Akademia Górniczo-Hutnicza
im. Stanisława Staszica w Krakowie

AGH University of Science
and Technology

Objective Video Quality Assessment Method for Face Recognition Tasks

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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 face recognition tasks.

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4. Develop a new concept for an objective model to evaluate video quality for face recognition tasks;
5. Train, test, and validate the model;
6. Show that it is possible to achieve a measure of model accuracy, expressed as the value of the F-measure parameter, of 0.87.

The Face Recognition Set

Figure: Example image № 0002 of Aaron Sorkin from LFW database

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4. Each face has a resolution of 250×250 and is labelled with the name of the person pictured.

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The Face Recognition Subset

Figure: The montage of selected SRC frames (from LFW database) for face recognition

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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.

Figure: The montage of selected SRC frames (from LFW database) for face recognition

Preparation of Hypothetical Reference Circuits (HRC)

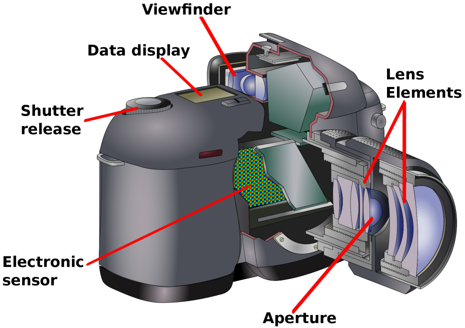

Figure: Diagram of a single-lens reflex camera with basic labels. Based on Reflex camera labels.svg. The author of the original base image is Jean François WITZ. By Astrocog – Own work, CC BY-SA 3.0

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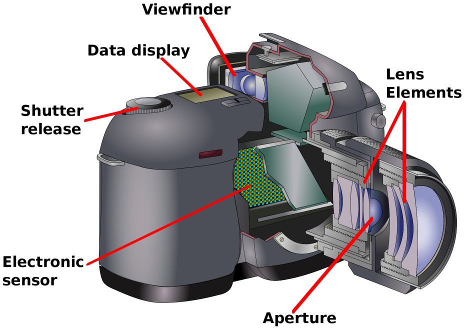

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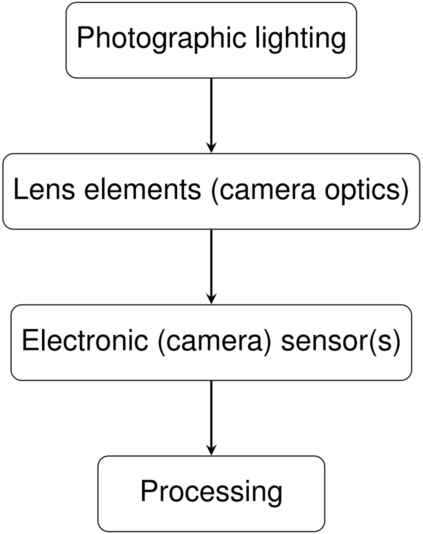

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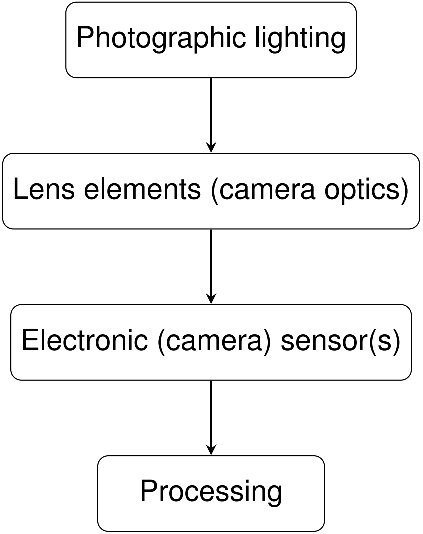

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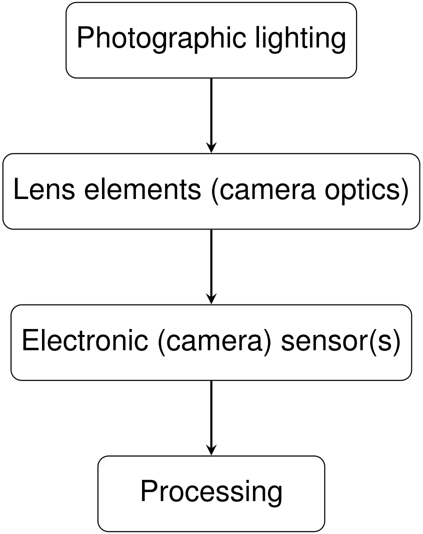

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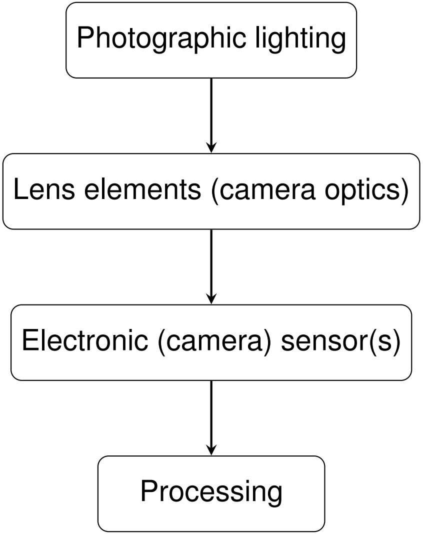

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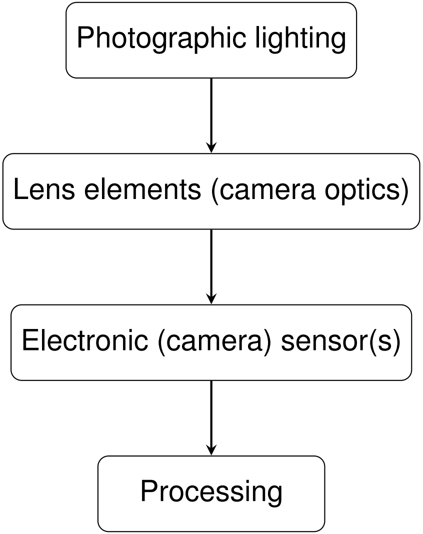

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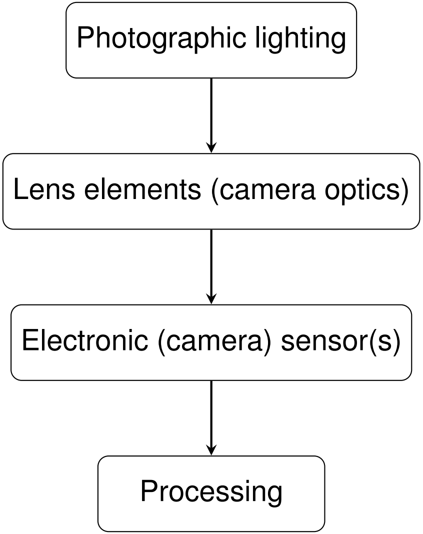

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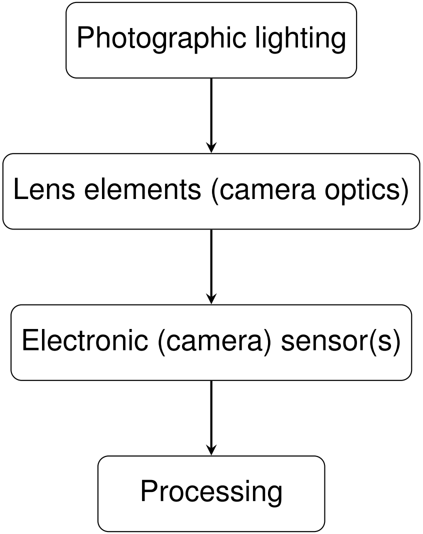

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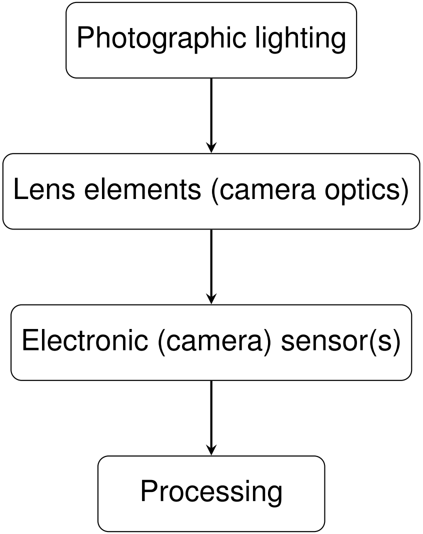

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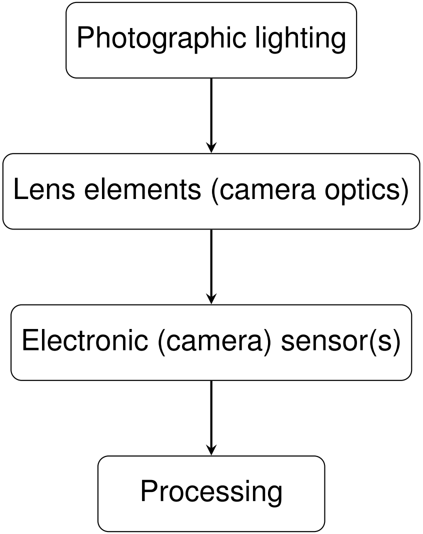

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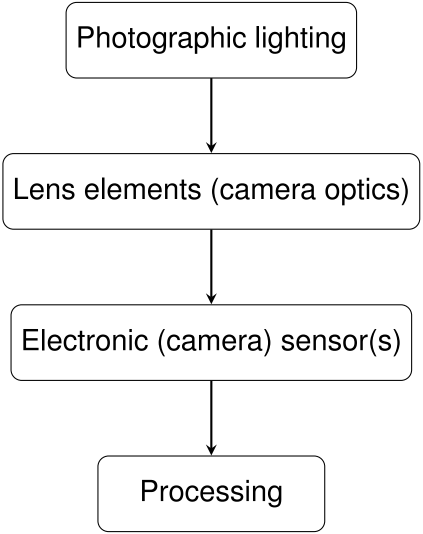


Preparation of Hypothetical Reference Circuits (HRC)

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

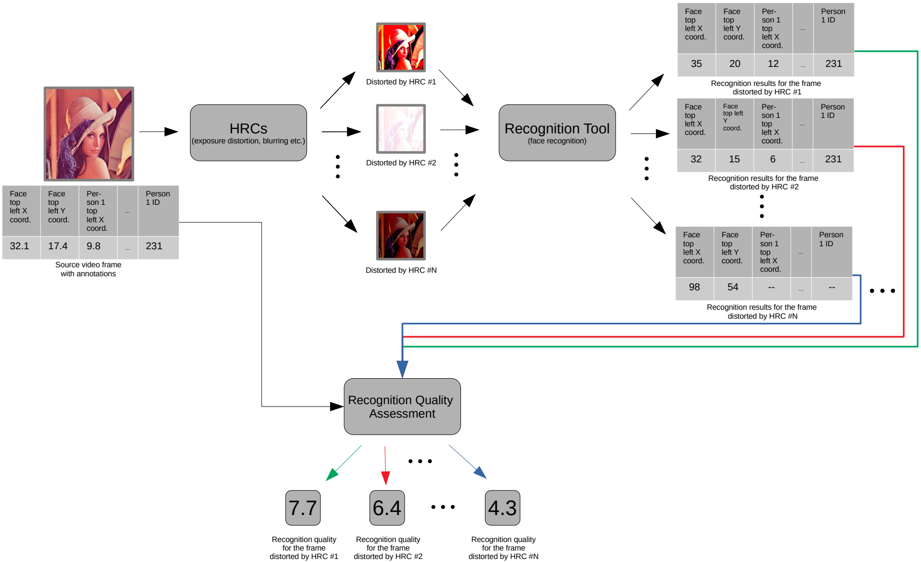
Table: Thresholds for specific Hypothetical Reference Circuits (HRC) – distortions (listed in rows)

Preparation of Hypothetical Reference Circuits (HRC)

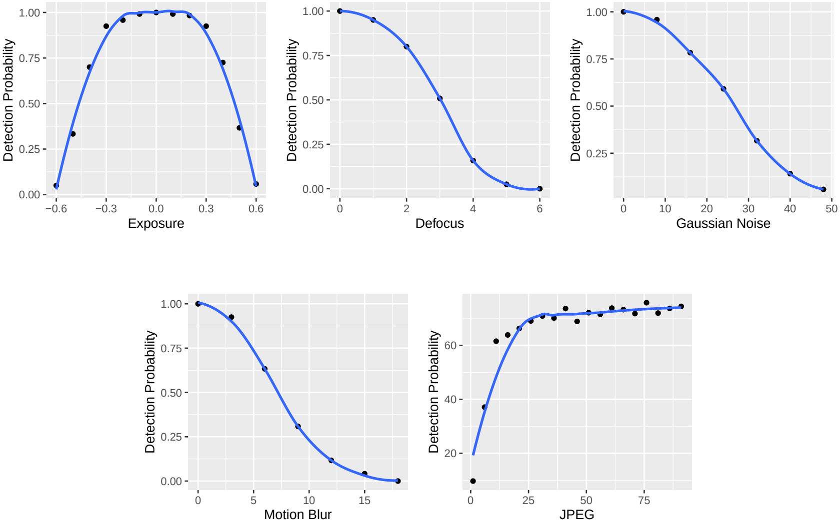
HRC	**#HRC**
Over/Under-Exposure (Photography)	12
Defocus (Blur)	6
Gaussian Noise	6
Motion Blur	6
JPEG	19
Motion Blur + Gaussian Noise	5
Over-Exposure + Gaussian Noise	5
Under-Exposure + Motion Blur	5
#PVS	**6720**

Table: Hypothetical Reference Circuits (HRC) – distortions

Recognition Experiment Overview



Face Recognition System



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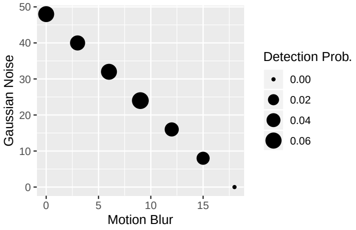

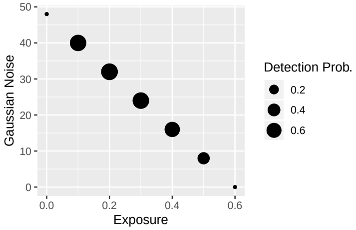

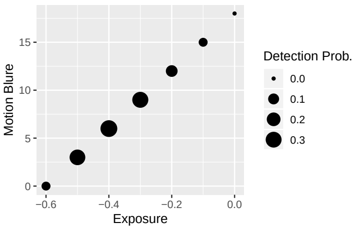

Face Recognition Time

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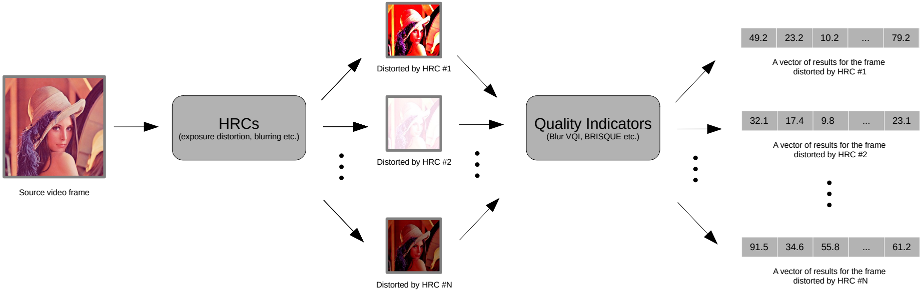
2. Importantly, execution times are evaluated using a PC with an Intel Core i5-8600K CPU.

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++

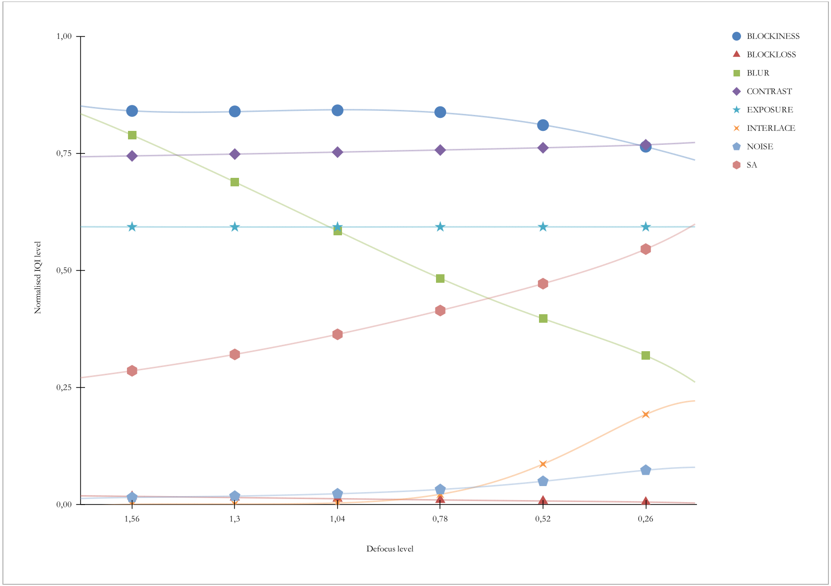
Indicators

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

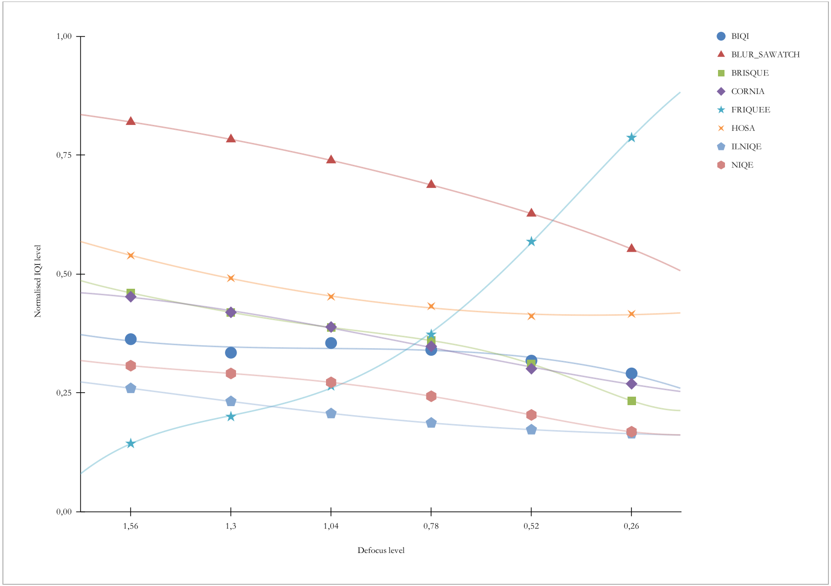
VQI Execution Time

Algorithm	Time [s]
BIQI	1.60
BRISQUE	1.67
NIQE	3.92
OG-IQA	5.72
FRIQUEE	40.79
IL-NIQE	10.70
CORNIA	7.71
HOSA	0.43
VQ AGH VQIs	0.12
Total	72.66

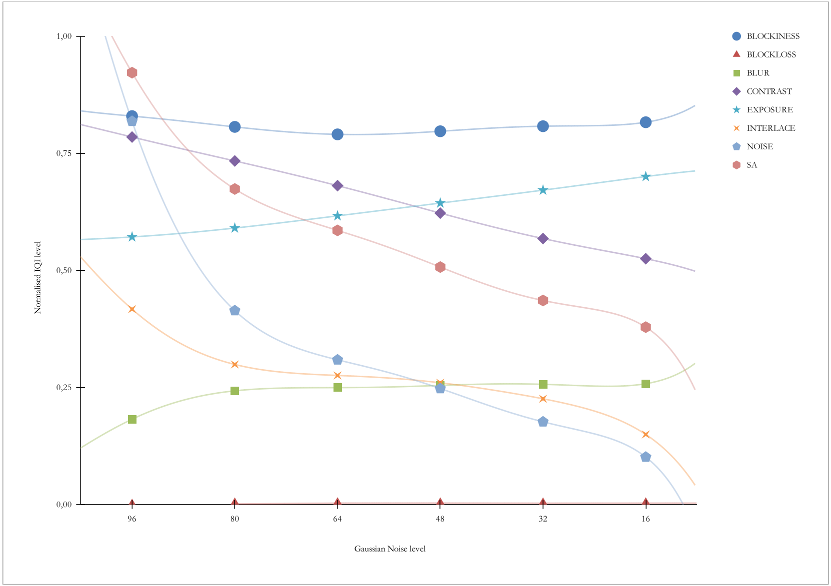
“Our” indicators vs. Defocus [σ/pixels]



"Other" indicators vs. Defocus [σ/pixels]



"Our" indicators vs. Gaussian Noise [σ/pixels]



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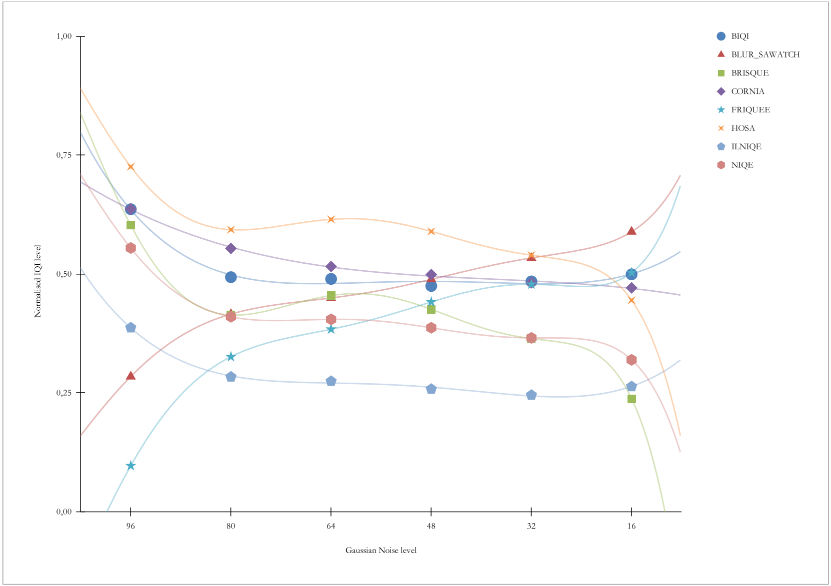
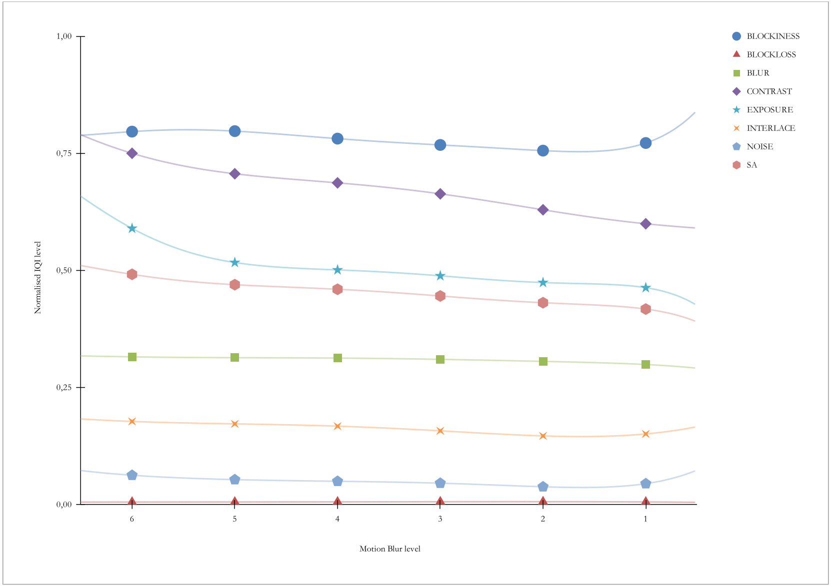


“Our” indicators vs. Motion Blur [σ/degrees]



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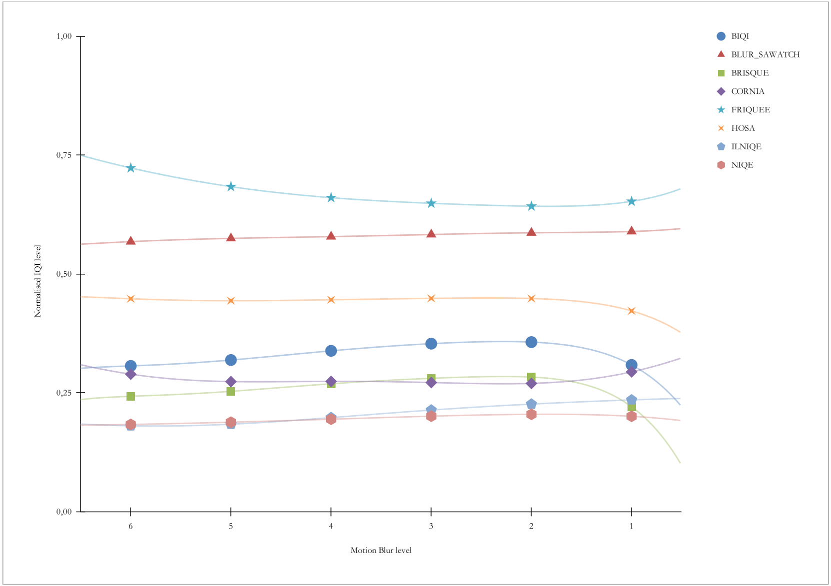
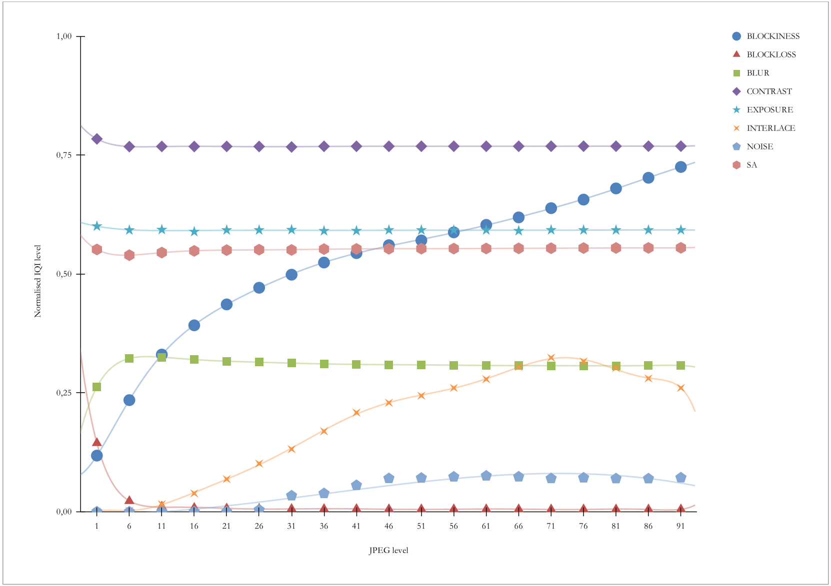


“Our” indicators vs. JPEG [quality units]



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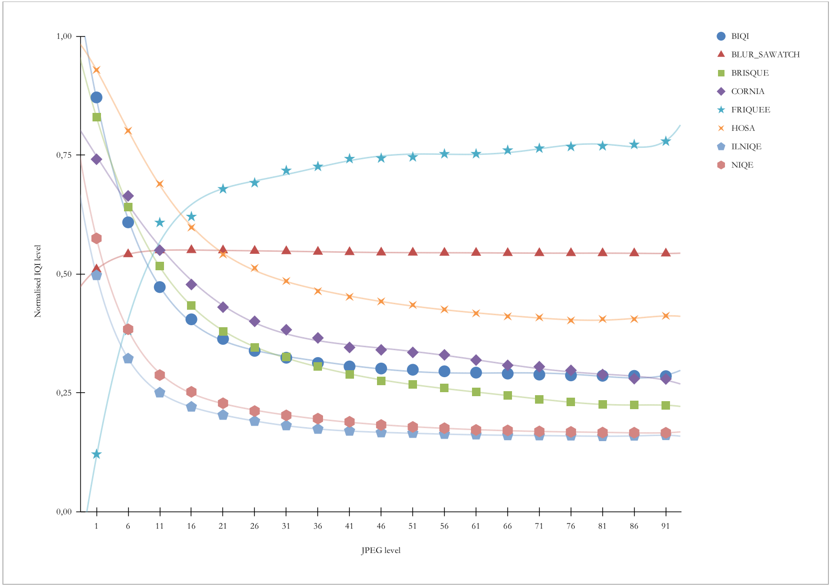

Results

	Precision	Recall	F-measure
All metrics	0.893	0.846	0.869
Only ours	0.870	0.791	0.829

Table: General results (Precision, Recall, F-measure) we receive for face recognition, using all metrics and only our ones

Results

All metrics	Algorithm claims it can recognise a face	Algorithm claims the face cannot be recognised
Face was recognised	$tp = 562$	$fn = 102$
Face was not recognised	$fp = 67$	$tn = 439$

Only ours	Algorithm claims it can recognise a face	Algorithm claims the face cannot be recognised
Face was recognised	$tp = 440$	$fn = 116$
Face was not recognised	$fp = 66$	$tn = 548$

Table: Detailed results (true positives – t_p, false positives – f_p, true negatives – t_n, and false negatives – f_n) we receive for face recognition

Results

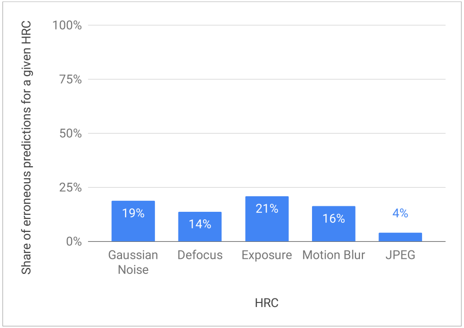

Figure: Share of erroneous predictions for a given Hypothetical Reference Circuits (HRC) in face recognition

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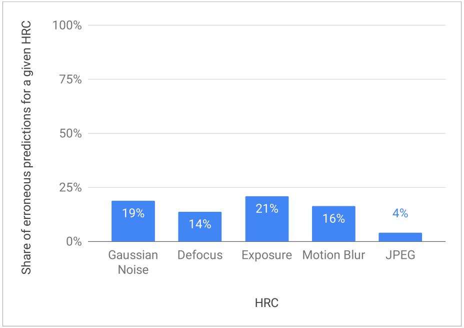
1. A more detailed analysis of the results obtained is also carried out.



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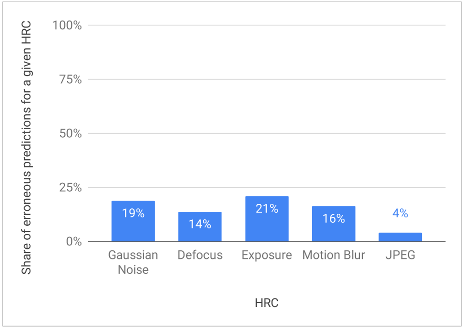

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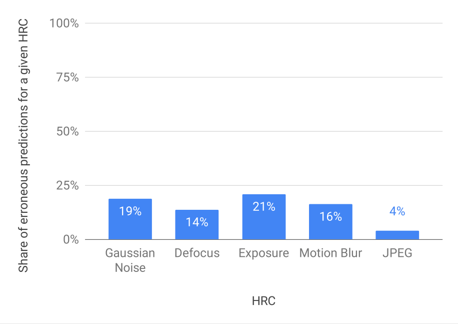

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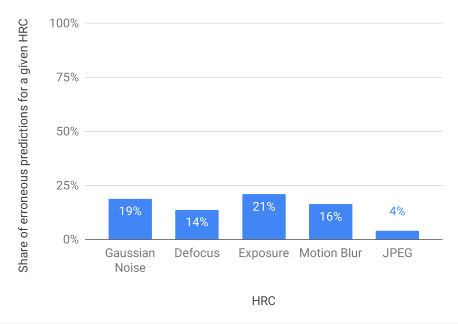
4. The exception is JPEG HRC, for which the model is much less mistaken – only for 4% of the cases.



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5. It is worth mentioning the most typical problems encountered by the models during their work.

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2. The achieved value of the model accuracy (F-measure parameter) is 0.87.
3. When all potential VQIs are used (VQIs by AGH and other research teams), the best modelling results are obtained.
4. Nevertheless, it is worth noting that the restriction of AGH VQI does not lead to a significant decrease in prediction accuracy (F-measure of 0.83).
5. It is worth mentioning the most typical problems encountered by the models during their work.
6. Our observations suggest that the characteristics of the initial scene are an important component that misleads the models.

Conclusions

1. We show in this study that the implementation of the new concept of an objective model to evaluate video quality for face recognition tasks is feasible.
2. The achieved value of the model accuracy (F-measure parameter) is 0.87.
3. When all potential VQIs are used (VQIs by AGH and other research teams), the best modelling results are obtained.
4. Nevertheless, it is worth noting that the restriction of AGH VQI does not lead to a significant decrease in prediction accuracy (F-measure of 0.83).
5. It is worth mentioning the most typical problems encountered by the models during their work.
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

AGH

Mikołaj Leszczuk, Lucjan Janowski, Jakub Nawała, and Atanas Boev, "Objective Video Quality Assessment Method for Face Recognition Tasks", Electronics 2022, 11(8), 1167,
https://doi.org/10.3390/electronics11081167