# EN.600.461 Computer Vision
# Final Project
# Recognizing and Translating Text from Images

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## Abstract

This work explores optical character recognition (OCR) in photos of typed and handwritten documents. It first explores basic preprocessing of photos of documents using `OpenCV` [1] functionalities for blurring, thresholding, and denoising. It next discusses the use of `tesseract-ocr` [2] to perform OCR. We then discuss the incorporation of the Google Cloud Translation API [3] to translate the OCR results to different languages. It finally discusses template matching using the Johns Hopkins University (JHU) logo and signatures of three U.S. presidents on sample document images.

## 1 Introduction

This work achieved the following main goals stated in the original proposal: 1) Given a photo of a document, convert it into a clean scanned version; 2) Take the scanned version and perform OCR. Optionally, this work took the OCR output and translated the text into different languages using the Google Cloud Translation API. This work also experimented with template matching using the JHU logo in order to determine whether the input document is an official JHU document or not. Lastly, this work performed CNN training on the MNIST handwritten digit dataset as an experiment.

## 2 Methods

In this section, we discuss the methods we took and external libraries used for each stage of our work.

### 2.1 Image Preprocessing

We implemented our program in Python using `OpenCV`. In order to feed the OCR algorithm clean input to achieve best performance, we used `cv2.medianBlur` to smoothen the input image with an aperture size of 5. Then, we performed binary thresholding on the smoothened image using `cv2.adaptiveThreshold` with *adaptiveMethod*= `ADAPTIVE_THRESH_GAUSSIAN_C`, *threshold = binary*, *blockSize=5x5*, and *C=2*. The adaptive method we selected uses the weighted sum of the *blockSize* x *blockSize neighborhood of pixel (x, y) - C* as its threshold value. Parameter values were chosen empirically.

Finally, we performed denoising on the thresholded image to remove noise and make the output clean. We used `cv2.fastNlMeansDenoising` with *templateWindowSize=7*, *searchWindowSize = 21*, and *h=7*. Parameters here were also chosen empirically. The motivation behind denoising in our work was that document scans usually have many random specs spread throughout. Such noise can greatly reduce OCR accuracy because an OCR algorithm may confuse a random spec with punctuation marks or associate a spec with an actual character near by (e.g. confuse an *l* and ' with an $i$).

### 2.2 OCR

In order to perform OCR on the preprocessed inputs, we used the `tesseract-ocr` library

[1] http://opencv.org/

[2] https://github.com/tesseract-ocr

[3] https://cloud.google.com/translate/

through its python wrapper pytesseract. We used the raw output from pytesseract's image_to_string method to pass into python's file writer and Google Cloud Translation API.

As a side experiment, we used the Keras[4] library to train the MNIST[5] dataset of 70,000 handwritten digits on three different convolutional neural networks (CNN). We referred to code available online[6] to build the three CNNs.

### 2.3 Text Translation

We made use of Google Cloud's Translation API in order to translate the OCR processed document into several different languages based on user command line input. We referred to external code[7] and modified the details to fit our purpose.

### 2.4 Template Matching

Aside from OCR, which was the main focus of this project, we experimented with template matching in images. We tested with various targets. First, we targeted to identify signatures of U.S. Presidents Barack Obama, George W. Bush, and Bill Clinton in document images. Our dataset consisted of hand-written letters written by the three presidents as input images and their respective signature images as templates. Performance for this experiment was poor, and we decided to experiment with an easier, fixed template. Potential reasons for low performance are described below.

After experimenting with signatures of U.S. presidents, we used the JHU logo to determine whether the input document was an official JHU document or not. We simply assumed that official JHU documents contained a JHU logo for our experimental purposes. We used cv2.matchTemplate with our input document as the source image, multiple JHU logo images (each with different sizes since cv2.matchTemplate is scale sensitive) as templates, and matching method cv2.TM_CCOEFF_NORMED. If the normazlied TM_CCOEFF value came out to be greater than 0.51 for any of the input JHU logo templates of various sizes, we determined that the input document contained a JHU logo in it. The matching method and determinant value of 0.51 were chosen empirically.

Performance for the JHU logo template experiments was better compared to that of the U.S. president signature experiments. The reason that the task is harder for the earlier experiment is that the JHU logo is fixed in terms of how it is comprised (lines, curves, color density, etc.) where as signatures vary each time it is signed (penstroke width, curvature, ratio of one part of the signature to another, etc.). Therefore, we think that the "signature matching task" bears more resemblance to an object recognition task than an OCR task.

## 3 Results

Here, we qualitatively discuss OCR results on typed and handwritten input documents.

### 3.1 Typed Documents

We ran our code on seven document images with different font types and font sizes. The images were cv_proj_description.png, cv_jchoi_proposal.png, aesop_fox.png, lav_notes1.png, aesop_miller.png, aesop_goose.png, and aesop_cat.png.

With the exception of aesop_goose.png, performance on all documents were nearly perfect. A sample input image is shown in Figure 1. The reason that aesop_goose.png did not produce satisfactory results was that the font in the document was relatively thick and bold. Therefore, after the preprocessing stage, the alphabet characters in the thresholded document were hollow with just the edges remaining. Therefore, the OCR algorithm could not recognize any of the characters in this text.

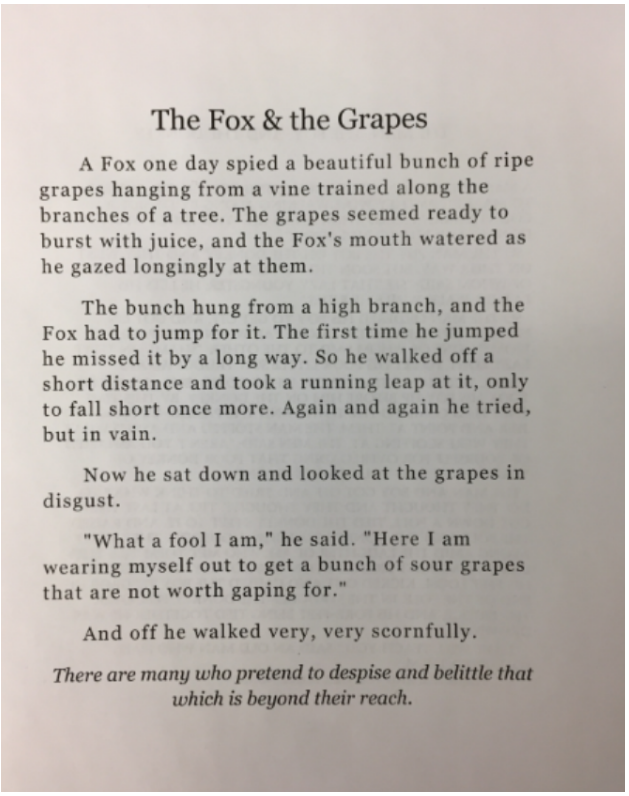
The two images cv_jchoi_proposal.png and lav_notes1.png were taken under sub-optimal conditions: irregular lighting, partial skew, and/or glossy surfaces. We ran our code on these two document images. Moreover, these documents had mixed font types and sizes, and the structure of the document was more complicated than the previous inputs. Despite the less optimal settings, we correctly denoised and thresholded the images and got similar results as before.

[4] https://keras.io/

[5] http://yann.lecun.com/exdb/mnist/

[6] http://machinelearningmastery.com/handwritten-digit-recognition-using-convolutional-neural-networks-python-keras/

[7] http://github.com/mouuff/mtranslate



The Fox & the Grapes

A Fox one day spied a beautiful bunch of ripe grapes hanging from a vine trained along the branches of a tree. The grapes seemed ready to burst with juice, and the Fox's mouth watered as he gazed longingly at them.

The bunch hung from a high branch, and the Fox had to jump for it. The first time he jumped he missed it by a long way. So he walked off a short distance and took a running leap at it, only to fall short once more. Again and again he tried, but in vain.

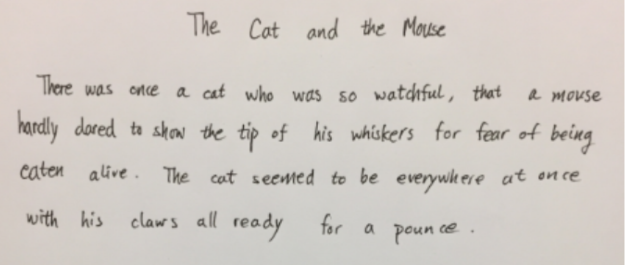
Now he sat down and looked at the grapes in disgust.

"What a fool I am," he said. "Here I am wearing myself out to get a bunch of sour grapes that are not worth gaping for."

And off he walked very, very scornfully.

*There are many who pretend to despise and belittle that which is beyond their reach.*

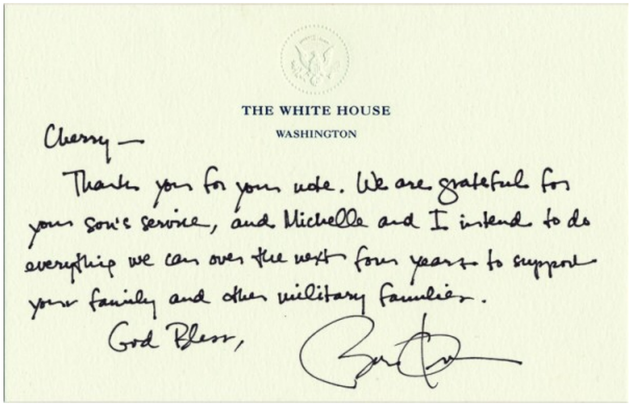
Figure 1: Sample typed document aesop_fox.png



The Cat and the Mouse

There was once a cat who was so watchful, that a mouse hardly dared to show the tip of his whiskers for fear of being eaten alive. The cat seemed to be everywhere at once with his claws all ready for a pounce.

Figure 2: Reasonably handwritten doc hand_cat.png



THE WHITE HOUSE
WASHINGTON

Cherry —

Thank you for your note. We are grateful for your son's service, and Michelle and I intend to do everything we can over the next four years to support your family and other military families.

God Bless,

Figure 3: Less neatly handwritten doc obama1.png

### 3.2 Handwritten Documents

We applied our code on photos of handwritten documents. Performance on very neatly written documents (hand_fox.png and hand_goose.png) was nowhere close to what we saw for the printed dataset. Moreover, any reasonably neatly handwritten documents (hand_miller.png and hand_cat.png) showed even poorer performance. Figure 2 shows one of our reasonably neat images hand_cat.png. Furthermore, our code was not able to detect a single word from document images with much less neat handwriting. Such images were obama1.png, obama2.png, obama3.png, bush1.png, bush2.png, clinton1.png, and clinton2.png. Figure 3 shows obama1.png.

## 4 Conclusion

We explored optical character recognition on photographed documents in various settings and formats. We tested with optimal and suboptimal photography settings, expreimented with documents using various fonts, and compared performance on printed and handwritten documents. For printed documents, we saw highly accurate results under both optimal and suboptimal settings, even if they contained various font sizes and font types. However, we were not able to achieve accurate results with handwritten document photos, disregarding the neatness of the handwriting. For sufficiently small portions of handwritten documents (e.g. a single word or a short sentence), the OCR algorithm was able to produce correct output occasionally. However, even this was not often enough to be considered reliable.

Nonetheless, on typed documents, we were able to effectively preprocess the document image and perform OCR on the cleaned data. Moreover, we leveraged the Google Cloud Translation API to translate documents into several different languages. Our final experiments on template matching also deserves future development into a project of its own.

## How to Run the Code

Please extract `FINAL_PROJECT_jchoi100.zip` to view and run the code.

Assuming that the user has installed Python 2.5+, `OpenCV`, `pytesseract`, and `tesseract` (with dependencies), run the following command in the same directory as `driver.py`.

**Command:**

```
$python driver.py {path-to-image-file} {list of target languages separated by single space}
```

**Sample usage:**

```
$python driver.py data/doc7.png es fr ko
```

The sample command above performs OCR on `doc7.png`, outputs the thresholded image, the text in the original input language, and the text translated in Spanish, French, and Korean.

## Saved Output from Run Experiments

The output that we created by running our code on all the images in our dataset are saved under `FINAL_PROJECT_jchoi100/code/data`.

## Acknowledgments

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