Background Subtraction Based on Phase and Distance Transform Under Sudden Illumination Change

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Outline

- **Introduction**
- **Background subtraction based on phase feature and distance transform**
- **Experimental results**
- **Conclusion**

Introduction (1)

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

- **Foreground detection under sudden illumination change is still a challenging problem.**

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Introduction (2)

- **Parametric density estimation technique**

  e.g. Gaussian Mixture Models (GMM)

- **Nonparametric density estimation technique**

  e.g. Kernel Density Estimation (KDE)

- **Region-based technique**

  e.g. Local Binary Pattern based (LBP)

Introduction (3)

- **Other methods**

e.g. Wallflower system

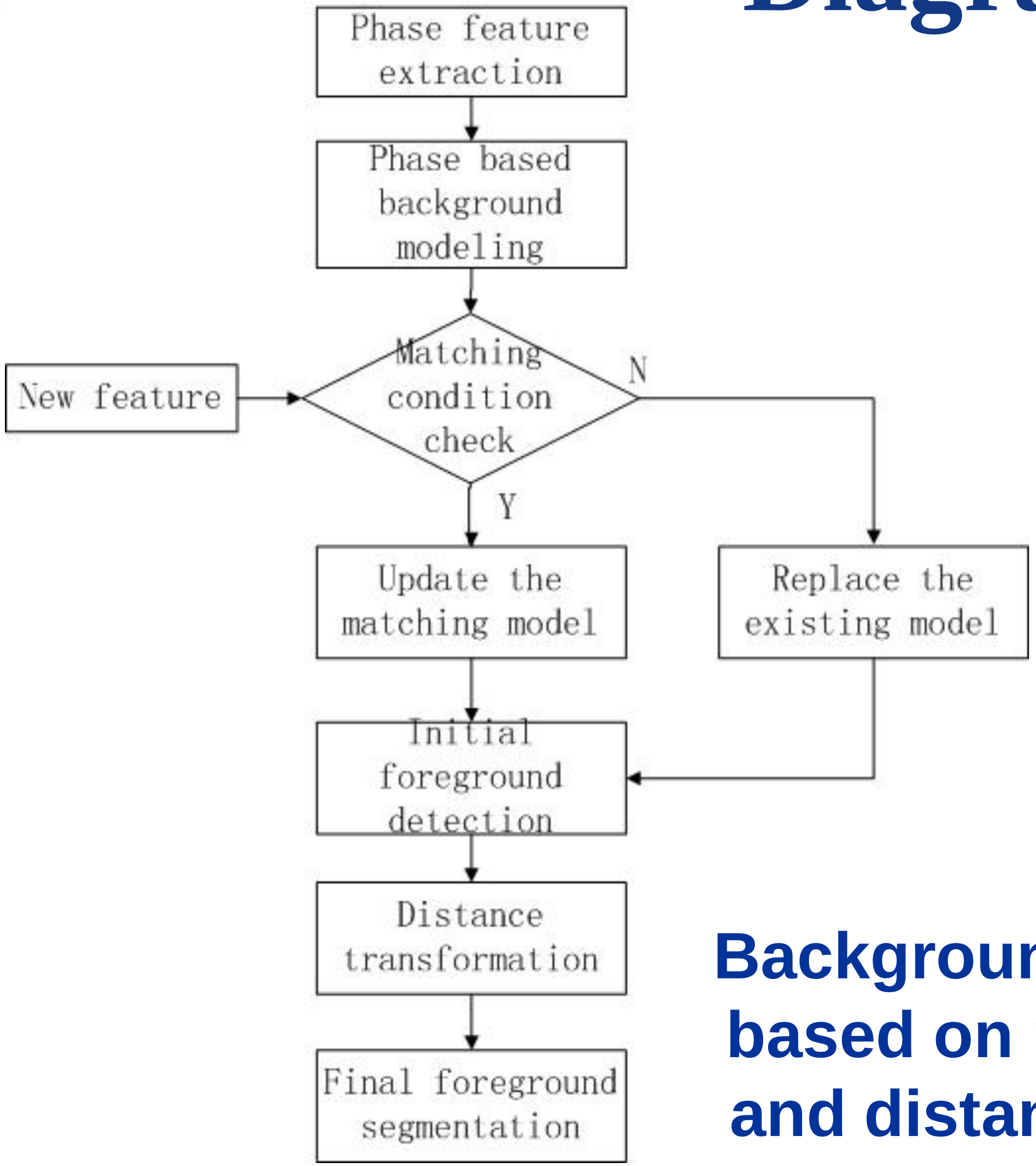
e.g. Pixel order information based

e.g. Pilet's method

Motivation

- Phase is insensitive to illumination change.
- The basic framework of GMM method.
- Blob aggregation using distance transform.

Diagram



Background subtraction based on phase feature and distance transform

Phase feature extraction (1)

- **The Gabor wavelet coefficient:**

$$G_{\mu,\nu}(z) = A_{\mu,z}(z) \cdot \exp(i\theta_{\mu,\nu}(z))$$

$A_{\mu,\nu}(z)$ **:amplitude item**

$\theta_{\mu,\nu}(z) \in [0,2\pi)$ **:phase item**

- **Each pixel has $\mu_{\max} \times \nu_{\max}$ wavelet coefficients**

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Phase feature extraction (2)

- **Phase extraction principle:**

  The larger amplitude of the coefficient is, the more efficient the coefficient represents the pixel information and the more discriminative of the corresponding phase is.

- **Multiple phase extraction reasons:**

  rotation property

  range of single phase is small

Phase feature extraction (3)

- **The phase feature is defined:**

$$p(z)=\sum_{i=1}^{L}\theta_i(z)$$

$p(z)$: the phase feature

$\theta_i(z)$: the Gabor phase corresponding to the i_{th} largest Gabor amplitude of the pixel

L : the number of phase to be extracted

- $N \times N$ **image subdivision**

Background modeling

- K **mixture of Gaussian distributions**

- k_{th} **Gaussian distribution represented by** μ_k **,** σ_k^2 **and** ω_k **, total weights** $\sum_{i=1}^{K}\omega_i=1$

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Model updating (1)

- **Set** $L = 3$**,** $p(z) \in [0, 6\pi)$

- **Singular regions exists, matching condition is in different expressions**

$$\begin{cases} \left|6\pi - \mu_k + X_t\right| \le 2.5\sigma_k & \text{if } X_t < \varepsilon \text{ and } 6\pi - \mu_k < \varepsilon \\ \left|6\pi + \mu_k - X_t\right| \le 2.5\sigma_k & \text{if } \mu_k < \varepsilon \text{ and } 6\pi - X_t < \varepsilon \\ \left|X_t - \mu_k\right| \le 2.5\sigma_k & \text{others} \end{cases}$$

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Model updating (2)

Condition satisfied

1. if $\mu_k < \varepsilon$ and $6\pi - X_t < \varepsilon$

$$\begin{cases} \mu_k = \mu_k + \alpha(X_t - \mu_k - 6\pi) \\ \sigma_k^2 = (1-\alpha)\sigma_k^2 + \alpha(X_t - \mu_k - 6\pi)^2 \end{cases}$$

2. if $X_t < \varepsilon$ and $6\pi - \mu_k < \varepsilon$

$$\begin{cases} \mu_k = \mu_k + \alpha(X_t - \mu_k + 6\pi) \\ \sigma_k^2 = (1-\alpha)\sigma_k^2 + \alpha(X_t - \mu_k + 6\pi)^2 \end{cases}$$

3. Others

$$\begin{cases} \mu_k = \mu_k + \alpha(X_t - \mu_k) \\ \sigma_k^2 = (1-\alpha)\sigma_k^2 + \alpha(X_t - \mu_k)^2 \end{cases}$$

Model updating (3)

- **Weights update** $\omega_k = (1-\alpha)\omega_k + \alpha M_k$

- μ_k **is beyond** $[0,6\pi)$

$$\begin{cases} \mu_k = \mu_k - 6\pi & \text{if } \mu_k \geq 6\pi \\ \mu_k = \mu_k + 6\pi & \text{if } \mu_k < 0 \end{cases}$$

- **Condition not satisfied**

New Gaussian replace $\mu = X_t, \sigma = \sigma_{init}$, low ω_{init}

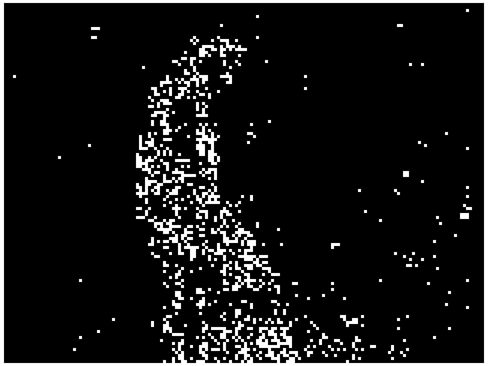
Foreground detection

- **Sorted in** ω/σ

- **Background distributions:**

$$B = \arg\min\left(\sum_{k=1}^{b}\omega_k > T\right)$$

Distance transform (1)



Initial detection result

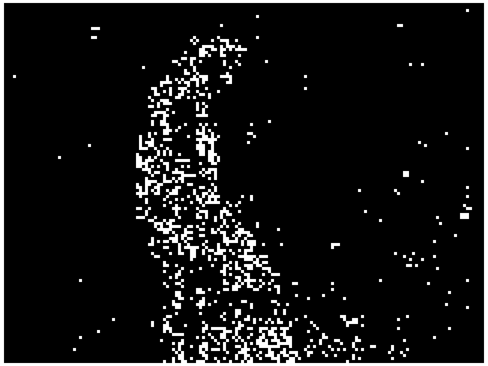
Distance transform (2)

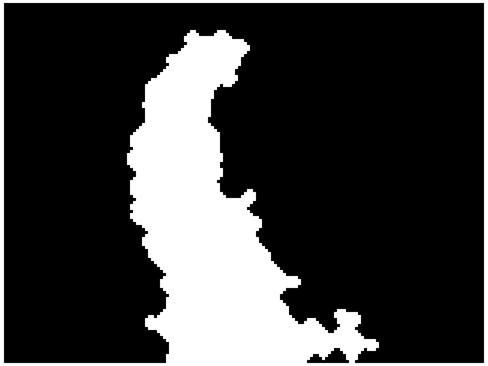
- **Euclidean distance transform of pixel** $a(i, j)$

$$d(i, j) = \min_{(x,y)\in W} \sqrt{(i-x)^2 + (j-y)^2}$$

Blob aggregation

- **Example results before and after blob aggregation**





Experiments (1)

- **Two sequences for testing.**

- **GMM and LBP 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 (2)

- **Parameter selection**

Gabor filter: $\nu_{\max} = 4 \quad \mu_{\max} = 6$

Phase extraction: $N = 4, L = 3$

Gaussian model: $K = 3, T_b = 0.7$

Segment value: $T_d = 1.2$

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Experiments (3)

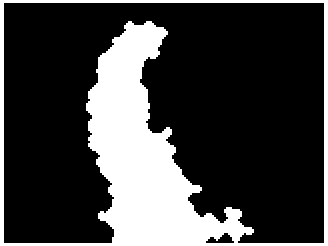

(a)


(b)


(c)


(d)


(e)


(f)

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Experiments (4)

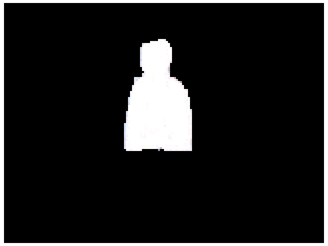
Precision and recall evaluation

	Precision	Recall
GMM	22.03	76.40
LBP	18.40	73.05
Our method	78.53	97.48

Experiments (5)

(a)

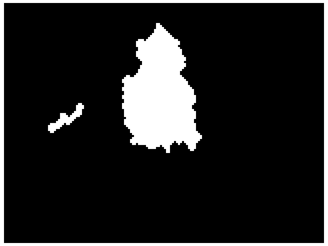
(b)



(c)

(d)

(e)



(f)

Experiments (6)

Precision and recall evaluation

	Precision	Recall
GMM	4.52	26.01
LBP	14.27	46.91
Our method	73.58	92.25

Conclusions

- **Pixel phase as feature.**
- **Novel matching condition and updating scheme.**
- **Distance transform on the initial detection results.**

Thank you !

Q and A

Backup slices

Gabor function

Gabor function:

$$\varphi_{\mu,\nu}(z) = \frac{\|k_{\mu,\nu}\|^2}{\sigma^2} e^{(-\|k_{\mu,\nu}\|^2 \|z\|^2 / 2\sigma^2)} [e^{ik_{\mu,\nu}z} - e^{-\sigma^2/2}]$$

$$k_{\mu,\nu} = (\frac{k_{jx}}{k_{jy}}) = (\frac{k_\nu \cos\phi_\mu}{k_\nu \sin\phi_\mu})$$

$$k_\nu = f_{\max} / 2^{\nu/2} \quad \phi_\mu = \mu(\pi / \mu_{\max})$$

$$\nu = 0, \cdots, \nu_{\max} - 1, \mu = 0, \cdots, \mu_{\max} - 1$$

ν is frequency, μ is orientation

Some questions

- **How to define sudden illumination change detection?**

  We think sudden illumination change detection means

  1. the whole illumination change abruptly.

  2. detect foreground in short frames after the whole illumination change. eg. within 15 frames

- **This is the single frame result, how about the result on other frames?**

  We have tested other frames after sudden illumination change on these two videos. They showed the similar results to this frame.

Some questions

- **Have you tested your method in other situations?**

  We have extended our work and test our method in other situations, eg. dynamic background, bootstrapping. They show comparable results to GMM, LBP. While our method outperforms others under sudden illumination change. This shows the effectiveness of our method. We have submitted this paper to a journal and now is under review.

- **How to choose the parameters?**

  Since our method has many parameters, we set parameter values mainly by experience. May be there exist good methods for exploration.