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Linear classification of chairlift images for presence analysis

Julien Muzeau^a, Patricia Ladret^a and Pascal Bertolino^a

^aUniv. Grenoble Alpes, CNRS, Grenoble INP, GIPSA-lab, 38000 Grenoble, France;

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1. INTRODUCTION

Ensuring security in mountain ranges has become a concerning and challenging task for the last decades. Most of the accidents in this field are indeed mainly due to human behaviour. It is specifically the case for skilifts: people often forget to lower the security railing, the chair (*a.k.a.* vehicle) can be overcharged, that means it hosts more persons than the number of available seats, a passenger loses one of his/her ski, ... All those cases can lead to a hazardous situation.

To prevent accidents, a computer vision system has been developed by a French company from Grenoble in the Alps: a camera, positioned around the first skilift pylon, monitors each chairlift departure, analyzes several features of the scene (*i.e.* a sequence of 50 to 100 frames) and concludes to a dangerous or a safe situation with a certain reliability. One of these features obviously is the presence of passengers on the vehicle. This paper provides a simple albeit effective method which aims at establishing whether the chair is occupied or not. We show this classification can be achieved without implementing complex and computationally expensive techniques such as deep learning approaches.

2. METHOD

The proposed method makes use of Fisher's famous Linear Discriminative Analysis (LDA).¹ We remind here that LDA is a dimensional reduction process alongside a classification tool. Our method consists in two steps: first, the model is trained with images under the form of feature vectors, knowing their class (vehicle occupied or empty). Then, the model is tested on each frame of a never seen sequence and predicts its class by taking a majority vote on all sequence images.

Several questions then arise. First, **which kind of input data?** Among several trials, it ended up that gray-level images, cropped and centered on the vehicle, give the best results. Examples of such images are shown in figure 1: it depicts 3 frames before desaturation taken at various times for each of 4 chairlifts.

Secondly, **which features to describe each image?** The idea is to mix statistical indicators and image processing metrics. The chosen features are then the following: maximum, minimum, mean, standard deviation, skewness and kurtosis of the gray-level image, contour length, number of connex components, contour variance, blur level and global contrast.

Finally, one can note from the images in figure 1 the large variability, inter and intra chairlifts, whether it comes from the chairlift geometry, the weather conditions, the time of the day, ... In order to stay as robust as possible, the process is performed, at first, chairlift by chairlift.

3. RESULTS

As we measure binary classification results, we naturally make use of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) counters. The metrics used to assess our model are the (P)recision, (R)ecall, (A)ccuracy and (F)-measure:

$$P = \frac{TP}{TP+FP} \quad R = \frac{TP}{TP+FN} \quad A = \frac{TN+TP}{TP+TN+FP+FN} \quad F = \frac{2.P.R}{P+R}$$

Further author information: (Send correspondence to J.M.)

J.M.: E-mail: julien.muzeau@gipsa-lab.grenoble-inp.fr, Telephone: +33 (0)4 76 82 71 34

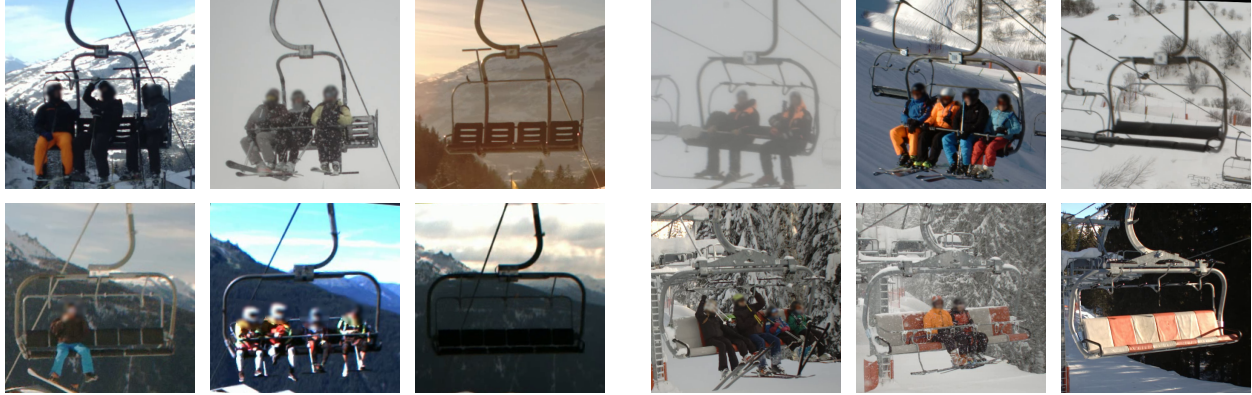


Figure 1. Variability demonstrated through 3 images taken from each of 4 different chairlifts (top-left, top-right, bottom-left and bottom-right). Blur is intentional for privacy reasons.

Table 1 presents an excerpt of the results obtained for 6 (3 with the highest and 3 with the lowest F-measure) out of the 20 different chairlifts. Each dataset, one for each chairlift, includes more than 10 thousand images. However, they are unbalanced: the number of empty vehicles is different from the number of occupied ones, as it is the case in real life situations. The LDA model is trained on a chosen 50% of each dataset in such a manner that the empty/occupied ratio is preserved, then tested on the other 50%. The whole process is repeated 30 times, the mean and standard deviation are displayed.

Table 1. Results of LDA applied to chairlift images. Averaged F-measure over all chairlifts is approximately 0.841 ± 0.082 . Chairlift 16 can subsequently be considered as outlier.

	P	R	A	F
Chairlift 4	0.737 ± 0.019	0.755 ± 0.036	0.737 ± 0.015	0.745 ± 0.018
Chairlift 5	0.677 ± 0.011	0.813 ± 0.025	0.661 ± 0.013	0.739 ± 0.012
Chairlift 9	0.944 ± 0.011	0.982 ± 0.007	0.955 ± 0.006	0.962 ± 0.005
Chairlift 12	0.943 ± 0.018	0.985 ± 0.019	0.946 ± 0.017	0.963 ± 0.012
Chairlift 16	0.744 ± 0.021	0.631 ± 0.021	0.754 ± 0.010	0.683 ± 0.013
Chairlift 17	0.928 ± 0.015	0.944 ± 0.009	0.901 ± 0.013	0.936 ± 0.008

4. CONCLUSION & PERSPECTIVES

As can be seen from table 1, although not ideal, the results are satisfactory, even with such a basic model. The most significant column is the F-measure, which is the harmonic mean of precision and recall.

Perspectives are numerous in order to improve our results: investigate other features (Signal-to-Noise Ratio, Total Variation, local contrast, histogram, ...), choose representative training images, set the right number of training images, make use of cross-validation procedures to determine the optimal train/test sets ratio, work with local patches instead of considering the image as a whole, study Quadratic Discriminative Analysis (QDA),² use elaborate classification tools such as Support Vector Machines³ or Random Forests,⁴ ...

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