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Object Color Estimation with Dominant Color in Automated Image Semantic Description Generation Tasks

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Abstract

The automated image tagging is an important part of modern search engines. The generated image tags can be constructed from object names and their attributes, for example, colors. This work presents an object color name detection real-time algorithm. It is applicable to any automatic object detection and localization systems. The presented algorithm is fast enough to run after the existing real-time object detection system, without adding visible overhead. The algorithm uses k-means to detect the dominant color and selects the correct name for the color via Delta E (CIE 2000).

Keywords: Dominant color, Image color palette, Color name selection, Object color detection, Image semantic analysis.

1. Introduction

Automated image semantic description generation is one of the fundamental problems in computer vision. One of the ways to generate a semantic description of the given image is the object detection and localization. There are many solutions, which can find objects by localizing and naming them. In recent years, neural networks have become a leading method for high-quality object detection tasks. They have enough accuracy to be used in different areas, such as self-driving cars, robotics, automatic surveillance and also in web search engines. In web search engines, the object detectors are used for automated image tagging. These tags allow the user to find images without any annotations using a simple keyword search. The simplest way to automatically generate image tags is to detect objects in the image and use the names of objects as tags. This kind of tags do not allow the user to find images, which contain an object with a specific attribute. To solve this issue, we can add additional attributes for each object. One of the main attributes for each object is color. This kind of addition will allow users to search, for example, a “red car” or a “white cat” and find the corresponding images.

This work presents an object color name detestation algorithm, which is applicable to automatic object detection systems. The presented algorithm is fast enough (28 ms on i7 CPU) to run after the existing object detection real-time system without adding visible overhead on each iteration.

2. Related Works and Methodology

The modern object detectors are based on Convolutional Neural Networks (CNN), such as Faster Region-based Convolutional Neural Network (Faster R-CNN) [1], Region-based Fully Convolutional Network (R-FCN) [2], Multibox [3], Single Shot Detector (SSD) [4] and YOLO: Real-Time Object Detection [5]: for example, networks can be used to generate image tags from the detected object names.

There are networks which, can generate a single caption [6], [7] for the given image. There are also networks, which can generate the image caption and detect the objects [8], [9]. Those works are not computing color for each object. All of these works can be used as object detectors for this work.

In [10], the authors present a method, which assigns a color attribute to a recognized object. They are using an image segmentation method based on graph cuts. After segmentation, they are filtering the results by “Attribute Recommender” [10]. This approach is slightly slow for real-time systems.

This work introduces a color name extraction method, which has a low computational cost. To exact color name for each detected object, we will detect the dominant color and then select the correct name for it.

3. Dominant Color Detection

At first sight, an image dominant color detection is a simple task, and we can compute the mean color for an image. But we will be disappointed, because we will get something close to gray (see Fig. 1).

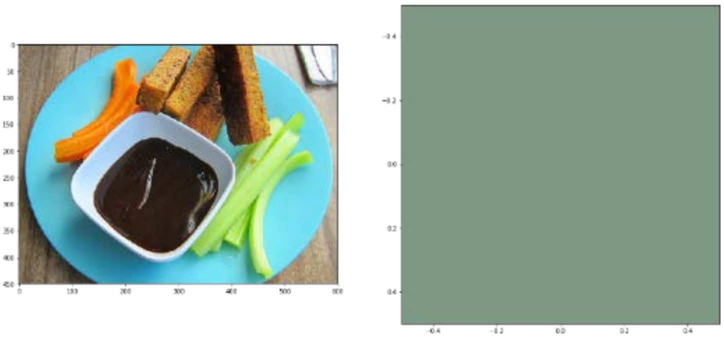


Fig. 1: Image and its mean color.

The second approach that we can apply, we can split the image as a grid, and then compute the mean value for each grid’s cell. This approach will be approximated to a downscaled image with an interpolation algorithm, which uses neighbor pixels, such as liner, bicubic or spline methods.

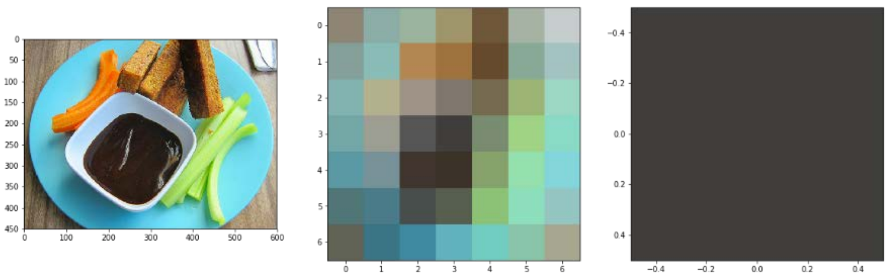


Fig. 2: Scaled image with bicubic interpolation and central color.

As we see in Fig. 2, we can’t select the central pixel color as the image dominant color of the downscaled image.

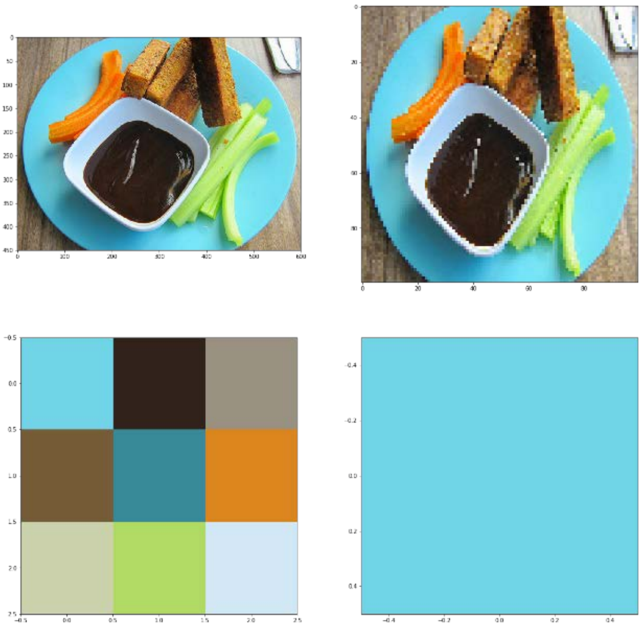


Fig. 3: Image color palette and dominant color.

To solve this problem, we will use a clustering algorithm to extract a color palette from the image. At first step, we will downscale our image to 100x100 dimensionality via bicubic interpolation method (see Fig. 3). This step will remove rarely encountered pixels by including them in the final pixel of the downscaled image. In addition, this technique will reduce the number of pixels, which will have a huge impact on the clustering algorithm. After that, we will cluster the image pixels in sRGB (standard Red Green Blue) color space via the k-means [11] clustering method. Experimentally we found that our color palette is more meaningful when the cluster count is equal to 9. The k-means cauterization will give as cluster indices (labels, per pixel mappings to their cluster) and the cluster center values (means). To get the image color palette, we will sort by clusters size in descending order. Each palette’s color will correspond to cluster centers (see Fig. 3). The first color of the pallet will be selected as the dominant color for the image.

4. Color Name Selection

As we have a dominant color value in sRGB color space, now we need to select a name for this color. Selection will be made from a predefined color table (see Table 1). We will compare each table's color with our computed value and find the nearest one. But we can't do this using the Euclidean distance (1), because visually close colors are not located near in sRGB space.

$$distance = \sqrt{(R_1 - R_2)^2 + (G_1 - G_2)^2(B_1 - B_2)^2}\,. \tag{1}$$

One of the best algorithms to compute the color visual difference (distance) - ΔE (2) between a sample color ($L_2,\ a_2,\ b_2$) and a reference color ($L_1,\ a_1,\ b_1$) is Delta E (CIE 2000) [12]:

$$\Delta E = \sqrt{\left(\frac{\Delta L'}{K_L S_L}\right)^2 + \left(\frac{\Delta C'}{K_C S_C}\right)^2 + \left(\frac{\Delta H'}{K_H S_H}\right)^2 + R_T\left(\frac{\Delta C'}{K_C S_C}\right)\left(\frac{\Delta H'}{K_H S_H}\right)}. \tag{2}$$

In equation (2) $\Delta L', \Delta C', \Delta H'$ and R_T values are computed by equations (3)-(4). We will take$K_L = 1$, $K_C = 1, K_H = 1$ by default.

$$\Delta L' = L_2 - L_1, \qquad \Delta C' = C_2' - C_1', \tag{3}$$

$$\Delta H' = 2\sqrt{C_1' C_2'}\sin\left(\frac{\Delta h'}{2}\right), \quad R_T = -R_C\sin(2\Delta\theta) \tag{4}$$

R_C and $\Delta\theta$ values are computed by equations (5)-(10).

$$\overline{H}' = \begin{cases} \dfrac{h_1' + h_2' + 360°}{2}, & \text{if } |h_1' - h_2'| > 180° \\ \dfrac{h_1' + h_2'}{2}, & \text{otherwise.} \end{cases} \tag{5}$$

$$T = 1 - 0.17\cos\left(\overline{H}' - 30°\right) + 0.24\cos\left(2\overline{H}'\right) + 0.32\cos\left(3\overline{H}' + 6°\right)$$
$$-0.20\cos(4\overline{H}' - 63°) \tag{6}$$

$$\Delta h' = \begin{cases} h_2' - h_1' & \text{if } |h_2' - h_1'| \le 180° \\ h_2' - h_1' + 360° & \text{else if } |h_2' - h_1'| > 180° \text{and } h_2' \le h_1' \\ h_2' - h_1' - 360° & \text{otherwise} \end{cases} \tag{7}$$

$$\Delta\theta = 30\exp\left\{-\left(\frac{\overline{H}' - 275°}{25}\right)^2\right\}, \qquad \overline{L}' = \frac{L_1 + L_2}{2}, \qquad \overline{C}' = \frac{C_1' + C_2'}{2} \tag{8}$$

$$S_L = 1 + \frac{0.015(\overline{L}' - 50)^2}{\sqrt{20 + (\overline{L}' - 50)^2}}, \qquad S_C = 1 + 0.045\overline{C}', \qquad S_H = 1 + 0.015\overline{C}'T \tag{9}$$

$$R_C = 2\sqrt{\frac{\overline{C}'^7}{\overline{C}'^7 + 25^7}} \tag{10}$$

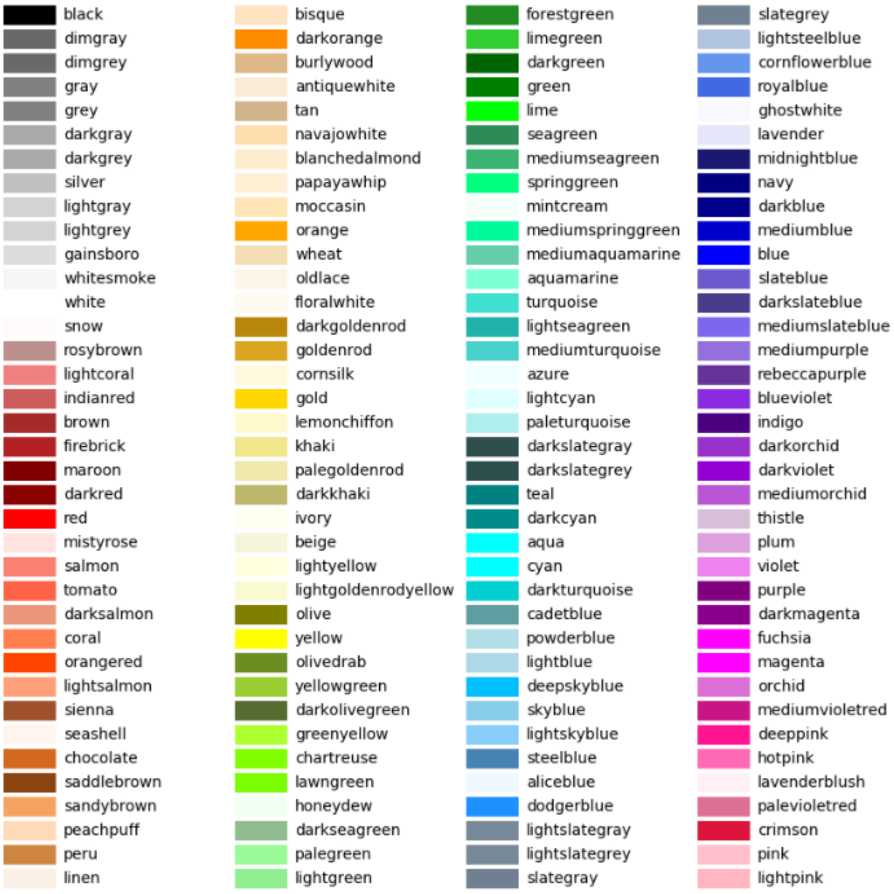
L_1, C_1', h_1' are computed by equations (11)-(12). Also, the L_2, C_2', h_2' values are computed in the same way.

$$C_1 = \sqrt{a_1^2 + b_1^2}, \qquad G = \frac{1}{2}\left(1 - \sqrt{\frac{\overline{C}^7}{\overline{C}^7 + 25^7}}\right), \qquad a_1' = a_1(1 + G) \tag{11}$$

$$C_1' = \sqrt{{a_1'}^2 + b_1^2}, \quad h_1' = \begin{cases} \arctan\left(\frac{b_1}{a_1'}\right), & \text{if } \arctan\left(\frac{b_1}{a_1'}\right) \geq 0, \\ \arctan\left(\frac{b_1}{a_1'}\right) + 360°, & \text{otherwise.} \end{cases} \tag{12}$$

We will use metric (2) to find the nearest color and get the color name from Table 1.

Table 1: CSS color table.



black
dimgray
dimgrey
gray
grey
darkgray
darkgrey
silver
lightgray
lightgrey
gainsboro
whitesmoke
white
snow
rosybrown
lightcoral
indianred
brown
firebrick
maroon
darkred
red
mistyrose
salmon
tomato
darksalmon
coral
orangered
lightsalmon
sienna
seashell
chocolate
saddlebrown
sandybrown
peachpuff
peru
linen

bisque
darkorange
burlywood
antiquewhite
tan
navajowhite
blanchedalmond
papayawhip
moccasin
orange
wheat
oldlace
floralwhite
darkgoldenrod
goldenrod
cornsilk
gold
lemonchiffon
khaki
palegoldenrod
darkkhaki
ivory
beige
lightyellow
lightgoldenrodyellow
olive
yellow
olivedrab
yellowgreen
darkolivegreen
greenyellow
chartreuse
lawngreen
honeydew
darkseagreen
palegreen
lightgreen

forestgreen
limegreen
darkgreen
green
lime
seagreen
mediumseagreen
springgreen
mintcream
mediumspringgreen
mediumaquamarine
aquamarine
turquoise
lightseagreen
mediumturquoise
azure
lightcyan
paleturquoise
darkslategray
darkslategrey
teal
darkcyan
aqua
cyan
darkturquoise
cadetblue
powderblue
lightblue
deepskyblue
skyblue
lightskyblue
steelblue
aliceblue
dodgerblue
lightslategray
lightslategrey
slategray

slategrey
lightsteelblue
cornflowerblue
royalblue
ghostwhite
lavender
midnightblue
navy
darkblue
mediumblue
blue
slateblue
darkslateblue
mediumslateblue
mediumpurple
rebeccapurple
blueviolet
indigo
darkorchid
darkviolet
mediumorchid
thistle
plum
violet
purple
darkmagenta
fuchsia
magenta
orchid
mediumvioletred
deeppink
hotpink
lavenderblush
palevioletred
crimson
pink
lightpink

4. Conclusion

We have developed a fast object color name extraction method. To test the algorithm on end to end system, we used a system, which generates the image caption, detects and localizes the objects [9]. For each detected object, we computed the object dominate color and found the correct name for that color. Each color name was used as an attribute for that object (see Fig. 4). For detections, which were predicated as humans, we did not use the color attribute.

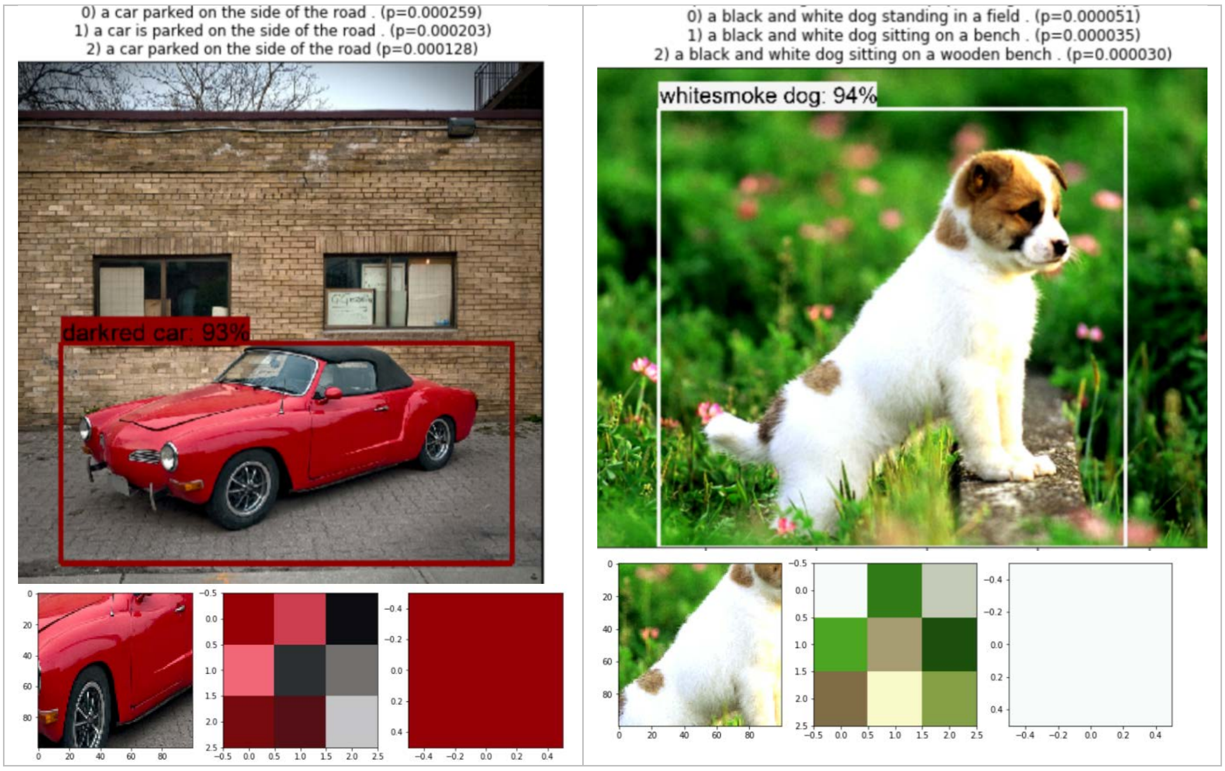

0) a car parked on the side of the road . (p=0.000259)
1) a car is parked on the side of the road . (p=0.000203)
2) a car parked on the side of the road (p=0.000128)
darkred car: 93%
0) a black and white dog standing in a field . (p=0.000051)
1) a black and white dog sitting on a bench . (p=0.000035)
2) a black and white dog sitting on a wooden bench . (p=0.000030)
whitesmoke dog: 94%

Fig. 4: Image caption generation, object detection, localization and color estimation, second row presents dominant color detection process.

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Օբյեկտների գույնի որոշումը դոմինանտ գույնի կիրառմամբ պատկերների իմաստաբանական նկարագրերի ավտոմատ գեներացման խնդիրներում

Աղասի Ս. Պողոսյան

ՀՀ ԳԱԱ Ինֆորմատիկայի և ավտոմատացման պրոբլեմների ինստիտուտ
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Ամփոփում

Ժամանակակից փնտրող համակարգերում մեծ դեր ունի պատկերների ավտոմատացված պիտակավորումը։ Պատկերի պիտակները ավտոմատ կարող են գեներացվել պատկերում գտնվող օբյեկտների անուններից և վերջիններիս հատկություններից, ինչպիսին, օրինակ, գույնն է։ Այս աշխատանքում ներկայացված է օբյեկտների գույնի անվանման հայտնաբերման արագ ալգորիթմ, որը կիրառելի է ավտոմատացված օբյեկտները հայտնաբերող համակարգի հետ։ Ներկայացված ալգորիթմը բավական արագ է (28 միլիվայրկյան), որ կարելի է համակցել իրական ժամանակում օբյեկտներ հայտնաբերող համակարգին՝ առանց տեսանելի ծախսեր ավելացնելու։ Ալգորիթմը կիրառում է k միջինների ալգորիթմը դոմինանտ գույնի հայտնաբերման և Delta E (CIE 2000) -ը՝ գույնի ճիշտ անվան ընտրության համար։

Բանալի բառեր՝ դոմինանտ գույն, պատկերի գունապնակ, գույնի անվան ընտրություն, օբյեկտի գույնի հայտնաբերում, պատկերի իմաստաբանական վերլուծություն։

Определение цвета объекта с использованием доминантного цветного в задачах автоматической генерации семантического описания изображений

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Аннотация

Автоматическая маркировка изображений является важной частью современных поисковых систем. Сгенерированные маркировки изображений могут быть построены из имен объектов и их атрибутов, например, цвета. В данной работе представлен быстрый алгоритм определения имени цвета объекта. Это применимо к любым системам автоматического обнаружения и локализации объектов. Представленный алгоритм достаточно быстр (28 мс) для запуска с существующими системами обнаружения объектов в реальном времени, без видимых дополнительных расходов. Алгоритм использует метод k-средних для обнаружения доминирующего цвета и Delta E (CIE 2000) для выбора правильного имени цвета.

Ключевые слова: доминирующий цвет, цветовая палитра изображения, выбор названия цвета, определение цвета объекта, семантический анализ изображения.