Research Article

Bipolar Log-Intensity-Variance Histogram Method for Local Image Patch Intensity Change Measurements

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For a fixed-position camera, the intensity changes of an image pixel are often caused by object movement or illumination change. This paper focuses on such a problem: given two adjacent local image patches, how can the causes of intensity change be determined? A bipolar log-intensity-variance histogram is proposed to describe the intensity variations on the chaos phase plot subspace. This is combined with two sigmoid functions to construct a probabilistic measure function. Experimental results show that the proposed measurements are more effective and robust than conventional methods to the cause of variation in image intensity.

1. Introduction

For a fixed-position camera, the intensity changes within two local adjacent image patches are always caused by illumination changes or object movement. To reduce false alarms caused by illumination changes for accurate motion- or change-detection [1–6], as conventional methods, many robust feature descriptors have been proposed [16–20]. For example, a local binary pattern (LBP) [21], which checks the relative difference between spatially neighboring pixels and not the absolute values of each pixel, illumination changes can be effectively overcome. Chua et al. [22] combined color patterns with a uniform local binary pattern (TC-LBP) to enhance the performance of illumination-invariant background subtraction. Kim et al. [23] exploited a simple yet powerful feature, illumination-invariant structural complexity (IISC), to describe the underlying structure of a local region in a video.

Different from conditional illumination-robust feature methods, accurately determining the causes behind variation in image intensity is another fresh and effective approach to reduce false alarms of motion detection. Peitgen [24] stated that the chaotic behavior of dynamical systems can be detected in the phase space plot created by a horizontal plane slicing the joint probability density between two Gaussian blurred images. Farmer [25] presented the so-called chaos phase plot space (CPPS) method and found that the fractal dimension in CPPS is robust under illumination changes. Song et al. [26] proposed a box-count dimension measure based on CPPS to reduce lip-motion detection false alarms caused by illumination changes. Similarly, Wang et al. [20] applied CPPS and the box-count dimension measure method to enhance top-view moving people detection system performance.

Although CPPS has been used as a feature space to construct metric functions of intensity changes, existing work on CPPS and box-count dimension measurements [20, 25, 26] has some notable shortcomings. First, the box-count dimension measure lacks a facility for deep analysis of the CPPS property under different types of intensity changes. Second, the effectiveness of the box-count dimension measurement function is restricted by the assumption that illumination changes always cause linear pixel changes, and moving objects always cause nonlinear pixel changes. Illumination change can also cause nonlinear pixel changes, as shown in Figure 1(a). As a result, CPPS and box-count measurement methods [20, 25, 26] fail in many cases, such as slight motion and strong illumination changes.

To construct a more effective and robust local patch intensity change measure function, this paper makes the following contributions. First, a new property of the chaos phase plot subspace under different types of intensity change behavior
performance has been found, with an entirely new view. Then, based on these observations, a bipolar log-intensity-variance histogram is proposed to describe intensity change behavior on the chaos phase plot subspace. Finally, a probabilistic, sigmoid-based measure function is constructed as a local image patch intensity change classification metric.

In this paper, we focus on the problem that given two local small patches extracted from adjacent images, how one can determine the causes for intensity changes, as Figure 1 shows. We only consider that an intensity change consists of illumination change and object movement for a fixed-position camera.

This paper is organized as follows. Section 2 first provides an overview of the principle of CPPS and describes our newly found property of the chaos phase plot subspace under different types of intensity change behavior. We then introduce the proposed bipolar log-intensity-variance histogram, corresponding measure function, and framework of the proposed intensity-classification method. Section 3 provides the experimental data and analysis. Concluding remarks are given in Section 4.

2. Proposed Intensity Change Classification Method

2.1. Overview of the Chaos Phase Plot Space. The chaos phase plot space [26] is extracted from an image difference \( I_{\text{diff}} \) of two adjacent gray level images \( I_t \) and \( I_{t+1} \). It consists of the amplitude of the intensity value delta on the horizontal axis (from -255 to 255) and full gray level (from 0 to 255) on the vertical axis.

The chaos phase plot space extraction process consists of three steps:

1. Converting the original two adjacent local RGB image patches to gray level images \( I_t \) and \( I_{t+1} \).

2. Computing the image patch difference \( I_{\text{diff}} \) with the two gray level image patches \( I_t \) and \( I_{t+1} \):

   \[
   I_{\text{diff}} = I_{t+1} - I_t
   \]  

3. Building a two-dimensional chaos phase plot space from the image difference \( I_{\text{diff}} \). The horizontal axis represents element values of image patch difference \( I_{\text{diff}} \) (from -255 to 255) and the vertical axis represents the full gray level value (from 0 to 255). Therefore, any data point on the chaos phase plot space can be represented by

   \[
   x_i = I_{\text{diff}} (m, n) \\
   y_i = I_t (m, n)
   \]

   where \( I_t (m, n) \) is the gray level value at the \( m \)th row and \( n \)th column of image \( I_t \), and \( I_{\text{diff}} (m, n) \) is the intensity value at the \( m \)th row and \( n \)th column of difference image \( I_{\text{diff}} \). Figure 2 shows the extraction process of the chaos phase plot space. When every intensity of \( I_t \) is projected to the chaos phase plot space according to (2), the completed chaos phase plot space extraction appears as shown in Figure 2.

2.2. Intensity Change Behavior on the Chaos Phase Plot Subspace. In this paper, we divide the original chaos phase plot space into positive and negative subspaces. The left side of the chaos phase space, from -255 to 0 on the horizontal axis, is called the negative subspace, and the right side, from 0 to 255 on the horizontal axis, is called the positive subspace.

Figure 3 shows an example of chaos phase plot subspace behavior for different causes of image intensity variation. From this example, an appearance property on the chaos phase plot subspace can be easily observed, as follows:
The data points of the chaos phase plot for intensity variation based on a positive illumination change almost only appear in the positive subspace, as Figure 3(a) shows.

In contrast, the data points of the chaos phase plot for intensity variation for a negative illumination change almost only appear in the negative subspace, as Figure 3(b) shows.

The data points of the chaos phase plot for intensity variation based on a positive illumination change are scattered across both the positive and negative subspaces, as Figure 3(c) shows.

The chaos phase plot subspace behavior under different causes illustrates that

1. Natural illumination change always generates image intensity monotonic variation. In particular, under a
positive change in illumination, almost all elements of the corresponding difference image $I_{\text{diff}}$ are positive. Under a negative change in illumination, all the intensity values of the difference image $I_{\text{diff}}$ are negative.

2) For intensity variation caused by object movement, we see nonmonotonic change. Therefore, the corresponding difference image $I_{\text{diff}}$ consists of both positive and negative intensity values.

2.3. Bipolar Log-Intensity-Variance Histogram. Based on a notable property of the chaos phase plot subspace, discussed in Section 2.2, a bipolar log-intensity-variance histogram is extracted to describe differences in intensity variation under an illumination change or object movement. The procedure for extracting the bipolar intensity-variance histogram is summarized as follows:

1) To extract a bipolar log-intensity-variance histogram, all data points of the chaos phase plot space $I_{\text{chaos}}$ are divided into two sets according to their horizontal ordinate values, positive subspace $I^+_{\text{chaos}}$, and negative subspace $I^-_{\text{chaos}}$, which are defined as

$$
I^+_{\text{chaos}} = \{(x^+, y) \mid x^+ \geq 0, (x^+, y) \in I_{\text{chaos}}\} \tag{3}
$$

$$
I^-_{\text{chaos}} = \{(x^-, y) \mid x^- < 0, (x^-, y) \in I_{\text{chaos}}\} \tag{4}
$$

where $(x, y)$ is any two-dimensional data point on the CPPS, $(x^+, y)$ is any data point on the chaos phase plot positive subspace $I^+_{\text{chaos}}$, and $(x^-, y)$ is any data point on the chaos phase plot negative subspace $I^-_{\text{chaos}}$.

2) Then the two bipolar gray level sets are defined by (5) and (6), respectively,

$$
S^+_{\text{chaos}} (i) = \{x \mid y = i, (x, y) \in I^+_{\text{chaos}}\} \tag{5}
$$

$$
S^-_{\text{chaos}} (i) = \{x \mid y = i, (x, y) \in I^-_{\text{chaos}}\} \tag{6}
$$

where $S^-_{\text{chaos}} (i)$ is the horizontal ordinate value set of the data points in the chaos phase plot negative subspace $I^-_{\text{chaos}}$, whose corresponding ordinate values are equal to $i$; $S^+_{\text{chaos}} (i)$ represents another horizontal ordinate value set of data points in the chaos phase plot positive subspace $I^+_{\text{chaos}}$, whose corresponding ordinate values are equal to $i$.

Figure 4 shows two examples of a bipolar gray level set on the chaos phase plot. The yellow rectangle represents $S^+_{\text{chaos}}(j)$, which consists of only one data point. The green rectangle represents $S^-_{\text{chaos}}(j)$, which consists of three data points.

3) The component of the bipolar log-intensity-variance histogram is then extracted from the bipolar gray level set with (7) and (8):

$$
H_P (i) = \begin{cases} 
\log (\text{var} (S^+_{\text{chaos}} (i))), & \text{if } S^+_{\text{chaos}} (i) \neq \emptyset \\
0, & \text{if } S^+_{\text{chaos}} (i) = \emptyset 
\end{cases} \tag{7}
$$

$$
H_N (i) = \begin{cases} 
\log (\text{var} (S^-_{\text{chaos}} (i))), & \text{if } S^-_{\text{chaos}} (i) \neq \emptyset \\
0, & \text{if } S^-_{\text{chaos}} (i) = \emptyset 
\end{cases} \tag{8}
$$

$$
\text{var} (X) = \frac{\sum_{i=1}^{N} (x_i - \mu)^2}{N} \tag{9}
$$

where $\text{Var}$ is a variance function that can accurately describe the degree of chaos phase plot point spread of every gray level, $\mu$ is the mean value of $x_i$, log is a logarithmic function designed to limit the amplitude of the variance, $H_P(i)$ is the ith component of the positive log-intensity-variance histogram $H_P$, and $H_N(i)$ is the ith component of the negative log-intensity-variance histogram $H_N$.

Finally, the proposed bipolar log-intensity-variance histogram can be represented by

$$
H_P = \{H_P (0), H_P (1), \ldots, H_P (255)\} \tag{10}
$$

$$
H_N = \{H_N (0), H_N (1), \ldots, H_N (255)\} \tag{11}
$$

where $H_P$ is the positive log-intensity-variance histogram, $H_N$ is the negative log-intensity-variance histogram, and both of these are 256-dimensional vectors.

The extraction process of the bipolar log-intensity-variance histogram is summarized as Algorithm 1.

Figure 5 shows examples of bipolar log-intensity-variance histograms for different forms of variation in image intensity. Figures 5(a)–5(c) show examples of a bipolar intensity-variance histogram under illumination positive change, illumination negative change, and object movement, respectively.
We can observe some interesting phenomena in Figure 5:

① Under illumination positive change, as Figure 5(a) shows, there is no nonzero component in $H_N$. Moreover, most $H_P$ components are smaller than a threshold $T_A$.

② Under illumination negative change, as Figure 5(b) shows, there is no nonzero component in $H_P$. Moreover, most $H_P$ components are smaller than a threshold $T_A$.

③ Under object movement, as Figure 5(c) shows, there are many components bigger than a threshold $T_A$, both in $H_N$ and $H_P$.

These phenomena illustrate that natural illumination change always generates monotone intensity changes. Moreover, natural gradual illumination change often leads to a change in intensity with a small variance for every gray level. Object movement always generates nonmonotonic intensity changes with significant variance in both positive and negative image intensity.

2.4. Probabilistic Measure Based on the Sigmoid Function. The bipolar log-intensity-variance histogram is a representation of different types of change in intensity. In this section, two sigmoid functions are extracted from bipolar log-intensity-variance histograms for use in a probabilistic measure of intensity variation, as follows:

$$ P(H_P, H_N, \alpha, T_N, T_A) = P^+ (H_P, \alpha, T_N, T_A) \times P^- (H_N, \alpha, T_N, T_A) $$

$$ P^+ (H_P, \alpha, T_N, T_A) = \frac{1}{1 + e^{-\alpha (N^+ - T_A)}} $$

$$ P^- (H_N, \alpha, T_N, T_A) = \frac{1}{1 + e^{-\alpha (N^- - T_N)}} $$

where $H_P$ is the positive log-intensity-variance histogram, $H_N$ is the negative log-intensity-variance histogram, $N^+$ is the number of elements in $H_P$ whose amplitude is larger than $T_A$, $N^-$ is the number of elements in $H_N$ whose amplitude is larger than $T_A$, $T_N$ is the number threshold, and $T_A$ is the amplitude threshold.

The proposed measure function $P(H_P, H_N, \alpha, T_N, T_A)$ in (12) has two parts [see (13) and (14)], which are extracted from the positive and negative log-intensity-variance histograms, $H_P$ and $H_N$, respectively. For object movement, as shown in Figure 5(c), the number of elements with larger amplitudes in $H_P$ and $H_N$ both are larger than the number threshold $T_A$. Therefore, $N^+$ and $N^-$ are both larger than $T_N$, and the final score of (12) is close to 1. However, as shown in Figures 5(a) and 5(b), for either positive or negative changes in natural illumination, the numbers of elements with larger amplitudes
Figure 5: Bipolar log-intensity-variance histogram for different forms of image intensity change: (a) positive illumination change; (b) negative illumination change; and (c) object movement.

in $H_P$ or $H_N$ must be smaller than the number threshold $T_A$. In these cases, either $N^+$ or $N^-$ must be smaller than $T_N$, and then the final scored of (12) is close to 0. Therefore, a threshold $T_m$ close to 0.5 can be employed for the proposed image intensity variation classification.

2.5. Framework of Intensity Change Classification. Based on bipolar log-intensity-variance histograms, the proposed image intensity variation classification method consists of four steps; see Figure 6. In the first step, two adjacent images are processed with a smooth filter to eliminate noise, and a difference image $I_{diff}$ is created by subduction. Then the chaos phase plot space $I_{chaos}$ is built from $I_{diff}$ and bipolar log-intensity-variance histograms $H_P$ and $H_N$ are extracted from the chaos phase plot positive subspace ($T_{chaos}^+$) and the chaos phase plot negative subspace ($T_{chaos}^-$), respectively. In
the third step, the proposed probabilistic measure function is employed to generate a classification score. In the fourth step, a fixed threshold $T_m$ is used to determine the cause of the variance in intensity.

3. Experiments and Analysis

3.1. Experimental Data. To evaluate the proposed measure function, a group of published image sequence databases (DBs) was selected to construct our test local image patch database. It consisted of two parts: an illumination change DB and motion change DB, both including indoor and outdoor scenes.

The extraction process of our test data is shown in Figure 7. In particular, for indoor scene illumination change DB1, 600 80-by-80 local patch pairs were randomly extracted from an indoor office scene image pair under artificial illumination change [27], as shown in Figure 7(a). For outdoor scene illumination change DB2, 600 80-by-80 local patch pairs were randomly extracted from an outdoor scene image pair under natural illumination change [28], as shown in Figure 7(b). For indoor scene motion change DB3, 206 80-by-80 local patch pairs were extracted from an indoor people-walking scene image sequence [29], as shown in Figure 7(c). For outdoor scene motion change DB4, 250 80-by-80 local patch pairs were extracted from an outdoor people-walking scene image sequence [30], as Figure 7(d) shows. For indoor scene motion change DB5, 290 80-by-80 local patch pairs were extracted from a top-view indoor people-walking scene image sequence [20] as Figure 7(e) shows. Therefore, our test local image patch pair DB consisted of five subdatabases: indoor illumination change DB1, outdoor illumination change DB2, indoor motion change DB3 and DB5, and outdoor motion change DB4. We employed 20% of DB data to estimate the optimal parameters of the proposed function, and the remaining 80% of DB data were used for a comparison experiment.

The information about scene description, adjacent local image patch pairs quantity, local image patch resolution, and video source of test data is summarized on Table 1.

3.2. Parameters of the Proposed Measure Function. The parameters of the proposed measure function are $a$, $T_A$, and $T_N$. To obtain optimal parameters, the successful classification (SC) is employed as the evaluating indicator. It is defined as

$$SC = \begin{cases} \text{Score of eq } (12) > T_m, & \text{for motionDB} \\ \text{Score of eq } (12) < T_m, & \text{for illuminationDB} \end{cases}$$

where $T_m$ is the threshold of the classification score ($T_m = 0.5$).

Figure 8 shows the results of an analysis of the proposed measure function’s performance when varying its sigmoid shape parameter $a$, amplitude threshold of bipolar log-intensity-variance histogram $T_A$, and number threshold of bipolar log-intensity-variance histogram large component $T_N$.

3.3. Experimental Setup and Some Examples. The proposed measure and those of conventional methods, i.e., the CPPS and box-count dimension measure [26], TC-LBP [22], and IISC [23], were calculated in a MATLAB 2017b environment on an Intel(R) Quad Core (TM) i5-459 CPU with 16 GB of memory. The parameters of the proposed method (obtained from the above parameter performance analysis) were set as follows for all the test databases: $a = 3$, $T_A = 3$, and $T_N = 37$.

Two groups of image patch data and corresponding chaos phase plot spaces were used to illustrate the innovation and advances of the proposed measure function compared to the conventional CPPS and box-count dimension metric [26]. Figure 9 shows two slight illumination change image patch pairs and two large motion image patch pairs, and Figure 10 shows two strong illumination change image patch pairs and small motion image patch pairs.

The measure scores under different methods [26] of the data in Figures 9 and 10 are summarized in Table 1. From the fourth column of Table 1, we can clearly see that the box-count dimension measure score [26] of slight illumination [Figures 9(a) and 9(b)] is smaller than that of large motion [Figures 9(c) and 9(d)]. Such performance illustrates that CPPS and the box-count dimension method are effective at intensity change classification for slight illumination change vs. large motion data. According to the conventional method [26], the box-count measure score of illumination change must be smaller than that of motion changes. However, we see in the last column of Table 1 that the scores of small motion changes are larger than those of strong illumination changes. Therefore, it is unable to select a fixed threshold to simultaneously obtain a correct classification result for illumination change and motion change, as in Figures 9(a), 9(b), 10(a), and 10(b) vs. Figures 9(c), 9(d), 10(c), and 10(d).
Figure 7: Parameter performance test local patch pair DB. (a) Indoor illumination change local patch pair DB1; (b) outdoor illumination change local patch pair DB2; (c) indoor motion change local patch pair DB3; (d) outdoor motion change local patch pair DB4; and (e) indoor top-view motion change local patch pair DB5.
The conventional method [26] is invalid because the box-count dimension measure uses the area of the chaos phase plot behavior to determine the reason for an intensity change. So, its effectiveness is affected by the amplitude relationship of motion and illumination change.

In contrast, from the third and seventh columns of Table 2, it is clear that the proposed measure scores of Figures 9 and 10 are identical. This example illustrates that the proposed bipolar log-variance-histogram measure function can provide a more accurate and robust metric to local image patch intensity change classification than the conventional CPPS and box-count dimension measure [26].

More experimental results of the proposed measure function’s performance are shown in Figure 11, which consists
Figure 9: Examples of performance data under slight illumination change vs. large motion data.

Table 1: Description of test DB.

<table>
<thead>
<tr>
<th>DB index</th>
<th>Scene description</th>
<th>Quantity and resolution</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>DB1</td>
<td>indoor, artificial illumination change</td>
<td>600 image pairs, $80 \times 80$</td>
<td>[27]</td>
</tr>
<tr>
<td>DB2</td>
<td>outdoor, natural illumination change</td>
<td>600 image pairs, $80 \times 80$</td>
<td>[28]</td>
</tr>
<tr>
<td>DB3</td>
<td>indoor, walking people</td>
<td>250 image pairs, $80 \times 80$</td>
<td>[29]</td>
</tr>
<tr>
<td>DB4</td>
<td>outdoor, walking people</td>
<td>206 image pairs, $80 \times 80$</td>
<td>[30]</td>
</tr>
<tr>
<td>DB5</td>
<td>indoor, top-view walking people</td>
<td>290 image pairs, $80 \times 80$</td>
<td>[20]</td>
</tr>
</tbody>
</table>

Table 2: Different measure scores of Figures 9 and 10.

<table>
<thead>
<tr>
<th>Data/Method</th>
<th>Ours</th>
<th>Ref. [26]</th>
<th>Data/Method</th>
<th>Ours</th>
<th>Ref. [26]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slight illumination change</td>
<td></td>
<td></td>
<td>Strong illumination change</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Figure 9(a)</td>
<td>0</td>
<td>0.8123</td>
<td>Figure 10(a)</td>
<td>0</td>
<td>1.4121</td>
</tr>
<tr>
<td>Figure 9(b)</td>
<td>0</td>
<td>0.9408</td>
<td>Figure 10(b)</td>
<td>0</td>
<td>1.3015</td>
</tr>
<tr>
<td>Large motion</td>
<td></td>
<td></td>
<td>Small motion</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Figure 9(c)</td>
<td>1</td>
<td>1.6991</td>
<td>Figure 10(c)</td>
<td>1</td>
<td>1.2174</td>
</tr>
<tr>
<td>Figure 9(d)</td>
<td>1</td>
<td>1.7542</td>
<td>Figure 10(d)</td>
<td>1</td>
<td>1.1665</td>
</tr>
</tbody>
</table>
of three groups of test data. Every group of test data is randomly extracted from DB1 (outdoor scene under natural illumination change), DB2 (indoor scene under artificial illumination change), DB3 (indoor moving object), and DB4 (outdoor moving object). The scores of the proposed measure under illumination change and object movement are clearly labeled by 0 and 1, respectively.

3.4. Comparison Experiments and Analysis. We tested the performance of the proposed method against other conventional analysis methods [22, 23, 26]. For TC-LBP [22], a histogram intersection was employed to construct a TC-LBP-based measure function

\[
F_{\text{TCLBP}}(h_1, h_2) = 1 - \frac{\sum_{i=1}^{k} \min(h_1(i), h_2(i))}{\sum_{i=1}^{k} h_2(i)}
\]

(16)

Figure 10: Examples of performance data under strong illumination change vs. small motion data.

Figure 11: Examples of experimental results in the test database.
Table 3: ROC performance of DB1 vs. DB3.

<table>
<thead>
<tr>
<th>Method</th>
<th>AUC (%)</th>
<th>1-EER (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed measure</td>
<td>98.8%</td>
<td>95.1%</td>
</tr>
<tr>
<td>Box-count measure [26]</td>
<td>80.7%</td>
<td>75.4%</td>
</tr>
<tr>
<td>TC-LBP [22]</td>
<td>85.1%</td>
<td>81.3%</td>
</tr>
<tr>
<td>IISC [23]</td>
<td>92.6%</td>
<td>89.9%</td>
</tr>
</tbody>
</table>

Table 4: ROC performance of DB1 vs. DB4.

<table>
<thead>
<tr>
<th>Method</th>
<th>AUC (%)</th>
<th>1-EER (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed measure</td>
<td>97.5%</td>
<td>93.8%</td>
</tr>
<tr>
<td>Box-count measure [26]</td>
<td>88.2%</td>
<td>82.6%</td>
</tr>
<tr>
<td>TC-LBP [22]</td>
<td>82.2%</td>
<td>78.7%</td>
</tr>
<tr>
<td>IISC [23]</td>
<td>94.7%</td>
<td>90.2%</td>
</tr>
</tbody>
</table>

Table 5: ROC performance of DB2 vs. DB3.

<table>
<thead>
<tr>
<th>Method</th>
<th>AUC (%)</th>
<th>1-EER (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed measure</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Box-count measure [26]</td>
<td>85.8%</td>
<td>81.6%</td>
</tr>
<tr>
<td>TC-LBP [22]</td>
<td>90%</td>
<td>85.5%</td>
</tr>
<tr>
<td>IISC [23]</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

where $h_1$ and $h_2$ are TC-LBP histograms of input image local patches $I_1$ and $I_2$, respectively, and $k$ is the length of vectors $h_1$ and $h_2$. For IISC [23], a difference rate was employed as an IISC-based measure function

$$F_{IISC}(f_1, f_2) = 1 - \frac{|f_1 - f_2|}{f_1}$$

where $f_1$ and $f_2$ are IISC scalar features of input local image patches $I_1$ and $I_2$, respectively.

A receiver operating characteristic (ROC) curve, area under curve (AUC), and equal error rate (1-EER) [32] are employed as evaluating indicators in this paper. Figure 12 presents a comparison of the performance of the proposed measure function and other conventional methods [22, 23, 26] using an ROC curve under different test database combinations.

Figure 12 shows the intensity variation classification performance of different methods under different test databases. Figure 12(a) displays the intensity variation classification results between the indoor illumination change and indoor object movement databases (DB1 vs. DB3). Figure 12(b) shows the intensity variation classification results between the indoor illumination change and outdoor object movement databases (DB1 vs. DB4). Figure 12(c) shows the intensity variation classification results between the outdoor illumination change and indoor object movement databases (DB2 vs. DB3). Figure 12(d) shows the intensity variation classification results between the outdoor illumination change and outdoor object movement databases (DB2 vs. DB4). Figure 12(e) shows the intensity variation classification results between the indoor illumination change and indoor top-view object movement databases (DB1 vs. DB5). Figure 12(f) shows the intensity variation classification results between the outdoor illumination change and indoor top-view object movement databases (DB2 vs. DB5).

Figures 12(c), 12(d), and 12(f) clearly indicate that the ROC performance of the proposed measuring method for natural illumination changes in outdoor scenes and the object moving database is perfect. There are almost no false positive alarms because global natural illumination changes always cause image intensity monotone variations. Compared with natural illumination change data, the ROC performance of the proposed method declined for the artificial illumination indoor scene and object movement data combination [Figures 12(a), 12(b), and 12(e)]. There were some false alarms in the ROC, because complex artificial illumination may generate nonmonotonic intensity changes at local regions in the image.

The ROC curve summarizes the experimental results for the classification of changes in image intensity for different thresholds. The red line represents the chaos phase plot measure, and the blue line represents the proposed measure. The pink line is the IISC measure and the dark line is the TC-LBP measure. In general, curves further to the top left, closer to the top left of the ROC space, exhibit better performance [28]. The proposed measure is obviously closer to the top left than the other conventional methods, with a higher true positive rate (TPR) and a lower false positive rate (FPR) for all the experiment results with different test databases.

Tables 3–8 present the performance of the proposed measure and the chaos measure for different test datasets in terms of AUC and 1-EER, which are computed from the ROC curve in Figure 12(a)–12(f). These tables illustrate that the proposed measure can more correctly classify changes in intensity due to illumination change and object movement.

Table 9 shows the computational cost of different methods. The average running times of the proposed measure,
Figure 12: ROC curves for intensity variation classification using the test datasets. (a) DB1 vs. DB3; (b) DB1 vs. DB4; (c) DB2 vs. DB3; (d) DB2 vs. DB4; (e) DB1 vs. DB5; and (f) DB2 vs. DB5.
### Table 6: ROC performance of DB2 vs. DB4.

<table>
<thead>
<tr>
<th>Method</th>
<th>AUC (%)</th>
<th>1-EER (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed measure</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Box-count measure [26]</td>
<td>75.8%</td>
<td>68.7%</td>
</tr>
<tr>
<td>TC-LBP [22]</td>
<td>91%</td>
<td>86.5%</td>
</tr>
<tr>
<td>IISC [23]</td>
<td>95.45%</td>
<td>91.5%</td>
</tr>
</tbody>
</table>

### Table 7: ROC performance of DB1 vs. DB5.

<table>
<thead>
<tr>
<th>Method</th>
<th>AUC (%)</th>
<th>1-EER (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed measure</td>
<td>96.9%</td>
<td>92.55%</td>
</tr>
<tr>
<td>Box-count measure [26]</td>
<td>80.8%</td>
<td>74.6%</td>
</tr>
<tr>
<td>TC-LBP [22]</td>
<td>91.8%</td>
<td>87%</td>
</tr>
<tr>
<td>IISC [23]</td>
<td>89.05%</td>
<td>84.5%</td>
</tr>
</tbody>
</table>

### Table 8: ROC performance of DB2 vs. DB5.

<table>
<thead>
<tr>
<th>Method</th>
<th>AUC (%)</th>
<th>1-EER (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed measure</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>Box-count measure [26]</td>
<td>83.8%</td>
<td>79.6%</td>
</tr>
<tr>
<td>TC-LBP [22]</td>
<td>89.3%</td>
<td>84.5%</td>
</tr>
<tr>
<td>IISC [23]</td>
<td>95.45%</td>
<td>91.2%</td>
</tr>
</tbody>
</table>

### Table 9: Computational cost of different methods.

<table>
<thead>
<tr>
<th>Method</th>
<th>Proposed</th>
<th>Box-count dimension [26]</th>
<th>TC-LBP [22]</th>
<th>IISC [23]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average running time (sec)</td>
<td>0.0275</td>
<td>0.0235</td>
<td>0.336</td>
<td>0.0061</td>
</tr>
</tbody>
</table>

### Table 10: Evaluation of top-view people detection with different methods.

<table>
<thead>
<tr>
<th>Method</th>
<th>Source image sequence of DB5</th>
<th>Detection probability</th>
<th>False alarm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single ACF model [31]</td>
<td></td>
<td>75.7%</td>
<td>5.71%</td>
</tr>
<tr>
<td>Subarea ACF models &amp; box-counting measure [20]</td>
<td></td>
<td>92.3%</td>
<td>6.39%</td>
</tr>
<tr>
<td>Subarea ACF models &amp; proposed measure</td>
<td></td>
<td>92.3%</td>
<td>0.98%</td>
</tr>
</tbody>
</table>

CPS and box-count dimension measure [26], TC-LBP [22], and IISC [23] are 0.0275, 0.0235, 0.336, and 0.0061 s, respectively. As can be seen, TC-LBP [22] is relatively slow. The computational cost of the proposed measure is similar to that of the CPPS and box-count measure [26]. IISC [23] is faster than the other methods. Therefore, the proposed measure can be applied to real-time computer vision applications.

3.5. Application of Proposed Measure. Reference [20] introduced a top-view walking people detection method. Firstly, multiple subarea ACF models [31] are proposed to generate coarse detection result. Then Chaos phase and box-counting measure are employed to remove false alarms. We apply proposed bipolar log-intensity-variance histogram measure to remove false detection results instead of box-counting measure. Figure 13 shows some examples of top-view people detection result with different methods. It is clear to see that some static false detection results such as chair, coat, and desk are filtered by proposed measure effectively.

Moreover, Table 10 presents a quantitative comparison of our approach and conventional methods. Evaluation result shows that, with the help of proposed measure, top-view people detection result performances lower false alarm while retaining high detection probability.

### 4. Conclusions

This paper presents a metric for the classification of variations in image intensity. First, a new analysis method is proposed for intensity changes on the CPPS; the behaviors of intensity variation on the chaos phase plot subspace are described by the proposed bipolar log-intensity-variance histograms. Second, two sigmoid functions are employed to construct a quantifiable classification measure. Experimental results show that, with the help of the new observed property of the chaos phase plot subspace, the proposed measure function can provide more effective determination. In particular, it is robust to the amplitude relationship of motion and
illumination change, outperforming the other conventional methods.

**Data Availability**

The data used to support the findings of this study are included within the article.

**Conflicts of Interest**

The authors declare that they have no conflicts of interest.

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**References**


