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Document Image Quality Assessment: A Brief Survey

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***Abstract*—To maintain, control and enhance the quality of document images and minimize the negative impact of degradations on various analysis and processing systems, it is critical to understand the types and sources of degradations and develop reliable methods for estimating the levels of degradations. This paper provides a brief survey of research on the topic of document image quality assessment. We first present a detailed analysis of the types and sources of document degradations. We then review techniques for document image degradation modeling. Finally, we discuss objective measures and subjective experiments that are used to characterize document image quality.**

I. Introduction

Document images may be degraded at various stages of their life cycle and degradations often lead to difficulties for image processing, analysis and recognition at subsequent stages. For example, degradations may result in a significant drop in the performance of Optical Character Recognition (OCR), as well as affect the performance of document image retrieval, layout analysis, logo detection and other document analysis tasks. In general, degradations decrease document readability resulting in unrecoverable information loss. Document image quality studies are also necessary ingredients in developing restoration and enhancement algorithms. It is important to understand the various types of degradations that may effect document images and develop reliable methods for estimating levels of degradations.

Previous work on Image Quality Assessment (IQA) has focused primarily on natural scene images. However, the properties of document images are very different and the objectives of Document Image Quality Assessment (DIQA) are also quite different from those of natural scene IQA. For example, DIQA may be performed with respect to OCR accuracy instead of human perception. Therefore methods developed for natural scene images may not be directly applied to document images. Furthermore, for the DIQA problem, non-distorted reference images are usually not available so quality assessment has to be performed in a no-reference fashion.

While there has been relatively little published on the DIQA problem, the objective of this paper is to present a brief survey of the topic as a baseline for future work. In this paper, we first present a detailed analysis on the types and sources of degradations that typically occur in document images (Section II) and an overview of document degradation modeling techniques (Section III). We then review techniques for predicting document image quality with respect to OCR software and human perception (Section IV). Finally, Section V reviews subjective experiments for DIQA.

II. Document Image Degradations

In this section, we describe the document image generation process and the types of degradations that may occur at each stage. By "degradation" we mean any "less-than-ideal" properties of the image [5] that reduce the information or visual quality with respect to the original source. Figure 1 shows one way a document image is generated, and where degradations can be introduced. These stages include: (1) **Creation**: Documents are used to convey information. The creation of a document is a process in which information in the form of symbols is written or printed upon a medium such as paper or palm leaf. Degradations at the creation stage are introduced because of the document medium (e.g. paper translucency/texture), the devices used to create the document (e.g. inadequate/heavy printing and noise in electronic components) and the production process (e.g. typesetting/handwriting imperfections). (2) **External degradation**: Once a document is created, it may be subject to various external degradations or manipulations by a human or the environment including paper aging, stains, thorn-off regions, readers annotations, carbon copy effect, scratches and cracks, for example. This pre-digitization noise is referred to as *physical noise* in [29], where it is defined as whatever "damage" the physical integrity and readability of the original information of a document. (3) **Digitization**: Document digitization is the process of generating digital representations, usually as a discrete set of pixels. A variety of devices can be used for digitization including for example, scanners, mobile phones and cameras. Digitization operations and hardware defects such as paper positioning variations (e.g. skew), pixel sensor sensitivity variations, vibration and other non-uniform equipment motion may further degrade the document image. (4) **Processing**: Processing refers to all types of processing applied to the digital document image after its creation. For example, given a gray scale document image, binarization is often a first step since many document analysis algorithms require a binarized image. The binarization process may introduce binarization noise. For the purpose of efficient storage, lossy compression algorithms such as JPEG or JPEG2k may be applied to document images and introduce compression noise. Furthermore, the quality of transmission network may affect the quality of document image at the receiver side. To recover information from the degradations arising from previous stages, various restoration and enhancement algorithms may be applied. However, an uninformed application of enhancement techniques may further degrade document images.

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It is worth noting that a document may go through multiple stages of printing, imaging, compression and transmission and as a result, one particular type of degradation may arise repeatedly, and they may combine in unexpected ways.

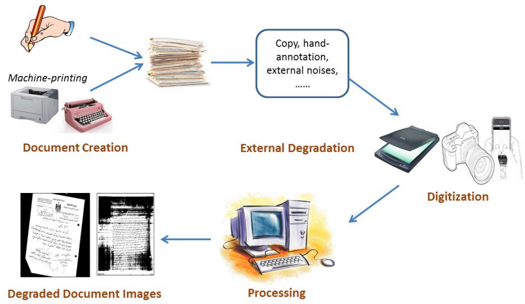

Fig. 1. Document image generation process.

Different degradations may result in similar visual artifacts in the final image, so it is natural to further consider document image artifacts based on the level at which they effect the document. The following list summarizes main artifacts at the document image stroke, line and page level: **Stroke Level**: (1) Touching characters; (2) Broken characters and (3) Additive noise: small speckle close to text and irregular binarization patterns. **Line Level**: touching, skewed or curved lines and line inconsistency. **Page Level**: (1) Background noise: margin noise, salt-and-pepper, ruled line, clutter, show through & bleed through or complex background binarization patterns and (2) Geometric deformation: warping, curling, skew or translation.

Noise components at different levels are not mutually exclusive. For example, additive noise at the stroke level may be part of the background noise at page level. Depending on the devices used for digitization, the types of degradations introduced at the digitization stage may also vary. For example, out-of-focus blur and motion blur are the two primary types of degradations in a camera-captured document image, while for a scanned document image, distortions may result from the choice of scanner parameters such as the diameter of the point spread function and the intensity threshold [7].

III. Document Image Degradation Modeling

This section briefly reviews the document image degradation models and their applications. Recent surveys on this topic can be found in *Baird* [5] and *Cheriet* and *Moghaddam* [11].

Given an ideal document image and user-specific parameters, a document image degradation model attempts to generate a set of degraded document images that approximate defective images in real applications. In developing any document image degradation model, [5] and [11] describe four fundamental issues needed to be addressed: (1) Parametrization: The model should be able to be calibrated by a small and fixed number of numerical parameters; (2) Randomization: The model should possess randomness such that it is resistant to over-training; (3) Validation: Given a real defective image, there should exist some values of the model parameters that will duplicate the defective image and (4) Parameter estimation: For any given set of defective images, it should be possible to estimate the distribution of the model parameters that closely fits the real distribution.

A document image defect model based on the physics of printing and imaging was proposed by *Baird* [1]. This model was designed to model degradations arising from printing and imaging. The model parameters include: the nominal text size, resolution, rotation, multiplicative scaling factors, translation offsets, jitter, blur, sensitivity and binarization threshold.

Methods to model calibration were further introduced by *Baird* [2] and there has been a great deal of subsequent work on the analysis and application of this model. An analysis of the capability of the model for making fine discriminations was presented in *Baird* [4]. *Baird* [3] and [6] used this model to generate a training set pseudo-randomly for improving the performance of classifiers. This model has also been used for large-scale simulation studies in image pattern recognition, which provides a means of estimating the intrinsic difficulty of concrete image recognition problems. The relationship between model parameters and human perception, image quality metrics or observable degradation features was studied in [14], [36], [38].

Kanungo et al [23] proposed a global distortion model for perspective distortion and non-linear illumination effects and a morphological model for local distortion due to perturbation in the optical scanning and digitization process. An optimization method for estimating degradation model parameters was introduced in [22].

Sural [40] proposed a two-state Markov chain model for modeling isolated pixel reversal as well as blurring of a larger document region. This model was validated using the model validation method in [20].

Degradation models for shadows and bleed-through effects have also been investigated [31], [43]. *Zi and Doermann* [43] used blurring and transformation operators to model shadow effects. *Moghaddam and Cheriet* [31] addressed physical degradation, such as aging and ink seepage, using a virtual diffusion process based model. They also developed a restoration method based on the proposed degradation model.

The degradation models introduced above were designed primarily for scanned document images, while for camera-captured document images a degradation model would typically involve a geometric transformation, an illumination model, blurring (optical and/or motion), spatial sampling (due to the CCD array) and a noise term. In *Capel and Zisserman* [10], a camera-captured degraded image is modeled by $\hat{m} = S \downarrow [h * \tau[l(s)]]$, where s is the high resolution image, $l(x)$ specifies illumination model, τ represents the geometric transformation of the image, h denotes Point Spread Function (PSF) of the imaging system, and $S \downarrow$ represents downsampling operator by a factor of S.

Degradation models for specific imaging systems have also been studied. *Barney-Smith* introduced a method for the characterization of degradations caused by scanning [7] and a method for scanner parameter estimation using bilevel scans of star charts [8]. A model of printing defects was introduced by *Norris and Barney-Smith* [32].

Model validation problems were discussed in [28], [20], [21]. *Li et al* [28] introduced a pragmatic method for model validation, where a model is validated when the OCR errors induced by the model are similar to the errors encountered when using the real scanned documents. This method validates the model-OCR combination. A statistical method which validates the model alone was introduced by *Kanungo et al* [21]. This method is based on nonparametric, two sample permutation test and can be used to statistically validate any document degradation model.

IV. Objective Document Image Quality Assessment

The goal of objective DIQA is to develop a computational model that can predict the quality of a document image automatically and accurately. The definition of document image quality, however, varies with its applications. When the consumer of a document image is machine, OCR software for example, document image quality may be defined as the OCR accuracy and DIQA metrics are factors that can be used to reliably predict OCR accuracy [13], [9], [15], [19], [25], [35], [39], [41]. On the other hand, when the consumer of a document image is a human, DIQA should be performed with respect to human perception [12], [13], [24], [26], [33], [34]. A summary of features used for objective DIQA is presented in Table I. In addition to predicting the quality of an individual document image, there is also some work on predicting the overall quality of a document image data set [16], [17], [34], [37].

A. Predicting OCR accuracy

At various levels of degradation, the performance of modern OCR software may suffer. Systems however may benefit from building a computational model to automatically predict the performance of OCR software. For example, in large scale document conversion operations, the prediction could be used to automatically filter out pages whose OCR accuracy is so low that manual entry would be more economical. Previous work on OCR accuracy prediction can be broadly classified into two categories: (1) Degradation-based approaches, where external degradations are considered as the main cause of decreased OCR accuracy and (2) Internal properties based approaches, where the primary target domain is handwritten document images and no external degradations are considered. In the former, metrics for quantifying the degree of degradations are used for predicting OCR accuracy and in the later OCR accuracy is mainly affected by the handwriting style.

1) Assessment based on Degradations: Cannon et al [9], *Junichi et al* [19] and *Souza et al* [39] proposed quality measures for binary typewritten document images which include: Font Size; Stroke Thickness; Small Speckle Factor (SSF) – a measurement of the amount of black background speckle; Touching Character Factor (TCF) – a measurement of the degree to which neighboring characters touch; White Speckle Factor (WSF) – a measurement of the degree to which strokes are fattened and Broken Character Factor (BCF) – a measurement of the degree to which strokes are broken. These measures are based on Connected Components (CCs) and have been used to predict the OCR accuracy and to choose the best restoration method for document enhancement. The definitions of these quality measures vary slightly as described in [9], [19], [39]. The computation of these factors relies on heuristics and involves many parameters that have to be determined for specific document data set.

Peng et al. [35] used the gradient of edge and the average character/word height-width ratio for predicting the degree of degradation on OCR accuracy. They focused primarily on camera-captured document images with out-of-focus blur degradation. The system has been shown effective in predicting the Normalized Word Error Rate, which accounts for the difference between the word error rate of non-degraded document image and the degraded image.

Ye and Doermann [41] proposed an unsupervised feature learning framework to learn effective and efficient features for predicting OCR accuracy of gray-scale historic document images. Specifically, this method extracts raw-image-patches from a set of unlabeled images to learn a dictionary in an unsupervised manner. Given an image, a set of raw-image-patches are extracted as local features, then they are encoded by the dictionary using soft-assignment encoding with max pooling to obtain effective image representations for quality estimation. Support Vector Regressor (SVR) was then used to learn a mapping from the image features to an image quality score.

Kumar and Ramakrishnan [25] proposed a set of metrics that evaluate the uniformity, sharpness, continuity, noise, stroke width variance, pulse width ratio, transient pixels density, entropy and variance of components to quantify the quality of a document image. Instead of directly predicting OCR accuracy, the proposed metrics are evaluated with respect to a human annotated description.

Recently a publicly and freely available dataset for DIQA was released by *Kumar et al* [27]. This dataset consists of camera-captured document image with varying levels of focal-blur introduced manually during capture. Character level OCR accuracy for each image is obtained using several different OCR softwares.

2) Assessment based on Handwriting Style: Chou and Yu [12] established an index for measuring the quality of handwritten Chinese characters. In this work, a character is defined to be of good quality if it is similar to the average of a large volume of that character category. In other words, "the way the most people write is good". This definition is based on the observation that in a handwritten Chinese character recognition system, the average behaviors of a large volume of samples belonging to the same category are usually taken to be the reference for that category. Handwritten characters from a particular category are sorted by their distances to the average sample of that category. Three types of features are extracted for quality sorting: (1) The stroke-density distribution of a Chinese character; (2) Histogram and (3) Crossing Count.

B. Predicting human perception

The problem of predicting document image quality with respect to human perception is well motivated in many applications where the receiver of a document image is human.

Lu et al. [30] proposed a distance-reciprocal distortion measure for binary document images. This measure is based on the observation that the distance between two pixels plays a major role in their mutual interference perceived by humans. Unlike other objective DIQA methods reviewed in this paper, this method requires the non-distorted reference image and is a full-reference IQA method.

Obafemi-Ajayi and Agam [33] designed a system that enables the learning and estimation of human perception of a typewritten document image quality at the character level. Three groups of features: morphological-based features, noise-removal-based features and spatial characteristics features were introduced.

Kumar et al [26] proposed a fast sharpness estimation method for smart-phone based document images where blur arising from camera-motion (or hand-shake), defocus, or inherent properties of the imaging system is the primary type of degradation. Specifically, the difference of differences in grayscale values of a median-filtered image (ΔDoM) is used as an indicator of edge sharpness.

TABLE I. FEATURES FOR OBJECTIVE DIQA.

Feature	Reference
Font Size	[39]
Normalized Font Size	[9]
Stroke Thickness	[39], [25]
Small Speckle Factor	[9], [39]
White Speckle Factor	[9], [19], [39]
Touching Character Factor	[9], [39]
Broken Character Factor	[9], [19], [39]
Number of pixels	[13]
Average width of CC	[13]
Average height of CC	[13]
Number of CC	[13]
Pixel density	[13]
Gradient of the edge	[35]
Average height-width ratio	[35]
Unsupervised Feature Learning	[41]
Foreground/Background Uniformity	[25]
Sharpness	[25]
Transient Region Density	[25]
Stability of CC values	[25]
Continuity	[25]
Noise measure based on Median Filtering	[25]
Pulse width ratio	[25]
Entropy	[25]
Stroke density distribution	[12]
Histogram	[12]
Crossing Count	[12]
Morphological-based features	[33]
Noise-removal-based features	[33]
Spatial characteristics features	[33]
ΔDoM	[26]

C. Evaluating Quality of Document Image Databases

Previous work on evaluating the quality of document image databases has focused primarily on hand-printed character databases [16], [17], [34], [37]. A character image database is necessary for training and testing a character recognizer and the performance of the character recognizer depends on the composition of the database. It is therefore useful to derive a quality measure for the entire character image database.

Hase [16], [17] proposed two entropy based quality metrics - variation entropy for a unit boundary length (VEUB) and variation entropy for a unit area (VEUA). The two metrics are applied to a handwritten Japanese character image database. An extension of this work for gray-scale images was introduced by *Park et al* [34], where they defined *extended average entropy* for gray-scale handwriting image, which is an extension of the *average entropy* for binary image.

D. Challenges

There are challenges and existing problems for objective DIQA. First, most objective DIQA methods are designed for specific types of document image and there are no existing standard DIQA dataset which can be used for comparing different DIQA methods. Second, existing methods all focus on one specific aspect of degradations, and some are limited themselves to studying degradations at character level. However a typical degraded document image may consist of degradations of various types at different levels and it is still not clear how to perform page-level DIQA for multiple types of degradations incorporating information at different levels.

V. Subjective Document Image Quality Assessment

When document image quality is defined with respect to human perception, it is necessary to construct a document image quality dataset with subjective labels provided by humans. Standard IQA datasets are available for natural scene images, but to the best of our knowledge, there are no existing human-perception based DIQA datasets, nor is there a principled way for conducting subjective DIQA experiment. In this section, we review subjective DIQA methods that were introduced in papers on objective DIQA for constructing the dataset used in their experiments. Two types of approaches have been used for subjective DIQA, including rating-based approaches and pair-wise comparison based approaches.

Rating-based methods require subjects to assign a categorical label to each image. The most widely used rating test for IQA is the Mean Opinion Score (MOS) test, in which subjects are asked to rate objects using an ordinal scale: “Bad”, “Poor”, “Fair”, “Good” and “Excellent”. Non-ordinal scales may also be used. For example, in [25], the five scales are described as: 1. Image with degradations caused by scanning; 2. Highly degraded document image; 3. Background degraded document image; 4. Slightly degraded document image and 5. Good document image.

Pair-wise comparison based approaches require subject to compare two images in one experimental unit. *Kumar et al* [26] conducted subjective DIQA in a crowd-sourced setting in which subjects were asked to evaluate document quality at page level and choose one preferred image among two degraded document images. *Hale* and *Barney-Smith* [14] used an electronic version of the graphic rating scale for psychophysical experiments. The survey was conducted on a computer showing two images of degraded characters with a slider below them. The subjects chose which image is preferred by moving the slider position toward the preferred image. In [33], for each pair of images, the subject is asked to make a decision about their quality relative to each other, i.e., decide whether the left or right image is better (or slightly better) or if they seem to be of identical quality.

There are still some open problems for subjective DIQA. Previous subjective IQA experiments have been performed at character level or for one specific type of degradation. It is still not clear how to design experiments to measure the overall subjective quality when multiple degradations are presented in one image. In paired comparison methods, when the number of images is n, the total number of image pairs is $n(n-1)/2$, which can be very large when n is large. It is not clear how to design the experiment to minimize the cost.

VI. Summary

DIQA is an important and challenging problem in document image analysis, however relative little effort has been

TABLE II. REFERENCE SUMMARY.

Document Degradation	
A. Model	[1], [7], [8], [10], [23], [31], [32], [40], [43]
B. Model Validation	[20], [21], [28]
C. Applications	[3], [6], [18], [42]
D. Analysis	[4], [14], [22], [36], [38]
Objective DIQA	
A. OCR	[9], [13], [15], [19], [25], [35], [39], [41]
B. Human perception	[12], [13], [24], [26], [33], [34]
C. Dataset	[16], [17], [34], [37]
Subjective DIQA	[14], [25], [26], [33]

devoted to this field. We have attempted to provide a brief review to recent developments in this field with the hope of drawing more attention to this field. Table II summarizes references in this paper.

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