Akademia Górniczo-Hutnicza
im. Stanisława Staszica w Krakowie
AGH University of Science
and Technology

Method for Assessing Objective Video Quality for Automatic License Plate Recognition Tasks

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Outline

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Introduction

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2. However, they are not suitable for video sequences used for recognition tasks (Target Recognition Videos, TRV).
3. Therefore, correctly estimating the performance of the video processing pipeline in both manual and Computer Vision (CV) recognition tasks is still a major research challenge.
4. In response to this need, we show in this paper that it is possible to develop the new concept of an objective model for evaluating video quality for Automatic License Plate Recognition (ALPR) tasks.

The ALPR Set

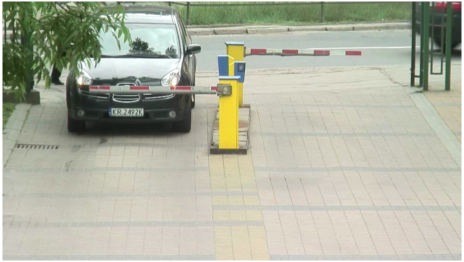

Figure: Frame of the AGH data set for video quality assessment in plate recognition

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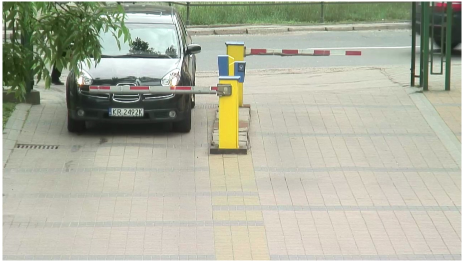

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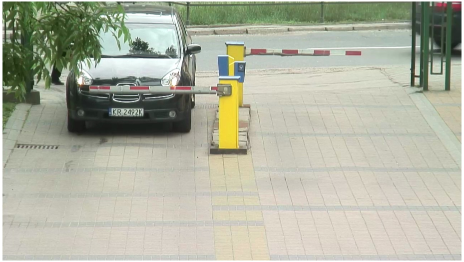

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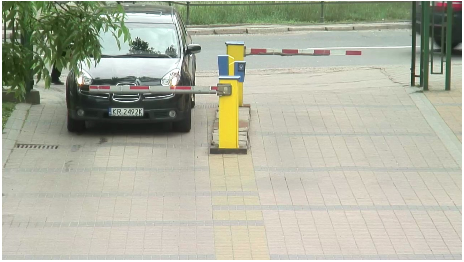
3. The data set contains video sequences, containing approximately 15,500 frames in total.



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The ALPR Subset

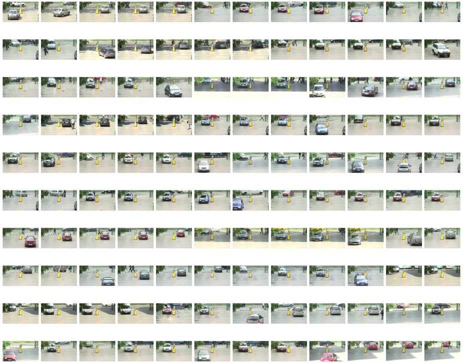
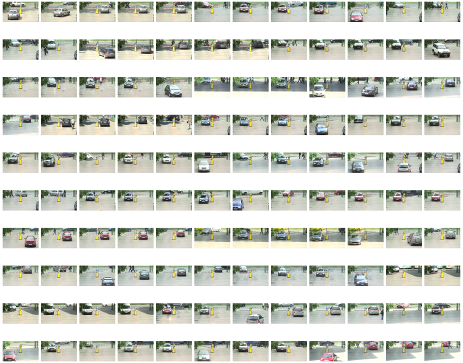


Figure: The montage of selected SRC frames for ALPR

The ALPR Subset

1. The whole set is subsampled, resulting in 120 images divided into a training set, a test set, and a validation set, in a ratio of 80 vs 20 vs 20, respectively.



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Preparation of Hypothetical Reference Circuits (HRC)

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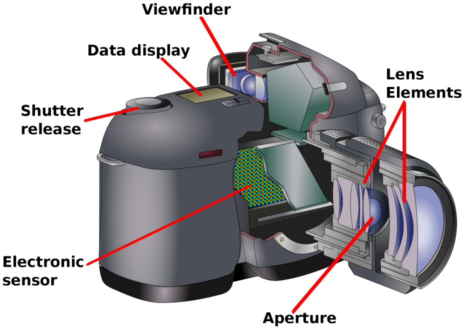

Figure: Diagram of a single-lens reflex camera with basic labels. Based on Reflex camera labels.svg. The author of the original base image is Jean François WITZ. By Astrocog – Own work, CC BY-SA 3.0

Preparation of Hypothetical Reference Circuits (HRC)

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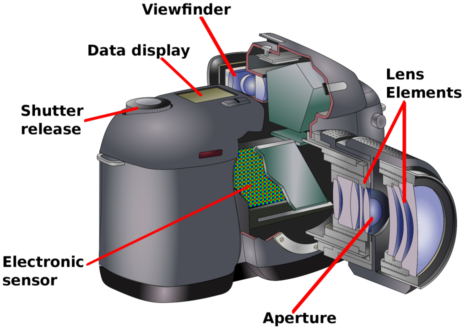
1. The HRC set is based on the digital camera model and how the luminous flux reflected from the scene eventually becomes a digital image.



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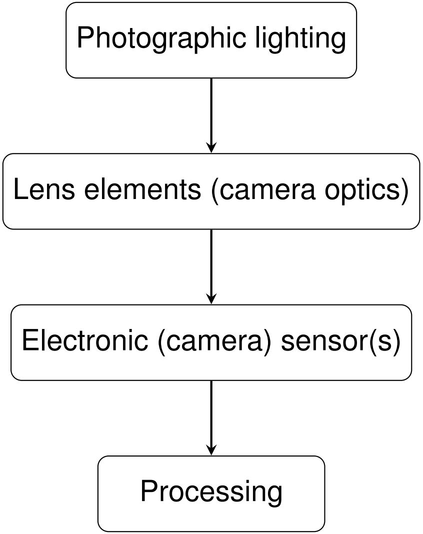

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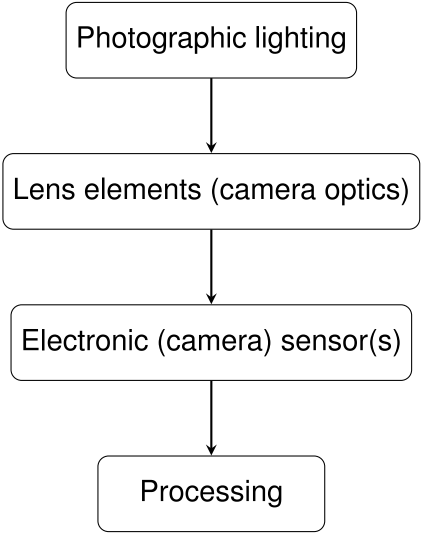

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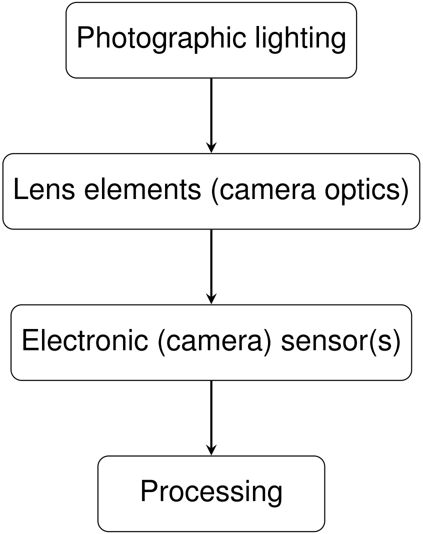

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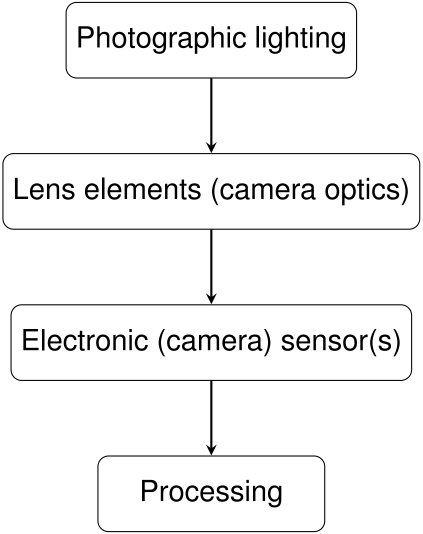

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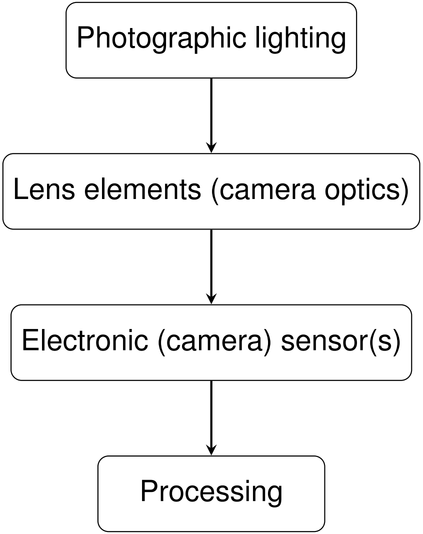

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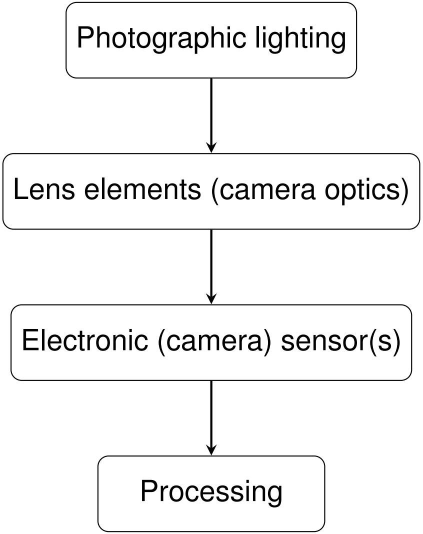

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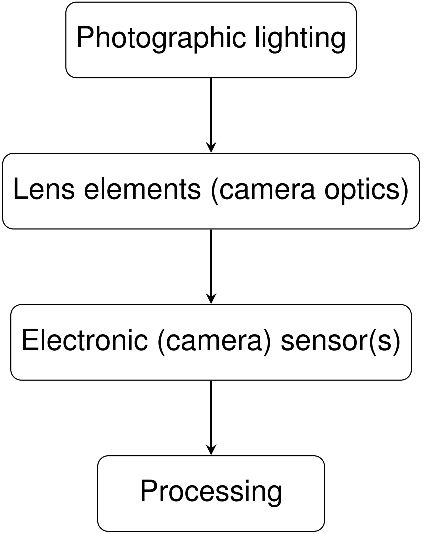

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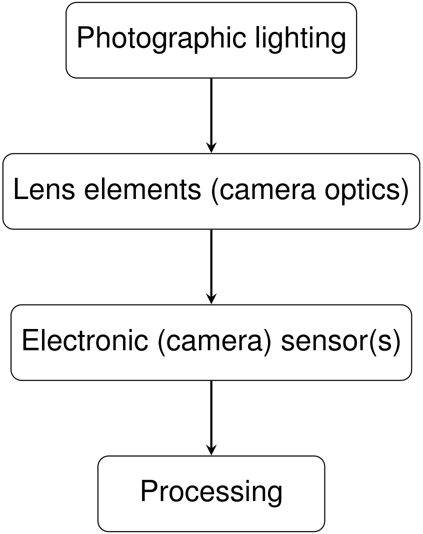

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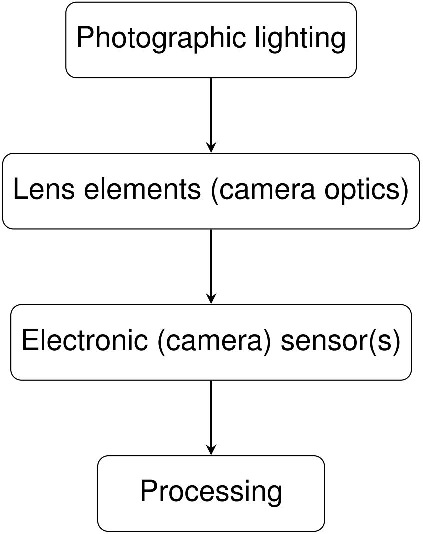

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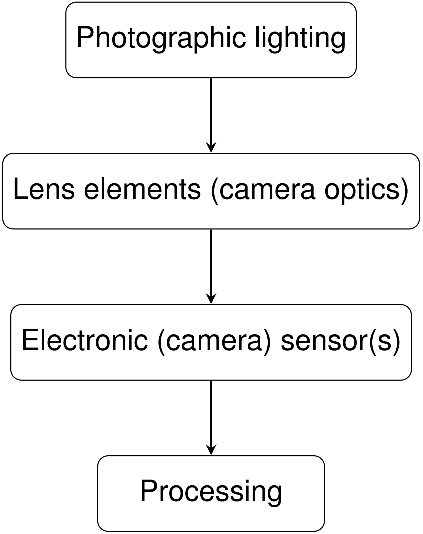
4. HRC related to processing:
   (5) JPEG compression



Preparation of Hypothetical Reference Circuits (HRC)

HRC	Unit	Min	Max
Under-Exposure	FFmpeg filter parameter	0	-0.6
Over-Exposure	FFmpeg filter parameter	0	0.6
Defocus (Blur)	ImageMagick filter parameter	0	6
Gaussian Noise	FFmpeg filter parameter	0	48
Motion Blur	ImageMagick filter parameter	0	18
JPEG	ImageMagick filter parameter	0	100

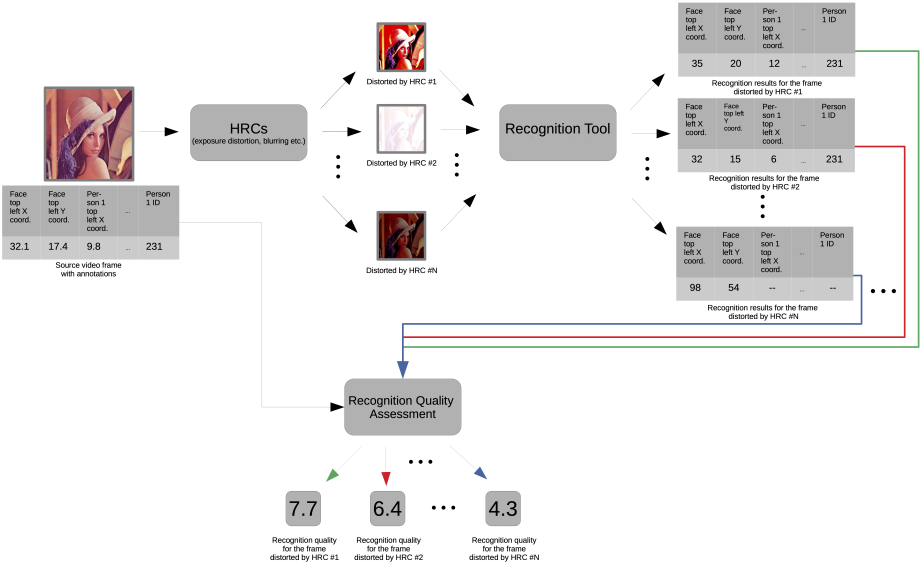
Table: Thresholds for specific Hypothetical Reference Circuits (HRC) – distortions (listed in rows)

Preparation of Hypothetical Reference Circuits (HRC)

HRC	#HRC
Over/Under-Exposure (Photography)	12
Defocus (Blur)	6
Gaussian Noise	6
Motion Blur	6
JPEG	19
Motion Blur + Gaussian Noise	5
Over-Exposure + Gaussian Noise	5
Under-Exposure + Motion Blur	5
#PVS	**6720**

Table: Hypothetical Reference Circuits (HRC) – distortions

Recognition Experiment Overview



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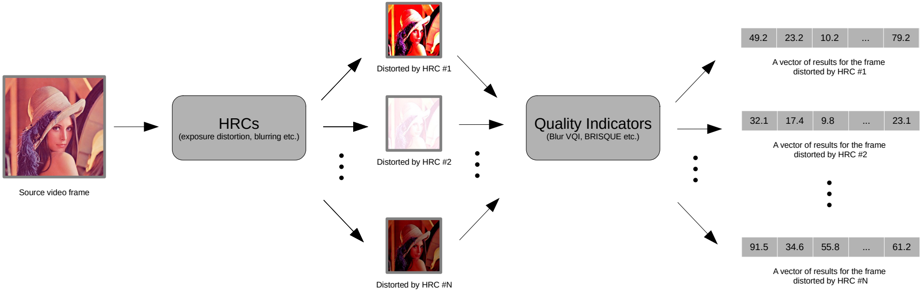
2. Importantly, execution times are evaluated using a PC with an Intel Core i5-8600K CPU.

Quality Experiment Overview



Indicators

No	Name	Authors	Language
1	Commercial Black		C/C++
2	Blockiness		C/C++
3	Block Loss		C/C++
4	Blur		C/C++
5	Contrast		C/C++
6	Exposure	VQ AGH	C/C++
7	Interlacing		C/C++
8	Noise		C/C++
9	Slicing		C/C++
10	Spatial Activity		C/C++
11	Temporal Activity		C/C++

Indicators

No	Name	Authors	Language
12	BIQI	LIVE	MATLAB
13	BRISQUE		MATLAB
14	NIQE		MATLAB
15	OG-IQA		MATLAB
16	FFRIQUEE		MATLAB
17	IL-NIQE		MATLAB
18	CORNIA	UMIACS	MATLAB
19	HOSA	BUPT	MATLAB

Results

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	Precision	Recall	F-measure
All metrics	0.779	0.776	0.777
Only ours	0.758	0.759	0.764

Table: General results we received for ALPR for 2 classes

Results

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Table: Confusion matrix for the test set, ALPR scenario, all metrics, and two classes

		Algorithm: Not more than 2 err.	Algorithm: Other cases
Truth	Not more than 2 err.	292	302
	Other cases	138	628

Results

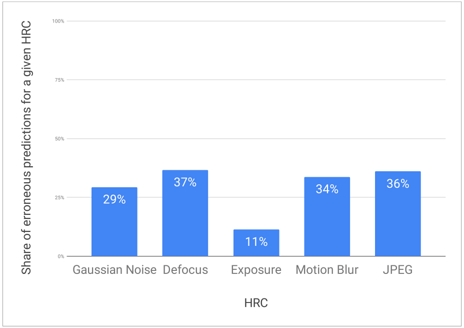

Figure: Share of erroneous predictions for a given Hypothetical Reference Circuits (HRC) in ALPR

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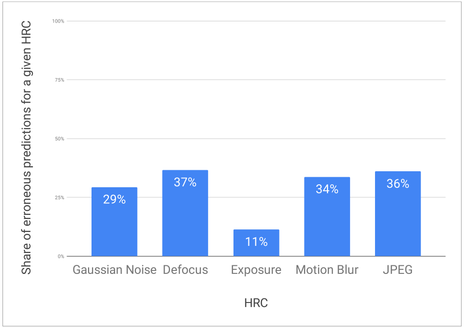
1. A more detailed analysis of the results obtained is also carried out.



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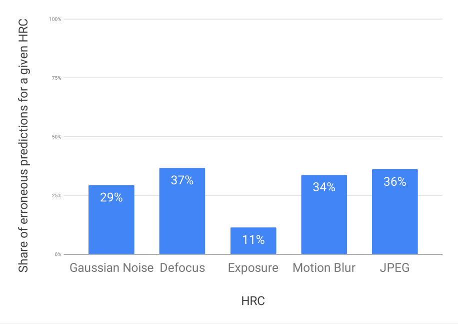

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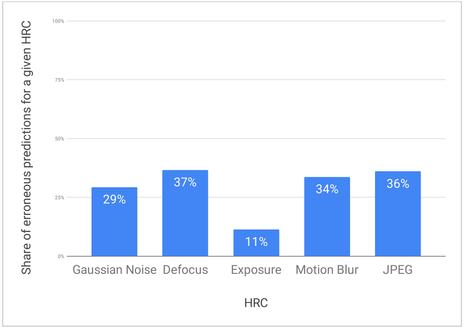

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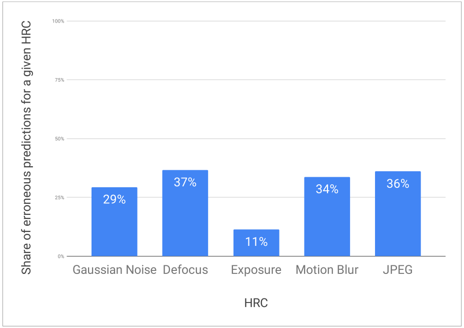
4. The exception is Exposure HRC, for which the model is much less mistaken, only for 11% cases.



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6. Our observations suggest that the characteristics of the initial scene are an important component that misleads the models.
7. VQI completely disregards this factor, which has a major impact on the accuracy of recognition.

Publication

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Leszczuk, M., Janowski, L., Nawała, J., Boev, A. (2022). Method for Assessing Objective Video Quality for Automatic License Plate Recognition Tasks. In: Dziech, A., Mees, W., Niemiec, M. (eds) Multimedia Communications, Services and Security. MCSS 2022. Communications in Computer and Information Science, vol 1689. Springer, Cham.
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