Salient Object Detection via Structured Matrix Decomposition

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Abstract—Low-rank recovery models have shown potential for salient object detection, where a matrix is decomposed into a low-rank matrix representing image background and a sparse matrix identifying salient objects. Two deficiencies, however, still exist. First, previous work typically assumes the elements in the sparse matrix are mutually independent, ignoring the spatial and pattern relations of image regions. Second, when the low-rank and sparse matrices are relatively coherent, e.g., when there are similarities between the salient objects and background or when the background is complicated, it is difficult for previous models to disentangle them. To address these problems, we propose a novel structured matrix decomposition model with two structural regularizations: (1) a tree-structured sparsity-inducing regularization that captures the image structure and enforces patches from the same object to have similar saliency values, and (2) a Laplacian regularization that enlarges the gaps between salient objects and the background in feature space. Furthermore, high-level priors are integrated to guide the matrix decomposition and boost the detection. We evaluate our model for salient object detection on five challenging datasets including single object, multiple objects and complex scene images, and show competitive results as compared with 24 state-of-the-art methods in terms of seven performance metrics.

Index Terms—Salient Object Detection, Matrix Decomposition, Low Rank, Structured Sparsity, Subspace Learning.

1 INTRODUCTION

VISUAL saliency has been a fundamental research problem in neuroscience, psychology and vision perception for a long time. It refers to the identification of a subset of vital visual information for further processing. As an important branch of visual saliency, salient object detection is the task of localizing and segmenting the most conspicuous foreground objects from a scene. It has received substantial attention over the last decade due to its wide range of applications in computer vision, such as object detection and recognition [1]–[4], content-based image retrieval [5], [6] and context-aware image resizing [7]–[10].

Many saliency models have been proposed to compute the saliency map of a given image and detect the salient objects. Depending on whether prior knowledge is used or not, current models fall into two categories: bottom-up and top-down. Bottom-up models [7], [11]–[17] are stimulus-driven and essentially based upon local and/or global center-surround difference, using low-level features, such as color, texture and location. The main limitations of these methods are that the detected salient regions may only contain parts of the target objects, or be easily mixed with background. On the other hand, top-down models [18]–[24] are task-driven and usually exploit high-level human perceptual knowledge, such as context, semantics and background priors, to guide the subsequent saliency computation. However, the high diversity of object types limits the generalization and scalability of these models.

A recent trend is to combine bottom-up cues with top-down priors to facilitate detection. A representative series of papers [25]–[28] are based on the low-rank matrix recovery (LR) theory [29]. For instance, Shen and Wu [26] propose a unified LR model (ULR) with feature transformation to combine traditional low-level features with high-level prior knowledge. Zou et al. [28] introduce the segmentation priors derived from image background and boundary cues to assist the low-rank matrix recovery (denoted as SLR). Lang et al. [27] present a low-rank representation (LRR) [30] based multi-task learning method, in which top-down priors are weighted and combined with multiple features to estimate saliency collaboratively. Generally, these LR-based saliency detection methods assume that an image can be represented as a combination of a highly redundant information part (e.g., visually consistent background regions) and a sparse salient part (e.g., distinctive foreground object regions). The redundant information part usually lies in a low-dimensional feature subspace, which can be approximated by a low-rank feature matrix. In contrast, the salient part deviating from the low-rank subspace can be viewed as noise or errors, which are represented by a sparse sensory matrix. Therefore, given the feature matrix \( \mathbf{F} \) of an input image, it can be decomposed as a low-rank matrix \( \mathbf{L} \) corresponding to the non-salient background and a sparse matrix \( \mathbf{S} \) corresponding to the salient foreground objects. Salient object detection can then be formulated as a low-rank matrix recovery problem [29]:

\[
\min_{\mathbf{L}, \mathbf{S}} \left\| \mathbf{L} \right\|_s + \lambda \left\| \mathbf{S} \right\|_1 \quad \text{s.t.} \quad \mathbf{F} = \mathbf{L} + \mathbf{S}, \tag{1}
\]

where the nuclear norm \( \left\| \cdot \right\|_s \) (sum of the singular values of a matrix) is a convex relaxation of the matrix rank.
function, $\|\cdot\|_1$ is the $\ell_1$-norm which promotes sparsity, and the parameter $\lambda > 0$ controls the tradeoff between the two items.

Though previous LR-based salient object detection algorithms ([26]–[28]) have produced promising results, there still exist several problems:

- Previous studies do not take into account the inter-correlation between elements in $S$, and thus ignore spatial relations, such as spatial contiguity and pattern consistency, between pixels and patches. Algorithms designed this way may suffer from two limitations: (1) the foreground pixels or patches in the generated saliency map tend to be scattered, as shown in Fig. 1 (LRR and ULR); and (2) the saliency values may be inconsistent within the same object, causing incompleteness of the detected object, as shown in Fig. 1 (LRR, ULR and SLR).
- According to the LR theory (a.k.a robust PCA) [29], the decomposition performance of an observation matrix degrades when there is high coherence between the underlying low-rank and sparse matrices. Therefore, when the background is cluttered or has similar appearance with the salient objects, it is difficult for previous LR-based methods to separate them, as shown in the last two rows of Fig. 1.

To address these issues, we propose a novel structured matrix decomposition (SMD) model that treats the (salient) foreground/background separation as a problem of low-rank and structured-sparse matrix decomposition. We enhance the traditional LR model in Eq. (1) with two important components. First, we introduce a tree-structured sparsity-inducing norm to constrain $S$, so that the spatial connectivity and feature similarity of image patches are taken into account in matrix decomposition. This constraint is essentially a hierarchical group sparsity norm over a tree structure, in which an $\ell_\infty$-norm is employed to enforce within-object patches to share consistent saliency values. Second, we integrate a Laplacian regularization to reduce the coherence between the low-rank and structured-sparse matrices. The regularizer takes into account the geometrical structure of the image, encourages local similar patches to share similar representation, and eventually separates the foreground objects from the background as much as possible. These properties enable the proposed SMD model to detect salient objects in jumbled scenes, even when the salient objects have a similar appearance to the background. In addition, SMD enhances object completeness which is sometimes hard to achieve by previous solutions.

The main contributions of this work are summarized as follows:

- We develop a novel structured matrix decomposition model, i.e., SMD, for salient object detection. Compared to the classical LR model used in [26]–[28], SMD not only captures the underlying structure of data, but also better handles the challenges arising from coherence of the low-rank and sparse matrices. To the best of our knowledge, this is the first work that explicitly pursues the hierarchical structure of data via structured sparsity in matrix decomposition. Based on the alternating sparsity in matrix decomposition. Based on the alternating direction method (ADM) [31], we derive an effective optimization algorithm to solve the proposed SMD model.
- We present an SMD-based salient object detection framework and evaluate the SMD method on five popular benchmarks involving various scenarios such as single object, multiple objects and complex scenes. Also, we compare our method with 24 state-of-the-art methods using six performance metrics, including the traditional measures, e.g., precision-recall curve and mean absolute error, and the recently proposed weighted $F$-measure [32]. In the experiments, our SMD-based algorithm achieves competitive results in comparison with other leading methods.

The remainder of this paper is organized as follows. Sec. 2 reviews existing saliency detection models, especially the LR-based methods. Sec. 3 describes the proposed SMD model and derives the ADM-based solution to the model. Sec. 4 presents the SMD-based salient object detection method and extends it to integrate high-level priors. Sec. 5 shows the experimental results, including a thorough comparison with recently proposed salient object detection algorithms and detailed analysis of the components in our algorithm. Finally, Sec. 6 concludes the paper.

2 Related Work

Recent years have witnessed significant advances in saliency detection that includes two major subfields: eye fixation prediction and salient object detection. Recent surveys on eye fixation prediction can be found in [33]–[35], and salient object detection is surveyed in [36], [37]. In this section, we mainly discuss the algorithms belonging to the second subfield, to which our work belongs. But before that, we briefly review some classical early studies that have paved the way to both subfields.

The foundation of most saliency detection algorithms can be traced back to the theories of center-surround difference [38] and multiple feature integration [39]. The most influential model based on the theories is proposed by Itti et al. [11], who derive saliency from the difference of Gaussians on multiple feature maps. Another early work is by Harel et al. [40] who define a graph on image and adopt random walks to compute saliency. Some learning-based methods [41], [42] are also proposed to predict saliency by combining multiple feature maps. Latter, researchers refine
theories by taking account of local [43], regional [45], and global [46] contrast cues, or by searching for saliency cues in the frequency domain [14], [47].

One of the earliest works on salient object detection is [48], which formulates saliency detection as a binary segmentation problem. Recent studies can be broadly categorized as either bottom-up or top-down. Bottom-up models are bio-inspired and only use low-level image features. The frequency tuning method [49] detects saliency by computing color deviation from the mean image color at the pixel level. Later, an improved solution [7] is proposed to highlight salient objects with respect to their contexts in terms of low-level feature distinction and global spatial relations. The global contrast method [12] identifies salient regions by estimating dissimilarities between Lab color histograms over all image regions. Saliency filters [50] improve the global contrast method [12] by combining color uniqueness and spatial distribution of image regions. Some other bottom-up techniques such as multi-scale modeling [51] and high-dimensional color transformation [17] have been explored for salient object detection. The effectiveness of other complementary cues such as texture [20], depth [52], [53] or surroundedness [54] have also been considered recently.

By contrast, top-down models usually estimate saliency via task-specific learning algorithms or high-level priors. The method in [48] identifies salient objects using a conditional random field (CRF) on a multi-scale contrast histogram and spatial distribution features. The latent variable model in [55] estimates saliency by jointly learning a CRF and a specific dictionary. Instead of direct training on image features, saliency aggregation [56] trains a CRF on saliency maps produced by other methods. The random forest model [57] predicts image saliency by training a regressor on discriminative regional features. Most recently, multiple kernel learning [58] and convolutional neural network [59] techniques have been introduced to learn more robust discrimination between salient and non-salient regions.

High-level priors have also been used in top-down models and proved to be effective. For example, a Gaussian fall-off function is frequently recruited to emphasize the center regions (i.e., center prior), either directly combined with other cues [19], [21], [60], or used as a spatial feature in learning [48], [57]. The prior belief that image boundary regions are more likely to belong to the background (i.e., background prior) is also commonly integrated for saliency computation. A representative work is the geodesic saliency [24], which defines boundary regions as terminal nodes when estimating saliency on an image graph. Alternatively, in [61], [62], boundary regions are used as pseudo-background queries and dictionary templates to facilitate detection. Later, a more robust boundary connectivity prior is introduced in [63]. Besides, the objectness prior, which estimates the likelihood of a region being a complete object [2], has been employed in some other saliency models [18], [64], [65].

Our study is related to recent methods that consider the sparsity prior in salient object detection. The method in [25] adopts an over-complete dictionary to encode image patches and then feed the coding vector to the LR model to recover salient objects. Later, a supervised method [26] is proposed to leverage feature transformation with the high-level center, color and semantic priors to meet the low-rank and sparse properties. To better fit the LR model, the segmentation prior derived from the connectivity between regions and image borders is exploited to guide matrix recovery [28]. As an extension of the LR model, low-rank representation (LRR) [27] introduces a self-representation scheme that reconstructs background regions from the image features themselves rather than by a dictionary. Multi-feature collaborative enhancement and top-down priors obtained from [66] are incorporated into the multi-task extension.

Difference to related LR-based methods. As an LR-based method, our SMD differs from the previous ones [25]–[28] in several aspects. (1) SMD pursues the low matrix rank in a purely unsupervised way, while [25] and [26] respectively resort to supervised sparse representation and feature transformation. The learnt representation or transformation in [25] and [26] is biased toward the training datasets, and therefore suffers from limited adaptability. (2) Our method explicitly encodes information about image structure, i.e., spatial relations and feature similarities of image patches, which are ignored in [25]–[28]. (3) Our method integrates high-level priors into the structured image representation (index tree), while other methods [26], [28] combine such priors by re-weighting the feature.

Discussion with Manifold Ranking (MR) methods. The use of the Laplacian regularization in our method is inspired by, but different from that in the MR algorithm [61]. (1) Our method uses the Laplacian regularization to smooth the feature representation, and to enlarge the difference between foreground objects and background in feature space. By contrast, MR exploits the regularization to enforce continuous saliency values over neighboring patches. (2) MR is built upon the semi-supervised ranking model [67], and defines saliency of an patch as its relevance to the given querying seeds. By contrast, our method uses the low-rank matrix decomposition framework and is purely unsupervised.

Difference to preliminary work. Some preliminary ideas in this paper appeared in the conference version [68]. Compared with [68], the proposed SMD model in this paper is more general, and subsumes the version in [68] as a special case. The new SMD model not only inherits the major advantages of the preliminary model, i.e., it produces a decomposition of an observation matrix into structured parts with respect to image structure, but it is also armed with the new capability to enlarge the separation between salient objects and background in the feature space. The experimental results (Sec. 5) show clearly that the new model is more robust and the resulting saliency maps (Fig. 8) are more visually favorable.

3 Structured Matrix Decomposition Model

3.1 Proposed Model

3.1.1 Basic formulation

Given an input image $I$, it is first partitioned into $N$ non-overlapping patches $P = \{P_1, P_2, \ldots, P_N\}$, e.g., superpixels. For each patch $P_i$, a $D$-dimension feature vector is extracted and denoted as $f_i \in \mathbb{R}^D$. The ensemble of feature vectors forms a matrix representation of $I$, denoted as $F = [f_1, f_2, \ldots, f_N] \in \mathbb{R}^{D \times N}$. The problem of salient object detection is to design an effective model to decompose the feature matrix $F$ into a redundant information part $L$ (i.e.,
non-salient background) and a structured distinctive part $S$ (i.e., salient foreground).

To address the issues discussed in Sec. 1, we propose a novel structured matrix decomposition (SMD) model as follows:

$$
\min_{L, S} \Psi(L) + \alpha \Omega(S) + \beta \Theta(L, S) \quad \text{s.t.} \quad F = L + S, \quad (2)
$$

where $\Psi(\cdot)$ is a low-rank constraint to allow identification of the intrinsic feature subspace of the redundant background patches, $\Omega(\cdot)$ is a structured sparsity regularization to capture the spatial and feature relations of patches in $S$, $\Theta(\cdot, \cdot)$ is an interactive regularization term to enlarge the distance between the subspaces drawn from $L$ and $S$, and $\alpha, \beta$ are positive tradeoff parameters.

3.1.2 Low-rank regularization for image background

Having observed that image patches from the background are often similar and approximately lie in a low-dimensional subspace, we apply low-rank regularization on the background feature matrix $L$ to pursue its intrinsic structure. Since directly minimizing a matrix’s rank with affine constraints is an NP-hard problem [30], we instead adopt the nuclear norm as a convex relaxation, i.e.,

$$
\hat{\Psi}(L) = \text{rank}(L) = \|L\|_* + \varepsilon, \quad (3)
$$

where $\varepsilon$ denotes the relaxation error.

To verify the rationality of the low-rank constraint, we evaluate the rank of feature matrices extracted from image background on five salient object datasets (Fig. 2). Specifically, we first divide each image into a regular grid of patches of size 10 × 10 pixels, excluding those “foreground” patches, which have over 10% pixels from the annotated salient objects. Then, each patch is represented by a feature vector encoding color, edge and texture information (as described in Sec. 4.1). Features from the same image are juxtaposed into a matrix to represent the image background. Finally, we estimate the rank of the feature matrix, denoted by $\hat{r}$, according to [72], [73]:

$$
\hat{r} = \arg \min_r (\text{RMSRE}(r - 1) - \text{RMSRE}(r)) \leq \epsilon, \quad (4)
$$

where RMSRE(r) is the root mean square reconstruction error between the original matrix and its rank-r approximation estimated by the singular value decomposition (SVD), and $\epsilon$ is a threshold with value 0.01. Fig. 2 shows the statistics of such estimated ranks of background feature matrices of the images in the five datasets. It shows that about 90% of these matrices can be approximated by a matrix with rank no greater than 10. This confirms our intuition that the image background usually lies in a low-dimensional subspace. Therefore, it encourages us to exploit a low-rank regularization to eliminate redundant information and pursue the intrinsic low-dimensional structure.

3.1.3 Structured-sparsity regularization for salient objects

In Eq. (1), the $\ell_1$-norm regularization treats the columns in $S$ independently and thus ignores spatial structure information, which can otherwise be used to improve salient object detection (see Fig. 1). In the following, we introduce a novel tree-structured sparsity-inducing norm to model the spatial contiguity and feature similarity among image patches so as to produce more precise and structurally consistent results.

Before detailing the structured regularization, we first give the definition of an index tree [74]. An index tree is a hierarchical structure, such that each node contains a set of indices (e.g., corresponding to the superpixels in our task) and the set is the union of the indices of its children. More specifically, for an index tree $T$ with depth $d$ over indices $\{1, 2, \ldots, N\}$, let $G_j^i$ be the j-th node at the i-th level. In particular, for the root node, we have $G_1^1 = \{1, 2, \ldots, N\}$. The nodes also satisfy two conditions: (1) there is no overlap between the indices of nodes from the same level, i.e., $G_j^i \cap G_k^i = \emptyset, \forall 2 \leq i \leq d$ and $1 \leq j < k \leq n_i$. Here, $n_i$ denotes the total number of nodes at the i-th level. (2) Let $G_j^{i-1}$ be the parent node of a non-root node $G_j^i$, then $G_j^i \subseteq G_j^{i-1}$ and $\bigcup_j G_j^i = G_j^{i-1}$. Fig. 3 shows an example tree with $N = 8$ indexes, drawn from hierarchical segmentation of an image.

We use an index tree $T$ to encode the spatial relation of image patches $P$. Details of index tree construction are postponed to Sec. 4.1. We encode the structurally meaningful tree constraint into a sparsity norm to regularize the matrix decomposition. In this way, we get a general tree-structured sparsity regularization as

$$
\Omega(S) = \sum_i \sum_j n_i \sum_j v_j^i \|S_{G_j^i}\|_p, \quad (5)
$$

where $v_j^i \geq 0$ is the weight for the node $G_j^i$, $S_{G_j^i} \in \mathbb{R}^{d \times |G_j^i|}$ (|\cdot| denotes set cardinality) is the sub-matrix of $S$ corresponding to the node $G_j^i$, and $\|\cdot\|_p$ is the $\ell_p$-norm$^5$, $1 \leq p \leq \infty$. In essence, $\Omega(\cdot)$ is a weighted group sparsity norm defined over a tree structure. It induces the patches within

\footnotetext{1}{For a matrix $A = (a_{ij}) \in \mathbb{R}^{m \times n}$, $\|A\|_p = (\sum_{i=1}^m \sum_{j=1}^n |a_{ij}|^p)^{1/p}$.}
the same group to share a similar representation, and also represents the subordinate or coordinate relations between groups. To enforce the patches from the same group to have identical saliency values, we impose the $\ell_\infty$-norm on $S_{G^j}$, i.e., $p = \infty$. It uses the maximum saliency value of patches within the group $G^j$ to decide whether the group is salient or not [75].

3.1.4 Laplacian regularization

When decomposing the feature matrix $F$ into a low-rank part $L$ plus a structured-sparse part $S$, we also hope to enlarge the distance between the subspaces induced by $L$ and $S$, so as to make it easier to separate the salient object from the background. To this end, we introduce a Laplacian regularization based on the local invariance assumption [76]: if two adjacent image patches are similar with respect to their features, their representations should be close to each other in the subspace, and vice versa. Thus motivated, we define the regularization as

$$\Theta(L, S) = \frac{1}{2} \sum_{i,j=1}^{N} \|s_i - s_j\|^2 w_{i,j} = \text{Tr}(SMFST),$$

where $s_i$ denotes the $i$-th column of $S$, $w_{i,j}$ is the $(i, j)$-th entry of an affinity matrix $W = (w_{i,j}) \in \mathbb{R}^{N \times N}$ and represents the feature similarity of patches $(P_i, P_j)$. $\text{Tr}(\cdot)$ denotes the trace of a matrix, and $M_F \in \mathbb{R}^{N \times N}$ is a Laplacian matrix. Specifically, the affinity matrix $W$ is defined as

$$w_{i,j} = \exp\left(-\frac{d_{ij}}{2\sigma^2}\right), \quad \text{if } (P_i, P_j) \in \mathcal{V},$$
$$= 0, \quad \text{otherwise},$$

where $\mathcal{V}$ denotes the set of adjacent patch pairs which are either neighbors (first-order) or "neighbors of neighbors" (second-order reachable) on the image. The $(i, j)$-th entry of the Laplacian matrix $M_F$ is

$$(M_F)_{i,j} = \begin{cases} -w_{i,j}, & \text{if } i \neq j, \\ \sum_{j \neq i} w_{i,j}, & \text{otherwise}. \end{cases}$$

It is interesting to find that the Laplacian regularization in Eq. (6) is explicitly related with $F$ and $S$, and can be transferred to be related with $L$ and $S$ according to $\Theta(F, S) = \Theta(L + S, S) = \Theta(L, S)$. Essentially, the Laplacian regularization increases the distance between feature subspaces by smoothing the vectors in $S$ according to the local neighborhood derived from the feature matrix $F$. It encourages patches within the same semantic region to share similar or identical representation, and patches from heterogeneous regions to have different representation. Fig. 4 shows the pairwise similarity of the elements in $F$ and $S$ before and after imposing the Laplacian regularization. It shows that a more distinct block affinity matrix is produced by using the regularization.

3.2 Optimization

Considering the balance between efficiency and accuracy in practice, we resort to the alternating direction method (ADM) [31] to solve the convex problem defined in Eq. (2). We first introduce an auxiliary variable $H$ to make the objective function separable, i.e., Eq. (2) becomes

$$\min_{L, S} \|L\|_* + \alpha \sum_{i=1}^{d} \sum_{j=1}^{n_i} v_j^i \|S_{G^j}\|_p + \beta \text{Tr}(HM_FHT)$$

s.t. $F = L + S$, $S = H$.

Then, the problem (9) can be solved with ADM, which minimizes the following augmented Lagrangian function $L$:

$$L(L, S, H, Y_1, Y_2, \mu) = \|L\|_*$$
$$+ \alpha \sum_{i=1}^{d} \sum_{j=1}^{n_i} v_j^i \|S_{G^j}\|_p + \beta \text{Tr}(HM_FHT)$$
$$+ \text{Tr}(Y_1^T(F - L - S)) + \text{Tr}(Y_2^T(S - H))$$
$$+ \frac{\mu}{2} \left( \|F - L - S\|_F^2 + \|S - H\|_F^2 \right),$$

where $Y_1$ and $Y_2$ are the Lagrange multipliers, and $\mu > 0$ controls the penalty for violating the linear constraints. To solve Eq. (10), we search for the optimal $L$, $S$ and $H$ iteratively, and in each iteration the three components are updated alternately. We outline the optimization procedure in Algorithm 1 and call it ADM-SMD. In the following, we provide the details for each iteration.

**Algorithm 1 ADM-SMD.**

**Input:** Feature matrix $F$, parameters $\alpha, \beta$, index tree $T = \{G^j\}$ and tree node weight $v_j^i$ (default as 1).

**Output:** $L$ and $S$.

1: Initialize $L^0 = 0$, $S^0 = 0$, $H^0 = 0$, $Y_1^0 = 0$, $Y_2^0 = 0$, $\mu = 0.1$, $\mu_{\text{max}} = 10^{10}$, $\rho = 1.1$, and $k = 0$.
2: While not converged do
3: $L^{k+1} = \arg \min_L L \in L \{L_{k+1}, S^k, H^k, Y_1^k, Y_2^k, \mu_k\}$
4: $H^{k+1} = \arg \min_H H \in H \{L^{k+1}, S^k, H^k, Y_1^k, Y_2^k, \mu_k\}$
5: $S^{k+1} = \arg \min_S S \in S \{L^{k+1}, S^k, H^{k+1}, Y_1^k, Y_2^k, \mu_k\}$
6: $Y_1^{k+1} = Y_2^k + \mu_k (F - L^{k+1} - S^{k+1})$
7: $Y_2^{k+1} = Y_2^k + \mu_k (S^{k+1} - H^{k+1})$
8: $\mu^{k+1} = \min (\rho \mu^k, \mu_{\text{max}})$
9: $k = k + 1$
10: End While
11: Return $L^k$ and $S^k$. 

$\mathbf{F}$. It encourages patches within the same semantic region to share similar or identical representation, and patches from heterogeneous regions to have different representation.
problem:
\[
L^{k+1} = \arg \min_L L(L, S^k, H^k, Y^k, Y^k_2, \mu^k)
\]
\[
= \arg \min_L \|L\|_* + \operatorname{Tr}((Y^k_1)^T (F - L - S^k))
\]
\[
+ \frac{\mu^k}{2} \|F - L - S^k\|_F^2
\]
(11)

where \(\tau = 1/\mu^k\) and \(X_L = F - S^k + Y^k_1/\mu^k\). The solution to Eq. (11) can be derived as
\[
L^{k+1} = U_T [\Sigma] V_T^T,
\]
(12)

Note that \(\Sigma\) is the singular value matrix of \(X_L\). The operator \(T_\tau[\cdot]\) is the singular value thresholding (SVT) [77] defined by element-wise \(\tau\) thresholding of \(\Sigma\). Specifically, let \(\sigma_i\) be the \(i\)-th diagonal element of \(\Sigma\), then \(T_\tau[\Sigma]\) is a diagonal matrix defined as
\[
T_\tau[\Sigma] = \text{diag}(\{(\sigma_i - \tau)_+\}),
\]
(13)

where \(a_+\) is the positive part of \(a\), namely, \(a_+ = \max(0, a)\).

**Updating H:** When \(L\) and \(S\) are fixed, to update \(H^{k+1}\), we derive from Eq. (10) the following problem:
\[
H^{k+1} = \arg \min_H \|H\|_2^2 + \alpha \operatorname{Tr}(H M_F H^T) + \beta \operatorname{Tr}((Y^k_2)^T (S^k - H))
\]
\[
+ \frac{\mu^k}{2} \|S^k - H\|_F^2
\]
(14)

Taking derivative of the objective function in Eq. (14) (the detailed derivation is presented in Appendix A), we have
\[
H^{k+1} = (\mu^k S^k + Y^k_2) (2\beta M_F + \mu^k I)^{-1}.
\]
(15)

**Updating S:** To update \(S^{k+1}\) with fixed \(L\) and \(H\), we get the following tree-structured sparsity optimization problem:
\[
S^{k+1} = \arg \min_S L(L^{k+1}, S, H^{k+1}, Y^k, Y^k_2, \mu^k)
\]
\[
= \arg \min_S \alpha \sum_{i=1}^d \sum_{j=1}^{n_i} v_j^i \|S_{G_j}^i\|_p
\]
\[
+ \operatorname{Tr}((Y^k_1)^T (F - L^{k+1} - S)) + \operatorname{Tr}((Y^k_2)^T (S - H^{k+1}))
\]
\[
+ \frac{\mu^k}{2} \||F - L^{k+1} - S||_F^2 + \|S - H^{k+1}\|_F^2
\]
(16)
\[
= \arg \min_S \lambda \sum_{i=1}^d \sum_{j=1}^{n_i} v_j^i \|S_{G_j}^i\|_p + \frac{1}{2} \|S - X_S\|_F^2
\]

where \(\lambda = \alpha/(2\mu^k)\) and \(X_S = (F - L^{k+1} + H^{k+1} + (Y^k_1 - Y^k_2)/\mu^k)/2\). The above problem can be solved by the hierarchical proximal operator [78], which computes a particular sequence of residuals obtained by projecting a matrix onto the unit ball of dual \(\ell_2\)-norm. The detailed procedure when using \(\ell_\infty\)-norm is presented in Algorithm 2.

### 4 SMD-based Salient Object Detection

In this section, we describe our salient object detection algorithm that uses the proposed SMD model. Our algorithm includes two major parts: the first one focuses on low-level features, while the second one incorporates high-level prior knowledge. Fig. 5 shows the framework of SMD-based salient object detection.

#### 4.1 Low-level Salient Object Detection

Our framework for low-level salient object detection consists of four steps: image abstraction, index tree construction, matrix decomposition and saliency assignment.

**Step 1: Image Abstraction.** In this step, an input image is partitioned into compact and perceptually homogenous elements. Following [26], we first extract the low-level features, including RGB color, steerable pyramids [79] and Gabor filter [80], to construct a 53-dimension feature representation. Then, we perform the simple linear iterative clustering (SLIC) algorithm [81] to over-segment the image into \(N\) atom patches (superpixels) \(P = \{P_1, P_2, \ldots, P_N\}\). Each patch \(P_i\) is represented by a feature vector \(f_i\), and all these feature vectors form the feature matrix as \(F = [f_1, f_2, \ldots, f_N] \in \mathbb{R}^{D \times N}\) (here \(D = 53\)).

**Step 2: Tree Construction.** On top of \(P\), an index tree \(T\) is constructed to encode structure information via hierarchical segmentation. To this end, we first compute the affinity of every adjacent patch pair using Eq. (7). Then, we apply a graph-based image segmentation algorithm [82] to merge spatially neighboring patches according to their affinity. The algorithm produces a sequence of granularity-increasing segmentations. In each granularity layer, the segments correspond to the nodes at the corresponding layer in the index tree. Specifically, the granularity is controlled by an affinity threshold \(T\). Finally, we obtain a hierarchical fine-to-coarse segmentation of the input image. Fig. 6 shows a visualized example of hierarchical segmentation, corresponding to a five-layer index tree structure.

**Step 3: Matrix Decomposition.** When both the feature matrix \(F\) and the index tree \(T\) are ready, we apply the proposed SMD model, formulated as Eq. (2) with \(\ell_\infty\)-norm, to decompose \(F\) into a low-rank component \(L\) and a structured-sparseness component \(S\). As shown in Step 3 of Fig. 5, after jointly imposing the structured-sparsity and Laplacian regularization, the input feature matrix \(F\) is decomposed into structured components \(L\) and \(S\).

**Step 4: Saliency Assignment.** After decomposing \(F\), we transfer the results from the feature domain to the spatial domain for saliency estimation. Based on the structured matrix \(S\), we define a straightforward saliency estimation function \(\text{Sal}(\cdot)\) of each patch in \(P\):
\[
\text{Sal}(P_i) = \|S_i\|_1,
\]
where \(s_i\) represents the \(i\)-th column of \(S\). A large \(\text{Sal}(P_i)\) means a high possibility that \(P_i\) belongs to a salient object.
After merging all patches together and performing context-based propagation (section 3.2 in [62]), we get the final saliency map of the input image.

### 4.2 Integrate High-level Priors

We further extend the proposed SMD-based saliency detection to integrate high-level priors. Inspired by the work of Shen and Wu [26], we fuse three types of priors, i.e., location, color and background priors, to generate a high-level prior map. Specifically, the location prior is generated by a Gaussian distribution based on the distances of the pixels from the image center. The color prior used here is the same as [26], which measures human eye sensitivity to red and yellow color. The background prior calculates the probabilities of image regions connected to image boundaries [63]. These three priors are finally multiplied together to produce the high-level prior map (see Fig. 5).

For each patch \( P_i \in \mathcal{P} \), its high-level prior, \( \pi_i \in [0, 1] \), indicates the likelihood that \( P_i \) belongs to a salient object based on high-level information. This prior is encoded into the SMD by weighting each component in the tree-structured sparsity-inducing norm differently. In particular, we define \( v_j \) as

\[
    v_j = 1 - \max \{ \pi_k : k \in G_j \} .
\]

Eq. (18) essentially boosts the saliency value of nodes with high prior values by associating them with small penalties \( v_j \). This way, the high-level prior knowledge is seamlessly encoded into the SMD model to guide the matrix decomposition and enhance the saliency detection. It is worth noting that if we fix \( v_j = 1 \) for each node \( G_j \), the proposed model is degraded to the pure low-level saliency detection model.

### 5 Experiment

To fully evaluate our algorithm, we conduct a series of experiments using five benchmark datasets involving various scenarios and include 24 recent solutions for comparison.

#### 5.1 Experimental Setup

##### 5.1.1 Datasets

We use five popular benchmark datasets to cover different scenarios. In particular, we use MSRA10K [69] and DUT-OMRON [61] for images with a single salient object, iCoSeg [71] and SOD [70] for cases with multiple salient objects, and ECSSD [21] for images with complex scenes. The size and detailed characteristic of these benchmark datasets are presented in Tab. 1.

<table>
<thead>
<tr>
<th>Name</th>
<th>Size</th>
<th>Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSRA10K</td>
<td>10,000</td>
<td>single object, collected from MSRA [48], simple background, high contrast</td>
</tr>
<tr>
<td>DUT-OMRON</td>
<td>[61]</td>
<td>5,168 single object, relatively complex background, more challenging</td>
</tr>
<tr>
<td>iCoSeg</td>
<td>643</td>
<td>multiple objects, various number of objects with different sizes</td>
</tr>
<tr>
<td>SOD</td>
<td>300</td>
<td>multiple objects, various size and location of objects, complex background</td>
</tr>
<tr>
<td>ECSSD</td>
<td>1,000</td>
<td>structurally complex natural images, various object categories</td>
</tr>
</tbody>
</table>

#### 5.1.2 Salient object detection algorithms

The proposed salient object detection algorithm is compared with 24 state-of-the-art solutions, including three LR-based methods (ULR [26], LRR [27] and SLR [28]), four methods ranked the highest according to the survey in [36] (SVO [18], CA [7], CB [19] and RC [12]), and 17 recently developed prominent methods (RBD [63], HCT [17], DSR [62], MC [83], GC [23], DRFI [57], PCA [22], HS [21], TD [20], MR [61], GS [24], SF [50], SS [15], SEG [13], FT [49], LC [16] and SR [14]). Tab. 2 summarizes all the algorithms involved in our experiments.

#### 5.1.3 Parameter settings

The parameters in the implementation of the proposed SMD detector are set as follows. In image abstraction, we set the number of patches \( N \) to 200. In tree construction, we set the affinity thresholds as \( T = [100, 400, 2000] \), producing three granularity-increasing segmentations. By adding the initial over-segmentation and the whole image, we build up a five-layer index tree. In matrix decomposition, we empirically...
set the bandwidth parameter $\delta^2$ to 0.05, and the model parameters $\alpha$ and $\beta$ to 0.35 and 1.1 respectively.

To retain a fair comparison with competing methods, we fix the parameters of our model for all the experiments. It is worth noting that by tuning the parameters on the datasets, our model still has some potential to be improved, as presented in Appendix B. For other algorithms in our comparison, we use the source or binary codes provided by the authors with default parameters. The source code of our method and all experimental results are publicly available at http://www.dabi.temple.edu/~hbling/SMD/SMD_Saliency.html. Our code is implemented in mixed C++ and Matlab, and its average runtime is 1.217 seconds per image on MSRA10K using a PC of 3.4 GHz and 4GB RAM, with only a single thread used.

### 5.1.4 Evaluation metrics
For comprehensive evaluation, we use seven metrics including the precision-recall (PR) curve, the F-measure curve, the receiver operating characteristic (ROC) curve, area under the ROC curve (AUC), mean absolute error (MAE), overlapping ratio (OR) and the weighted F-measure (WF) score.

Precision is defined as the percentage of salient pixels correctly assigned, while recall is the ratio of correctly detected salient pixels to all true salient pixels. F-measure is a weighted harmonic mean of precision ($P$) and recall ($R$): $F_\beta = (1 + \beta^2)P \cdot R / (\beta^2 P + R)$, where $\beta^2$ is set to 0.3 to stress precision more than recall [49]. The PR and F-measure curves are created by varying the saliency threshold that determines whether a pixel belongs to the salient object. The ROC curve is generated from true positive rates and false positive rates which are obtained when we calculate the PR curve.

The terms Sp, Ce, Co, Bg and Ob represent sparsity, center, color and objectness priors, respectively.

### 5.2 Comparison with State-of-the-Arts
The proposed SMD algorithm is evaluated on the five benchmark datasets and compared with 24 recently proposed algorithms. The results are summarized in Tab. 3 and Fig. 7. Besides, Fig. 8 shows some qualitative comparisons.

The results show that, in most cases, SMD ranks first or second on the five benchmark datasets across different criteria. It is worth noting that, although DRFI [57] is the best performing method, it is a supervised one requiring a large amount of training. In contrast, our method is an unsupervised one, which skips the training process and therefore enjoys more flexibility.

#### 5.2.1 Results on single-object images
The test on images with a single object is conducted on the MSRA10K [69] and DUT-OMRON [61] datasets. The PR and F-measure curves are shown in Fig. 7(A and B), and the WF, OR and MAE scores in Tab. 3(A and B).

On MSRA10K (Tab. 3(A)), SMD achieves the best performance in terms of WF, OR and MAE, while DRFI [57] obtains the best AUC score. In the PR curves (Fig. 7(A)), DRFI [57] and SMD are the best two among those competitive methods. In the F-measure curves, SMD is superior, as it achieves relatively good results over a large range.

On DUT-OMRON (Tab. 3(B)), all the methods perform worse than on MSRA10K due to the large diversity and complexity of DUT-OMRON. SMD performs the second best in terms of WF and OR, with a very minor margin (0.003) to the best results. The best MAE and AUC scores are achieved by DRFI [57]. This is because DRFI takes advantage of multi-level saliency maps fusion to improve its robustness. The fusion strategy is effective and general, as discussed in Appendix C. In the PR curves (Fig. 7(B)), the precision of SMD is less impressive at low recall rates, but it is competitive at the high recall rates. In terms of F-measure, SMD obtains relatively superior performance, especially when segmenting saliency maps with high thresholds.

#### 5.2.2 Results on multiple-object images
Experiments on images with multiple salient objects are conducted on iCoSeg [71] and SOD [70]. The PR and F-measure curves are shown in Fig. 7(C and D), and the WF, OR, AUC and MAE scores in Tab. 3(C and D).

On iCoSeg (Tab. 3(C)), SMD achieves the best performance in terms of WF, OR and MAE. The AUC score of SMD is a little lower than the best, achieved by DRFI [57]. Fig. 7(C) shows that the PR and F-measure curves of SMD are superior or comparable to other methods. In particular, SMD’s F-measure remains high over a wide range, indicating its insensitivity to the selection of a threshold.

On SOD (Tab. 3(D)), SMD performs the best in terms of WF, the second in OR and third in MAE. The PR of SMD...
### 5.2.3 Results on complex scene images

Our last comparison with the competing methods is conducted on ECSSD [21], which is known to involve complex scenes. As reported in Tab. 3(E), SMD obtains the best performance in terms of WF, the second or third best in OR, AUC and MAE. According to Fig. 7(E), the PR curve of SMD is the second best among those methods, while the area under the F-measure curve is the best. These results validate SMD’s strong potential in handling images with complex scenes.

#### 5.2.4 Visual comparison

Fig. 8 shows some visual comparisons of the best methods in the experiments. For single-object images, SMD accurately extracts the entire salient object with few scattered patches, and assigns nearly uniform saliency values to all patches within the salient objects. For images with multiple objects, some methods (e.g., SLR [28], ULR [26] and MR [61]) miss detecting parts of the objects, while some (e.g., HS [21] and HCT [17]) incorrectly include background regions into detection results. By contrast, SMD pops out all the salient objects successfully. For the images with complex scenes, most methods fail to identify the salient objects, while SMD locates them with decent accuracy. Finally, for the images whose foreground and background share similar appearance, SMD successfully separates the salient objects from the background, while other methods often fail. These results illustrate the robustness of the SMD algorithm, and confirm the effectiveness of the proposed structural constraints in separating the coherent low-rank and sparse subspaces.

#### 5.3 Experimental Analysis of the Proposed Method

##### 5.3.1 Analysis of components in the proposed model

To further understand the effects of the components in the proposed SMD algorithm, we test four variations of SMD on the MSRA10K dataset. In particular, each variation is slightly lower than that of DRFI [57], but better than the others. In the F-measure curves, SMD performs the best at higher threshold ranges, while DRFI performs the best at lower ranges. Both are consistently superior to the others.

<table>
<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>WF↑</td>
<td>0.704</td>
<td>0.666</td>
<td>0.685</td>
<td>0.582</td>
<td>0.656</td>
<td>0.576</td>
<td>0.642</td>
<td>0.604</td>
<td>0.473</td>
<td>0.561</td>
<td>0.612</td>
<td>0.584</td>
<td>0.339</td>
</tr>
<tr>
<td>OR↑</td>
<td>0.741</td>
<td>0.723</td>
<td>0.716</td>
<td>0.674</td>
<td>0.654</td>
<td>0.694</td>
<td>0.693</td>
<td>0.656</td>
<td>0.576</td>
<td>0.605</td>
<td>0.599</td>
<td>0.434</td>
<td>0.245</td>
</tr>
<tr>
<td>AUC↑</td>
<td>0.547</td>
<td>0.657</td>
<td>0.834</td>
<td>0.847</td>
<td>0.825</td>
<td>0.843</td>
<td>0.824</td>
<td>0.833</td>
<td>0.839</td>
<td>0.815</td>
<td>0.788</td>
<td>0.833</td>
<td>0.644</td>
</tr>
<tr>
<td>MAE↓</td>
<td>0.104</td>
<td>0.214</td>
<td>0.128</td>
<td>0.128</td>
<td>0.128</td>
<td>0.128</td>
<td>0.128</td>
<td>0.128</td>
<td>0.128</td>
<td>0.128</td>
<td>0.128</td>
<td>0.128</td>
<td>0.128</td>
</tr>
</tbody>
</table>

1 The up-arrow ↑ indicates the larger value achieved, the better performance is, while the down-arrow ↓ indicates the smaller, the better.
2 The best three results are highlighted with red, green and blue fonts, respectively.

![Table 3: Results on five datasets in terms of WF, OR, AUC and MAE.](table3.png)
corresponds to an objective function listed in Table 4, and parameters for each model are tuned separately to obtain optimal results. Furthermore, only low-level features are used to avoid the influence of high-level prior knowledge.

The quantitative results are shown in Fig. 9(left and middle), leading to the following observations. (1) By comparing LR-$\ell_1$ with LR-Tree$_1$, we see that encoding tree-structure information gives in average improvement of 4.69% (precision) and 2.76% (true positive rate) over the plain $\ell_1$-norm.

![Fig. 7. Quantitative comparison on five datasets in terms of PR and F-measure curves.](image)

We further analyze the underlying reasons for the above observed improvements by comparing the saliency maps. As shown in Fig. 11, we observe that: (1) The salient regions identified by LR-Tree$_1$ tend to be connected, whereas the regions identified by LR-$\ell_1$ tend to be scattered. This shows that the tree-structured constraint guides matrix decomposition along a structurally meaningful direction. (2) The $\ell_\infty$-norm embedding in the structured sparsity $s$-lightly improves the $\ell_1$-norm (comparing LR-Tree$_1$ and LR-Tree$_\infty$). (3) The use of the Laplacian regularization significantly improves the LR-Tree$_\infty$ model. These observations indicate that the introduced regularizers are effective and complementary, and, when combined together, lead to excellent performance as reported in the previous subsection.

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### Table 4

<table>
<thead>
<tr>
<th>Model</th>
<th>Objective Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>LR-$\ell_1$</td>
<td>$\min_{L,G} |L|_1 + \alpha |S|_1$</td>
</tr>
<tr>
<td>LR-Tree$_1$</td>
<td>$\min_{L,G} |L|<em>1 + \alpha \sum</em>{G \in T} |S_G|_1$</td>
</tr>
<tr>
<td>LR-Tree$_\infty$</td>
<td>$\min_{L,G} |L|<em>1 + \alpha \sum</em>{G \in T} |S_G|_\infty + \beta \text{Tr}(SMFS^T)$</td>
</tr>
<tr>
<td>SMD</td>
<td>$\min_{L,G} |L|<em>1 + \alpha \sum</em>{G \in T} |S_G|_\infty + \beta \text{Tr}(SMFS^T)$</td>
</tr>
</tbody>
</table>
same group to share identical values. (3) The final SMD model produces foreground-background separated maps, whose saliency values are consistent within regions. This is attributed to Laplacian regularization. To make this point clear, we introduce a metric (Sec. 3.2.2 of [84]) to compute the projection distance $d(L,S)$ between the feature subspaces of salient objects ($S$) and background ($L$): 

$$d(L,S) = \|LL^T - SS^T\|_F^2.$$ 

By evaluating the change of $d(L,S)$ before and after imposing the Laplacian regularization, we observe that the projection distance $d(L,S)$ is significantly enlarged, as shown in Fig. 9(right). It shows that the Laplacian regularization boosts the gap between foreground and background.

5.3.2 Analysis of parameters and implementation details

We also analyze the sensitivity of our model to changes of the main parameters $\alpha$ and $\beta$. The analysis is conducted by fixing one parameter and tuning the other on MSRA10K. The performance changes are shown in Fig. 12. We observe that, when $\beta$ is fixed ($\beta = 1.1$), the WF performance initially increases, spikes within a range of $\alpha$ from 0.2 to 0.5, and then decreases. When fixing $\alpha$ to be 0.35 and increasing $\beta$, the performance rapidly increases as $\beta$ approaches 0.6, and then flattens when $\beta$ crosses 0.8. These observations indicate that our model has only a small sensitivity to changes of the parameters. It works well under a large range of parameter settings, such as $\alpha$ ranging from 0.25 to 0.5, and $\beta$ ranging from 0.8 to 1.2.

To further analyze the proposed method, we evaluate the effects of some implementation details on the performance. We conduct an comparison experiment to evaluate whether more complex features can affect the model. Specifically, we replace the original 53-dimensional color, edge and texture features with the 93-dimensional discriminative regional features used in DRFI [57], and perform SMD in the same setting. From the experimental results shown in Appendix D, we observe that the complex features perform comparable or slightly superior to the original low-lever features (comparing SMD_regFeat and SMD). It tells us that, to some extend, our method is robust to features. We also evaluate different saliency assignment functions and analyze the effects of the context-based propagation used in our method. The detailed experimental results and analysis are presented
complementary to the low-rank regularization in matrix
the structured-sparsity and Laplacian regularizations are
calculated over the ground truth (GT). This implies that
LR methods, and their rank distribution is similar to that
estimated by SMD achieve the lowest ranks among all the
in Fig. 10 (rightmost). The results show that the matrices
L
achieves the best performance over all metrics. It indicates
models are improved as validated in Fig. 10. SMD again
In particular, the improvement of SMD over ULR [26] in-
tently outperforms other LR-based methods in all metrics.
We proceed to compare the proposed SMD method with
5.3.3 Comparison with LR-based methods
Fig. 11. Saliency maps produced by variations of the SMD model.
in Appendix E and F.

5.3.3 Comparison with LR-based methods
We proceed to compare the proposed SMD method with
other LR-based saliency detection methods on MSRA10K
under two conditions: with and without high-level priors.
In the case of pure low-level saliency detection (i.e.,
without high-level priors), Fig. 10 shows that SMD consist-
tently outperforms other LR-based methods in all metrics.
In particular, the improvement of SMD over ULR [26] in-
dicates that the integration of image structure information
is superior to the learnt feature transformation in matrix
decomposition.

When taking high-level priors into account, all the LR
models are improved as validated in Fig. 10. SMD again
achieves the best performance over all metrics. It indicates
that both the structured regularization and high-level priors
are beneficial for salient object detection.

Last, rank statistics of the background feature matrix
L
are collected for the above LR methods, as summarized
in Fig. 10 (rightmost). The results show that the matrices
estimated by SMD achieve the lowest ranks among all the
LR methods, and their rank distribution is similar to that
calculated over the ground truth (GT). This implies that
the structured-sparsity and Laplacian regularizations are
complementary to the low-rank regularization in matrix
decomposition for estimating the intrinsic rank of image
features.

5.3.4 Failure cases
Our method exploits the low-rank regularization to recover
image background, therefore it may be difficult to suppress
some small background regions with distinctive appear-
ances, as shown in Fig. 13. The underlying reason is that
the feature vectors of those regions are not in the low-
dimensional subspace and may be incorrectly highlighted
as foreground. Besides, for the salient objects with partial
occlusion (see the third column in Fig. 13), SMD fails to con-
sistently highlight the salient object because the constructed
index-tree is not precise enough. Exploring more effective
region grouping methods, such as [85], may alleviate this
problem.

6 Conclusion
In this paper, we have presented a structured matrix decom-
position (SMD) model, which formulates the task of salient
object detection as a problem of low-rank and structured-
sparse matrix decomposition. A hierarchical tree-structured
sparsity-inducing norm has been proposed to encode the
underlying structure of the image in the feature space, while
a Laplacian regularization has been introduced to enlarge
the distance between the representation of salient objects
and that of the background. High-level prior knowledge has
also been integrated into the model to enhance the detection.
Experiments on five public datasets have shown that our
model achieves encouraging performance compared to the
state-of-the-art methods.
For future work, we will consider integrating metric learning or discriminative analysis to explicitly separate the low-rank and structured-sparse matrices in terms of regional difference. In addition, the exploration of more robust and general high-level priors may merit further study.

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Fig. 13. Some failure cases of our method.