Task-Oriented Visual Servo System of Robot Arm for 3D Object based on Automatic Multilayer Networks Learning Approach

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***Abstract*—Visual servo systems are widely applied on industrial robot arm recent years. A visual servo system could provide additional perception of robot arm, and make it more robust in different applications. In this paper, we proposed an intelligent visual servo system which could automatically learn the model of unknown 3D objects, and self-supervised the results. Unlike traditional vision-based learning approaches, proposed learning system is task-oriented which means learning approaches only concern the relation between input and target rather then each individual part. To construct connections between input and target,the learning approach is established based on multi-layers networks. Multi-layers networks is used to model necessary knowledges in different domains. The experiment results show the feasibility of proposed structure for automatic learning, and multi-layers networks could effectively transfer knowledge between different domains.**

***Index Terms*—Visual servo system, Multi-layers network, Machine learning**

I. Introduction

ROBOT arm with visual servo system had been widely applied in automatic industrial production line recent years[1]. Visual servo system provides additional perception of environment, and make robot arm become more adaptive to complete various tasks. The visual servo based robot arm systems are generally divided into two parts in previous works [2-4]. One is vision system which is used to detect or track targets, and estimate the states of targets for robot arm. The other is robot arm which could use received states and execute pre-programmed scenario to complete tasks. Although many present works is already robust enough for real practice, there are still some issues have to be concurred.

For vision system, model-based recognition methods are commonly used in industrial application. Model-based methods are famous for efficiency and robustness. The performance is mainly related to the input data which is captured manually. Hence, the system is hard to adapt with the changing of work pieces, manufactured processing,etc. For 2D object recognition, users need to capture numerous raw data of target objects in specific poses. These cumbersome works would become much more complex while the methods are expanded to 3D object recognition. Even though the states of objects had been precisely estimated, the states have to be further transformed to the coordination of robot. The coefficients of coordinate transformation also have to be manually adjusted depend on different cases. These manual works not only increase the labor cost, but also point out present vision-based robot unable to automatically adapt to various assignments. To solve these issues,we desire to proposed a intelligent tasked-oriented visual servo based system which could automatically learn image models of targets, and able to self-refined the relative function of input and target.

In general industrial purposes, we do not really concern about all details of entire target. Instead, the relation between input and target is the key point for completing the tasks like pick and place, work pieces arrangement, components insertion,etc. Take pick and place as an example, in task-oriented view, system tend to manipulate robot arm to pick work pieces and place them in specific pose. Therefore, proposed system focus on constructing relation between input images and rotation angles of robot arm, rather than a delicate 3-D object model. The input of system is 2-D image data, and output is rotation angle of robot arm in Cartesian space. Unfortunately, the input and output are different feature domains(image space to Cartesian space), so the traditional single model learning approach[5] is not enough to solve our problem.

The features in different domains can be quantified and integrated into a multilayer networks. The most well-known multilayer networks are multilayer perceptron (MLP). MLP is feed forward neural networks with multiple layers neurons. Although MLP had been well studied and enable to apply in wide variety of research field, MLP requires input and output is in the same domains such as feature to feature, or object to object. Hence, we proposed a new multilayer networks structure which tend to integrate different levels information, and further infer the relationship between different domains. The distribution of different domains is not possible the same, and also hard to be modelled thorough limited data, so the learning of different domains have to be relied on transfer learning[6-9]. Transfer learning methods are arise while source domain and target domain are different or data is easily outdated[13]. In our case, the network is composed by three different domains: image, object and Cartesian space. To integrate three domains into one network, we build relative functions between each domains for mapping the information between different domains. The parameters of relative functions are able to be refined through proposed transfer learning approach.

In proposed system, the final poses of target objects are essential prior of proposed system, because final poses would be different dependent on different requirements. For a 3-D objects, this prior only provides information of target face, but other faces are unknown. Hence, building a descriptor which can be used to infer the relations of input and target poses is necessary. Constructing descriptor of object is a pervasive topic in areas of computer vision, and there are many brilliant existed approaches with high quality and low computation cost [10-14]. Most of these methods are focus on building descriptor from strong sparse features in input image. The sparse features are selected based on designed approaches, and weak feature points would be wiped out. Therefore, some information might lose in selecting process. Different faces of the same object might derive different strong feature points, so more information is needed for inferring relation in our issue. Instead of choosing sparse features, uniform distributed feature is more suitable for finding obscure co-features in different viewpoints. Unfortunately, uniform distributed feature such as RGB and texture are easily affected by environment, and these uncertainties would reduce the robustness of descriptors.

To conquer the uncertainties of low-level feature, we proposed a descriptor which is constructed based on Markov Logic Network (MLN) [15]. MLN is an approach combines first-order logic and probabilistic graphical model. Probabilistic graphical models are famous for handling uncertainty. First-order logic enable compactly representing a wide variety of knowledge, and widely applied on statistical relational learning [16-18]. Therefore, MLN is used to describe the structure of an object in different view-point (image domain), and build 2-D descriptors which are constructed by first-order logic formulas. MLN-based descriptors could be further applied to connect the relation between different faces of the same object by matching co-features. The relational model of 3-D object is consisted by multiple 2-D descriptors, and is represented by vector in Cartesian Space. Therefore, the relational model is not only integrate 2-D descriptors into 3-D object, but also utilize to derive rotation angle of robot arm through vector in Cartesian Space. By doing so, the relation between input and target could be established, and help robot arm to complete assign task.

In this paper,we start with briefly overview of system design and structure in section 2. The MLN-based descriptor for recognized object would be revealed in section 3. Section 4 introduces how to model the proposed multilayer networks, and build up and refine the structure of databased for matching. Then, we compare the performance of proposed system with several different features and descriptors in section 5. Finally, the performance review and conclusion would be discussed in final section.

II. System Architecture

The main purpose of this system is that desire to automatically derive the orientation relationship between input poses and target poses without 3-D model of input objects, and guide robot arm to pick and complete assigned tasks. The target poses of work pieces have to be given by users. Users then only need to put the work pieces on the conveyor arbitrarily, and the relationship would be learned by proposed approach automatically. This system is consisted by three main parts: Firstly, camera 1 in fig. 1 capture all input work pieces with arbitrary poses, and classify the features of each single work piece through clustering or segmentation method [19-23]. For each work piece, camera 1 would capture serial images while work pieces move into FOV as shown in fig. 2(a). The descriptors of every input work pieces would be constructed by these serial images. Hereafter, system would search matched descriptors from database, and guide robot arm to pick the work pieces and rotate to target pose. Otherwise, the system would infer the most possible result through proposed method, and guide robot arm to pick works pieces based on inferred results.

For the second part of system, camera 2 plays a role as supervisor of learning. The results would be labelled as true or false. The constructed descriptors with labels become the input of multilayer networks. The third part is learning approach of multilayer networks. The labelled data would be added

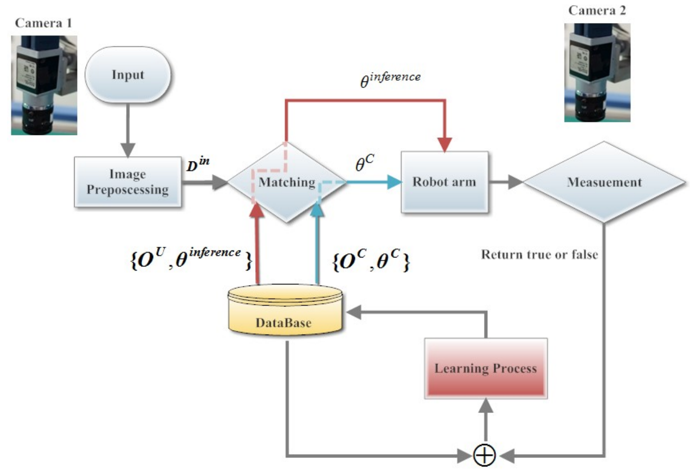
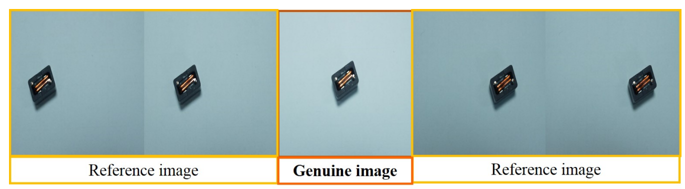
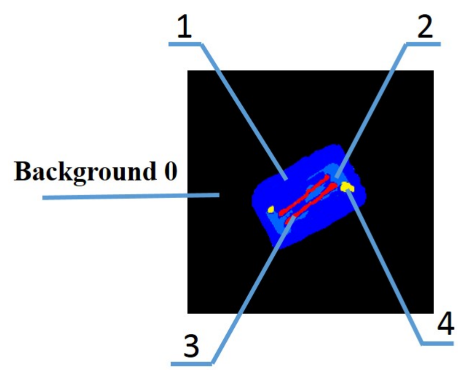


Fig. 1. System architecture



(a) Serial captured frames



(b) Result of background subtracting and clustering

Fig. 2. Preprocessing of input objects

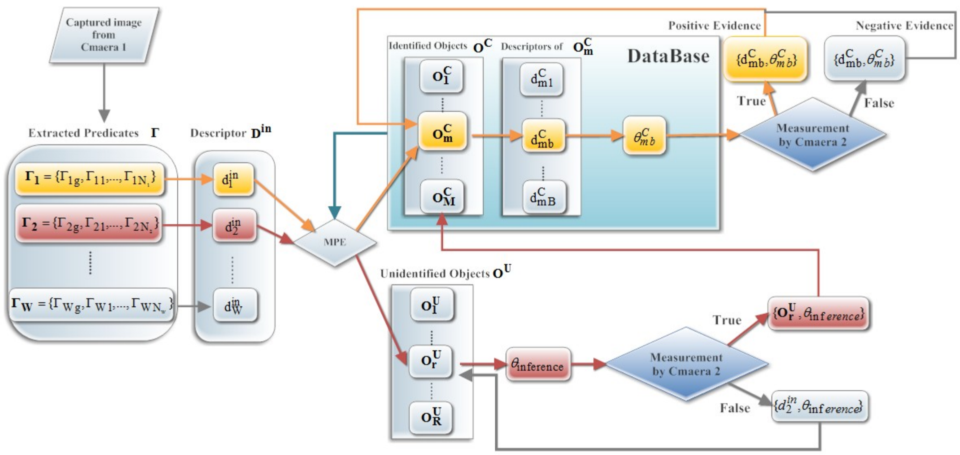


Fig. 3. Example flow of variables in multi-layers networks

to the networks after each cycle of system. The labels are used to refine the training result of multilayer networks. Based on these three parts, this system can automatically learn the relative model for robot arm to complete tasks without any manual operation.

The variables of our model can be classified into six types:

$$\{\mathbf{\Gamma}, \mathbf{D^{in}}, \mathbf{O^C}, \mathbf{O^U}, \mathbf{D^C_m}, \mathbf{D^U_n}, \mathbf{\Theta}\}$$

The relation between each variable is illustrated in fig. 3. Γ is a set of object 1 to W from camera 1 in feature domain. $\mathbf{\Gamma_w}$ is a set of serial captured frames of an object w, which is composited by genuine and reference images in fig. 2. Γ_{wg} is the genuine image, and Γ_{wn} is number n reference frames. $\mathbf{D^{in}}$ is constructed by $\mathbf{\Gamma}$ based on proposed 2-D descriptor-constructing method in section 3. Descriptor d_w^{in} would be classified to identified object($\mathbf{O^C}$) or unidentified object ($\mathbf{O^U}$) based on Most Probable Explanation (MPE). In fig.3, d_1^{in} is delivered to identified object set $\mathbf{O^C}$. the system would further assign d_1^{in} to the most possible belonging object $\mathbf{O^C_m}$. Since a 3-D is composed by multiple 2-D images, one object in our system is defined by multiple 2-D descriptors. $\mathbf{O^C_m}$ is a set of 2-D descriptors of object m. d_1^{in} is considered as new input data of most possible descriptor couple d^C_{mb} in fig.3. Each descriptor couple includes the rotation angle information between input pose (based on 2-D descriptor) and target pose. θ^C_{mb} is the rotation angle which can make robot arm rotate object m from input to target pose. The result would be checked by camera 2. If it is true, the result is considered as positive evidence, and merged to the learning process. Otherwise, the result is negative evidence.

Similarly, d_2^{in} is assigned to the unidentified set $\mathbf{O^U}$. Unidentified set $\mathbf{O^U}$ is a set of descriptors which hadn't identified the rotation angle of target prior pose. For unidentified $\mathbf{O^U}$, the system would infer the possible rotation angle $\theta_{inference}$ for input descriptor. The result would be supervised by camera 2. If result is true, the descriptor would be delivered to the identified object set $\mathbf{O^C}$ as a new discovered face of corresponding object. Otherwise, the descriptor would feedback to unidentified object set $\mathbf{O^U}$, and record the inference result to avoid the same fail predication. By doing so, the system is ensured to be converged, and all objects could be identified if the input is sufficient enough.

III. MLN-based Descriptor

A. The concept of constructing MLN-based descriptor

Being an automatically system, deriving more valuable information from raw data could help system deriving exact result, and adapt to numerous suspected input. Most of present image descriptors [10-14] are constructed based on strong extracted feature, because strong sparse feature points are consistent even in different environment. Although these kind of descriptors could efficiently and precisely match given object, the descriptors could not suit for cases which need to infer the relation between existing and unknown data. The sparse feature based descriptor would purge weak feature points of input face, but purged points might be valuable for inferring unknown input from existing data. Hence, the descriptor not only need to be robustness, but also provide sufficient information for constructing relationship. The normal distributed features are compact with our requirement which could provide all detail information of input image. Unfortunately, the normal distributed features such as RGB, HSV, edges, etc. are easily affected by environment. The segmented or clustering results might be different even two images belonging the same object, so the segmented results are hard to match with each other directly.

Considering the uncertainties of clustering results of normal distributed features, probabilistic model is the best choice for conquering uncertainties. Although there are several attributes changed due to environment effect (e.g. size of clusters), most of geometric relations between each cluster are relative robustness. We desire to construct the probabilistic-based model in MLN by relations between clusters. Segmented results are used to proposed MLN-based descriptor. The main concept of MLN is that use weighted feature function to soft the hard constrains of first-order logic formulas. If a world violate one formula, it become less possible but not impossible. Take our case as example, when a clustering result of image capture by camera 1 have several clusters different from the result in repository, the MLN-based descriptor would only reduce the probability of candidate rather than wipe out of consideration. Hence, probability-based descriptor has more uncertainty tolerance than the other descriptors which are only modelled by the structure of key feature points.

Markov logic network L is a set of pairs (F_i, W_i), where F_i is a feature function of first-order logic and W_i is weighting of corresponding formula. The first-order logic formulas converted to **clauseform** (also known as **Conjuctive Nornal Form CNF**) Each node in L means one feature of each feature function F_i. The value of F_i is 1 if formula is true and 0 otherwise. The MLN aim to model the joint distribution of a set of variables $\mathbf{\Gamma_w} = \{\mathbf{\Gamma_{wg}}, \mathbf{\Gamma_{w1}}, \mathbf{\Gamma_{w2}}, \dots, \mathbf{\Gamma_{wN_w}}\}$ in fig.3. The genuine image Γ_{wg} is the image which center of object is closest to center of camera, so genuine image could be considered as most representative 2-D face of a 3-D object in serial frames. The probability distribution of $\Gamma_w g$ over possible world Γ_w specified by MLN is given by:

$$P(\mathbf{D^{in}} = \mathbf{d_g^{in}}) = \mathbf{P}(\mathbf{\Gamma_w} = \mathbf{\Gamma_{wg}}) = \frac{\mathbf{1}}{\mathbf{Z}} \mathbf{exp}(\sum_{\mathbf{i=1}}^{\mathbf{F}} \mathbf{w_i n_i}(\mathbf{\Gamma_{wg}}))$$

$$\mathbf{Z} = \sum_{\mathbf{\Gamma_{wn}} \in \mathbf{\Gamma_w}} \mathbf{exp}(\sum_{\mathbf{i=1}} \mathbf{w_i n_i}(\mathbf{\Gamma_{wn}})) \tag{1}$$

Where $\mathbf{F}$ is number of formulas in Γ_{wn} and $n_i(\Gamma_w g)$ is number of grounding of true grounding of $\mathbf{F_i}$ in Γ_{wg}.

For proposed MLN-based descriptor, the first order logic are consisted by conjunction form of predicates. Predicate $ne(s_j, s_{neighbor})$ is used to represent the conjunctive neighbours of each clusters. We consider cluster s_j as key atom and sample conjunctive neighbour $s_{neighbour}$ to derive predicate. Each center atom acquire one formula. Therefore, if an object is segmented to **J** kinds of segmented features, it descriptor would would be constructed by **J** firs-order formulas.

Based on this concept, the MLN-based descriptor could be constructed by following process: The background of input image are subtracted through MOG [21](supported by open source library OpenCV), and each isolated object is clustered according to RGB features. RGB features are classified into 4 parts for each channel through K-means clustering [22], so the max size N of feature S is 64 in this paper. N can be adjusted dependent on selected clustering method. Fig. 2(b) shows the background subtracted result of genuine image of fig. 2(a), and different classes of feature are labelled different number such as fig. 2(b). The black part means subtracted background and is label 0. The other label number is between 1 and N. Then, taking fig. 2(b) as example, the object is segmented to 4 kinds of features, and predicates and first-logic formulas are shown in table 1.

The complexity of formulas constructing process depend on the number of different kinds of segmented. From table 1, there are some equivalent predicates (e.g. $ne(1, 2)$ and $ne(2, 1)$) which might be repeated sampled. To reduce the complexity, we use dynamic programming algorithm in algorithm 1 to enhance efficiency. The algorithm can define all equivalent predicates in one iteration, and avoid repeated sampling.

Table I. Example of predicates and first-order logic formulas

Key Atom	1	2	3	4
Predicates	ne(1,2)	ne(2,1)	ne(3,1)	ne(4,1)
	ne(1,3)	ne(2,3)	ne(3,2)	ne(4,2)
	ne(1,4)	ne(2,4)		
	ne(1,0)			
Formulas	ne(1,2)∩ne(1,3) ∩ne(1,4)∩ne(1,0)	ne(2,1)∩ne(2,3) ∩ne(2,4)	ne(3,1) ∩ne(3,2)	ne(4,1) ∩ne(4,2)

Algorithm 1 Algorithm for sampling neighbours of key atoms

Function Sampling(S_img, S, S', S^*)
Input :
S_img, segmented input image
$S[ns, p, l]$, the contour point p of ns^{th} cluster with label l
S', contour pixel of each cluster
$S^*[ns, p^*, l^*]$, neighbour pixel p^* of $S.p$ with label l^*
Output :
$neighbour[n, ln, la]$, the neighbour with label ln of n^{th} key atom with label la

Random(Point in S_img)
for k← 1 to number of cluster **do**
  $n \leftarrow k$
  $S' \leftarrow \emptyset$
  for i←1 to size of contour **do**
    $S' \leftarrow$ contour pixel of label ln
    $S^*.p^* \leftarrow$ neighbour of S' with different label
    if $S^*.label$ is changed **then**
      $n \leftarrow n + 1$
      $neighbour[n, ln, la] \leftarrow$
        $neighbour[n, S^*.l^*, S.l]$
    end if
    for $j \leftarrow\ k\ to\ n - 1$ **do**
      $neighbour[j, ln, la] \leftarrow$
        $neighbour[j, ln, S^*.l^*]$
    end for
  end for
  $S[ns, p, l] \leftarrow S[k, S', S.l]$
  $S^* \leftarrow S^* - S$
end for

Random (S^*)
Until $S^* = \emptyset$
Return $neighbour[n, ln, la]$

B. Inference and Weight learning of MLN-based descriptor

The weights of MLN-based descriptor is learned by maximizing the pseudo-log-likelihood. Since each descriptor can be considered as a closed world, we only need to consider the atoms which derive from captured serial frames. Comparing with uniform sampling approach, maximizing pseudo-log-likelihood is more efficient, because pseudo-log likelihood only need to considered relational data. The pseudo-log - likelihood of eq.(1) can be written as:

$$\log P_w^*(\mathbf{\Gamma_k} = \Gamma_{kg}) = \sum_{i=1}^{L} \log P_w(\mathbf{F_{kg}} = f_{kgl} | \mathbf{MB_{\Gamma_k}}(\mathbf{f_{kgl}})) \tag{2}$$

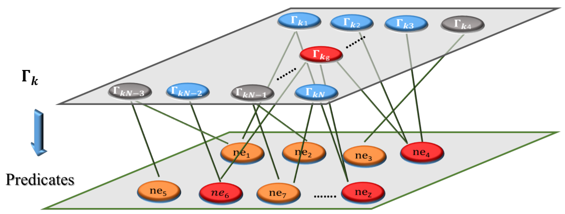


Fig. 4. Example of sampling Markov blanket

$\mathbf{F_{kg}}$ is a set if first-order logic formulas Γ_{kg}, and f_{kgl} is l^{th} ground truth value of $\mathbf{F_{kg}}$. Instead sampling all predicates $\mathbf{\Gamma_k}$, the strongest formulas in serial images should be more concerned. For every members of $\mathbf{\Gamma_k}$ including the same predicates with f_{fgl}, the the set of formulas which include common predicates is considered as Markov blankets $\mathbf{MB_{\Gamma_k}(f_{kgl})}$. Fig.4 demonstrates the construction of Markov blanket. We set formula f_{kgl} in $\Gamma_k g$ is composted by predicate $\mathbf{ne_4}$,$\mathbf{ne_6}$ and $\mathbf{ne_Z}$, so, based on the concept, sampling approach only need to sample the other members of $\mathbf{\Gamma_k}$ which are also composted by $\mathbf{ne_4}$,$\mathbf{ne_6}$ and $\mathbf{ne_Z}$. The set of sampled formula is considered as $\mathbf{MB_{\Gamma_k}(f_{kgl})}$. Hence, in the case fig.4, Γ_{k1},Γ_{k2}, Γ_{k3},Γ_{kN-2}, and Γ_{kN} would be sampled.

Hereafter, the MLN weights are learned generatively by maximizing the pseudo-log-likelihood of Markov blanket. The gradient of the pseudo-log-likelihood with respect to the weights is:

$$\frac{\partial}{\partial w_i}\log P_w^*(\mathbf{\Gamma_k}=\Gamma_{kg}) =$$

$$\sum_{l=1}^{L}\{n_i(\Gamma_{kg}) - P_w(\mathbf{F_{kg}}=0|\mathbf{MB_{\Gamma_k}}(f_{kgl}))n_i(f_{kgl}=0)$$
$$-P_w(\mathbf{F_{kg}}=1|\mathbf{MB_{\Gamma_k}}(f_{kgl}))n_i(f_{kgl}=1)\} \qquad (3)$$

Where $n_i(f_{kgl}=0)$ is the number of true grounding of i^{th} formula while set $\mathbf{F_{kg}}=0$, and similar for $n_i(f_{kgl}=1)$. The learning of pseudo-log-likelihood in our approach are further boosted by the L-BFGS optimizer [24], to make entire process become more efficiency.

C. Matching of MLN-based descriptors

For each constructed input descriptor d_k^{in}, system would search for the matching descriptor in the database, and further arrange it to the proper set of identified($\mathbf{O^C}$) or unidentified object ($\mathbf{O^U}$) as shown in fig.3. The elaborate structure of multilayer networks in the databased can be illustrated as fig.5. The objects in the repository are composited by multiple rotation angles and descriptors. Each descriptor except the descriptor of target pose has one and only one corresponding rotation angle to guide robot are rotate object to the target pose. Since a descriptors is the combinations of predicates, the matching of descriptors can use the same concept of inference in section 3.2. The descriptors in the database which have common predicates with query would be considered as evidence, and use maximum likelihood to derive the matching result. The pseudo-log-likelihood of descriptors matching could be formulated as:

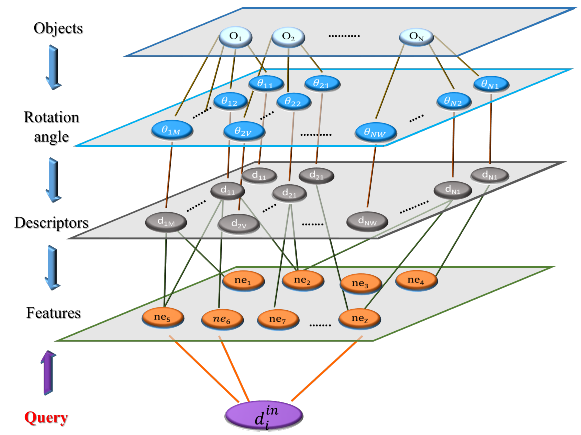


Fig. 5. Example of sampling Markov blanket

$$L(\mathbf{D^{in}}=d_k^{in}|\mathbf{B}=\mathbf{d_m}) \quad = P(\mathbf{B}=\mathbf{d_m}|\mathbf{D^{in}}=d_k^{in})$$
$$= \prod_\eta P(\mathbf{d_m}=d_{m\eta},\mathbf{D^{in}}=d_k^{in}) \qquad (4)$$

$$\hat{d_k^{in}}_{MLE} = \mathbf{argmax}_{B=d_m}\hat{l}(\mathbf{D^{in}}=d_k^{in}|\mathbf{B}=\mathbf{d_m^*}) \qquad (5)$$

$\mathbf{d_m}$ represents the set of descriptor which are belonging object m, and acquire common predicates with d_k^{in}. The system would only consider one input object at a time.If descriptors in the sampled object have common predicates with the query descriptor, the descriptors would be considered as Markov blanket of d_k^{in}, and calculate likelihood function for all possible objects. The query descriptor would be matched the descriptors in the database depend on the result of maximum likelihood. $\mathbf{d_m^*}$ is the Markov blanket which has maximum likelihood of $d_k^i n$.If likelihood of a input descriptor is lower than a threshold for every candidates, the descriptor would become a new unidentified object and save in the repository. Reminding that the descriptors in unidentified object class are not abandoned, but need more information to merge into identified object class.

IV. Inference and Learning of Mapping between MLN-based Descriptor and Rotation Angle

Since MLN-based descriptors are matched according to the neighborhoods of clusters, the descriptor is scale and pose invariant. To make robot arm place input objects to corresponding target pose, the relation between descriptor and rotation angle have to be constructed, and make knowledge could be transferred between different domains in proposed multilayer network. We assume different faces of same object include at least one common predicates, and the common predicates can be used to infer the relation between input and target pose. Set of rotation angle Θ is composited by θ_R, θ_P, and θ_Y which represent roll, pitch and yaw angle of 3-DOF end effector of robot arm. Θ is unknown at first, because there is no prior knowledge of rotation angle for proposed system as mention before. Θ can be only predict by the common predicates between descriptors. For two matched descriptor, the common predicates has significant possibility to be the same parts of object, so the relation between common predicates in Cartesian space can be used to predicate possible rotation angle, and make inferred results reliable and accurate in several iteration. The mass center of each cluster is considered the position of each cluster in Cartesian space, and the center of images is origin of coordinate. Firstly, we sample the center atoms of common predicates between input and target descriptor, and compare the difference of position between each center atom. The differences are represent by vector which is formulated as:

$$\vec{V_c} = \vec{V_c^T} - \vec{V_c^{in}} \tag{6}$$

Where $\vec{V_c}$ is the vector of key atom c. $\vec{V_c^T}$ and $\vec{V_c^{in}}$ are the position vector of key atom c of target and input descriptor. According to the MLN-based descriptors, the formula with higher weighting means more reliable. Reminding the example in table 1, every predicates of a formula belong to the same key atom, so the weight of each formulas could be further considered as the reliability of each center atom. Hence, we choice key atom which is included in the formula with the highest weight firstly, and transfer to rotation angle for robot arm. The result would be checked by camera 2. While the number of inputs grows, the results would become the set of vector $\vec{V}_{mb}$ which means the set of vector of descriptor b in object m. The set of vector $\vec{V}_{mb}$ is used to build up a Markov network model which could refine the predicating result based on the historical results which are identified by camera 2. Since the uncertainty of probabilistic descriptor that the matched input descriptor for same target descriptor might not be totally same one, we would like to build up a transfer function which can predict ideal rotation angle depend on different input descriptors. There are two factors have to be concerned: (1) the distribution of historical vector $\vec{V}_{mb}$. (2) likelihood of input and target descriptor. Hence, the transfer function could be formulated by joint distribution:

$$P(L(d_{kT}^{in}|d_m^T), \vec{\mathbf{V}}_{\mathbf{mb}}) =$$

$$\frac{1}{Z_V} exp(\textstyle\sum_k \sum_b \lambda_t \mathbf{F}\{L(d_k^{in}|d_m^T) = l(d_k^{in}t|d_{mt}^T), \vec{\mathbf{V}}_{\mathbf{mb}} = \vec{v}_b\}) \tag{7}$$

Where $L(d_{kT}^{in}|d_m^T)$ is a set of likelihood of input descriptor k and target descriptor during a period of time T. $l(d_k^{in}t|d_{mt}^T)$ is the likelihood at time t. $\mathbf{F}\{*\}$ is feature function which is 1 while $*$ is true, and 0 otherwise. λ_t is weight if feature function. This transfer function represents the mapping between set of input descriptors and the same target descriptor d_m^T. While derive a new input descriptor, the predicated result can be derived by:

$$\mathbf{argMax} P(\vec{V^*}_{\vec{V}-\vec{V}_{fail}}) = P(\vec{V}^*|l(d_t^{in}|d_m^T), L(d_{t-1}^{in}|d_m^T), \tilde{\mathbf{V}}_{\mathbf{mb}}) \tag{8}$$

V. Experiments

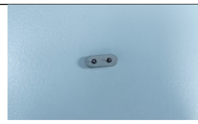
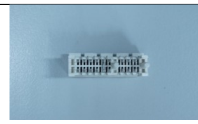
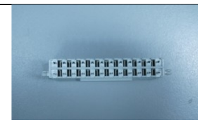
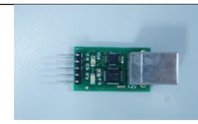
The inputs of proposed system are serial images of each object, so most of open source databases can not be applied for proposed system, and also not suit for purposes in this paper. Therefore, the experiments are implemented through our own dataset. The testing dataset is constructed by twenty different kinds of chosen work pieces as shown in table 2. The experiment is implemented based on several assumptions: The input objects are not occluded, and not adjacent with each other. The input objects are placed on conveyor with random poses, and we assume the probability of every faces showing on top is uniform distribution.

The testing work pieces are classified into three classes in table 2. For class **WP1**, the work pieces are featureless and small, so it's hard to construct robustness descriptor even building relational model for entire model. For class **WP2**, all work pieces acquire similar shapes or size, so, for general method, this kind of object is easily mismatch in the matching process. The work pieces in **WP3** are matched group of this experiment. The work pieces acquire sufficient feature for descriptor, and have plenty of information for identifying and constructing relational model. In the first stage of experiment, we would like to compare the performance of proposed system between different classes in different environments. The results of different classes are shown in fig.6. In fig.6(b), the environment lighting is controlled by on-axis lighting source, so the information of object are more complete and distinct than images with lighting control in fig.6(a). The accuracy of recognized result is average of 100 times repeatedly testing.

The system is considered convergence while accuracy is over 95%, and stop learning approach. If the accuracy is under 95% again, the learning approach would be re-excuted. Comparing the results, in both cases, class **WP3** could be convergent with least input sample, and convergent time of class **WP2** is slowest. The results shows the efficiency of learning could be slightly improved by environment constrain, but the accuracy is not effected, and always over 95% after learning approach stopped. Similarly, twenty kinds of work pieces are included in learning stage in the same time, and the results are shown in fig. 7. The accuracy of each test is also the average of 100 times repeatedly testing. The results show that system need more inputs to convergent while more kinds of objects are included in learning stage. The performance is also slightly improved while environment is lighting controlled. In brief, these two experiments verify proposed system is competent to learn the relational model automatically. Although the learning rate would be dragged by the kinds of input objects, the learning rate still can be convergent by reasonable number of inputs. The result shows the system can be convergent by less than 1000 sample pieces with random poses. Furthermore, the accuracy of recognition is stable once learning approach completing, and would not be under threshold(95%) again unless adding new kind input.

The experiment in fig. 6 and 7 testified the performance of proposed system could automatically learn the relational model of variant kinds of objects. Then, we would like to compare the performance of proposed system with other advanced approaches. Since none of similar systems could handle this issue in our survey, so the comparisons would be done by dividing our system into two parts. One is 2-D descriptors for each face of objects, and the other is machine

Table II. Three classes of testing work pieces for experiments

WP1		WP2		WP3	
WP1.1	WP1.5	WP 2.1	WP 2.5	WP3.1	WP3.5
					
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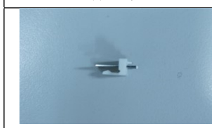
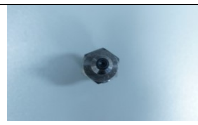
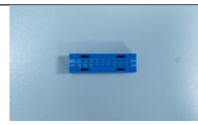
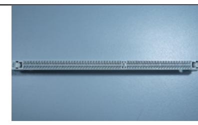
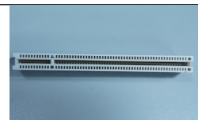
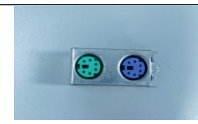
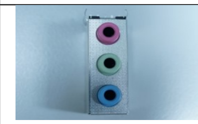
					
WP1.3	WP1.7	WP 2.3		WP3.3	WP3.7
					
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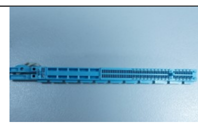
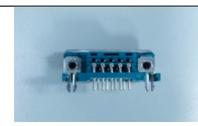
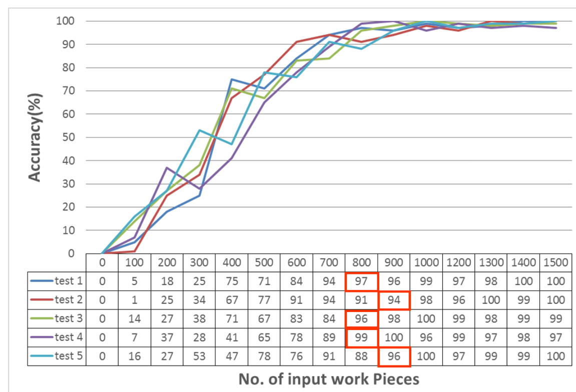
					

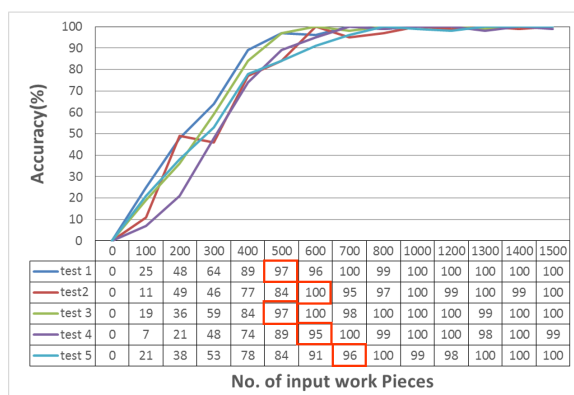
(a) Performance without environment constrains

(b) Performance with environment constrains

Fig. 6. Experimental Results of different classes in different environment constrains



(a) Performance without environment constrains



(b) Performance with environment constrains

Fig. 7. Experimental Results of all work pieces in different environment constrains

learning approach for learning relational model.

For the descriptor part, four kinds of other descriptors are chosen to compare with proposed system. B-SIFT[25]and Edge-SIFT[26] are modified versions of SIFT approach

Table III. Comparisons of system performance with different 2-D descriptors

		Descriptor				
		MLN-based	B-SIFT	Edge-SIFT	BRISK	ZM
With prior	WP1	0.9781	0.9664	0.8384	0.9556	0.9788
	WP2	0.9630	0.9766	0.9233	0.9676	0.9523
	WP3	0.9901	0.9963	0.9454	0.9899	0.9949
	All	0.9594	0.8982	0.8066	0.9432	0.9634
Without prior	WP1	0.9611	0.7688	0.6544	0.8103	0.7787
	WP2	0.9505	0.7043	0.7123	0.7197	0.7979
	WP3	0.9718	0.8044	0.7963	0.8243	0.8231
	All	0.9543	0.6431	0.6144	0.7741	0.7670

Table IV. Comparisons of different transfer learning approach

		Transfer learning approach			
		Proposed	LEW	TSVM	WNN
With prior	WP1	0.9781	0.9802	0.9511	0.9513
	WP2	0.9630	0.9763	0.9690	0.9601
	WP3	0.9901	0.9899	0.9799	0.9684
	All	0.9594	0.9677	0.9567	0.9541
Without prior	WP1	0.9611	0.9601	0.9543	0.9103
	WP2	0.9505	0.9543	0.9558	0.9197
	WP3	0.9718	0.9788	0.9699	0.9346
	All	0.9603	0.9553	0.9497	0.9486

which enhanced the accuracy of feature point registration. BRISK[13] descriptor is constructed based on binary robust invariant scalable key points, and Zernike Moment (ZM)[11] phase-based descriptor is a moment-based descriptor which use the phase information of signal. All of these descriptors are representative methods in relative field recent years, and had been testified by plenty of researchers. To compare the robustness and accuracy, the performance is testified by two conditions. One is relationship of each faces is prior of system, and the descriptors only provide information for object matching. The experiments are implemented by the same learning approach which proposed in previous section.The other is no prior for learning approach that information of descriptor need to use for inferring the relational model. The ZM descriptor have the best performance in the condition without prior, but accuracies of descriptors are close. In condition without prior, the MLN-based descriptor acquire best performance which testified MLN-based descriptor is suited for automatic learning system.

Hereafter, the performance of different learning methods should be further discussed. The learning approach in proposed system need to learn the distribution of different domains, so regular learning approaches is hard to applied on proposed structure directly. The transfer learning methods are famous for handling cross domains problem, so the other three kinds of transfer learning approaches: Locally Weighted Ensemble approach(LWE)[7], Transductive SVM(TSVM)[8], and Weighted Neural Network(WNN)[9] are chosen to compare with proposed method. Similarly, the experiments are divided into two parts as shown in table 4. The result shows LEW had the best accuracy in the condition with prior, and proposed learning approaches acquire greatest performance in condition without prior, but, in both two conditions, the performance between different methods are pretty close. It's seem the results are mainly effected by the performance of the descriptor. The performance of descriptor not only influence the result of 2-D image, but also the relational model of each faces, so the experiments are reasonable. Furthermore, the results showed proposed system acquire best performance in automatic learning part.

VI. Conclusion

The automatic learning approaches for visual-servo system is an important part in industrial application. In this work, we reverse the concept of traditional visual-servo system. The robustness of feature points and descriptor is not the thing which should be most concerned. Instead, the relational model between input and output is the most important.

To learn the relationship between input and output, we proposed a system architecture which can automatic learning and self-supervised the performance of learning or inference results. Since the relationship between input and output is consisted by multiple different domains, the relational model is further segmented into three domain:2-D descriptor, 3-D object and Cartesian space of robot arm. Instead of modelling by three independent networks, these three domains are integrated into one multi-layers networks. Comparing with traditional multi-layers percetron, proposed multi-layer networks is not used to model a complex non-linear distribution, but model the transfer function between different layers. The knowledge in different domains could be transfer between different layers through transfer functions which are called relational models in this paper. Furthermore, a MLN-based descriptor is further proposed to assist inference relationship of each 2-D descriptor while the relational model is unknown. The experiments result shows the system could automatic learning the relational model, and performance could compete with other excellent methods.

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