Automatic Generation of Synthetic Retinal Fundus Images: Vascular Network

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Motivation and aim

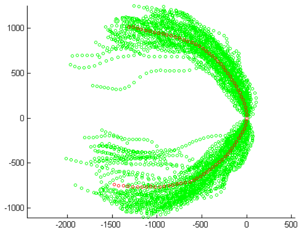
Retinal Image Analysis (RIA) aims to develop computational and mathematical techniques for helping clinicians with the diagnosis of diseases such as diabetes, glaucoma and cardiovascular conditions, that may cause changes in retinal blood vessel patterns. RIA algorithms have to be validated and, in turns, validation requires ground truth in the form of significant volumes of images annotated by medical experts. Obtaining such annotations is expensive, laborious, and not always feasible. This motivates the creation of a synthetic dataset. This work is part of an ongoing project aimed to generate synthetic retinal fundus images. It focuses on the generation of retinal vessels (arteries and veins) and their integration with non-vessel regions (i.e. retinal background, fovea and optic disc) to yield complete fundus camera images[1].

Methods

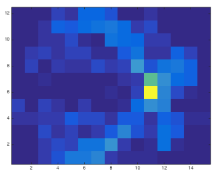
The proposed approach consists of a learning phase and a generation phase. In the former phase, data describing vascular morphology and texture are collected from annotations of real images. Models are specified and their parameters learned from the training data. In the latter phase, the models obtained are used to create synthetic vascular networks. Arteries and veins are created separately with the same protocol, and then combined together.

1. Vascular Morphology

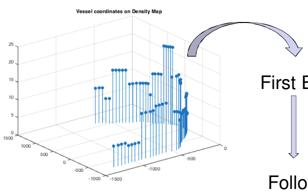
An example-based method, the Active Shape Model[2], is used to synthesize reliable vessels' shapes.
The data describing the shape of the vessels have been collected from 50 retinal fundus images of the GoDARTS bioresource[3]. Vessel shapes are aligned into a coordinate system using a rigid transformation. Using Principal Component Analysis we could generate each new synthetic vessel.



Synthetic vessels are then connected to create the vascular network skeleton.



Spatial density distribution map of all bifurcation points annotated on real images.



Probability score for each point of the vessel to become a bifurcation point.

First Bifurcation Point

N times

Following Bifurcation Point

=

one of the points having maximum score located at a distance $d \in \left[\frac{L}{2N}, \frac{L}{N}\right]$ from the previous one.

L = length of the vessel.
N = desired number of bifurcations.

Synthetic vascular tree

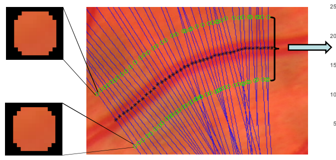
For each branch originating from a bifurcation point we compute its orientation and calibre using the bifurcation model described by Murray's Law.[4]

All vessels should be inside the Field of View (FOV), but outside the foveal region, avoiding intersections between vessels of the same type, and converging toward the fovea.

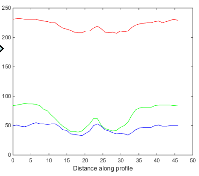
2. Vascular Texture

An approach based on Kalman Filtering combined with an extension of the Multiresolution Hermite vascular cross-section model has been developed capturing the transition of intensities between vessels and background.

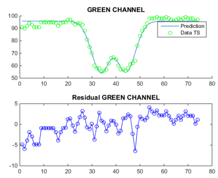
⇨ Data collection



Cross-sections spaced by 5px along the vessel centreline.



Intensity RGB profile extraction



Green channel fitted with a weighted NonLinear Least Squares model using a 6-parameters Extended Multiresolution Hermite Model (EMHM)[6].

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At the extremities (green circles) we computed five statistical texture descriptors (Mean, Std, Skewness, Kurtosis and Entropy) on two near-circular windows of 6px radii.

⇨ Generation of Vessel Textures

GREEN CHANNEL

6 EMHM parameters
5x2 background texture descriptors

for a total of 975 artery and 1593 vein profiles collected from 15 healthy subjects of HRF dataset[5]

=

the measurements for the Kalman Filter technique.

Each new intensity profile of the green channel is generated taking into account the previous one and the surrounding background.

BLUE CHANNEL

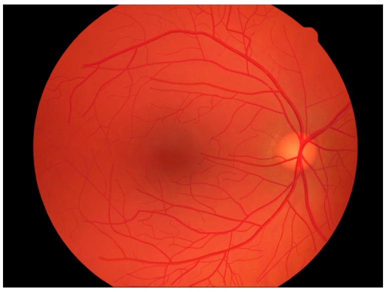
average intensity profile of the training ones

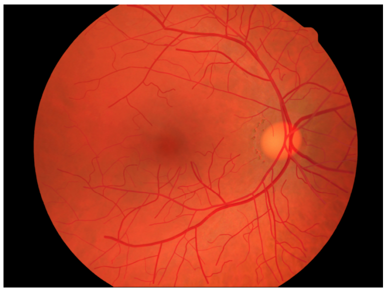
RED CHANNEL

average intensity profile of the training ones weighted with underlying background red intensity level

Synthetic RGB profile then cut with Full Width at Half Maximum algorithm

Results





Conclusions

The proposed method is able to generate realistic synthetic vascular networks with morphological properties that guarantee the correct flow of the blood and the oxygenation of the retinal surface observed by fundus cameras. The validity of our synthetic retinal images has been demonstrated by qualitative assessment and quantitative analysis.

References

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[2] Cootes, T.F., Taylor, C.J., Cooper, D.H., Graham, J., Active shape models - their training and application. Computer vision and image understanding 1995;61(1):38–59.

[3] GoDARTS bioresource: http://medicine.dundee.ac.uk/godarts

[4] Murray, C.D.,The Physiological Principle of Minimum Work Applied to the Angle of Branching of Arteries. The Journal of General Physiology 1926;9(6):835–841.

[5] HRF database: http://www5.cs.fau.de/research/data/fundus-images/

[6] Lupascu, C. A., Tegolo, D., Trucco, E., Accurate estimation of retinal vessel width using bagged decision trees and an extended Multiresolution Hermite Model. Medical Image Analysis, 2013;17(8):164–1180.

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