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Research of Invariant Moments and Improved Support Vector Machine in Micro-Targets Identification

Xiangjin Zeng, Xinhan Huang and Min Wang
Key Laboratory of Image Processing and Intelligent Control, Department of Control Science and Engineering, Huazhong University of Science and Technology, Wuhan, 430074, China

Abstract: In order to identify multi micro objects, an improved support vector machine algorithm is present, which employs invariant moments based edge extraction to obtain feature attribute and then presents a heuristic attribute reduction algorithm based on rough set's discernibility matrix to obtain attribute reduction, with using support vector machine to identify and classify the targets. According to the feature attribute, the effectiveness of identifying multi micro objects using support vector machine is compared with the proposed improved support vector machine classification method. The experiment results under micro vision environment show that the proposed improved support vector machine classification method can meet the system application requirement, with the resolution is 95%.

Key words: Invariant moments, improved support vector machine, rough set, attribute reduction, targets identification

INTRODUCTION

In order to operate multi micro objects under micro-vision, it is necessary that identifies firstly these objects. In pattern recognition field, the feature of image shape is an important object when extracts feature. Moment feature is one of the shape feature that be used in extensive application. The most basic two-dimensional shape features have a direct relationship with the moment. Image gravity center, the long axis and the short axis inertia moment and a number of very useful invariant moments can be computed directly from the moment. Invariant moments are the statistical properties of image, meeting that the translation, reduction and rotation are invariance, which has been used widely in the field of image recognition. An automatic method for generating affine moment invariants (Liu *et al*., 2007). For closed structure and not closed structure, because the moment feature can not calculate directly, it need construct firstly regional structure (Chen, 1993). Besides, because the moment involves in the calculation of all the pixels of intra-regional and border, it means that it can be more time-consuming. Therefore, we apply the edge extraction algorithm to process image firstly and then calculate the edge image's invariant moments to obtain the feature attribute, which solves the problem discussion above.

After feature attribute extraction, the classification algorithm should be provided during the final target identification. The main classifier used at present can be divided into three categories: One is the method statistics-based and its representative is such as the bayes methods, KNN method, like centre vector and SVM and so on; One is the method rule-based and its representative is decision tree and rough sets. The last one is the method based on artificial neural network. Being SVM algorithm is a convex optimization problems (Emanuela *et al*., 2003), its local optimal solution must be global optimal solution, which is better than the others learning algorithms. So, For solving the small sample, non-linear and high-dimensional pattern recognition, SVM has many good performances and advantages (Jose *et al*., 2004; Yi and James, 2003), especially in the text SVM classification. Therefore, we employ SVM classification algorithm to classify the targets. However, the classic SVM algorithm is established on the basis of the quadratic planning. That is, it can not distinguish the attribute's importance from training sample set. Bas presents a method that omits the insignificant training data based on pruning error minimization in least squares support vector machines. In additional with, It is high time to solve for the large volume data classification and time series prediction, which must improve its real-time data processing and shorten the training time and reduce the occupied space of the training sample set.

For the problem discussion above, presents an improved support vector machine classification, which

Corresponding Author: Xiangjin Zeng, Key Laboratory of Image Processing and Intelligent Control, Department of Control Science and Engineering, Huazhong University of Science and Technology, Wuhan, 430074, China

applies edge extraction's invariant moments to obtain object's feature attribute. In order to enhance operation effectiveness and improve classification performance, a feature attribute reduction algorithm based on rough set has been developed (Leung *et al*., 2008), with the good result to distinguish training data set's importance. The experiments of multi micro objects identifying using the propose method have been given. The results show that the improved SVM classifier can meet the application requirements, with the resolution of 95%.

INVARIANT MOMENTS THEORY

In the pattern recognition field, the shape feature of image is an important feature target for extraction. Some basic two-dimensional shape features have a direct relationship with the moment. Because the invariant moments have many advantages such as translation, reduction and rotation invariance, Therefore, we employ the invariant moments to describe the feature attributes of image.

Image (p+q) order moments: we presume that f (i, j) represents the two-dimensional continuous function. Then, it's (p+q) order moments can be written as (1).

$$M_{pq} = \iint i^p j^q f(i,j)\,di\,dj \quad (p,q = 0,1,2\ldots) \tag{1}$$

In terms of image computation, we use generally the sum formula of (p+q) order moments shown as (2).

$$M_{pq} = \sum_{i=1}^{M}\sum_{j=1}^{N} f(i,j)\, i^p j^q \quad (p,q = 0,1,2\ldots) \tag{2}$$

where, p and q can choose all of the non-negative integer value, they create infinite sets of the moment. According to papulisi's theorem, the infinite sets can determine completely two-dimensional image f (i, j). For the binary image, if its background value is 0 and the region value is 1, zero-order moment can represent area of the shape region. So, we can obtain the result from image moment divided by zero-order moment, it has the invariance of the shape scale changes.

Image (p+q) order center moment: In order to ensure location invariance of the shape feature, we must compute the image (p+q) order center moment. That is, calculates the invariant moments using the center of object as the origin of the image. The center of object (i', j') can obtain from zero-order moment and first-order moment. The centre-moment formula can be shown as (3).

$$M_{pq} = \sum_{i=1}^{M}\sum_{j=1}^{N} f(i,j)(i-i')^p (j-j')^q \quad (p,q = 0,1,2\ldots) \tag{3}$$

If we use the area of the shape to normalize the center moment, namely, use M_{pq}/M^r_{00} to replace M_{pq}, then the invariant moments obtained can meet the independence of the scale changes of the shape.

At present, most studies about the two-dimensional invariant moments focus on extracting the moment from the full image. This should increase the computation amount and can impact on the real-time of system. Therefore, we propose the invariant moments method based on edge extraction, which gets firstly the edge image and then achieve the invariant moments feature attribute. Obviously, it keeps the region feature of moment using the propose method. In addition, being the role of edge detection, the data that participate calculation have made a sharp decline, reducing greatly the computation amount.

The invariant moments is the function of the seven moments, meeting the invariance of the translation, rotation and scale. The calculation formula is shown in (4).

$$\begin{aligned}
&\Phi_1 = m_{20} + m_{02}\\
&\Phi_2 = (m_{20} - m_{02})^2 + 4m_{11}\\
&\Phi_3 = (m_{30} - 3m_{12})^2 + (3m_{21} - m_{03})^2\\
&\Phi_4 = (m_{30} + m_{12})^2 + (m_{21} + m_{03})^2\\
&\Phi_5 = (m_{30} - 3m_{12})^2 (m_{30} + m_{12})[(m_{30} + m_{12})^2 - 3(m_{21} + m_{03})^2]\\
&+(3m_{21} - m_{03})(m_{21} - m_{03}) * [3(m_{30} + m_{12})^2 - (m_{21} + m_{03})^2]\\
&\Phi_6 = (m_{20} - m_{02})[(m_{30} + m_{12})^2 - 3(m_{21} + m_{03})^2] +\\
&4m_{11}(m_{30} + m_{12})(m_{21} + m_{03})\\
&\Phi_7 = (3m_{12} - m_{30})^2 (m_{30} + m_{12})[(m_{30} + m_{12})^2 - 3(m_{21} + m_{03})^2]\\
&-(m_{03} - 3m_{21}) * [3(m_{30} + m_{12})^2 - (m_{21} + m_{03})^2]
\end{aligned} \tag{4}$$

IMPROVED SUPPORT VECTOR MACHINE AND TARGET IDENTIFY

Support vector machine theory: SVM method is a machine learning method in statistical learning theory and it builds on the VC theory and the principle of structure risk minimization (Bas and Theo, 2003; Jing *et al*., 2003). The method finds the best middle course between the complexity of the model and learn ability, which expects to obtain better generalization ability. The basic idea of SVM is that applies a nonlinear mapping Φ to map the data of input space into a higher dimensional feature space and then does the linear classification in this high-dimensional space.

Presumes that the sample set (x_i, y_i), $(i = 1,\ldots, n)$, $x \in R_d$ can be separated linearly, where x is d dimensional feature vector and $y \in \{-1, 1\}$ is the class label. The general form of judgement function in its linear space is $f(x) = wgx + b$, Then, the classification hyperplane equation can be shown as (5).

$$w \bullet x + b = 0 \tag{5}$$

If class m and n can be separated linearly in the set, there exists (w, b) to meet formula as (6).

$$\begin{aligned} w \bullet x_i + b > 0, (x_i \in m) \\ w \bullet x_i + b < 0, (x_i \in n) \end{aligned} \tag{6}$$

where, w is weight vector and b is the classification threshold. According to (5), if w and b are zoom in or out at the same time, the classification hyperplane in (5) will keep invariant. We presume that the all sample data meet $|f(x) \geq 1|$ and the samples that is closest classification hyperplane meet $|f(x) = 1|$, then, this classification gap is equivalent to $2/||w||$. So the classification gap is biggest when $||w||$ is minimum.

Improved support vector machine: For the completion of the sample training, it is a usually method that all the feature attribute values after normalization have been used for modeling, which will increase inevitably the computation amount and may lead to misjudge the classification system being some unnecessary feature attributes. Therefore, bringing a judgement method to distinguish the attribute importance may be necessary for us. So we employ rough set theory to complete the judgement for samples attribute's importance. Then, we carry out SVM forecast classification based the reduction attributes (Andrew and Srinivas, 2003; Kaibo *et al*., 2002; Mantero *et al*., 2005).

Now, we introduce rough set theory. The decision-making system is S = (U, A, V, f), where U is the domain with a non-null limited set and A = CUD. C, D represents conditions and decision-making attributes set respectively. V is the range set of attributes $(V = \bigcup_{a \in A} V_a)$, V_a is the range of attribute a. f is information function (f:UXA→V). If exists f (x, a) ∈ V_a under ∀x∈U a∈A and ∀B⊆A is a subset of the conditions attributes set, we call that Ind(B) is S's un-distinguish relationship. Formula Ind(B) = {(x, y)∈UXU|∀a∈B, f(x, a) = f(y, a)} represents that x and y is indivisible under subset B. Given X⊆U, $B(x_i)$ is the equivalent category including x_i in term of the equivalent relationship $\underline{B(X)}$. We can define the next approximate set $\overline{B(X)}$ and the last approximate set $\overline{B(X)}$ of subset X as follows:

$$\underline{B(X)} = \{x_i \in U \mid B(x_i) \subseteq X\}$$

$$\overline{B(X)} = \{x_i \in U \mid B(x_i) \cap X \neq \phi\}$$

If there is $\overline{B(X)} - \underline{B(X)} = \phi$, the set X is able to define set based on B. Otherwise, call X is the rough set based on B. The positive domain of X based on B are the objects set that can be determined to belong to X based knowledge B. Namely, $POS_B(X) = \underline{B(X)}$. The dependence of decision-making attributes D and conditions attributes C can be defined as follows.

$$\gamma(C,D) = card(POS_C(D))/card(U)$$

where, card(X) is the base number of the set X.

The attributes reduction of rough set is that the redundant attributes have been deleted but there is not loss information (Richard and Shen, 2004, 2007). The formula R = {R R⊆C, γ(R, D)= γ(C, D)} is the reduction attributes set (Yu *et al*., 2006). Therefore, we can use equation attributes dependence as conditions for terminating iterative computing.

In order to complete the attribute reduction, we present a heuristic attribute reduction algorithm based-on rough set's discernibility matrix, which applies the frequency that attributes occurs in matrix as the heuristic rules and then obtains the minimum attributes's relative reduction.

The discernibility matrix was introduced by Skowron and has been defined as (7):

$$(c_{ij}) = \begin{cases} a \in A : r(x_i) \neq r(x_j) & D(x_i) \neq D(x_j) \\ \varnothing & D(x_i) = D(x_j) \\ -1 & \forall r, \exists r(x_i) = r(x_j) \quad D(x_i) \neq D(x_j) \end{cases} \tag{7}$$

According to formula (7), The value of elements is the different attributes combination when the attributes for the decision-making are different and the attributes for the conditions are different. The value of elements is null when the attributes for the decision-making are same. The value of elements is -1 when the attributes for the decision-making are same and the attributes for the conditions are different.

If p (a) is the attribute importance formula of attribute a, we can propose the formula as (8) according to the frequency that attribute occurs:

$$p(a) = \gamma \frac{1}{|U^2|} \sum_{a \in c_{ij}} \frac{1}{|c_{ij}|} \tag{8}$$

where, γ is the general parameter and c_{ij} are the elements of the discernibility matrix. Obviously, the greater the frequency that attribute occurs, the greater its importance. Therefore, we can compute the importance of attributes and eliminate the attributes that it's importance is the smallest using the heuristic rules in formula (8). And then, we can obtain the relative reduction attributes.

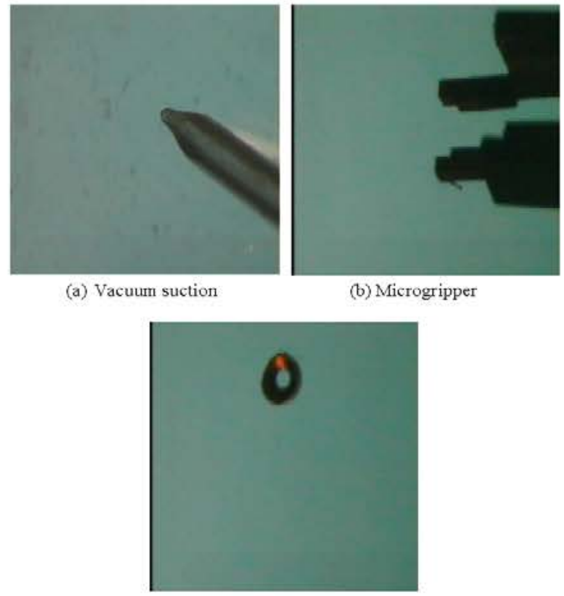
Now, we give the heuristics attribute reduction algorithm based-on rough set's discernibility matrix.

Input: The decision-making table (U, AUD, V, f)

Output: The relative attribute reduction
Algorithm steps:

- Computes the identification discernibility matrix M
- Determines the core attributes and find the attributes combination that the core attributes is not included
- Obtains conjunctive normal form $P = \wedge(\vee c_{ij} : (i = 1, 2, 3...s; j = 1, 2, 3...m))$ of the attributes combination by step (2), where c_{ij} are elements of each attribute combination. And then converts the conjunctive normal form to disjunctive normal form
- Determines the importance of attribute according to formula (8)
- Computes the smallest importance of attributes by steps (4) and then eliminate the less importance attribute to obtain the attributes reduction

After the attribute has been reduced, the samples feature attributes will send to SVM for establishing model. Finally, we can finish the classification of the final prediction data (Xiu and Yu, 2006; Wang *et al*., 2007).



(a) Vacuum suction (b) Microgripper

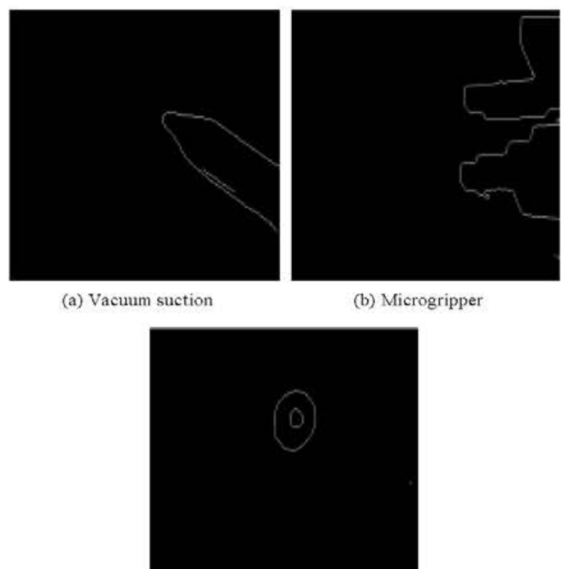
(c) Cylindrical metal part

Fig. 1: The original image of operation targets and manipulator in microscopic environment

MATERIALS AND METHODS

Feature extraction and data pretreat: The main task of classification is to identify and classify the manipulator (microgripper, vacuum suction) and operation targets (cylindrical metal part, glass ball), which can provide convenience for follow-up visual servo task. Figure 1 shows the original image of operation targets and manipulator in microscopic environment.

Usually, when the moment feature is calculated, operation is conducted on a full gray image. Then, a lot of pixel points must be processed, meaning that a mass of calculation data need be participated. In additional with, the feature attribute of the invariant moments can not also descript fully the shape feature of object. Therefore, we pretreat the classified objects with edge extraction algorithm, which makes data in a sharp decline and reduces greatly the computation amount. The edge information of object can also express correctly the shape feature of the object. Figure 2 is the image after edge extraction of operation targets and manipulator in microscopic environment.



(a) Vacuum suction (b) Microgripper

(c) Cylindrical metal part

Fig. 2: The image using edge extraction of operation targets and manipulator in microscopic environment

Table 1 gives the feature attribute's normalization value of four different objectives using invariant moments algorithm. We compute the feature attribute of objects in all directions and only list one of the feature attribute.

Result of identification and analysis: We compare firstly the data classification effectiveness on a number of micro objects using the traditional support vector machines algorithm and rough set + SVM and the results are shown in Table 2.

Table 1: The feature attribute's normalization value of different objects using invariant moments algorithm

Category	Feature 1	Feature 2	Feature 3	Feature 4	Feature 5	Feature 6	Feature 7
Cylindrical metal part	1.0000	-0.9910	0.9935	-0.1600	0.1076	1.0000	-0.5762
Glass small ball	1.0000	0.9900	-0.9946	0.1822	0.1178	0.9952	-0.5486
Micro gripper	-0.9897	-0.7610	-1.0000	-1.0000	-0.9999	0.9554	-1.0000
Vacuum suction	0.1673	0.9993	0.3131	0.9915	0.9857	-0.9577	0.9861

Table 2: The comparison results of using two classification methods

	SVM		Rough set+SVM	
	Correction rate	Classification time	Correction rate	Classification time
Micro object	93.45%	2108.24	95.89%	357.65

Table 3: The comparison results of classification accurateness using SVM and SVM+rough set classification

Times	Property	SVM classification accurateness (%)	SVM+rough set classification accurateness (%)
1	10	90.00	95.10
2	15	90.25	96.00
3	9	89.00	92.87
4	21	92.15	97.08
5	15	90.80	92.33
6	12	90.00	93.50
7	12	94.00	95.22
8	20	92.16	97.40

According to Table 2, the correction rate of classification based on the proposed SVM classification algorithm has been over 95%, being higher than the single SVM algorithm's correction rate. So, we can draw the conclusion that the attribute reduction improves the classification ability. Besides, compared with the single SVM algorithm's calculation time, It can be seen clearly from Table 2 that the calculation time of the proposed algorithm is less than about five times, meaning that the system becomes more effective.

Then, Table 3 provides the comparison results of classification accuracy using SVM classification and SVM+rough set classification with joining the other 25 feature attributes (gray, area, perimeter, texture, etc.). In Table 3, the number of conditions attributes of the final classification for entering to SVM is 14.25, less than 25 features attribute. Thus it simplifies the follow-up SVM forecast classification process.

CONCLUSION

For identifying multi micro objects, an improved support vector machine classification algorithm is present, which employs invariant moments based edge extract to obtain feature attribute and then presents a heuristic attribute reduction algorithm based on rough set's discernibility matrix to obtain attribute reduction. According to the feature attributes, the effectiveness of identifying multi micro objects using support vector machine is compared with the proposed improved support vector machine classification method. The results show that the improved support vector machine classification method can meet the application requirement, with the resolution is 95%, which provides a visual servoing possible for operating multi micro objects in microscope vision environment.

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