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To Detect The Text Stroke In Degraded Document Images Using Canny's Map Binarization Technique

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Abstract

Nowadays a very difficult is Segmentation of text from degraded document images due to the high inter/intra variation between the document background and the foreground text of different document images. In this paper, we propose a novel canny's map binarization technique that addresses these issues by using adaptive image contrast. In the proposed system using canny's map detector to detect text stroke and background estimate using post processing procedure for degraded document images. The adaptive image contrast is a combination of the local image contrast and the local image gradient that is tolerant to text and background variation caused by different types of document degradations. In the proposed method, an contrast map is first constructed for an input degraded image. The contrast map is then binarized into 0's and 1's and combined with Canny's edge map to detect the text stroke edge pixels. The document text is segmented by a local threshold value that is estimated based on the intensities of detected text stroke edge pixels within a local window using edge detection techniques. The proposed method is simple, robust, and involves many parameter . Experiments on the Bickley diary dataset that consists of several challenging bad quality document images also show the superior performance .

Keywords::-Adaptive image contrast, document analysis, document image processing, degraded document image binarization ,pixel classification.

Introduction

CLASSICAL methods for image expansion such as bilinear interpolation or splines can be understood as linear filtering operations on a given image, and their support and coefficients are designed based on top-down assumptions, e.g., the image is a piecewise polynomial and smooth at the knots. However, these assumptions are not necessarily true for natural images. Alternatively, the support and coefficients of the filter can be learned from real image data. Arguably, learning-based approaches can yield better performance than top-down strategies . In principle, a learning-based filter design can use arbitrary size support. This is in contrast to the bilinear interpolator, which uses at most four low-resolution pixels when determining the value of a pixel in the high-resolution expanded image. The support should be simple for efficient processing of the images and for preventing overfitting; however, excessively simple ones will fail to capture the useful information contained in the surrounding pixels. The compactness of the support is beneficial when we want a fast and high-quality image interpolator, especially when we apply it in small embedded systems such as digital cameras and mobile phones. In this paper, we aim to resolve the tradeoff between high quality and low cost. Let be an integer magnification factor. The task of image expansion is: given an image , estimate expanded image. In our framework, the interpolator expands the image by replacing each pixel in the given low-resolution image by an high-resolution image patch. Of course, since estimating pixel values is impossible from only one pixel value, we use the low-resolution pixel patch surrounding the pixel to be replaced (Fig. 1). This local interpolation is repeated for every pixel in the given image, and the expanded image is constructed by tessellating the high-resolution patches. Vector-valued function maps an low-resolution patch to an high-resolution patch. We address the problem of determining optimal supports by formulating the image interpolation task from a viewpoint of sparse Bayesian estimation. A simple method to determine the optimal shape of the support would be to perform discrete optimization that compares different shapes of the support. Obviously, this approach soon becomes intractable when gets

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larger. Alternatively, sparse Bayesian methods offer continuous parameters that regulate the importance of each pixel, and the less important pixels for the estimation of high-resolution patches are automatically pruned from the support of the filter. The learning of filter coefficients has been considered by Triggs ,emphasizing low-level vision and reducing aliasing, and by Atkins , whose proposal, called resolution synthesis (RS), uses a mixture of linear

Architecture diagram

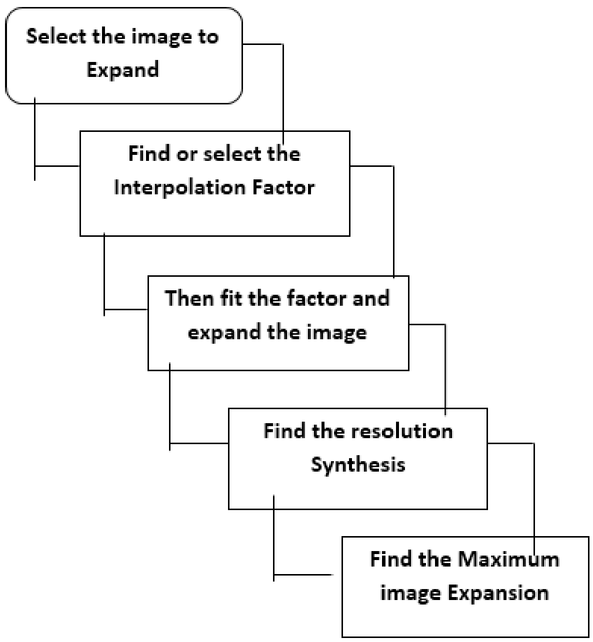

Figure 1.Architecture diagram

Interpolators for image expansion. In the interpolator is learned from pairs of the original images and their synthetically smoothed and subsampled images by optimizing several error metrics including and norms (which is equivalent to maximum-likelihood estimation). Triggs reported that the shapes of the learned interpolators resemble the sin function and are robust to the change of error metrics or anti-aliasing smoothing kernels. He also investigated the influence of support size and found that the variation of test interpolation errors between is significant, but beyond the learned filters have similar test performance .Atkins's RS is modeled by a Gaussian mixture that is trained by maximum- likelihood estimation utilizing the expectation-maximization (EM) algorithm. Ni and Nguyen refined RS by replacing linear interpolators with nonlinear support vector regressors. RS can be considered an image super resolution method because its regressors contain information from external training data other than the given image.

Existing system

Reconstruction-based super resolution methods that invert a generative model from a high-resolution image to multiple low-resolution images.RS by replacing linear interpolators with nonlinear support vector regressors.Super resolution methods that hallucinate a high-resolution image by searching patches in the large database. Before this method they used Top down method and learning based method for expanding the image. Learning based method is better than top down method. In the learning based method they used the arbitrary size support, this is in contrast to the bilinear interpolator, which uses at most four low resolution when determining the value of pixel in the high resolution expanded image.

Problem identification

Experiments on test data show that learned interpolators are compact yet superior to classical ones.Modeling direction for estimating high-resolution images from low-resolution images dataset that consists of a large number of low- and high-resolution patches so that the filter learns the relationship between them. To determining optimal supports by formulating the image interpolation task from a viewpoint of sparse Bayesian estimation.

Proposed system

To acquiring compact yet high-performance image expansion filters based on sparse Bayesian estimation. We propose a framework for expanding a given image using an interpolator that is trained in advance with training data, based on sparse Bayesian estimation for determining the optimal and compact support for efficient image expansion. Experiments on test data show that learned interpolators are compact yet superior to classical ones. To derived an efficient learning procedure for its parameters on the basis of variation approximation. When plenty of computational resources is available, or when the observation process is too severe to recover by mere linear filtering, the complicated image expansion methods will be preferred. In this method, at first we find out the interpolator of the given image. Then replace the low resolution pixel by the interpolator

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(high resolution pixel).After Expanding the image does not scattered. We aim to resolve the tradeoff between high quality and low cost.

1) Edge Width Calculation

Algorithm 1 Edge Width calculation

Require: The Input Degraded Image *I* and CorrespondingBinary Text Stroke Image *S*

Ensure: The Calculate Text Stroke Image Width *SW*

1: Get the *width* and *height* of *I*

2: **for** Each Row *R* = 1 to *height* in *S* **do**

3: Scan from left to right to find text stroke that meet thefollowing criteria:

a) its label is 0 (background);

b) the next pixel is labeled as 1(text).

4: Examine the intensity in *I*of those stroke selected in Step 3, and remove those stroke that have a lower intensity than the following stroke next to it in the samerow of *I* .

5: Match the remaining adjacent stroke in the same row intopairs, and calculate the distance between the two stroke in pair.

6: **end for**

7: Construct a histogram distances between two strokes.

8: Use the frequently occurring distance as the estimated

stroke width *SW*'

2)Post-Processing

Once the initial binarization result is derived from Equation 5 as described in previous subsections, the binarization result.

Algorithm 2 Post-Processing Techniques

Require: The Input Document Image *I* , Initial Binary Result

$D_i$and Corresponding Binary Text Stroke Image*S*

Ensure: The Final Binary Result D_F

1: Find out all the connect components of the stroke pixels in *S*.

2: Remove those stroke that do not connect with other stroke.

3: **for** Each remaining edge pixels (i, j): **do**

4: Get its neighborhood pairs: $(i-1, j)$and $(i+1, j)$; $(i, j-1)$ and $(i, j+1)$

5: **if** The pixels in the same pairs belong to the same class

(both text or background) **then**

6: Assign the pixel with lower intensity to foreground

class (text), and the other to background class.

7: **end if**

8: **end for**

9: Remove single-stroke artifacts along the text stroke

boundaries after the document thresholding value.

10: Store the new binary result to Df .

can be further improved by incorporating certain domain knowledge as described in Algorithm 2. First, the isolated foreground pixels that do not connect with other foreground pixels are filtered out to make the edge pixel set precisely. Second, the neighbourhood pixel pair that lies on symmetric sides of a text stroke edge pixel should belong to different classes (i.e., either the document background or the foreground text). One pixel of the pixel pair is therefore labelled to the other category if both of the two pixels belong to the same class. Finally, some single-pixel artifacts along the text stroke boundaries are filtered out by using several logical operators as described .

Implementation

Modules:

1)Filter the image

In this module select the image and expand it. In our framework, interpolator expands the image by replacing each pixel in the given low-resolution image by an high-resolution image patch. Of course, since estimating pixel values is impossible from only one pixel value, we use the low-resolution pixel *patch* surrounding the pixel to be replaced . This local interpolation is repeated for every pixel in the given image, and the expanded image is constructed by tessellating the high-resolution patches. Vector-valued function maps an low-resolution patch to an high-resolution patch.

2)Find the training and testing dataset

Training and test datasets were generated by the following procedures. The pixel values are first converted into double-precision floating points within and transformed to luminance values if the original image has color channels. High-resolution patches are prepared by cutting them into non-overlapping pieces. To make low-resolution patches, first the high-resolution images are blurred by an anti-aliasing filter and subsampled by specified factor to extract overlapping patches of size. For the training datasets, low-resolution patches stemming from the boundaries are discarded, and the corresponding high-resolution patches are not used. For test datasets, to extract patches near the boundaries, the low-resolution image is extended by pixel replication.

3)Interpolation

Determining optimal supports by formulating the image interpolation task from a view point of sparse Bayesian estimation. A simple method to determine

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the optimal shape of the support would be to perform discrete optimization that compares different shapes of the support. Obviously, this approach soon becomes intractable when gets larger. Alternatively, sparse Bayesian methods offer continuous parameters that regulate the importance of each pixel, and the less important pixels for the estimation of high-resolution patches are automatically pruned from the support of the filter.

4)Automatic relevance determination

The prior for filtering matrix (8) is the key to the sparsity. This resembles the priors used in sparse Bayesian estimation and is called *automatic relevance determination* (ARD), which was first introduced for neural networks . Parameters work as regularizers that pull toward prior mean 0. Therefore, if the values of are very large, the estimated values of become very small. It is theoretically known that in this sparse Bayesian type of estimation, that satisfy a certain condition diverge to infinity; therefore, the corresponding elements of become zero and hence are pruned from the filtering supports. In other words, the elements of irrelevant to filtering are automatically switched off. The experiments in Section V will actually illustrate such behaviours. Since a detailed account of ARD is beyond the scope of this manuscript, for an in-depth discussion of ARD and sparse Bayesian estimation.

5)Variational inference

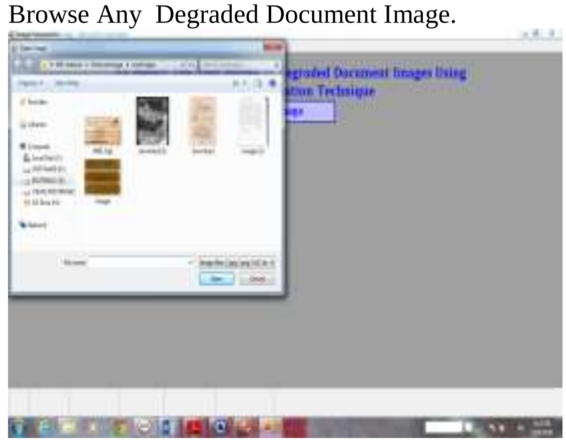
Variational Bayesian methods, also called *ensemble learning*, are a family of techniques for approximating intractable integrals arising in Bayesian inference and machine learning. They are typically used in complex statistical models consisting of observed variables (usually termed "data") as well as unknown parameters and latent variables, with various sorts of relationships among the three types of random variables, as might be described by a graphical model. As is typical in Bayesian inference, the parameters and latent variables are grouped together as "unobserved variables". Variational Bayesian methods can provide an analytical approximation to the posterior probability of the unobserved variables, and also to derive a lower bound for the marginal likelihood of several models with a view to performing model selection. It is an alternative to Monte Carlo sampling methods for taking a fully Bayesian approach to statistical inference over complex distributions thatare difficult to directly evaluate.

Figure2 .To detect the text stroke and background estimation in degraded document image.

Results and discussion

For Authentication Purpose Use User Name And Password.

Browse Any Degraded Document Image.



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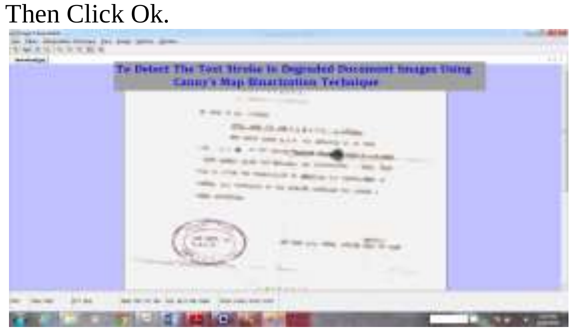
This Is The Degraded Document Image .

Choose Filters→Brightness

Adjust The Brightness Level Then Click Ok.

After Adjusted Image.

Filters→Constrast-->Adjust The Contrast Factor Then Click Ok.



Conclusion

In document image binarization technique that is tolerant to different types of document degradation such as uneven illumination and unnecessary mark. The proposed method is simple easy and robust.it works for different kinds of degraded images. The proposed method makes use of the local image contrast that is evaluated based on the local threshold value. The proposed method has been tested using canny's map edge detector for degraded document images to detect the text stroke in document images . Experiments show that the proposed method outperforms most reported document binarization methods using line by line scanning method.

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