Foreground Detection: Combining Background Subspace Learning with Object Smoothing Model

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Outline

1. Introduction
2. Our method
3. Experiments
4. Conclusion
Introduction

Foreground Detection

an active research subject in computer vision

challenging in dynamic background
Introduction

Previous Works

Gaussian Mixture Models (GMM)

Kernel Density Estimation (KDE)

signals separation methods
Basic Form:

\[ Y = D + F \]

- **Y**: observed signals
- **D, F**: background and foreground signals
Introduction

Typical methods

Robust Principal Component Analysis (RPCA)

Independent Component Analysis (ICA)

Sparse method (Sparse)
Motivation

1. subspace learning for $D$

2. spatial clustered property in $F$
A novel framework for foreground detection simultaneously uses the properties of D and F

An effective solution method

subspace learning for D

an object smoothing model on F
Background subspace learning

The PCA based method

*computationally intensive*

The \((2D)^2\) PCA based method
Background subspace learning

1. mean image computation

\[
\bar{A} = \frac{1}{N} \sum_{i=1}^{N} A_i
\]

2. covariance matrices construction

\[
C_{\text{row}} = \frac{1}{N} \sum_{i=1}^{N} (A_i - \bar{A})^T (A_i - \bar{A})
\]

\[
C_{\text{column}} = \frac{1}{N} \sum_{i=1}^{N} (A_i - \bar{A})(A_i - \bar{A})^T
\]
3. projection matrices construction

\( \Phi^{\text{column}} \) and \( \Phi^{\text{row}} \)

respectively select \( M \) eigenvectors

4. new image projection

\[
Z = (\Phi^{\text{column}})^T (A_t - A)(\Phi^{\text{row}})
\]
5. new image reconstruction

\[ \hat{A}_t = \Phi^{\text{column}} Z (\Phi^{\text{row}})^T + \overline{A} \]

6. getting the difference matrix

\[ G = A_t - \hat{A}_t \]
Results by thresholding the matrix G

(a) 1 eigenvector
(b) 10 eigenvectors
(c) 30 eigenvectors
(d) 40 eigenvectors

Background subspace learning
Foreground refinement

Properties in G

1. Foreground clustered
2. Number, position, and size of clusters are not known
3. Isolated noises exist
Foreground refinement

Object smoothing model

\[
\hat{H} = \arg \min_{H} \frac{1}{2} \sum_{i=1}^{r} \sum_{i'=1}^{c} (G_{i,i'} - H_{i,i'})^2 + \lambda_1 E_1
\]

\[
E_1 = \sum_{i=2}^{r} \sum_{i'=1}^{c} |H_{i,i'} - H_{i-1,i'}| + \sum_{i=1}^{r} \sum_{i'=2}^{c} |H_{i,i'} - H_{i,i'-1}|
\]

Properties

- More flexible
- Global optimization technique
- On numerical matrices
Foreground refinement

\[ \hat{H} = \arg \min_H \frac{1}{2} \sum_{i=1}^{r} \sum_{i'=1}^{c} (G_{i,i'} - H_{i,i'})^2 + \lambda_1 E_1 + \lambda_2 E_2 \]

\[ E_2 = \sum_{i=1}^{r} \sum_{i'=1}^{c} |H_{i,i'}| \]

only use the spatial smoothing constraint \( E_1 \)

Final results: \( |\hat{H}| > Th \)
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Three sequences for testing

GMM, KDE, Sparse methods for comparison

*F*-score metric is used for evaluation

\[
F - score = \frac{2TP}{2TP + FN + FP}
\]
Experiments

Parameter selection

Our method: 20 training frames, 3 eigenvectors
\[ \lambda_1 = 35, \text{Th} = 25 \]

Sparse method: 20 training frames, Th = 25

GMM method: \[ K = 3, T_b = 0.7 \]

KDE method: WindowLeng th = 100, \( T_b = 0.3 \)
Experiments

Results comparisons

wavingtrees

GMM  KDE  Sparse  Ours

ripplingwater

campus
## F-score evaluation

<table>
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<tr>
<th>Method</th>
<th>GMM</th>
<th>KDE</th>
<th>Sparse</th>
<th>Ours</th>
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</tr>
</tbody>
</table>
Conclusion

A framework coming subspace learning and object smoothing model

$(2D)^2$ PCA based background subspace learning

A flexible object smoothing model for foreground refinement
Thank You!

Q and A
Backup slices
Why do you select 3 eigenvectors for projection matrices construction?

This value is set according to our experience. Actually, the number of eigenvectors to be selected in the range from 3 to 10 would yield comparable results. For simplicity and fair comparisons, we select 3 eigenvectors.

How do you solve the object smoothing model?

The model can be considered as a simplified version of 2D fused Lasso model, whose solution package ‘flsa’ using ‘R’ language has been provided. Thus, we use this package for our model solution.
Some questions

How much time does this method cost for processing a frame?

In this paper, we provide an alternative solution for this framework, which first learns the background subspace, and then refines the foreground. As these two steps are separated and implemented using different languages (Matlab and R), it is difficult to give the accurate time cost. However, this is one of our future works.
What’s the difficult to solve the novel framework?

Currently, we are difficult to give an effective way to quantitatively describe the performance of background subspace learning, so we provide an alternative solution method instead with fixed parameters. However, we are studying it and hoping to solve the problem.