Link to data: https://atreus.informatik.uni-tuebingen.de/seafile/d/8e2ab8c3fdd444e1a135/?p= %2FTINY-CNN-Pupil%20Detection&mode=list

Tiny convolution, decision tree, and binary neuronal networks for robust and real time pupil outline estimation



Figure 1: The used process to train tiny models and improve their runtime as well as the used model.

ABSTRACT

In this work, we compare the use of convolution, binary, and decision tree layers in neural networks for the estimation of pupil landmarks. These landmarks are used for the computation of the pupil ellipse and have proven to be effective in previous research. The evaluated structure of the neural networks is the same for all layers and as small as possible to ensure a real-time application. The evaluations include the accuracy of the ellipse determination based on the Jaccard Index and the pupil center. Furthermore, the CPU runtime is considered to make statements about the real-time usability. The trained models are also optimized using pruning to improve the runtime. These optimized nets are also evaluated with respect to the Jaccard index and the accuracy of the pupil center estimation. Link to the framework and models.

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CCS CONCEPTS

• Computing methodologies → Machine learning; Image processing; Shape analysis;

KEYWORDS

Eye tracking, pupil ellipse, pupil center, neuronal network, binarization, pruning, quantization, decision tree

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1 INTRODUCTION

Eye tracking is finding more and more new areas of application such as driver monitoring [Braunagel et al. 2017; Liu et al. 2002], virtual reality [Duchowski et al. 2000; Guenter et al. 2012; Patney et al. 2016], augmented reality [Ishimaru et al. 2014; Pfeiffer and Renner 2014], surgery [Eivazi et al. 2016; Fuhl et al. 2016e; Oltean et al. 2001], market research [Hervet et al. 2011; Wedel and Pieters 2008], self-diagnostic systems [Anderson and Colombo 2009; Karahan et al. 2017; Tennant 1988], human computer interaction [Bulling 2016;

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Bulling and Gellersen 2010], sharing expert knowledge [Kübler et al. 2015; Reingold and Sheridan 2011] and many more.

One challenge that this diverse field of application brings with it is the need for a non-invasive solution that exists through imagebased eye tracking [Duchowski 2002]. However, different and new challenges arise due to lighting conditions, imaging techniques like RGB and NIR, but also due to the diversity of people [Fuhl et al. 2016f; Tonsen et al. 2016]. Another challenge that faces us today is the use of eye tracking on mobile devices. This is compounded by the challenges of the limited computing resources available on mobile devices and the limited runtime of the devices under full load. This resource restriction leads to the fact that still classical algorithms are used on mobile devices [Fuhl et al. 2016b, 2017a, 2016d; Santini et al. 2018]. These have the disadvantage that a constant runtime cannot be guaranteed and that they perform significantly worse than machine learning approaches under everyday conditions [Fuhl et al. 2019a, 2018c, 2019b]. In addition, classical algorithms have the disadvantage that they cannot be adapted to new challenges through training. Usually parts or the whole algorithm has to be revised or redesigned. The use of modern machine learning methods has already delivered significant improvements in pupil recognition [Fuhl et al. 2019a, 2018c, 2019b] but there has been little development in the area of real-time capable algorithms on limited resources.

In this work, we deal with resource-saving approaches of neural networks for pupil recognition. This is due to the fact that neural networks have a constant runtime, the training is simple compared to other machine learning approaches, and is not as susceptible to unbalanced data. On the one hand, we focus on the real time capability on only one CPU core. Furthermore, our evaluation evaluates individual challenges separately to better assess the applicability of the algorithms. For all evaluations, the runtime as well as the pupil center and pupil area are used. In the following, a summarizing list of key points is given for a a quick overview.

- **1** Trained models for real time pupil ellipse detection.
- 2 Runtime optimized Framework to train and use the models.
- **3** Evaluation for different challenges separately.
- 4 Evaluation regarding runtime, pupil center, and pupil area.

2 RELATED WORK

Work in the field of pupil detection is mainly concerned with the issue of robust and reliable detections. For this purpose, there are already a number of rule-based approaches that have been summarized for head-mounted eye tracking [Fuhl et al. 2016f; Tonsen et al. 2016]. Images for head-mounted eye tracking differ strongly from images for remote eye tracking, which is why these areas were considered separately over a long period of time [Fuhl et al. 2016a]. Their main differences are the lower resolution of the eye area for remote eye tracking as well as a changing perspective due to the movement of the head which leads to partial occlusions of one eye by the nose for example [Fuhl et al. 2018a].

In this work, we deal with pupil detection on images regarding head mounted eye tracking. Therefore, already published approaches in this field are described in detail in the following. The first major breakthrough in this area for pupil detection was the use of edges [Świrski et al. 2012]. Since edge images contain a

certain amount of noise, filtering methods were introduced which make it easier to detect the pupil in them [Fuhl et al. 2015, 2016d]. Based on this, methods for edge combination were presented to further improve the detection rate [Fuhl et al. 2016d; Santini et al. 2018]. The disadvantage of the purely edge-based methods is the exact positioning of the edges, which is strongly influenced by motion blur alone. To overcome this disadvantage, there were several approaches like Blob Detection [Fuhl et al. 2016d] and adaptive thresholding [Haro et al. 2000]. Based on the segmented image over a threshold, the detection rate could be further improved by splitting the segment into sub-segments [Javadi et al. 2015]. Each of these segments is then evaluated and the outline of the pupil is determined by several good subsegments [Javadi et al. 2015]. In the field of machine learning, there were also approaches for pupil detection. In the field of neural networks there was a window-based approach [Fuhl et al. 2016c, 2017b] which even fulfilled the real time runtime on a single CPU core. Window-based in this context means that an image is divided into small partial images and each partial image is classified individually. Other approaches were based on transposed convolution layers and generated segmentations [Fuhl et al. 2019a; Vera-Olmos and Malpica 2017; Vera-Olmos et al. 2019; Yiu et al. 2019]. A regression with integrated landmark detection was also presented which was trained in combination with a segmentation [Fuhl et al. 2019b]. Further approaches which are executable on a CPU core in real time compared to neural networks for landmark detection and segmentation are CBF [Fuhl et al. 2018c] and BORE [Fuhl et al. 2018b]. CBF [Fuhl et al. 2018c] is based on decision trees and a circular selection of features. BORE [Fuhl et al. 2018b], on the other hand, is based on an optimization procedure that can learn unsupervised and uses circularly oriented features. This unsupervised optimization is based on the selection of the best edges for a circular or elliptical object.

In this work, we evaluate neuronal network architectures for landmark detections which have a real-time executability on one CPU core as a requirement. With this, we follow the approaches of tiny architectures [Fuhl et al. 2016c] and landmark detection [Fuhl et al. 2019b] from the state of the art. In addition, we include the validity loss [Fuhl and Kasneci 2019] to obtain a quality measure for each landmark and therefore, a validity of the entire pupil.

3 METHOD

Figure 1 shows our initial model where we used the same architecture for the convolution and decision tree [Fuhl et al. 2020] based nets. Between the individual convolution blocks, max pooling is used. In addition, before the first fully connected layer of 1024 neurons, a 50% dropout is used to compress the learned weights. This compression of the weights is important for the pruning operation. The input of our model is a 144×192 gray scale image and the output are eight *x*, *y*, *validity* triplets. To train this small architecture successfully, we used model distillation [Hinton et al. 2015]. Here the small model is additionally trained by a large pre-trained model (See Figure 1). This is done by including the output of the large mesh as an additional loss function. For the large model, we used a ResNet34 and trained it first on the training data. As a regression target for our model, we used eight landmarks, which lie on the pupil ellipse, as was also done in [Fuhl et al. 2019b]. In addition, Tiny neuronal networks for pupil outline estimation

we used the validity loss [Fuhl and Kasneci 2019] with which a validity value can be assigned to each pupil ellipse, which, in our case, corresponds to the mean value of all eight validity values. To determine the ellipse parameters, we applied the OpenCV ellipse fit to the eight landmarks.

Since this small architecture alone is not enough to get a real real-time model, we applied two additional techniques for runtime reduction. One is binarization [Courbariaux et al. 2014] and the other is clipping. With binarization, all weights greater than zero are set to the fixed value of one and the negative weights to the value minus one. This means that for execution, the sign only has to be reversed in the case of minus one. We only used this binarization for the convolution layers, since the model would otherwise become too imprecise. For pruning, however, we used an iterative approach [Castellano et al. 1997]. This approach deactivates a convolution or decision tree and checks the influence on the accuracy by evaluating the model on the training data. The same applies to the individual neurons in the penultimate fully connected layer. In each iteration, all possibilities were tested and the one with the least influence was selected. This was continued until only 20% of the original model was left.

To further improve the accuracy of the pruned nets (pruning is also applied to the models with binary weights), we have used fine tuning. Here, the learning rate of the convolution layers is set to zero and only the fully connected layers are trained. For this step, we have used a learning rate of 10^{-7} . For the general training, we used a fixed learning rate of 10^{-5} . Additionally, we used the Adam optimizer with the parameters 0.9 for momentum and 0.999 for the second momentum. Weight decay has been disabled. The batch size was set to 200 and the whole training ran for two weeks on a server, which corresponds to an epoch number of $\approx 100,000$. For data augmentation, random noise, random occlusions, image overlays as reflections, image shifts, and bluring are used and applied online to the data.

4 EVALUATION

For the training, we used the data from [Fuhl et al. 2019a]. These are segmentations of the known pupil in the wild dataset [Tonsen et al. 2016]. For the evaluation, we used the segmented data from [Fuhl et al. 2019b] and an additional 1,000,000 images from the same studies [Kasneci et al. 2014; Sippel et al. 2014]. Thus, our algorithms were evaluated on over 1.8 million images.

In table 1 the naming convention of each challenge evaluated and its description as well as parameters are shown. Examples for each challenge are shown in Figure 2. As you can see, none of the challenges used, nor the combinations (C9 and C10), pose a problem for a human being. The algorithms, however, behave differently.

Figure 3 shows the cumulative accuracy of the algorithms separately for each challenge. The x-axis is the Euclidean distance between the found and true pupil center. As you can see, the slight blurring is not a problem for any algorithm (C1 and C2), but even a slight addition of noise (C3, C4, and C5) is enough to reduce the performance of the classical algorithms (ElSe and Pure) by almost half. In the case of reflections, however, (C6, C7, and C8) only clearly visible reflections have an enormous influence (C8 see also Figure 2). Compared to the classical algorithms all neural networks are very

 Table 1: Naming convention and description of the evaluated challenges and algorithms.

Challenge	Description
C0	Original images
C1, C2	Blur with filter size 9×9 and $\sigma = 1.1$, $\sigma = 1.2$
C3, C4, C5	10%, 20%, and 30% random noise
C6, C7, C8	Reflections with 20%, 40%, and 60% intensity
C9	C1, C3, and C6 combined
C10	C2, C4, and C7 combined
Algorithm	Description
ElSe	Edge filtering and selection
PuRe	Edge filtering and combination
ConvP	Pruned tiny neural network
BinP	Pruned and binarized tiny neural network
TreeP	Pruned tiny tree neural network



Figure 2: The different challenges applied to an image.

robust against the challenges regarding the accuracy of the pupil center.

Figure 4 shows the Jaccard index $(\frac{GT \cap DT}{GT \cup DT})$, with GT = Ground Truth Ellipse and DT = Detected Ellipse) or mean intersection over union cumulatively for each challenge separately. For the Jaccard index, a value of 50% or higher is generally considered good. As you can see, the classic edge-based approaches are more accurate as long as they can handle the challenge. However, as with accuracy, it is obvious that only a small amount of noise (C3,C4, and C5) has a huge impact. For clearly visible reflections (C8), the tiny neural networks also have problems extracting a clean pupil ellipse. Overall, however, the neural networks are much more robust compared to the classical algorithms. If one now evaluates the methods with Figure 3 and Figure 4, one can clearly see that the conventional convolution is the most accurate and robust (ConvP). In second place are the decision tree based convolutions (TreeP) and finally the binarized convolutions (BinP).

However, if the runtime is also taken into account (Figure 5), this changes, because the decision-tree-based neural networks only require about one third of the runtime. In addition, one can see that



Figure 3: Cumulative accuracy in euclidean distance of the estimated pupil center to the ground truth for all algorithms and separated per challenge.



Figure 4: Jaccard index $(\frac{GT \cap DT}{GT \cup DT})$ between the estimated and ground truth pupil for all algorithms and separated per challenge.

the classical algorithms are constant on average but need significantly more computing time for certain images where many curved edges are present (Red crosses in Figure 5).

Table 2 serves to compare the validity signal of the algorithms. Our validity signal correlates with the accuracy of the result, since we have used the validity loss of [Fuhl and Kasneci 2019]. However, this does not apply to the classical algorithms (ElSe and Pure). Therefore, we decided to use an evaluation based on recall and precision. To apply percision and recall, we have used a validity threshold of 5 pixels. This means that if an estimated pupil center is closer than 5 pixels to the annotation, it is considered correct, otherwise it is considered false. For each algorithm, the threshold value for the validity signal was determined iteratively optimal to



Figure 5: The runtime of ElSe and Pure in comparison to the pruned versions of the convolution, tree, and binary neuronal network using Whisker plots. Evaluated on one single CPU core (i5). The red crosses are outliers of the fitted normal distribution.

Table 2: Precision (TP/AllPositives) and Recall TP/(TP + FN) with the optimal selected validity threshold evaluated over all challenges.

Algorithm	Precision	Recall
ElSe Pure	100% 100%	53.37% 80.21%
TreeP BinP	100% 100% 100%	89.56% 86.83% 75.65%

achive the best recall result. (TP/(TP + FN)). This makes it easier for algorithms that generally have a worse accuracy (See Figure 3), but gives a good indication of the reliability of the validity signal. As you can see, all algorithms achieve a precision of 100%, which is because there were more correct than incorrect pupil centers and therefore, it was weighted heavier for the recall calculation. It can be seen that ConvP and TreeP are the best performers. Pure is also good but this is influenced by the much lower detection rate over all challenges.

5 CONCLUSION

In this work we presented different neural networks for real-time use on a single CPU core. For this, we used modern methods like distillation and pruning. As an additional comparison, we have binarized a neural network. All networks were evaluated with respect to their accuracy and reliability under different challenges and also the runtime was considered. The trained models and a runtime optimized framework are made available to the public together with this work. Tiny neuronal networks for pupil outline estimation

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