Confidence Score for Unsupervised Foreground Background Separation of Document Images

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1. Introduction

Foreground-background separation is an important problem in document image analysis. Popular unsupervised binarization methods (such as the Sauvola's algorithm) employ adaptive thresholding to classify pixels as foreground or background. In this work, we propose a novel approach for computing confidence scores of the classification in such algorithms. This score provides an insight of the confidence level of the prediction. The computational complexity of the proposed approach is the same as the underlying binarization algorithm. Our experiments illustrate the utility of the proposed scores in various applications like document binarization, document image cleanup, and texture addition.

2. Computation of scores

The score for each pixel is computed using the following Equations.

$$C_W^b(p) = \begin{cases} \frac{I(p)-T_W(p)}{\max(I)-T_W(p)} & \text{if } I(p) > T_W(p) \\ 1 - \frac{T_W(p)-I(p)}{T_W(p)-\min(I)} & \text{otherwise} \end{cases} \quad (1)$$

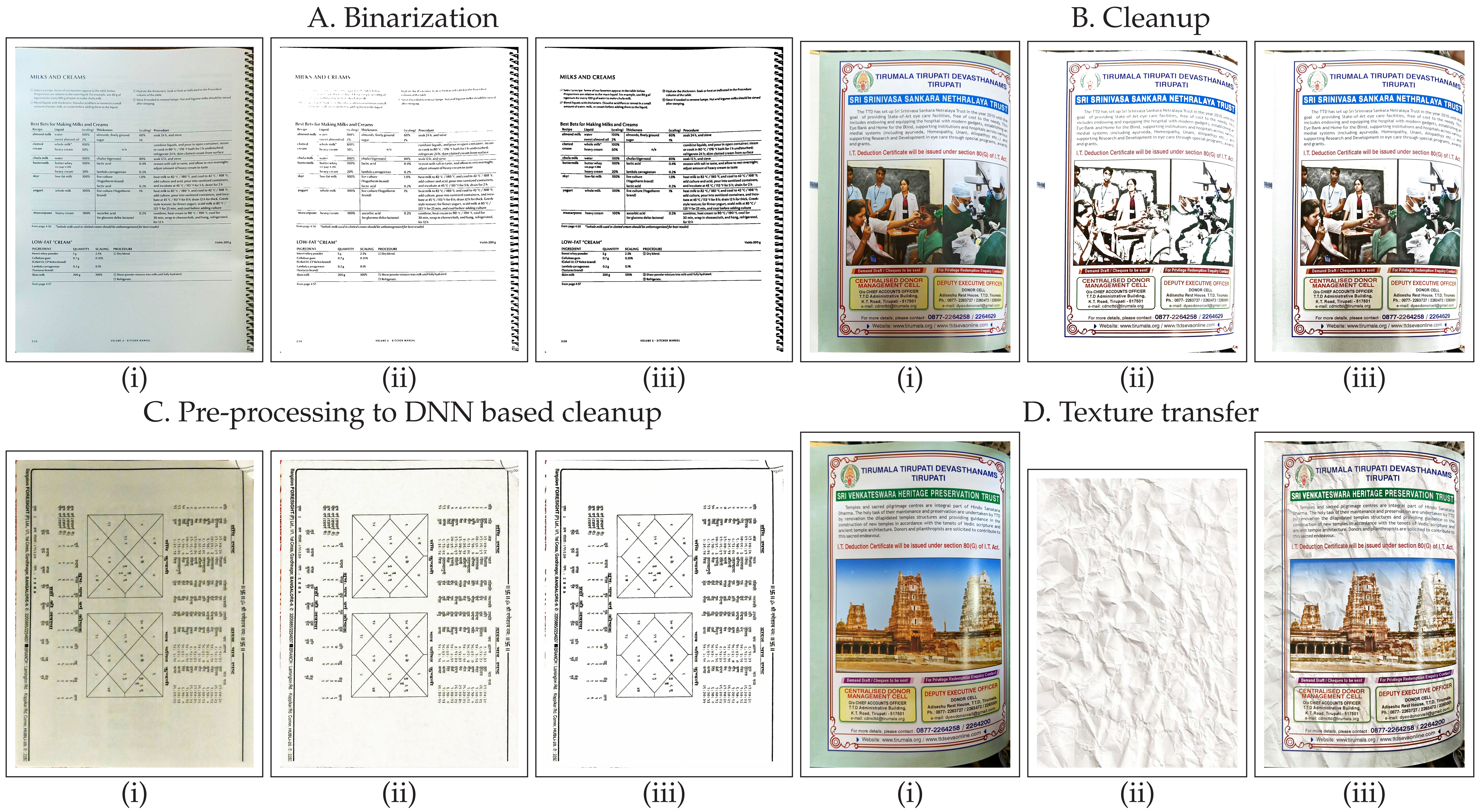
$$C_W^f(p) = 1 - C_W^b(p) \quad (2)$$

Here, max(I) and min(I) represent maximum and minimum value of any pixel of an input image I, respectively. It should be noted that the confidence score lies in the interval $[0, 1]$. The proposed confidence scores can be generated with any adaptive thresholding approach. For empirical comparison, we considered Sauvola's thresholding algorithm [2] as the base method. The threshold is computed for each pixel ($T_W(p)$) using the Eq 3, where, for an input image I, $R = \frac{\max(I)-\min(I)}{2}$.

$$T_W(p) = m_W^p \times [1 + k \times (\frac{s_W^p}{R} - 1)] \quad (3)$$

The threshold is computed for each pixel (p) based on a window W of size $n \times n$ surrounding it, where m_W^p, s_W^p respectively represent mean and standard deviation of W around pixel p, and k lies between $0 \le k \le 1$.

3. Applications of Confidence Scores



(A,B,C,D)(i) input images; A(ii) binary image using [2]; A(iii) improved binary image using the proposed scores; B(ii) image cleanup using [2]; B(iii) image cleanup using the proposed scores; C(ii) image cleanup using [9]; C(iii) image cleanup using [9] with proposed score based pre-processing; D(ii) texture to be transferred to D(i); D(iii) texture transferred image using proposed scores.

4. References

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