OCR for TIFF Compressed Document Images Directly in Compressed Domain Using Text segmentation and Hidden Markov Model

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Abstract—In today’s technological era, document images play an important and integral part in our day to day life, and specifically with the surge of Covid-19, digitally scanned documents have become key source of communication, thus avoiding any sort of infection through physical contact. Storage and transmission of scanned document images is a very memory intensive task, hence compression techniques are being used to reduce the image size before archival and transmission. To extract information or to operate on the compressed images, we have two ways of doing it. The first way is to decompress the image and operate on it and subsequently compress it again for the efficiency of storage and transmission. The other way is to use the characteristics of the underlying compression algorithm to directly process the images in their compressed form without involving decompression and re-compression. In this paper, we propose a novel idea of developing an OCR for CCITT (The International Telegraph and Telephone Consultative Committee) compressed machine printed TIFF document images directly in the compressed domain. After segmenting text regions into lines and words, HMM is applied for recognition using three coding modes of CCITT- horizontal, vertical and the pass mode. Experimental results show that OCR on pass modes give a promising results.

Index Terms—Compressed OCR, Compressed document images, text segmentation, projection profiling.

I. INTRODUCTION

Document Image Analysis (DIA) [1], [3] is a technique like any other digital image analysis that takes scanned document images as input, and performs major operations like feature extraction, segmentation and recognition, in order to accomplish the dream of moving towards paperless office. One major problem with scanned document images is that they occupy large storage space for archival and high bandwidth for transmission [1], [3]. Therefore, in the literature, various compression techniques have been evolved to make the task of storage and archival very economical. Image acquisition devices now come with default compression algorithms, as a result, in the real world most of the images are made available in the compressed form. Now in order to operate with these compressed images there are two ways, the first way is to decompress the image and operate over it, and subsequently compress it again for the efficiency of storage and transmission which is termed as conventional image analysis [13]. The other way is to use the characteristics of the underlying compression algorithm to directly process the images in the compressed form without using decompression and re-compression stages is called as compressed domain analysis. Many interesting research works have been reported in the field using both handcrafted features and deep learning features, all executed directly in the compressed representations [3], [14], [15], [16], [17], [18], [19], [20]. The different stages involved in a typical conventional image processing (case of feature extraction) involving decompression is illustrated through Figure-1. The aim of this research paper is to accomplish feature extraction, segmentation and Optical Character Recognition (OCR) directly in compressed document images without involving decompression and re-compression operations.

Although a lot of work has been reported in developing OCRs for uncompressed images/documents [13], not much work has been carried out in realizing OCRs for compressed document images. The initial idea to work with the compressed documents images directly was thought off by some researchers in the early 1980’s [2]. There are several efforts being made to directly handle the images intelligently in the compressed form [3]. Some of those operations are feature extraction, segmentation, image rotation, skew detection, connected component analysis etc [3]. In all these operations either the run length information is used from the uncompressed form or either some sort of partial decoding is done to carry out the operations. In this work we present a system that will recognize the text directly from the CCITT compressed TIFF images [1].

The OCR model proposed in this paper is similar to that of [2] that extracts the feature points marked by the pass modes directly from the compressed file using Hidden Markov Models (HMMs) as recognizer. HMMs become an obvious choice when we are dealing with data comprising of a lot of noise. The pass mode features extracted from the compressed file are similar to noise. HMMs perform better in the presence of noise and hence they are extensively used in speech and
handwriting recognition. However, this research paper fulfills two research gaps mentioned in [2]. The first contribution here is to accomplish the novel idea text segmentation into lines and words directly in compressed text using three modes: horizontal, vertical and pass modes of CCITT Group 4 compression. The second contribution here is using three modes for realising OCR, and further experimentally proving that pass mode is better for OCR and other document image related operations to be performed in the compressed domain. Rest of the paper is organized as follows- Section II gives brief idea of the proposed model with feature extraction, text line segmentation and HMM, section III reports experimental results and related analysis, and finally section IV summarizes the research paper.

II. PROPOSED MODEL

The OCR proposed in this paper follows three major stages - feature extraction, text segmentation and OCR using HMM. The different stages are illustrated through the Figure-2.

A. Feature extraction

The feature extraction module is used to extract feature points by handling the images directly in the compressed domain. Now as we are dealing with the compressed images so it is pretty evident that the feature points shall be sparse, so, the pass codes are extracted from: left to right / top to bottom, right to left / bottom to top. Thus in two different ways the feature points are extracted and overlaid on top of one another and given as an input to the segmentation module which will perform projection profiling on it and finally it is given as an input to the recognition module. Our recognition module is based on Hidden Markov Model (HMM) discussed in detail in section 5. It is a probabilistic model based on Markov Chains which computes the hidden state based on the state that is present i.e. the state that can be observed by making inferences(probabilistic inferences).

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1) Group 3 One Dimensional Coding: As the name suggests the Group 3 One Dimensional algorithm processes the image line by line from top to bottom. While processing each line the number of consecutive pixels of the same colour (black or white) are counted and a sequence of numbers or run-lengths are generated which represent a line (shown in Fig. 3.1). Each transition in the pixels in the image causes an entry in the coded image. Now to make the representation unique, it is assumed that each line begins with a white pixel. If a line actually starts with a black pixel than the number of leading white pixels is zero. This coding scheme is called run-length coding.

Now this simple coding scheme has both its pros and cons. If there are long homogeneous runs of same colored pixels then only few values are needed to code the image and heavy compression can be achieved but on the other hand if there are frequent transitions between black and white many values shall be needed. So, in the worst case no compression may be achieved at all. Because in real life not all numbers of run-lengths occur with same probability, an additional Huffman coding is used for further compression.

2) Group 3 Two Dimensional Coding: In Group 3 One Dimensional coding where each line is treated independently without considering the previous and the following line. But in almost all cases, images lines depend on their context, i.e., the preceding and the following lines. This fact can be used for more elaborated coding techniques. In the CCITT group 3 two-dimensional coding scheme both the preceding and the following lines are considered for both compression as well as decompression. In this coding scheme five points are of special interest: $a_0$ the last known pixel in the actual line, $a_1$ the first transition pixel to the right of $a_0$, $a_2$ the second transition pixel to the right of $a_0$, $b_1$ on the previous line the first transition pixel to the right of $a_0$ and finally $b_2$ on the previous line the first transition pixel to the right of $a_0$.

Now depending on the position of the above points three coding modes are defined:

1) The horizontal mode, when $|a_1 - b_1| > 3$
2) The vertical mode, when $|a_1 - b_1| \leq 3$
3) And the pass mode, when $|a_1 - b_2| > 0$

Now the horizontal mode represents one-dimensional run length coding, the vertical and the pass modes concerns the structure of the previous line. In pass modes $b_1$ and $b_2$ are are on the left side of $a_1$. To avoid the use of large number for coding the run length between $a_0$ and $a_1$, a special mark is set right below $b_2$. This allows to reconstruct the colour of the pixels in the actual line to the position below $b_2$, which has the same colour as $a_0$. The position of this special mark is called pass code.

Extraction of these points is quite straightforward. Figures 6, 7, 8 shows the feature points marked by horizontal, vertical &pass modes respectively for the input image shown in Figure 5.

B. Text line & word segmentation using pass modes

The output of the feature extraction module is then given as an input to the segmentation module to perform profiling. A projection profile is a histogram of the number of set pixels along the parallel lines and horizontal lines. On the
basis of that we shall perform segmentation both word and line segmentation. For an image consisting of 'm' rows and 'n' columns, mathematically we can define the Horizontal Projection Profile (HPP) and Vertical Projection Profile (VPP) as:

$$HPP(x) = \sum_{1 \leq y \leq n} f(x, y)$$

$$VPP(y) = \sum_{1 \leq x \leq m} f(x, y)$$

Now the run histograms generated by projection profiling can be used to analyze our feature set, like the amount of blank spaces available within the input i.e. between the lines and words in the document. The same has been demonstrated in the figures 11 and 12 where the blue lines represent the run of pixels and the red line representing the break between the respective lines/words for the input set and feature set shown.
in Fig 9 and Fig 10 respectively.

It is so ordered.
The idea of marriage.
The constitution grants them this right.
They ask for equal dignity in the eyes of law.

Fig. 9. Input image

Now after this much pre-processing the feature set shall be given as an input to our recognition module.

C. Recognition Module

In this section we shall discuss what Hidden Markov Models are and how we used them to do OCR.

1) Markov Chains: Hidden Markov Models (HMMs) are elicited from a concept of mathematics called Markov Chains. Markov Chain is a probabilistic model that helps us compute the probabilities of a sequence of random variables which takes up values from some pre-defined sets, these pre-defined sets can be anything like symbols, colors, text etc. The sate in which the system is presently at it makes an prediction/assumption of the future state. So, the states preceding the present state have no influence on the prediction e.g on the basis of the even that’s happening right now you have to predict the future event without having access to any other information like the events that have preceded the current event. Figure 13 contains two different examples of the Markov Chains 13(a) for weather and 13(b) for words clearly showing different states and transitions between them. Now a starting probability distribution is required \( \pi = [0.2, 0.4, 0.4] \) for (a) and this would mean that 0.2 is probability of starting with HOT, and both COLD and WARM have a probability of 0.4 to start with. And rest of them are the transition probabilities i.e., the probabilities of going from one state to another.

It consists of the following components :

1) \( Q = q_1, q_2, q_3, \ldots, q_n \)
   A set of \( N \) states.

2) \( T = t_{11}, t_{12}, t_{13}, \ldots, t_{nm} \)
   A transition probability matrix \( T \), each \( t_{ij} \) represents the probability of transitioning from state \( i \) to state \( j \) such that \( \sum_{i=1}^{n} t_{ij} = 1 \) \( \forall i \).

3) \( \prod = \pi_1, \pi_2, \ldots, \pi_n \)
   Set of initial probability distribution representing the probability of the Markov Chain to start with a specific state. Also \( \sum_{i=1}^{n} \pi_i = 1 \).

2) Hidden Markov Models: Now when we need to predict something on the basis of what we observe a Markov Chain seems to be an possible choice e.g. on the basis of the weather outside we wish to predict the mood of someone. We call this event hidden because this cannot be observed directly.

Now Hidden Markov Model is a probabilistic model based on Markov Chains that allows us to figure out these hidden states.

A Hidden Markov Model comprises of :

1) \( Q = q_1, q_2, q_3, \ldots, q_n \)
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3) \( \prod = \pi_1, \pi_2, \ldots, \pi_n \)
   Set of initial probability distribution representing the probability of the Markov Chain to start with a specific state. Also \( \sum_{i=1}^{n} \pi_i = 1 \).

4) \( O = o_1, o_2, o_3, \ldots, o_m \)
   A sequence of \( M \) observations.

5) \( B = b_i(o_t) \)
   Set of emission probabilities.

Figure 14 shows a sample HMM for the ice cream task. The two hidden states (H and C) correspond to hot and cold weather, and the observations (drawn from the alphabet \( O = 1, 2, 3 \)) correspond to the number of ice creams eaten by the person on a given day.

3) Recognition using HMMs: Each and every test letter is treated as a new observed sate and we try to compute the hidden state, i.e., the most likely character for the observed state.

To compute the hidden state the Hidden Markov Model makes use of three different probabilities:

1) Initial Probabilities
   Initial probability is the probability of the test character being the first character of any statement.

2) Transition Probabilities
   Transition probabilities are the probabilities of transitioning from one character to another, i.e., if the test character is ‘a’ what is probability of ‘a’ transition to ‘b’, ‘c’ ans so on.

3) Emission Probabilities
   Emission probability is the probability of the test character under consideration representing a particular English language character. Naive Bayes’ Theorem is used to compute these probabilities.

After computing all the above probabilities its time for character recognition ans we carried out character recognition in two different ways:

- A Simplified Approach
  The algorithm used in this approach rather than using all the three probabilities used only two of the three and those are the emission probabilities and the initial probabilities of the characters. As we are not considering the transition probabilities so, there is no connection between two different hidden states. The final character that is being assigned to the test character is solely based on the emission probability and the probability of
occurrence of that very character.

- **Viterbi Algorithm**

This algorithm finds the most likely sequence of the hidden states also known as the **Viterbi Path**. It considers all three probabilities and would store the most likely previous character and the probability of transitioning from the previous character to the current character times the emission probability of the current character. And once the entire probability table is populated using Viterbi algorithm we shall backtrack and find the most likely state.

### III. Experiments & Results

To check the efficiency of the above discussed model we conducted various experiments. In all the experiments random sequences of words were used. For our experiment we assumed the text size is of size 25 x 16 pixels. Apart from the known text size we also assume the test character set only contains lowercase/uppercase 26 English alphabets, 10 digits, and seven special symbols/punctuation marks (",",":".

If our test character set have \( n \) characters so, we shall have
where large images/documents are stored and/or transmitted.

Potential applications of the systems may be huge in the fields presented model for further enhancing the performance and compressed images but there is definitely a potential in the clearly lower than that of the systems that works on un-

Finally the efficiency of the model studied in this work is improving the capability of the system so that it can recognize text having different fonts and sizes.

Hidden Markov Models is used to recognize the text using two-dimensional algorithm. A probabilistic model based on group 3 (The International Telegraph and Telephone Consultative Committee) accuracy than other horizontal and vertical mode.

The above eq(i) can be re-written using Bayes’ Theorem from the data that we shall use to train the system and then using the inferences (probabilistic inferences) we shall try to guess the most appropriate character that can be assigned to given test character. The experimental results of the OCR on a single document image using all the three different modes are given in Table I. From the table it is clear that pass modes are giving good accuracy than other horizontal and vertical mode.

| Number of characters | Horizontal Mode | Vertical Mode | Pass Mode |
|----------------------|-----------------|--------------|-----------|
| / words              | Number of characters correctly recognized | Accuracy | Number of characters correctly recognized | Accuracy | Number of characters correctly recognized | Accuracy |
| 14/4                 | 0               | 0            | 5         | 35/11 | 13 | 92.85 |
| 17/4                 | 1               | 3.88         | 3         | 17/64 | 16 | 94.11 |
| 34/6                 | 0               | 0            | 4         | 11/67 | 34 | 100 |
| 35/7                 | 2               | 5.71         | 7         | 20    | 34 | 97.14 |
| 40/9                 | 1               | 2.5          | 8         | 20    | 38 | 95 |
| 40/7                 | 3               | 7.5          | 12        | 30    | 37 | 92.5 |
| 46/8                 | 1               | 2.71         | 7         | 15/21 | 43 | 93.47 |
| 50/10                | 0               | 0            | 9         | 18    | 48 | 96 |
| 50/11                | 0               | 0            | 14        | 28    | 48 | 96 |
| 51/9                 | 0               | 0            | 6         | 11/76 | 48 | 94.11 |
| 55/14                | 0               | 0            | 7         | 12/72 | 48 | 87.27 |
| Average              | -               | 2.26%        | -         | 20.07% | - | 94.40% |

IV. CONCLUSION

In this work we have studied a system that is capable of extracting machine printed text directly from the compressed images. The feature set that gave the best results out of the all three modes in the pass mode, which are extracted from the image compressed using CCITT (The International Telegraph and Telephone Consultative Committee) group 3 two-dimensional algorithm. A probabilistic model based on Hidden Markov Models is used to recognize the text using the feature set.

There are a lot of things which if addressed can improve the efficiency of the given model like: taking into consideration the grammar and frequently used patterns of the language, improving the capability of the system so that it can recognize text having different fonts and sizes.

Finally the efficiency of the model studied in this work is clearly lower than that of the systems that works on uncompressed images but there is definitely a potential in the presented model for further enhancing the performance and potential applications of the systems may be huge in the fields where large images/documents are stored and/or transmitted.

REFERENCES

[1] K. Sayood Introduction to Data Compression Morgan Kaufmann Publishers.
[2] U. V. Marti, D. Wymann and H. Bunke, OCR on Compressed Images using pass modes and Hidden Markov Models.
[3] M. Javed, P. Nagabhushan, and B. B. Chaudhuri, A review on document image analysis techniques directly in the compressed domain, Artificial Intelligence Review, Volume 50(4), Pages 539–568, 2018
[4] W. Kou, Digital image compression algorithms and standards, Kluwer Academic Publishers, 1995.
[5] Speech and Language Processing, Daniel Jurafsky and James H. Martin, 2019.
[6] L. Likforman-Sulem, A. Zahour, and B. Taconet, “Text line segmentation of historical documents: a survey,” International Journal of Document Analysis and Recognition (IJDAR), vol. 9, pp. 123–138, April 2007.
[7] Viterbi, A. J. (1967). Error bounds for convolutional codes and an asymptotically optimum decoding algorithm. IEEE Transactions on Information Theory, IT-13(2), 260–269.
[8] Jelinek, F. (1997). Statistical Methods for Speech Recognition. MIT Press.
[9] Forney, Jr., G. D. (1973). The Viterbi algorithm. Proceedings of the IEEE, 61(3), 268–278.
[10] Baum, L. E. and Petrie, T. (1966). Statistical inference for probabilistic functions of finite-state Markov chains. Annals of Mathematical Statistics, 37(6), 1554–1563.
[11] Rabine, L. R. (1989). A tutorial on hidden Markov models and selected applications in speech recognition. Proceedings of the IEEE, 77(2), 257–286.
[12] Y. Lu and C. L. Tan, Word Searching in CCITT Group 4 Compressed Document Images 1989.
[13] H. R. Shiva Kumar and A. G. Ramakrishnan, Lipi Gnan: A Versatile OCR for Documents in any Language Printed in Kannada Script, ACM TALIP, 19/4, 2020
[14] Mohammed Javed, P. Nagabhushan, and B.B. Chaudhuri, Automatic Extraction of Correlation-Entropy Features directly from Run-length Compressed Documents in the IEEE Proceedings of 13th International Conference on Document Analysis and Recognition (ICDAR2015), Pages 1-5, Nancy, France, 2015
[15] Mohammed Javed, P. Nagabhushan, and B.B. Chaudhuri, “A Direct Approach for Word and Character Segmentation in Run-Length Compressed Documents and its Application to Word Spotting”, in the IEEE Proceedings of 13th International Conference on Document Analysis and Recognition (ICDAR2015), Pages 216-220, Nancy, France, 2015
[16] P. Nagabhushan, Mohammed Javed, B.B. Chaudhuri, “Entropy Computation of Document Images in Run-Length Compressed Domain”, In Proceedings of Fifth International Conference on Signal and Image Processing (ICSIIP2013), Pages January 8-10, 2014, Bengaluru, India
[17] Balla Rajesh, Mohammed Javed, P. Nagabhushan, “Automatic Tracing and Extraction of Text-Line and Word Segments Directly in JPEG Compressed Document Images”, Published Online in IET Image Processing, April 02, 2020

$O = o_1, o_2, o_3, ... , o_n$ and $n$ hidden states $H = h_1, h_2, h_3, ..., h_n$. On the basis of this we would compute:

$$P(h_1, h_2, h_3, ..., h_n|o_1, o_2, o_3, ..., o_n)$$  (i)

The above eq(i) can be re-written using Bayes’ Theorem from the data that we shall use to train the system and then using the inferences (probabilistic inferences) we shall try to guess the most appropriate character that can be assigned to given test character.

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[18] Bulla Rajesh, Mohammed Javed, P. Nagabhushan "FastSS: Fast and Smooth Segmentation of JPEG Compressed Printed Text Documents using DC and AC Signal Analysis", in Multimedia Tools and Applications, 2021

[19] Bulla Rajesh, Priyanshu Jain, Mohammed Javed, David S. Doermann ,"HH-CompWordNet: Holistic Handwritten Word Recognition in the Compressed Domain", Accepted in IEEE Data Compression Conference (DCC2021), March 23-26, 2021, UTAH, USA

[20] Bulla Rajesh, Mohammed Javed, Ratnesh, Shubham Srivastava, ” DCT-CompCNN: A Novel Image Classification Network Using JPEG Compressed DCT Coefficients”, Published in IEEE CICT2019, December 6-8, 2019, IIIT Allahabad, India