Foreground Estimation Based on Robust Linear Regression Model

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Outline

- Introduction
- Foreground estimation based on robust linear regression model
- Experimental results
- Conclusion

Introduction

- Moving object detection is an active research subject in computer vision.

- Foreground detection under dynamic scenes is a challenging problem.

Introduction

- Parametric density estimation technique

  e.g. Gaussian Mixture Models (GMM)

- Nonparametric density estimation technique

  e.g. Kernel Density Estimation (KDE)

- Sparse error estimation technique

  e.g. Sparse method

Motivation

- Linear regression is a common used method to analyze the relationship between two variables.
- Cast foreground as observation errors to estimate.
- A new robust regression model which separates sparse outlier from noises is proposed for robust regression.

Linear regression model

simple expression:

$$y_i = x_{i1}w_1 + \cdots + x_{iD}w_D + e_i$$

x_i : explanatory variable

y_i : dependent variable

w_i : regression coefficient

e_i : observation error

$i = 1, 2, \cdots, M$: observation numbers

D : model order with $M > D$

compact expression:

$$\mathbf{y} = \mathbf{X}\mathbf{w} + \mathbf{e}$$

Linear regression model

- Estimate the coefficients by minimizing a given objective function.

- Least square criterion:

$$\hat{\mathbf{w}} = \mathbf{argmin} \parallel \mathbf{y} - \mathbf{X}\hat{\mathbf{w}} \parallel_2$$

- Sensitive to outliers

Robust linear regression model

Our regression model:

$$\mathbf{y} = \mathbf{X}\mathbf{w} + \mathbf{t} + \mathbf{n}$$

$\mathbf{y}, \mathbf{X}, \mathbf{w}$: same to ordinary linear regression model

$\mathbf{t} = \{t_1, t_2, \ldots t_M\}$:sparse outlier

$\mathbf{n} = \{n_1, n_2, \ldots n_M\}$:assumed to be Gaussian noise

$N \sim (0, \sigma^2)$

Robust linear regression model

- Objective function:

$$(\hat{\mathbf{w}}, \hat{\mathbf{t}}) = \mathbf{argmin} \| \mathbf{y} - \mathbf{X}\hat{\mathbf{w}} - \hat{\mathbf{t}} \|_{\mathbf{2}} + \boldsymbol{\lambda} \| \hat{\mathbf{t}} \|_{\mathbf{0}}$$

$\boldsymbol{\lambda}$ is a regularization parameter

- Solution method:

Compute the orthogonal matrix $\mathbf{F}$ to matrix $\mathbf{X}$, such that $\mathbf{FX} = \mathbf{0}$

Robust linear regression model

- multiplying our model by $\mathbf{F}$, we get:

$$\mathbf{y}' = \mathbf{F}\mathbf{t} + \mathbf{n}'$$

$\mathbf{y}' = \mathbf{F}\mathbf{y}$ and $\mathbf{n}' = \mathbf{F}\mathbf{n}$

- by relaxing l_0 norm to l_1 norm, we get new objective function:

$$(\hat{\mathbf{t}}) = \mathbf{argmin} \parallel \mathbf{y}' - \mathbf{F}\hat{\mathbf{t}} \parallel_{\mathbf{2}} + \boldsymbol{\lambda} \parallel \hat{\mathbf{t}} \parallel_{\mathbf{1}}$$

Robust linear regression model

- This is a classic LASSO problem and can be solved by sparse recovery method.

- We choose $\boldsymbol{\lambda} = \sigma\sqrt{2\log M},$ σ is a scale estimation parameter.

Proposed Detection Method

```
Set the parameters σ , model order D, number of subregions
L, Th value for foreground determination
➢ Regressor construction step
    For i = 1 to D
        For j = 1 to L
            get j_th subregion of i_th background frame and
                translate into 1D column vector x_ij
            set x_ij to i_th column of matrix X_j
        End
    End
    For j = 1 to L
        compute the orthogonal matrix F_j to matrix X_j
    End
➢ Foreground detection step
    For k = 1 to length(videos)
        For j = 1 to L
            get subregion and change into 1D vector y_kj
            compute the vector with F_j to get y_kj'
            estimate the outlier according to new function
            change the estimation vector t_kj into subregion
        End
        Foreground = |t_k| > Th
    End
```

Experiments

- Two dynamic sequences for testing.
- GMM, KDE, and Sparse methods are employed for comparison.
- Visual and numerical evaluation are used Precision and Recall as the metrics.

$$Precision = \frac{TP}{TP+FP} \times 100\% \qquad Recall = \frac{TP}{TP+FN} \times 100\%$$

Experiments

- Parameter selection

Subregion number: $L = 4$

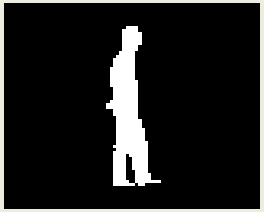
Model order: $D = 20$

Threshold value: $\mathbf{Th} = 30$

Experiments

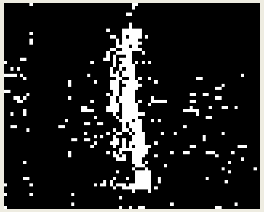
- rippling water sequence

(a)

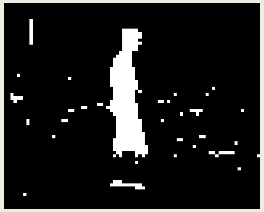


(b)

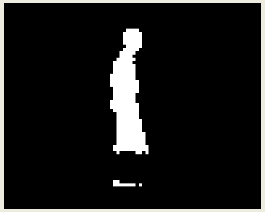
(c)



(d)



(e)



(f)

Experiments

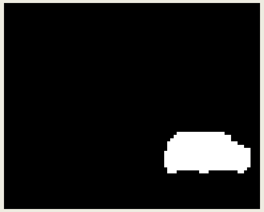
Precision and recall evaluations

	Precision	Recall
GMM	67.22	80.00
KDE	56.31	69.38
Sparse	81.55	75.31
Ours	99.32	72.59

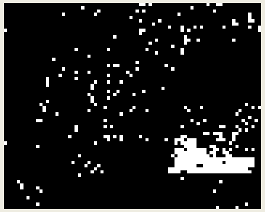
Experiments

- campus sequence

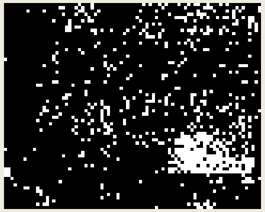
(a)



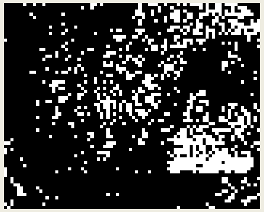
(b)



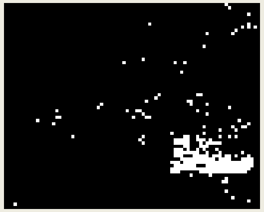
(c)



(d)



(e)



(f)

Experiments

Precision and recall evaluations

	Precision	Recall
GMM	47.81	59.93
KDE	28.68	65.41
Sparse	20.96	68.84
Ours	66.11	54.11

Conclusion

- a new foreground estimation method cast foreground as outlier estimation problem.
- a new model separates the sparse outlier from noise term
- our method can effectively detect foreground under dynamic scenes

Thank you !

Q and A