Robust Structured Group Local Sparse Tracker Using Convolutional Neural Network Features

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Introduction

➢ Tracking
   – Following a specific target throughout consecutive frames to determine its relative movement with respect to other objects.
Introduction

➢ Challenges
  – Deformation
  – Moving Camera
  – Scale Variation
  – Occlusion
  – Illumination Variation
  – Fast Motion
  – Background Clutter
  – …
Introduction

- Challenges
  - Deformation
  - Moving Camera
  - Scale Variation
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  - Illumination Variation
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  - ...

4
Introduction

- Challenges
  - Deformation
  - Moving Camera
  - Scale Variation
  - Occlusion
  - Illumination Variation
  - Fast Motion
  - Background Clutters
  - …
Introduction

- Applications:
  - Surveillance
  - Human motion analysis
  - Transportation
  - Navigation
  - …
Introduction

➤ Literature Review
  – Tracking algorithms can be classified into following categories:
    – Discriminative:
      – They formulate a decision boundary to separate the target from the background [1,2]
    – Generative:
      – They adopt a model to represent the target and formulate the tracking as a model-based searching procedure to find the most similar region to the target [4,5]
    – Correlation filter
      – They regress all the circular shift of the input features to a target Gaussian function in the Fourier domain [6,7]
    – Convolutional Neural Network
      – They use pre-trained network and/or train a new model for better feature representation [8,9].
Proposed method

- Motivation

- We propose a robust deep features-based structured group local sparse tracker (DF-SGLST), which exploits the convolutional neural network (CNN) deep features of the local patches inside a target candidate and represent them in a novel convex optimization model.
Proposed method

Contributions of the proposed DF-SGLST

- Proposing a deep features-based structured local sparse tracker, which employs CNN deep features of the local patches within a target candidate and attains the spatial structure among the features of local patches inside a target candidate.
- Developing a convex optimization model, which introduces a group-sparsity regularization term to encourage the tracker to sparsely select the corresponding local patches of the same subset of templates to represent the CNN deep features of local patches of each target candidate.
- Designing a fast and parallel numerical algorithm based on the alternating direction method of multiplier (ADMM), which consists of two subproblems with closed-form solutions to efficiently and quickly solve the optimization model.
Proposed method
Proposed method
Proposed method
Proposed method
Proposed method

Pre-Trained VGG19

Templates: k

28 28 512
Proposed method

Pre-Trained VGG19

Conv5-4

Up-sample
Proposed method

Local Feature Extraction

Pre-Trained VGG19

Local Patch: \( l \)

Templates: \( k \)

14×14×512

\[ 28 \times 28 \times 512 \]
Proposed method
Proposed method

Pre-Trained VGG19

Templates: $k$
Proposed method
Proposed method

Pre-Trained VGG19

Templates: k

28 28 512

28 512

#1

#2
Proposed method

#1

#2

Pre-Trained VGG19

Templates: k

28 28 512

28 512

28 28 512
Proposed method

Pre-Trained VGG19

Templates: $k$

28
512

28
512
Proposed method
Proposed method
Proposed method

Pre-Trained VGG19
Proposed method

\[ D = [D_1, \ldots, D_k] \in \mathbb{R}^{d \times (lk)} \]

Pre-Trained VGG19

Local Feature Extraction

PCA

Local Patch: \( l \)

Templates: \( k \)

Templates: \( k \)
Proposed method

\[ D = [D_1, \ldots, D_k] \in \mathbb{R}^{d \times (lk)} \]

Pre-Trained VGG19

Local Feature Extraction

Local Patch: \( l \)

PCA
Proposed method

\[ D = [D_1, \ldots, D_k] \in \mathbb{R}^{d \times (lk)} \]

Pre-Trained VGG19

Local Feature Extraction

Local Patch: \( l \)

PCA

[Diagram showing the flow of data processing with arrows and boxes labeled Pre-Trained VGG19, PCA, and Local Feature Extraction.]

\[ \text{Local Feature Extraction} \]

\[ \text{Templates: } k \]

\[ \text{Local Patch: } l \]
Proposed method

\[
D = [D_1, \ldots, D_k] \in \mathbb{R}^{d \times (lk)}
\]

\[
X = [X_1, \ldots, X_n] \in \mathbb{R}^{d \times (ln)}
\]
Proposed method

\[ D = [D_1, \ldots, D_k] \in \mathbb{R}^{d \times (lk)} \]

\[ X = [X_1, \ldots, X_n] \in \mathbb{R}^{d \times (ln)} \]

\[ \min_{C \in \mathbb{R}^{(lk) \times l}} \| X_j - DC \|_F^2 + \lambda \| [C_1(\cdot) \ldots C_k(\cdot)]^T \|_{1,\infty} \]

subject to \( C \geq 0 \), \( \text{(1b)} \)

\( 1_{lk}^T C = 1_l^T \), \( \text{(1c)} \)
Proposed method-Numerical Method

\[
\begin{align*}
\text{minimize} & \quad \|X_j - DC\|_F^2 + \lambda \| [C_1(\cdot) \ldots C_k(\cdot)]^T \|_{1,\infty} \\
\text{subject to} & \quad C \geq 0, \\
& \quad 1_{\text{tr}}^T C = 1_{\text{tr}}^T, \\
& \quad 1_{\text{tr}}^T C = 1_{\text{tr}}^T,
\end{align*}
\]
Proposed method - Numerical Method

\[
\begin{align*}
\text{minimize} \quad & \|X_j - DC\|_F^2 + \lambda \left\| \left[ C_1(\cdot) \ldots C_k(\cdot) \right]^T \right\|_{1,\infty} \\
\text{subject to} \quad & C \geq 0, \quad \text{(1a)} \\
& I_{1k}^T C = I_f^T, \quad \text{(1c)} \\
\end{align*}
\]

\[
\begin{align*}
\text{minimize} \quad & \|X_j - DC\|_F^2 + \lambda I_k^T m \\
\text{subject to} \quad & C \geq 0, \quad \text{(2a)} \\
& I_{1k}^T C = I_f^T, \quad \text{(2c)} \\
& m \odot I_kI_f^T \geq C. \quad \text{(2d)}
\end{align*}
\]
Proposed method - Numerical Method

\[
\begin{align*}
\text{minimize} \quad & \|X_J - DC\|_F^2 + \lambda \left\| [C_1(\cdot) \ldots C_k(\cdot)]^T \right\|_{1,\infty} \\
\text{subject to} \quad & C \geq 0, \quad I_{1k}^T C = I_1^T, \\
& 1_{1k}^T C = 1_1^T,
\end{align*}
\]  

(1a)  

(1b)  

(1c)

\[
\begin{align*}
\text{minimize} \quad & \|X_J - DC\|_F^2 + \lambda I_k^T m \\
\text{subject to} \quad & C \geq 0, \quad I_{1k}^T C = I_1^T, \\
& m \otimes I_1^T \geq C.
\end{align*}
\]  

(2a)  

(2b)  

(2c)  

(2d)

\[
\begin{align*}
\text{minimize} \quad & \|X_J - DC\|_F^2 + \lambda I_k^T m \\
\text{subject to} \quad & C \geq 0, \quad I_{1k}^T C = I_1^T, \\
& m \otimes I_1^T = C + U, \\
& U \geq 0.
\end{align*}
\]  

(3a)  

(3b)  

(3c)  

(3d)  

(3e)
Proposed method - Numerical Method

\begin{align*}
\text{minimize} \quad & \|X_j - DC\|_F^2 + \lambda \|C_1(\cdot) \ldots C_k(\cdot)\|_{1,\infty}^T \\
\text{subject to} \quad & C \geq 0, \\
& 1_{1,k}^T C = 1_k^T.
\end{align*}

\begin{align*}
\text{minimize} \quad & \|X_j - DC\|_F^2 + \lambda I_k^T m \\
\text{subject to} \quad & C \geq 0, \\
& I_{(1,k)}^T C = 1_k^T, \\
& m \otimes 1_k I_k^T \geq C.
\end{align*}

\begin{align*}
\text{minimize} \quad & \|X_j - DC\|_F^2 + \lambda I_k^T m \\
\text{subject to} \quad & C \geq 0, \\
& I_{(1,k)}^T C = 1_k^T, \\
& m \otimes 1_k I_k^T = C + U, \\
& U \geq 0.
\end{align*}

\begin{align*}
\text{minimize} \quad & \|X_j - DC\|_F^2 + \lambda I_k^T (C + U) 1_k \\
\text{subject to} \quad & C \geq 0, \\
& I_{(1,k)}^T C = 1_k^T, \\
& E(C + U) = I_k \otimes 1_k I_k^T (C + U), \\
& U \geq 0.
\end{align*}
Proposed method-Numerical Method

\[
\text{minimize} \quad \|X_j - DC\|_F^2 + \lambda \left\| \begin{bmatrix} C_1(\cdot) & \cdots & C_k(\cdot) \end{bmatrix}^T \right\|_{1,\infty} \\
\text{subject to} \quad C \geq 0, \\
\quad \quad I_{1k}^T C = I_f^T, \tag{1a}
\]

\[
\text{minimize} \quad \|X_j - DC\|_F^2 + \lambda I_f^T m \\
\text{subject to} \quad C \geq 0, \\
\quad \quad I_{1k}^T C = I_f^T, \quad m \otimes I_f \geq C. \tag{2a}
\]

\[
\text{subject to} \quad C \geq 0, \\
\quad \quad I_{1k}^T C = I_f^T, \\
\quad \quad m \otimes I_f \geq C. \tag{3a}
\]

\[
\text{minimize} \quad \|X_j - DC\|_F^2 + \frac{\lambda}{2} I_{1k}^T (C + U) I_f \\
\text{subject to} \quad \hat{C} \geq 0, \\
\quad \quad I_{1k}^T \hat{C} = I_f^T, \\
\quad \quad E(C + U) = \frac{I_k \otimes I_f^T}{l} (C + U), \\
\quad \quad \hat{U} \geq 0, \\
\quad \quad C = \hat{C}, \quad U = \hat{U}. \tag{5f}
\]

\[
\text{minimize} \quad \|X_j - DC\|_F^2 + \frac{\lambda}{2} I_{1k}^T (C + U) I_f \\
\text{subject to} \quad C \geq 0, \\
\quad \quad I_{1k}^T C = I_f^T, \\
\quad \quad E(C + U) = \frac{I_k \otimes I_f^T}{l} (C + U), \\
\quad \quad U \geq 0. \tag{4e}
\]
Proposed method - Numerical Method

\[ \text{minimize} \quad \left\| X_j - DC \right\|_F^2 + \lambda \left\| \left[ C_1(\cdot) \ldots C_k(\cdot) \right]^T \right\|_{1,\infty} \]

subject to
\[ C \geq 0, \quad I_{lk}^T C = I_1^T, \]

(1a)

(1b)

(1c)

\[ \mathcal{L}(C,U,\hat{C},\hat{U},A_1,A_2) = \left\| X_j - DC \right\|_F^2 + \frac{\lambda}{2} \left\| I_{lk}^T (C + U) I_1 \right\|_F^2 \]
\[ + \frac{\mu_1}{2} \left\| C - \hat{C} \right\|_F^2 + \frac{\mu_2}{2} \left\| U - \hat{U} \right\|_F^2 \]

(6)

\[ \text{subject to} \quad \hat{C} \geq 0, \quad I_{lk}^T \hat{C} = I_1^T, \quad E(C + U) = \frac{I_k \otimes I_1^T}{l} (C + U), \]
\[ \hat{U} \geq 0, \quad C = \hat{C}, \quad U = \hat{U}. \]

(5a)

(5b)

(5c)

(5d)

(5e)

(5f)
Proposed method—Numerical Method

\[
\begin{align*}
\text{minimize} & \quad \|X_j - DC\|_F^2 + \lambda \|C \|_1 \text{ s.t.} \\
\text{subject to} & \quad C \geq 0, \\
& \quad I_{(ik)}^T C = I^T_l, \\
& \quad I_{(lk)} C = I^T_l.
\end{align*}
\] (1a) (1b) (1c)

\[
\begin{align*}
\mathcal{L}_\mu(C, U, C', U', A_1, A_2) &= \|X_j - DC\|_F^2 + \frac{\lambda}{2} \|I_{(ik)}(C + U)I_l\|_F^2 \\
& \quad + \frac{\mu_1}{2} \|C - C'\|_F^2 + \frac{\mu_2}{2} \|U - U'\|_F^2
\end{align*}
\] (5a)

\[
\text{subject to} \\
& \quad C \geq 0, \\
& \quad I_{(ik)}^T C = I^T_l, \\
& \quad E(C + U) = I_k \otimes I_l^T (C + U), \\
& \quad \hat{U} \geq 0, \\
& \quad C = \hat{C}, \quad U = \hat{U}.
\] (5b) (5c) (5d) (5e) (5f)

\[
(C^{t+1}, U^{t+1}) := \text{arg min}_{C, U, C', U', A_1, A_2} \mathcal{L}_\mu(C, U, C', U', A_1, A_2) \\
\text{subject to} \ (5d)
\] (7)

\[
(\hat{C}^{t+1}, \hat{U}^{t+1}) := \text{arg min}_{C, U, C, U, A_1, A_2} \mathcal{L}_\mu(C^{t+1}, U^{t+1}, C, U, A_1, A_2) \\
\text{subject to}\ (5b), (5c), (5e).
\] (8) (9)

\[
\begin{align*}
A_1^{t+1} &= A_1^t + \mu(C^{t+1} - \hat{C}^{t+1}) \\
A_2^{t+1} &= A_2^t + \mu(U^{t+1} - \hat{U}^{t+1})
\end{align*}
\]
Proposed method-Numerical Method

For 7
Proposed method - Numerical Method

\[
\begin{align*}
\text{minimize} & \quad \|X_j - DC\|_F^2 + \lambda \left[ C_1(\cdot) \ldots C_k(\cdot) \right]^T \\
\text{subject to} & \quad C \geq 0, \\
& \quad I_{1k}^T C = I_1^T, \\
& \quad m \otimes I_{1k}^T \geq C. 
\end{align*}
\]  

(1a) – (1c)

\[
L_\mu(C, U, \hat{C}, \hat{U}, A_1, A_2) = \|X_j - DC\|_F^2 + \frac{\lambda}{2} I_{1k}^T (C + U) I_1 \\
+ \frac{\mu}{2} \left\| C - \hat{C} + \frac{A_1}{\mu} \right\|_F^2 + \frac{\mu}{2} \left\| U - \hat{U} + \frac{A_2}{\mu} \right\|_F^2
\]  

(6)

\[
(C_t^{i+1}, U_t^{i+1}) := \arg \min_{C, U \in \mathbb{R}^{(8k)x1}} L_\mu(C, U, \hat{C}, \hat{U}, A_1, A_2) \quad \text{subject to (5d)}
\]  

(7)

\[
(\hat{C}_t^{i+1}, \hat{U}_t^{i+1}) := \arg \min_{C, U \in \mathbb{R}^{(8k)x1}} L_\mu(C_t^{i+1}, U_t^{i+1}, \hat{C}, \hat{U}, A_1, A_2) \quad \text{subject to (5b), (5c), (5e)}
\]  

(8) – (9)

For 8 & 9
Experimental results

- We evaluate the performance of the proposed DF-SGLST and its two variants (i.e. SGLST_Color and SGLST_HOG) on the object tracking benchmark (OTB), which contains fully annotated videos with substantial variations. We evaluate these three trackers on both OTB50 and OTB100 benchmarks for fair comparison since not all the trackers provide the results on both benchmarks.

- We utilize two metrics, namely, bounding box overlap ratio and center location error.

- Using these two metrics, we plot success plots and precision plots for all trackers.
Experimental results

- **OTB50:**
  - This benchmark consists of 50 annotated sequences, where 49 sequences has one annotated target and one sequence *jogging* has two annotated targets.
Experimental results

- **OTB100:**
  - This benchmark extends OTB50 by adding 50 additional annotated sequences.
Results on Sequences

Car4
Results on Sequences

Faceocc1
Results on Sequences

walking2
Results on Sequences

football
Thank you