

Optimal Combinations of Color Space Components for Detection of Blood Vessels in Eye Fundus Images

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Introduction

The eye fundus is the part of human body, where microvasculature can be observed directly. The vascular changes in the retina are useful for diagnosing complications of diabetes, atherosclerosis, hypertension. A lot of efforts are dedicated to automate the analysis of retinal images. Among the problems of computerized retinal analysis is detection of blood vessel tree. [1]

Blood vessel detection is difficult because of vessel crossings, bifurcations, and vascular reflex – the bright region in the center of the vessel. Sometimes it misleads the vessel tracing algorithms causing them to lose the right way. Vascular reflex is generally considered to be a specular highlight [2], thus the color of its specular component is similar to white. This indicates that the vascular reflex might be separated from the vasculature in some suitable color space [3].

While in many other medical images only greyscale information is accessible [4][5], fundus images contain full color information. Nonetheless, most of the studies so far used the green (G) component of RGB color space for blood vessel recognition with some using luminance (Y) from YIQ color space [6]. However, the suitability of such choice and possible alternatives has not been sufficiently explored yet.

In this study, we sought remedy to vascular reflex degrading blood vessel detection performance by looking for optimal linear combinations of RGB color space components that could be used as the pre-processing stage in existing blood vessel detection algorithms.

The paper is organized as follows: at first, the eye fundus images used in the study are discussed, then the methods used for experiments are explained, finally the results of those experiments are given and the conclusions made.

Eye fundus images

The images from the freely available DRIVE database [7] were used in our experiments. This database was developed using the results of a screening program in

the Netherlands and it is often used as the reference in different studies analysing eye fundus images. The database also includes images with blood vessels marked manually by experts thus it is of great value in development and testing of blood vessel detection algorithms. The images are divided into training set (20 images, 3 with pathology) and test set (20 images, 4 with pathology). The size of each image is 768x584 pixels. About 12.5% of eye fundus pixels belong to blood vessels.

Fig. 1 shows an example of the blood vessel profile with the vascular reflex. It can be seen that the vascular reflex is present in the individual RGB components, but it is decreased or even removed in various differences of RGB components, indicating possibility to improve the blood vessel detection by choosing the optimal color combination.

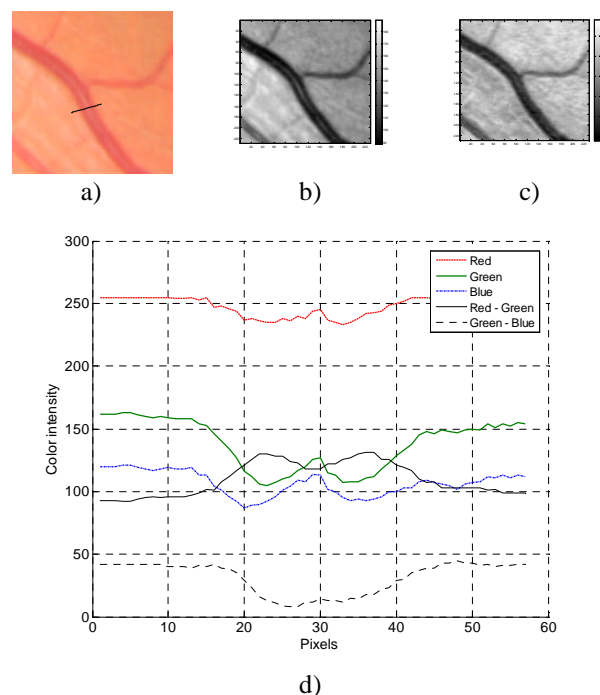


Fig. 1. Fragment of fundus image in RGB color space with blood vessel slice (a), green channel (b), channel difference G-B (c), and vessel cross-section profile (d)

Methods and Experiments

The search for optimal color combination in RGB space can be mathematically formulated as the optimisation problem of linear discriminant function:

$$d(I_R, I_G, I_B) = a_1 I_R + a_2 I_G + a_3 I_B \begin{cases} \geq T \Rightarrow BV, \\ < T \Rightarrow BG, \end{cases} \quad (1)$$

here I_R, I_G, I_B - intensities of individual components (red, green and blue) describing one pixel; a_1, a_2, a_3 - weights of color components (to be defined); T - decision threshold, BV - pixels belonging to blood vessel class, BG - pixels belonging to background class.

The vector of optimal weights \mathbf{a}_{opt} was found during training procedure:

$$\mathbf{a}_{opt} = \operatorname{argmax}_{a_1, a_2, a_3} \{ \bar{A}_{ROC}(a_1 I_R + a_2 I_G + a_3 I_B) \}, \quad (2)$$

here \bar{A}_{ROC} - average area under the receiver operating characteristic (ROC) curve. ROC curve shows the relationship between the true positives rate and false positives rate when threshold T is varied between T_{min} and T_{max} . The larger \bar{A}_{ROC} , the better classifier.

Three different criteria during training procedure have been used to find the optimal color combinations. In the first case, areas under ROC curves for all images of the training set were calculated and average area was maximized ("global" classification). In the second case, the images have been divided into 40x40 pixel blocks and average area under ROC curve for all blocks with at least 5 blood vessel pixels and at least 5 non-blood vessel pixels has been maximized ("local" classification). In the third case, the area under ROC curve for the whole training set has been maximized ("superglobal" classification). In all three cases simple threshold based classifiers exploiting only the color combination values for the pixels being classified were assumed. Simplex search by Nelder-Mead algorithm was used to find the optimal weights \mathbf{a}_{opt} in all three training procedures. The process of training is summarised in Fig. 2.

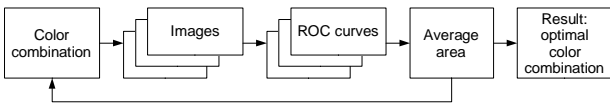


Fig. 2. The simplified diagram of process of finding the optimal color combination

The resulting optimized color combinations were introduced as the pre-processing stage (see Fig. 3) and have been compared with the green color according to the blood vessel detection performance, achieved by two different blood vessel detection methods: 1) segmentation method [8] and 2) tracing method [9]. In case of segmentation method, the threshold was chosen by the algorithm automatically, while in case of the tracing method the sensitivity parameter was fixed in the middle of recommended interval - 1.5.

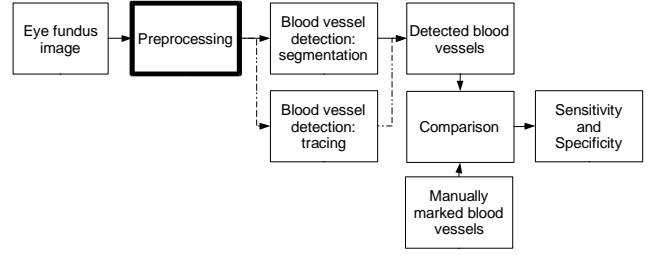


Fig. 3. The simplified diagram of validating preprocessing stage introduction in blood vessel detection algorithms

The performance of those methods was estimated by sensitivity (proportion of correctly identified blood vessel pixels), specificity (proportion of correctly identified non-blood vessel pixels) and Matthews correlation coefficient (considered useful when classes are of different sizes) [10]:

$$M = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}, \quad (3)$$

where TP, FP, TN and FN - numbers of true and false positives, and true and false negatives. To rule out the overfitting, those performance estimates were evaluated using the testing set of the DRIVE database images.

Results

The color combinations, optimal for blood vessel detection "globally", "locally" and "superglobally" are shown in Table 1.

Table 1. Optimal weights of RGB color components for the three training procedures

Color combination	Coefficients for color intensities			Average area under ROC curve
	Red	Green	Blue	
"Global"	-0.1053	0.5265	-0.3682	0.7503
"Local"	-0.0512	0.7565	-0.1923	0.8375
"Superglobal"	-0.0085	0.4685	-0.4458	0.6606

The "superglobal" color combination is essentially equivalent to the difference between green and blue color intensities.

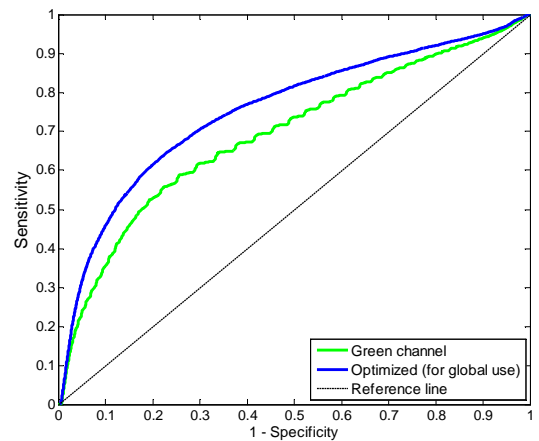


Fig. 4. Example ROC curves (for green color and color combination optimized for "global" classification) of the first image from DRIVE database training set

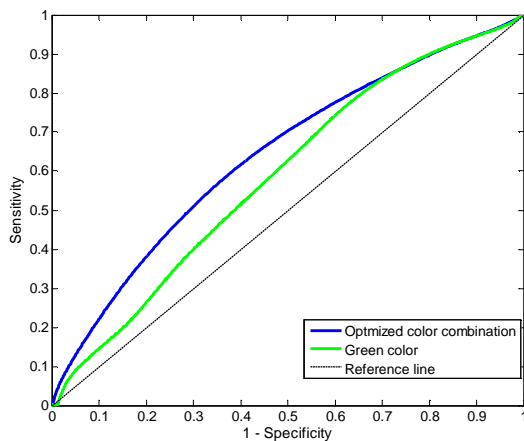


Fig. 5. ROC curves (for green color and color combination optimized for “superglobal” classification) of the images from DRIVE database training set

Fig. 4 and Fig. 5 compare the sample ROC curves for green color and color combination optimized for “global” and “superglobal” classification, respectively. It can be seen that in both cases the ROC curve of the optimal color combination is above the ROC curve of the green channel, illustrating its superiority for blood vessel detection when no information about neighboring pixels is used.

Fig. 6 illustrates the results of blood vessel tree detection using segmentation based method [8] without image preprocessing and with the proposed optimal preprocessing schemes. It can be observed that the method using the optimized color combinations finds additional true blood vessels that were not found by the same method using the green channel alone.

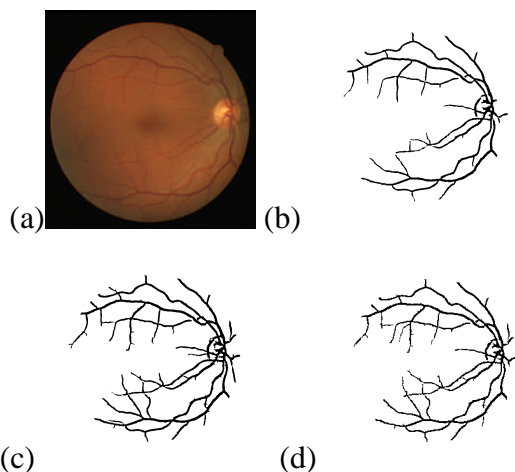


Fig. 6. Original image (a) and results of vessel detection using different color combinations: green channel (b), optimized for “global” classification (c), optimized for “local” classification (d)

The following tables compare blood vessel detection results in terms of sensitivity and specificity on testing set of images from DRIVE database.

Table 2 shows performance of segmentation algorithm using different color combinations for test set of DRIVE database. It can be seen that in this case the use of “local” color combination results in both higher sensitivity and higher specificity and use of “global” and “superglobal” color combinations results in higher sensitivity and lower specificity. It can also be noted that

Matthews correlation coefficient using “local” and “global” color combinations is higher than without such preprocessing.

Table 2. Average performance indexes of blood vessel detection in test set of DRIVE database with segmentation algorithm using different color combinations

Color combination	Sensitivity	Specificity	MCC
Green channel	63.26%	97.20%	63.14%
“Local”	63.75%	97.34%	64.00%
“Global”	67.93%	96.70%	64.30%
“Superglobal”	72.31%	95.23%	62.06%

Table 3 shows performance of tracing algorithm using different color combinations for test set of DRIVE database. It can be seen that in this case the use of “local” color combination results in slightly lower sensitivity and specificity (the difference of means of sensitivity, specificity and MCC were found to be statistically insignificant with significance level 0.05) while use of “global” and “superglobal” color combinations results in significantly lower sensitivity and specificity values.

Table 3. Average performance indexes of blood vessel detection in test set of DRIVE database with tracing algorithm using different color combinations

Color combination	Sensitivity	Specificity	MCC
Green channel	69.77%	95.21%	60.14%
“Local”	69.59%	95.12%	59.64%
“Global”	69.43%	93.16%	53.20%
“Superglobal”	67.56%	90.97%	47.82%

Conclusions

Linear RGB color combinations optimal for classification of pixels of eye fundus images have been found. It has been shown that the use of color combination optimized for “local” classification instead of green color improves results of the segmentation algorithm and retains the quality of results of tracing algorithm. On the other hand, color combinations optimized for “global” and “superglobal” classification improve the sensitivity of segmentation algorithm at the price of specificity. Those results indicate the suitability of use of optimized color combinations even in case of blood vessel detection methods developed for use with green channel only. We expect that the results would be similar for images made using different fundus cameras.

The results of this study indicate possibility of developing blood vessel detection algorithms that would combine advantages of different color combinations.

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References

1. **Grušėckij M., Marozas V., Ulickiene R., Jegelevičius D.** Kraujagyslių tinklo optiniuose akies dugno vaizduose trasavimo algoritmas // *Elektronika ir elektrotechnika*. – Kaunas: Technologija, 2005. – Vol. 2(58). – P. 83–87.
2. **Hammer M., Leistriz S., Leistriz L., Schweitzer D.** Light paths in retinal vessel oximetry // *IEEE Transactions on Biomedical Engineering*. – 2001. – Vol. 48(5). – P. 592–598.
3. **Patašius M., Marozas V., Jegelevičius D., Lukoševičius A.** Ranking of color space components for detection of blood vessels in eye fundus images // 4th European Conference of the International Federation for Medical and Biological Engineering. – Antwerp, Springer, 2008. – Vol. 22. – P. 464–467.
4. **Paulinas M., Miniotas D., Meilūnas M., Ušinskas A.** An Algorithm for Segmentation of Blood Vessels in Images // *Electronics and Electrical Engineering*. – Kaunas: Technologija, 2007. – Vol. 8(80). – P. 25–28.
5. **Bartnykas K., Ušinskas A.** An Algorithm for Segmentation of Blood Vessels in Images // *Electronics and Electrical Engineering*. – Kaunas: Technologija, 2009. – Vol. 2(90). – P. 35–38.
6. **Oloumi F., Rangayyan R. M., Oloumi F., Eshghzadeh-Zanjani P., Ayres F. J.** Detection of blood vessels in fundus images of the retina using gabor wavelets // *Engineering in Medicine and Biology Society, 2007 (EMBS 2007). 29th Annual International Conference of the IEEE*. – 2007. – P. 6451–6454.
7. **Staal J., Abràmoff M. D., Niemeijer M., Viergever M. A., van Ginneken B.** Ridge based vessel segmentation in color images of the retina // *IEEE Transactions on Medical Imaging*. – 2004. – Vol. 23(4). – P.501–509.
8. **Chanwimaluang T., Fan G., Fransen S. R.** Correction to "hybrid retinal image registration" // *IEEE Transactions on Information Technology in Biomedicine*. – 2007. – Vol. 11(1). – P.110–110.
9. **Sofka M., Stewart C. V.** Retinal vessel extraction using multiscale matched filters, confidence and edge measures // *IEEE Transactions on Medical Imaging*. – 2006. – Vol. 25(12). – P. 1531–1546.
10. **Baldi P., Brunak S., Chauvin Y., Andersen C. A. F., Nielsen H.** Assessing the accuracy of prediction algorithms for classification: an overview // *Bioinformatics*. – 2000. – Vol. 16. – P. 412–424.

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Most of the studies so far have used the green component of RGB for blood vessel recognition in eye fundus images with some using luminance. However, the suitability of such choice and possible alternatives have not been sufficiently explored. We aimed to find the linear color combinations that would be optimal for classification of the eye fundus image pixels. It has been shown that the use of color combination optimized for "local" classification instead of green color improves results of the segmentation algorithm and retains the quality of results of tracing algorithm, while color combinations optimized for "global" and "superglobal" classification improve the sensitivity of segmentation algorithm at the price of specificity. The results indicate possibility of developing blood vessel detection algorithms that would combine advantages of different color combinations. Ill. 6, bibl. 10 (in English; summaries in English, Russian and Lithuanian).

М. Паташюс, В. Марозас, Д. Егелевичюс, А. Лукошявичус. Комбинации компонентов цветовых пространств, оптимальные для распознавания кровяных сосудов в изображениях очечного дна // *Электроника и электротехника*. – Каунас: Технолоҗия, 2009. – № 3(91). – С. 53–56.

Пока в большинстве исследований для распознавания кровяных сосудов в изображениях очечного дна использовался зелёный компонент цветного пространства RGB. В остальных случаях использовалась яркость цвета. Однако, пригодность этого выбора и возможные альтернативы пока ещё не были достаточно исследованы. В этой статье мы стремимся найти линейные комбинации цветов, которые были бы оптимальными для классификации пикселей изображений очечного дна. Оказалось, что использование цветной комбинации, оптимизированной для «локальной» классификации, улучшает результаты работы исследованного алгоритма сегментации и поддерживает качество алгоритма трассирования. Цветные комбинации, оптимизированные для «глобальной» и «сверхглобальной» классификаций в свою очередь увеличивают чувствительность алгоритма сегментации за счёт специфичности. Эти результаты позволяют надеяться, что есть возможность создать алгоритмы для распознавания кровяных сосудов, которые использовали бы преимущества некоторых цветных комбинаций. Ил. 6, библи. 10 (на английском языке; рефераты на английском, русском и литовском яз.).

M. Patašius, V. Marozas, D. Jegelevičius, A. Lukoševičius. Optimalios spalvų erdvės komponentų kombinacijos kraujagyslėms aptikti akies dugno vaizduose // *Elektronika ir elektrotechnika*. – Kaunas: Technologija, 2009. – Nr. 3(91). – P. 53–56.

Kraujagyslėms aptikti daugumoje tyrimų iki šiol naudojamas žalias RGB spalvų erdvės komponentas. Kitais atvejais naudojamas skaidis. Tačiau tokio pasirinkimo tikslingumas ir galimos alternatyvos dar nebuvo reikiamai išnagrinėta. Šiame straipsnyje siekiama rasti tiesines spalvų kombinacijas, kurios optimaliai tiktų akies dugno vaizdų pikseliams klasifikuoti. Paaiškėjo, kad spalvų kombinacijos, optimizuotos „lokaliai“ klasifikacijai, pagerina išbandyto segmentavimo algoritmo darbo rezultatus ir išlaiko trasavimo algoritmo rezultatų kokybę. O „globaliai“ ir „superglobaliai“ klasifikacijai optimizuotos spalvų kombinacijos padidina segmentavimo algoritmo jautrumą specifiškumo sąskaita. Šie rezultatai leidžia tikėtis, kad įmanoma sukurti kraujagyslių radimo algoritmus, išnaudojančius skirtingų spalvų kombinacijų pranašumus. Il. 6, bibl. 10 (anglų kalba; santraukos anglų, rusų ir lietuvių k.).