Multi-Scale Colour Completed Local Binary Patterns for Scene and Event Sport Image Categorisation

Taha H. Rassem, Member, IAENG, Bee Ee Khoo, Nasrin M. Makbol, and AbdulRahman A. Alsewari

Abstract—The Local Binary Pattern (LBP) texture descriptor and some of its variant descriptors have been successfully used for texture classification and for a few other tasks such as face recognition, facial expression, and texture segmentation. However, these descriptors have been barely used for image categorisation because their calculations are based on the gray image and they are only invariant to monotonic light variations on the gray level. These descriptors ignore colour information despite their key role in distinguishing the objects and the natural scenes. In this paper, we enhance the Completed Local Binary Pattern (CLBP), an LBP variant with an impressive performance on texture classification. We propose five multi-scale colour CLBP (CCLBP) descriptors by incorporating five different colour information into the original CLBP. By using the Oliva and Torralba (OT8) and Event sport datasets, our results attest to the superiority of the proposed CCLBP descriptors over the original CLBP in terms of image categorisation.

Index Terms—Local Binary Pattern (LBP), Texture Descriptors, Completed Local Binary Pattern (CLBP), colour CLBP (CCLBP), Image Categorisation.

I. INTRODUCTION

TEXTURE features are vital in many of today’s applications such as human detectors [1], face recognition [2], [3], image retrieval [4], [5], finger detection [6], texture segmentation [7], and visual object recognition [8]–[10]. Previous literature identifies many textures feature algorithms for robust and distinctive texture features. Zhang et al. [11] classified the texture feature algorithm methods into three categories, namely, the statistical algorithm methods, the model-based methods, and structural methods. Many studies have comprehensively reviewed these texture algorithm methods [11], [12].

In 1996, Ojala et al. [13] calculated the absolute difference between the gray level of the centre pixel of a specific local pattern and its neighbours to construct a histogram representing the image texture. This absolute difference, instead of the magnitude, was subsequently used to construct the Local Binary Pattern (LBP) texture descriptor [14]. LBP has become an interesting research topic for many computer vision researchers for its ability to discern the micro-structures of an image, such as edges, lines and spots. LBP has been proposed for rotation invariant texture classification and has been extended for several applications, such as face recognition [15], and image retrieval [5].

Fig. 1 shows two steps of the LBP, namely, the thresholding step and the encoding step. The former compares the values of the central pixel with the values of all neighbouring pixels to convert the values of the neighbouring pixels into binary values (0 or 1). The latter encodes and converts these binary values into decimal numbers to characterise a structural pattern.

Many LBP variants have been suggested to increase the discriminating property of the texture feature extraction. These variants include the Center-Symmetric Local Binary Pattern (CS-LBP) [16], the Dominant LBP (DLBP) [17], the Local Ternary Pattern (LTP) [18], the Completed Modelling of LBP (CLBP) [19], and Completed Ternary Pattern (CLTP) [20], and Local Orientation Adaptive Descriptor (LOAD) [21].

Although many texture features have been successfully used for many tasks such as texture classification, face recognition, facial expression and texture segmentation, these features are rarely used for visual object class recognition. Although colour is important information in visual object recognition, many texture features do not consider the colour information because many of their calculations are based on the gray scale image and texture features are only invariant to monotonic light variations on the gray level. Incorporating colour into the texture operators enhance the operators’ photometric invariance and discriminating properties [22], [23], as well as helping them to distinguish the objects and the natural scenes.

Zhu et al. [22] proposed and used six colour LBP for visual object class recognition. The multi-scale LBP histogram was extracted from each colour channel, and then
all the colour and multi-scale histograms for the colour space channels were concatenated to construct the final LBP histogram. Banerji et al. [23] also incorporated LBP with different colour information for visual object class recognition. In [24], the PHOG descriptor was combined with the colour LBP to achieve high quality recognition results. Fig. 2 shows the calculation of the colour LBP.

Inspired by the CLBP texture descriptor, five novel multi-scale colour CLBP texture descriptors (CCLBP) are proposed in this paper to enhance the photometric invariance and discriminative power of the original CLBP. Guo et al. [19] proposed a Completed Modelling of LBP (CLBP) by comparing both the sign and the magnitude of the pattern’s central gray level value with its neighbours and by combining them with all central values of the patterns. The sign difference, the magnitude difference, and the threshold of the central grey values of the patterns are combined in different ways to construct three CLBP operators [19], namely, CLBP\_S, CLBP\_M and CLBP\_C, respectively, which are, in turn, calculated based on five different colour spaces, namely, RGB, HSV, Opponent colour, Transformed-colour, and Ohta colour spaces. These descriptors are then combined to construct the CCLBP descriptor. The performances of the proposed CCLBP descriptors are evaluated and analysed experimentally for image categorisation.

The rest of this paper is organised as follows. Sections II and III briefly review LBP and the Completed Local Binary Pattern (CLBP) texture descriptors, respectively. Section IV presents the proposed CCLBP descriptors. Section V discusses the experimental results of the OT8 and the Event sport datasets. Lastly, Section VI concludes the paper.

II. LOCAL BINARY PATTERN (LBP)

The LBP calculation can be described mathematically as follows:

\[
LBP_{P,R} = \sum_{p=0}^{P-1} 2^p s(p, i, c), \quad s(x) = \begin{cases} 
1, & x \geq 0, \\
0, & x < 0,
\end{cases}
\]

(1)

where \(i, c, p\) denote the grey values of the centre pixel and the neighbour pixel on a circle of radius \(R\), respectively, and \(P\) denotes the number of neighbours. Bilinear interpolation estimation method is used to identify the neighbours that do not lie in the exact centre of the pixels.

Ojala et al. [14] also improved the original LBP into the rotation invariant LBP (LBP\_RI) and the uniform rotation invariant LBP (LBP\_RIU). After encoding these LBP types, i.e., LBP, LBP\_RI and LBP\_RIU, the descriptor histogram is constructed based on the following equation:

\[
H(k) = \sum_{i=0}^{I} \sum_{j=0}^{J} f(LBP_{P,R}(i,j), k), \quad k \in [0, K],
\]

\[
f(x, y) = \begin{cases} 
1, & x = y, \\
0, & \text{otherwise},
\end{cases}
\]

(2)

where \(K\) is the maximal LBP pattern value.

III. COMPLETED LOCAL BINARY PATTERN (CLBP)

Fig. 2 shows the decomposition of the image local difference into two complementary components, namely, the sign component \(s_p\) and the magnitude component \(m_p\) which can be mathematically expressed as follows:

\[
s_p = s(p, i, c), \quad m_p = |p - c|\]

(3)

\(s_p\) is used to construct CLBP\_S, whereas \(m_p\) is used to construct CLBP\_M. These two operators are mathematically expressed as follows:

\[
CLBP\_S_{P,R} = \sum_{p=0}^{P-1} 2^p s(p, i, c), \quad s_p = \begin{cases} 
1, & i \geq i, \\
0, & i < i,
\end{cases}
\]

(4)

\[
CLBP\_M_{P,R} = \sum_{p=0}^{P-1} 2^p t(m_p, c),
\]

\[
t(m_p, c) = \begin{cases} 
1, & |p - c| \geq c, \\
0, & |p - c| < c,
\end{cases}
\]

(5)

where \(i, c, R, P\) and \(p\) are defined in (1), while \(c\) denotes the mean value of \(m_p\) in the entire image.

CLBP\_S is equivalent to LBP, whereas CLBP\_M measures the local variance of the magnitude. Guo et al. constructed the CLBP-Centre (CLBP\_C) by thresholding the values of each pattern using the average grey level of the entire image. CLBP\_C is expressed mathematically as follows:
null
and shift-invariant with respect to light intensity. However, due to the combination of Hue with the remaining information; i.e., saturation and value, the HSV-CCLBP has no invariant properties.

3) Opponent CCLBP: The Opponent CCLBP operators are obtained by computing CLBP independently in all three channels of the Opponent colour space and by concatenating the results together. The Opponent colour channels can be described by the following equation:

\[
\begin{pmatrix}
O_1 \\
O_2 \\
O_3
\end{pmatrix} = \begin{pmatrix}
\frac{R-G}{\sqrt{2}} \\
\frac{R+G-2B}{\sqrt{6}} \\
\frac{G+2B+R}{\sqrt{6}}
\end{pmatrix}
\]

(12)

where \(O_1\) and \(O_2\) represent the colour information while \(O_3\) represents the intensity information.

Based on Equation (12), the \(O_1\) and \(O_2\) has shift-invariant property while no invariant properties for the intensity channel \(O_3\). So, the Opponent CCLBP has invariant property against light intensity changes.

4) Transformed CCLBP: The Transformed-CCLBP is obtained by computing CLBP independently in all three channels of the Transformed colour space and by concatenating the results together. The Transformed colour channels can be described by the following equation:

\[
\begin{pmatrix}
\hat{R'} \\
\hat{G'} \\
\hat{B'}
\end{pmatrix} = \begin{pmatrix}
\frac{R-\mu_R}{\sigma_R} \\
\frac{G-\mu_G}{\sigma_G} \\
\frac{B-\mu_B}{\sigma_B}
\end{pmatrix}
\]

(13)

where \(\mu_R\), \(\mu_G\) and \(\mu_B\) are the mean values of R, G and B channels, respectively, and \(\sigma_R\), \(\sigma_G\) and \(\sigma_B\) are the standard deviation of each channel.

The Transformed CCLBP has invariant property against the light intensity changes and shifts (scale-invariant and shift-invariant). This is due to the subtraction and the normalisation as shown in Equation (13). This descriptor is also invariant to light colour change and shift because the Transformed colour space has these invariant properties [26], [29].

5) Ohta CCLBP: The Ohta CCLBP is obtained by computing CLBP independently in all three channels of the Ohta colour space [30] and by concatenating the results together. The Ohta colour channels can be described by the following equation:

\[
\begin{pmatrix}
I_1 \\
I_2 \\
I_3
\end{pmatrix} = \begin{pmatrix}
\frac{R+G+B}{2} \\
\frac{R-B}{2G-R-B} \\
\frac{G+2B+R}{2G-R-B}
\end{pmatrix}
\]

(14)

where \(I_1\) represents the intensity component while \(I_1'\) and \(I_3\) represent the approximate orthogonal colour components. The Ohta colour space (only \(I_2\) and \(I_2\)) has only the shift invariant property. This is due to the subtraction as shown in following equation:

\[
\begin{pmatrix}
I_2 \\
I_3
\end{pmatrix} = \begin{pmatrix}
\frac{R-B}{2G-R-B} \\
\frac{(R+o_1)-(B'+o_1)}{2(2G+o_1)-(R'+o_1)-(B'+o_1)}
\end{pmatrix} \begin{pmatrix}
\hat{R'}-\hat{B'} \\
2G'-R'-B'
\end{pmatrix}
\]

(15)

The Ohta colour has not invariant to the light colour changes and shifts, and to the light intensity changes (scale invariant). So, the Ohta-CCLBP has the same properties.

B. Mathematical Models of CCLBP

Similar to Equations (4), (5) and (6), CCLBP operators can be calculated in each channel as follows:

\[
(CCLBP_{S,P,R})^{C_1} = \sum_{p=0}^{P-1} 2^p s(i_p - i_c),
\]

\[
s_p = \begin{cases}
1, & i_p \geq i_c, \\
0, & i_p < i_c,
\end{cases}
\]

(16)

\[
(CCLBP_{S,P,R})^{C_2} = \sum_{p=0}^{P-1} 2^p s(i_p - i_c),
\]

\[
s_p = \begin{cases}
1, & i_p \geq i_c, \\
0, & i_p < i_c,
\end{cases}
\]

(17)

\[
(CCLBP_{S,P,R})^{C_3} = \sum_{p=0}^{P-1} 2^p s(i_p - i_c),
\]

\[
s_p = \begin{cases}
1, & i_p \geq i_c, \\
0, & i_p < i_c,
\end{cases}
\]

(18)

where \(C_1\), \(C_2\), and \(C_3\) are the colour space channels. The final CCLBP can be calculated as follows.

\[
CCLBP_{S,P,R} = [(CCLBP_{S,P,R})^{C_1} (CCLBP_{S,P,R})^{C_2} (CCLBP_{S,P,R})^{C_3}]
\]

(19)

Similar to equation (5), the CCLBP can be calculated as follows:

\[
CCLBP_{M,P,R} = [(CCLBP_{M,P,R})^{C_1} (CCLBP_{M,P,R})^{C_2} (CCLBP_{M,P,R})^{C_3}]
\]

(20)

To construct the remaining operators, the CCLBP, CCLBP and CCLBP are for each colour channel are combined jointly or hybridized similar to the method that are explained in Section III. The final CCLBP operators, which are the concatenation of all colour channel operators, can be mathematically described as follows:

\[
CCLBP_{S,M,P,R} = [(CCLBP_{S,M,P,R})^{C_1}(CCLBP_{S,M,P,R})^{C_2}(CCLBP_{S,M,P,R})^{C_3}]
\]

(21)

\[
CCLBP_{S,M,P,R} = [(CCLBP_{S,M,P,R})^{C_1}(CCLBP_{S,M,P,R})^{C_2}(CCLBP_{S,M,P,R})^{C_3}]
\]

(22)

\[
CCLBP_{M,C,P,R} = [(CCLBP_{M,C,P,R})^{C_1}(CCLBP_{M,C,P,R})^{C_2}(CCLBP_{M,C,P,R})^{C_3}]
\]

(23)

\[
CCLBP_{S,M,C,P,R} = [(CCLBP_{S,M,C,P,R})^{C_1}(CCLBP_{S,M,C,P,R})^{C_2}(CCLBP_{S,M,C,P,R})^{C_3}]
\]

(24)

\[
CCLBP_{M,C,P,R} = [(CCLBP_{M,C,P,R})^{C_1}(CCLBP_{M,C,P,R})^{C_2}(CCLBP_{M,C,P,R})^{C_3}]
\]

(25)

V. EXPERIMENTS AND DISCUSSION

Experiments are performed to evaluate the proposed CCLBP. The OT8 and the Event sport datasets are used in these experiments.
A. Dissimilarity Measuring Framework

Several metrics are proposed to measure the dissimilarity between the two histograms, such as log-likelihood ratio, histogram intersection, and chi-square statistic. Similar to [19], these experiments use the chi-square statistic. The \( \chi^2 \) distance between two histograms \( H = h_i \) and \( K = k_i \) (where \( i = 1, 2, 3, \ldots B \)) can be mathematically described as follows:

\[
\text{Dissimilarity}_{\chi^2}(H, K) = \sum_{i=1}^{B} \frac{(h_i - k_i)^2}{h_i + k_i}
\]

These experiments use the nearest neighbourhood classifier for classification.

B. Experimental Results on OT8 Scene Dataset

The Oliva & Torralba dataset (OT8) has a total 2,688 colour images [32]. The dataset contains eight categories, namely, coast, forest, mountain, open country, highway, inside city, tall building, and street. These images are in JPG format and have an average size of 265 \times 265 pixels. Figure 4 shows some examples of OT8 images. The OT8 scene dataset is used in these experiments to evaluate the proposed CCLBP and to compare its performance with the gray CLBP operators. As shown in Figs. 9(d) and 9(e), the performances of the Opponent CCLBP operators when \( R = 1 \) and \( P = 8 \) have outperformed the other CLBP operators. Finally, all Opponent CCLBP operators have outperformed the gray CLBP operators. Finally, all Opponent CCLBP operators have achieved the best classification accuracy, which has reached up to 58.49%.

Figs 8(a) to 8(f) show the performances of the texture operators of the \( R = 2 \) and \( P = 16 \) texture pattern. The following observations can be obtained from these figures. Firstly, the gray CLBP operators have all exhibited better performance than other CLBP operators. Secondly, aside from the Opponent CCLBP operators, all remaining CCLBP operators have outperformed the gray CLBP operators. Finally, similar to the performance of the Opponent CCLBP operators when \( R = 1 \) and \( P = 8 \), these operators have exhibited the worst performance except in Fig. 8(f) where the Opponent CCLBP operators have outperformed the gray CLBP operators as the number of training images was increased. The RGB CCLBP_S/M/C operator has achieved the best classification accuracy, achieving up to 58.07%. Figs. 9(a) to 9(f) show the performances of the texture operators of the \( R = 3 \) and \( P = 24 \) texture pattern. The following observations can be made from these figures. Firstly, the gray CLBP operators and CLBP operators have a better performance than the other CCLBP operators. Secondly, aside from the Opponent CCLBP operators, all remaining CCLBP operators have outperformed the gray CLBP operators. As shown in Figs. 9(d) and 9(e), the performances of the Opponent CCLBP operators and the Opponent CCLBP operators improved upon increasing the number of training images. The Opponent CCLBP operators have achieved the best classification accuracy, which has reached up to 54.17%. Lastly, CCLBP_M/C, CCLBP_S/M/C, CCLBP_S/M and CCLBP_S/M/C operators have all
outperformed the gray CLBP operators. The Transformed CCLBP\_S/M/C operator has achieved the best classification accuracy, achieving up to 57.25%. Generally speaking, the performances of CCLBP operators have outperformed the gray CLBP operators. Aside from the Opponent CCLBP operators, the performances of all CCLBP operators are approximately the same. Table I shows the classification accuracy results on OT8 database in details.

C. Experimental Results on Event sport Dataset

The Event sport dataset has eight categories, namely, rowing, badminton, polo, bocce, snow boarding, croquet, sailing, and rock climbing [33]. Figure 6 shows some examples of Event sport images. Similar to the OT8 datasets, the Event sport dataset is used to evaluate the proposed CCLBP and to compare its performance with the gray CLBP under various numbers of training images. In each class \( N = (5, 10, 20, 30, 40, 50, 60) \) is used as the training images, while the remaining images are used as testing images. The final classification accuracy is determined by the average percentage over a hundred random splits. The comparison is performed on different texture patterns, namely, \( (P = 8 \text{ and } R = 1), (P = 16 \text{ and } R = 2), \) and \( (P = 24 \text{ and } R = 3) \). Figs. 10, 11 and 12 show the performances of the gray CLBP and the proposed CCLBP operators.

Figs. 10(a) to 10(f) present the performances of the texture operators of the \( R = 1 \) and \( P = 8 \) texture pattern. The following observations can be formulated based on these figures. Firstly, Opponent CCLBP\_S and Opponent CCLBP\_M have performed the worst, whereas the Transformed CCLBP\_S/M/C, HSV CCLBP\_S/M/C and RGB CCLBP\_S/M/C have achieved top-ranking performances. Secondly, unlike the other CLBP operators, the
Fig. 7. Recognition accuracy as a function of the number of training images for OT8 image dataset using the gray CLBP descriptors and the proposed CCLBP descriptors when R=1 and P=8. 7(a) CLBP_S and CCLBP_S. 7(b) CLBP_M and CCLBP_M. 7(c) CLBP_M/C and CCLBP_M/C. 7(d) CLBP_S/M/C and CCLBP_S/M/C. 7(e) CLBP_S/M and CCLBP_S/M. 7(f) CLBP_S/M/C and CCLBP_S/M/C.
Fig. 8. Recognition accuracy as a function of the number of training images for OT8 image dataset using the gray CLBP descriptors and the proposed CCLBP descriptors when $R=2$ and $P=16$. (a) CLBP$_S$ and CCLBP$_S$. (b) CLBP$_M$ and CCLBP$_M$. (c) CLBP$_M$/C and CCLBP$_M$/C. (d) CLBP$_S$/M and CCLBP$_S$/M. (e) CLBP$_S$/M/C and CCLBP$_S$/M/C.
Fig. 9. Recognition accuracy as a function of the number of training images for OT8 image dataset using the gray CLBP descriptors and the proposed CCLBP descriptors when $R=3$ and $P=24$. 9(a) CLBP$_S$ and CCLBP$_S$. 9(b) CLBP$_M$ and CCLBP$_M$. 9(c) CLBP$_M$/C and CCLBP$_M$/C. 9(d) CLBP$_S$/M/C and CCLBP$_S$/M/C. 9(e) CLBP$_S$/M and CCLBP$_S$/M. 9(f) CLBP$_S$/M/C and CCLBP$_S$/M/C.
Opponent CCLBP_M/C operator has outperformed the gray CLBP_M/C and remaining CCLBP_M/C operators. Thirdly, the gray CLBP_M/C and CCLBP_S/M/C operators have performed worse than all CCLBP_M/C and CCLBP_S/M/C operators, respectively. Lastly, the performances of the gray CLBP_S/M/C and the Opponent CCLBP_S/M/C operators are approximately the same and have performed worse than the remaining CCLBP_S/M/C operators. The Transformed CCLBP_S/M/C operator has achieved the best classification accuracy, which reached up 55.05%, while the best classification accuracy in both OT8 and Event Sport experiments, which has achieved 48.86% classification accuracy.

Figs. 11(a) to 11(f) show the performances of the texture operators of the R = 2 and P = 16 texture pattern. The following observations can be obtained from these figures. Firstly, the gray CLBP_M operator has outperformed all CCLBP_M operators, while the remaining CCLBP_M operators have performed better than the Opponent CCLBP_M operator. Secondly, aside from the Opponent CCLBP_S and Opponent CCLBP_M operators, the remaining Opponent CCLBP operators have outperformed the gray CLBP and the other CCLBP operators. Finally, the Opponent CCLBP_S/M/C operator has achieved the best classification accuracy, which has reached up to 55.54%, and is closely followed by the Transformed CCLBP_S/M/C, which has achieved a 52.84% classification accuracy.

Figs. 12(a) to 12(f) demonstrate the performances of the texture operators of the R = 3 and P = 24 texture pattern. The following observations can be obtained from these figures. Firstly, the responses of the CLBP operators are nearly similar to their responses of the R = 2 and P = 16 texture pattern, except for the Opponent CCLBP_M/C and Opponent CCLBP_S/M/C operators, which have outperformed the other CLBP operators. Secondly, only the gray CLBP_M operator has outperformed the CCLBP_M operators while the remaining CCLBP operators have outperformed the remaining gray CLBP operators. Lastly, the Opponent CCLBP_S/M/C operator has achieved the best classification accuracy, which has reached up to 55.05%, and is followed by the Transformed CCLBP_S/M/C at 52.49% classification accuracy. Table II shows the classification accuracy results on Event database in details. Generally speaking, the CCLBP operators have outperformed the gray CLBP operators.

Overall, the CCLBP_S/M/C operators have achieved the best classification accuracy in both OT8 and Event Sport experiments. Table III summarizes the CCLBP_S/M/C operators results. In OT8 experiments, the best classification accuracy that is achieved using the gray CLBP operators is 55.83% by CCLBP_S/M/C1,8, and 58.49% by Transformed CCLBP_S/M/C1,8. On the other hand, the CCLBP_S/M/C1,24 has achieved the best classification accuracy in Event Sport experiments, which reached up 55.05%, while the best classification accuracy that is achieved using the gray CLBP operators is 49.85% by CCLBP_S/M/C2,16.

VI. CONCLUSION

This paper incorporated the Completed Local Binary Pattern (CLBP) with different colour information to enhance its photometric invariance and its discriminating property. Five novel multi-scale colour CLBP (CCLBP) texture descriptors were proposed and evaluated for image categorisation. OT8 and Event sport datasets were used to evaluate the proposed CCLBP and to compare it with the gray CLBP. The results attested to the superiority of the proposed CCLBP over the original gray CLBP.

VII. FUTURE WORK

In the future work, the latent features feature strategy will be used to combine all the proposed colour CLBP (CCLBP) feature descriptors. In addition, the proposed CCLBP will combine with different descriptors such as SIFT, and CLTP.
Fig. 10. Recognition accuracy as a function of the number of training images for Event sport image dataset using the gray CLBP descriptors and the proposed CCLBP descriptors when R=1 and P=8
10(a) CLBP_S and CCLBP_S. 10(b) CLBP_M and CCLBP_M. 10(c) CLBP_M/C and CCLBP_M/C. 10(d) CLBP_S/M/C and CCLBP_S/M/C. 10(e) CLBP_S/M and CCLBP_S/M. 10(f) CLBP_S/M/C and CCLBP_S/M/C.
Fig. 11. Recognition accuracy as a function of the number of training images for Event sport image dataset using the gray CLBP descriptors and the proposed CCLBP descriptors when R=2 and P=16. (a) CLBP_S and CCLBP_S. (b) CLBP_M and CCLBP_M. (c) CLBP_M/C and CCLBP_M/C. (d) CLBP_S/M/C and CCLBP_S/M/C. (e) CLBP_S/M and CCLBP_S/M. (f) CLBP_S/M/C and CCLBP_S/M/C.
Fig. 12. Recognition accuracy as a function of the number of training images for Event sport image dataset using the gray CLBP descriptors and the proposed CCLBP descriptors when R=3 and P=24. 12(a) CLBP\_S and CCLBP\_S. 12(b) CLBP\_M and CCLBP\_M. 12(c) CLBP\_M/C and CCLBP\_M/C. 12(d) CLBP\_S/M/C and CCLBP\_S/M/C. 12(e) CLBP\_S/M and CCLBP\_S/M. 12(f) CLBP\_S/M/C and CCLBP\_S/M/C.

(Advance online publication: 24 May 2017)
### TABLE II

#### ACCURACY RESULTS

<table>
<thead>
<tr>
<th>Dataset</th>
<th>OTS</th>
<th>HSVC</th>
<th>OHTA_S</th>
<th>OPP</th>
<th>RGB_C</th>
<th>R=1,P=8,0&lt;gamma&lt;60</th>
<th>R=1,P=8,0&lt;gamma&lt;60</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gray CLBP/S/M/C</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>45.14 ± 0.48</td>
<td>44.33 ± 0.44</td>
</tr>
<tr>
<td><strong>HSV CLBP/S/M/C</strong></td>
<td>59.18</td>
<td>52.70</td>
<td>56.74</td>
<td>55.76</td>
<td>55.83</td>
<td>43.44 ± 0.44</td>
<td>42.61 ± 0.43</td>
</tr>
<tr>
<td><strong>OHTA_S CLBP/S/M/C</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>50.41 ± 0.47</td>
<td>49.32 ± 0.45</td>
</tr>
<tr>
<td><strong>OPP CLBP/S/M/C</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>47.64 ± 0.46</td>
<td>46.59 ± 0.43</td>
</tr>
<tr>
<td><strong>RGB CLBP/S/M/C</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>51.22 ± 0.45</td>
<td>50.20 ± 0.43</td>
</tr>
<tr>
<td><strong>Event</strong></td>
<td>54.86</td>
<td>49.83</td>
<td>54.24</td>
<td>53.16</td>
<td>54.45</td>
<td>46.57 ± 0.44</td>
<td>45.59 ± 0.43</td>
</tr>
<tr>
<td><strong>S/M/C</strong></td>
<td>52.60</td>
<td>52.68</td>
<td>55.06</td>
<td>55.08</td>
<td>55.05</td>
<td>51.67 ± 0.45</td>
<td>50.89 ± 0.43</td>
</tr>
<tr>
<td><strong>CLBP</strong></td>
<td>51.87</td>
<td>52.40</td>
<td>52.45</td>
<td>52.45</td>
<td>52.53</td>
<td>47.74 ± 0.42</td>
<td>46.71 ± 0.43</td>
</tr>
<tr>
<td><strong>Gray CLBP/S/M/C</strong></td>
<td>51.12</td>
<td>51.44</td>
<td>51.49</td>
<td>51.49</td>
<td>51.49</td>
<td>47.74 ± 0.42</td>
<td>46.71 ± 0.43</td>
</tr>
</tbody>
</table>

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### REFERENCES