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Investigation of Ways to Improve the HOG Method in the Classification of Histological Images by Machine Learning Methods

Farkhod Meliev[1], Fatto Meliev[2]

[1]Doctoral student, Research Institute for the Development of Digital Technologies and Artificial Intelligence
[2]Assistant Professor, Uzbekistan-Finland pedagogical institute

Abstract
This study analyzes ways to improve the performance of the histogram of oriented gradients (HOG) method for histological image classification using machine learning methods. We propose applying HOG to each color channel of the image, which improves the extraction of texture features characteristic of histological data. A comparative analysis of the traditional HOG and the improved approach is conducted, including an experimental evaluation of their accuracy and processing time using SVM, RF, DT, KNN, and NB classifiers. The results show that the proposed improvements improve the classification accuracy, which makes the modified HOG method promising for application in biomedical analysis.

Keywords: Features, HOG, histological images

Introduction

In recent years, machine learning (ML) methods have played a key role in automating the analysis of medical images, especially histological ones [1]. One of the widely used approaches to extract features from images is the histogram of oriented gradients (HOG) method. This method was originally developed for object detection tasks, but its successful application in other areas, such as computer vision, makes it promising for histological image analysis as well [2].

The HOG method was first proposed by Dalal and Triggs (2005) for the task of recognizing pedestrians in images. This method works based on local gradients in an image, computing their orientation and distribution. HOG has proven to be effective in object recognition due to its robustness to illumination and scale changes, which has led to its widespread use in computer vision. However, in medical imaging, and in particular in histology, this method has been applied much less frequently [3].

Some researchers have considered the application of HOG to medical image analysis. For example, in the work [4], HOG was used to segment and classify facial images for medical applications. This experience showed that HOG can effectively extract contours and texture features, making it suitable for complex structures found in histological images.

Successful development of efficient methods for automatic classification of histological images requires taking into account advances in image processing, machine learning, and bioinformatics. The histogram of oriented gradients (HOG) method is widely used for texture and shape analysis, making it suitable for application to histological image classification problems, but its use in this area has not yet been sufficiently explored.

The histogram of oriented gradients (HOG) method has proven to be one of the most effective approaches for feature extraction in image classification, including medical data [5]. However, when working with histological images, where complex texture structures and sample variability play an important role, the standard implementation of HOG does not always provide sufficient accuracy. This raises the need to research and develop new ways to improve this method. In this paper, we will consider how a modified way of applying HOG can improve its efficiency in histological image classification tasks. Particular attention will be paid to the integration of HOG with modern machine learning methods, as well as improving the parameters of the method for accurate extraction of key features of histological samples.

Statement of the problem

Let a set of histological images be given $X = \{x_1, x_1, \ldots, x_N\}$, where x_i is the i-th image of size $m \times n$ pixel. Each image is associated with a class label $y_i \in \{1,2, \ldots, K\}$, where K is the total number of classes (e.g., pathology types).

The objective of improving the HOG method is to:

Determining the optimal methods application of HOG to improve the representation of textural features of histological images and increase classification accuracy:

$$h_i' = HOG_{mod}(x_i) \qquad (1)$$

where $\mathrm{HOG_{mod}} -$ is a modified version of the HOG method. Modified HOG methods create more informative features that better represent the textures of histological images.

After feature extraction h_i' modified way, the classification problem is to find a function $f: R^d \rightarrow \{1,2, \ldots, K\}$ that can predict the class y_i based on these features:

$$f(h_i') = \hat{y}_i, \text{ where } \hat{y}_i \approx y_i \qquad (2)$$

Depending on the classification method chosen, the model is built to minimize the prediction error, which can be achieved using various optimization approaches, such as minimizing the loss functions that best fit the specific task.

The h_i' features obtained after the modified application of the HOG method serve as input to machine learning algorithms that perform classification.

Methods

Let us consider a color histological image presented in RGB format. The image can be designated as $\mathrm{I(x, y)}$, where x and are $y$the pixel coordinates. The color channels of the image can be identified as:

- Red Channel :$R(x, y)$
- Green channel :$G(x, y)$
- Blue channel :$B(x, y)$

To apply the HOG method, we must first calculate the gradients for each color channel. The gradients can be calculated using the Sobel or Pruitt operators [6]. The gradients G_x and G_y can be calculated as follows:

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}, \; G_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \qquad (3)$$

The gradients for each channel will be calculated as:

$$G_x^R = R_x = R * G_x$$
$$G_y^R = R_y = R * G_y$$
$$G_x^G = G_x = G * G_x \quad (4)$$
$$G_y^G = G_y = G * G_y$$
$$G_x^B = B_x = B * G_x$$
$$G_y^B = B_y = B * G_y$$

Once the gradients are obtained, the magnitude and direction of the gradient for each channel can be calculated:

$$Mg = G = \sqrt{G_x^2 + G_y^2} \quad (5)$$

$$Or = \theta = arctan\left(\frac{G_y}{G_x}\right) \quad (6)$$

Next, for each pixel a histogram of oriented gradients is created within a window of size n×n (e.g. 8×8). Histograms can be calculated as:

$$H(\theta) = \sum_{i=1}^{N} Mg_i \cdot \delta(\theta_i - \theta) \quad (7)$$

where δ is the Dirac function, which determines in which bin the angle θ is located , and N is the number of pixels in the window.

To improve robustness to changes in lighting and contrast, histograms are normalized, which can be expressed as follows:

$$H_{norm} = \frac{H}{\sqrt{H^2 + \epsilon^2}} \quad (8)$$

where $\epsilon$is a small parameter to prevent division by zero.

Histograms for all channels can be combined into a single feature vector:

$$F = [H_{norm}^R, H_{norm}^G, H_{norm}^B] \quad (9)$$

Thus, the final feature vector obtained from all three channels can be represented as:

$$F_{final} = F^R \oplus F^G \oplus F^B \quad (10)$$

where $\oplus$is the vector union operation.

These steps represent a formalized approach to applying the HOG method to each color channel of histological images, allowing the extraction of characteristic features for further classification or analysis.

The extracted features were then fed as input to the classifiers Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), Naive Bayes (NB).

Experimental research

The tables below show the comparative classification results of the colon (Table 1) and lung (Table 2) images based on the extracted features using the HOG and HOG_{mod} methods.

Table 1: Results of classification of histological images of the large intestine using feature extraction methods HOG And HOG_{mod}.

Classification method	HOG				HOG_{mod}			
	Time(s)		Accuracy(%)		Time(s)		Accuracy(%)	
	Train .	Test	Train .	Test	Train .	Test	Train .	Test

SVM	182.2	397.2	9 7	78	730.7	1435	98	81
kNN	0.07	3.77	64	56	0.2	8.65	63	56
DT	67.57	0.15	98	61	189.3	0.44	98	59
RF	46.9	0.47	97	69	83.8	0.8	96	68
N.B.	0.65	1.15	62	60	1.92	3.30	62	61

Table 2: Results of classification of histological images of the lungs using feature extraction methods HOG And HOG_{mod}.

Classification method	HOG				HOG_{mod}			
	Time (s)		Accuracy(%)		Time (s)		Accuracy(%)	
	Train .	Test	Train .	Test	Train .	Test	Train .	Test
SVM	39.65	78.05	98	97	1000	1438	99.1	99.3
kNN	0.04	3.74	60	54	0.14	10.1	61	54
DT	109.6	0.10	99	84	201.9	0.33	99	83
RF	92.44	0.31	96	96	153.4	0.53	98	98
N.B.	0.51	0.93	96	96	1.43	2.54	97	97

Conclusion

From the presented data, several key conclusions can be drawn that highlight the potential of the method HOG_{mod} in comparison with the classical one HOG.

For both datasets (colon and lung images), the method HOG_{mod} shows a small but significant improvement in classification accuracy compared to classic HOG:

- **colon** image classification , the method HOG_{mod} improves testing accuracy by 3% for SVM (from 78% to 81%) and by 2% for Naive Bayes (from 60% to 61%).
- **lung** image classification, the accuracy gain is also clear: 2.3% for SVM (from 97% to 99.3%) and 2% for Random Forest (from 96% to 98%). These results are especially important for tasks that require high accuracy, such as disease diagnosis.

The main limitation of the method HOG_{mod} is the increase in training and testing time, which can be explained by a more complex feature extraction procedure (HOG for each color channel). On average, training time increases by 2-4 times compared to the classic HOG:

- **For the colon, the training time for SVM increased from 182.2 to 730.7 seconds.**
- **For the lungs, the training time using SVM increased from 39.65 to 1000 seconds, which is a significant increase.**

However, it should be noted that for methods where time is critical (e.g. kNN or Naive Bayes), the increase in time is not so significant and may be acceptable in practical applications.

For more complex models (such as SVM and Random Forest) HOG_{mod} demonstrates not only high accuracy, but also stable results on both training and testing datasets.

For example, when classifying **lung images,** the accuracy of the method HOG on test data using SVM is 99.3%, which is higher than that of the classic HOG (97%). A similar picture is observed when using Random Forest.

The method HOG_{mod} shows significant advantages in terms of classification accuracy, especially for models with high computational complexity such as SVM and Random Forest . This makes it a

promising approach for tasks that require maximum accuracy, such as diagnosis from histological images.
Despite the increased training and testing time, the gain in accuracy makes it particularly useful in medical research where accuracy can be critical to decision making.
Therefore, HOG_{mod} it can be considered a promising method for histological image analysis tasks, especially in cases where accuracy is more important than computation time.

References

1. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A., Ciompi, F., Ghafoorian, M., ... & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. Medical image analysis, 42, 60-88.
2. Yi, X., Li, L., & Fang, L. (2015). Adaptive weighted HOG for classification of histopathology images. 2015 IEEE International Conference on Image Processing (ICIP), pp. 3064-3068.
3. Dalal, N., & Triggs, B. (2005). Histograms of Oriented Gradients for Human Detection. 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05), Vol. 1, pp. 886–893.
4. Yin, H.-F.; Wu, X.-J.; Hu, C.; Song, X. Face Recognition via Compact Second-Order Image Gradient Orientations. Mathematics 2022, 10, 2587. https://doi.org/10.3390/math10152587
5. Kumar, R., Srivastava, R., & Srivastava, R. (2018). Texture and shape-based classification of mammograms using HOG features. Journal of Digital Imaging, 31(6), 887–895. DOI: 10.1007/s10278-018-0066-y.
6. González, R. C., Woods, R. E., & Masters, B. R. (2009). Digital Image Processing, Third Edition. Journal of Biomedical Optics, 14, 029901.
7. Borkowski, AA, Bui, MM, Thomas, LB, Wilson, CP, DeLand, LA and Mastorides, SM, 2019. Lung and colon cancer histopathological image dataset (lc25000). arXiv preprint arXiv:1912.12142.

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