AUTOMATIC FACE ROTATION: IMPROVED DISPLAY ORIENTATION FOR HANDHELD DEVICES USING CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT

We propose an improved method of rotating smartphones, tablets, and other device displays with Automatic Face Rotation using a convolutional neural network (CNN). Many users of smartphones and tablets experience a problem with their device screen being oriented the wrong way during use. This paper introduces a new algorithm to fix that issue by correctly orienting the screen relative to the user’s face using a CNN. The CNN model is trained to predict the rotation of faces in a variety of environments. The algorithm uses a confidence threshold and analyzes multiple images to be robust. Our solution solves the existing rotation problem, is battery and CPU efficient, and causes no noticeable lag to the user during use.

1 INTRODUCTION

The current basic method to orient handheld displays on devices like smartphones and tablets is to use gravity. Unfortunately, this method fails when a user lies down to one side, or when the device is flat as figure 1(a) illustrates. In a survey of 513 smartphone and tablet users from 2012, 91% reported that they have experienced incorrect autorotation with their devices, and 42% answered that they experience it several times a week or more [11]. To combat this issue, devices commonly have a native software feature to lock the current rotation state. For example, the original Apple iPad (released in 2010) has a hardware switch to lock and unlock the native gravity-based rotation. This solution requires user input, and 58% of users forget to unlock the rotation [11]. These statistics show need for a solution.

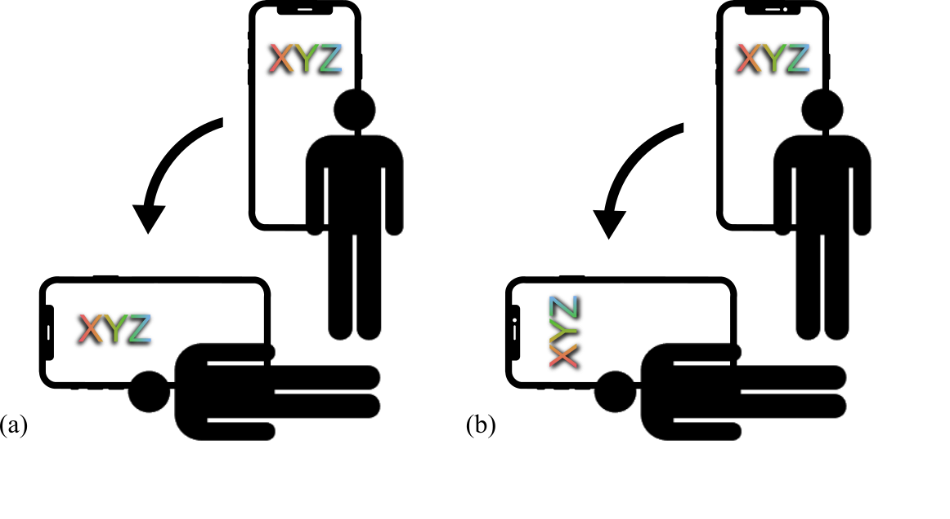
We propose Automatic Face Rotation (Auto-Face) which correctly orients a display requiring no user input. This paper introduces a new robust algorithm in section 2 which analyzes multiple images from the front-facing camera using a VGG-style convolutional neural network (CNN). Auto-Face yields correct orientation because it rotates the display relative to the user’s face and how the device is being used rather than simply relative to gravity. Experiments in section 3 show that Auto-Face is battery efficient, robust, and does not introduce noticeable lag when rotating.

Figure 1. The user lies down and the screen rotates incorrectly in (a). The correct orientation is shown in (b).

2 AUTOMATIC FACE ROTATION

We present Automatic Face Rotation (Auto-Face) which uses gravity to detect rotation changes, then uses a CNN to provide correct orientation. It is possible to constantly use a CNN without gravity-based input, but it is drastically more efficient to use the two together as Table 4 in section 3 shows.



Figure 2. **Auto-Face Overview.** Rotation is detected relative to gravity, then 2 images are analyzed by the CNN. Then, if there is low confidence or inconsistent analyses, more images are taken for analysis. Otherwise, the display is oriented according to the users face.

Once a rotation change is detected, it is immediately known that there are only two possible orientations: the previous orientation or one relative to gravity (*portrait* or *landscapeLeft* in Figure 2, step 1). This is because there is always only one orientation relative to gravity, and there is a possibility that the user lied down and the display should remain at the previous orientation. The next step is to capture images from the front-facing camera and analyze them with a CNN. At this point, more images are captured and analyzed if there is low confidence or inconsistency in the analysis. Finally, Auto-Face either confirms that the gravity orientation is correct or will override gravity orientation and keep the previous orientation. With this method, the user can lie down and maintain correct orientation on their device without explicit input.

2.1 CUSTOM CNN

We’ve created and trained a custom convolutional neural network to identify the face of the user and determine the correct orientation. Orienting a display is framed as a 4-class classification problem: classify an input image as one of four orientations: *portrait*, *upsidedown*, *landscapeLeft*, and *landscapeRight*. The *upsidedown* orientation can most likely be omitted in the future because only 1 user responded that they use their device *upsidedown* about once a week. With fewer classes, the CNN can be smaller and therefore more efficient. The model was trained using categorical cross-entropy so it outputs four numbers that sum to 1, each representing the confidence of the image belonging to its class (refer to Table 2).

**Architecture Design.** The CNN architecture is most important for engineering efficient image analysis models. The size and efficiency of CNNs are characterized by the number of parameters they have, which depends on the architecture. The number of parameters directly influences the number of calculations that are executed during image analysis, and of course, more calculations take more time. A CNN that is too big (has too many parameters) will not be able to analyze images quickly. On the other hand, a CNN that is too small will not learn very well and will have many misclassifications.

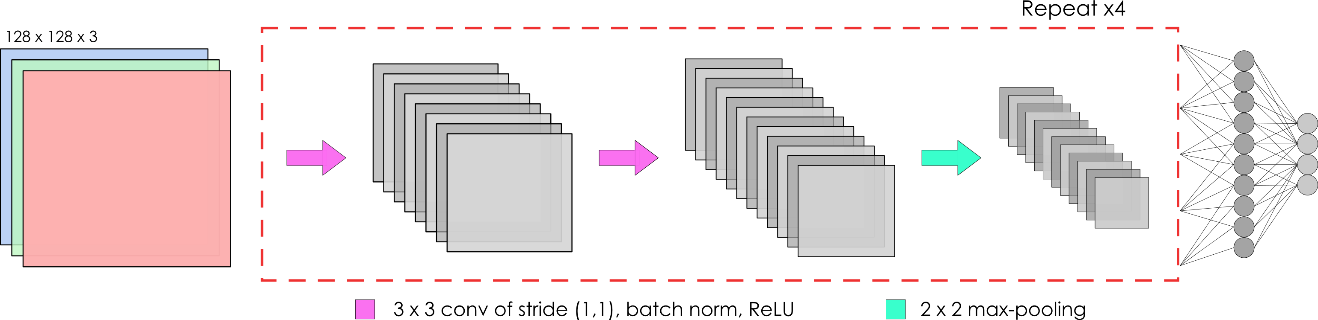


Figure 3. **Network** **Architecture.** Images are scaled once to 128x128 pixels then fed through a series of 3x3 convolutions with a stride of 1 in both and directions, batch normalization, and ReLU activation. After max-pooling, those layers are repeated 4 times. The last two layers are fully connected.

Our network needs to be small enough to quickly analyze images so that the user does not notice lag before rotation. Our model uses a VGG-B style [13] network shown in figure 3. The architecture is composed of four iterations of two convolutional layers followed by a single max-pooling layer. In our testing, adding more iterations and reducing the neurons in the second to last layer helped the model’s accuracy and reduced its size.

**Training.** We selected the Helen dataset to train our network because the majority of images had faces that were looking at the camera lens, which is like how a user would be looking at a smartphone or tablet’s display while using it. To create our training data, every image was flipped horizontally, then rotated three times. Finally, the images were scaled down to 128x128 pixels. Additional data augmentation was used during training such as minor random rotations and brightness alterations. The images were also linearly blurred to simulate the user shaking their device while rotating. These techniques create a robust training set which allows our model to generalize well and increase accuracy.

During training, a dropout layer was used after each max-pooling layer to prevent overfitting. Our final network achieved 0.997 validation accuracy with 23,090 parameters.

2.2 ALGORITHM DETAILS

This algorithm should be invoked when the device changes rotation relative to gravity. It is the core logic of how Automatic Face Rotation makes decisions.

|  |
| --- |
| **Algorithm 1** Classifier with Confidence Threshold and Multiple Image Analysis |
| 1: *imageQueue =* analyzeImages  2: **do**: |
| 3: *imageQueue* += analyzeImages  4: *override* = true |
| 5: **for** *image* **in** *imageQueue*:  6: **if** *image*.confidence < **and** isInconsistent(*image*.prediction): |
| 7: *override* = false  8: **if** *override*:  9: return ‘OVERRIDE’  10: *imageQueue*.pop |
| 11: **while** (not analyzed images)  12: return ‘Low Confidence or Inconsistent’ |

**Confidence.** Misclassification may occur if an image is terribly blurry, dark, or bright, or if the user’s face is obstructed. To combat this, we define a confidence threshold on line 6. In order for the CNN to override gravity-based orientation, it needs to reach a confidence greater than some threshold on two consecutive images that it analyzes. If the first two images fail to meet the confidence threshold, then the program will continue to analyze images from the front camera up to images.

**Consistency.** The *isInconsistent* function ensures that the current image has predicted an orientation consistent with the other predictions from images in the *imageQueue*: if the orientation differs, then it is not consistent. The function also verifies that the prediction is one of the two possible orientations out of four because only two orientations are possible when rotating: relative to gravity and previous orientation. This is depicted in step 1 of Figure 2 when Auto-Face knows that either a *landscapeLeft* or *portrait* orientation is possible.

**ImageQueue.** Auto-Face analyzes a set of images (the *imageQueue*) to ensure correctness. This technique is analogous to using multiple keys to authorize a military strike in movies: all keys need to work in order to execute the operation. The parameter specifies how many images, or keys, to use in order to override gravity. The loop on line 5 ensures that all images in the *imageQueue* are above the confidence threshold and are consistent. Setting greater than 1 helps prevent misclassifications.

**Multiple Images.** To be robust, the algorithm may analyze up to images than are in the initial *imageQueue*. When the CNN is not confident or if the predictions are inconsistent, an image in the *imageQueue* is discarded and one new image is analyzed. This creates a sliding window that shifts over one image in the camera feed up to times. A total of images may be analyzed, but “OVERRIDE” is returned (line 9) as soon as Auto-Face is confident with its prediction. Thus, as few as images will be analyzed.

2.3 EXAMPLE OUTPUT

Auto-Face either returns “Low Confidence or Inconsistent” and the display is oriented based on gravity, or returns “OVERRIDE” and gravity is overridden. In Table 2, parameter equals 2 which means two successive images must meet threshold and consistency requirements. In the first sample output, the result is an override because both images are above a confidence of and are consistent. In the second example however, the first two analyzed images are below the confidence threshold. When this happens, a third image is analyzed and the first one is dropped. Unfortunately, the third image has low confidence as well, so the CNN predictions are discarded, and Auto-Face falls back on gravity orientation. No more images are analyzed because is set to 3, which is the maximum number of images to analyze before giving up and using gravity.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model | Class Confidence | | | | Result |
| *portrait* | *upside*  *down* | *landscape*  *Left* | *landscape*  *Right* |
| Gravity |  |  |  | 1 | OVERRIDE:  ***portrait*** |
| CNN | **0.93** | 0.05 | 0.01 | 0.01 |
| CNN | **0.93** | 0.06 | 0.01 | 0.00 |
| Gravity |  |  |  | **1** | Low Confidence:  ***landscapeRight*** |
| CNN | 0.54 | 0.23 | 0.11 | 0.12 |
| CNN | 0.56 | 0.20 | 0.11 | 0.13 |
| CNN | 0.51 | 0.26 | 0.11 | 0.12 |  |

Table 2: **Sample Outputs and Results from Algorithm 1.** Parameters: , , . CNN(1) is the first analyzed image, and CNN (2) is the second.

3 EXPERIMENTS

We tested Auto-Face in real-world environments to gauge its effectiveness. Using 20 participants (14 male) we put them through two tests and asked survey questions.

**Speed test.** In order to determine if there was any noticeable lag introduced with Automatic Face Rotation, users tested the speed of rotations on two apps: one with native rotation in iOS 12.4 (presumably gravity) and one running Auto-Face. Users were asked to identify if they were the same speed or if one was faster than the other on an iPhone 6 and an iPhone XS.

|  |  |  |  |
| --- | --- | --- | --- |
|  | Native is faster | Auto-Face is faster | Same speed |
| iPhone 6 | 7 | 0 | 13 |
| iPhone XS | 3 | 2 | 15 |

Table 4. **Noticeable Lag Test.** Users compared the rotation speed of native rotation vs Auto-Face. Parameters and were set to 2, 8, and 0.75 respectively (see Algorithm 1).

The majority of users were unable to determine which app was faster, especially on the iPhone XS with its faster processor. From the results in Table 4 we conclude that Auto-Face introduces no noticeable lag to the user on an iPhone XS, and that most users will not be able to notice lag on an iPhone 6.

Of course, Auto-Face does in fact take more time because of the additional image processing. On average, it takes 32 milliseconds (ms) to analyze a single image on an iPhone 6, and just 9ms on an iPhone XS (Table 5). We asked users if they would enable or disable Auto-Face knowing that there may be some minor lag during each rotation. All 20 users responded that they would enable the feature.

**Real-World Performance.** Users were instructed to hold the device in portrait and then lay down where it was recorded if Auto-Face oriented the display correctly. Then, still laying to one side, the user successively rotated the device 4 times and read a portion of a pre-loaded webpage at each rotation. This was then repeated, laying down to the other side. Data was collected for each rotation. To best simulate real-world use, users were unaware of the camera being used and they were given a webpage with text to read and scroll as necessary. Furthermore, tests were performed in random locations on couches and beds to provide various backgrounds and lighting conditions for the CNN. Overall, Auto-Face correctly oriented the display in 61% of trials. This is an improvement over the previous solution from [11] who reported 10.7% accuracy with similar tests.

**Privacy Survey.** We asked users if they would use Automatic Face Rotation (as if it were programmed into the operating system) despite the front camera taking pictures every time the device was rotated. 18 users said they would use it, and 2 said it depended on the device manufacturer’s reputation since some companies have a history of negligence and/or intentional misuse of users’ data.

We then asked if users would allow random anonymous image data to be collected to improve Auto-Face. 10 users said yes, 3 said it depended on the manufacturer’s reputation, and 6 said they would not allow it. One person said that they would allow it only if they could choose what pictures were sent. For example, a notification to review the images would allow them to deny or allow them to be sent.

**CPU and Memory Usage.** We collected data about the CPU and memory usage using Xcode 10.3.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Idle\* | Analysis at 30 FPS~ | Max CPU+ | |
| 2 images | 8 images |
| iPhone 6” | 1.5% | 20% | 4.5% | 7.5% |
| iPhone 6 |  |  |  |  |
| iPhone XS | 0.5% | 7% | 1.5% | 2.2% |

Table 3. **CPU Usage of Auto-Face.** *\*Capturing images with the front camera at 30 frames per second (FPS) with default settings in iOS 12.4. ~Average over 2 minutes during constant analysis of 30 FPS. +The maximum amount of CPU used during a single rotation.*

4 RELATED WORK

Our work is most related to the work of [11] who presented iRotate: an automatic screen rotation method by augmenting the gravity-based solution. They used the same technique of running a facial detection algorithm when a rotation change is detected and orienting the screen based on the face. Instead of creating a custom CNN, they used a pre-built facial feature detection API from iPhone Operating System (iOS) 5. The API was not suited for the application, and the authors deemed it infeasible to use outside of informal experimentation. This paper proposes a custom CNN and introduces a novel algorithm for analyzing multiple images.

Another camera-based approach attempted to rotate a display by tracking the head tilt of user’s faces [6]. Unfortunately, this suffered from a narrow range of degree tilt (about 47 degrees away from *portrait*) [7].

Gravity-based solutions are popular, and various types of sensors have been used including mercury switches [1] and one or more accelerometers [2, 3, 8]. These give incorrect rotations when a user lies down or when the device is flat, but offer a manual toggle to correct it. Our solution fixes the problem when a user lies down, and requires no user input.

Further methods use the way a user holds their phone to distinguish orientations. One solution explores the position of thumbs on the edges of the front screen [9], and another senses an entire grasp from the placement of fingers around the edges and the palm on the back [10].

5 DISCUSSION AND FUTURE WORK

IR camera on iPhones can be used [4, 5]. Flat rotation can be improved.

A ALGORITHM DETAILS

C AUTO-FACE EFFICIENCY

We tested the efficiency of Auto-Face (algorithm 1) by setting to be three different numbers. Even though the CNN takes most of the time in the algorithm, table 3 times the entire algorithm 1 which includes some if statements and memory accessing.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Average time in milliseconds to analyze images | | | |
|  | 2 | 5 | 8 | 1\* |
| iPhone 6 | 65 | 163 | 260 | 32 2 |
| iPhone XS | 20 | 47 | 77 | 9 2 |

Table 5. **Average time taken to analyze images.** The time in milliseconds to analyze 2, 5, and 8 images was averaged over 20 trials. \**Average time per image plus or minus the standard deviation across all trials.*

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Laplacian edge detection