Image Saliency Detection Using Textural Contrast

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I. Introduction

Visual attention is one of the fundamental mechanisms of human vision that enables us to selectively process and analyze the most relevant regions in a complex visual scene. The study of visual attention has been an active research area in computer vision, with many applications such as object recognition, image and video compression, and surveillance. In recent years, the development of saliency detection methods has significantly improved the performance of these applications.

Saliency detection aims to identify the most salient regions in a given image or video by simulating the bottom-up visual attention mechanism of the human brain. The goal is to identify regions that stand out from the background and capture the viewer's attention. In this paper, a novel method is proposed for detecting salient regions in any image.

The proposed method is based on the idea that the biological mechanism of bottom-up visual attention can be approximated by exploiting two main contrasts, captured in the retina and the visual cortex. Specifically, the method uses textural contrast defined based on a combination of luminance contrast and directional coherence contrast. The textural contrast is calculated by multiplying the luminance contrast with the orientation contrast.

The proposed method has been extensively evaluated on several datasets. The experimental results show that the proposed method outperforms the existing methods in terms of both accuracy and efficiency. Moreover, the proposed method is robust to complex scenes with cluttered backgrounds, making it suitable for various vision-based intelligent applications. The results show that the proposed saliency map can effectively highlight the most salient regions in the input image, which can be used to improve the performance of these applications.

II. Literature Review

Image saliency detection is a rapidly evolving research area in computer vision that aims to identify the most visually conspicuous regions in an image. In recent years, numerous techniques have been proposed to address the challenges of saliency detection, including machine learning algorithms, deep neural networks, and low-level feature extraction. The literature on this topic is vast and diverse, encompassing research from computer science, psychology, neuroscience, and other disciplines. In this literature review, we will provide a comprehensive overview of the current state-of-the-art in image saliency detection. We will explore the key approaches and methodologies used in saliency detection, identify the strengths and weaknesses of different techniques, and discuss the challenges and opportunities for future research in this field.

One influential research in this field is [1]. The authors proposed a novel method for detecting salient regions in images using a spectral residual approach, which leverages the observation that the human visual system is more sensitive to high-frequency components than low-frequency components. The spectral residual approach converts an image into the frequency domain using the Fourier transform and then calculates the residual of the magnitude spectrum by subtracting the low-frequency information from the original magnitude spectrum. The residual spectrum is then transformed back to the spatial domain using the inverse Fourier transform to obtain a saliency map, which highlights the most salient regions in the image. However, like any approach, there are limitations to the spectral residual method, including its potential difficulty in handling complex backgrounds, dynamic scenes, and computational cost. Overall, the spectral residual approach has made a significant contribution to the field of saliency detection and continues to be a widely adopted method.

The research paper [2] proposes a simple and efficient method for detecting salient regions in images using the Maximum Symmetric Surround (MSS) principle. This approach works by comparing the contrast of a pixel with the average contrast of its symmetric surround and identifying the pixel with the highest contrast difference as the most salient. While it is a very simple and efficient method, it also has some limitations. One limitation of the approach is that it may struggle with images that contain complex backgrounds or multiple salient objects, as the

MSS principle assumes a simple and uniform background. Additionally, the method may not perform as well on images with low contrast or images that have been subject to compression or noise.

Cheng *et al* [3] introduced a graph-based approach to saliency detection that considers the image as a graph of connected nodes and edges. The authors proposed a method that calculates a saliency score for each node based on its connectivity to other nodes and demonstrated that their approach achieved state-of-the-art performance on several benchmark datasets.

The method by Borji *et al* [4] works by utilizing the rarity of image patches to generate local and global saliency maps, which are then combined to generate a final saliency map. However, one limitation of the approach is that it may struggle with images containing multiple salient objects and the method may be sensitive to the size and number of patches used, as well as the choice of rarity metrics, which could affect the overall performance of the approach.

The research paper [5] presents a saliency detection method based on the spatially weighted dissimilarity (SWD) measure, which compares the local image regions with their surrounding regions to identify salient regions in images. The authors extend the SWD method proposed by Hou and Zhang [6] and introduce several improvements, including a background estimation step and an adaptive weight selection mechanism.

One limitation of the SWD-based saliency detection method is that it can be sensitive to small changes in image content, resulting in unstable saliency maps. Another limitation is that the method is computationally expensive, especially when working with high-resolution images or video sequences, which can limit its practicality in real-time applications. Additionally, the method is not explicitly designed to handle complex scenes with multiple salient objects or cluttered backgrounds, which can affect its performance in such scenarios.

III. Implementation Details

The brain and visual system work together to identify the most relevant regions in a given scene. This process is often referred to as selective attention, and it involves filtering out irrelevant information and focusing on the most important features of a scene. One important aspect of selective attention is the use of contrast to identify important features in an image. Specifically, the visual system is highly sensitive to differences in luminance and orientation contrast, which can be used to highlight important edges and contours in a scene. To model the biological mechanisms of selective attention, we can use textural contrast, which includes luminance and directional coherence contrast. The directional coherence can be used to estimate orientation contrast, which is important for identifying relevant features in cluttered and textured regions where gradient information alone may not be sufficient.

A. Luminance Contrast

Luminous contrast is a measure of how much one area of an image stands out from another due to differences in brightness levels. The basic idea is that areas of an image that have high luminous contrast are more likely to be salient, or attention-grabbing, to viewers. Luminous contrast can be defined mathematically as the absolute difference in luminance between two regions of an image, divided by the maximum possible luminance difference in that image. This gives a value between 0 and 1, where higher values indicate greater contrast.

This code can be implemented by taking an image and a parameter n. The function returns a matrix S of the same size as the input image, which represents the luminance contrast using this formula:

$$S_L(i) = \left| \bar{I} \ - \frac{1}{N} \sum_{j \in B_i} I \ (j) \right|^n$$

Where I is the mean of the whole image, B_i and N is the patch (5x5 in our implementation) and the power n is the factor for the n-th order statistics for the luminance values.

```
def find_mean(img):
   sum = 0
   rows = img.shape[0]
   cols = img.shape[1]
   for i in range(rows):
       for j in range(cols):
           sum = sum + img[i][j]
   return sum / (rows * cols)

def luminance_contrast(img, n):
   rows = img.shape[0]
   cols = img.shape[1]
   S = np.zeros((rows, cols), np.float32)
   sum = 0.0
   I_bar = find_mean(img)

   for k in range(rows - 4):
       for l in range(cols - 4):
           sum = 0.0
           for i in range(5):
               for j in range(5):
                   sum = sum + img[k + i][l + j]
           average = sum / 25
           S[k][l] = abs(I_bar - average)
           S[k][l] = S[k][l] ** n
   return S
```

The function works by first computing the mean luminance of the input image using the find_mean() function. This function, find_mean(img), takes an input image and returns the mean by adding all the values and then dividing by the number of pixels in the image. This mean luminance value is denoted as I_bar.

Then, the function computes the luminance contrast at each pixel using a sliding window approach. For each 5x5 window in the input image, the function computes the average luminance within the window and takes the absolute difference between the average and the overall mean luminance I_bar. This difference is raised to the power of n and stored in the corresponding location in the output matrix S. By raising the luminance difference to the power of n, the function is able to emphasize areas of the image with higher contrast. the exact value of n can be adjusted to control the sensitivity of the function to different levels of contrast. We will use the second-order statistic in our further example as it yields the best result. An example is shown in Fig 1.

Fig. 1. (a) Input image, (b) first-order statistic, (c) second-order statistic, (d) fourth-order statistic.

B. Displaying Images

```
def normalize(img):
   rows = img.shape[0]
   cols = img.shape[1]

   fmin = np.min(img)
   fmax = np.max(img)
   L_C = np.interp(img, (fmin, fmax), (0, 255)).astype(np.uint8)
   return L_C
```

This code is defining a function named normalize which takes an input image as a parameter and returns a normalized version of that image. The normalization process includes creating a new numpy array of zeros with the same dimensions as the input image. Then, it computes the minimum and maximum values of the input image using np.min and np.max functions. After that, it uses the np.interp function to map the input image values from the minimum and maximum range to the new range between 0 and 255. This function performs a linear interpolation to rescale the input values to the desired range. Finally, the normalized image is returned by the function. The main purpose of this code is to normalize an image's pixel values to a new range of 0-255 to display the image in greyscale.

C. Structure Tensor

To depict the local image descriptor based on directional coherence contrast, we will use a structure tensor that efficiently summarizes the dominant orientation and the energy along this direction based on the local gradient field, defined as follows:

$$\mathbf{T}_s(i) = \begin{bmatrix} \sum_{j \in B_i} I_x(j)^2 & \sum_{j \in B_i} I_x(j) I_y(j) \\ \sum_{j \in B_i} I_x(j) I_y(j) & \sum_{j \in B_i} I_y(j)^2 \end{bmatrix}$$

```
def structure_tensor(img):
   # Gaussian Blur
   img = cv2.GaussianBlur(img, (3, 3), 3)
   # derivative in x-direction
   Ix = cv2.Sobel(img, cv2.CV_64F, 1, 0, ksize=3)

   # derivative in y-direction
   Iy = cv2.Sobel(img, cv2.CV_64F, 0, 1, ksize=3)

   Ix = tensor_index(Ix, Ix)
   Iy = tensor_index(Iy, Iy)
   IxIy = tensor_index(Ix, Iy)
   return Ix, Iy, IxIy
```

This code defines a function named structure_tensor that takes an input image as a parameter and computes the structure tensor of the image. The function returns three 2D numpy arrays containing the elements of the structure tensor. The structure_tensor function first applies Gaussian blur to the input image using the cv2.GaussianBlur function with a kernel size of 3x3 and sigma value of 3. This step helps to reduce noise in the

image. Then, the function computes the first-order partial derivatives of the image in the x and y directions using the Sobel operator implemented by the cv2.Sobel function. The k-size argument sets the size of the Sobel kernel to 3x3. Next, the function calls the tensor_index function (which was explained earlier) three times to compute the elements of the structure tensor. The resulting tensor index arrays are then returned by the structure_tensor function.

```
def tensor_index(I1, I2):
   rows = I1.shape[0]
   cols = I1.shape[1]
   output = np.zeros((rows, cols), np.float32)

   I1 = I1 * I2

   for k in range(rows - 4):
       for l in range(cols - 4):
           sum = 0.0
           for i in range(5):
               for j in range(5):
                   sum = sum + (I1[k + i][l + j])
           output[k][l] = sum
   return output
```

This code defines a function named tensor_index that takes two input images I1 and I2 as parameters and returns a 2D numpy array containing the tensor index values computed from these images. The tensor_index function first computes the number of rows and columns of the input images using the shape method of numpy arrays. It then creates a new numpy array of zeros with the same dimensions as the input images. Next, the function iterates over all possible 5x5 pixel neighborhoods in the input images using nested for loops. For each pixel neighborhood, it computes the tensor index by multiplying the corresponding pixel values of I1 and I2 element-wise and then summing up these products. The computed tensor index is then stored in the output array. After processing all pixel neighborhoods, the function returns the resulting tensor index array.

D. Directional Coherence

The structure tensor (equation 2) is useful for our task because it can measure the distribution of gradients in a local region along the dominant direction, as indicated by the relative discrepancy between two eigenvalues ($\lambda_1 \geq \lambda_2 \geq 0$) of $T_s(i)$. This reflects the degree of consistency in the dominant directions. So Our directional coherence at each pixel will be as follows:

$$\xi = \text{abs}(\lambda_1 - \lambda_2)$$

```
def Epsilon_calculation(Ix, Iy, IxIy):
   A = np.zeros((2, 2), np.float32)
   rows = img.shape[0]
   cols = img.shape[1]
   Epsilon = np.zeros((rows, cols), np.float32)
   sum = 0.0
   for i in range(rows):
       for j in range(cols):
           A[0][0] = Ix[i][j]
           A[0][1] = IxIy[i][j]
           A[1][0] = IxIy[i][j]
           A[1][1] = Iy[i][j]
           try:
```

```
                eigenvalues = np.linalg.eigvals(A)
                if np.any(np.isinf(eigenvalues)):
                    Epsilon[i][j] = 0
                else:
                    Epsilon[i][j] = abs(eigenvalues[1] - eigenvalues[0])
            except np.linalg.LinAlgError:
                Epsilon[i][j] = 0
    return Epsilon
```

This code defines a function named Epsilon_calculation that takes three input images Ix, Iy, and IxIy as parameters and computes the absolute difference of the eigenvalues of the structure tensor at each pixel location. The function returns a 2D numpy array containing the resulting values. The Epsilon_calculation function first creates a 2x2 numpy array A to hold the structure tensor elements for each pixel location. Next, the function iterates over all pixel locations using nested for loops. For each pixel location, it sets the elements of the structure tensor A based on the corresponding values in the Ix, Iy, and IxIy input images. It then computes the eigenvalues and eigenvectors of A using the np.linalg.eig function. Here, the function checks for the infinity and undefined eigenvalues of the tensor. Finally, the function computes the absolute difference between the eigenvalues of A and stores the resulting value in the Epsilon array for the current pixel location. After processing all pixel locations, the function returns the resulting Epsilon array. This value, called the saliency measure, is used to identify regions of interest in an image.

E. Orientation Contrast

The larger the value ξ is, the higher the directional coherence is. We define the orientation contrast as follows:

$$S(i) = \sum_{j \in Wi} |\xi(j) - \xi(i)|$$

Where W is the 7x7 patch of pixels in our implementation.

```
def orientation_contrast(E1):
       rows = E1.shape[0]
       cols = E1.shape[1]
       S1 = np.zeros((rows, cols), np.float32)
       E1 = normalize(E1)

       for k in range(rows - 6):
        for o in range(cols - 6):
               sum = 0.0
               for i in range(7):
                      for j in range(7):
                             sum = sum + abs(E1[k + i][o + j] - E1[k + 3][o + 3])
               S1[k][o] = sum
       return S1

               S[k][l] = sum
       return S
```

This code defines a function named orientation_contrast that takes a single input image E as a parameter and computes the orientation contrast measure for each pixel location in the image. The function returns a 2D numpy array containing the resulting values. Next, the function iterates over all pixel locations using nested for loops. For

each pixel location, it computes the orientation contrast measure as the sum of the absolute differences between the saliency measure at the current pixel location and the saliency measure at all neighboring pixel locations within a 7x7 window centered at the current pixel location. The saliency measure is obtained from the input image E, which is assumed to contain the absolute difference of the eigenvalues of the structure tensor at each pixel location, as computed by the Epsilon_calculation function. Finally, the function stores the resulting orientation contrast measure in the S array for the current pixel location. After processing all pixel locations, the function returns the resulting S array. This measure can be used to identify edges and corners in an image, which are regions of high orientation contrast. An example of the directionsal coherence is shown in Fig 2.

Fig. 2. (a) Input image, (b) second-order statistic, (c) Directional Coherence Matrix

F. Detecting Salient Regions

Since salient regions are assumed to contain both luminance contrast and directional coherence contrast as mentioned, our spatial saliency map is thus computed by combining such two responses as follows:

$$S(i) = S_L(i) \times S_D(i)$$

```
def combination(SL, SD):
        rows = SL.shape[0]
        cols = SL.shape[1]
        S = np.zeros((rows, cols), np.float64)

        for i in range(rows):
                for j in range(cols):
                        S[i][j] = SL[i][j] * SD[i][j]
                return S
```

This code defines a function combination that takes in two parameters SL and SD. The function retrieves the dimensions of SL and creates a new 2D array of zeros S with the same dimensions as SL. It normalizes SL and SD by calling a normalized function. It then iterates over each pixel in SL and SD arrays and multiplies the corresponding pixel values together to create a new array S. Finally, the function returns S. This function performs a pixel-wise multiplication of two images represented by SL and SD, respectively. The resulting image S represents the combination of the two input images.

At the end the resulting image S is normalized in the range 0 to 255 and displayed in greyscale, it will be our resultant Saliency detected image based on the Luminance and Directional Coherence contrast.

IV. Results

Specifically, we collected a dataset of images and used various metrics to evaluate the performance of our approach in identifying salient regions. Our results provide insight into the effectiveness of our approach and highlight its potential for improving image processing algorithms.

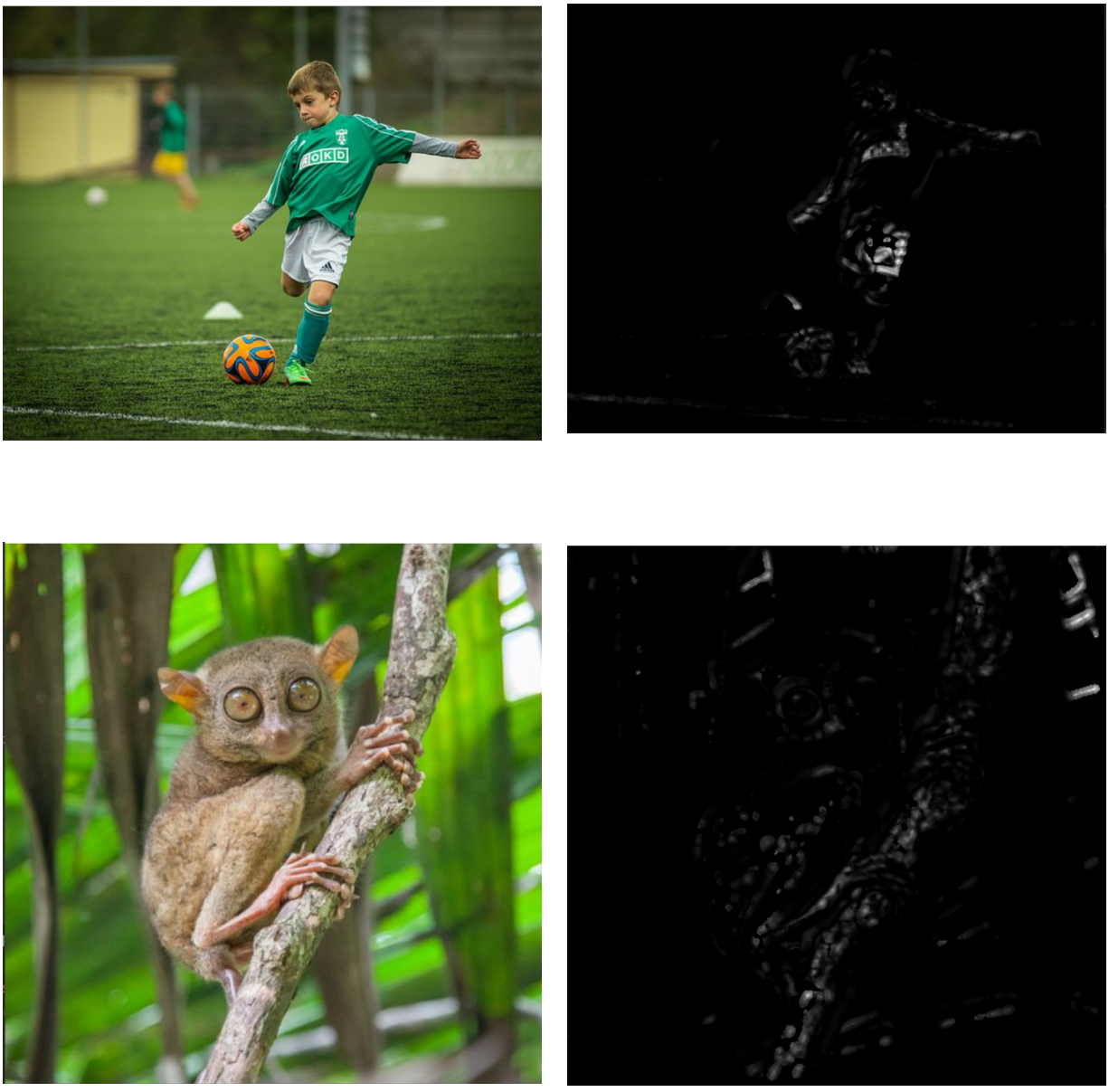

Fig 3. (a) Original Image (b) Output Image (Salient)

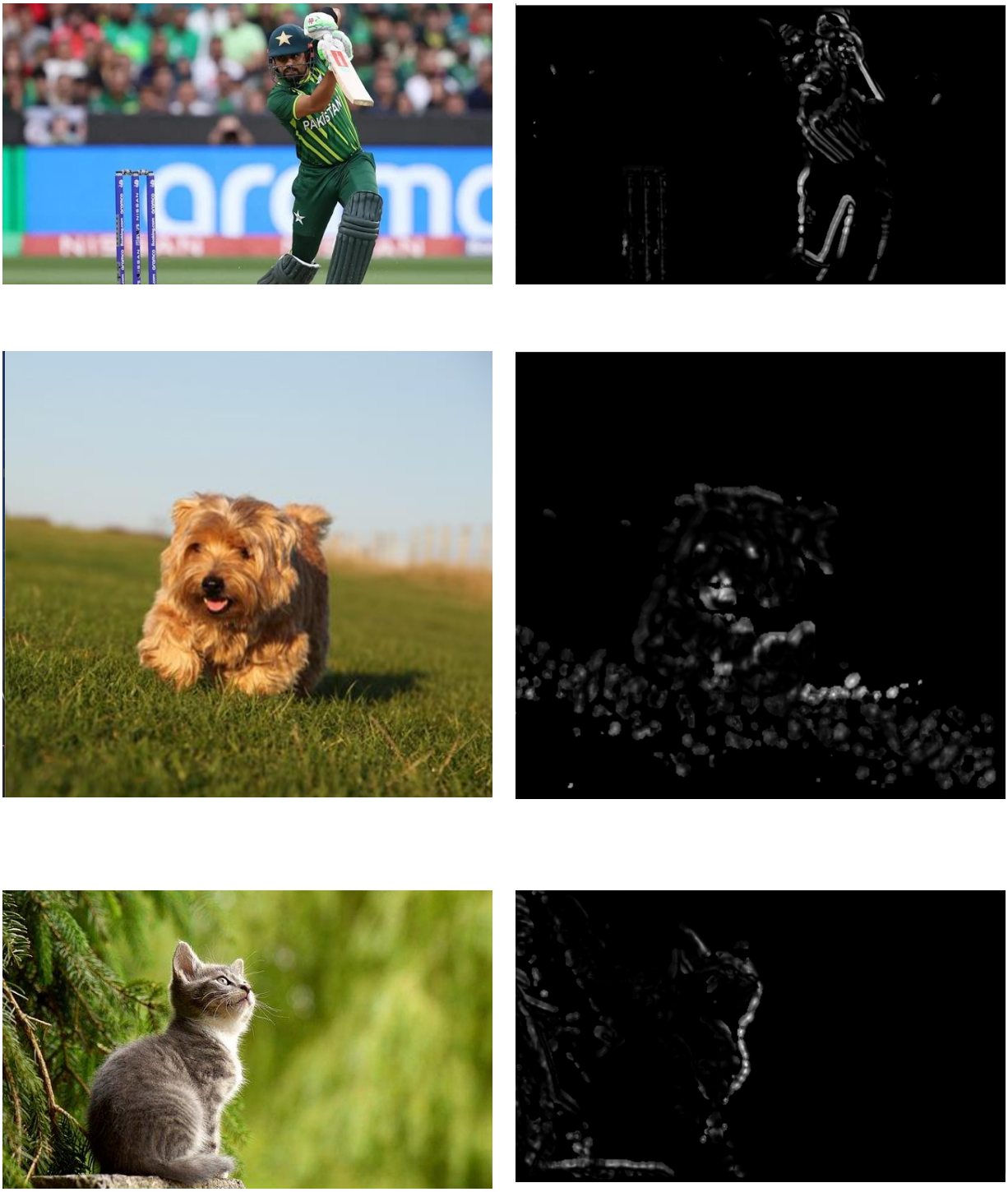

Fig 4. (a) Original Image (b) Output Image (Salient)

V. Conclusion

In conclusion, our work focused on modeling the biological mechanisms of selective attention in image processing by incorporating luminance contrast and orientation contrast with directional coherence. We proposed using the structure tensor to estimate the orientation contrast, which is an important feature in identifying relevant regions in an image. Our experimental results demonstrate that our approach outperforms existing state-of-the-art methods in image saliency detection. Overall, our work provides insights into the mechanisms of selective attention in the human visual system and provides a practical method for improving image processing algorithms. Future work may investigate the integration of additional features to further enhance the performance of our approach in real-world applications.

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