An Analysis of Background-bias for Person Re-identification

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***Abstract*—This work considers an analysis of the background impact in the problem of domain shift in Person Re-Identification. The most of current methods of Person Re-Identification are focused on Deep Learning methods and they fail to generalize to domains different from that used to train. Some methods using Deep Learning can even make well-generalizing systems, but in some contexts like pedestrian detection they didn't make a good performance. Our goal is to make an analysis of the impact of eliminating background from pedestrian's image.**

***Index Terms*—Person Re-Identification, Pedestrian Detection, Deep Learning, Image Processing**

I. Introduction

The process of Person Re-Identification consists in get images from the same person in different cameras and identify correctly this person. Generally, the person is represented by a vector, so each person in the same image must be a different vector.

Person Re-Identification has become a relevant research area in computer vision. Systems like surveillance, pedestrian detection, monitoring, and forensic have demands on processes that can identify the same person in images captured by different cameras. As we can see in [1], the number of papers in Person Re-Identification has increased in the last few years.

II. Objective

Actually, the most of methods to perform person re-identification was implemented by using Deep Neural Networks, more precisely, Convolutional Neural Networks (CNN). They have several problems when need to deal with domain shift [1]. However, some novel methods in recent years have been demonstrated to solve this problem and outperform the state-of-the-art [2]–[5]. Most of them were tested in datasets like [9], [10].

However, [6] have used OSNet [3] in a pedestrian detection task and it had a bad performance. The crucial point to consider in this problem is the shift domain problem, once [3] could not generalize Re-Identification in the dataset used. [6] uses a Track-Wild dataset, that was not tested by the models that say generalizing Re-Identification. Our goal is to make an analysis of removing background image to know if that background bias really affects the Re-Identification process. We intend to make this using OSNet [3] in Market-1501 Dataset [9].

III. Justification

One of the biggest problems in Person Re-Identification is the overfitting, once the performance decrease in data different from that used to train. Recently works have proposed generalizable Person Re-Identification, but they fail in pedestrian-in-the-wild datasets [8]. None of them try to remove a background image, so we will analyze the results and make important insights about that.

This work proposes an analysis in background removal to create insights to help to build a generalizable solution that works for every data no matter the training domain.

Fig. 1. Some images from Pedestrian Dataset in [10]

IV. Mhetodology

We intend to recreate the Market-1501 Dataset [9], removing the background of each image. Actually, this dataset has the training, testing, ground-truth bounding box, and query data, so we will use [15] to make people segmentation and get only the person content of each one image of these data. In total, we will perform segmentation at 61295 images.

In our analysis, we must perform different kinds of tests. Like training in original data, and testing in data without background, training, and testing in data without background. The metrics we are going to use are mAP and Rank. These metrics are famous in Re-Identification problems and will be our reference to see if the changes are good or not. We also are going to use the OSNet [3] technique to perform the training and testing. We decide to use OSNet because of the facility to run and change the Convolutional Neural Network parameters. OSNet is implemented using the Pytorch tool and we intend to use an NVIDIA GTX 1060 to perform the analysis.

In Fig. 1 we have samples from a famous dataset used to Person Re-Identification methods. Note that we have images from different people at different angles and positions. We will work in images like that.

V. Schedule Activity

Month	Week					
07	12	13	14	15	16	Bibliography review
07	19	20	21	22	23	Deployment
07	26	27	28	29	30	Deployment
08	2	3	4	5	6	Experiments
08	9	10	11	12	13	Experiments and Analysis
08	16	17	18	19	20	Finish writing

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