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Image Denoising By Exploring External and Internal Correlations

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ABSTRACT:
Single image de noising suffers from limited data collection within a noisy image. The image de noising scheme explores both internal and external correlations with the help of web images. Reduction of noise is done by a two stage strategy using different filtering approaches. If the image contains some text data, then detect the text data in the de noised image using visual text features (VTF).The MSER algorithm is used to detect the text areas. Then using optical character recognition (OCR) recognizes the text data correctly. The combined image de noising and image matching yields a better result.

Keywords:
Internal correlation, External correlation, VTF, OCR.

INTRODUCTION:
Image denoising is a well-known, ill posed problem in image processing and computer vision. Theoretically, it is hard to precisely recover an image from noise since it is a highly under-constrained problem. During the past few decades, many intelligent methods have been proposed to improve single image based denoising performance. From pixel level filtering methods, such as Gaussian filtering, bilateral filtering and total variation regularization, to patch level filtering methods, such as non-local means block-matching 3D filtering (BM3D) , and low-rank regularization , single-image based denoising performance has greatly improved, with image details well recovered when the image is slightly noisy.

However, with the increase of noise levels, the denoising performance is dropping seriously. The reason is that although patch based denoising methods try different methods to improve denoising performance, they share the same strategy: grouping similar patches together and then recovering their common structures. When the noise level is high, the patch matching accuracy will suffer from significant loss and this will result in smooth denoising result. The camera phone has evolved substantially over the recent years, being equipped with higher resolution cameras and more processing power.

These hardware improvements make possible many applications that employ image processing and computer vision techniques, such as location recognition [1] , product recognition[2] , or document search. Most of these applications rely on compact forms of local image features, such as SIFT, or CHoG, to reduce the data sent over the network. Demonstrations of these technologies compelled MPEG to initiate the Compact Descriptor for Visual Search (CDVS) standardization effort. All of these advances are based on descriptors that summarize the visual appearance of image patches. When text appears in an image, it is simply treated like any other visual feature without exploiting its special properties.

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We may think of local image feature algorithms, such as SIFT [3] or CHoG, as illiterate. A new class of features based text is located within the image using robust text detection algorithms [4]. Then, an Optical Character Recognition (OCR) engine is used to recognize the characters and their locations. From the extracted visual text information, we generate VTFs in a way that resembles image features. Thus, we can use VTFs analogously to, and in combination with, image features to perform image matching.

SYSTEM MODEL

De-An Huanget al [6], have proposed novel self-learning based image decomposition framework. Based on the recent success of sparse representation, the proposed framework first learns an over-complete dictionary from the high spatial frequency parts of the input image for reconstruction purposes. Madison Gray McGaffin et al [7] have proposed image de-noising algorithms for edge preserving regularization that play to the strengths of GPUs, the exemplar of this parallelism trend. By avoiding operations like inner products or complex preconditioners and minimizing memory usage, the proposed GCD algorithms provide impressive convergence rates. The additional increase in performance provided by Nesterov's first-order acceleration is exciting. Xianhua Zeng et al [10], have proposed a two-dimensional image de-noising model, namely, the Dictionary Pair Learning (DPL) model, and we design a corresponding algorithm called the Dictionary Pair Learning on the Grassmann-manifold (DPLG) algorithm. propose a two-stage based denoising scheme, which is illustrated in Fig. 1. Each stage includes four components: registration, external denoising, internal denoising and combining of the two results. We adopt image registration to improve the geometric correlations between the noisy image and external images, which will improve the following patch matching accuracy. The external denoising in the first stage is graph-cut based patch matching. The internal denoising is hard thresholding on transform coefficients of 3D cubes built by similar patches retrieved from the noisy image itself.

The combining procedure is to combine the power of the two denoising results. The first stage produces a preliminary denoising result $I^{\sim 1st}$. and its noise is assumed to be greatly attenuated. Therefore, it can help improve the denoising performance in the second stage in three ways. First, it can improve image registration since we can get more accurate matching points. Second, it can improve patch matching accuracy both in external and internal denoising. Third, we can estimate the Wiener filtering parameters according to $I^{\sim 1st}$. The second external denoising is Wiener filtering on a noisy patch using adaptive transform bases calculated from matched external patches. The internal denoising is Wiener filtering on noisy 3D cubes with parameters calculated from $I^{\sim 1st}$. After combining the external and internal denoising results in the second stage, we obtain the final denoising result $I^{\sim 2nd}$. After the denoising if the image contains some text data move to stage 2.The text is detected in the denoised image using virtual text features (VTF).The MSER algorithm is used to detect the text data. On text areas are found and removed by making use of connected components of MSER regions. After that merge them for further processing. Then using OCR recognize the text data correctly.

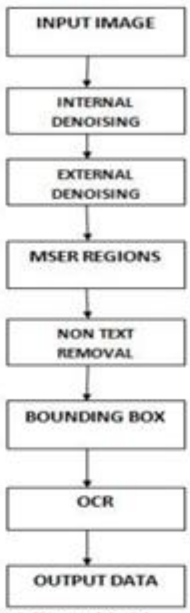

Fig.1 System Model

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VISUAL TEXT FEATURES

The fig.2 shows the block diagram of the VTF processing pipeline. In the extraction stage, detect text in the image and perform recognition on the detected text patches. In the coding stage, generate the VTFs from the recognized characters and compress the data.

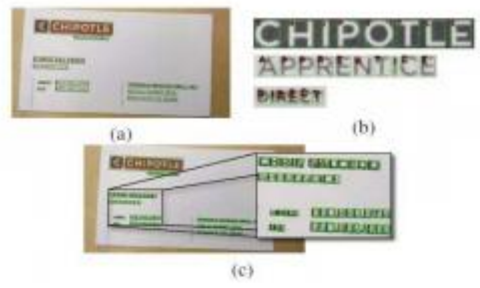

Fig 2.VTF Pipeline

VISUAL TEXT EXTRACTION

In the first step of the extraction, use an edge enhanced MSER-based text detection algorithm to find text regions in a given image, see Fig. 3 (a). Then fix the input size of the given image to have a maximum dimension of 640 pixels to match the size of typical visual search input images and there solution of typical video capturing devices. However, rescale the image to a size of td pixels using bicubic interpolation to a larger size before extracting MSERs to reduce sampling effects. After text lines are detected from the image, extract image patches of these text lines. Then scale the patch to a fixed size t_p, and use an OCR engine to recognize the text, see Fig. 3 (b). Since detect text lines of multiple orientations, typically do not know which direction is upwards. Thus, perform recognition for both the original direction and a 180 degree rotated version to deal with upside-down text. The results with the highest confidence score given by the OCR engine are selected. In scenes where complex backgrounds appear in the image, the OCR engine typically fails to find the correct threshold for binarizing the text. Thus, to improve the recognition performance, use results of the text detection MSER masks to binarize the text patches.

Along the borders of the text detection mask, calculate the average intensity of a region that is 1/5 the width of the character stroke width. This threshold is then used to binarize the text patch. Finally, after the characters and their bounding boxes have been recognized in the text patch, project the bounding boxes back to the original image, as shown in Fig. 3(c).

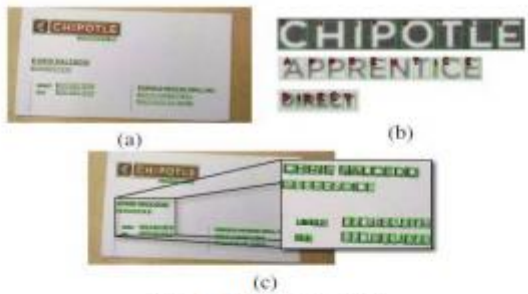

Fig 3.VTE example

3.2. Visual Text Feature Generation and Coding

From the recognized characters and their bounding boxes, generate VTFs that’s analogous to image features. The location of a VTF is calculated as the center of the recognized characters bounding box. The scale is the radius of the minimal bounding circle of the bounding box. The orientation is the direction of the text line the recognized character came from. The scale and orientation are typically not needed for image matching. The descriptor of the VTF comprises the recognized character, the word from which the recognized character came from, and the position of the character in the word.

Image Matching with VTF

When using image features for image matching, features from two images are paired based on descriptor similarity. A ratio test typically is used to rule out ambiguous matches. Then, RANSAC is used to estimate an affine model from the locations of the matching features. Since VTFs are akin to image features, the conventional image matching pipeline can be adapted easily. One challenge is that the recognized characters have only a very limited set of values, and hence multiple common (Fig.4 (a)).

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The ratio test cannot be used because the distance of the recognized characters are either 1 for being the same or 0 for being different. The large percentage of invalid feature correspondences can easily confuse RANSAC. Thus, we propose to use the surrounding word as part of the VTF to disambiguate character based feature matches. To determine the distance between two VTFs, calculate a word-distance which define as the sum of the editing distance between the strings preceding the examined character and between the strings following the examined character. By using the word distance for feature pairing, the VTFs becomes much more discriminative and avoid irrelevant feature matches, as shown in Fig. 4 (b).

(a) (b)

Fig 4. (a) Pairwise feature matches using the recognized character. (b) Pairwise feature matches using word distances.

CONCLUSION

The novel image denoising scheme by exploring both internal and external correlations. Given one noisy image, first retrieve its correlated image set from web images as assisted information, instead of using general natural image priors. After combining the internal and external denoising results in frequency domain, we obtain a basic denoising result, and its noise has been greatly attenuated. Therefore, it is utilized to improve the second stage denoising result in three ways: image registration, patch matching and providing an estimation results, we obtain the final denoising result. After denoising present a new type of visual text features based on recognized text from an image. To have useful visual text features, a reliable visual text extraction pipeline needs to be built. By using the edge enhanced MSER text detection and an OCR engine, we are able to get good visual text extraction performance on our image set.

Additionally, cues from the OCR engine, such as the confidence score, is used to select useful features. Of the Wiener filtering parameters.

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