Automatic Creation of an Efficient Image Filter based on the Genetic Algorithm for Evaluation of Veins

Koji Kashihara
Institute of Techonology and Science, The University of Tokushima, 2-1 Minamijyousanjima, Tokushima, Japan

Keywords: Genetic Algorithm, Expectation Maximization Algorithm, near Infrared Camera, Image Filtering.

Abstract: Instead of expensive and complicated diagnostic equipment, low-cost infrared cameras can record vein images noninvasively and simply. However, the recorded image may induce low contrast and a worse signal-to-noise (S/N) ratio. To solve this problem, an effective image filtering method to catch vein shapes will enable the early detection of disease. Therefore, a new filtering method based on the genetic algorithm (GA) with the expectation maximization (EM) algorithm was proposed for the analysis of vein images acquired from a near-infrared (780 nm) CCD camera. The new filter was automatically designed by the GA to modify the worse S/N ratio of vein images, with an unknown correct image answer. If the proposed filtering method is incorporated into the e-healthcare application, it could be widely distributed through smart phones or tablets.

1 INTRODUCTION

Sitting on a narrow seat during long air travel increases the risk of dyspnea and acute myocardial infarction triggered by leg deep venous thrombosis (Feltracco, Barbieri, Bertamini, Michieletto, and Ori, 2007). Venous insufficiency may also cause varicose veins owing to incompetent valves (Callam, 1994). Medical doctors and experts must operate large, expensive, and complicated medical equipment such as ultrasonic diagnostic equipment and X-ray systems (Bergqvist and Jaroszewski, 1986) to diagnose patients with circulatory diseases.

Instead of such equipment, a near-infrared camera (Kashihara, Ito, and Fukumi, 2012; Zharov, Ferguson, Eidt, Howard, Fink, and Waner, 2004) can easily and noninvasively visualize venous shapes. However, vein images taken by the near-infrared camera may result in low contrast and a worse signal to noise (S/N) ratio. The auto-tuning function or manual camera settings of photographic parameters may also induce low image quality. Accordingly, creating an effective image filter will address this issue and lead to the accurate detection of venous states.

Standard image processing such as equalization and binarization (Soni, Gupta, Rao, and Gupta, 2010; Yakno, Saleh, and Rosdi, 2011) can enhance a low-contrast image; on the other hand, important information on complicated and thin lines may be lost. If the filter kernel parameters determining the feature of each image are explored in detail, optimal image processing would be obtained instead of the customary methods.

The purpose of this study was to create an effective filtering method to detect vein shapes in the low-contrast image from a near-infrared camera. The image filter was automatically designed by the genetic algorithm (GA) with the expectation maximization (EM) algorithm (GA-EM algorithm). The GA-EM algorithm could find the best combination of convolution kernel values for a new filter.

2 DESIGN OF A NEW FILTER

A new filter for vein images was designed by real coded GA with the EM algorithm. The GA approach can search for the convolution filter kernel at the maximum fitness. The EM algorithm search for the optimal parameter in Gaussian mixture models (Bilmes, 1998). The EM algorithm could separate the area of target veins from background, estimating parameters for two components of the Gaussian mixture model.

Kashihara K..
Automatic Creation of an Efficient Image Filter based on the Genetic Algorithm for Evaluation of Veins.
DOI: 10.5220/0004913505060510
In *Proceedings of the International Conference on Health Informatics* (HEALTHINF-2014), pages 506-510
ISBN: 978-989-758-010-9

2.1 Ga Process

An individual is represented by an array of real values indicating the convolution kernel values. The GA consists of the following three operators: selection, crossover, and mutation.

The initial population of individuals is randomly generated within a set range. Each individual is represented by real numbers; its score is calculated from a fitness function. The fitness function for the GA is based on a convolution filter kernel values to an input image. The convolution kernel updated by the GA could highlight a region of interest (ROI), reducing external noise in the image.

A selection operation determines the individuals for the generation of offspring. Next, a crossover operation combines two individuals to generate an offspring. A blend crossover (BLX-α) operator (Eshelman and Schaffer, 1993) was selected for this study. Furthermore, a mutation operator randomly changes some individuals, altering the variables of a selected individual to facilitate the diversity in the population. The mutation can avoid falling into a local solution.

The above GA operators were repeated to update the population and created the next generations, improving the fitness of the population. The GA program stopped after some generations.

2.2 EM Algorithm

The fitness function values for the GA were computed from the log likelihood of the Gaussian mixture model. The Gaussian mixture model is described as:

$$p(x) = \sum_{k=1}^{K} \pi_k G(x|\theta_k), \tag{1}$$

where $x = [x_1, ..., x_d]^T$ is the d-dimensional data vector. π_k is the mixture ratio of a distribution and the ratio must be $\pi_k \geq 0$ and $\sum_{k=1}^{K} \pi_k = 1$. G means the normal distribution with the parameters of $\theta_k = \{\mu_k, \Sigma_k\}$ corresponding to the mean vector and the covariance matrix. K shows the number of the models (K = 2, the vein and background for this study).

The EM algorithm consists of the expectation (E-step) and maximization (M-step) steps, which are alternately applied until the log-likelihood value converges to an optimal value. The observed data $\boldsymbol{x}$ mean the brightness values after applying a proposed filter (d = 1), and $\boldsymbol{x} = \{x_1, ..., x_N\}$ (N data samples, the total number of pixels in a target image). The parameter values (π_0, μ_0, and Σ_0) were initialized, and the E-M steps were repeated.

2.2.1 E-step

The posterior probability of the latent variables (z) for the Gaussian mixture model can be calculated as follows.

$$\gamma(z_{ik}) = \frac{\pi_k G(x|\mu_k, \Sigma_k)}{\sum_{j=1}^{K} \pi_j G(x|\mu_k, \Sigma_k)}, \tag{2}$$

2.2.2 M-step

The new parameters [$\theta^{(t+1)}$] are identified by estimating the latent variables (z_{ik}) in order to maximize the log likelihood of the complete data. This process is consistent with calculating the parameters $\pi_k^{(t+1)}$, $\mu_k^{(t+1)}$, and $\Sigma_k^{(t+1)}$ for the Gaussian mixture model:

$$\begin{cases} \pi_k^{(t+1)} = \dfrac{N_k}{N}, \quad \mu_k^{(t+1)} = \dfrac{\sum_{i=1}^{N} \gamma(z_{ik}) x_i}{N_k} \\ \Sigma_k^{(t+1)} = \dfrac{\sum_{i=1}^{N} \gamma(z_{ik})(x_i - \mu_k)(x_i - \mu_k)^T}{N_k} \end{cases}, \tag{3}$$

where $N_k = \sum_{i=1}^{N} \gamma(z_{ik})$.

3 EVALUATION METHODS

The novel image filter was evaluated for the detection of actual venous changes with an unknown image answer.

3.1 Measurement Environment

Figure 1 shows the measurement environment for vein shapes. Finger veins as a target for image analysis were recorded by a CCD camera (Toshiba Teli Co., CS8620Hi) with near-infrared light-emitting diodes (wavelength of 780 nm). A filter to cut visible light (Fuji Film Co., IR760) was set in the front of the camera. Photographic parameters in the camera (contrast, focus, gain, exposure, etc.) were manually set to optimal values before the actual measurement. The recorded images were modified by the filters (Microsoft Visual C++ 2010 with Open CV Ver. 2.1).

Figure 1: Measurement environment for vein shapes and states during the measurement of blood pressure.

The subjects were healthy male volunteers (n = 4; age ± S.D. = 26.8 ± 8.2 years). The experiment was conducted in accordance with the Declaration of Helsinki. A signed informed consent form was obtained from each participant. The participants refrained from eating, drinking, or smoking at least two hours prior to the experiment.

3.2 Procedures

To induce a great change in the venous states, the forearm was pressed by a sphygmomanometer and finger veins were recorded by a CCD camera. The vein images were extracted at the prestimulus (before 10 s of starting the blood pressure measurement), maximum pressure, and recovery (after 90 s of stopping the measurement) period.

3.3 Applied Filters

After a typical Gaussian filter was applied to a target image, the GA process was performed. The fitness function for the GA was a convolution filter kernel. The kernel values were updated by the GA and it was applied to vein images within the ROI (60 × 120 pixels).

The initial population of individuals (kernel values) in the GA parameters is randomly generated within a set range between -10 and 10. The population size was set at 40; the tournament size for selection was 20; the crossover probability was 0.6; the mutation probability was 0.1. The parameter for a blend crossover (BLX-α) operator was set at α = 0.4. The procedure for the GA was repeated until reaching 100 generations. The designed filter kernel had a fixed size array (3 × 3) of numerical coefficients. Once the novel image filter was created under the prestimulus condition in each subject, the same filter kernel was applied to the target images in all experimental conditions.

The EM algorithm for the GA was iterated five times, considering the computing time. The repeat count was determined by considering the calculation time for the GA. The pixel values in a target image were initially normalized. The initial parameters for the Gaussian mixture model were set at π_0 = (0.5, 0.5), μ_0 = (-0.5, 0.5), and Σ_0 = (0.1, 0.1) in the two distributions. In the case of division by zero or an infinite value, the fitness function value received a large penalty score. To avoid the singular value problem, white or black (0 or 255) areas of an image also had a penalty if over 1%.

3.4 Analysis

To confirm the strict accuracy in the novel filter, the venous changes during a blood pressure stimulus were evaluated by the Gaussian fitting of a venous line. So that the target venous line and X axis would cross at a right angle, the image was rotated at an angle of some degrees. The ROI (20 × 10 pixels) was set for the part of a venous line, and 10 pixel values of the inverted Y axis were averaged at every point on the X axis. The Gaussian approximation based on a modified Levenberg-Marquardt method was applied to the target distribution:

$$y = a \exp[(-(x-b)^2) / (2c^2)] + d \quad (4)$$

The x and y are the values of the X axis and the estimated brightness levels, respectively. The parameters a and c indicate the amplitude and width of the distribution, b is the peak location, and d is the offset value.

4 EXPERIMENTAL RESULTS

Figure 2 shows the vein images with and without image filtering under the prestimulus, maximum pressure, and recovery period (90 s later). The ROI was set for the area of the middle finger, referencing a fixed marker. The average values (n = 4) of systolic and diastolic pressures were 116.5 ± 14.7 and 68.3 ± 11.7 mmHg, respectively. The pulse wave was 71.3 ± 6.2 beats/min.

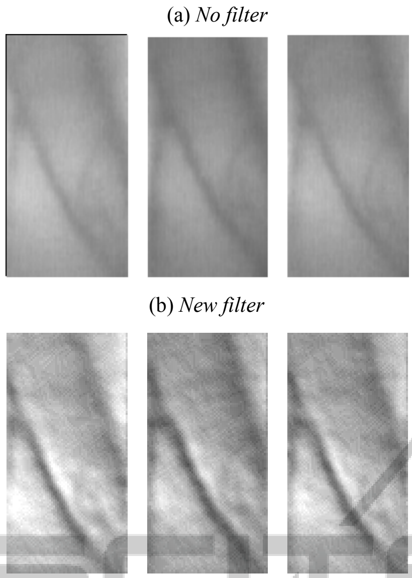

Figure 2: A typical example of vein images before (a) and after (b) the image filtering process within the region of interest (ROI) at the prestimulus (*left*), maximum pressure (*middle*), and recovery period (*right*).

The recorded images showed low-contrast resolution and contained external noise. The venous lines appeared to be thicker at the maximum pressure than at the prestimulus and the recovery period. The new filter was especially effective for highlighting the vein shapes.

Figure 3 represents the change in the maximum values of the fitness function during the GA process (n = 4). These values remarkably increased after five generations; they gradually converged to a constant value at around 50 generations.

The intensity histogram of vein images with no filter and the new filter included bimodal distribution, indicating the area of veins and background. Although venous changes were quantified by using the EM algorithm, the left distribution (i.e., low intensity) showing venous areas was not able to be modified by the fitting function without an image filter. On the other hand, the features of venous areas were sufficiently extracted by using the EM algorithm under the proposed filtering process. The distance of the two distributions was longer with the proposed filter than with no filter, showing the separation of the veins and background area.

As shown in Figure 4, Gaussian fitting was applicable to the intensity distribution in the ROI vertically across a venous line in order to estimate the accuracy of the proposed filter during a blood pressure stimulus. Table 1 summarizes the estimated

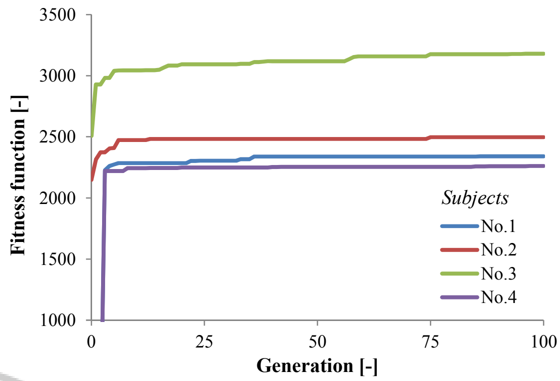

Figure 3: Change in the maximum value of the fitness function during the GA process (n = 4).

parameters of a Gaussian function. Sensitivity of venous changes was increased by applying the new filter, and the difference in the image characteristics was enlarged. A greater change of the parameters was observed at the maximum pressure period. In special, the parameter c would have reflected the increased amount of deoxyhemoglobin and the enlarged venous areas. This result suggests the detection of venous changes with high accuracy.

Table 1: Fitting parameters for experimental conditions.

Conditions	**Gaussian Fitting Parameters**			
	Amplitude (a)	***Peak location (b)***	***Width (c)***	***Offset (d)***
Prestimulus	86.7 (55.5)	10.1 (1.5)	7.2 (7.3)	-2.3 (63.2)
Max. pressure	102.4 (67.0)	10.8 (1.4)	8.0 (7.9)	1.4 (71.7)
Recovery	67.1 (24.3)	10.7 (2.5)	5.8 (4.1)	29.8 (18.5)

a to d, parameters in Eq. (4); ( ) means S.D.

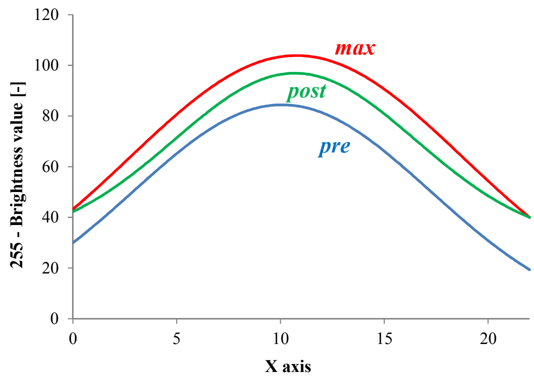

Figure 4: Gaussian fitting functions (average responses; n = 4) at the prestimulus (*blue*), maximum pressure (*red*), and recovery period (*green*).

5 DISCUSSION

Vein images from a near-infrared camera may result in the low quality because of the worse S/N ratio. Therefore, the efficient filtering process will be necessary for quantifying venous changes. The proposed filtering method based on the GA-EM algorithm sufficiently modified the low-contrast vein images during a blood pressure stimulus, under an unknown correct image answer. However, the ability of the EM algorithm is influenced by the method of selection of the initial parameters. Furthermore, the design of a novel filter with the EM algorithm must avoid singularity or note identifiability (Casella and Berger, 2002).

The same filtering procedure is not optimal for all situations because the accuracy of image processing depends on inter- or intra- individual variability of vein shapes. The typical image processing will need the adjustment of the camera or filtering parameter settings every measurement environment or an acquired image, by trial and error. The proposed filtering method will sufficiently improve the images obtained from such situations.

6 CONCLUSIONS

The image filter made by the GA-EM algorithm was able to efficiently detect vein shapes recorded by an infrared camera. The filtered images were quantified with the EM algorithm to assess venous changes during the blood pressure measurement. The proposed imaging filter was able to modify its kernel array, adapting the feature of target images. In future studies, the optimal range of parameters for the GA-EM algorithm should be investigated to catch abnormal veins at an early stage. If the proposed filtering method is incorporated into the e-healthcare application, it could be widely distributed through smart phones or tablets.

ACKNOWLEDGEMENTS

This study was partially funded by a Grant-in-Aid for Scientific Research (C) from Japan Society for the Promotion of Science (KAKENHI, 25330171).

REFERENCES

Feltracco, P., Barbieri, S., Bertamini, F., Michieletto, E., Ori, C., 2007. Economy class syndrome: still a recurrent complication of long journeys. *Eur. J. Emerg. Med.*, vol. 14, pp. 100–103.

Callam, M. J., 1994. Epidemiology of varicose veins. *Br. J. Surg.*, vol. 81, pp. 167–173.

Bergqvist, D., Jaroszewski, H., 1986. Deep vein thrombosis in patients with superficial thrombophlebitis of the leg. *Br. Med. J. (Clin. Res. Ed.)*, vol. 292, pp. 658–659.

Kashihara, K., Ito, M., Fukumi, M., 2012. Estimation of venous shapes acquired from CMOS camera images. *Proc. of the Eighteenth Korea-Japan Joint Workshop on Frontiers of Computer Vision (FCV2012)*, pp. 47–52.

Zharov, V. P., Ferguson, S., Eidt, J. F., Howard, P. C., Fink, L. M., Waner, M., 2004. Infrared imaging of subcutaneous veins. *Lasers Surg. Med.*, vol. 34, pp. 56–61.

Soni, M., Gupta, S., Rao, M. S., Gupta, P., 2010. A new vein pattern-based verification system. *International Journal of Computer Science and Information Security*, vol. 8, pp. 99–105.

Yakno, M., Saleh, J. M., Rosdi, B. A., 2011. Low contrast hand vein image enhancement. *Proc. of 2011 IEEE International Conference on Signal and Image Processing Applications (ICSIPA)*, pp. 390–392.

Bilmes, J. A., 1998. A gentle tutorial of the EM algorithm and its application to parameter estimation for Gaussian mixed and hidden Markov models. U.C. Berkely, TR–97–021.

Eshelman, L. J., Schaffer, J. D., 1993. Real-coded genetic algorithms and interval-schemata. *Foundations of genetic algorithms*, vol. 2, pp. 187–202.

Casella, G., Berger, R. L., 2002. *Statistical Inference*, 2nd ed., Pacific Grove, CA: Duxbury.