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CISC 642

Final Project

Our project goal is to count the number of heads in a given image taken from an overhead angle. First, we needed to extract globs from the image that have the potential to be heads. Then we calibrate Adaboost, a machine learning algorithm that we train with images containing heads and images without heads in them. Then our candidates are given to Adaboost, and using the thresholds we’ve established in our training data, the candidates are classified as heads or non-heads.

We tried many different methods to extract candidates for our Adaboost algorithm. In our first attempt, we used an algorithm that detects circles in an image and returns their center point and radius. This failed, because not all heads are circular. People with long hair do not produce a circular shape when their picture is taken from above. We also tried detecting hair by searching for blobs in the image and creating a window around the centroid. This proved ineffective, as some people’s hair (particularly women with blonde highlights) wouldn’t be detected as a blob due to having multiple colors. We also tried detecting candidates obtaining a binary matrix from the Laplacian of the image, then apply connected component labeling to join alike features to establish regions within the image. Markers for checking heads would be placed at the borders of different regions. This failed as well, because there would be too much noise in the image to accurately grab head-like objects. The method we settled on using is background subtraction.

We used training data to train Adaboost for head identification. Our training data consists of pictures that contain a head and pictures that don’t contain a head. We use 3 measures to classify images, contrast (measure of intensity contrast between a pixel and its neighbor over the entire image), the SSD of the inverse Gaussian, and entropy (for texture analysis) of the images. We then set arbitrary thresholds for each of measurements in an attempt to maximize the amount of correct head classifications and minimize the incorrect classifications.

We used various approaches to improve the feature space. These approaches include: Best SSD match and best mean match to baseline head images we took, SSD match to Gaussian and inverse Gaussian, image circle count, texture at center of image using Canny, Surf and Harris features, entropy, and contrast. We also attempted various ways to simplify the image: erosion, Gaussian and mean filtering, multi-level thresholding, binary images, background subtraction, and morphological opening. For future implementations, we could use a still camera to obtain images so that we apply background subtraction to its fullest ability and then attempt many of the techniques we had tried before. We think due to our difficulty with getting good features we would likely move away from Adaboost in the future for a more robust segmentation strategy.

Because of our poor performance with Adaboost, we attempted another algorithm that we will call back\_entropy for sake of discussion. Back\_entropy worked by first performing frame differencing background subtraction. This form of background subtraction does better with cameras that are not perfectly still which was our case. From that we perform erosion twice using a disk to further segment the image and reduce noise. To further reduce noise we perform a median filter of the image. We then label connected components giving us a number of heads.

This algorithm proved to work much better, and in our test images where it counted heads with a error 1 head. While this algorithm was not our primary focus, we still wanted to complete the task of head counting with a small error. We can also use this to compare to Adaboost. This shows that Adaboost is not a particularly effective algorithm for top down head counting.

Overall, we encountered many problems in our attempts to count heads. Unusual hair colors, hats, and hoodies make it difficult to distinguish a head from an object. Views from above force us to rely mostly on hair, so we can’t use facial recognition techniques to identify a head. Our attempt to tackle this problem was unique in that we were trying to use only one image for head detection. This proved to be much harder than we thought it would be, and after switching our method to include background subtraction we noticed a sizeable improvement in the quality of our candidate selection.

Resources:

<https://www.microsoft.com/en-us/research/wp-content/uploads/2011/02/Alvaro_Soto.pdf>

<http://crcv.ucf.edu/projects/crowdCounting/index.php>

<https://www.youtube.com/watch?v=TPjmsha6gWY>

<http://www.vanaheim-project.eu/assets/BalaSubburamanDescampsCarincotte-PETS-2012.pdf>

https://www.ics.uci.edu/~dramanan/teaching/cs117\_spring13/lec/bg.pdf