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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. These candidates are given to Adaboost, a machine-learning algorithm, to determine if the extracted object is actually a head.

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

The method we settled on applied a Laplacian filter to the image to capture the gradients of the image. Then we use connected component labelling to distinguish different regions within the image. Then we iterate through this new matrix, looking for border regions. Once a border is found, a marker is placed and the borders in the surrounding area are erased to prevent duplicate areas being covered by the Adaboost algorithm. The result is a series of relatively evenly spaced points in which surrounding area is most likely to contain a head. This process involved a lot of guessing and checking algorithms to get the best results.

We use 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: SSD best and 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. Looking to the future we would definitely use a still camera to obtain images so that we could use 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 method for finding candidates could have be improved by implementing background subtraction to separate moving objects in the foreground from the objects in the background. This could speed up our candidate finding process and make it more accurate, but we opted to try identification through one still image because we lacked the equipment to take pictures from a consistent overtop angle. We attempted background subtraction from the images we had but it proved to help very little as the pixels were not lined up. We also went over dozens of different combinations of calculations to achieve the best possible accuracy for our head classifications, but could obtain little accuracy due to the differences in heads from person to person.

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