Cognitive Template-Clustering Improved LineMod for Efficient Multi-object Pose Estimation

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Abstract
Various types of theoretical algorithms have been proposed for 6D pose estimation, e.g., the point pair method, template matching method, Hough forest method, and deep learning method. However, they are still far from the performance of our natural biological systems, which can undertake 6D pose estimation of multi-objects efficiently, especially with severe occlusion. With the inspiration of the Müller-Lyer illusion in the biological visual system, in this paper, we propose a cognitive template-clustering improved LineMod (CT-LineMod) model. The model uses a 7D cognitive feature vector to replace standard 3D spatial points in the clustering procedure of Patch-LineMod, in which the cognitive distance of different 3D spatial points will be further influenced by the additional 4D information related with direction and magnitude of features in the Müller-Lyer illusion. The 7D vector will be dimensionally reduced into the 3D vector by the gradient-descent method, and then further clustered by K-means to aggregate templates and automatically eliminate superfluous clusters, which makes the template matching possible on both holistic and part-based scales. The model has been verified on the standard Doumanoglou dataset and demonstrates a state-of-the-art performance, which shows the accuracy and efficiency of the proposed model on cognitive feature distance measurement and template selection on multiple pose estimation under severe occlusion. The powerful feature representation in the biological visual system also includes characteristics of the Müller-Lyer illusion, which, to some extent, will provide guidance towards a biologically plausible algorithm for efficient 6D pose estimation under severe occlusion.

Keywords Müller-Lyer illusion · Cognitive template-clustering · Brain-inspired computation · LineMod · 6D pose estimation

Introduction
The evolutionary procedure of the mammalian brain has resolved the problem of 6D pose estimation by integrating different related brain regions, hundreds of specifically designed neuron types, and functional microcircuits. However, a challenge remains in discovering the mysterious black box of the brain and designing the most efficient biologically plausible model for 6D pose estimation.

With significant development of computer science and cognitive robot theory, various types of theoretical algorithms have been proposed [1] in the research area of 6D pose estimation, e.g., the point pair method, template matching method, Hough forest method, and deep learning method. However, these efforts in machine learning and robotics are still a considerable distance from the performance of the natural biological system. They still face fundamental problems such as sensitivity to illumination changes, noise, blur, and occlusion.

The Müller-Lyer illusion is a special kind of functional phenomenon in the procedure of visual information processing of the brain [2], in which the cognitive distance of different 3D spatial points will be further affected by additional features related to direction and magnitude. Figure 1 shows the three basic types of Müller-Lyer illusion, e.g., the distance illusion in Fig. 1a, direction illusion in Fig. 1b, and angle illusion in Fig. 1c, respectively. These illusions in the visual system contribute to feature detection and object identification during 6D pose estimation, especially in cases of severe occlusion.

Extended author information available on the last page of the article.
In order to estimate 6D pose in the case of multiple objects with occlusion and motion blur, as well as decrease the computation cost as much as possible, we firstly focused on the standard Patch-LineMod method for its accuracy and efficiency. Patch-LineMod is an improved version of the LineMod method, which separates points into different patches by the K-means method and makes possible multi-object 6D pose estimation.

Inspired by the Müller-Lyer illusion, a cognitive template-clustering improved LineMod (CT-LineMod) model was proposed. The model uses a 7D cognitive feature vector to replace standard 3D spatial points in the clustering procedure of Patch-LineMod, in which the cognitive distance of different 3D spatial points is further affected by additional 4D features related to direction and magnitude in the Müller-Lyer illusion. The 7D vector is dimensionally reduced into the 3D vector by gradient-descent method, and then further clustered by K-means method to aggregately match templates and automatically eliminate superfluous clusters, which makes template matching possible on both holistic and part-based scales.

The CT-LineMod model can be considered as an integration of powerful 7D feature representation from Patch-LineMod and efficient cognitive template-clustering based on the Müller-Lyer illusion. The model was verified on the standard Doumanoglu dataset and performed perfectly, demonstrating the accuracy and efficiency of the proposed model on cognitive feature distance measurement and template selection on multiple pose estimation with severe occlusion.

**Related Works**

Four main types of models have been proposed in the research area of 6D pose estimation, including the point pair method, template matching method, Hough forest method, and deep learning method.

For point pair–based algorithms, Drost et al. proposed a point pair feature algorithm, which successfully integrates global description, local point pair features, and local-global matching conversion for better recognition performance in the case of noise, clutter, and partial occlusions [3]. However, it performs poorly in detecting objects with similar background clutter and ignores valuable edge information of objects. Hinterstoisser proposed a new sampling and voting point pair scheme [4] to reduce the harmful effects of clutter and sensor noise. However, this method is extremely sensitive to occlusion and cannot recover the complete object location information. A cognitively inspired 6D motion estimation method is proposed based on solving the Perspective-n-Point problem and the Kalman filter [5].

For template matching–based algorithms, Hinterstoisser et al. proposed the LineMod algorithm, which utilizes the gradient information and normal features of the surface of an object for template matching [6, 7]. However, LineMod shows poor performances on real-time template matching. One possible reason for this is it only focuses on the strong edges during feature extraction. Hodan et al. proposed BOP [8] as a novel and standard benchmark to use with current datasets. However, it focuses more on different single objects rather than multiple overlapping objects in a single scene.

For Hough forest–based algorithms, Gall et al. proposed a target detection algorithm [9], which constructs a random forest to extract image blocks, and then makes a template judgment within each decision tree, and votes in the Hough space. Tejani et al. proposed the latent-class Hough forest model, which integrates a new template-based segmentation function into the regression forest [10]. However, this is limited by the manually designed features for different objects in different overlapped scenes.

For deep neural network (DNN)–based algorithms, Kehl et al. proposed a single-shot multi-box detection algorithm, which constructs a random forest to extract image blocks, and then uses the projection properties to analyze the inferred points and in-plane rotation scores [11]. A similar convolutional neural network (CNN) based on category detectors has also been used [12]. A robust 3D object detection and pose estimation pipeline based on RGB-D images has been constructed, which can detect multiple
objects simultaneously while reducing false positives [13]. For heavy clutter scenes and occlusion problems, Bonde et al. proposed a highly robust real-time object recognition framework, which uses an iterative training scheme to classify the position and posture of 3D objects [14]. Xiang et al. proposed a new pose-CNN for 6D pose estimation by introducing a new loss function named ShapeMatch-Loss [15]. Feifei et al. proposed heterogeneous DenseFusion architecture based on PoseCNN, which uses an end-to-end iterative gesture fine-tuning program and performs excellently on both YCB-Video and LineMod datasets [16]. Euclidean distance, scalable nearest neighbor search method, and CNN are integrated as an efficient model to capture both the object identity and 3D pose [17, 18]. Park et al. proposed a novel architecture Pix2Pose based on CNN [19], which predicted the coordinates of each pixel after feature extraction, and then calculated the position and orientation by voting. Although this effort largely improved the robustness of pose estimation, especially under heavy occlusion, the computation cost was relatively expensive considering a comparable accuracy can be achieved with other methods.

Besides 6D pose estimation, many clustering methods have also been proposed for intelligent patch identification, especially in cases involving severe occlusion. Nazari et al. proposed a clustering ensemble measurement framework, which is based on the cluster-level weighting, can assign weights into each cluster with different reliability, and has high robustness, clustering quality, and time complexity [20]. Rashidi et al. proposed a clustering ensemble framework, which is based on the integration of undependability concepts and cluster weighting, and also uses hierarchical agglomerative clustering and bi-partite graph formulation to estimate the cluster dependability and certainty [21]. Some semi-supervised clustering methods have also been proposed for better information representation [22].

Unfortunately most of the models mentioned above are not as efficient and robust as the human brain. Further inspiration from the biological system is necessary for human-comparable algorithm on efficient 6D pose estimation.

**Standard LineMod and Patch-LineMod**

LineMod is a template-based approach for 6D pose estimation [6]. It can handle untextured objects under massive clutter by taking a short training time. However, this template-based effort will inevitably fail on the identification of “multiple” objects in complex scenes. The number of features in this method cannot be greater than a predesigned parameter, for example, 64, which dramatically limits the higher performance of the algorithm. Besides, the recognition rate of the LineMod algorithm will drop rapidly under occlusion. The training procedure of LineMod is shown in Fig. 2a.

Different with LineMod which makes the pose estimation mostly based on the similarity of target object and whole template, the Patch-LineMod [8] separates the whole template into different small templates (e.g., patch templates) by K-means clustering, and then makes the similarity between training patches and target patches for the identification of 6D pose with some parts of object under occlusion. The training procedure of the Patch-LineMod is shown in Fig. 2b. Both the LineMod and Patch-LineMod algorithms contain training and testing phases:

- The training phase is shown in Fig. 2a and b: LineMod and Patch-LineMod load the RGB-D images of a specific object from different training directions and preprocess it with Gaussian blur and Sobel operator. Then both of them calculate the gradient direction and magnitude above the predefined threshold as the 7D cognitive feature. Finally, the template matching is used for the learning procedure of pose identification.
- The test phase is shown in Fig. 2d: A predefined sliding window is used for the matching process, which is from both horizontal and vertical directions, respectively. The similarity of 7D cognitive features between trained objects (or patches with K-means in Patch-LineMod) and target objects is calculated, and then the trained object with the biggest similarity will be selected as the estimated pose.

**Cognitive Template-Clustering Improved LineMod**

Comparisons between the different processing steps of LineMod, Patch-LineMod, and CT-LineMod are shown in Fig. 2. All three methods contain training and test phases.

For the standard LineMod method, it will determine the similarity measurement of these features directly with the target object by template matching. However, this matching cannot detect an object when it is affected by an occlusion. For example, by using LineMod method in Fig. 2a, only one object (and also one pose) is identified in the test phase in Fig. 2d.

For Patch-LineMod method in Fig. 2b, the simple K-means clustering method is used based on purely spatial locations (e.g., the X, Y, and Z positions of points), which will generate different patches for different modalities, hence will detect more objects in the test phase, for example, two objects are detected in Fig. 2d.
The Müller-Lyer illusion can provide a new 3D cognitive feature vector to replace the original 3D spatial location. The cognitive feature vector is the dimensional reduction from the 7D cognitive feature vector. The distance between two points (e.g., the 3D spatial information) will be affected by their neighborhood features (e.g., the direction and magnitude of the gradient feature in another 4D vector), as shown in Fig. 2e. This illusion will change the feature characteristics of objects; for example, the features near the edges or borders will contribute more to the feature identification. Hence, after the cognitive template-clustering in Fig. 2c, the CT-LineMod will successfully detect all of the three objects in Fig. 2d.

The 7D Cognitive Feature Vector

The 7D cognitive feature vector contains the 3D spatial feature vector (with the X, Y, and Z spatial locations), and also another 4D vector for gradient direction, gradient magnitude, surface-normal direction, and surface-normal magnitude, as shown in Fig. 3.

The LineMod-type methods contain both gradient modalities and surface normal modalities. For good template matching algorithms, the templates after selection should be robust to scale change, color variance, and severe occlusion. The 7D cognitive feature vector has the potential of integrating different types of cognitive features. For example, the distances between different features will all contribute to the patch allocation. The intrinsic links between these feature points will further help the next-step multiple 6D pose estimation.

Cognitive Template-Clustering

The cognitive template-clustering is the improvement of patch clustering in Patch-LineMod with Müller-Lyer illusion, as shown in Fig. 2e. The templates are aggregated based on the similarity matching of all 7D cognitive feature vectors, e.g., locations (with three dimensions), magnitudes (with two dimensions), and directions (with two dimensions).

The overall procedure of CT-LineMod is shown in Fig. 4. After loading of the raw images in Fig. 4a, e.g., the 3D cloud points, the four additional features are calculated for each 3D points in Fig. 4b. Features in the neighborhood area with size $s \times s$ are integrated as the templates in Fig. 4c. Then the patches of templates are allocated based on the K-means clustering method with updated spatial 3D vectors.
Fig. 3 The 7D cognitive feature vector

Multiple modalities

Gradient modalities

Surface normal modalities

Scale change

Color variance

Under occlusion

(1) Spatial location X;
(2) Spatial location Y;
(3) Spatial location Z;
(4) Gradient direction;
(5) Gradient magnitude;
(6) Surface normal direction;
(7) Surface normal magnitude;

after Müller-Lyer illusion, as shown in Fig. 4d. Finally, the templates from input images will be matched with templates from training images in Fig. 4e, and the matched templates will contain the estimated 6D pose.

Information in Feature Level

The information in feature level is shown in Fig. 4b and Eq. (1). \( F_p^I \) and \( F_p^M \) are the features calculated from input image \( I \) and trained image \( M \) respectively in the position of point \( p \).

\[
\begin{align*}
F_p^I &= \{ p^I_X, p^I_Y, p^I_Z, p^I_{gd}, p^I_{gm}, p^I_{sd}, p^I_{sm} \} \\
F_p^M &= \{ p^M_X, p^M_Y, p^M_Z, p^M_{gd}, p^M_{gm}, p^M_{sd}, p^M_{sm} \}
\end{align*}
\]

\( p^I \) is the raw pixel in the input 3D RGB-D image \( I \), \( p^M \) is the raw pixel in the trained image \( M \), \( p^I_X \), \( p^I_Y \), and \( p^I_Z \) are the spatial locations of point \( p \) in \( X \), \( Y \), and \( Z \) axes in image \( I \). \( p^I_{gd}, p^I_{gm}, p^I_{sd}, \) and \( p^I_{sm} \) represent features from gradient direction, gradient magnitude, surface-normal direction, and surface-normal magnitude respectively.

Information in Template Level

The template-level information is shown in Fig. 4c and Eq. (2), in which \( s \) is the calculation step in template \( T_p \), and \( p \) is the center point template \( T \) with an area of \( s \times s \).

\[
\begin{align*}
T_p^I &= \frac{1}{s^2} \sum_{p \in P} F_p^I(\text{gd}, \text{gm}, \text{sd}, \text{sm}) \\
T_p^M &= \frac{1}{s^2} \sum_{p \in P} F_p^M(\text{gd}, \text{gm}, \text{sd}, \text{sm})
\end{align*}
\]

Müller-Lyer Illusion from 7D to 3D Feature Space

The Müller-Lyer illusion can be considered as the dimension reduction of the information in feature level from the

Fig. 4 a–e The architecture of hierarchical information processing in CT-LineMod
Algorithm 1. The Training and Test Procedure of CT-LineMod

\begin{align*}
\text{ICPPostProcessing} &= \text{pose correction, and pose verification} \quad [24] \\
\text{CT} &= \text{remove the duplicate poses based on the evaluation scores}, \\
\text{ICP} &= \text{we use the iterative closest point (ICP) algorithm to}\ \\
\text{pose estimation} &= \text{looking for} \\
\text{SimilarityMeasurement} &= \text{max similarity template features from image I, which}\ \\
\text{ICPPostProcessing} &= \text{are most closely with the template features in dataset image } M, \\
\text{Sim} &= \text{with the condition of the patch search area identified}\ \\
\arg\max_{p \in I_M} &\text{by the K-means method. The function Sim() is the cosine}\ \\
\text{ICPPostProcessing} &= \text{similarity, which measures the angle of the two input}\ \\
\text{ICPPostProcessing} &= \text{vectors.}
\end{align*}

\section{Information in Patch Level}

The patch-level information is represented as $P_i$. For the standard Patch-LineMode method, the patch clustering will be based purely on the spatial information $p'_X$, $p'_Y$, and $p'_Z$, as shown in Eq. (8).

\begin{align*}
\{ P_i = K\text{means}(p'_X, p'_Y, p'_Z), p \in I, M \} \\
\{ P_i^CT = K\text{means}(\hat{p}'_X, \hat{p}'_Y, \hat{p}'_Z) \text{ if } (\hat{p} \in I, M) \} \\
\{ P_i^CT = K\text{means}(p'_X, p'_Y, p'_Z) \text{ if } (\hat{p} \notin I, M) \}
\end{align*}

\section{Similarity Measurement for Pose Estimation}

As shown in Eq. (10), the pose estimation is looking for the max similarity template features from image $I$, which are most closely with the template features in dataset image $M$, with the condition of the patch search area identified by the K-means method. The function Sim() is the cosine similarity, which measures the angle of the two input vectors.

\begin{align*}
\text{Sim} &= \arg\max_{p \in I_M} \sum_{p} \text{Sim}(T_p, T_p^M) \\
\text{ICP Post Processing}
\end{align*}

We use the iterative closest point (ICP) algorithm to remove the duplicate poses based on the evaluation scores, which is the non-maximum suppression algorithm for pose calculation, pose correction, and pose verification [24].

\section{The Training and Test Procedure of CT-LineMod}

The two phases of training and test procedures for CT-LineMod-based 6D pose estimation are shown in Algorithm 1.
Fig. 5 The RGB-D images of cup and box in Doumanoglou dataset and the feature maps during training procedure (a1, a2). The RGB-D raw images for cup and box (b1, b2). The masks of objects (c1, c2). 3D spatial positions in Patch-LineMod (d1, d2). Clustering results in Patch-LineMod (e1, e2). 3D spatial positions in CT-LineMod (f1, f2). Clustering results in CT-LineMod.

Algorithm 1 The algorithm for CT-LineMod model.

1. Raw samples generation from 3D cloud point; the 7D cognitive vector assignment; Template-Clustering variables configuration; the setting of feature size $s$.
2. Start training procedure:
   2.1. Load training samples;
   2.2. The 7D cognitive feature generation with Eq. (1);
   2.3. The templates calculation with Eq. (2);
   2.4. The Müller-Lyer illusion from 7D to 3D feature space with Equations from (3) to (7);
   2.5. The patch-level information calculation with Eq. (9);
   2.6. Pose estimation with Eq. (10);
   2.7. The ICP post processing of estimated 6D poses.
3. Start test procedure:
   3.1. 3D sliding window for target selection with feature size $s$.
   3.2. Template matching for feature identifiers.
   3.3. Multiple pose estimation.
4. End pose learning and estimation.

Experimental Results

RGB-D Doumanoglou Dataset

The 3D point cloud cup and box datasets are the main parts of the Doumanoglou dataset [25], as shown in Fig. 5. It contains the training set and test set, in which the training set contains 4740 rendered images, and the test set contains 177 images. The range of object distances is from 455 to 1076 mm, the azimuth range is from 0 to 360°, and the elevation range is from $-58$ to $88^\circ$.

Figure 5a1 shows the raw images of a mini coffee cup in 360° at different observation angles. The clustered feature maps during the training procedure include the RGB-D image, mask image in Fig. 5b1, and initial feature map in Fig. 5c1 and c1. Figure 5d1 shows the clustered feature map based on the Patch-LineMod method, in which the K-means method is used for the 3D spatial location clustering. Figure 5f1 shows the clustering of the Müller-Lyer illusion from 7D to 3D feature space. It is easy to find out that the cognitive template-clustering method will generate better feature point clustering, which could well separate the corners, edges, and plane of the cups. Additionally, it can generate more uniformly distributed feature points compared with the Patch-LineMod, which also contributes to the performance of 6D pose estimation under occlusion.

Similar with the coffee cup, the box dataset is also processed by both the Patch-LineMod and CT-LineMod from Fig. 5a2 to f2. The source code in this paper is forked from Patch-LineMod project1, and then updated into the CT-LineMod2.

6D Pose Estimation

6D pose estimation is the task of detecting 6D poses of cups and boxes, which contain the locations and orientations of different objects. The awareness of position and orientation of objects in a scene is sometimes referred to as six degrees of freedom pose.

After feature calculation and patch generation, we use the segmented template to perform the sliding window matching in the horizontal and vertical directions, respectively, and calculate the similarities in these windows. Figure 6 shows the improved CT-LineMod compared with

1https://github.com/meiqua/patch_linemod
2https://github.com/brain-cog/Brain_inspired_Batch
standard Path-LineMod on identifying the number of targets and the accuracy of pose estimation of coffee cups and boxes.

- The first line of Fig. 6 shows the raw RGB-D images and detected feature points after the candidate-feature filtering. This image contains 12 cups, and the AprilTag is used for the spatial calibration [26].
- The second line of Fig. 6 shows the detected 6D pose with the top-1 target, which shows the one with the highest confidence in all of the candidate object poses. For a different viewpoint, the detected best pose candidate object is different.
- The third line of Fig. 6 shows the multiple pose estimation of the images, in which more than one candidate poses are calculated by both the CT-LineMod and also the Patch-LineMod methods. Moreover, for most of the cases, the CT-LineMod will get more pose candidates. This result will also be verified in the compared results in Tables 1 and 2.
- The fourth line of Fig. 6 shows raw detected modalities, and the white color represents gradient modalities.

### The Experimental Comparisons

We use the recall and $F_1$ values to show the performance of proposed CT-LineMod on the dataset with severe occlusion, which includes detected-correct, detected-incorrect, and undetected results of 6D pose estimation. $N_{top}$ is the top $N$ pose estimates with highest confidence, which is evaluated by two kinds of objects in each scene (i.e., 56 RGB-D pictures for coffee cup, 60 RGB-D pictures for juice box, and 61 RGB-D pictures for both of them, and the total is 177 test samples) in the Doumanoglou-dataset [25].

As shown in Table 1, we select three kinds of scenes, including the coffee cup scene, the juice box scene, and the mixed scene. Moreover, the three methods are compared with the configuration of $N_{top}$ maximum, e.g., the standard LineMod, Patch-LineMod, and CT-LineMod methods. From the figure, the proposed CT-LineMod method will largely improve the recall performance compared with other methods. The CT-LineMod can identify most of the targets, except the ones hidden in the bottom or under severe occlusion.

### Table 1 The comparison of recall values for three algorithms on three datasets

| Scenes       | LineMod | Patch-LineMod | CT-LineMod |
|--------------|---------|---------------|------------|
| Coffee cup   | 0.051   | 0.412         | 0.443      |
| Juice box    | 0.253   | 0.439         | 0.459      |
| Mixed scene  | 0.017   | 0.373         | 0.384      |
| Mean values  | 0.107   | 0.408         | 0.422      |

### Table 2 The comparison of $F_1$ scores between our method and other state-of-the-art methods

| Methods       | Coffee cup | Juice box | Mean   |
|---------------|------------|-----------|--------|
| LineMod       | 0.819      | 0.494     | 0.656  |
| PPF           | 0.867      | 0.604     | 0.735  |
| Hough forest  | 0.877      | 0.870     | 0.873  |
| Doumanoglou   | 0.932      | 0.819     | 0.875  |
| Ours          | 0.947      | 0.913     | 0.93   |
Besides, we have tested our method on full Doumanoglou dataset (with heavy occlusion scenes) in the “Sixd Challenge”, and make the further $F_1$ score comparison with other states of the art methods with the configuration of $N_{top} = 1$. The LineMod algorithm [6], PPF (point pair Feature) algorithm [3], Hough forest algorithm [10], Doumanoglou algorithm [25], and our proposed model are verified. The mean is the average of the performance on two datasets. The $F_1$ scores of these methods are calculated, as shown in Table 2, which shows the power of the proposed CT-LineMod model compared with other state-of-the-art methods.

Conclusions

The LineMod method is a kind of template matching method which is more efficient for 6D pose estimation compared with other methods based on point pair, Hough forest methods, and DNNs. However, the standard LineMod method can only detect a single target (i.e., the one with the maximum confidence value) and cannot engage with multiple object occlusion and motion blur. One of the primary motivations of the paper is trying to find an efficient way to make possible multiple 6D pose estimation under occlusion.

Hence, inspired by the Müller-Lyer illusion, a cognitive template-clustering improved LineMod model, i.e., CT-LineMod model, is proposed. The model uses a 7D cognitive feature vector to replace standard 3D spatial points in the clustering procedure of Patch-LineMod, in which the cognitive distance of different 3D spatial points is further influenced by the additional 4D information related to direction and magnitude of features in Müller-Lyer illusion. The Müller-Lyer illusion is a kind of sensation illusion in the visual system, which contributes to a better feature generation, feature representation, and also 6D pose estimation under severe occlusion. Finally, the CT-LineMod method has been verified by its performance of 6D pose estimation on the Doumanoglou dataset, in which the model’s accuracy and efficiency were demonstrated.

Author Contributions Tielin Zhang, Yang Yang, and Yi Zeng conceived the idea and formulated the problem. Tielin Zhang and Yang Yang performed the simulations and wrote the paper. Tielin Zhang and Yuxuan Zhao analyzed the results.

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Compliance with Ethical Standards

Conflict of Interest The authors declare that they have no conflict of interest.

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

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