RE-RANKING BASED IMAGE CATEGORIZATION USING SALIENCY DRIVEN NONLINEAR DIFFUSION FILTERING

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ABSTRACT

The new technique is proposed for Re-ranking based image categorization using saliency driven nonlinear diffusion filtering. The image categorize based on Re-ranking, using multi-scale information fusion based on the original image. The foreground features, which are important for image categorization and the background image regions, whether considered as contexts of the foreground or noise to the foreground, can be globally handled by fusing information from different scales. To preserve the foreground feature and deal effectively with background use saliency driven nonlinear diffusion filtering and Re-ranking categorize the image.

Keywords: *Re-ranking, image categorization, Saliency detection, nonlinear diffusion, multi-scale information fusion.*

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1. INTRODUCTION

Image categorization is a very active research topic which has developed researches in many important areas of computer vision. It is an 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 categorization.

Zhang et al. [11] experimentally analyzed the influence of the background on image classification. They demonstrated that although 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. Image classification is faced with the partial matching problem some features obtained from images in the same class differ significantly from one image to another because of background clutter and occlusion of the foreground objects by other objects.

The effect of background on image categorization varies. Only semantically important contexts, such as object co-occurrence, or particular object spatial relations are helpful for image categorization. Backgrounds which contain only clutter provide no information to support image categorization. It is interesting to filter out background. To deal effectively with the background information use a saliency driven nonlinear diffusion filtering [1] to generate a multi-scale space, in which the information at a scale is complementary to the information at other scales and merging of information from different scales. After this apply Re-ranking which categorize the image. A nonlinear diffusion [12] which has been widely used in image de-noising, enhancement, etc, can preserve or even enhance the semantically important image structures, such as edges and lines.

Saliency detection techniques [4] can be used to estimate the foreground and background regions according to the saliency distribution. During the diffusion process, the image gradients in the salient regions are increased while those in non-salient regions are decreased. The background information gradually fades out while the foreground information is preserved and important structures in the foreground are enhanced. The saliency driven multi-scale space of an image can be used to handle uncertain background information. After saliency driven nonlinear diffusion, an image is represented by the set of its multi-scale images and the fusion of information from different scales. Then apply re-ranking to categorize image. Re-ranking will improve the image categorization using saliency driven nonlinear diffusion filtering.

To categorize the images based on input image needs to extract the features of input image. In the proposed system used Content Based Image Retrieval (CBIR) to extract the image features and Graph based Visual Saliency (GBVS) preserve foreground content and clutter the background content. All the images categorize based on re-ranking which arranged as per hit indexing.

2. LITERATURE REVIEW

Weiming Hu[1]proposed saliency driven image multi-scale nonlinear diffusion filtering. The resulting scale space in general preserves or even enhances semantically important structures such as edges, lines, or flow-like structures in the foreground, and inhibits and smoothes clutter in the background. The image is classified using multi-scale information fusion based on the original image, the image at the final scale at which the diffusion process converges, and the image at a mid-scale.

Huaizu Jiang[2] proposed saliency map computation as a regression problem. This method, which is based on multi-level image segmentation, uses the supervised learning approach to map the regional feature vector to a saliency score, and finally fuses the saliency scores across multiple levels, yielding the saliency map. Saliency estimation as a regression problem and learned a regresses that directly maps the regional feature vector to a saliency score. Address the salient object detection problem using a discriminative regional feature integration approach. To integrate a lot of regional descriptors to compute the saliency scores, rather than heuristically compute saliency maps from different types of features and combine them to get the saliency map.

Koen E.A. van de Sande[3] Image category recognition is important to access visual information on the level of objects and scene types. So far, intensity-based descriptors have been widely used for feature extraction at salient points. To increase illumination invariance and discriminative power, colour descriptors have been proposed. Because many different descriptors exist, a structured overview is required of colour invariant descriptors in the context of image category recognition. Proposed the invariance properties and the distinctiveness of colour descriptors in a structured way, it can be derived that invariance to light intensity changes and light colour changes affects object and scene category recognition.

S. Goferman, L. Zelnik-Manor, and A. Tal [4] proposed a new type of saliency – context-aware saliency– which aims at detecting the image regions that represent the scene. This definition differs from previous definitions whose goal is to either identify fixation points or detect the dominant object. The benefits of the benefits of the proposed approach are evaluated in two applications where the context of the dominant objects is just as essential as the objects themselves. In image retargeting, demonstrate that using our saliency prevents distortions in the important regions. Approaches are evaluated in two applications where the context of the dominant objects is just as essential as the objects themselves. In image retargeting we demonstrate that using our saliency prevents distortions in the important regions.

Y. Chai [5] proposed the unsupervised segmentation of image training sets into foreground and background in order to improve image classification performance. Multi-task modification of BiCoS for co-segmenting multiple images sets each corresponding to a different class. BiCoS seems to concur with the well-known fact that devising appropriate feature representations has a higher impact on the performance of computer vision systems.

X.-H. Shen and Y. Wu [6] proposed a unified model to incorporate traditional low-level features with higher-level guidance to detect salient objects. An image is represented as a low-rank matrix plus sparse noises in a certain feature space, where the non-salient regions can be explained by the low-rank matrix, and the salient regions are indicated by the sparse noises. Saliency is then jointly determined by low-level and high-level cues in a unified way.

Zhang et al. [7] experimentally analyzed the influence of the background on image classification. They demonstrated that although 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.

X. Hou and L. Zhang [8] proposed a method for the visual saliency detection. It is independent of features, categories, or other forms of prior knowledge of the objects. Analyzed the log spectrum of an input image, extract the spectral residual of an image in spectral domain, and propose a fast method to construct the corresponding saliency map in spatial domain.

Shotton et al. [9] proposed an algorithm for recognizing and segmenting objects in images, using appearance, 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.

3. PROPOSED SCHEME

The phases of proposed method are shown by following flow diagram.

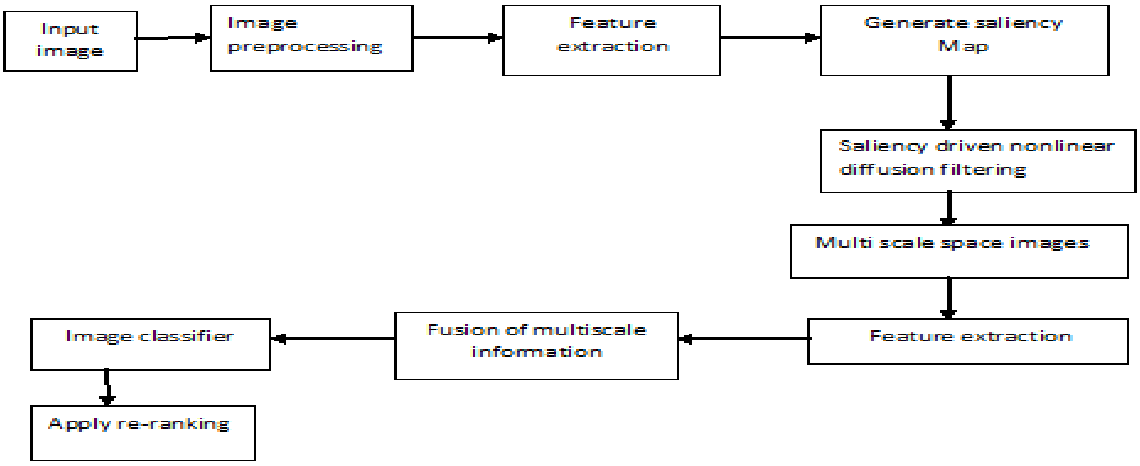

Fig.1. Block Diagram of Proposed Method

In first phase take input image and pre-process the image. In second phase extract feature to generate saliency map using diffusion. During the diffusion process, the image gradients in the salient regions are increased while those in non-salient regions are decreased. Saliency driven nonlinear diffusion filtering, it is clear that, based on the saliency map, the background regions corresponding to non-salient regions are smoothed and the foreground corresponding to salient regions with important image structures is preserved. After saliency driven nonlinear diffusion, in next phase an image is represented by the set of its multi-scale images and the fusion of information from different scales and after this use classifier for image categorization. In next phase to improve the performance of image categorization apply re-ranking. Images will be suggested on the basis of re-ranking.

4. EXPERIMENTAL RESULT

Fig. 2 Input Image

Give an input image for image categorization. In above figure horse image give as an input for image categorization.

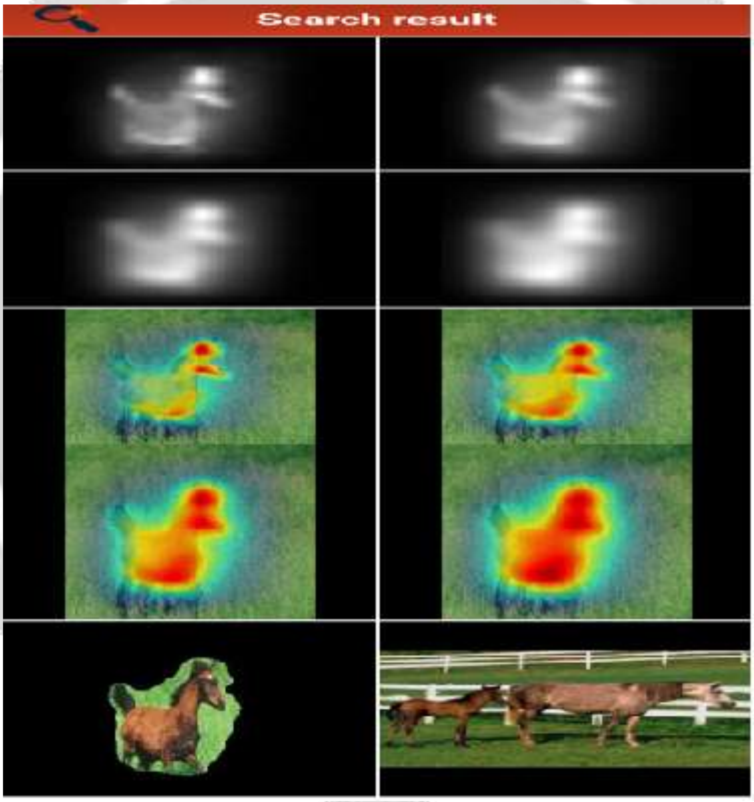

Fig.3. Saliency map, Multi-scale Images, Image Overlay, and Most salient region

Input image features extract using Content Based Image retrieval (CBIR) technique. To extract color based feature used HSV histogram, Auto correlogram and color moment and to extract shape based feature used Gabor wavelet and wavelet transform. Graph Based Visual Saliency (GBVS) technique used to generate saliency map of input image and it preserves only image foreground contents. The image 1^{st} shows saliency map of horse and image 2^{nd}, 3^{rd} and 4^{th} of multi-scale. This saliency mask overlays on input image which is shown in image 5^{th}, 6^{th}, 7^{th} and 8^{th} and image 9^{th} shows only horse and its background content are hidden.

4.1 GRAPH BASED VISUAL SALIENCY (GBVS) STEPS:

1. Compute raw feature map from input image.
2. Compute activation map from feature map.
3. Normalize activation map.
4. Average across map within each feature channels.

5. Divide each feature channel by number of maps in that channel.
6. Sum across feature channels.
7. Blur better result.
8. Save descriptive, rescaled output for user.

Fig.4. Image categorization output before Re-ranking

The above figure shows horse images before re-ranking which are generated based on the similar features of input image. Before Re-ranking used SVM classifier for image categorization.

Fig.5. Hit image

Hit any image from the previously categorized output images.

Fig.6. Image categorization output after Re-ranking

The above figure shows the horse images which are generated after re-ranking. Based on previous figure hitting image all the images are re-ranked.

5. COMPARATIVE ANALYSIS

In existing system, Scale Invariant Feature Transform (SIFT) is used and in proposed system Content Based Image Retrieval (CBIR) technique is used for feature extraction. In below figure the comparison between SIFT and CBIR is shown.

Fig.7.Results of SIFT (Existing System) and CBIR (Proposed System) technique

The above figure shows the comparison of SIFT and CBIR. It gives horse image as an input. SIFT produces only 7 images similar to the input image and CBIR produces 19 similar images among 20. From this analysis we have examined the accuracy of Content Based Image Retrieval (CBIR) is better than SIFT. SIFT takes 17.21 Sec to produce the output images but CBIR takes only 1.47 Sec to produce the output images.

5.1 COMPARATIVE RESULT TABLE OF SIFT (EXISTING SYSTEM) AND CBIR (PROPOSED SYSTEM) TECHNIQUE:

In this comparison, horse, flower, mountain and bus images with SIFT and CBIR are checked. The below table shows comparative results of SIFT (Existing System technique) and CBIR (Proposed System Technique) based on time required to generate output images which match to the input image and accuracy.

Image	In Existing System Time taken by SIFT (In Sec)	In Proposed System Time taken by CBIR (In Sec)
Horse	17.21	1.47
Flower	14.64	1.50
Mountain	15.10	1.47
Bus	16.12	1.49

Table 1.Time Based Analysis of SIFT and CBIR

Image	In Existing System Accuracy of SIFT (In %)	In Proposed System Accuracy of CBIR (In %)
Horse	35	95
Flower	40	95
Mountain	30	90

Bus	45	90

Table 2.Accuracy Based Analysis of SIFT and CBIR

6. CONCLUSION

This paper achieved Re-ranking based image categorization using saliency driven nonlinear diffusion filtering. The saliency driven nonlinear not only preserves but also enhances important image local structures, such as lines and edges, at large scales. Re-ranking improves an image categorization by indexing.

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