Self-Taught Visual Servo System for 3D Object Recognition by Hierarchical Model

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***Abstract*—Visual servo systems for 3D object recogntion are widely applied on industrial robot arm recent years. In most of tasks, we only cares about the relation between input image and result rather than a delicate model of 3D object. we propose an intelligent visual servo system which can automatically constructed relational model for input and output by proposed self-taught learning method with only 2D image input. The relational model is established based on hierarchical Model. 2D images are used to inferred the rotation angle for robot in Cartesian space, so we proposed a MLN-based descriptor which is born for inferring relational model by finding co-cluster. The experiment results show the feasibility of proposed structure that can transfer knowledges in different domains, and complete assigned task by only modelling the relation between input and output.**

***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[1-4]. Visual servo system provides additional perception of environment, and make robot arm become more adaptive to complete various tasks. For vision system, model-based recognition methods are commonly used in industrial application. The performance is mainly related to the labeled data which is captured manually. Hence, the system is hard to adapt with adding new kinds of work pieces. For 2D object recognition, users need to capture numerous raw data of target objects in specific poses. These cumbersome works lift to much more complex level while the methods are expanded to 3D object recognition. These manual works not only increase the labor cost, but also point out the dilemma of present vision-based robot which is unable to automatically adapt to various assignments.

In general industrial purposes, we do not really concern about all details of entire 3D object. Instead, the relation between input and target is the key point for completing the tasks like pick and place,etc. To solve these issues, we propose an intelligent tasked-oriented visual servo based system which acquires ability of learning relational model of input and target automatically. In task-oriented view, system tends to learn the relation between input and target rather than delicate models for target 3D objects. Therefore, the state problem is that We only provide labeled data which face of 3D objects are desired to be placed on top by robot arm, but the other faces of 3D objects are unknown. The labeled data is considered as target face, and the input faces are arbitrary objects with random faces on top. The input of system is 2-D image data, and output is rotation angle of robot arm in Cartesian space which are different feature domains. Therefore, the traditional single layer model[HMM,SVM, GMM] which end in a linear or kernel classifier is not enough. We introduced a multilayer model to tackle our problems.

The learning of multilayer model achieve dramatically success recent years while deep learning architectures showed up. Hinton et al. [deep learning algorithm] proposed a hierarchical structure which hidden layers are formed by lower level feature to higher level, and had been successfully applied on different research fields[Deep learning application]. Comparing with traditional **ANN** model[Ref. of neural network], the deep learning method is aim to learn the representation of data in different level rather than produces classifiers through features in the same level. Enlightening by deep learning methods, hierarchical structure is applied to our model which is constructed by four layers: **Feature** (image based), **Descriptor**, **Object** and **RotationAngle** (for robot arm).

Through this model, the feature in different domains could be correlated through hierarchical structure, but the system still can not automatically learn the relation between input images and output rotation angle. Being a self-taught system, the ability which could ”infer” latent edges between labeled and unlabeled data in is needed. Latent edge means two variables in different layers exist an edge in graph model if prior data is sufficient, but, in our case, system only have small amount of prior data. Hence, there are many latent edges which are waiting to be revealed through learning process.

The most challenge part of state problem is that the appearance of different faces of a single object might be huge different, so we design three modules to tackle self-taught problem. Firstly, we design a probabilistic based image descriptor. Extracting scale- and rotation-invariant sparse feature is a pervasive topic in areas of computer vision. Although many brilliant methods[10-14] provide high quality performance by extracting sparse features, the sparse feature is not compact on inferring the relational model. The sparse feature only model strong features of observed face shows on top, but most of faces is unknown in our cases. we need a descriptor which can provide sufficient information for inferring latent edges, but still retain scale- and rotation-invariant. Proposed probabilistic based descriptor is established based on the Markov Logic Network (MLN) [15]. MLN is an approach combines first-order logic and probabilistic graphical model. First-order logic enable compactly representing the neighborhood of feature points. Probabilistic graphical model can reveal latent edges by proper inference method, and also handle the uncertainty.

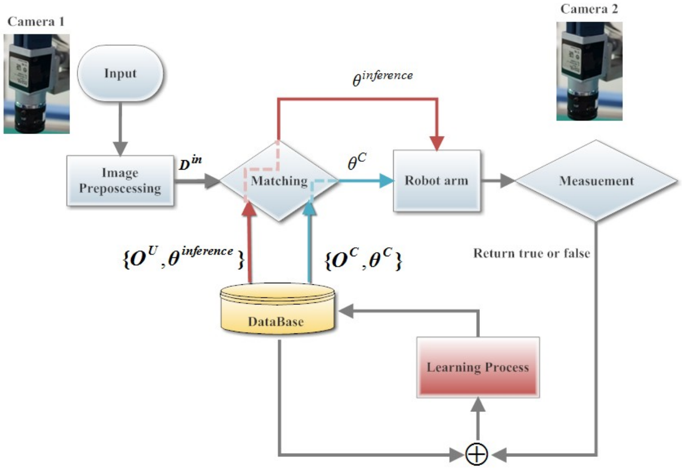


Fig. 1. System architecture

Secondly, transfer information module is proposed for constructing latent edge. Transfer information module is realized by Self-taught Clustering algorithm [refer.]. Self-taught Clustering algorithm is a transfer learning method [6-9....need more] which is built for enhancing model through large amount of auxiliary unlabeled data. The input face can be considered auxiliary unlabeled data, and find co-cluster between priors face in the dataset. Hereafter, we further utilize the distribution of co-cluster to infer the possible rotation angle for robot arm, and robot arm would rotate the object from input face to output face by rotating inferred angle. Finally, the validation module is an eye-to-hand camera which used to validate the error between the output face and desired target face. Hereafter, the validation module feedback the error to the model to refined the model. Through these three module, proposed system can automatically learn the relation between input image and output rotation angle with only labeled the target face of each object.

In this paper, we start with briefly overview of system design and structure in section 2. The MLN-based descriptor for recognized object is described in section 3. Section 4 introduces how to model the proposed multilayer networks, build up and refine the structure of database 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 are presented in final section.

II. System architecture

The main purpose of this system is that desire to automatically derive the relationship between input face and target face of 3D assigned objects. The only prior knowledge are the target face. Input is arbitrary assigned object with random face on top, so it is very likely a unknown face of assigned object rather than prior target face. Therefore, system has to infer the correlation between input and existed prior target face in the pool. Proposed system is shown in Fig. 1. camera 1 captures images of all input objects with random faces on top, and construct MLN-based descriptor for each input. Then, system match the input with data in Database and output rotation angle for robot arm. After robot arm placing a input object, camera 2 would validate result, and feedback error for refining existed model. The system architecture in Fig. 1 is realized by a hierarchical-deep model in Fig. 2.

The variables in the same layer are independent, and vertical adjacent two layers are full connected. Variables in **Feature($\mathbf{\Gamma^{C}}$)** layer are extracted image features, and variables in both **Classified Descriptor($\mathbf{D^{C}}$** and **Unclassified Descriptor($\mathbf{D^{U}}$)** are MLN-based descriptor. Variables in **Rotation angle($\mathbf{\Theta^{C}}$)** and **Inferred Rotation angle($\mathbf{\Theta^{U}}$)** is rotation angle (Row (α), Pitch(β) , Yaw(γ)) respect to target faces. Finally, variables in **Object($\mathbf{O^{C}}$)** is combination of rotation angle.

The difference between classic **Deep Belief Networks**(**DBN**)[Ref.] is that proposed model exist two parallel parts as shown in Fig. 3. $\mathbf{D^{C}}$**-**$\mathbf{\Theta^{C}}$ and $\mathbf{D^{U}}$**-**$\mathbf{\Theta^{U}}$ have no connection between each other, but both have full connection with deepest layer $\mathbf{O^{C}}$ and first layer $\mathbf{\Gamma^{C}}$. To handle tons of unknown data, the structure of connection will dynamically change with observed evidences. Sparse coding method is used to constructs edge in the model, most of connection is zero which is called latent edge in this paper. Latent edge might become non-zero while some new evidence has been discovered. For variable d_w^C in layer $\mathbf{D^{C}}$, the sparse coding result should be formulated as:

$$d_w^C = \sum_{i\in d_w^C} a_i\Gamma_i + \sum_{j\notin d_w^C} b_j\Gamma_j \tag{1}$$

Although Eq.(1) can handle the problem of latent edge, it's impractical to sample all possible conditions whenever new evidence showing up. Therefore, proposed model separate descriptor layer into two parallel parts as:

$$d_w^C = \sum_{\Gamma_i\in d_w^C} a_i\Gamma_i \tag{2}$$

$$d_r^U = \sum_{\Gamma_j\in d_r^U} b_j\Gamma_j \tag{3}$$

d_w^C is considered a prior descriptor which the edge between $\mathbf{\Theta^{C}}$ and $\mathbf{O^{C}}$ had been established. Therefore, the left part of parallel layers can be considered as static model until there is a query classified to the $\mathbf{D^{U}}$. $\mathbf{D^{U}}$ layer is the set of descriptors which we haven't known that these descriptors are corespondent to which object. Therefore, we propose a inference method to infer the possible rotation angle, and camera 2 will checks the results. If inference is success, variable d_r^U and $\theta^{inference}$ become new variables of **Classified Descriptor($\mathbf{D^{C}}$)-Rotation angle($\mathbf{\Theta^{C}}$)**. Meanwhile, new edges of left part of parallel layers are established which can be considered latent edges become visible. By transfer variable between two parallel parts, variables in $\mathbf{D^{C}}$ will dynamically grow with number of inputs.

III. MLN-based Descriptor

A. The concept of constructing MLN-based descriptor

Being an self-taught system, deriving more valuable information from raw data helps system deriving more reliable

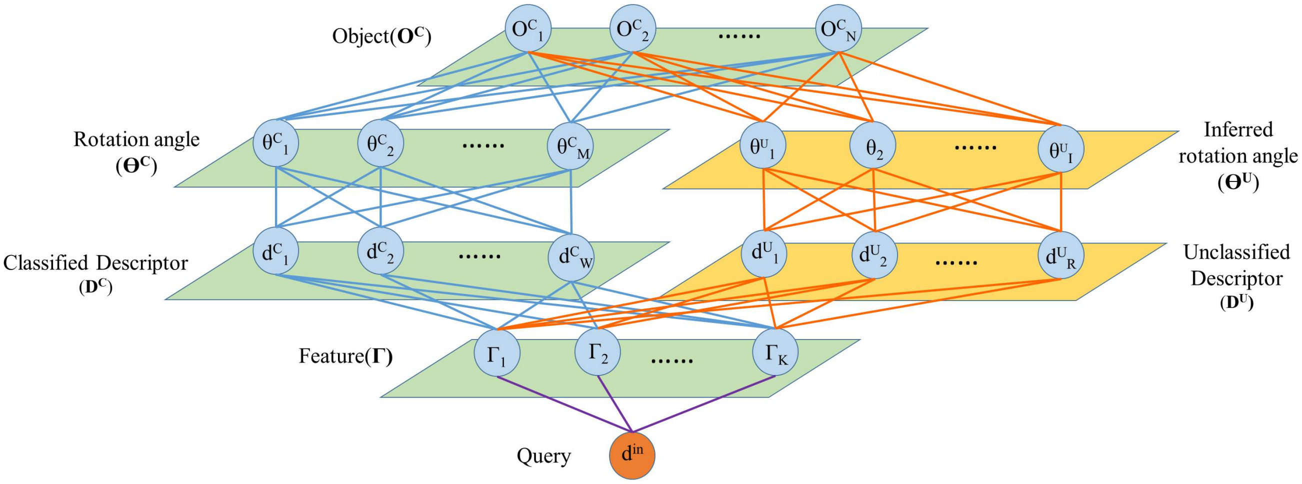
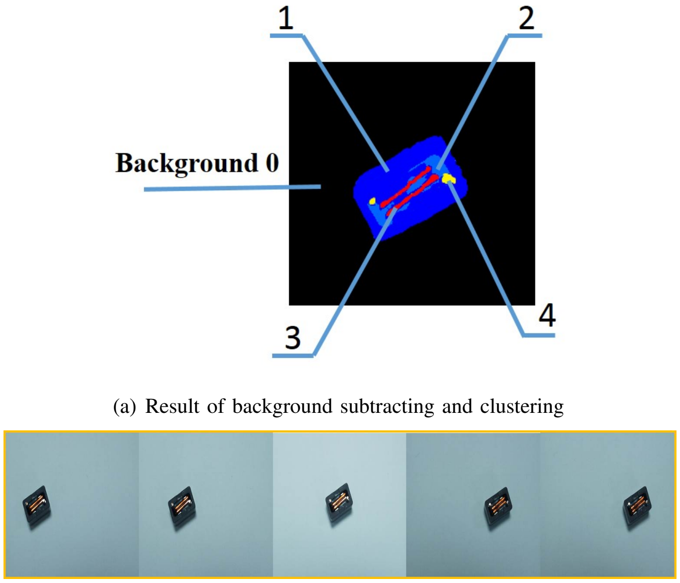


Fig. 2. Hierarchical-deep model for self-taught system



(a) Result of background subtracting and clustering

(b) Serial captured frames

Fig. 3. Preprocessing of input objects

results with poor prior knowledge. Most of present image descriptors [10-14] are constructed based on strong sparse feature point, because these points are consistent even in different environment. These kinds of descriptor can efficiently and precisely match given image. Nevertheless, most of observed face is not in prior data, so we need a descriptor which can infer the relation between observations and priors. To avoid lose of information, we choose normal distributed feature instead of sparse feature. Since different faces of an object may exist different strong features, normal distributed feature is more suit for our case.

For prepossessing of input images, each channel of RGB domain is classified into 5 parts, and get 125 classes in RGB domain. An input image will be segmented by these classes. In Fig. 3(a), an observed face of input object is segmented into 4 classes, and class 0 is background. Hereafter, predicates for MLN networks are constructed by segmented results. We have only two kinds of predicate *ne(a,v)* and *des(x)* for MLN model. Variable a is an atom cluster, and variable v is a neighbor of atom cluster. Variable x is a MLN-based descriptor. The variables of feature layer in Fig. 2 are predicates *ne(a,v)*. Since every classes can be the atom cluster, we have $\binom{125}{2}$ binary variables in feature layer.

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)			

Taking Fig. 3(a) as an example, the predicates of preprocessed image are shown in Table 1, and first order logic is formulated as:

$$\forall a \forall v \quad ne(a,v) \Rightarrow des(x) \tag{4}$$

Each image will further be down sampled, and derived several images with different scales. For each image, we derive **F*S** formulas where F is number of serial captured images and S is number of images with different scales. Through these formulas, a MLN model can be constructed. The probability distribution over possible world d^in specified by MLN is given by:

$$P(\mathbf{D^{in}} = \mathbf{d^{in}}) = \frac{\mathbf{1}}{\mathbf{Z}}\mathbf{exp}(\sum_{\mathbf{j=1}}^{\mathbf{F*S}} \mathbf{w_j n_j(d^{in})})$$

$$\mathbf{Z} = \sum_{\mathbf{d^{in} \in D^{in}}} \mathbf{exp}(\sum_{\mathbf{j=1}}^{\mathbf{F*S}} \mathbf{w_j n_j(d^{in})}) \tag{5}$$

Where $n_j(d^{in})$ is the number of true grounding of formula j in d^{in}, and w_j is weight of formula j .

Consequently, probability distribution Eq.(5) is a MLN-based descriptor for 2D face recognition.

The complexity of formulas constructing process depend on the number of different kinds of segmentation. 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 avoid repeated sampling.

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.(5) can be written as:

$$\log P_w^*(\mathbf{D^{in}} = d^{in}) = \sum_{j=1}^{F*S} \log P_w(\mathbf{D^{in}} = d^{in} | \mathbf{MB}(d^{in})) \tag{6}$$

Where $\mathbf{MB}(\mathbf{d^{in}})$ is Markov blanket while d^{in} is observed. 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 weight is:

$$\begin{aligned} &\frac{\partial}{\partial w_i} \log P_w^*(\mathbf{D^{in}} = d^{in}) = \\ &\textstyle\sum_{j=1}^{F*S} \{n_i(d^{in}) - P_w(\mathbf{D^{in}} = 0 | \mathbf{MB}(d^{in}))n_i(d^{in} = 0) \\ &\qquad -P_w(\mathbf{D^{in}} = 1 | \mathbf{MB}(d^{in})n_i(d^{in} = 1)\} \end{aligned} \tag{7}$$

Where $n_i(d^{in} = 0)$ is the number of true grounding of j^{th} formula while force $\mathbf{d^{in}} = 0$, and similar for $n_i(d^{in} = 1)$. 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 matched descriptor in the database, and further arrange it to the proper layer of $\mathbf{D^C}$ or $\mathbf{D^U}$ as shown in fig.2. Since input is possible to be assigned to one of parallel layers, matching step is separated into two parts. One is utilized pseudo-log-likelihood to decide that observation should be assigned to which layer. The pseudo-log-likelihood of descriptors matching could be formulated as:

$$\begin{aligned} &\mathbf{argMax} P(\mathbf{D^C} = d_w^C | \mathbf{D^{in}} = d^{in}, \mathbf{\Gamma}_{k \in d^{in}}) \\ &= \mathbf{argMax} P(d^{in} | \mathbf{MB}(d^{in}) P(d_w^C | \mathbf{MB}(d^{in})) \end{aligned} \tag{8}$$

If input descriptor doesn't match any descriptor in $\mathbf{D^C}$ layer, the descriptor become a variable of $\mathbf{D^U}$ layer. For a variable in $\mathbf{D^U}$, we would like to infer rotation angle to make input object can be placed on corresponding target face. Since the rotation angles for descriptors in $\mathbf{D^U}$ had been identified, the second part for matching is try to find a descriptor in $\mathbf{D^C}$ which have max co-cluster with input descriptor. Finding max co-cluster can be alternately considered as minimizing loss of information as:

$$\mathbf{argMin}(I(d^i n, \mathbf{\Gamma}_{k \in d^{in} \cap d_w^C}) - I(d_w^C, \mathbf{\Gamma}_{k \in d^{in} \cap d_w^C})) \tag{9}$$

Consequently, the common feature $\mathbf{\Gamma}_{k \in d^{in} \cap d_w^C}$ is further represented by co-Markov Blanket of d^{in} and d_w^C, and the loss of mutual information can be further formulated by KL divergence [Ref.] as:

$$\begin{aligned} &\mathbf{argMin} D(P(d^{in}, \mathbf{MB}(d^{in}, d_w^c)) || P(d_w^c, \mathbf{MB}(d^{in}, d_w^c))) \\ &= \mathbf{argMin} \textstyle\sum_{\Gamma_k \in \mathbf{MB}(d^{in}, d_w^c)} P(\Gamma_k) D(P(d^{in} | \Gamma_k) || P(d_w^C | \Gamma_k)) \end{aligned} \tag{10}$$

By Eq.(10), classified descriptor d_w^C with min DL-divergence is considered acquired max co-cluster with d^{in}. The relation between the co-cluster become the evidence for inferring rotation angle of $d^i n$. Through Eq.(8) and Eq.(10), the input descriptors had been classified to corresponding layer, and become inputs of $\mathbf{\Theta^C}$ or $\mathbf{\Theta^U}$ layer.

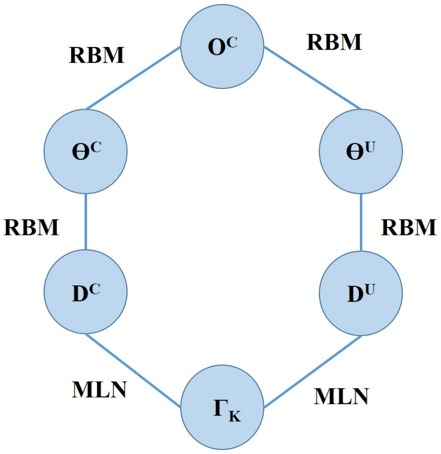


Fig. 4. Structure configuration of proposed model

IV. Hierarchical-deep model

A. Inference of rotation angle in $\mathbf{\Theta^U}$ layer

Inference rotation angle $\theta_{\mathbf{i}}^{\mathbf{U}}$ is based on max co-cluster between d^in and d_w^C. A set of co-cluster $\{C_{w1}, C_{w2}, ..., C_{wL}\}$ can be derived by minimizing KL divergence. The center of co-cluster with respect to center of camera in Cartesian space can derived two set $\mathbf{V^{in}}$=$\{v_1^{in}$, v_2^{in}, ..., v_L^{in} $\}$ and $\mathbf{V_w^C}$=$\{v_{w1}^C$, v_{w2}^C, ..., v_{wL}^C $\}$. The roll angle α of robot arm is calculated by:

$$\alpha = \cos^{-1} \frac{1}{L} \sum_{l=1}^{K} \frac{v_{wl}^C - v_l^{in}}{|v_{wl}^C - v_l^{in}|} \tag{11}$$

Where roll angle α is the mean angle of co-cluster in two descriptor. For pitch angle β and yaw angle γ, since we don't have depth information, the pitch and yaw angle are impossible to be estimated by 2D descriptor. Hence, we random sample these two angle in value $\pi/2$, and $-\pi/2$ initially, and approximate to actual angles by algorithm 1 though several iteration.

B. Inference and learning of hierarchical-deep model

Proposed hierarchical-deep model is a generative model of Deep Belief Network (DBN)[REF.]. Structure between each layer is shown in Fig. 4. each layer is considered as an Restricted Boltzmann Machine ($\mathbf{RBM}$)[REF.] except $\mathbf{\Gamma_K}$, $\mathbf{D^C}$, and $\mathbf{D^U}$. The MLN is trained by pseudo-log=likelihood as mention before, and RBM is trained by greedy layer-wise training [Ref.].

Initially, left part of model ($\mathbf{\Gamma_K}$-$\mathbf{D^C}$-$\mathbf{\Theta^C}$-$\mathbf{O^C}$) are trained with prior target face of objects, and number of variables $\mathbf{N}$ in $\mathbf{O^C}$ equal to the number of prior target face. The right part of model is activated only while a new observed is classified into $\mathbf{D^U}$. The activation probability of θ_i^U is a sigmoid activation function:

$$P(\theta_i^U|\mathbf{D^U}) = \frac{\mathbf{1}}{\mathbf{1+exp}\big(\mu{*}\mathbf{b_l}-\sum_{\mathbf{r}}\mathbf{d_r^U w_{lr}}\big)}$$
$$\mu = \begin{cases} 0 & \text{, if inference succeed} \\ 1 + logP(\theta_i^U|\mathbf{\Theta^U}) & \text{, if inference fail} \end{cases} \tag{12}$$

Table II. Comparison of MLN-based descriptor to state of art on $\mathbf{Caltech-101}$

Methods	Accuracy
$\mathbf{MLN-based}$	**74.6**
LLC	73.1
P-LLC	78.75
P-FV	80.1
M-HMP	82.5
ImageNet-pretrained convnet	86.5

Table III. Comparison of MLN-based descriptor to state of art on $\mathbf{Caltech-256}$

Methods	45	60
$\mathbf{MLN-based}$	**66.7**	**69.6**
LLC	45.3	47.7
P-LLC	44.9	48.0
P-FV	44.9	52.6
M-HMP	54.8	58
ImageNet-pretrained convnet	72.7	74.2

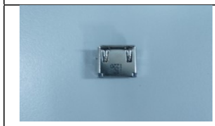
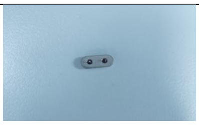
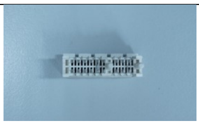
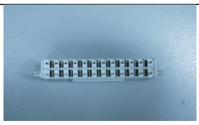
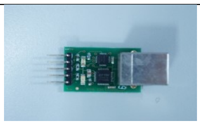
where μ is penalty factor which decrease the probability while the inference is failed. μ is depended on log-likelihood of θ_i^U which can lead to lower activation probability if inference result had failed several times, and avoid system derives wrong results over again. In the other hand, for both $\mathbf{\Theta^U}$ and $\mathbf{\Theta^C}$ layer, if results are correct, the model will retrained by greedy layer-wise training. If validated result is derived from left part of Fig.(4), the generative model is defined by the joint distribution of top layers $P(\mathbf{O^C}, \mathbf{D^C})$, and if the result is derived from right part, the generative model is defined by $P(\mathbf{O^C}, \mathbf{D^U})$. By doing so, the relation between prior and observations can be self-taught from numerous random unlabelled inputs, and self-inferred possible relational model while new assigned objects involve to proposed model.

V. Experiments

The experiments for proposed model are separated into two parts. Firstly, we would like to evaluate the performance of MLN-based descriptor by standard object recognition datasets: $\mathbf{Caltech-101}$ and $\mathbf{Caltech-256}$ [Ref]. Results shown in table 2 are comparisons with recently published state of art. The images in the datasets will be rescaled into five different scales for training proposed MLN-based descriptor. For $\mathbf{Caltech-101}$, we following general procedure randomly selecting 30 images for each class, and, for $\mathbf{Caltech-256}$, selecting 45 and 60 images each class, and trained by pseudo-log likelihood. Although, the result doesn't outstanding in $\mathbf{Caltech-101}$, but the accuracy in $\mathbf{Caltech-256}$ is only behind r ImageNet-pretrained model[Ref.]. In the other scope, the result shows that MLN-based descriptor keep well performance even increasing categories. Most of state of art get dramatically decreasing of accuracy while categories increase from 101 to 256. Therefore, it;s proved that MLN-based descriptor is compatible to be a descriptor in large amounts of unlabelled data.

For the second part of experiment, we would like to implement proposed system in real industrial case. The prior knowledges are target face of assigned object, and there are

Table IV. 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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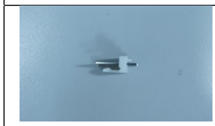
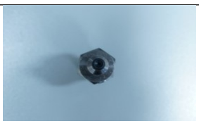
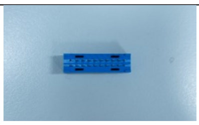
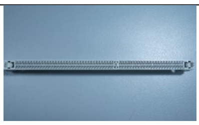
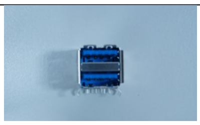
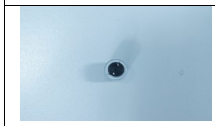
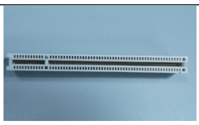
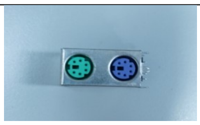
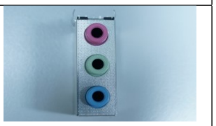
					
WP1.3	WP1.7	WP 2.3		WP3.3	WP3.7
					
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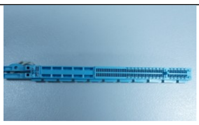
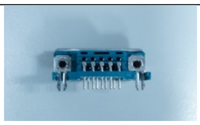
					

twenty kinds of assigned object in our experiment. Table 4 shows twenty target face for each assigned object. The experiment is implemented based on several assumptions: The input objects are not occluded, and not adjacent with each other. Hereafter, the inputs of self-taught system are that random choose assigned objects with random face on top.

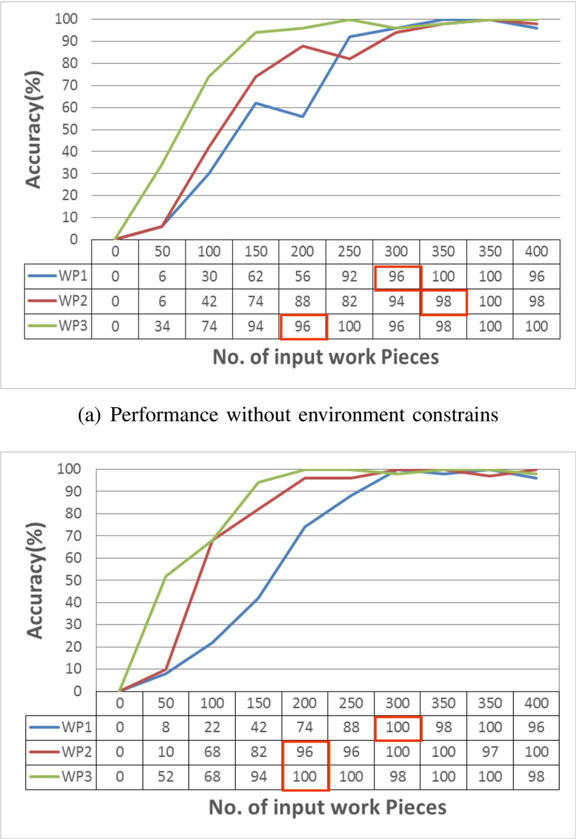
The testing objected are classified into three classes in table 4. For class **WP1**, the work pieces are featureless and small, so it's hard to construct robustness descriptor even building relational model for entire model. For class **WP2**, all work pieces acquire similar shapes and size, so this 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.5. In Fig.5(b), the environment lighting is controlled by on-axis lighting source, so the information of object are more complete and distinct than images without lighting control in Fig.5(a). The accuracy 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,

Fig. 6 shows the result while all twenty kinds of assigned object are involved in the same time. The result shows that system need more inputs to convergent while more kinds of objects are involved, but the system still slightly converge, and accuracies are all over 95% for both conditions. 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 number of assigned objects, the learning rate still can be convergent by reasonable number of inputs.

The experiment in Fig. 5 and 6 testified the performance of proposed system can meet our requirements. 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 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 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 as shown in Table 5. 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



	0	50	100	150	200	250	300	350	350	400
WP1	0	6	30	62	56	92	96	100	100	96
WP2	0	6	42	74	88	82	94	98	100	98
WP3	0	34	74	94	96	100	96	98	100	100

(a) Performance without environment constrains

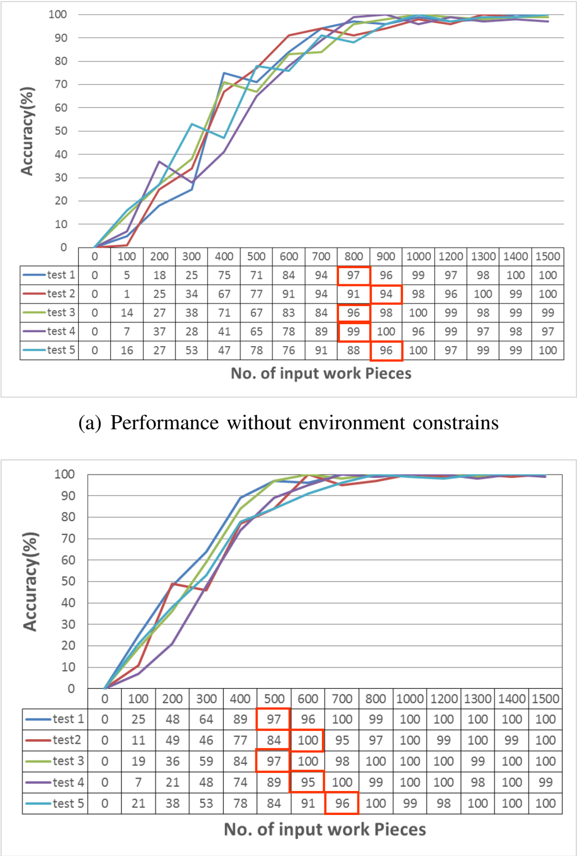
	0	50	100	150	200	250	300	350	350	400
WP1	0	8	22	42	74	88	100	98	100	96
WP2	0	10	68	82	96	96	100	100	97	100
WP3	0	52	68	94	100	100	98	100	100	98

(b) Performance with environment constrains

Fig. 5. Experimental Results of different classes in different environment constrains

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 self-taught system.

Hereafter, the performance of different learning methods should be further discussed. 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 6. The result shows LEW acquires the best accuracy in the condition with priors, and proposed learning approach acquire greatest performance in condition without prior, but, in both two conditions, the performance between different methods are pretty close. It's seem that 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 results are reasonable.



	0	100	200	300	400	500	600	700	800	900	1000	1200	1300	1400	1500
test 1	0	5	18	25	75	71	84	94	97	96	99	97	98	100	100
test 2	0	1	25	34	67	77	91	94	91	94	98	96	100	99	100
test 3	0	14	27	38	71	67	83	84	96	98	100	99	98	99	99
test 4	0	7	37	28	41	65	78	89	99	100	96	99	97	98	97
test 5	0	16	27	53	47	78	76	91	88	96	100	97	99	99	100

(a) Performance without environment constrains

	0	100	200	300	400	500	600	700	800	1000	1200	1300	1400	1500
test 1	0	25	48	64	89	97	96	100	99	100	100	100	100	100
test2	0	11	49	46	77	84	100	95	97	100	99	100	99	100
test 3	0	19	36	59	84	97	100	98	100	100	100	99	100	100
test 4	0	7	21	48	74	89	95	100	99	100	100	98	100	99
test 5	0	21	38	53	78	84	91	96	100	99	98	100	100	100

(b) Performance with environment constrains

Fig. 6. Experimental Results of all work pieces in different environment constrains

Table V. 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 VI. 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

VI. Conclusion

The self-taught 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 a 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 hierarchical-deep model which combines the concept of deep learning and transfer learning. The model acquires self-taught ability which can infer relational model and self-supervised the performance of learning results. Being a self-taught system, tackling large amount of unlabelled data and inferring relation with labelled data is our top tasks. The MLN-based descriptor is born for inferring the relational model. Since MLN-based model is a probability distribution of features, the relation between features can be represented as a discriminative distribution. Through these discriminative distribution, KL divergence is further involved to fined the max co-cluster, and the relational model is constructed based on max co-cluster between labelled and unlabelled data. The experiment result shows the MLN-based descriptor is compatible to face numerous unlabelled data.

Moreover, hierarchical-deep model can separate different level knowledge by multilayer structure, so the features in different domains can be easily transferred and learned. proposed system include image feature, descriptor and rotation angle for robot arm. Distribution of this features is impossible to approximate by traditional single layer model. Hence, the transferring knowledge in different domains owe to hierarchical-deep model, and experiments results prove proposed system can recognized 3D object by only learned relational model. We believe this system is piratical in real industrial production line, and become a real automatic visual-servo system which can save tons of labor cost.

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