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COMPUTER ANALYSIS OPTICAL COHERENCE TOMOGRAPHY IMAGES BY USING UNSUPERVISED MACHINE LEARNING ALGORITHM

Abstract. In recent years, computer image analysis has been developing rapidly. In the field of medicine has been identified to a new level that has greatly helped for the diagnostic system. There are many information systems in the field of ophthalmology and cardiology. Advanced technologies not only accelerate the work of doctors but also help to diagnose the disease in a timely manner and prescribe the treatment. In this research paper was carried out an analysis of the machine learning algorithm using a database of tomographic images of blood vessels in the eye system. Were studied the used methods for calculating several reasons in order to select a specific model, methods for calculating its properties and advantages. The main goal of this research is that doctors can not only check the current condition of the patient's eye but also diagnose certain diseases, such as diabetes and anemia.

Keywords: linear discriminant analysis, subretinal fluid segmentation, level set, local Gaussian pre-fitting energy**.**

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Аңдатпа. Сонғы жылдары суреттерді компьютерлік анализ жасау қарқынды дамып келе жатыр. Медицина саласында диагноз кою жүйесі үшін көптеген көмегін тигізу аркылы жаңа деңгейге шығарды. Қазіргі таңда офтальмология және кардиология саласында ақпараттық жүйелер көптеп кездеседі. Дамыған технологиялар дәрігерлердің жұмыстарын тездетіп қана қоймай ауру жағдайын ерте анықтап, ем тағайындауға көмектеседі. Бұл ғылыми мақалада көз жүйесіндегі қан тамырларының томографиялық суреттерің дерекқорын қолдана отырып машиналық оқытудың алгоритмдерінің анализі жасалынды. Белгілі бір модельді таңдаудың бірнеше себептерін, оның қасиеттерін, кейбір артықшылықтарын және маңыздылығын есептеу үшін қолданылатын әдістерді зерттелді. Бұл зерттеу жұмыстарының басты мақсаты дәрігерлер өздерінің емделушінің көзінің қазіргі жағдайын тексеріп қана қоймай, диабет және анемия сияқты белгілі бір ауру жүйелеріне диагноз қоя алуы.

Түйін сөздер: сызықтық дискриминанттық талдау, сұйықтықтың субретинальды сегментациясы, деңгей жиынтығы, жергілікті Гаусстың алдын-ала орнатылатын энергиясы.

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Аннотация. В последние годы компьютерный анализ изображений развивается быстрыми темпами. В области медицины был выведен на новый уровень, оказав большую помощь для диагностической системы. На сегодняшний день существует множество информационных систем в области офтальмологии и кардиологии. Передовые технологии не только ускоряют работу врачей, но и помогают своевременно диагностировать заболевание и назначать лечение. В данной научной статье был выполнен анализ алгоритма машинного обучения с использованием базы данных томографических изображений кровеносных сосудов в глазной системе. Были изучены используемые методы для расчета нескольких причин в целях выбора конкретной модели, а также методы для расчета его свойств и методы для расчета некоторых преимуществ и значимости. Основная цель этого исследования состоит в том, что врачи могут не только проверить текущее состояние глаза пациента, но и диагностировать определенные заболевания, такие как диабет и анемия.

Ключевые слова: линейный дискриминантный анализ, сегментация субретинальной жидкости, набор уровней, локальная гауссова энергия предварительной подгонки.

Introduction

Linear Discriminant Analysis (LDA) are methods used in statistics, pattern recognition and machine learning to find a linear combination of characteristics which describes or splits two or more classes of objects. The resulting combination may be used as a linear classifier. LDA is closely related to Principal Component Analysis (PCA) [2] for both of them are based on linear and matrix multiplication, transformations. In case of PCA, the transformation is based on minimizing mean square error between original data vectors and data vectors that can be estimated for the reduced dimensionality data vectors and the PCA does not considers any difference in class. However, for LDA the transformation is based on maximizing a ratio of “between-class variance” to “within-class variance” to lower data variability in the same class and increasing the separation between classes.

Main part

To find out LDA, we need to aware what is the "between-class variance" and "within-class variance". Then we have to maximize the ratio between these two. Assume we have a set of D-dimensional samples

$$X = \left\{x^1, x^2, ..., x^m\right\}, N_1 \tag{1}$$

of which belong to class C_1 and N_2 belong to class C_2. In our case, class C_1 is fluid associated region, and class $C_2$is outer region, respectively. For this case we also assume the mean vector of two classes in X space:

$$u_k = \frac{1}{N_k} \sum_{i \in C_k} x^i \tag{2}$$

where $k=1,2$, and in y space:

$$\hat{u_k} = \frac{1}{N_k} \sum_{i \in C_k} y^i = \frac{1}{N_k} \sum_{i \in C_k} \theta^T x^i = \theta^T u_k \tag{3}$$

where $k=1,2$. One of the ways to define a measure of separation between two classes is to choose the distance between the projected means, which is in$y$ space, so the between-class variance is:

$$\hat{u}_2 - \hat{u}_1 = \theta^T(\hat{u}_2 - \hat{u}_1) \quad (4)$$

and within-class variance for each class C_k is:

$$\hat{s}_k^2 = \sum_{i \in C_k} (y^i - \hat{u}_k)^2 \quad (5)$$

Final Fisher criterion in terms of some measure scatters as following:

$$J(\theta) = \frac{\theta^T S_B \theta}{\theta^T S_W \theta} \tag{6}$$

where

$$S_B = (u_2 - u_1)(u_2 - u_1)^T \quad (7)$$

$$S_W = \sum_k \sum_{i \in C_k} (x^i - u_k)(x^i - u_k)^T \quad (8)$$

The easiest way to maximize the object function J is to derive it and set it to zero.

$$\frac{\partial J(\theta)}{\partial \theta} = \frac{\partial}{\partial \theta}\left(\frac{\theta^T S_B \theta}{\theta^T S_W \theta}\right) \quad (9)$$

By solving above equation we get the direction of the θ, which is the:

$$\theta^* \infty S_W^{-1}(u_2 - u_1) \quad (10)$$

Intensity inhomogeneity phenomenon presents a systematic change on intensities of both object and background and usually manifests itself as a smooth spatially varying function across the image [3]. A novel region based model is proposed to segment image with intensity inhomogeneity. The model consists of three components: linear discriminant analysis, region scalable fitting energy and regularization term of the level set function. The local discriminant analysis is used to classify pixels to background and foreground, while energy functional and regularization term are used to differentiate the image differences between the foreground and the background of an object, and iteratively evolve the initial contours. According to above analysis, new feature space obtained by linear discriminant analysis can be incorporated into the LBF energy functional to assist in image segmentation. So the final energy functional can be expressed as:

$$E^{RSFLDA} = \sum_{i=1}^{2} \iint K_\sigma(x,y)\left[|I(y) - f_i(x)|^2 + \alpha |Y(y) - u_i(x)|^2\right] \times H_i(\phi(y))dydx. \quad (11)$$

where α is nonnegative constant and $Y(y)$ is a new feature space obtained from Eq.(1). α is a parameter of linear discriminant analysis (LDA) term, it used to balance the effects of LDA term. $f_i(x)$ and $u_i(x)$ denote the intensity means for the image $I(x)$ and $Y(x)$, accordingly. By combining the regularization term and energy functional, the final fitting energy functional is given by:

$$\mathrm{E}(\phi) = E^{RSFLDA} + \mu P(\phi) \quad (12)$$

$E(\phi)$ is minimized with respect to the functions $f_i(x)$ and $u_i(x)$, which satisfy the following:

$$f_i(x) = \frac{\int K_\sigma(x,y) H_i(\phi(y)) I(y) dy}{\int K_\sigma(x,y) H_i(\phi(y)) dy} \quad (13)$$

$$u_i(x) = \frac{\int K_\sigma(x,y) H_i(\phi(y)) Y(y) dy}{\int K_\sigma(x,y) H_i(\phi(y)) dy} \quad (14)$$

Keeping $f_i(x)$ and $u_i(x)$ fixed, $E(\phi)$ is minimized with respect to ϕ, resulting in the evolution formula of the level set function ϕ:

$$\frac{\partial \phi}{\partial t} = -\delta(\phi)\left(e_1 - e_2 + \nu div\left(\frac{\nabla \phi}{|\nabla \phi|} \right) \right) + \mu\left(\nabla \phi - div\left(\frac{\nabla \phi}{|\nabla \phi|} \right) \right) \quad (15)$$

$$e_i = \int K_\sigma(x,y)\left(|I(y) - f_i(x)|^2 + \alpha |Y(y) - u_i(x)|^2 \right) dy, \; i=1,2 \quad (16)$$

where $\delta(\phi)$ is the derivative of the function $H(\phi)$, $div(.)$ denotes the divergence operator, and $e_i(x)$ simultaneously quantifies the image difference between foreground and background for the original image. In contour evolution, the level set function ϕ was initially assigned to a positive constant 1 outside a region and -1 inside. σ was assigned to 25 to balance the convergence rate and computational efficiency. Δt and μ were related by $\Delta t * \mu = 0.1$ to satisfy the Courant Friedrichs Lewy (CFL) condition for numerical stability [4] and they were set $\Delta t = 0.1$, $\mu = 1$, respectively. The parameter ν was set $\nu = 0.007 \times 255 \times 255$.

Fig. 1 gives the preview of our system. Automated initialization stage targets to find candidate fluid zone by estimating region of interest. Then level set method with Linear Discriminant Analysis is applied to segment subretinal fluid.

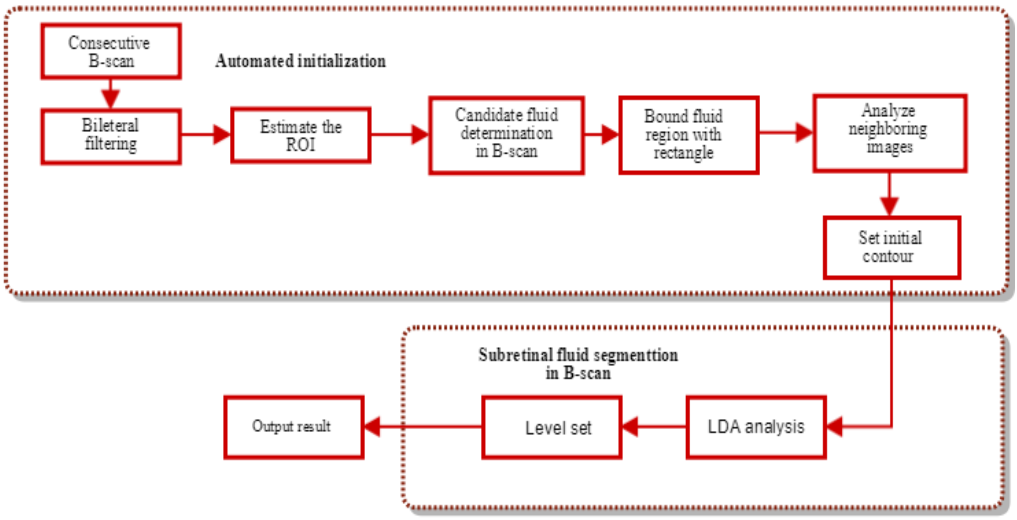

Fig. 1 Overview of proposed method

Result

The developed linear discriminant analysis is used to construct the intensity fitting term $|Y(y) - u_i(x)|^2$. This causes that the proposed method has potential for handling intensity inhomogeneity and avoiding unnecessary contour evolution in segmentation by classifying image information to foreground and background, respectively. To demonstrate the performance of the proposed method, 23 longitudinal SD-OCT cube scans from 12 eyes of 12 patients acquired with the Cirrus OCT device (Carl Zeiss Meditec, Inc., Dublin, CA) were used in which all the subjects were diagnosed with CSCR with only NRD. Fig. 4.2 and Fig.4.3 demonstrates the performance of proposed model to segment NRD associated subretinal fluid. In a qualitative comparison (Fig. 4.2), the proposed method provided a smooth boundary of the fluid region, while the LPHC and SS-KNN method do not guarantee the smoothness of the contour. The LPHC method suffers from a strong label propagation constraint. If the retinal structure changes dramatically, the regions might be segmented (delineated by the dashed yellow ellipse).The automatic layer segmentation is not always correct, which may result in failure of layer segmentation method results, because of NRD which affects to retinal layer structure. Our model surpasses other state-of-art methods and generates the segmentation results

similar to the ground truths. The results in Table 1 summarize the PPV and DSC. Overall, the proposed method is capable to produce a higher segmentation results without utilizing any layer segmentation results.

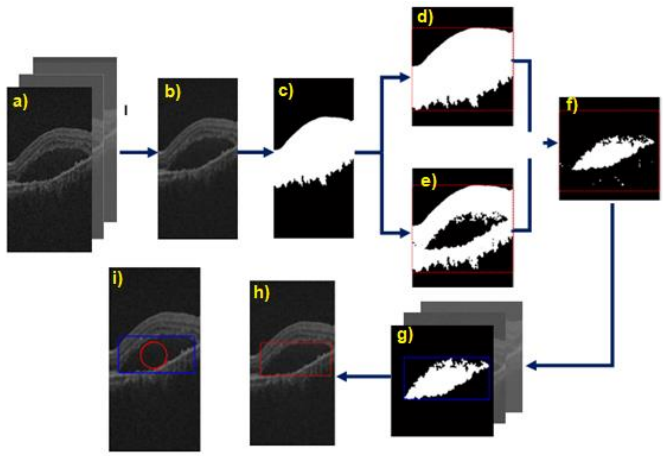

Fig. 2 Flowchart of processing

Table 1. To summarize the quantitative findings (mean ± standard deviation) between the segmentations and the manual gold standards (segmentations of two individual experts).

Methods	Expert 1		Expert 2	
	PPV	DSC	PPV	DSC
LPHC[9]	54.6±12.3	64.3±9.4	54.8±11.8	64.7±9.5
SS-KNN [22]	90.9±3.8	85.1±3.1	90.8±2.8	84.9±3.1
FLSCV [4]	85.2±6.3	77.9±20.7	85.8±6.3	78.4±1.2
CMF [23]	92.0±2.4	92.9±1.5	93.0±2.5	93.3±1.6
EFD [5]	92.0±3.8	92.7±3.0	93.1±4.3	93.6±3.1
Proposed	95.52±0.013	93.79±1.2	96.59±0.1	94.4±1.6

Conclusion

In summary, we report a fully automatic method for the segmentation of subretinal fluid. Our framework can handle intensity in homogeneity which can

be seen in B-scan images. Compared with the other existing methods, the advantage of our method as follows: firstly, this method limits the spatial extent of the fluid region in B-scans by incorporating region of interest and thus improves the segmentation performance. Second, the experimental results reveal that two-stage automatic framework is robust to possible errors of automatic layer segmentation compared with SS-KNN method. Furthermore, linear discriminant analysis based level set segmentation can provide a smooth boundary of the subretinal fluid.

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