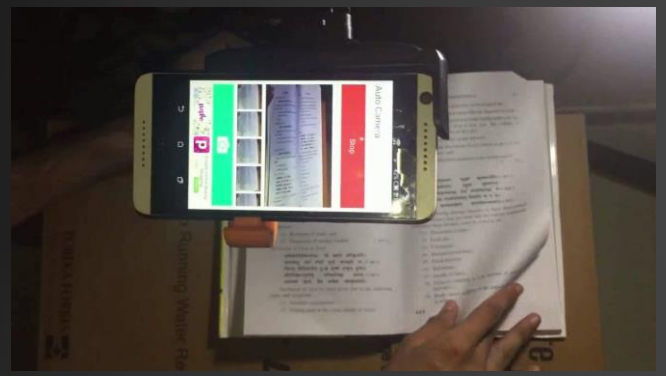
DEWARPING CURVED DOCUMENT IMAGES WITH MATLAB

CHI ZHANG, COURSE PROJECT FOR

CPSC 635 - IMAGE ANALYSIS AND COMPUTER VISION - FALL 2017

M. Zucker, "Page dewarping," 2016. [Online]. Available: https://mzucker.github.io/2016/08/15/page-dewarping.html. [Accessed: 26-Oct-2017].

2 INTRODUCTION: DIGITIZING DOCUMENTS WITH CELL PHONE CAMERA



Digitizing books

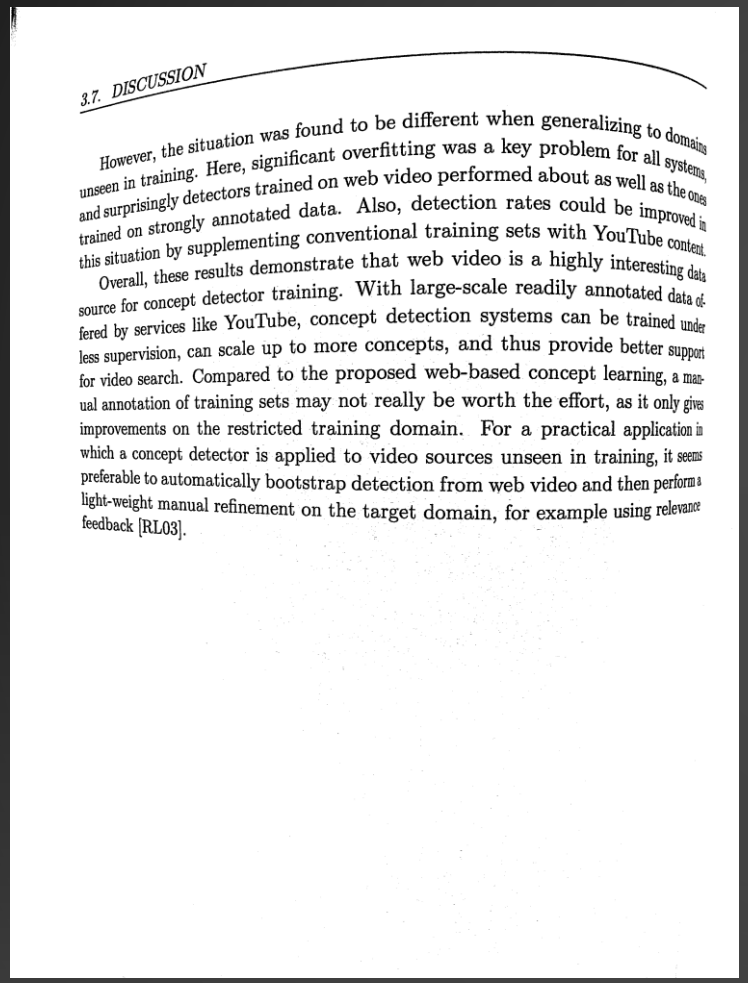
Foreign language translation

Archiving rare documents

MOTIVATION: MOBILITY VS ACCURACY

3

DISTORTED IMAGE



3.7. DISCUSSION

However, the situation was found to be different when generalizing to domains unseen in training. Here, significant overfitting was a key problem for all systems, and surprisingly detectors trained on web video performed about as well as the ones trained on strongly annotated data. Also, detection rates could be improved in this situation by supplementing conventional training sets with YouTube content.

Overall, these results demonstrate that web video is a highly interesting data source for concept detector training. With large-scale readily annotated data offered by services like YouTube, concept detection systems can be trained under less supervision, can scale up to more concepts, and thus provide better support for video search. Compared to the proposed web-based concept learning, a manual annotation of training sets may not really be worth the effort, as it only gives improvements on the restricted training domain. For a practical application in which a concept detector is applied to video sources unseen in training, it seems preferable to automatically bootstrap detection from web video and then perform a light-weight manual refinement on the target domain, for example using relevance feedback [RL03].

OCR RECOGNIZED TEXT

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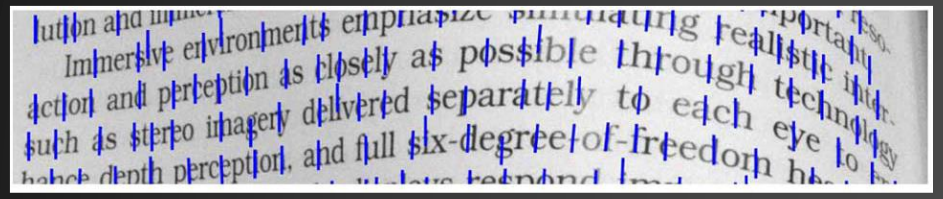
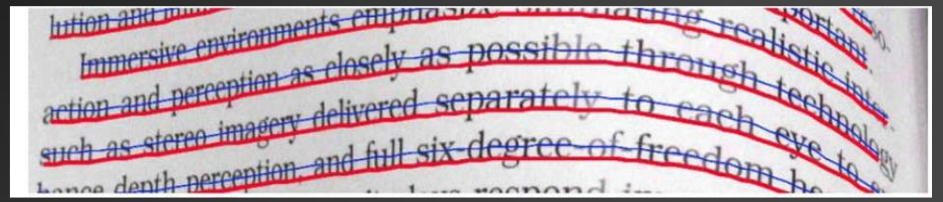
BACKGROUND: METHODS

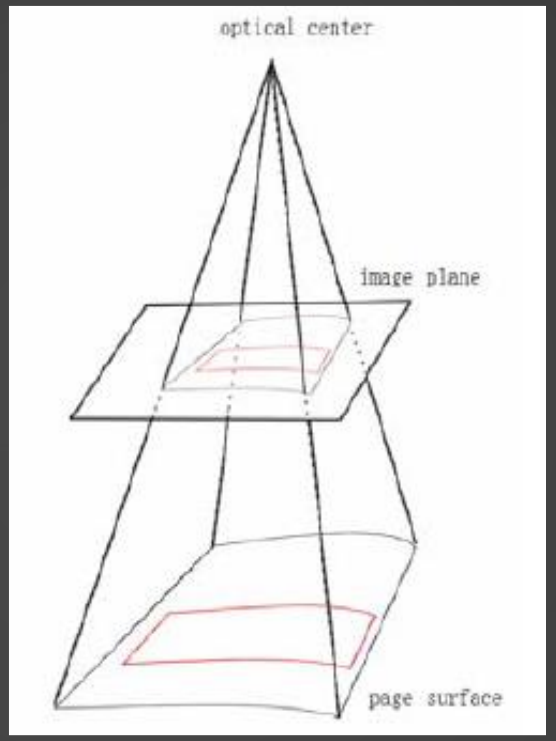
Warp: to bend or twist out of shape, especially from a straight or flat form
Dewarp: reverse process of warp



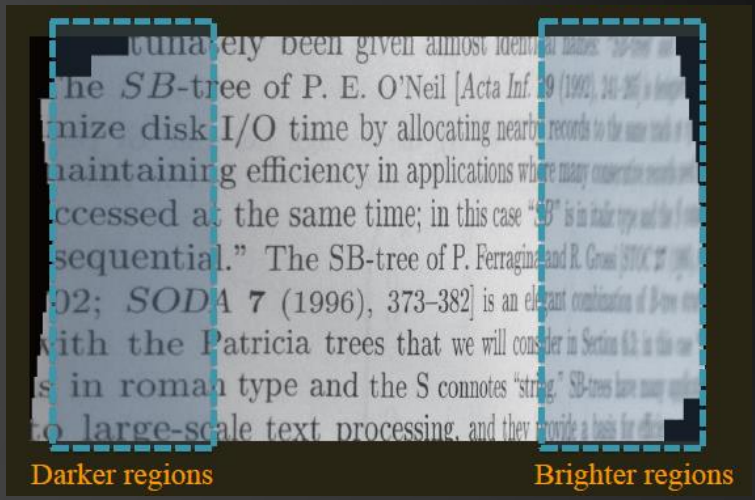
Stroke analysis



Baseline detection



3D transform model

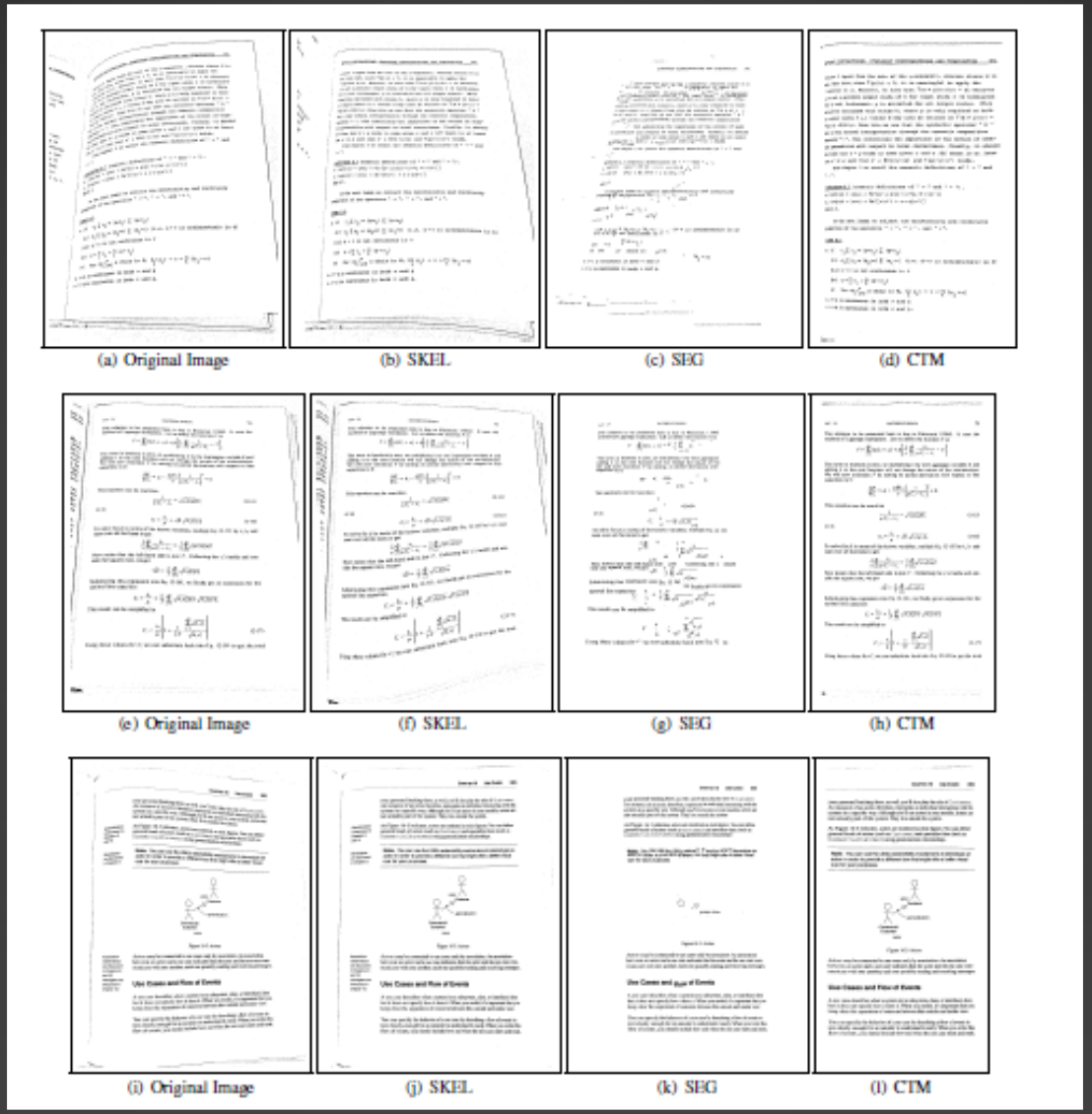


Brightness contrast

Y. Tian and S. G. Narasimhan, "Rectification and 3D reconstruction of curved document images," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, pp. 377–384, 2011.

B. Fu, M. Wu, R. Li, W. Li, Z. Xu, and C. Yang, "A model-based book dewarping method using text line detection," Proc. 2nd Int. Work. Camera …, pp. 63–70, 2007.

BACKGROUND: RESULTS



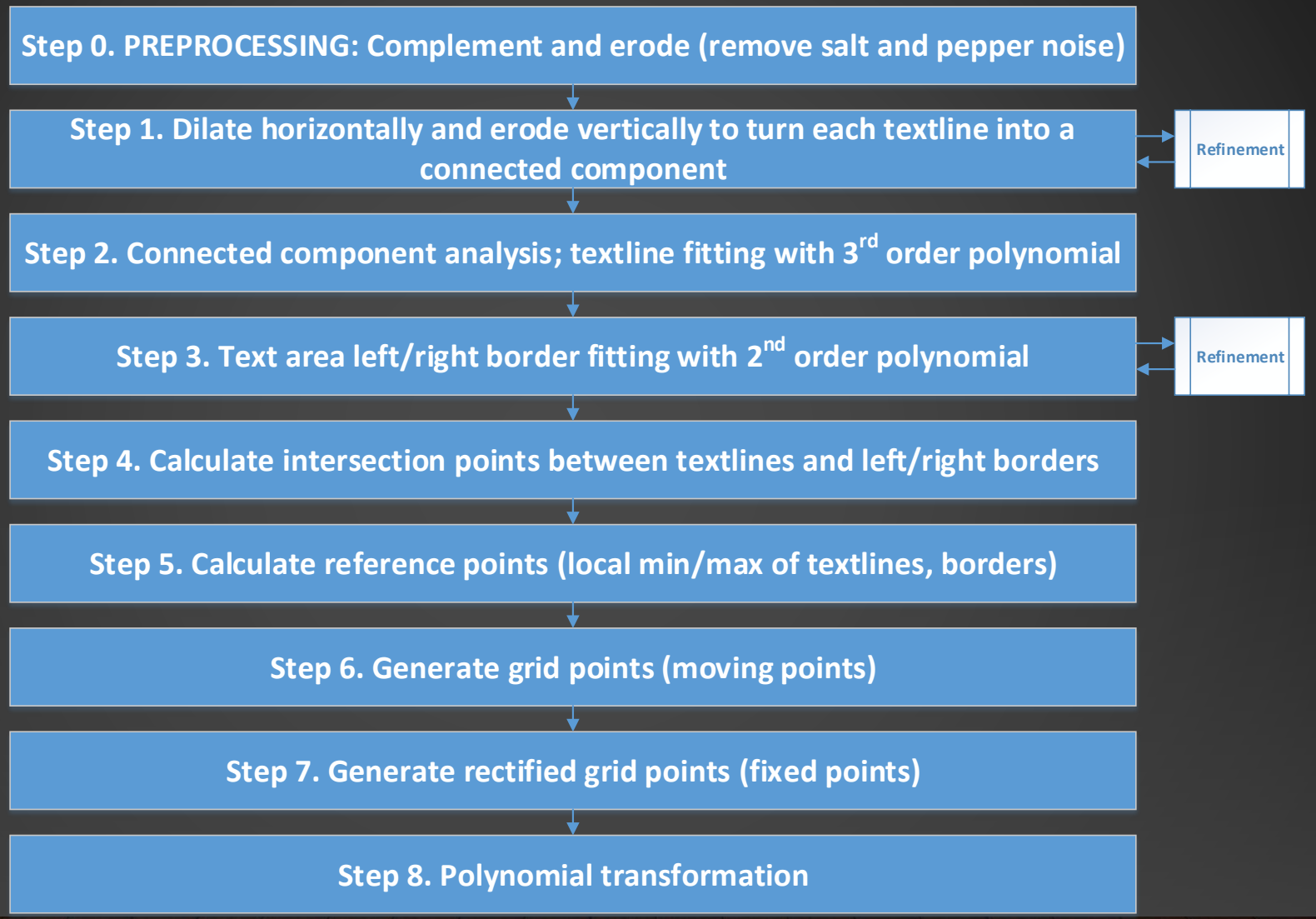
Best reported results:
OCR accuracy 95-100%

F. Shafait and T. Breuel, "Document Image Dewarping Contest," *2nd Int. Work. Camera-Based Doc. Anal. Recognit. (CBDAR-2007), Sept. 22, Curitiba, Brazil.*, pp. 181–188, 2007.

METHODOLOGY (1)

- Objective: dewarp document images with Matlab implementation; no external libraries
- IUPR 2011 Dataset (images of warped and scanned documents)
- http://didcontest2011.blogspot.ca/
- Image dimensions: 2592 pixels x 3456 pixels
- Assumptions
  1. images of individual pages from book
  2. focal plane almost normal to page surface
  3. text areas are in upright orientation (preprocessed through rotation)

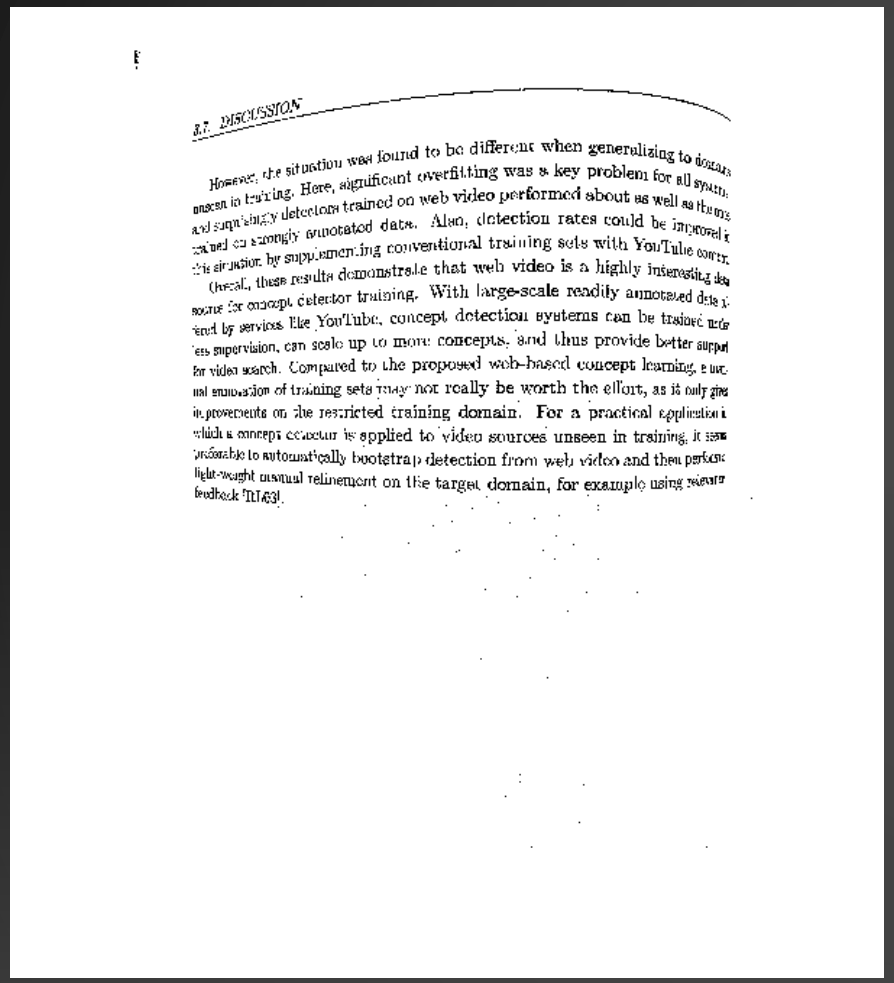
METHODOLOGY (2)



STEP 0. COMPLEMENT AND ERODE TO REMOVE SALT AND PEPPER NOISE

8

BEFORE



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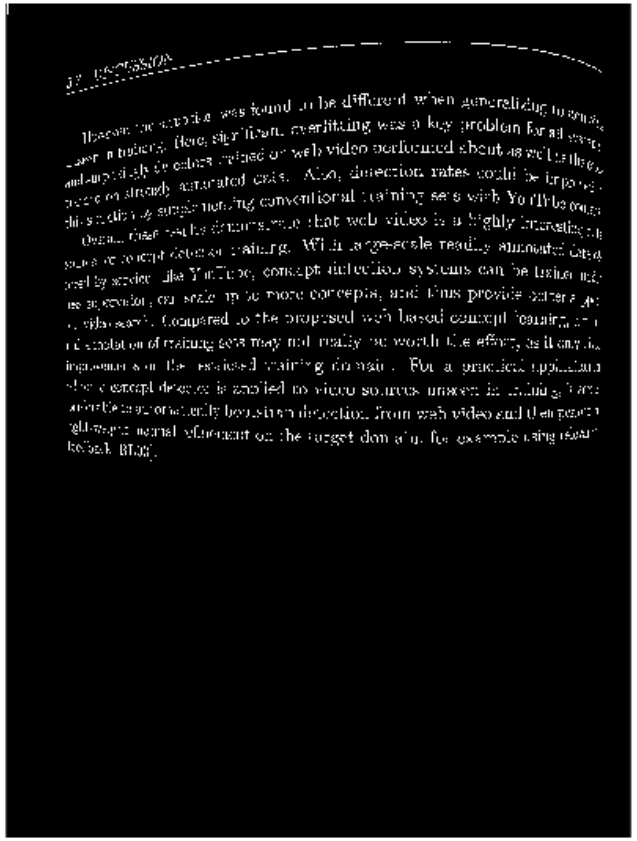
However, the situation was found to be different when generalizing to domains unseen in training. Here, significant overfitting was a key problem for all systems, and surprisingly detectors trained on web video performed about as well as detectors trained on strongly annotated data. Also, detection rates could be improved in this situation by supplementing conventional training sets with YouTube content.

Overall, these results demonstrate that web video is a highly interesting data source for concept detector training. With large-scale readily annotated data delivered by services like YouTube, concept detection systems can be trained under less supervision, can scale up to more concepts, and thus provide better support for video search. Compared to the proposed web-based concept learning, a manual annotation of training sets may not really be worth the effort, as it only gives improvements on the restricted training domain. For a practical application in which a concept detector is applied to video sources unseen in training, it seems preferable to automatically bootstrap detection from web video and then perform light-weight manual refinement on the target domain, for example using relevance feedback [RL03].

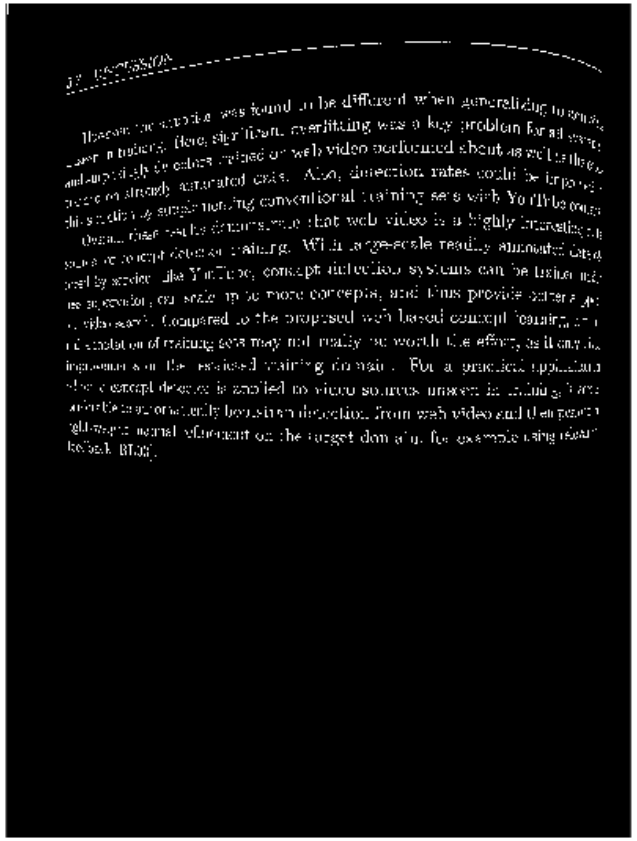
AFTER



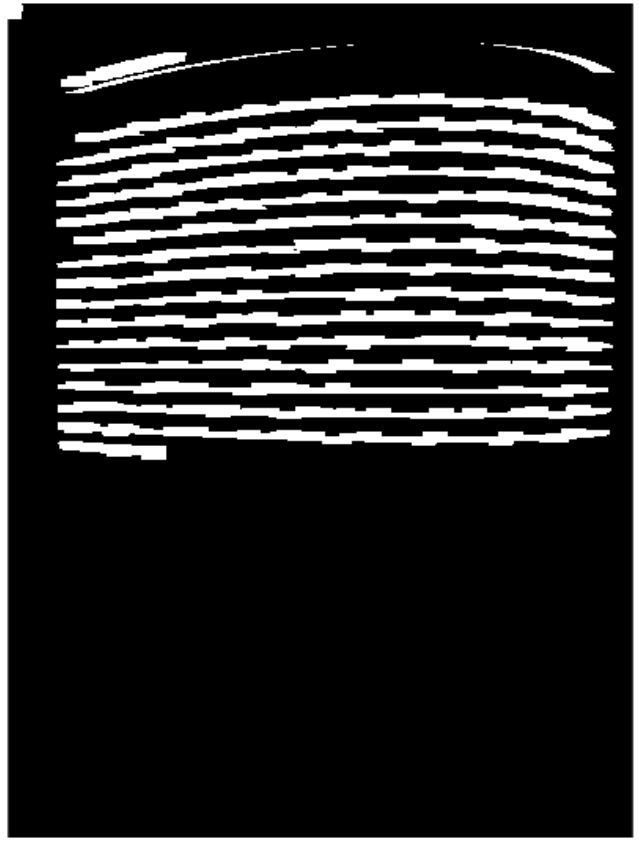
STEP 1. DILATE WITH HORIZ. ELEMENT / ERODE WITH VERT. ELEMENT

9

BEFORE



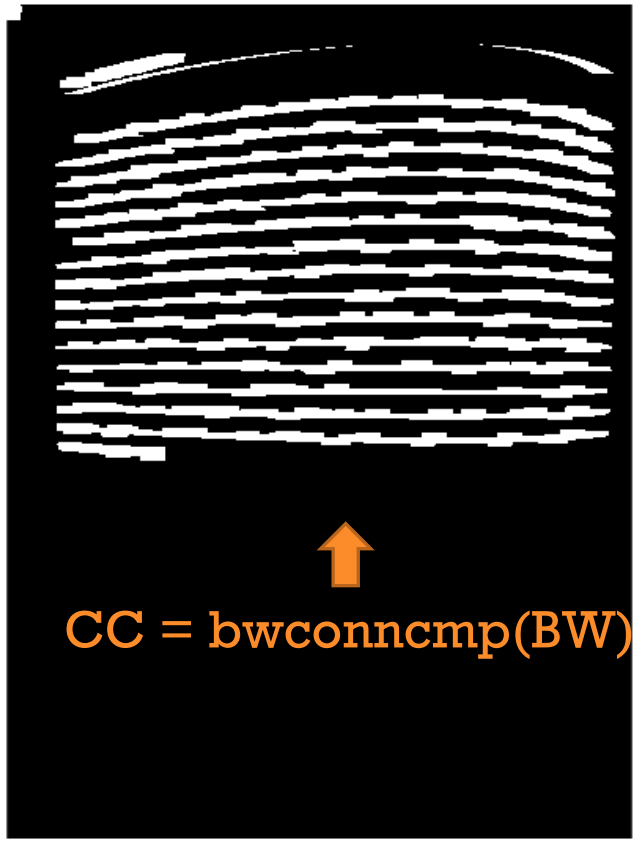
AFTER



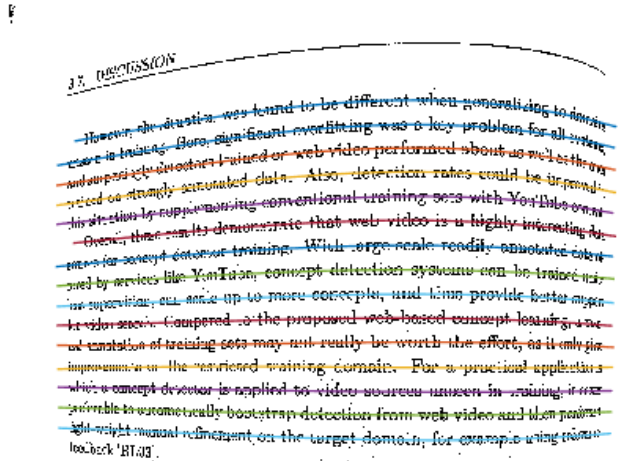
STEP 2. CONNECTED COMPONENTS ANALYSIS; TEXTLINE FITTING WITH CUBIC (3RD ORDER) POLYNOMIAL

10

BEFORE



AFTER

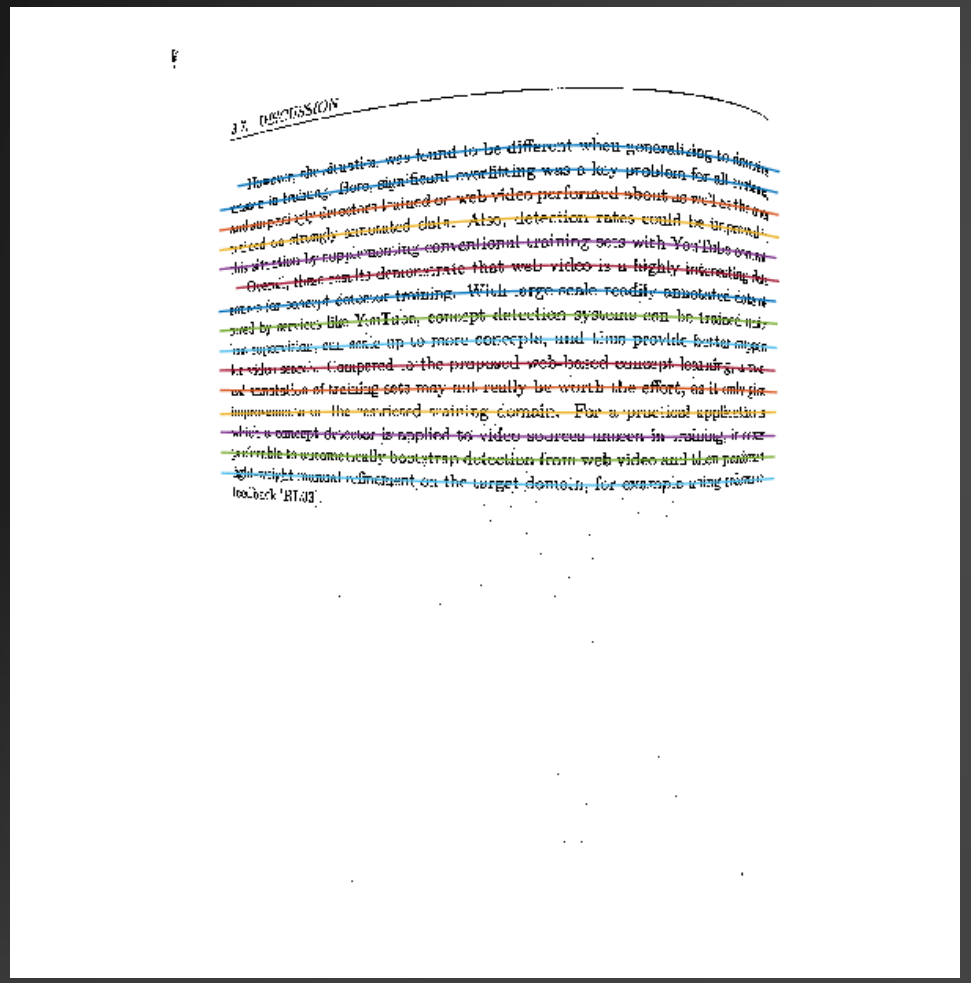


MATLAB Documentation

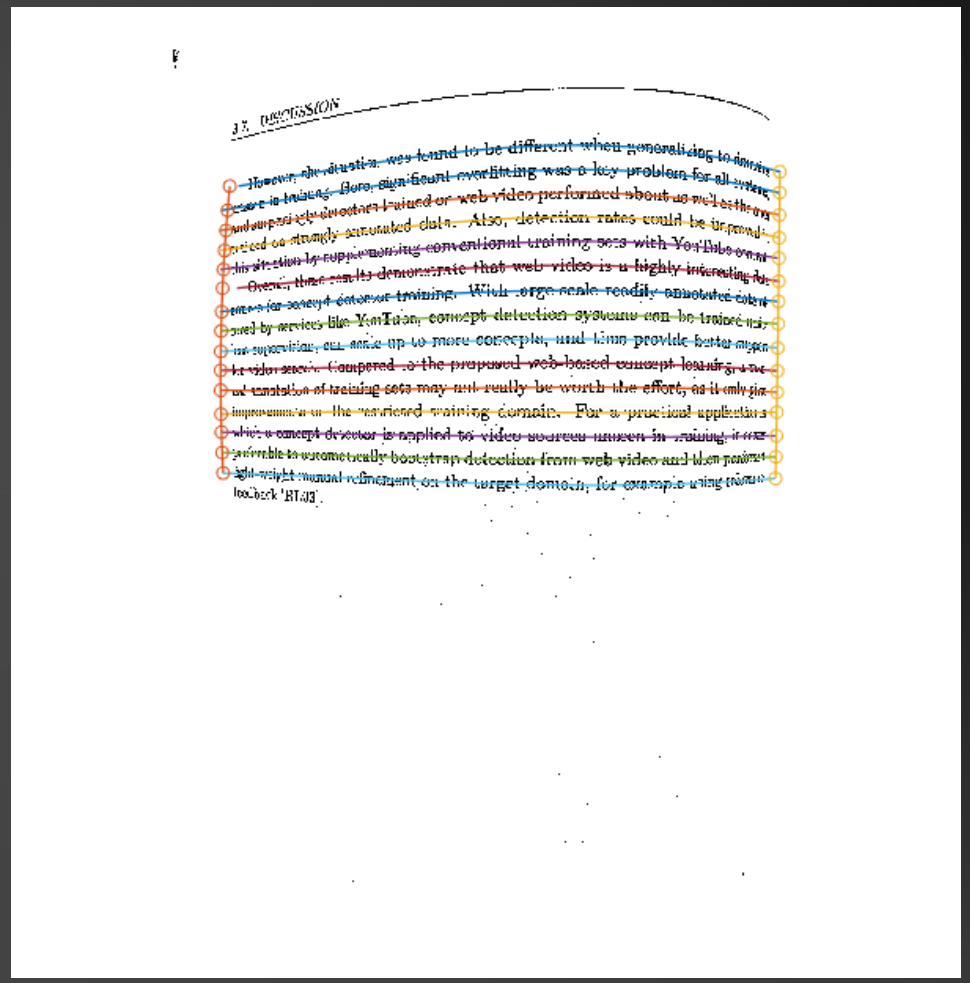
STEP 3. LEFT, RIGHT BORDER FITTING WITH QUADRATIC (2ND ORDER) POLYNOMIAL

11

BEFORE



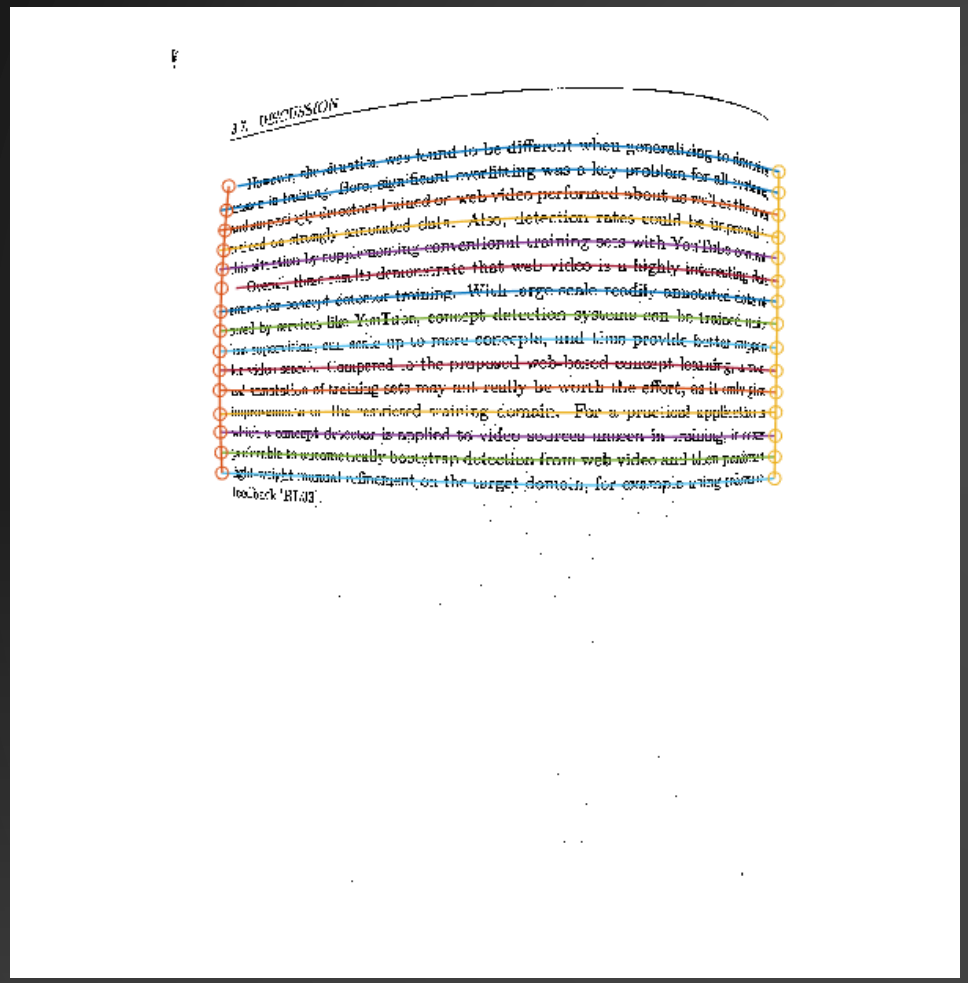
AFTER



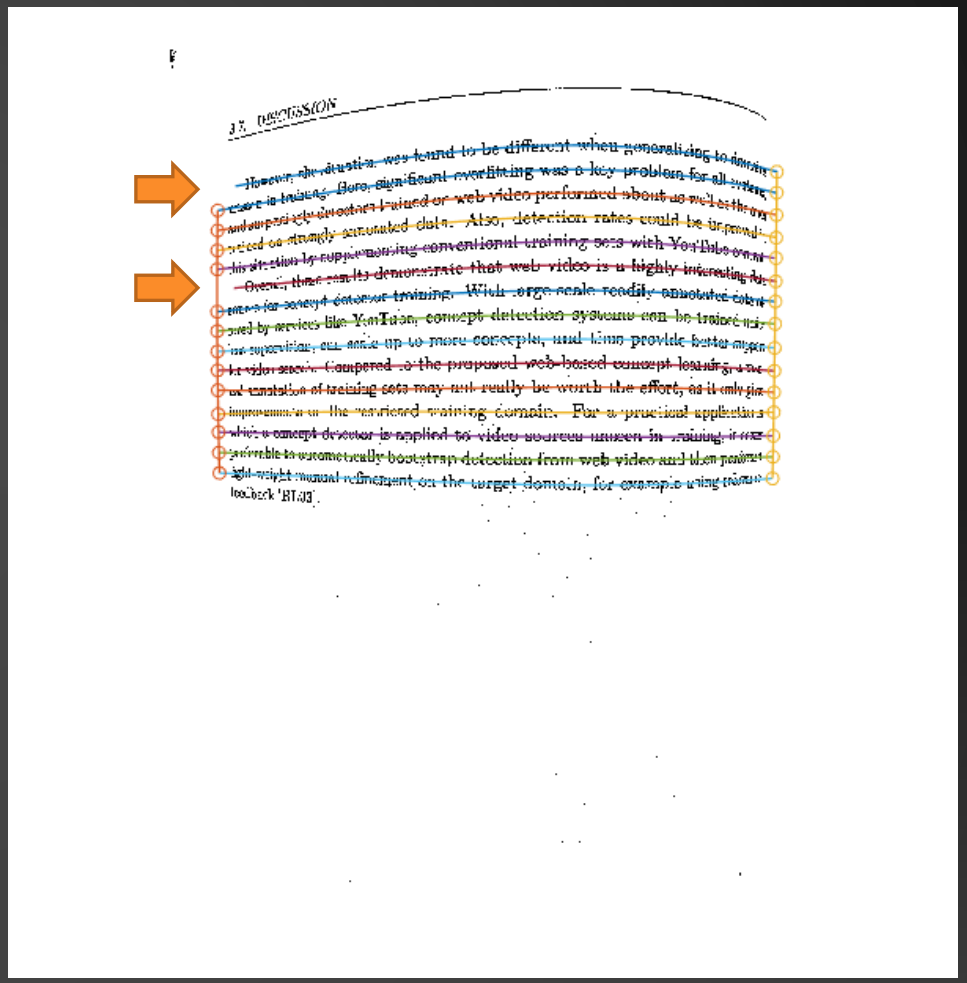
STEP 3A. REFINING LEFT BORDER (REMOVE INDENTATION)

12

BEFORE



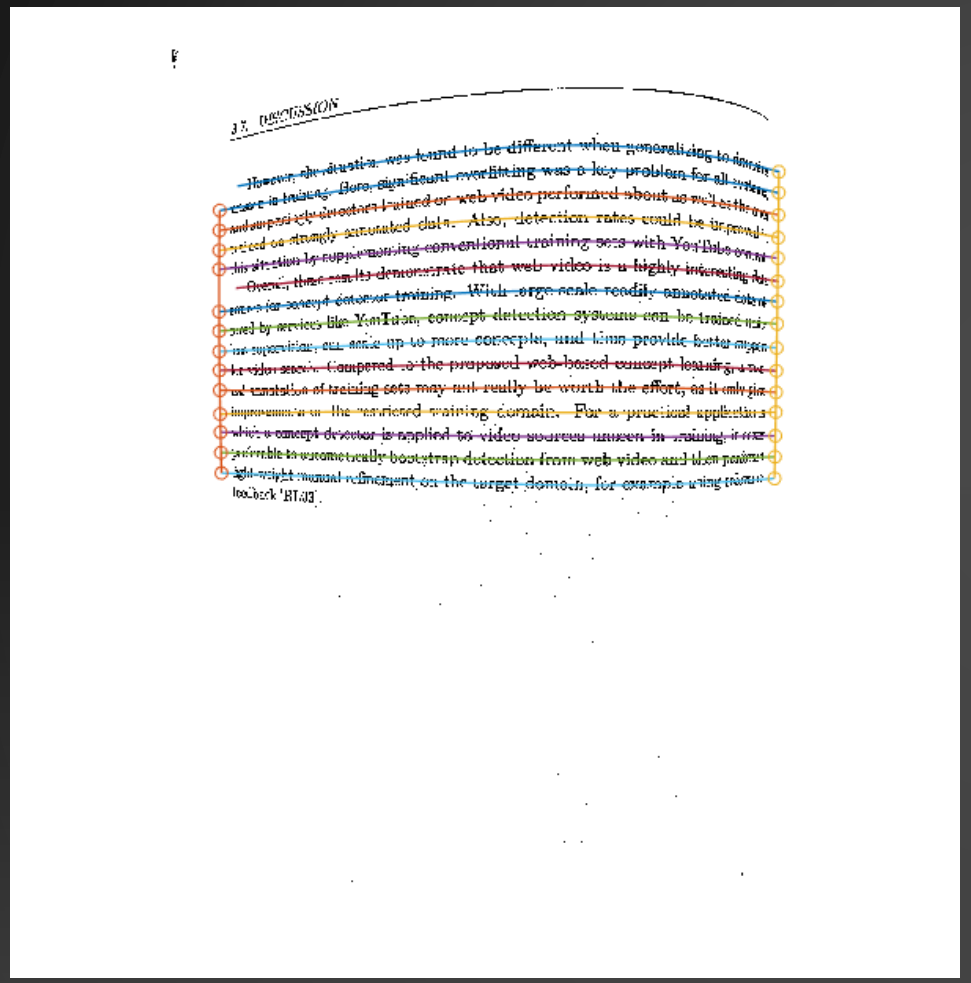
AFTER



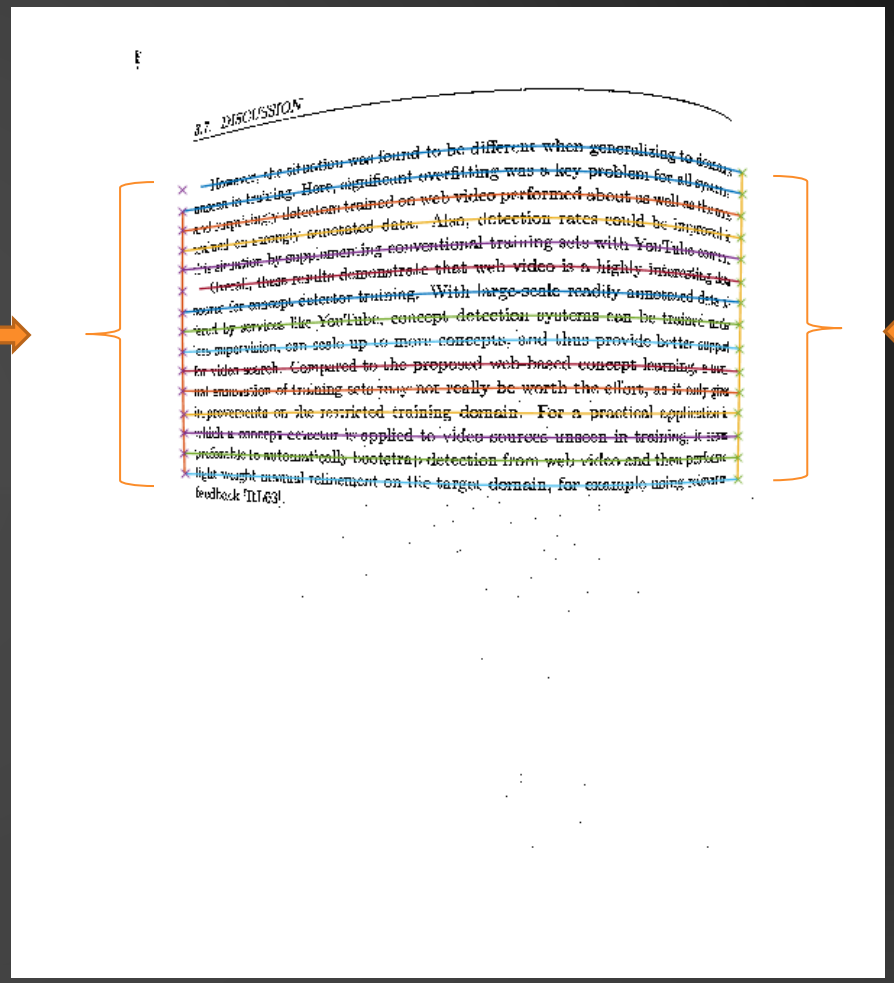
STEP 4. INTERSECTION POINTS BETWEEN LEFT/RIGHT BORDERS AND TEXTLINES

13

BEFORE

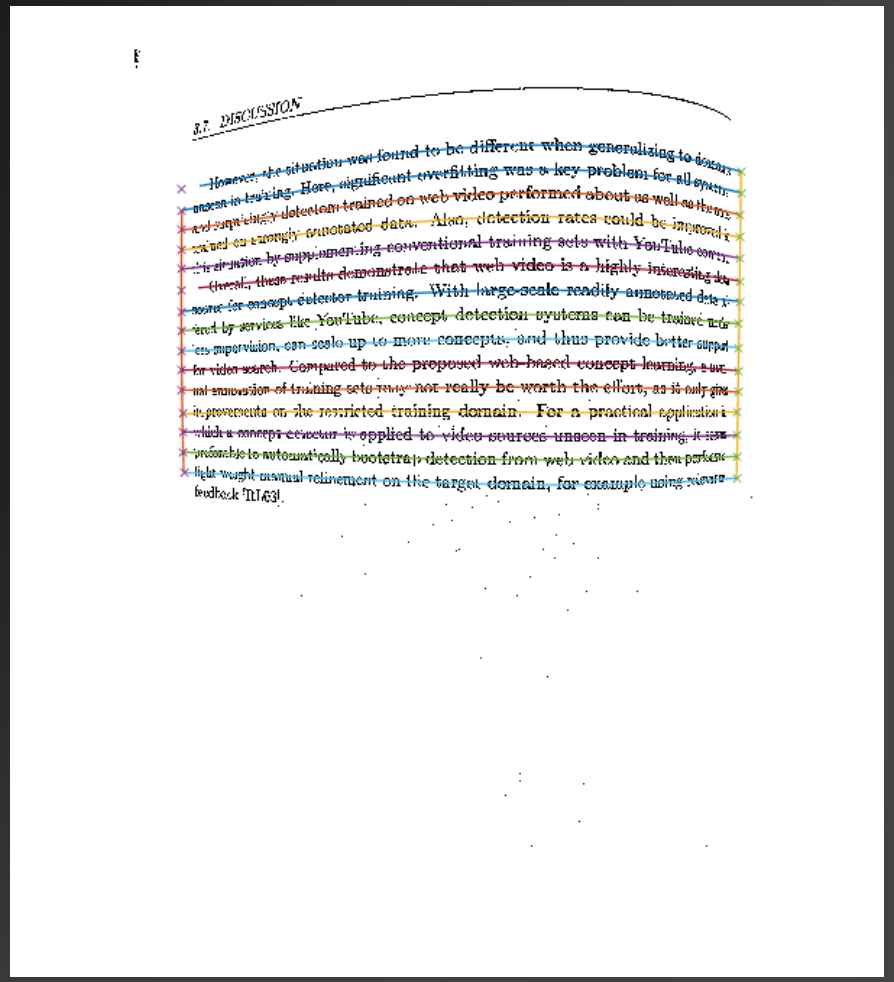


AFTER

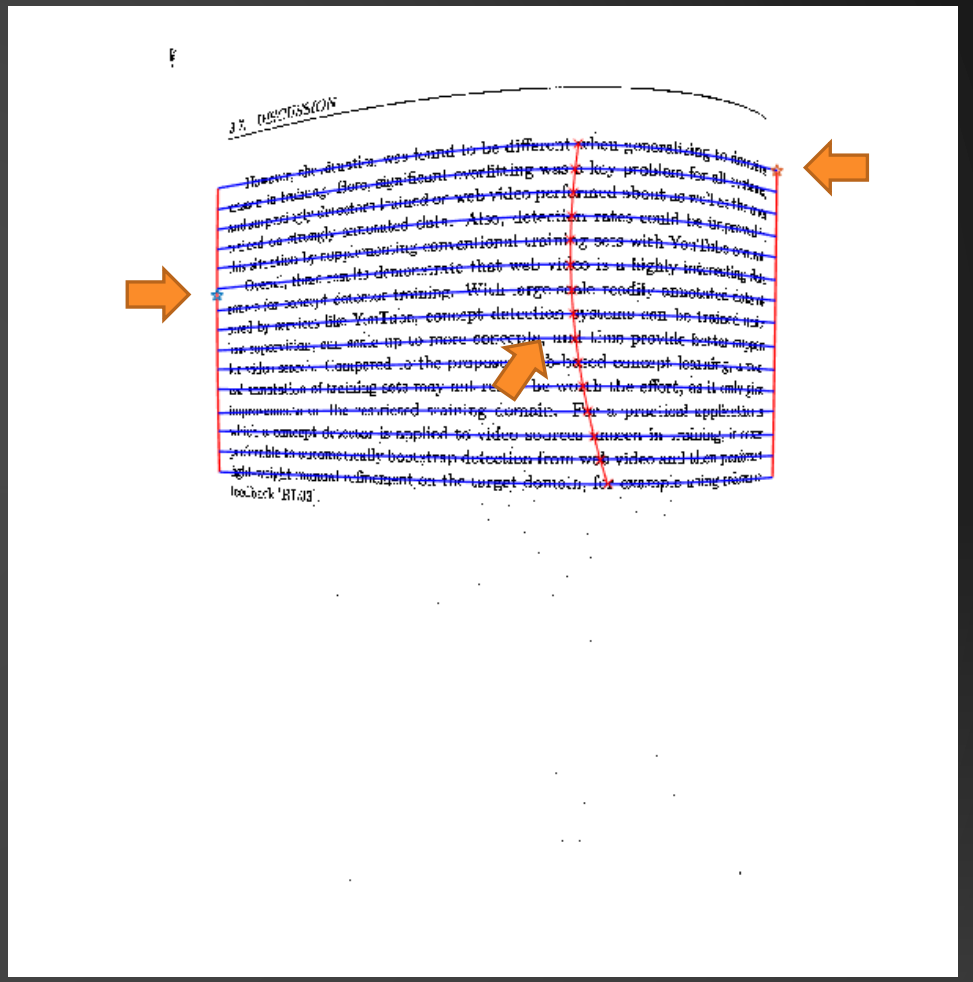


STEP 5. CALCULATE REFERENCE POINTS (LOCAL MIN/MAX OF TEXTLINES, LEFTMOST POINT ON LEFT BORDER, RIGHTMOST POINT ON RIGHT BORDER)

BEFORE



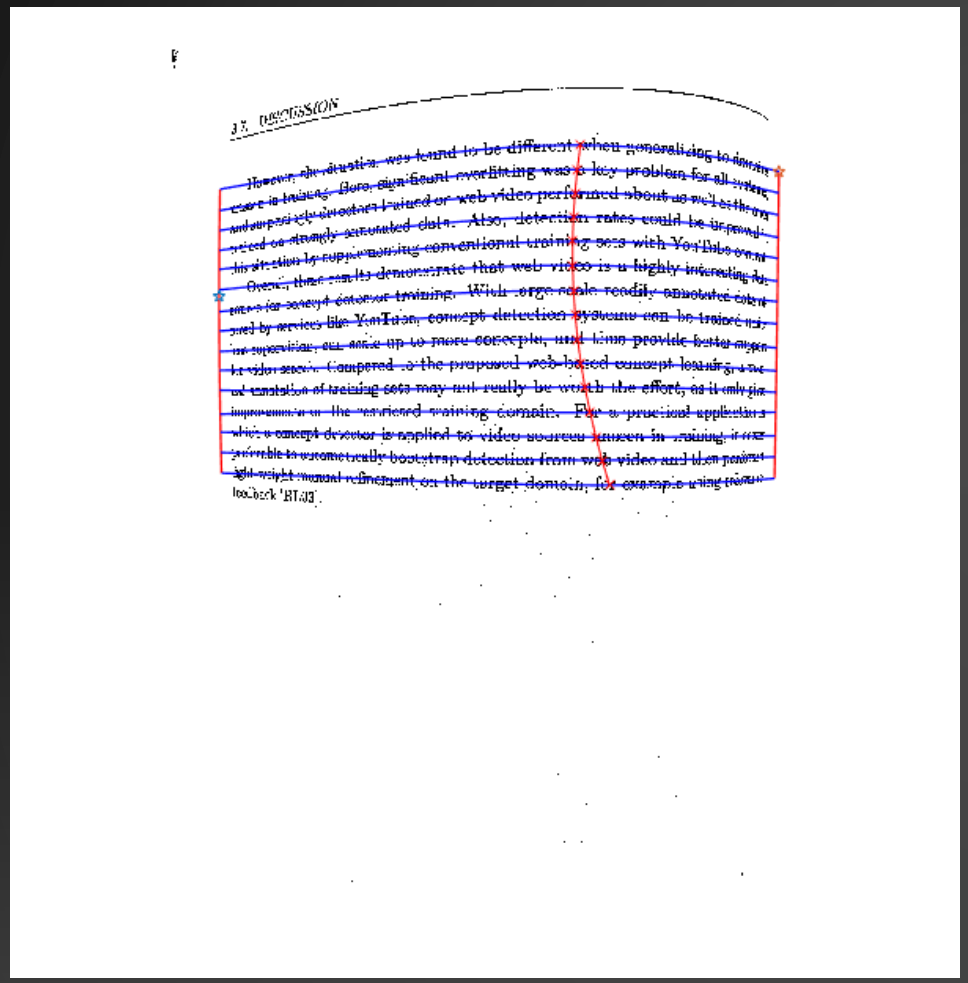
AFTER



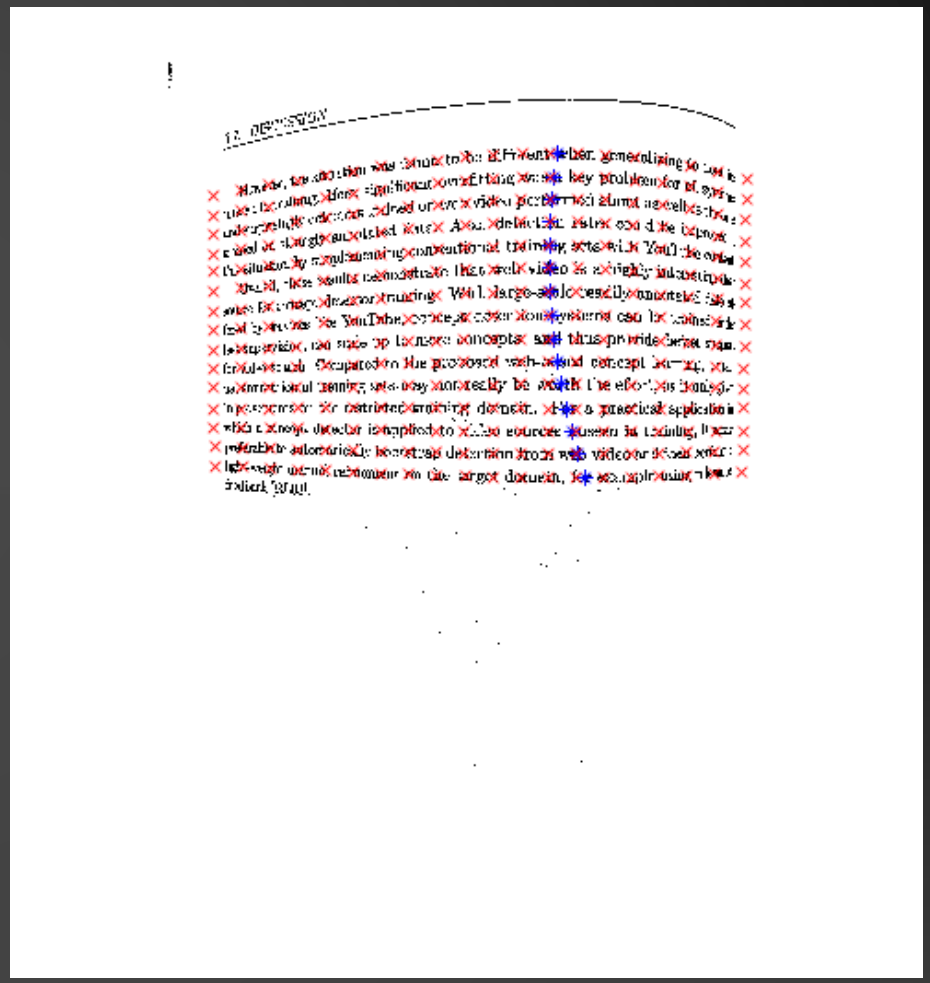
STEP 6. GENERATE MOVING POINTS (INITIAL GRID POINTS) ON TEXTLINES

15

BEFORE



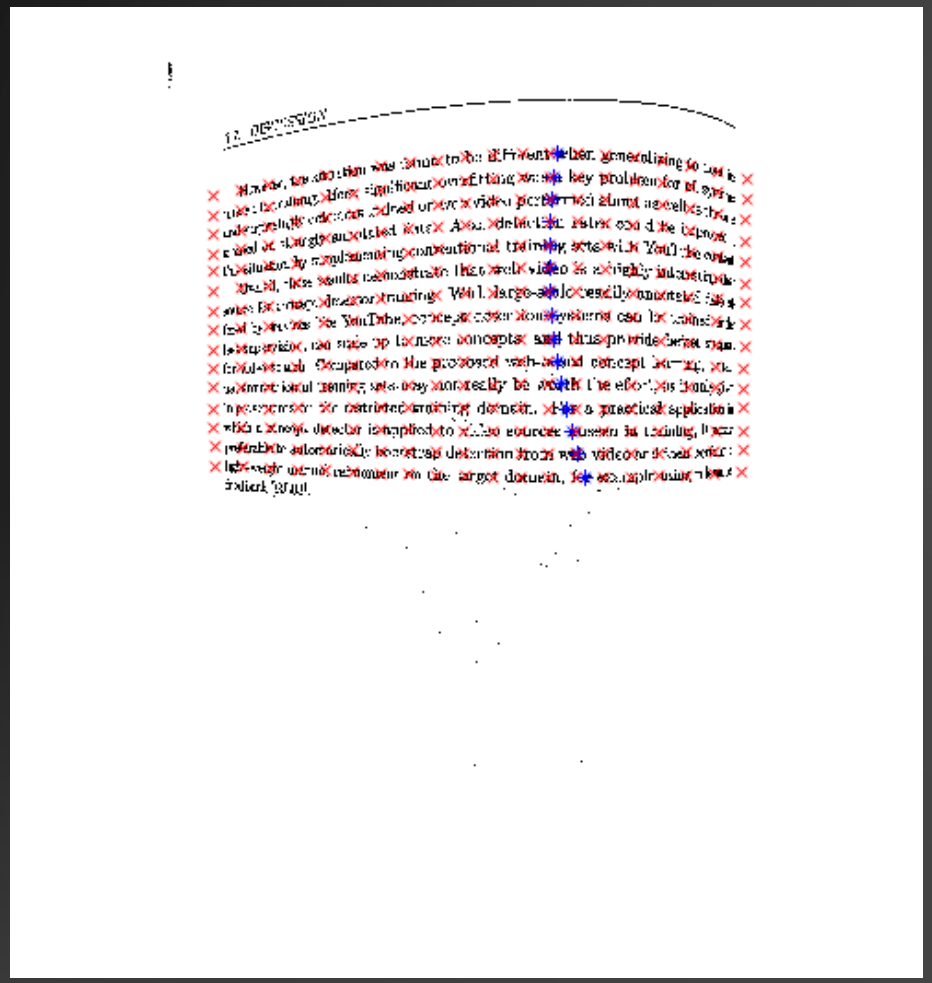
AFTER



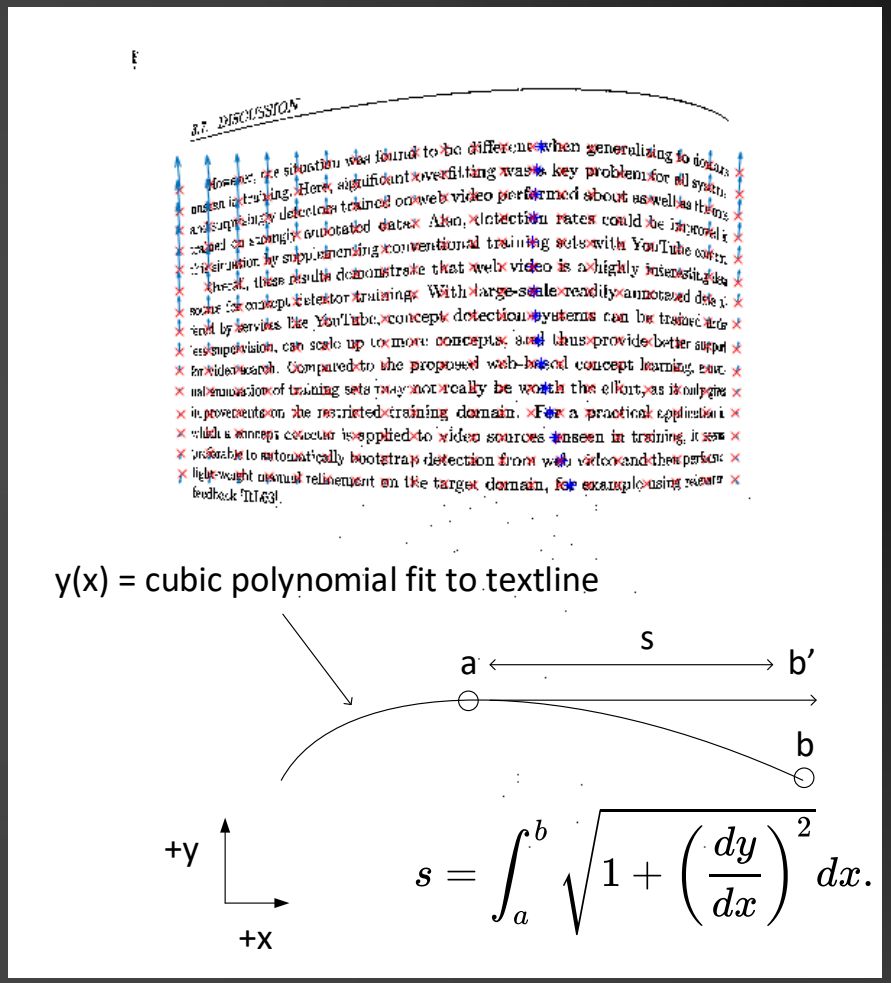
STEP 7. CALCULATE FIXED POINTS (MODIFIED GRID POINTS)

16

BEFORE



AFTER



y(x) = cubic polynomial fit to textline

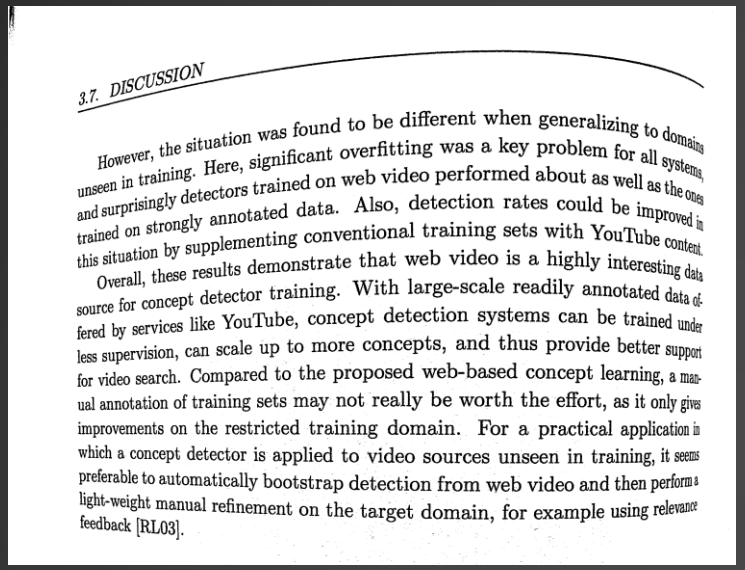
$$s = \int_a^b \sqrt{1 + \left(\frac{dy}{dx}\right)^2}\, dx.$$

RESULTS (1): DEWARPED IMAGES

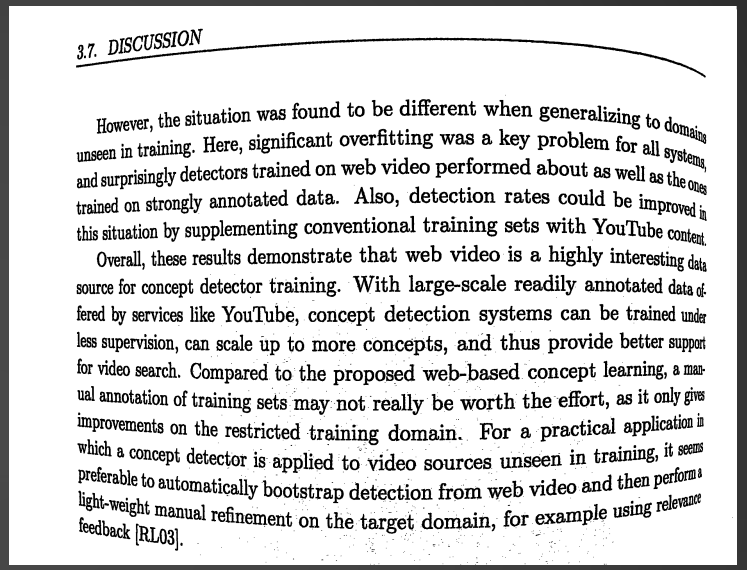
17

tform = fitgeotrans(movingPoints, fixedPoints, 'polynomial', N)

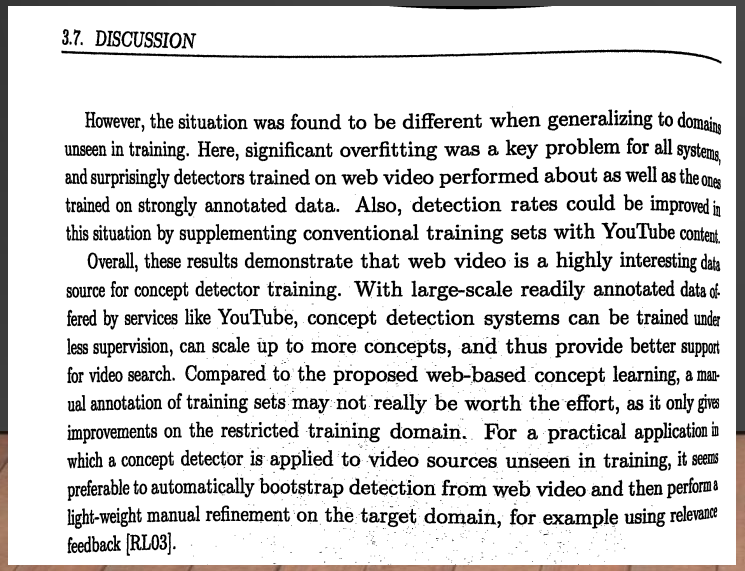
Original



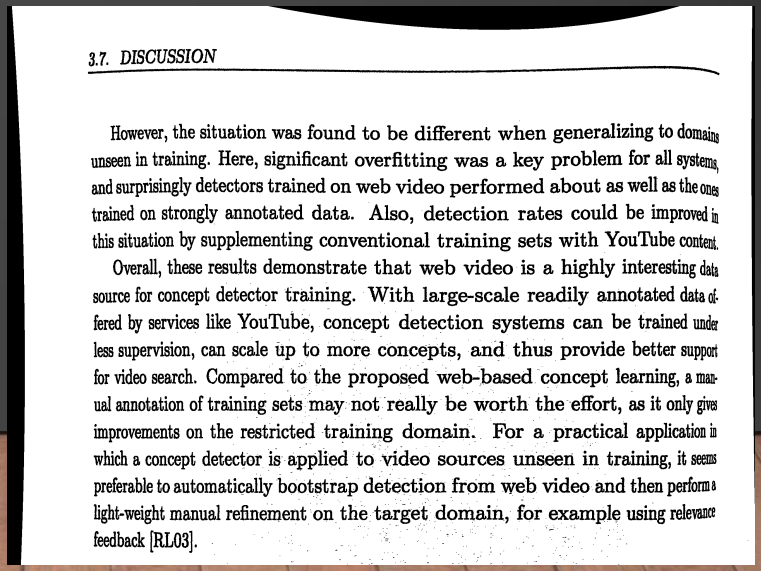
N = 2



N = 3



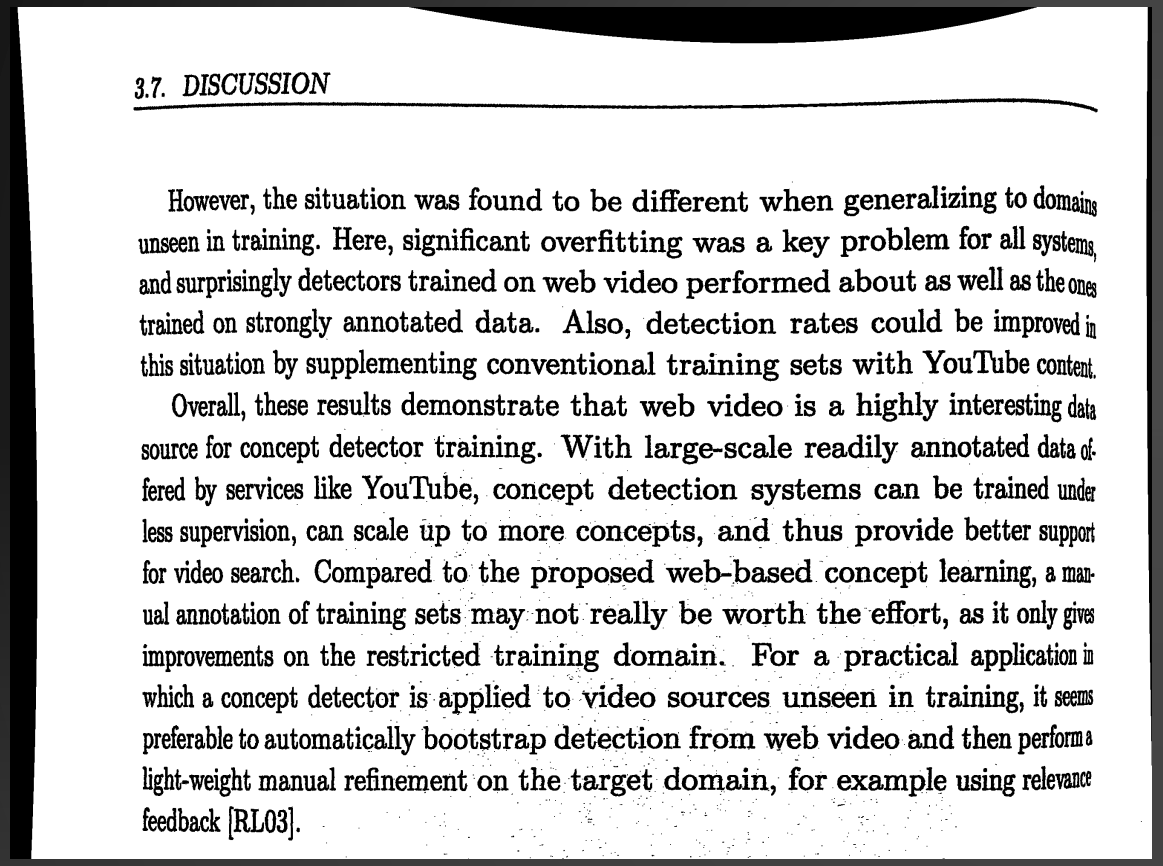
N = 4



RESULTS (2): OCR PROCESSING OF DEWARPED IMAGE

18

POLYNOMIAL TRANSFORM (N = 4)



3.7. *DISCUSSION*

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OCR RECOGNIZED TEXT

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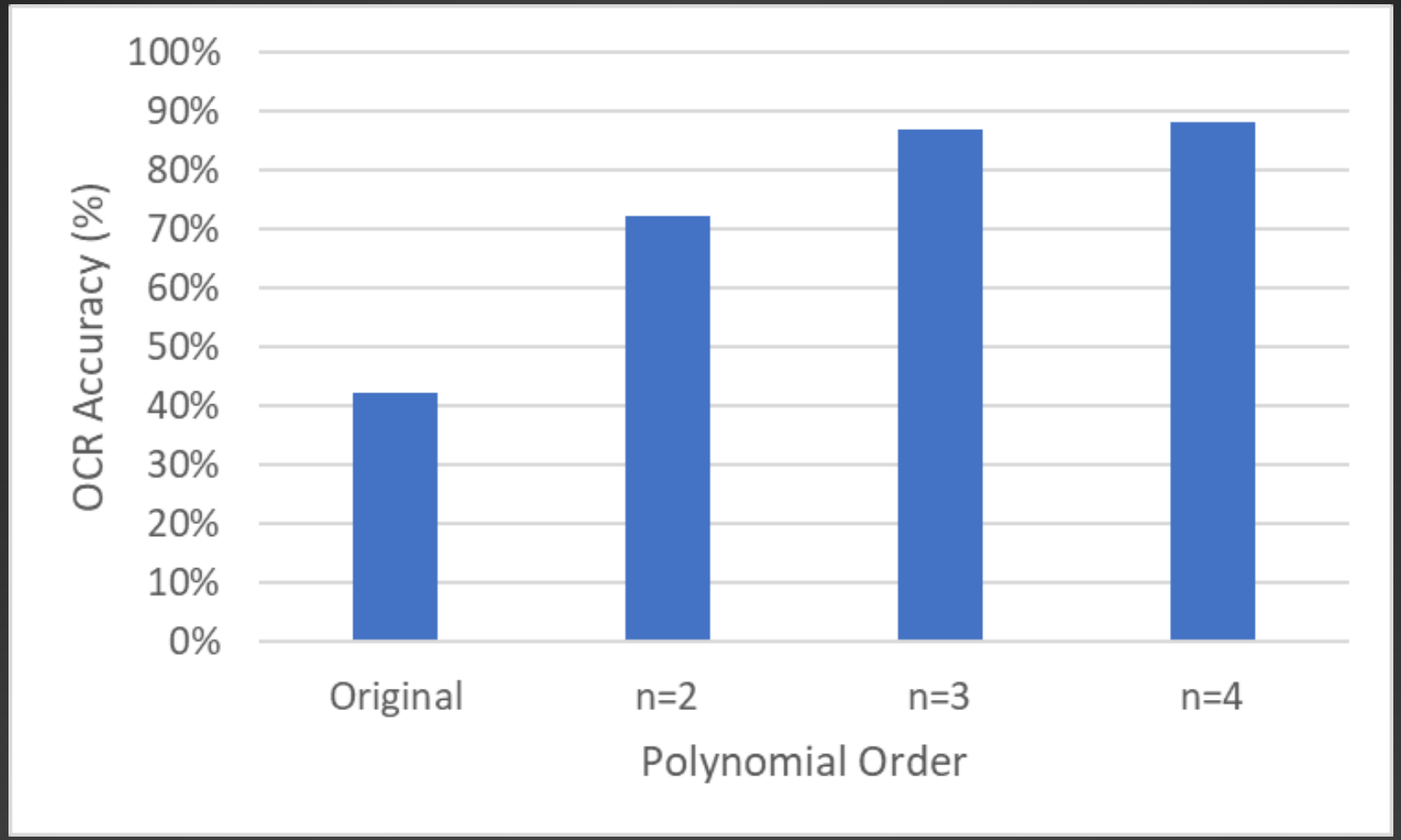
Overall, these results demonstrate that web videos is a highly interesting data source for concept detector training. eWith large-scale readily annotated data offered by services like YouTube', tconceplit detection systems can be trained under less supervision, can scale up to more concepts, 5and{ thus provide better support for video search. Compared the proposed 'vve___b-l__lb_ased.ii"concept learning, a manual annotation of training ysetslfrnay:-notl.'réallyS be lvvorth-' the "effort, as it only gives improvements on the restricted —trainin.g domain;. For pracfltical applicationin which a concept detector' is'-applied eto:i{vfide¢ sources': yl11l_r1.'sLe'ely1 training, it seems preferable to automatically "bootstrapl detection pfrolm vveb videofand then perform lightweight manual refinementon,.the;*tvargetf for example using relevance feedback [RL03l- s r _ g v = =

RESULTS (3): OCR ACCURACY VS POLYNOMIAL ORDER



DISCUSSION

- Run time: ~10 seconds per image
- Top OCR Accuracy: 88%, (n = 4)
- Best reported OCR Accuracy: 95-100% [REF]
- Requires manual adjustments to connected component analysis
- Dewarping method is least effective near left/right borders
- No line/paragraph spacing adjustment

Y. Tian and S. G. Narasimhan, "Rectification and 3D reconstruction of curved document images," *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, pp. 377–384, 2011.

CONCLUSION

- Most basic dewarping method is implemented from scratch using Matlab, binary image processing, vector calculus
- Better open source algorithms available in C, Matlab, Python, and possibly many others
- Chi Zhang, chi.zhang@ucalgary.ca