A multi-workpieces recognition algorithm based on shape-SVM learning model

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Abstract. In order to achieve the goal of the robot which has capability of learning and grasping the predetermined workpieces actively on the assembly line, a multi-workpieces recognition algorithm based on SSLM (shape-SVM learning model) is proposed. In contrast to traditional feature model which requires great effort to establish model library for the specific workpiece, SSLM is much easier to train and learn, even when it is applied to different object across complex environment in our experiments, the excellent performance can be achieved by almost same settings of SSLM. To make the training recognition algorithm free from the influence of workpieces dimension and rotation, SVH (Shape vector histogram) is created to express and wrap the contour features, and then SVM is adopted to complete the training and prediction of workpiece type in this paper. More than 2000 workpieces are identified in term of proposed algorithm which has an accuracy rate of 98%.

1. Introduction
With the rapid development of image process and artificial intelligence, machine vision has been widely used in various fields, such as industrial detection, aerospace industry, medical apparatuses[1,2,3]. In recent years, many machine vision systems are widely adopted in the assemble pipeline to complete workpiece recognition and grasping actively. However, the traditional algorithms of recognizing workpiece by model library and feature matching[4,5,6]which uses the sample features such as gray, color, corner, wavelet transform, geometric primitives, so that related algorithms are proposed like moment information, SIFT, color space. However, these algorithms are lacking the ability of generalization and perception changes actively in the unstable environment. Related research about deep learning for solving the problem of object recognition become hot topic, and it does have obvious advantages in between recognition accuracy and generalization ability, but it is difficult to acquire huge samples to train for deep learning algorithm as CNN, RNNS, Sparse coding[7,8]. [9]designed a novel electromagnetic inductive sensor array similar to those used in the electromagnetic tomography (EMT) to address workpiece recognition, and proposed a partial tensor approach, which shows that a 2D tensor is capable of distinguishing the material difference and recognising the geometric dominance of workpieces. In [10], the authors identify the object workpiece by matching the extracted contours with the object contour from the template image by Hu moment invariants, and this method putted forward the workpiece position and direction base on Opencv, but this method can not adapt to the change of complex environment. [11] used a binocular stereo vision system for automatically locating the position and posture of workpieces, and the authors proposed a method of background subtraction to extract the edge line of the foreground area. And an algorithm that combines epipolar constraint with gray value similarity was proposed to quickly and accurately realize the feature points matching. Fast image matching algorithm[12] based on wavelet and shape
A template is proposed to match object, and the method uses the low-frequency signal of decomposition to reduce computation cost of image matching and compress image.

Aiming at the problem of low intelligence level and poor flexibility of robot sorting, a multi-workpiece recognition algorithm based on shape-SVM learning model is presented, and it achieves good results in practical experiments [13,14,15].

2. Shape recognition algorithm

The dark box combined with the industrial LED ring light is mounted to improve the contrast of the workpiece. On the basis of acquiring workpiece contour by OSTU threshold and the Freeman 8 chain code, the multi-workpieces recognition algorithm is put forward. The detailed image preprocess steps will not be given, and the specific contents may refer to the [16, 17]. The proposed method is comprised of 3 parts from constructing feature vectors, generating the learning model and calculating grasping datum. Meanwhile, the algorithm execution contains two stages: training the sample set and the predicting object category. The main flow chart is shown in Figure 1.

The shape recognition algorithm of workpiece is achieved as follow steps: firstly, the sample base of workpiece is established and the specific sample in library is labeled. To ensure the generalization capability of the predicting model, the training samples could contain all kinds poses as far as possible. In order to ensure that the recognition algorithm is not affected by the geometric transformations of the workpiece, such as translation, rotation and scaling, and the dimension unification of classifier input when constructing feature vectors of the target, the initial features are statistically expressed and wrapped by SVH. Then the SVM model is introduced to classify the workpiece types, furthermore, classifier verification base on SVH distribution information is used to decrease tolerance rate of predicting model, finally, the recognition and grabbing of workpiece is completed in term of robot.

3. The generation of shape feature vectors

The generation of feature vectors based on polar radius is defined by Euclidean distance in the $R^2$ space, and it can be understood as the specific topology which detection wave meet hinders centered as the centroid point when wave emits the inner contour. Assumed that the any point $C_i(x_i, y_i)$ on the contour, the expression of the normalized feature vectors $R_{i,nor}$ based on polar radius is defined as (1) (2), and $O(x_0, y_0)$ represent contour center.

$$R_i = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2}$$ (1)

$$R_{i,nor} = R_i / R_{max}$$ (2)

It can be seen from the formula (1) that the geometric relationship between the center and the points set in the contour will not alter with the change of the workpiece position. In addition, the normalized feature vector is simply to do with the geometric shape of the workpiece and not be influenced by the change of the target scale. The figure 2 illustrates $R_{i,nor}$ distribution of two workpieces in different positions(rotation and scaling), and the point is that the value trend of $R_{i,nor}$ is
exactly consistent with the changes of specific workpiece shape. The similarity of homomorphic contour and diversity of specially shaped contour is an important index to the performance of the target descriptor. To prove this from Figure 2, it is easy to find that feature wave form of the same kind of workpiece is basically similar (except for the discrepancies in dimension and phase), meanwhile, different types of workpieces have completely different waveform distribution.

Figure 2. The figure indicates the waveform change of feature vectors of both the same workpieces in different positions (as the (a), (b), (c) in the first row or (d’), (e), (f) in the row) and different workpieces in the same posture (in the same column).

There are 3 problems with feature vector in workpiece expressing and SVM learning model.

- In feature expression aspect, the number of sampling points is different because of the scale transformation and types of the workpiece, which leads to the dimension difference of the feature vector even the same workpiece.
- There is dislocation of the feature waveform in space when workpieces principal axis locates different direction, such as (b) and (f), (b’) and (f’) in Figure 2. Because the object distance between the camera and the object to be identified is fixed. Moreover, the workpiece position is random, and the phase dislocation of feature waveform caused by the rotation is more common.
- For the general machine learning model, it is indispensable to ensure the dimension unification of feature input.

How to maintain the dimension unification and important description information of feature vector is the core content of this section. So the SVH is proposed in the this section to solve the affect between feature dimension and the subsequent learning model and similarity verification, which is convenient for subsequent practical operation, the specific steps are as follows:

1. The shape feature vector which is defined as \( S=\{S_i|S_i, i=1,2, N\} \) is obtained by formula (1) (2), and the value of each element of vector is between 0 and 1. N is not a constant due to the uncertainty of the number of sampling points change.

2. Establishing a histogram with containing M bin, so statistical range of each bin is that \( bin_m \in [(m-1)/M, m/M) \). And the counter of the bin adds 1 (its initial value starts from 0) when a feature vector value satisfies the corresponding bin value.

3. The normalization process of the SVH is completed by each corresponding counter divided by N, so the distribution value of SVH is mapped to 0 to 1, then taking normalization distribution of SVH as the input of the learning model.

The distribution map of SVH with bin=30 under different poses in corresponding Figure 2 is illustrated in Figure 3. It can be seen that the SVH distribution of the same workpiece is basically not influenced by the geometric transformation, and also SVH distributions of the different workpieces exists large differences, which is propitious to improve the classification accuracy of subsequent learning model.

The SVH solves dimension difference of the feature vector and dislocation of the feature waveform caused by the scale and rotation of workpieces respectively. Further more, the ultimate dimension of the shape feature is only related to the bin of the SVH, which is irrelevant to the number of sampling
points. The bounds for the bin of SVH depends on the complexity of the workpieces, and it is obtained by the compromise between accuracy and time of algorithm in experiment. Finally, the SVH is used as the input of the classifier SVM.

Figure 3. The distribution of SVH of two workpieces in different postures, the (a), (b), (c), (d), (e), (f) are the SVH distributions of corresponding label in graph 2 respectively. The SVH distribution of the same workpiece type in different posture is basically similar, but the SVH distribution of different workpieces exists large differences.

4. Learning model

4.1. Classification model

The key of SVM is to construct the best classification hyperplane in sample space, so that the largest geometric interval between samples can be obtained. In order to explain the principle of SVM classification to workpieces to be identified, the two types of workpieces are taken as an example[18]. Assuming that training sample is defined as \((x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\), \(x\) is the SVH features vector, \(y\) is corresponding label for supervised learning and \(n\) is the number of training samples, and it is known from the 3.0 section that \(x_i \in [0, 1)\). For the case that the SVH features vector of samples can be linearly separable (if feature vector is linear nonseparable, it is be processed by a kernel function), classification hyperplane can be obtained as:

\[
\omega^T x + b = 0
\]

The equivalent equation which satisfies the constraint conditions is defined as after derivation

\[
\text{min } \Phi(\omega) = \frac{\|\omega\|^2}{2}
\]

Then model parameters are obtained by introducing Lagrange multiplier and derivation, and the specific expression be computed as

\[
\max \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j (x_i, x_j)
\]

\[
\sum_{i=1}^{n} \alpha_i y_i \geq 0 (i = 1, 2 \ldots, n)
\]

The linear kernel functions are brought into the SVM learning model to make the nonlinear feature vectors of low dimensional space into high dimensional vectors that is linear separable, which make it possible for adopting linear method to complete sample classification in high dimensional space. In order to improve the fault tolerance of SVM further, the slack variable \(C\) is defined to quantify the influence of error samples to classification hyperplane in training, and its objective function is
\[ f(\omega, b, \varepsilon) = \frac{1}{2} ||\omega||^2 + C \sum_{i=1}^{N} \varepsilon_i \] (6)

Due to SVM is only two classes of classifiers, Multiple cascades SVM with 1:M is employed to complete workpieces recognition, meanwhile, greedy learning strategy is used to in the searching space to obtain local optimal solution and strengthen decision-making ability of the model.

4.2. Validation model

In order to decrease the misclassification of learning model and improve the accuracy of recognition, the SVH information is adopted to verify the result of SVM classifier. The main strategy is to calculate the similarity between the corresponding shape histogram (that is, the standard sample of the workpiece is calculated Off-line), and its matching cost function is constructed by using the SC algorithm [19] (Shape Context, shape context), as shown in the following (7).

\[ C_{i,M} = C(p_i, q_M) = \frac{1}{2} \sum_{k=1}^{K} \left[ h_i(k) - h_M(k) \right]^2 \] (7)

Where, \( C_{i,M} \) represent the similarity between classifier prediction type i and corresponding standard sample M. K represents the number of bin values of SVH, and the decision criteria is

\[ g(C_{i,M}) = \begin{cases} 1 & \text{if } C_{i,M} \leq T \\ 0 & \text{else} \end{cases} \] (8)

Where, \( G(C_{i,M}) \) represents the discriminant function of class verification. If its function value is 1, the classifier's type is correct, otherwise the classifier's discriminant result is wrong, and T is defined as the of the system tolerance to the expected result.

5. Experimental analysis and conclusion

5.1. Experimental Analysis

(1) To verify the advantage of SVM learning model in the workpiece recognition, the test of the accuracy and real-time recognition algorithm is done comparing with RandomForest and BP-neural network. In experiment, the sample types is 50 and the sample numbers of each type is 100. The test set of each type is 25, and the performance of each learning model is shown as table 1.

| Learning model   | Accuracy of algorithm | Time of algorithm |
|------------------|-----------------------|-------------------|
| SVM              | 98%                   | 15ms              |
| RandomForest     | 85%                   | 12.3ms            |
| BP-neural network| 87%                   | 20.3ms            |

It can be seen that the RandomForest takes the least time, because it is mainly comprised of many tree structures to complete logical judgment, the accuracy is the lowest. The BP neural network recognition algorithm has the longest time and the recognition accuracy is inferior to the SVM due to the small sample cannot play the powerful generalization performance of the network. However, the SVM has better performance than other machine learning models in small sample data learning and it uses very few support vectors in the sample space to determine the classification hyperplane. It is reasonable to adopt SVM as the learning model to complete workpiece recognition based on the above analysis.

(2) In order to test the validity of the verification model, the samples with 18 the same types workpieces and 2 other similar types of workpieces are mixed into the SVM classifier deliberately, and the C value distribution of the formula (8) is shown as shown in the Fig. 4.
Figure 4. The distribution of C on the experiment, though the workpiece 11 and 16 are misclassified by classifier, the corresponding C is far higher than the other same type samples. It also proves the validity of the class verification model, and the range of threshold T is relatively flexible which is less affected by the data fluctuation.

5.2. Conclusion
In this paper, we have proposed multi workpiece recognition algorithm based on SSLM for robot grasping, we create SVH to express and wrap the contour features to make the training recognition algorithm free from the influence of workpieces dimension and rotation. Then validation model is constructed to eliminate the misclassification of learning model and improve the accuracy of recognition. The accuracy and generalization of recognition have been greatly improved, which has some advantages over other conventional recognition algorithms. In the future, we will study the recognition of occlusion objects and build a more stable local recognition descriptor to improve the performance of the robot grasping.

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