ARABIC DOCUMENT LAYOUT ANALYSIS USING MACHINE LEARNING AND CONNECTED COMPONENTS BASED FEATURES

By

Rana Sobhy Mostafa Saad

A Thesis Submitted to the
Faculty of Engineering at Cairo University
in Partial Fulfillment of the
Requirements for the Degree of
MASTER OF SCIENCE
in
Electronics and Communications Engineering

FACULTY OF ENGINEERING, CAIRO UNIVERSITY
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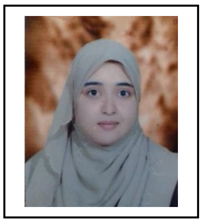

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Title of Thesis:

Arabic Document Layout Analysis Using Machine Learning And Connected Components Based Features

Key Words:
Page segmentation, Document Layout Analysis, Arabic dataset

Summary:
Document Layout Analysis (DLA) is a key preprocessing stage for optical character recognition (OCR). It locates and defines text and non-text regions of a document image. Arabic DLA is less addressed compared to other languages due to the lack of appropriate publicly available research datasets. A full pipeline of DLA procedure is composed of several stages: Input document Preprocessing, Document Physical layout Analysis (PLA), Document Logical Layout Analysis (LLA), and document analysis output representation.

In this thesis, CCs geometric features are used to represent the Arabic document images These CCs features are classified by means of Support Vector Machines (SVM) and Random Forests (RF) classifiers into text and non-text components to perform PLA for scanned Arabic book pages.

Experiments on BCE-v1, and other researcher's datasets showed remarkable performance of both the SVM and RF based solutions. Comparing to other classical and state-of-the-art systems showed much strength to the proposed system and promise further application to wider problem domains.

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List of Abbreviations

AGA	Adapted Genetic Algorithm
ASAR	Arabic And Script Driven Analysis And Recognition
ASFS	Adapted Sequential Forward Selection
BB	Bounding Box
BCE	Boston University-Cairo University-Electronics Research Institute
CAE	Convolutional Auto Encoder
CC	Connected Components
CNN	Convolutional Neural Networks
CRF	Conditional Random Field
CS	Correct-Segmentation
DIVA	Document, Image And Voice Analysis Group
DLA	Document Layout Analysis
DPI	Dot Per Inch
DSE	Document Structure Elements
DSECN	Document Structure Element Characteristic Number
ECDP	Ensemble Based Classification Of Document Patches
ER	Extraction Rate
FA	False Alarm
FV	Feature Vector
GEDI	Groundtruthing Environment For Document Images
GLCM	Grey Level Co-Occurrence Matrix
GUI	Graphical User Interface
HOG	Histogram Of Gradient
ICDAR	International Conference On Document Analysis And Recognition
IHP	Islamic Heritage Project
KNN	K-Nearest Neighbors
LLA	Logical Layout Analysis
MBA	Main Body Area
MDI	Multi Document Interface
ML	Machine Learning
MLP	Multi-Layer Perceptron
MR	Misclassification Rates
MSE	Missed-Segmentation Error
NN	Neural Networks
OSE	Over-Segmentation Error
PAGE	Page Analysis And Ground Truth Elements
PDF	Portable Document Format
PLA	Physical Layout Analysis
RBF	Radial Basis Function
RF	Random Forests
RLSA	Run Length Smearing Algorithm
ROI	Region Of Interest
SBS	Sequential Backward Selection
SFS	Sequential Forward Selection
SFTGS	Spectral Filtering Text-Graphics Separation Algorithm
SILC	Simple Linear Iterative Clustering
SOM	Self-Organizing Map

SVM	Support Vector Machines
SW	Stroke Width
USE	Under-Segmentation Error
UW	University Of Washington
WEKA	Waikato Environment For Knowledge Analysis
XML	Extensible Markup Language.

Abstract

Document Layout Analysis (DLA) is a key preprocessing stage for optical character recognition (OCR). It locates and defines text and non-text regions of a document image. Arabic DLA is less addressed compared to other languages due to the lack of appropriate publicly available research datasets.

A full pipeline of DLA procedure is composed of several stages: Input document Preprocessing, Document Physical layout Analysis (PLA), Document Logical Layout Analysis (LLA), and document analysis output representation. Preprocessing includes several image enhancement processes: binarization, noise removal, skew detection and correction, etc. PLA decomposes the document image into meaningful homogenous regions and then identify the type of their content as text or non-text. LLA identifies the functional role of textual regions within the document as header, footer, main body text, page number, and etc. The output representation is how the analysis resulting information is arranged and transcribed for text recognition systems to use.

In literature, PLA approaches are either: top-down segmentation, bottom-up segmentation, or hybrid segmentation. The top-down approaches perform recursive divisions of the top level (document page) until a desired region of interest (e.g. paragraph, textline) is reached. On the contrary, bottom-up approaches cluster the document's small primitives (pixels, Connected Components (CCs), or image patches) to form the Region of Interest (ROI). Both approaches could be implemented using: rule-based or learning-based algorithms.

Bottom-up approach achieves high performance systems regardless the high computational cost. Using CCs with bottom up approach is a better trade-off compared to pixels.

In this thesis, CCs geometric features are used to represent the Arabic document images. These CCs features are classified by means of Support Vector Machines (SVM) and Random Forests (RF) classifiers into text and non-text components to perform PLA for scanned Arabic book pages.

All classifier parameters tuning and testing experiments are performed on BCE-v1 Arabic dataset [1], the first publicly-available Arabic dataset of scanned book pages that have been collected to support DLA research. Experiments on BCE-v1, and other researcher's datasets showed remarkable performance of both the SVM and RF based solutions. Comparing the proposed system results to other classical and state-of-the-art systems showed much strength to the proposed system and promise further application to wider problem domains.

The results over BCE-Arabic on CCs level for SVM based system show 98.8% classification accuracy while other private datasets as RDI, Hesham et al., ASAR2018 Set-A, ASAR2018 Set-B, and ASAR2018 Set-C are 96.5%, 90.8%, 78.6%, 83.8%, and 97.19% respectively. However RF has 91%, 92.8%, 75.5%, 80.89%, 95.46 % classification accuracy for RDI, Hesham et al., ASAR2018 Set-A, ASAR2018 Set-B, and ASAR2018 Set-C respectively.

Chapter 1 : **Introduction**

Scanned documents are considered an important source of digital information, either these documents are resulting from daily data exchange production or resulting from projects of preserving ancient inheritance. These scanned documents are basically images of text rather than accessible text files; therefore there is a need to make their content accessible and editable. Accessibility requires extracting the elementary components of the document image and identifying their different types either: (1) graphics like diagrams, sketches, charts, maps, etc. , (2) images like photographs, halftones, paintings, etc. , (3) structured text like: tables or body text which could be recognized later by an optical character recognition (OCR) system to make it editable. This process is defined as document layout analysis (DLA).

Document layout analysis is a prerequisite stage to several information extraction procedures like OCR. Consequently, if a DLA process failed, OCR receives badly segmented text which leads to inaccurate recognition results in addition to meaningless symbols. Therefore, accurate DLA procedure is highly demanded

The generation of editable and searchable document content is necessary for several applications such as automatic indexing and retrieval, automatic summarization, automatic translation, Table of Content (TOC) generation, text to speech conversion, etc. and for visually impaired Assistive technology.

Since two decades, most DLA publications address English and Latin-script derived languages. Some attention is given to other languages like Chinese, Hindi, Urdu, Devanagari, Tamil, and Telugu. On the other hand, Arabic DLA is yet the least addressed. Regardless the fact that Arabic is spoken by more than 300 million people, and is ranked as the 5th top-spoken language worldwide[2]. Several reasons could be leading to this issue on the top of which is the absence of publicly-available annotated datasets to work on, and the complex nature of the Arabic script.

The DLA system includes several stages. Some stages are optional according to the desired output representation. These stages include: preprocessing, physical layout analysis, logical layout analysis, and output (document) representation.

The preprocessing stage details depend on the input document quality. Degraded historical documents, old newspapers could suffer low resolution, skews, tears, ink bleeds, shadowing, see-through and many defects. Therefore, most preprocessing basically includes:

1. Binarization
2. Noise detection and removal.
3. Image quality enhancement
4. Skew detection and correction.

Physical layout analysis (PLA) aims to decompose the document image into homogenous regions and identify the type of content in these regions as text, and non-text. On the other hand, logical layout analysis (LLA) defines each textual component's functional role within the document for example as being a header, footer, figure caption, text body, etc.