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

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Introduction

Background subtraction based on phase feature and distance transform

Experimental results

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

Foreground detection under sudden illumination change is still a challenging problem.
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)
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.
Background subtraction based on phase feature and distance transform
Phase feature extraction (1)

The Gabor wavelet coefficient:

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

- \( A_{\mu,\nu}(z) \) : amplitude item
- \( \theta_{\mu,\nu}(z) \in [0,2\pi) \) : phase item

Each pixel has \( \mu_{\text{max}} \times \nu_{\text{max}} \) wavelet coefficients
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
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 $\mu_k, \sigma^2_k$ and $\omega_k$, total weights $\sum_{i=1}^{K} \omega_i = 1$
Model updating (1)

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

- **Singular regions exists, matching condition**

is in different expressions

\[
\begin{cases}
|6\pi - \mu_k + X_t| \leq 2.5\sigma_k & \text{if } X_t < \varepsilon \text{ and } 6\pi - \mu_k < \varepsilon \\
|6\pi + \mu_k - X_t| \leq 2.5\sigma_k & \text{if } \mu_k < \varepsilon \text{ and } 6\pi - X_t < \varepsilon \\
|X_t - \mu_k| \leq 2.5\sigma_k & \text{others}
\end{cases}
\]
Model updating (2)

Condition satisfied

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

$$
\left\{
\begin{array}{l}
\mu_k = \mu_k + \alpha(X_t - \mu_k - 6\pi) \\
\sigma_k^2 = (1 - \alpha)\sigma_k^2 + \alpha(X_t - \mu_k - 6\pi)^2
\end{array}
\right.
$$

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

$$
\left\{
\begin{array}{l}
\mu_k = \mu_k + \alpha(X_t - \mu_k + 6\pi) \\
\sigma_k^2 = (1 - \alpha)\sigma_k^2 + \alpha(X_t - \mu_k + 6\pi)^2
\end{array}
\right.
$$

3. Others

$$
\left\{
\begin{array}{l}
\mu_k = \mu_k + \alpha(X_t - \mu_k) \\
\sigma_k^2 = (1 - \alpha)\sigma_k^2 + \alpha(X_t - \mu_k)^2
\end{array}
\right.
$$
Model updating (3)

Weights update

\[ \omega_k = (1-\alpha)\omega_k + \alpha M_k \]

\( \mu_k \) 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 \( \mu = X_t, \sigma = \sigma_{\text{init}}, \text{ low } \omega_{\text{init}} \)
Sorted in $\omega/\sigma$

Background distributions:

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

Initial detection result
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.

\[
\text{Precision} = \frac{TP}{TP + FP} \times 100\% \quad \text{Recall} = \frac{TP}{TP + FN} \times 100\%
\]
Parameter selection

Gabor filter: \( \nu_{\text{max}} = 4 \quad \mu_{\text{max}} = 6 \)

Phase extraction: \( N = 4, L = 3 \)

Gaussian model: \( K = 3, T_b = 0.7 \)

Segment value: \( T_d = 1.2 \)
Experiments (3)

(a)  
(b)  
(c)  
(d)  
(e)  
(f)
### Precision and recall evaluation

<table>
<thead>
<tr>
<th>Method</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>GMM</td>
<td>22.03</td>
<td>76.40</td>
</tr>
<tr>
<td>LBP</td>
<td>18.40</td>
<td>73.05</td>
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<tr>
<td>Our method</td>
<td>78.53</td>
<td>97.48</td>
</tr>
</tbody>
</table>
Experiments (5)

(a)  

(b)  

(c)  

(d)  

(e)  

(f)
## Experiments (6)

### Precision and recall evaluation

<table>
<thead>
<tr>
<th>Method</th>
<th>Precision</th>
<th>Recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>GMM</td>
<td>4.52</td>
<td>26.01</td>
</tr>
<tr>
<td>LBP</td>
<td>14.27</td>
<td>46.91</td>
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<tr>
<td>Our method</td>
<td>73.58</td>
<td>92.25</td>
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</tbody>
</table>
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:

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

\[
k_{\mu, \nu} = \left( \frac{k_{jx}}{k_{jy}} \right) = \left( \frac{k_{\nu} \cos \phi_{\mu}}{k_{\nu} \sin \phi_{\mu}} \right)
\]

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

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

\(\nu\) is frequency, \(\mu\) 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.