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Classification of Images Based On Saliency Driven Non-Linear Diffusion Filtering

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Abstract – The saliency driven multiscale nonlinear diffusion filtering resulting scale space in general preserves or even enhances semantically important structures such as edges, lines, or flow-like structures in the foreground, inhabits and clear clutter in the background. The image is classified using multiscale information fusion based on the original image, the image at the final scale at which the diffusion process converges, and the image at a midscale. Our algorithm maintains the foreground features, which are important for image classification. The background image regions, whether considered as noise to the foreground, can be globally handled by fusing information from different scales.

Index Terms – Nonlinear diffusion, image classification, multiscale information fusion.

1. INTRODUCTION

In image classification, it is very important but difficult task to deal with the background information. The background is often treated as noise; nevertheless, in some cases the background provides a context, which may increase the performance of image classification. Backgrounds which contain only clutter provide no information to support image classification. It is interesting to filter out background clutter and simultaneously use the background context to increase the performance of image classification.

- ✓ In the nonlinear scale space, semantically important image structures are preserved or enhanced at large scales, and the locations of the important image structures are not shifted after diffusion at any scale.
- ✓ This differs from the Gaussian scale space in which parts of important image structures may be smoothed and detected edges are shifted from their true locations after Gaussian convolution.
- ✓ The background image regions can be partly dealt with by fusing information from different scales, no matter whether the background is a context for the foreground or is only noise as far as the foreground is concerned.

This saliency driven nonlinear multiscale representation can be easily supplied as input to any existing image classification algorithm.

Fig.1.1. An example of saliency driven diffusion filtering. The original image, the image after diffusion, and the saliency map.

2. RESEARCH METHOD

Image classification is a very active research topic which has accelerated researches in many important areas of computer vision, including feature extraction and feature vision, the generation of visual vocabulary, the quantization of visual patches to produce visual words pooling methods and classifiers.

T. Liu, Z. Yuan, J. Sun, J. Wang, N. Zheng, X. Tang, et al.,[5] formulates salient object detection problem as a binary labelling task where we separate the salient object from the background. Here they proposed a set of novel features, including multiscale contrast, center-surround histogram, and color spatial distribution, to describe a salient object locally, regionally, and globally. Further, extend a proposed approach to detect a salient object from sequential images by introducing the dynamic salient features. B. Abdollahi, A. El-Baz, and A. A. Amini, et al., [10] presents an enhancement method based on nonlinear diffusion filter and statistical intensity approaches for smoothing and extracting 3-D vascular system from Magnetic Resonance Angiography (MRA) data. This method distinguishes and enhances the vessels from the other embedded tissues. The non-linear diffusion filter smooth's the homogeneous regions while preserving edges. The Expectation Maximization technique finds the optimal statistical parameters based on the probability distribution of the classes to discriminate the tissues in the image. C.C. Chang and C.J. Lin, et al., [1] LIBSVM employs Classification methods for more number of images. However, this article does not intend to teach the practical use of LIBSVM, for instructions of using LIBSVM.

P. Gehler and S. Nowozin, et al.,[2] To overcome the problem of variability, one strategy is to design feature descriptors which are highly invariant to the variations present within the classes. Invariance is an improvement. Here address the problem of object category classification by combining multiple diverse feature types. For a given test image the learned classifier has to decide which class the image belongs to. This problem is challenging because the instances belonging to the same class usually have high intra-class variability. J. Weickert, B. Romeny, and M. A. Viergever, et al., [11] this novel schemes use an additive operator splitting (AOS), which guarantees equal treatment of all coordinate axes. They are only stable for very small time steps, which leads to poor efficiency and limits their practical use. Zhang et al. [12] experimentally analyzed the influence of the background may have correlations with the foreground objects, using both the background and foreground features for learning and recognition yields less accurate results than using the foreground features alone. Overall, the background information was not relevant to image classification. Shotton et al. [13] proposed an algorithm for recognizing and segmenting objects in images, using appearances, shape, and context information. They assumed that the background is useful for classification and there are correlations between foreground and background in their test data. Heitz and Koller [15] showed that spatial context information mat help to detect objects. Galleguillos et al. [14] proposed an algorithm that uses spatial context information in image classification. The input image was first segmented into regions and each region was labelled by a classifier. Then, spatial contexts were used to correct some of the labels based on object co-occurrence. The result shows that combining co-occurrence and spatial contexts improves the classification performance.

3. PORPOSED MODELLING

The entire proposed modelling and architecture of the current research paper should be presented in this section. This section gives the original contribution of the authors. This section should be written in Times New Roman font with size 10. Accepted manuscripts should be written by following this template. Once the manuscript is accepted authors should transfer the copyright form to the journal editorial office. Authors should write their manuscripts without any mistakes especially spelling and grammar.

4. METHODOLOGY

Saliency detection methods can be grouped into supervised and unsupervised. Supervised methods detect saliency using a classifier which is trained using samples for which saliency is well labelled. The underlying assumption is that images sharing a globally similar visual appearance are likely to share similar saliencies. This supervised saliency detection needs a very large well-labelled image database, which is not easy to obtain. Unsupervised saliency detection usually starts with features of image structures known to be salient for the human visual system (HVS). These structure features include the intensity of salient regions, and the orientation, position and color of edges. Local structures should be salient with respect to their surroundings frequently occurring features should be suppressed. The salient pixels should be grouped together, rather than scattered across the image. The characteristic of Goferman's method is that the regions that are close tothe foci of attention are explored significantly more than far-away regions. As a result, some background regions near to the salient structures are included in the saliency map, but foreground regions are rarely incorrectly classified as background regions. The limitation of Goferman's method is that it often produces high values of saliency at the edges of an object but lower saliency within the object. Histogram-based contrast method to measure saliency algorithm and also separates a large object from its surroundings, and enables the assignment of similar saliency values to homogenous object regions, and highlights entire objects. Here takes advantages of Goferman's method and Cheng's method by averaging the two saliency maps obtained using these two methods to form the saliency map that used. The edges and the interiors of the foreground objects tend to have comparatively high saliency values. In this way, the saliency map tends to include as much foreground as possible.

Combine the saliency map as prior knowledge with nonlinear diffusion filtering. Let I_s be the saliency map. To introduce the saliency information into the diffusion process, combine Is and D. Where D defined as a function of g of I_s and ∇_u.

In this way, the saliency map tends to include as much foreground as possible The larger the value of the parameter m, the more quickly the flux changes in response to changes in I_s

and ∇_u. When $I_s\_\nabla_u\_$ is very large, the diffusion function value approximates 0. When $I_s\_\nabla_u\_$ is very small, it approximates 1.The optimization of the parameters C, λ, and m is presented. The above saliency driven nonlinear diffusion filtering can be used directly only for gray images. For color RGB images, there is a single application in which the gradients from the RGB channels are combined: the diffusion filtering is applied to the l_2 norm of the gradients obtained from the three channels.

Diffusion filtering use of all the three channels smooth's out errors from the RGB channels an image at different scales and its saliency map. It is seen that saliency driven nonlinear diffusion leads to image simplification in the non-salient region. In the salient region, the evolution of scales preserves or even enhances semantically important structures, such as edges and lines compares the result of our saliency driven nonlinear diffusion with the result of nonlinear diffusion omitting the saliency map at scale 10. It is clearly seen that the background regions are smoothed more effectively by using saliency information, while the foreground regions are preserved. The images produced by our saliency driven nonlinear diffusion are more suitable for image classification than those produced by normal nonlinear diffusion. Although these examples are taken from static background and still images, our work can be adapted to time-varying background from moving platforms, because our saliency driven nonlinear diffusion filtering can effectively deal with the background information.

The optimization of the parameters C, λ, and m is important for our saliency driven nonlinear diffusion filtering. In the following, we first discuss the properties of these three parameters, and then give a method for determining their values. After edge detection, a binary edge map is obtained for each image. Edges with $I_s\_\nabla_\mu\_ < \lambda$ are filtered out, and edges with $I_s\_\nabla_\mu\_ > \lambda$ are preserved. It is necessary to preserve edges in the salient regions as much as possible, and to ignore edges within the non-salient regions as much as possible. We define $G_s(\lambda)$ and $G_n(\lambda)$ to describe the preserved edges in the salient regions and the non-salient regions respectively. For color images, the edges in the three channels are combined together, i.e., at each pixel, the maximum value of the magnitudes of gradients in the three channels is used for determining λ. The RGB color space is utilized to determine the value of the parameter λ for color images, because it is required that the components of the color space should have comparable ranges for determining λ. compares the edges from the original image, saliency masked edges, and the edges preserved using the optimal λ. It is seen that the edges preserved using the optimal λ are mainly distributed in the foreground region.

Here proposes to classify images using the saliency driven multi-scale image representation. Images whose foregrounds are clearer than their backgrounds are more likely to be correctly classified at a large scale, and images whose backgrounds are clearer are more likely to be correctly classified at a small scale. So, information from different scales can be used to acquire more accurate image classification results. Each image is represented by its multi-scale images. Then for each scale t, scale invariant feature transform (SIFT) features, which are widely used to represent image regions, are extracted, and the bag-of-words model is used to generate a word frequency histogram ht. The distances between the images obtained at different scales are combined to yield the final distance d (h1, h2) between images:

$$d(h_1, h_2) = \frac{\sum_{t \in T} w_t d(h_1^t, h_2^t)}{\sum_{t \in T} w_t}$$

Where w_t is a weight for scale t, and T is a chosen set of scales. By selecting appropriate weights, the distances between samples in the same class can be reduced and the distances between samples in different classes can be enlarged.

The weights w0, wTm, and wTM are determined empirically using the training samples. The values of the weights w_0, wT_m, and wT_M reflect the situation of the correction segmentation of the foreground in the training samples. The final distance d (h_1, h_2) between images obtained by combining the distances at the three scales, it transformed to a kernel which is used by an SVM for classification. Used to the extended Gaussian kernels:

$$K\ (h_1, h_2) = \exp\left(-\frac{1}{A} d\ (h_1, h_2)\right)$$

where A is a scaling parameter that can be determined by the cross-validation. An SVM classifier is trained using the kernel matrix of the training images.

Saliency driven nonlinear multi-scale representation has several advantages. First, the nonlinear diffusion-based multiscale space can preserve or enhance semantically important image structures at large scales. In particular, the saliency driven nonlinear diffusion can divide the foreground from the background at large scales, with only a little loss of the foreground information. Second, our method can deal with the background information no matter whether it is a context or noise, and then can be adapted to backgrounds which changeover time. Third, our method can partly handle cases in which the saliency map is incorrect, by including the original image at scale 0 in the set of scaled images used for classification. Finally, this saliency driven multi-scale representation can be easily combined with any existing image classification algorithms. The baseline of our work is nonlinear diffusion filtering. We extend the baseline in the following ways. The saliency detection technique is combined with nonlinear diffusion filtering. Multi-scale fusion is used to combine the information from the saliency driven nonlinear diffusion filtering applies the proposed filtering and fusion method to image classification.

5. EXPERIMENTAL RESULTS

Tested the image classification algorithm based on the proposed saliency driven nonlinear diffusion filtering and multi-scale fusion on people dataset:

Fig. 1.2.Example images from the people dataset. Single pedestrian, two people with occlusion, a group of people with occlusions, diverse background conditions and background clutter.

Methods	Recognition rate (%)	
	Dense sampling	Harrislaplace sampling
Scale 0	89.03	83.72
Scale T_m	89.12	85.89
Scale T_M	92.71	86.68
Multi-scale fusion	94.03	87.42

Table 1.1 The recognition rates of different scales and fusions of multi-scales on the people dataset

6. CONCLUSION

The performance of the proposed system is high compared to the techniques that are used to identify the images. The process can be further developed by recognizing method and classification methods. The features used can be further changed which recognizes the persons in a better way. For feature extraction additional features such as SURF features can be used. The process can be developed to identify the persons or security purposes. In order to recognize the action or reaction of the person some other classifiers can be used. The classifiers such as Probabilistic Neural Network classifier, multi class ad boost classifiers can be used for this purpose.

In future work, can adopt other strategies to further improve the discriminative power of HOL descriptor. The features used can be further changed which recognizes the persons in a better way. For feature extraction additional features such as SIFT features SURF features can be used. In order to recognize the person some other classifiers can be used which recognizes the person. The classifiers such as KNN classifier, minimum distance classifier can be used. The calculated performance can be compared with some other methods.

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