# Color Edge Saliency Boosting using Natural Image Statistics

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## Abstract

*State of the art methods for image matching, content-based retrieval and recognition use local features. Most of these still exploit only the luminance information for detection. The color saliency boosting algorithm has provided an efficient method to exploit the saliency of color edges based on information theory. However, during the design of this algorithm, some issues were not addressed in depth: (1) The method has ignored the underlying distribution of derivatives in natural images. (2) The dependence of information content in color-boosted edges on its spatial derivatives has not been quantitatively established. (3) To evaluate luminance and color contributions to saliency of edges, a parameter gradually balancing both contributions is required.*

*We introduce a novel algorithm, based on the principles of independent component analysis, which models the first order derivatives of color natural images by a generalized Gaussian distribution. Furthermore, using this probability model we show that for images with a Laplacian distribution, which is a particular case of generalized Gaussian distribution, the magnitudes of color-boosted edges reflect their corresponding information content. In order to evaluate the impact of color edge saliency in real world applications, we introduce an extension of the Laplacian-of-Gaussian detector to color, and the performance for image matching is evaluated. Our experiments show that our approach provides more discriminative regions in comparison with the original detector.*

## Introduction

Vision is one of the most important sensory mechanisms for intelligent living organisms as well as machines, and is conventionally regarded as processing primarily achromatic information. Early findings in biological vision indicated that visual form is perceived only from luminance, whereas the role of color is limited to filling perceived forms subsequently [1] [2]. However, color perception is also a central component in primate vision. Experimental evidence has shown that objects in colored scenes are more easily detected, more easily identified, more easily grouped, and more easily remembered than objects in gray-level scenes [3]. In addition, studies on early visual processing suggest that color is processed not in isolation, but together with information about luminance and visual form, by the same neural circuits, to achieve a unitary and robust representation of the visual world [4] [5].

Human visual attention is guided by complex interactions of at least two complementary mechanisms: environment-driven, bottom-up saliency and knowledge-driven, top-down guidance [6]. The visual form and color are also two representative attributes that could handle visual attention [7].

In computer vision, local features are very successfully used to represent the visual form due to their robustness with respect to occlusion and geometrical transformations [8]. These local features, also called interest regions, are generally detected based on the luminance signal, and focus on highly informative visual forms, typically corner and blob structures in the image [9].

Although the use of color information is limited by various practical difficulties, the conversion to gray-value has a number of side-effects that are particularly undesirable for local feature detection [10]. It is well known that gray-value versions of color images do not preserve chromatic saliency, i.e. regions that exhibit chromatic variation often lose their distinctiveness when mapped to scalars based on isoluminance. In this article, we extend local feature detection to color in a bottom-up manner, where we aim these features to be salient both from a color perspective and a visual form perspective, exploiting the spatiochromatic properties of natural images, instead of use a top-down approach that depends on the task [11].

From the viewpoint of information theory, it is known that the information content of an event is dependent on its frequency or probability, i.e. events which occur rarely are more informative. Therefore, our hypothesis is that egdes detected based on the statistical properties of luminance and color in natural images, and weighted according to its information content will provide us with highly informative regions and therefore better performance in real-world applications.

Moreover, in this work, we propose a generalized color saliency boosting algorithm that exploits the statistical properties of natural images, modeled as a generalized Gaussian distribution, applying a vector transformation (i.e. transforming the chromatic and intensity components). Furthermore, we show that for images with a Laplacian distribution, the color-boosted edge magnitude reflects their information content. In order to evaluate our hypothesis, we introduce an extension of the Laplacian-of-Gaussian to color, which is a vector approach to combine color channels in a mathematically sound manner, then investigate the impact of color edge saliency in local feature detection for image matching applications using an experimental framework.

## Our Approach

The color saliency boosting algorithm proved to be an efficient method for color feature detection. It was proposed by van de Weijer et al. [12] and it has been successfully applied to image retrieval and image classification [13] [14]. The method is based on information theory and the analysis of the statistics of color derivatives on the 40,000 images of the Corel database. In addition, psychophysical experiments have shown that this method provides accurate predictions of saliency with respect to human perception [15].

For local feature detection, the distinctiveness of features can be measured by its information content, which is dependent on its probability. Let $\mathbf{f}$ be a color image and $\mathbf{f}_x = (R_x\ G_x\ B_x)^T$ its corresponding directional spatial derivative. The information content of the first order derivative in a local neighborhood is given by

$$I(\mathbf{f}_x) = -log(p(\mathbf{f}_x)), \tag{1}$$

where $p(\mathbf{f}_x)$ is the probability of the spatial derivative. Note that a derivative has a higher content of information if it has a low probability of occurrence.

 

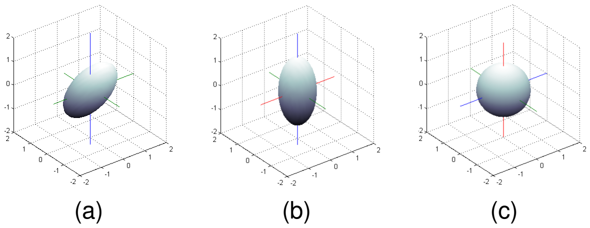

*Figure 1. Transformation of the color derivative distribution by the color saliency boosting algorithm. It first decorrelates the original distribution, and then applies a scaling of the axes. (a) Original distribution (b) Decorrelated distribution (c) Whitened distribution*

The study of color derivative statistics showed that this distribution is dominated by a principal axis of maximum variation, caused by the luminance, and two minor axes, attributed to chromatic changes. This means that changes in intensity are more probable than chromatic changes and therefore have less information content. Thus this algorithm transforms the original distribution to a more homogeneous distribution, so that intensity and chromatic changes contain equal information content, ensuring that both contributions have the same impact for feature detection. This is illustrated in Fig. 1.

However, during the design of this algorithm, some issues were not addressed in depth:

1. The method has ignored the underlying distribution of derivatives in natural images.
2. The dependence of information content in color-boosted edges on its spatial derivatives has not been established.
3. A parameter to gradually balance both contributions can be useful to evaluate luminance and color contributions to the saliency of first order derivatives.

These issues will be addreses in this paper.

## Natural Image Statistics

To be able to derive the information content of color edges knowledge of its underlying statistical distribution is indispensable. We therefore briefly review relevant works on image statistics and models.

Natural images are significantly redundant, thus their statistical properties can be well characterized [16]. The regularities in the information of natural images are not limited only to the spatial structure, but much of the information in natural images is contained in the spatial pattern of luminance and color [17]. One of the most well known properties is that the amplitude spectra of natural images are relatively scale invariant, however, this property does not characterize much of the global statistics in natural images [18].

Studies on natural image statistics have shown that the probability distribution of first order derivatives are not Gaussian, highly peaked at zero and have heavy tails [3] [17]. In addition, previous studies have successfully modeled the statistics of natural images using the Laplace distribution, the generalized Gaussian and the Weibull distribution [19] [20] [21] [22] [23] [24].

A recent study [25] has analyzed the statistical distributions of luminance and chromatic edges in natural scenes. Based on mutual information, they have shown that luminance and chromatic edges are independent. This means that information of luminance and chromatic edges are not redundant but provide independent sources of information for image understanding. This study is especially relevant to our work because we evaluate the impact of these contributions in local feature detection.

In this work, we characterize the statistical properties of first order derivatives in natural images using a generalized Gaussian probability distribution. For simplicity in explanation, considering the image $\mathbf{f}$ as a one-dimensional signal and its corresponding directional derivatives $\mathbf{f}_x$, then the marginal probability distribution of the derivatives is defined by

$$p(\mathbf{f}_x) = \frac{\gamma}{2\beta\Gamma(\frac{1}{\gamma})} \, exp\left(-\left|\frac{\mathbf{f}_x}{\beta}\right|^{\gamma}\right), \tag{2}$$

where $0 < \gamma \leq 2$ is the shape parameter, $\beta > 0$ is the scale parameter and the variance of this distribution is $\frac{\beta^2\Gamma(\frac{3}{\gamma})}{\Gamma(\frac{1}{\gamma})}$.

## Color Edge Saliency Boosting

As discussed above, our aim is to find a color boosting function which transforms color derivatives to a space in which derivatives of equal vector norm possess equal information content. In the new space the statistics of color edges will be isotropic.

The first step in this transformation is to find new axes where the original distribution is not correlated. The second step is to scale the new axes to obtain a new distribution with the same variance in all directions. This is illustrated in Fig. 1.

A well-known decorrelation technique is principal component analysis (PCA), which is suitable for Gaussian probability distributions [26]. However, we consider the generalized Gaussian probability distribution as a model to better approximate the actual distribution; therefore a more general technique is required. In this work we propose to use independent component analysis (ICA), which has been designed specifically for non-Gaussian distributions [27]. Here we show some relevant mathematical aspects of the proposed algorithm.

From the statistical properties of the first order derivatives we know that the distribution is centered at the origin of coordinates, i.e. mathematically $E[\mathbf{f}_x] = 0$. Thus, the covariance matrix is defined by

$$\Sigma_x = E[\mathbf{f}_x\mathbf{f}_x^T]. \tag{3}$$

From this matrix we can estimate the derivative energy as

$$\xi(\mathbf{f}_x) = trace(\Sigma_x). \tag{4}$$

Applying the singular value decomposition, we can determine the principal axes of the distribution and their corresponding squared relative half-lengths $\lambda_1, \lambda_2$ and $\lambda_3$:

$$\Sigma_x = U \begin{pmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{pmatrix} V^T, \tag{5}$$

where $U$ is a 3x3 matrix whose $k$th column is the $k$th eigenvector of $\Sigma_x$. These eigenvectors are the new axes of the three-dimensional first order derivatives distribution. To transform this pattern into a more isotropic one (whitening, or also called sphering), a linear transformation is applied using the inverse square root matrix $\Sigma_x^{-\frac{1}{2}}\mathbf{f}_x$.

So far we have done the preprocessing steps of ICA. It has been shown that this algorithm can produce axes rotated with respect to the actual distribution, in these cases we estimate this rotation by using the algorithm proposed by Comon [28]. Therefore, the desired energy-normalized *color boosting function* can be obtained by

$$g(\mathbf{f}_x) = \tau\Sigma_x^{-\frac{1}{2}}\mathbf{f}_x. \tag{6}$$

This function has changed the probability distribution of the derivatives in a white distribution, i.e. the color-boosted channels are uncorrelated and their variances are close to unity. Replacing eq. (6) and (5) we obtain

$$g(\mathbf{f}_x) = \tau\, U \begin{pmatrix} \frac{1}{\sqrt{\lambda_1}} & 0 & 0 \\ 0 & \frac{1}{\sqrt{\lambda_2}} & 0 \\ 0 & 0 & \frac{1}{\sqrt{\lambda_3}} \end{pmatrix} V^T \mathbf{f}_x, \tag{7}$$

where $\tau$ is the rate of derivative energy and is defined as

$$\tau = \sqrt{\frac{\xi(\mathbf{f}_x)}{\xi(\Sigma_x^{-\frac{1}{2}}\mathbf{f}_x)}}. \tag{8}$$

This ensures energy conservation, i.e. $\xi(\mathbf{f}_x) = \xi(g(\mathbf{f}_x))$ and the idempotent property $g(g(\mathbf{f}_x)) = g(\mathbf{f}_x)$.

In real-world applications we need a distinctiveness and signal-to-noise trade-off. For this purpose the $\alpha$ parameter is proposed, which allows for choosing a balance between signal-to-noise $\alpha = 0$, and information content, $\alpha = 1$:

$$g^{\alpha}(\mathbf{f}_x) = \tau\Sigma_x^{-\frac{\alpha}{2}}h(\mathbf{f}_x). \tag{9}$$

For $\alpha = 0$ this is equal to color gradient-based salient point detection. The impact of this parameter will be studied in our performance evaluation experiments. Similar equations hold for $p(\mathbf{f}_y)$. The theory can be straightforwardly extended to higher image structures.

Fig. 2 illustrates two examples of edge detection obtained by the proposed algorithm. Note the significant contribution of the luminance at the edges of color compared to the contribution of color. Moreover, the color-boosted edges show that chromatic changes that are less frequent provide more distinctiveness.

### *Information content of color-boosted edges*

The original color boosting algorithm [12] transforms color derivatives with equal information content to a space in which they possess an equal vector norm. However this theory does not provide a framework to combine the information content of various derivatives. To be able to do so, we need to transform the derivatives to reflect their corresponding information content.

To simplify our analysis on the behavior of information content in natural images, considering the image $\mathbf{f}$ as a one-dimensional signal and its corresponding directional derivatives $\mathbf{f}_x$, then we can easily analyze the information content of the edges on images.

From the definition of content information in eq. (1) and the probability in eq. (2), we obtain the dependence of the information content on its derivatives:

$$I(\mathbf{f}_x) = log\left(\frac{2\beta\Gamma\left(\frac{1}{\gamma}\right)}{\gamma}\right) + \left|\frac{\mathbf{f}_x}{\beta}\right|^{\gamma}. \tag{10}$$

An important observation here is that if the variance of this probability distribution is close to one (i.e. $\beta = \sqrt{\frac{\Gamma(\frac{1}{\gamma})}{\Gamma(\frac{3}{\gamma})}}$), which

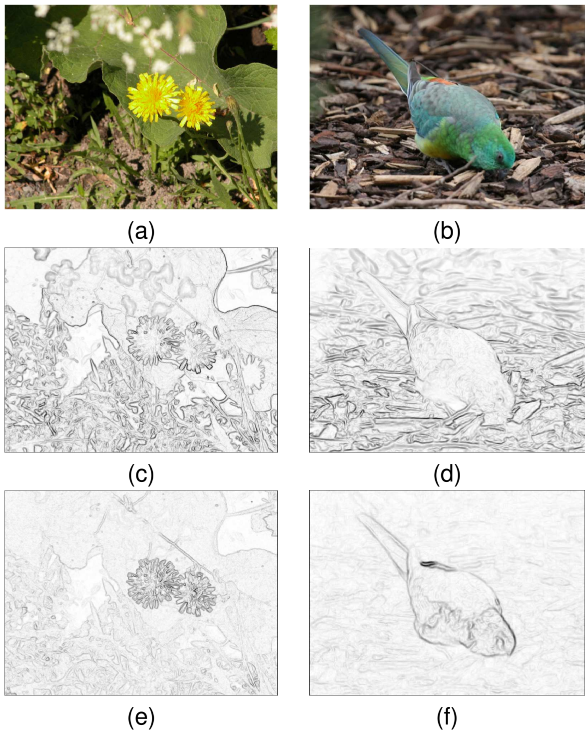

***Figure 2.*** *Comparative results obtained for edge detection (a),(b) input images, (c),(d) color edges, i.e. alpha=0, (e),(f) color-boosted edges, i.e. alpha=1*

was done during whitening, and using the constrains of the parameters $\gamma$ and $\beta$ from the eq. (2) to the eq (10), we know that $log(\frac{2\beta\Gamma\left(\frac{1}{\gamma}\right)}{\gamma}) < 1$ and $\beta^2 \le 2$.

Therefore, the information content can be considered proportional to the absolute value of the directional first order derivatives to the $\gamma$-th power (i.e. $I(\mathbf{f}_x) \propto |\mathbf{f}_x|^{\gamma}$) when

$$log(\frac{2\beta\Gamma\left(\frac{1}{\gamma}\right)}{\gamma}) << \left|\frac{\mathbf{f}_x}{\beta}\right|^{\gamma}. \tag{11}$$

This shows that using a generalized Gaussian distribution to model the natural image statistics, the strength of the color-boosted edges in natural images reflects its information content. In addition, notice that when $\gamma = 1$ (i.e. a conventional Laplace distribution) the proportionality is direct.

## Color Laplacian-of-Gaussian Detector

We will evaluate the saliency of color edges on an image matching task. Therefore we first need to extend the local feature detectors to the color domain.

A suitable framework to handle image structures at different scales has been the scale-space theory [29]. However, relatively little effort has been made to extend this theory to color, and in particular, on how to combine the differential structure of color images in a principled way. Luminance edges are still the main source of information for feature detection.

According to their invariance model, local features can be classified as multi-scale, scale-invariant and affine-invariant features. A detailed description of state-of-the-art of local features is provided by [9].

### *Multi-scale features*

A multi-scale representation consists of a stack of images at different discrete levels of scale [30]. It is crucial for many applications, and especially for local feature detection and extraction. Koenderink [31] showed that spale-space satisfies the diffusion equation for which the solution is a convolution with a unique Gaussian kernel, which has also been confirmed in other studies [32]. Images at coarse scales are obtained by smoothing images at finer scales with a circularly symmetric kernel and parameterized by one scale factor $\sigma$.

The semi-group property reduces the computational complexity of scale-space representation. Nevertheless, it is possible to accelerate the operation by sampling the coarser scale image with the corresponding scale factor after every smoothing operation. However, it is important to be careful choosing the scale and the sampling factor as it may lead to aliasing problems. Moreover, additional relations have to be introduced in order to find the corresponding point locations at different scale levels. This makes any theoretical analysis more complicated, but computationally very efficient. This representation is often referred to as the scale-space image pyramid [33].

Generally, the pyramid representations are based on the spatial convolution [34] [35]. It is well known in image processing that in the spatial domain the processing time increases exponentially with respect to the kernel size [36], thus a trade-off between spatial convolution and Fourier filtering performance can be useful [37]. A very similar approach is a hybrid multi-scale representation [38] which was tested for local feature detection in [39].

When an interest operator is applied on multiple scales we call the detections multi-scale interest regions. A very well-known example is the Harris operator [40].

### *Scale-invariant features*

The number of multi-scale features extracted from images is very high for practical applications. Thus, instead of extracting regions for every scale level, automatic scale selection techniques determine one of a few characteristic scales at each location. Scale-invariant features are obtained by performing automatic spatial and scale selection [41]. The Laplacian detector extracts image regions whose locations and characteristic scales are given by scale-space maxima of the Laplace operator. A desirable property for a scale-space differential operator is that it should always produce the same response to an idealized scale-invariant structure. However, we cannot just take a blurred derivative because we will obtain weaker responses at larger scales. This motivates the definition of scale-normalized differential operators, whose output remains constant if the image is scaled or resized by an arbitrary factor.

Mikolajczyk [42] evaluated different scale selection criteria for scale-invariant image matching environments. Apart from the Laplacian he studied the squared image gradients, the Difference-of-Gaussians and the Harris function. His evaluation shows that the Laplacian operator selects the highest percentage of correct characteristics scales.

Since the original Laplacian-of-Gaussian is a scalar operator, its entry is an gray-level image. Thus, the definition of the scale-normalized Laplacian detector is

$$LoG(\sigma) = \sigma^2 |L_{xx} + L_{yy}|, \tag{12}$$

where $L_{xx}$ and $L_{yy}$ represent the second-order derivatives of a gray-level input image. One local feature is scale-invariant if this operator simultaneously achieves a local maximum with respect to the scale parameter and the spatial variables.

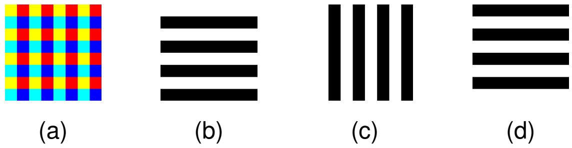


***Figure 3.*** *A colored pattern and its components (a) RGB channels, (b) red, (c) green, and (d) blue channel. The square structure which is clearly visible in the color pattern is not present in any of the channels.*

### *From luminance to color*

From a mathematical perspective color images are vector signals, thus their derivatives cannot be represented only as changes in magnitude (or intensity) but also angular (or chromatic) changes should be considered. In general, this produces several theoretical and practical difficulties. For instance, if we consider only changes in intensity, smoothing a color image introduces new chromaticities in edges. In addition, a combination of corner or blob information from the separate channels might fail. This is illustrated in Fig. 3. The structures generated by our visual perception are not reflected in the separate channels of the image, therefore cannot be detected properly.

The extension from luminance to color signals is an extension from scalar-signals to vector-signals. A basic approach to extend existing detectors to color is compute the derivatives of each channel, separately, and then combine the partial results. However, combining the first derivatives with a simple addition of the separate channels results in cancellation in the case of opposing vectors [43], and the same situation occurs for second-order derivative operators. Therefore, new methods are required to combine the differential structure of color images in a principled way [10].

The definition of the Laplacian-of-Gaussian operator comes from the Hessian matrix. Thus, in order to extend to color this operator we need a precise mathematical definition of the Hessian matrix for color images, which considers the problem of opposing channels. Shi et al. [44] showed an extension of this matrix to color using a quaternic representation of color images. From this definition it can be demonstrated that it is possible to derive an extension to color by combining channels in a vector fashion. Therefore, we propose to extend the Laplacian-of-Gaussian detector to multiple channels by combining responses of individual channels using a generalized scale normalized Laplacian operator, defined by

$$Color\ LoG(\sigma) = \sigma^2 \|(\mathbf{L_{xx}} + \mathbf{L_{yy}})\|, \tag{13}$$

where $\mathbf{L_{xx}} = (\ \mathrm{R}_{xx}\ \mathrm{G}_{xx}\ \mathrm{B}_{xx}\ )^T$ and $\|\cdot\|$ is the vector norm. This simple extension leads to a scale-space representation which includes the contributions of luminance and chromatic components in a scalar-valued representation. This is an appropriate representation to exploit the saliency of both luminance and color edges in images.

## Experiments

We adopt the evaluation framework constructed by Mikolajczyk et al. [45]. They evaluate the discriminative power and invariance over various imaging conditions. Discriminative power for any detector and descriptor combinations can be evaluated over different: illumination intensity, viewpoint changes, blurring and JPEG compression. In order to obtain quantitative results, this software exploits ground-truth information, which was provided by mapping the regions detected on the images in a set to a reference image using homographies.

In this experiment we evaluate the impact of the color edge saliency algorithm on the performance of the color Laplacian-of-Gaussian detector for the transformations defined by the framework. We vary the luminance and color contributions to the saliency of edges by changing the $\alpha$ parameter from eq. 9. Note that $\alpha = 0$ is equal to feature detection on normal RGB channels. An $\alpha = 1$ is equal to the theoretical optimal for color edge saliency boosting.

Because we want to evaluate whether the color information provides more discriminative local features, we only detect 200 points per image. We have tested the matching score based on two descriptors, namely SIFT [46] and C-Color SIFT [47]. Here we report the mean matching score as a function of $\alpha$. These values are obtained by averaging over all frames of the sequence.

Fig. 4 shows the performance evaluation based on the matching score. Table 1 summarizes the results obtained for all sequences, showing the percentage increase in the matching score. The results show that boosting color edges has a positive impact on the performance for four sequences. For the graffiti sequence after an initial improvement the results drop for increased $\alpha$ (alpha).

**Table 1. Increase in Matching Scores for $\alpha$=1.**

| Transformation | Matching Score (incr.%) |
|---|---|
| Viewpoint | 09 |
| Zoom+rotation | 08 |
| Blur | 11 |
| Light | 11 |
| Compression | -52 |

### *Discussion*

The most significant changes are obtained in the ubc sequence, where the images have variable amount of JPEG compression. The dramatic drop in performance is caused by the fact that color is significantly more compressed than the luminance signal. This effect occurs because artifacts caused by compression modify the probability distribution in the image, making the probabilistic model used inadequate. Applying the proposed algorithm to these images amplifies the JPEG artifacts. From this it can be concluded that this algorithm should not be applied on significantly compressed images.

Apart from this sequence the proposed algorithm improves the matching score in four of six remaining sequences, and only slightly deteriorates for the graffiti sequence. The optimal amount of luminance and color contribution to color edge boosting varies for each sequence. This indicates that more research is needed to automatically select optimal settings.

Other studies also have investigated the impact of luminance and color for feature detection [48] [49], however they report their results only in terms of repeatability, i.e. from a theoretical viewpoint. We have chosen to report our results from a practical approach using matching scores. Notice also that previous studies exploting color information for detection have shown the same strongly negative behavior with respect to image compression [50].

## Conclusions

In this work we have extended the color boosting theory. By modelling the first order derivatives as a Laplace distribution, we established a direct relationship with the information content of color edges in natural images. Furthermore, we introduced and evaluated a generalized color edge saliency boosting based on independent component analysis.

To evaluate luminance and color contributions to the saliency of edges, we have extended the Laplacian-of-Gaussian to the color domain. Experiments on matching applications show that our detector outperforms the original detector. For variations in scale, blur and lightening color boosting provides more discriminative regions and therefore improves the results. However, it was found to be very sensitive (and hence unusable) to JPEG compression.

Our results suggest that detection of color information could improve the performance of matching score around 10%. However, there is still the drawback of automatically setting the best parameters to obtain good performance.

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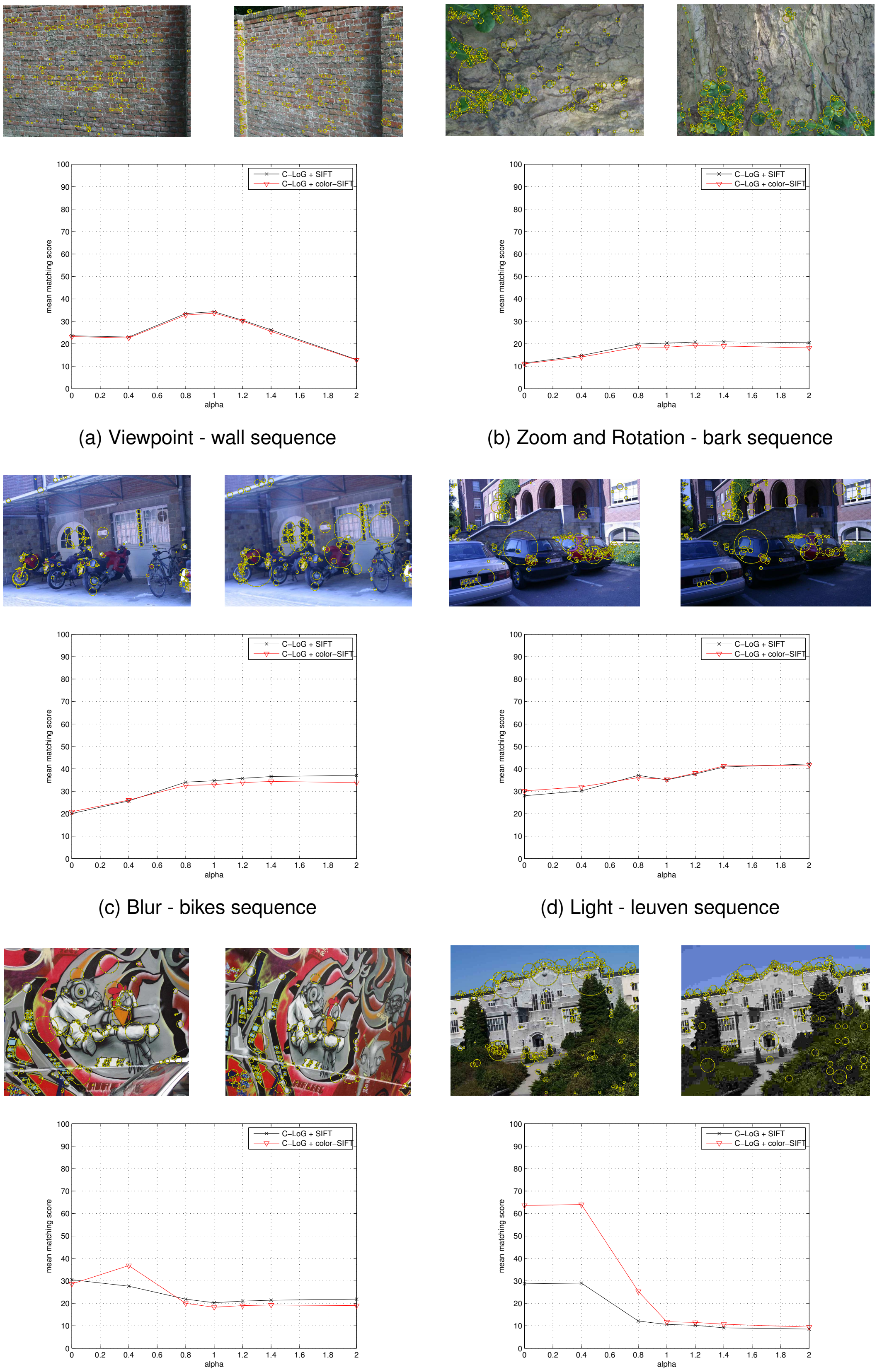


(a) Viewpoint - wall sequence

(b) Zoom and Rotation - bark sequence

(c) Blur - bikes sequence

(d) Light - leuven sequence

(e) Viewpoint - graffiti sequence

(f) JPEG compression - ubc sequence

***Figure 4.*** *Matching scores for different transformations using two descriptors: SIFT and Color-SIFT. Examples of dataset images are shown above the matching score plots*

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