Google Coral-based edge computing person reidentification using human parsing combined with analytical method

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Abstract

Person reidentification (re-ID) is becoming one of the most significant application areas of computer vision due to its importance for science and social security. Due to enormous size and scale of camera systems it is beneficial to develop edge computing re-ID applications where at least part of the analysis could be performed by the cameras. However, conventional re-ID relies heavily on deep learning (DL) computationally demanding models which are not readily applicable for edge computing. In this paper we adapt a recently proposed re-ID method that combines DL human parsing with analytical feature extraction and ranking schemes to be more suitable for edge computing re-ID. First, we compare parsers that use ResNet101, ResNet18, MobileNetV2, and OSNet backbones and show that parsing can be performed using compact backbones with sufficient accuracy. Second, we transfer parsers to tensor processing unit (TPU) of Google Coral Dev Board and show that it can act as a portable edge computing re-ID station. We also implement the analytical part of re-ID method on Coral CPU to ensure that it can perform a complete re-ID cycle. For quantitative analysis we compare inference speed, parsing masks, and re-ID accuracy on GPU and Coral TPU depending on parser backbone. We also discuss possible application scenarios of edge computing in re-ID taking into account known limitations mainly related to memory and storage space of portable devices.

Keywords: Person reidentification, human parsing, Google Coral, edge computing, quantization.

1 Introduction

Computer vision (CV) is a cornerstone of conventional computer science due to its importance for image and video analysis, robotics, autonomous vehicles, manufacturing, and others. CV plays a crucial role in video surveillance which in turn is becoming indispensable for security in modern cities. Along with well-known topics such as object detection and face recognition, person re-identification (re-ID) plays an important role in ensuring public safety by focusing on person identification across camera systems.

Nowadays the most high-performance re-ID methods rely on deep learning (DL) [1]. However, there is a known problem of poor generalization where model’s performance decreases...
when applied to previously unseen data [2]. Furthermore, large model size originating from
tens to hundreds of millions of parameters associated with deep learning architectures makes
some models unusable when computational resources and storage space are limited. This
complicates their application in edge computing when some computations are performed by
the camera module [3]. Such applications demand as compact DL models as possible. This
inspired, for instance, the development of MobileNet [4] which is yet to be applied to re-ID
tasks.

Recently we proposed re-ID method which combines deep learning-based human parsing
with analytical feature extraction [5]. It showed potential to improve generalization by being
dataset-agnostic relying on DL for human parsing only with most of the analysis conducted
using a simple analytical model. However, the original implementation of our method relied
on a parser that used ResNet-101 backbone [6] which diminished the benefits of low space
requirements that the analytical method provided. In this paper we show that this combined
method can be implemented using a significantly more compact backbone with little reduction
in re-ID accuracy metrics. This allows us to create an edge computing application which can
perform a full re-ID cycle.

Google Coral Dev Board (Coral) is a single board computer developed by Google [7].
Coral has a single Edge Tensor Processing Unit (TPU) processor for neural network operation
acceleration [8]. Coral has been shown to have the best performance for inference time and
power consumption among similar edge computing platforms: Asus Tinker Edge R, Raspberry
Pi 4, Google Coral Dev Board, Nvidia Jetson Nano, and microcontroller Arduino Nano 33
BLE [9].

The motivation for this study is two-fold. First, we aim to show that our combined method
proposed in [5] can be implemented with compact parsers without any significant accuracy
loss. Second, we explore the possibility of transferring parsers based on different backbones
to Google Coral. Finally, full re-ID cycle is performed on Coral and application scenarios of
edge computing re-ID model are discussed.

The rest of the paper is organized as follows: Section 2 outlines methodology with re-
spect to parser training and its transfer to Coral, Section 3 summarizes experimental results,
Section 4 provide a discussion and Section 5 concludes the paper.

2 Methodology

2.1 Human parsing for re-ID

Human parsing is subset of image segmentation algorithms which focuses specifically on hu-
mans. It provides parsing maps where every image pixel is assigned a class specific to human
body parts and clothes. Human parsing is often performed using DL-based models trained
on dedicated datasets such as LIP [10] or Pascal [11].

Human parsing was previously used as part of DL-based re-ID models in [12, 13]. However,
feature extraction and comparison were also performed in those studies by neural networks
making the complete model rather large and not particularly suitable for edge computing
applications. To address this issue parser size should be minimized along with further simpli-
fication of the model and performing analytical feature extraction and similarity ranking will
significantly reduce the total size of the model.
Table 1. Accuracy metrics of the combined re-ID method depending on parser backbone.

| Backbone    | Original rank-1 | Original rank-10 | Original mAP | Quantized rank-1 | Quantized rank-10 | Quantized mAP | Coral rank-1 | Coral rank-10 | Coral mAP |
|-------------|-----------------|------------------|--------------|-----------------|------------------|---------------|--------------|--------------|----------|
| ResNet101   | 92.1            | 97               | 24           | 90.5            | 96.2             | 22.1          | 90.2         | 96.5         | 22.1     |
| ResNet18    | 89.7            | 95.4             | 21.8         | 88.3            | 94.7             | 20.3          | 88           | 94.9         | 17.8     |
| MobileNetV2 | 89.3            | 96.7             | 20.2         | 89.3            | 95.9             | 20.2          | 88.9         | 96           | 20.1     |
| OSNet       | 89.6            | 96.6             | 20.3         | 91.2            | 97               | 21            | 91.2         | 96.9         | 21       |

In this study we investigate the possibility of changing the parser backbone to reduce its size, preferably with minimal loss in accuracy. We make a number of changes to the parser architecture proposed in [6] which in turn relies on CE2P architecture [14]. This parser consists of a backbone and three branches, namely Edge, Decoder, and Fusion, and only the backbone is changed in our experiments while the branches remain unchanged. However, the number of parameters in the branch layers depends on the number of feature channels in backbone’s layers, so it decreases for more compact backbones. The modifications are discussed in detail in the next subsection.

2.2 Parser modification and its transfer to Coral

To perform inference on Coral a neural network model has to be compiled with edgetpu compiler. This compilation is possible only for quantized TensorFlow Lite (tflite) models. To obtain such models the original SCHP-parser implemented using PyTorch [15] is converted as follows. First, it is converted into ONNX format [16], then to OpenVINO format [17] and then to Tensorflow using openvino2tensorflow convertor [18]. Finally, the obtained model which has format of “saved model” is quantized into tflite model. It should be noted that we substitute CUDA-dependent InplaceABNSync layers [19] in SCHP parser which are not supported by ONNX converter with BatchNorm and ReLU. OpenVINO and openvino2tensorflow convertors allow us to change dimensions order in model tensors, which are different in PyTorch and Tensorflow formats.

TensorFlow post-training integer quantization requires “a representative dataset” (further referred to as quantization dataset) for processing. This is necessary to choose quantization coefficients for better translation of float input data to integer values. We used random subsets of LIP dataset for quantization, and we discuss the influence of the quantization dataset size in Section 3.3. Finally, tflite model is compiled with edgetpu compiler which is possible only when all layers are supported by edge TPU. However, Coral also has a limitation on input tensor size due to memory restrictions which prevents compilation of the SCHP-parser with initial tensor size of 473. Considering that height and width dimensions of input tensor must be multiples of certain values, we change input tensor size to 286. For comparison consistency we apply the described changes, i.e. layer substitution and input tensor size modification, to all models. Then we train parsers with ResNet-101, ResNet-18 [20], MobileNetV2 [21], and OSNet [22] backbones on LIP dataset and then use inference masks obtained for re-ID datasets to calculate re-ID accuracy. Comparing pure human parsing accuracy metrics such as mean intersection over union (mIOU) is out of scope of this paper.
Table 2. Compilation details of studied models depending on backbone.

| Parameter/backbone                  | ResNet-101 | ResNet-18 | MobileNetV2 | OSNet |
|-------------------------------------|------------|-----------|-------------|-------|
| Number of parameters, mln           | 42.8       | 11.4      | 4.2         | 2.2   |
| Number of operations                | 217        | 87        | 121         | 390   |
| Compilation time, s                 | 88.0       | 1.6       | 0.9         | 4.0   |
| Quantized model size, MiB           | 65.13      | 12.27     | 2.73        | 3.93  |
| Output size, MiB                    | 65.65      | 12.42     | 3.39        | 4.88  |
| Used memory*, MiB                   | 6.35       | 6.68      | 3.13        | 3.03  |
| Remaining memory**, KiB             | 6.25       | 2.0       | 4536.32     | 1.5   |
| Off-chip memory***, MiB             | 57.87      | 5.48      | 0           | 0.88  |

* On-chip memory used for caching model parameters.
** On-chip memory remaining for caching model parameters.
*** Off-chip memory used for streaming uncached model parameters.

3 Experiments

3.1 Changes in re-ID accuracy depending on parser backbone choice

Table 1 shows accuracy depending on parser backbone and model type: original (PyTorch), quantized (tflite), and Coral (which is compiled with edgetpu-complier). All backbones were first trained on GPU in supervised learning fashion using LIP dataset for 100 epochs with starting learning rate of 0.0035. Re-ID accuracy calculation requires parsing masks for query and test images. For original models, parsing inference masks were obtained on GPU. For quantized models, parsers were quantized as discussed in Section 2.2 with 5000 images in quantization dataset and inference masks were obtained on GPU using quantized parsers. For Coral models, quantized parsers were transferred to Coral and parsing masks were obtained on Coral. Re-ID metrics were calculated on the same CPU using the analytical method. Parsers were trained on a server with Intel i9-9900K 3.60GHz CPU with 64GB RAM and NVIDIA Quadro P5000 with 16GB RAM.

Conventional re-ID accuracy metrics, namely rank-1, rank-10, and mean average precision (mAP), were used to evaluate the performance of studied models [23]. All experiments were conducted on Market1501 dataset consisting of 19732 test images and 3368 queries [24]. It should be stressed that all parsers were trained on original LIP dataset and not on re-ID datasets which makes them re-ID dataset agnostic.

3.2 Backbone performance comparison with Coral

Models modified in accordance with Section 2.2 with input tensor size of 286 were successfully compiled with edgetpu complier. Table 2 shows that model size (in MiB) increases from MobileNetV2 to ResNet-101. An interesting observation is that OSNet, while its size is slightly bigger than that of MobileNetV2, has the smallest number of parameters and the highest number of operations (even exceeding ResNet-101). This is because OSNet has very complex structure with large number of calculations despite of its small size and number of parameters, so it has high compilation and inference time inferior only to those of ResNet-101,
Table 3. Inference time in ms.

| Type/backbone    | ResNet-101 | ResNet-18 | MobileNetV2 | OSNet      |
|------------------|------------|-----------|-------------|------------|
| Original (GPU)   | 39 → 13    | 200 → 5   | 37 → 5      | 110 → 14   |
| Quantized (GPU)  | 920 → 740  | 120 → 104 | 72 → 51     | 202 → 183  |
| Coral (TPU)      | 300 → 280  | 50 → 40   | 32 → 26     | 58 → 49    |

Arrows indicate change in time between first and consequent inferences.

Figure 1. OSNet parsing masks for different numbers of images in quantization dataset.

as shown in Table 3. Nevertheless, the inference time for OSNet is still sufficiently small for real-time applications. The difference in time between the first and consequent inferences is a common phenomenon related to the necessity to upload data and initialize the model for the first inference. In should be noted that for tflite models, both quantized and Coral, the reduction in inference time reaches up to 20%, whereas for PyTorch models on GPU it is even more significant.

3.3 The effect of quantization dataset size on parsing quality

To study the effects of quantization dataset size on re-ID accuracy, we performed experiments using a parser with OSNet backbone while changing the number of images in the quantization dataset. We conduct experiments for the dataset sizes of 10, 50, 200, 1000, 2500, 5000, and 10,000 images. Figure 1 shows how parsing masks change for two sample queries. In general, the increase in the dataset size leads to increase in parsing quality: the number of misclassified regions decreases, noisy predictions such as random class spots are vanishing, etc. Figure 2 shows how re-ID accuracy metrics change with dataset size. It shows rapid increase in accuracy up to 200 images which then slowly increasing up to 5000 images and then starting to decrease. It should be mentioned that the correlation between changes in parsing masks and re-ID accuracy is not straightforward, and significant changes in masks can correspond to small changes in re-ID accuracy, as discussed in detail in the next Section.
4 Discussions

4.1 The effects of backbone change on human parsing quality and re-ID accuracy

Table 1 shows that the highest accuracy for all three metrics is achieved by the original version of ResNet-101. However, the overall accuracy reduction due to backbone change is not significant – within 3% for rank-1, 2.5% for rank-10, and 4.5% for mAP. The decrease in mAP is larger compared to other metrics, though lower mAP is a known feature of studied method. At the same time the number of parameters, size of the model, and inference speed decrease significantly, as shown in Tables 2 and 3. This result shows that smaller parsers can indeed be used with the proposed re-ID method with small accuracy reduction.

It should be noted that ResNet-101 parser used in this study has 1% higher rank-1/rank-10 accuracies and 1.2% lower mAP accuracy than the ResNet-101 SCHP parser used in [5]. A possible reason for this is that when parsing masks are extremely precise, the requirements for similarity estimation also become stricter. At the same time the effects of illumination and posture change also become more noticeable for precise masks, and these effects are the most profound sources of reidentification errors. Hence, having less precise parsing masks loosens similarity criteria allowing the same person found in different camera views be identified correctly. However, this also makes it more likely that different people will be incorrectly identified as looking similar which is reflected in reduced mAP.

Table 1 also shows that for three backbones the accuracy decreases after quantization. However, quantized and Coral versions of OSNet outperform other backbones and almost reach the accuracy of the original ResNet-101. This observation implies that this backbone is the most promising for edge computing applications. The accuracy also only slightly changes between quantized and Coral models despite of change of the processor’s architecture from GPU to TPU.
Figure 3 shows generated parsing masks for two sample queries using studied backbones. The left query represents a simple case where a person is clearly visible, and it is parsed relatively well by all backbones. There are several cases where left hand is not parsed correctly, and it sometimes disappears after quantization. However, classification errors are more significant for OSNet since whereas the parsing mask is overall correct, there are patches of mixed classes on body and arms. It should be noted that in general the masks obtained using the quantized parsers do not differ dramatically from those obtained using the original networks. This is surprising because there was a lot of transformations in network architecture associated with the conversion which include quantization, i.e., a transition from almost continuous floating point accuracy weights to their one-byte discrete version.

The right query is more challenging since it includes partial occlusion of person’s legs by the bag which does not have a corresponding class in LIP. Some parsers misclassified it as “pants”, others excluded it from the masks though it often resulted in exclusion of legs, too. These masks are very noisy and include both region boundary errors and region misclassification errors. There is a tendency for ResNets to lose some regions after quantization, whereas changes are less dramatic for MobileNetV2 and OSNet.

It is interesting that whereas parsing masks can change significantly, the results in Table 1 show that this fact has only small influence on re-ID accuracy. This means that the proposed re-ID method is robust with respect to parsing errors, since large changes in masks lead to little changes in accuracy. In our opinion, there are two reasons for this. First, parsers partially rely on colors when classifying image regions, so misclassification adds similar colors to class histograms in our method. Moreover, such regions often include shadows which are present in every class, resulting in slight shifts in feature channel histograms without causing significant disturbance. Second, the size of misclassified areas is often small, so they have proportionally little effect on feature channel histograms. Furthermore, semantically similar classes are merged in our analysis which increases tolerance to misclassification [5]. However, errors that affect large regions would negatively affect the accuracy. Nevertheless, the discussed influence of parsing errors on re-ID accuracy clearly distinguishes this study from pure DL-based human parsing experiments where each pixel or area misclassification contributes to accuracy reduction [25]. Therefore, the use of smaller parser in pure DL-based human parsing tasks should be undertaken with extra care, whereas for the proposed re-ID method such operation is justified, as shown by Table 1 and Figure 3.

It should be noted that we trained parsers only for 100 epochs out of 150 epochs commonly used in human parsing studies [14, 6]. This implies that the parsing results can be improved further, especially if self-correction is applied [6]. However, since improving human parsing accuracy is not the main goal of this study, we present the results for 100 epochs to further emphasize the point that the proposed combined re-ID method is robust with respect to human parsing inaccuracies.

4.2 Application scenarios for edge computing Coral-based re-ID

Whereas re-ID metrics in Table 1 were calculated on a PC, the possibility of evaluating person similarity solely on Coral was also verified. Coral performed the complete similarity evaluation pipeline by parsing an image and using the obtained mask together with the image to calculate feature vectors. We also performed a similarity ranking experiment on Coral using 500 images from Market1501 which shows that re-ID can in principle be realized on Coral.
However, Coral has limited RAM and CPU, so using it for large-scale re-ID with thousands or millions of images is not possible. It should be noted that Coral still performs sufficiently fast for real-time human parsing, so we propose two possible application scenarios for Coral-based re-ID.

4.2.1 Coral as an edge computing image processing camera

As we mention above, Coral is capable of real-time human parsing and calculation of feature vectors. Thus, it can act as a useful edge computing device that transmits preprocessed data to a server that performs final operations for re-ID. In a conventional scheme such server works with raw video streams from camera systems, which might include hundreds and thousands of cameras. Therefore, parsing enormous amounts of video streams and calculating features is an extremely resource demanding task. On the contrary, only similarity score calculation and ranking are to be performed when server obtains parsing masks and feature vectors from the camera. It is easy to see that the advantage of such scheme is proportional to the number of cameras in the system, making it most suitable for video surveillance in smart cities.

4.2.2 Coral as a re-ID detector

In addition to the above point, there is another role that Coral can play. We have mentioned that the main limitation for the Coral-based re-ID is memory, but Coral can store a small database to compare observed people with. This is useful when a query person is, for instance,
expected to appear in certain area and Coral can send a message to an operator when a match is found. In this scheme Coral performs real-time comparison but does not necessarily store data other than IDs of matches which can be transferred to the operator along with masks and feature vectors. This is extremely useful for rapid response in case of searching for lost people or looking for perpetrators. All tested backbones provide the possibility to conduct this analysis in real time.

5 Conclusions

This paper studies the possibility of developing a compact and computationally undemanding re-ID method and realizing it using Google Coral Dev Board. We use a recently proposed combined re-ID method where only human parsing section relies on DL and study the effects of changing parser backbones. We show that re-ID accuracy decreases slightly when substituting ResNet-101 backbone with ResNet-18, MobileNetV2, and OSNet, whereas number of parameters and model size exhibit more than ten- and twenty-fold reduction. We discuss necessary modifications to DL models to make them Coral-compatible and apply said modifications to all models. We quantize all models and transfer them to Coral with re-ID accuracy decreasing slightly for ResNet-101, ResNet-18, and MobileNetV2 compared to GPU. However, both quantized and Coral versions of OSNet show higher accuracy than its GPU version also being the highest among all transferred models. This makes OSNet the most promising candidate for edge computing re-ID applications. We also show that the reduction in parsing mask accuracy is greater than the reduction in re-ID accuracy when backbones change and argue that this indicates robustness of our method with respect to parsing errors. We also discuss the effects of quantization dataset size on re-ID accuracy and suggest range of suitable sizes. Finally, we show that all models can perform in real-time and discuss how Coral can act as edge computing parser or perform complete re-ID cycle.

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