Edge detection in non-linear scalable space

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Abstract. Automatic image processing and computer vision applications often include object extraction and recognition. To extract object boundaries better, high-quality methods of edge detection are required. Objects in real-world photos usually have complex structure, and discovering their edges with higher precision is a very important and tough task. Better edge detection drastically increases the quality of the entire process. Unfortunately, edge detection problem still has no satisfactory solution in the case of real-world color images, because efficient approaches exist for grayscale images only. Known edge detection techniques usually either consist of special filters applied to a grayscale image, or implement rather unpredictably behaving artificial intelligence solutions. We propose a new powerful mathematical tool to extract edge information not only from intensity but from color distribution as well. Correctness of edge detection gets better by means of an adaptive mathematical model of non-linearly scalable color space. In our research, we consider flexible non-linear transformation of the color space with a few parameters. It helps reliably extracting otherwise faded edges delimiting the objects. We compare the results of edge detection process based on this new technique to well-known base-line approaches of Canny, Prewitt, Sobel and Wallace filters.

1. Introduction

Edge detection technique is a necessary stage in almost all image recognition algorithms [1]. As its result, the processed image is transformed into a set of connected curves separating objects. This way the volume of processed data decreases dramatically. Spacious removed domains carry much less information because they have relatively smooth uniform or gradient hue. The most important morphological properties of the image are saved during this transformation. At the same time, edge detection quality is not desirably high even in processing ordinary color images. Boundaries detected in the real world images are usually rough and discontinued: multiple edge parts need joining into a single edge line. On the other hand, false edges can appear because of noise and processing artefacts.

Edge detection approaches fall into two major groups: maxima location techniques [2] and zero location methods. Methods of the first group compute approximately the first spatial derivative (gradient). Loci of maxima of its norm correspond to higher spatial change of brightness that is supposed to be an edge. Zero location methods are based on the estimation of the second derivative (Laplacian) zeros. Modern methods allow compute these values approximately even in the presence of noise and detect edges by analyzing pixel neighborhood [3]. Ad hoc methods based on standard edge detection filters and different statistical approaches are developed to process images of special structure [4–7].

Various edge detection methods use different border filters, to mention a few: Sobel, Prewitt, Wallace, etc. figures 11 – 13 demonstrate the results of base-line edge detection procedures in
comparison with our results shown in figures 5 - 7. The goal of this research is to construct a new method able to detect edges better using hue information. Through the figures in this paper, we highlight edges after binarization stage with white lines.

The transformation of an image from RGB color space into grayscale form is usually performed \([5]\) by linear weighting the color components:

\[
\bar{Y} = 0.299R + 0.587G + 0.144B = \bar{R} + \bar{G} + \bar{B},
\]

where \(\bar{R}, \bar{G}, \bar{B}\) are weighted according to human perception coordinates of red, green and blue color components respectively of primary physical color values \(R, G, B\). Without loose of generality we use simple normalization: \(0 \leq \bar{R}, \bar{G}, \bar{B} \leq 1\). Three-component color vectors coming from very different colors may produce the same value of intensity \(\bar{Y}\). No grayscale filter is capable to detect corresponding edges, while a human can easily notice it in the original color image.

Of all edge detection filters mentioned above, the Canny filter usually shows the best results \([8 - 10]\). The reason is that it mimics human notion of edges most precisely. Unfortunately, we do not know any mathematically consistent definition of what ideal edges are. Canny method just produces a better approximation to what trained humans consider an edge.

The straightforward way to deal with a color image is to apply the filter to each color channel separately and to join the results afterwards. During the further processing, obtained raw image edge matrices corresponding to different color channels are processed statistically to remove false and double contours. The problem of such generally used approach is that statistically often the edge is scarcely noticeable in all three color channels and thus ignored. Nevertheless, there may exist another color model (say, YUV, HSL, etc.) allowing extracting the edges reliably. We propose a new general approach to employ multiple color decompositions simultaneously to detect such kind of edges. The more color decompositions are involved, the higher edge detection reliability and computational complexity are. The rest of the article describes the method of such color spaces construction and joining the results of channel-by-channel edge detection.

2. Non-linear color space transformation

The main idea is to introduce a set of \(N\) “new decomposition colors” which we call further on hues. Each such a color is in fact a normalized vector function of standard decomposition colors \(\bar{R}, \bar{G}, \bar{B}\) and can be plotted as a point in standard RGB color space. We choose nonlinear color space scaling, in order to tune up flexibly the impact of small and large color components:

\[
\bar{r}_p = \mu_{rn} \bar{R}^p, \bar{g}_n = \mu_{gn} \bar{G}^n, \bar{b}_n = \mu_{bn} \bar{B}^n, \mu_{rn} + \mu_{gn} + \mu_{bn} = 1, n = 1, ..., N,
\]

where \(p > 0\) allows nonlinear scaling of color components.

**Figure 1.** Color surface according to the equation (2) in case of \(p = \frac{1}{2}\).  

**Figure 2.** Color surface according to the equation (2) in case of \(p = 1\).
Color-dependent weights $\mu_{r,n}$, $\mu_{g,n}$, $\mu_{b,n}$ set the proportion of nonlinearly processed original color components present in each new color component (hue). The value of $p$ is the same for all decomposition colors. Only any two parameters out of three ($\mu_{r,n}$, $\mu_{g,n}$, $\mu_{b,n}$) define new color because they sum up to unity in (2). Figures 1 – 4 show examples of equal-intensity color surfaces in transformed color space for different $p$.

The surface grid lines intersections in the figures 1-4 are possible introduced color decomposition components sharing the same intensity (color surface). Denser grid rises edge detection quality. The algorithm includes the following steps:

1. Set initial expected number of hues $N$.
2. For $n = 1, \ldots, N$, for each original image pixel perform computation of $n$-th hue according to (2). While original image contains three matrices of color planes, each new decomposition color component is a single matrix of the same size as image. At every iteration, the method tries to distribute hues as evenly in the color surface as possible.
3. A standard grayscale-oriented edge detector processes every of $N$ hue planes and results in extracted edge fragments that are especially highlighted in this color component. This leads to $N$ bi-level images: one means white pixel, zero means a black pixel, as usual.
4. All extracted edge fragments coming from different color components are melt together using a decision rule. The simplest decision rule here is morphological OR. In order to eliminate double edge effect, more complex state of the art rules are applicable, e.g. false edges appeared only in minority of tones are removed.
5. We find reasonable number $N$ of hues adaptively based on source image. Our observation is that the quality of binarization increases with the number $N$ of used hues in a sublinear (slower than linear) way. On the other hand, complexity greatly depends on the number of edge extraction procedure calls and thus is roughly proportional to $N$. The algorithm stops increasing $N$ at the point additional quality gain becomes too little to justify further complexity increase. If the quality enhancement is still sufficient, set $N = N+1$ and perform the steps 2-5 for a new hue added and update resulting edges using it.

The success of the Canny procedure and consequent binarization greatly depends on correct threshold selection. To calculate threshold values in the Canny filter the Otsu method is usually used [11]. The lower and upper bounds make interclass dispersion minimal in image histogram. This algorithm is applicable to images with different brightness histograms.

3. Experiments

Figure 5 shows a sample source image transformed into grayscale image for the publication.
The Otsu method provides the upper threshold $T_H$ of the binarization process [11]. We select the lower threshold $T_L = T_H/2$ during the experiments. The cases of $N = 5$, 7, 10 and 12 hue matrices have been tested for all images. For decomposition into 5 and 7 hues, important elements for edge detection are as a rule still absent. Starting with $N=10$ hues the lost edge parts typically begin to appear and after $N=12$ almost no further improvement is achieved in most cases. So, in this experiment 10 hue matrices have been used to extract edges (see also the figure 9). Thus, 10 hue channels often suffice in this case. In our experiments, we retained only edges appeared in more than $c_l$ hue channels. Binarized images for $c_l = 1, 2, 4$ are presented in the figures 6 – 8.

Figure 8 makes it clear that in case of $c_l = 4$ significant structural information on the shape of the road sign is lost. More edge information survives with $c_l = 2$ (figure 7). After the experiments with more than 30 images we found that in the majority of cases the best results have been achieved with the smallest $c_l = 1$(figure 6): edges appeared even in a single hue channel make sense according to human perception of the final image procession results.
Another research topic in our project addresses edge length that is just a number of white pixels left after the binarization process. This metric allows evaluating edge persistence (power) depending on number of hues used and the value of $p$. The dependence of edge length as a function of the number of hue matrices $N$ is shown in the figure 9. One can conclude that edge length usually almost stops increasing when number of matrices exceeds 10. If one takes more decomposition hues, the quality of binarization saturates but computational costs raise.

![Figure 9](image)

*Figure 9. Dependence of edge length on number $N$ of applied hue matrices (channels).*

![Figure 10](image)

*Figure 10. Dependence of edge length on parameter of color space $p$ in equation (2).*

The dependence of edge length on the parameter $p$ setting non-linearity of color space transformation (2) is presented in the figure 10. The values from the range $p = 1/4...1/2$ experimentally correspond to the longest edges. At the same time, important informational features have been detected in the case of $p = 1/2$ and they have been gradually lost towards $p = 1/4$. The perceptive analysis lets us choose value $p = 1/2$ as the most appropriate in most of our experiments.

Figures 11 – 13 help comparison of our results with outputs of state-of-the-art edge detection filters by Prewitt, Sobel and Wallace. After the filter had been applied, its result in the current pixel was compared with the threshold value. Pixels lower than the threshold are black, above it are white.

![Figure 11](image)

*Figure 11. Binarization with the Prewitt filter (the threshold value is 180).*

![Figure 12](image)

*Figure 12. Binarization with the Sobel filter (the threshold value is 120).*
Figure 13. Binarization with the Wallace filter (the threshold value is 130).

The best result has been achieved by means of the Sobel filter (figure 12): the shape and inner content of the road sign are clearly observable and even the rhombus content can be easily guessed. In the two other cases, the road sign is unrecognizable with inner structure damaged (left car symbol disappeared) and the upper rhombus sign interior lost. Resulted images of our method (figures 6-7) demonstrate much better accuracy: inner structure of the road sign can be easily recognized and in the figure 6 the structure of the upper road sign survives completely. Choice of threshold values in all cases is based on the Otsu method.

4. Conclusion
The edges provided by the proposed method are very close to human perception and supersede tested vanilla methods, such as Prewitt, Sobel and Wallace filters (figures 11 – 13) [5 – 7]. In our experiments, the minimal number \( N \) of color decomposition channels (hue matrices) is moderate and is in the range 9-24, larger values provide no negative impact to the quality, just increase number of operations linearly. Color space nonlinear scaling parameter \( p = 1/2 \) in the equation (2) is perceptually good for most images. The reason is that the corresponding color space is concave and thus provides higher hue resolution. In turn better hue sensitivity lets the method detect finer edges, otherwise not discovered. For all images we experimented with, its optimal value lies in the range \([1/2, 2]\) and depends on hue and intensity distribution of the processed image. The edges obtained with our method are less noisy than in case of other methods [5 – 7] even without additional refinement.

Our further research concerns optimal hue grid search in color space (figures 1-4). We found that various images require different \( p \) and minimal number of hues \( N \), because each image has its own distribution of colors, brightness and saturation. Another direction of the further research is better prediction of optimal parameters \( N \) and \( p \).

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