the visual processing system, which inspires the design of the VCIM (see Fig. 2). Both the two models have certain similarities and connections in structure and function. For example, the layer structure of the VCIM is a module organization similar to the V1 cortex, which consists of several column structures; the recognition process of the VCIM is similar to the visual information flow path, which is a phased process, and can identify multiple features simultaneously.

Structure

From Fig. 1, the V1 area is a modular organization with different structures in the horizontal and vertical direction. Based on the biological information, the VCIM structure formed by column → module → layer.

- Column: Stores a geometric face of the CAD model. Each column is divided into five pieces, which in turn stores five different properties of the geometric face, which is shown in Fig. 2.

- Module: A more advanced collection of columns. Each module stores a class of columns with the same definition or similarity.
- Layer: A more advanced form of module. A layer contains one or more different modules.

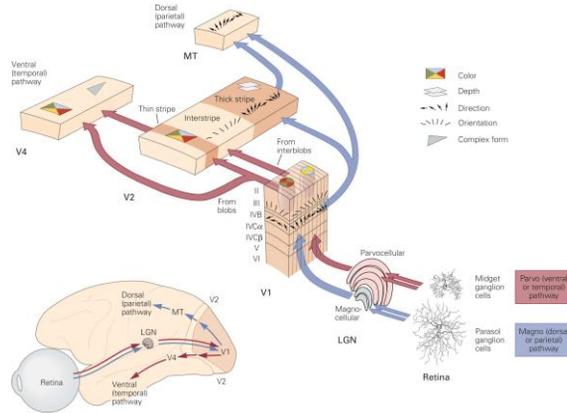


Fig. 1: Biological model of visual processing system [6].

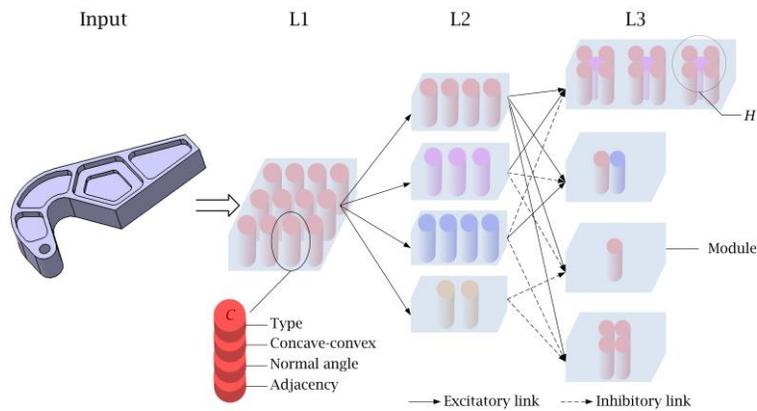


Fig. 2: VCIM network structure.

The column can be defined as  $C = t, l, \theta, A$ , where  $t$ ,  $l$  and  $\theta$  are the type, concavity and convexity of the outer loop, and normal angle of the face separately. The type of face can be plane, cylinder, or ruled face, and can be expressed as  $t \in Plane$ ,  $t \in Cylinder$  and  $t \in RuledFace$ . If the outer loop is a concave loop, and then  $l \in cLoop$ . If the outer loop is a convex loop, and then  $l \in vLoop$ . Otherwise  $l \in mLoop$ . The aircraft structural parts are generally flat, and the machining features are mostly concentrated on the front of the structural parts. We take the bottom surface when the front side is placed as a horizontal plane (x-y plane), and the z direction is perpendicular to the x-y plane.  $\theta$  is the acute angle between the z direction and the face normal direction.  $A$  is a collection that stores the sequence numbers of the faces that are smoothly connected to the current face. If  $C_x$  and  $C_y$  are smoothly connected, and then they can be expressed as  $C_x A \sim C_y A$ .

Except the Input layer, the other layers are represented as  $L_i, i = 1, 2, 3, \dots$ , and there is

$$L_i = M_i^j \mid j = 1, 2, \dots, n_i \quad (2.1)$$

Where  $M_i^j$  is the  $j$ -th module of  $L_i$ , and  $n_i$  is the number of modules in  $L_i$ . For any module  $M_i^j$ , there is

$$M_i^j = C_h \mid h \in N^* \quad (2.2)$$

One thing to notice is that the serial number  $h$  is only related to the corresponding face number in the CAD model.

The number of layers and the number of modules of the VCIM are optional. Here the VCIM selects a four-layer network structure where  $L_1$  has one module that stores all the columns of the CAD model. There are four modules in  $L_2$ , which store side columns, bottom face columns and top face columns in turn. Another module contains faces that do not belong to the other three columns.  $L_3$  also uses four modules to store four kinds of features, slot, protrusion, through hole and outer contour, which are marked from  $M_3^1$  to  $M_3^4$  in turn.

In particular, considering that a feature module in  $L_3$  may contain more than one feature, the paper use a hyper-column to store a feature, therefore

$$M_3^j = H_3^{jk} \mid H_3^{jk} = \{C_h\}, k = 1, 2, \dots, n_3^j \quad (2.3)$$

Where  $n_3^j$  is the number of hyper-columns in  $M_3^j$ . Any hyper-column  $H_3^{jk}$  has one or more columns.

#### Activation Functions

The activation function of the neural network is used to calculate the weight of neurons, and introduce nonlinear characteristics to the network. However, the activation functions of the VCIM are to perform logical operations on the geometric faces (columns) of the CAD model, and different kinds of activation functions are used between different layers.

##### 1) Distribution function

The distribution function takes the CAD 3D model as input, assigns a column to each geometric face, and stores the attribute information of the face. The output is the column of  $L_1$ . The distribution function is defined as

$$C_h = D(f_h) \quad (2.4)$$

Where  $f_h$  is the  $h$ -th face of the CAD model, and  $D()$  represents the distribution function.

##### 2) Judgment function

The judgment function judges each column of the layer  $L_1$ , calculates the module types to which it belongs, and stores it in the corresponding module of the layer  $L_2$ . The judgment function is related to the judgment factor and is defined as the following expression:

$$M_2^j = C_h \mid \varphi_j(C_h) = T \quad j = 1, 2, 3, 4 \quad (2.5)$$

$\varphi_1(C_h)$ ,  $\varphi_2(C_h)$ ,  $\varphi_3(C_h)$ , and  $\varphi_4(C_h)$  are the judgment factors of the side, bottom face, top face and else face separately. If and only if the judgment factor of a certain column is true, and then the column is the element of the module corresponding to the current judgment factor. The specific forms of the four judgment factors are

$$\begin{aligned} \varphi_1(C) &= (l \in vLoop \vee l \in mLoop) \wedge \theta \in [90^\circ - \alpha, 90^\circ] \\ \varphi_2(C) &= t \in Plane \wedge (l \in cLoop \vee l \in mLoop) \wedge \theta \in [0^\circ, \beta] \\ \varphi_3(C) &= (t \in Plane \vee t \in RuledFace) \wedge l \in vLoop \wedge \theta \in [0^\circ, \gamma] \\ \varphi_4(C) &= \varphi_1(C) \neq T \wedge \varphi_2(C) \neq T \wedge \varphi_3(C) \neq T \end{aligned} \quad (2.6)$$

Where  $\alpha, \beta, \gamma$  are critical angles in corresponding modules. Specifically, if a face is smoothly connected to a side, then the face is a side too. This can be expressed as  $\varphi_1(C_h) = C_x A \sim C_y A, C_y A \in M_2^1$ .

### 3) Selection function

The selection function selects the appropriate module and its internal columns from the layer  $L_2$  to form different types of machining features. The faces associated with the machining features can be divided into two types, one is an element face directly forming the machining features, stored in the excitatory column  $E$ ; the other is a limit face adjacent to the element face and playing a limiting role, stored in the inhibitory column  $I$ . The two types of faces collectively define the machining features, namely  $H(E, I)$ . The definition expression of the selection function is shown in Tab. 1.  $H$  in Fig. 2 does not display  $I$  for view convenience.

<i>Machining feature</i>	<i>Element face</i>	<i>Limit face</i>	<i>selection function</i>
Slot	Side, bottom	Top	$M_3^1 = \{H   E \subset M_2^1 \wedge E \subset M_2^2, I \subset M_2^3\}$
Protrusion	Side, top	Bottom	$M_3^2 = \{H   E \subset M_2^1 \wedge E \subset M_2^3, I \subset M_2^2\}$
Through hole	Side	Bottom, else	$M_3^3 = \{H   E \subset M_2^1, I \subset M_2^2 \wedge I \subset M_2^4\}$
Contour	Side	Top, else	$M_3^4 = \{H   E \subset M_2^1, I \subset M_2^3 \wedge I \subset M_2^4\}$

Tab. 1: Machining feature with element face and limit face.

### Procedure

In Fig. 1, the visual processing process with LGN as the starting point and the V4 region and the MT region as the end point goes through three stages. Similarly, VCIM recognizing machining features are divided into three steps as well.

- Phase 1: With a CAD 3D model as input, distribute a column to each face.
- Phase 2: Based on the judgment factors, place the columns in the appropriate modules of  $L_2$ .
- Phase 3: Select the appropriate  $E$  and  $I$  to obtain  $H$ , and finally identify all features.

### Examples

In this paper, the CAD 3D model shown in Fig. 2 is input into the VCIM. In the experiment, seven features are finally recognized, which are 5 slots with different shapes, 1 through hole and 1 contour. The recognition results are shown in Tab. 2. The first parenthesis contains the element face numbers, and the second parenthesis shows the limit face number of the feature.

<i>Feature result</i>	<i>Face composition</i>
Slot 1	(1,32,2,33,3,34,4,35,47), (55)
Slot 2	(36,6,37,7,38,8,39,5,58), (55)
Slot 3	(9,40,10,41,11,42,12,43,13,44,59), (55)
Slot 4	(14,45,15,46,16,47,17,48,60), (55)
Slot 5	(18,49,19,50,20,51,21,52,22,53,61), (59)
Through hole 1	(54), (55,56)
Contour 1	(23,24,25,26,27,28,29,30,31), (55,56)

Tab. 2: Recognition results of VCIM for a CAD model.

Another example is shown in Fig. 3. This aircraft structural part has 12 slots, 16 through holes and 1 contour. One of the main differences between Example 2 and Example 1 is that the features in Example 2 have fillets, but this does not influence the recognition of the VCIM. From Fig. 3(b), there are 141 faces in the part, and they eventually form 29 hyper-columns, corresponding to 29 features.

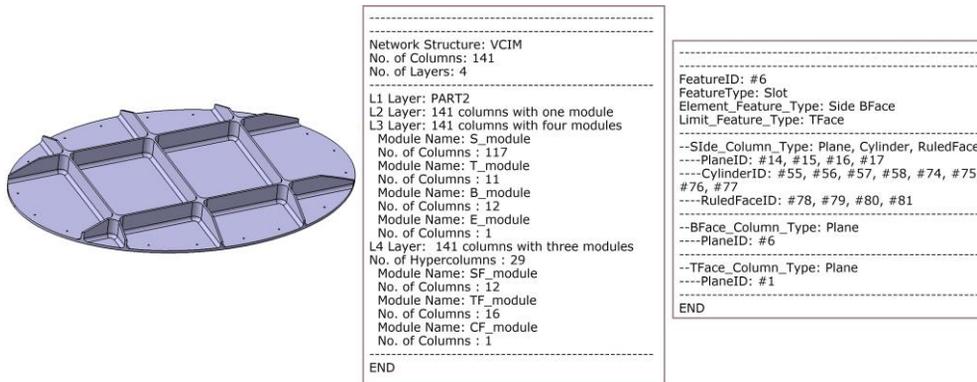


Fig. 3: Recognition Example 2: (a) an aircraft structural part, (b) the VCIM structure, and (c) a slot feature recognition result.

### Conclusions:

In this paper, a new network structure called VCIM is established for machining feature recognition in aircraft structural parts, which is different from the traditional ANNs in the following innovations:

- 1) The VCIM has column, hyper-column and module organization similar to cerebral cortex.
- 2) The VCIM creates three new activation functions for logical operations.
- 3) New machining features can be identified once the judgment factor and selection function expression in the activation functions are changed.
- 4) The configuration structure of each layer can be dynamically configured as needed.

Future work will further verify the feature recognition of more complex CAD models, and study the identification of intersecting features and composite features.

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