Automatic Colorization

Gustav Larsson

TTI Chicago / University of Chicago

Joint work with Michael Maire and Greg Shakhnarovich

NVIDIA @ SIGGRAPH 2016

Colorization

Let us first define “colorization”

Colorization

Definition 1: The inverse of desaturation.

Original

Colorization

Definition 1: The inverse of desaturation.

Original

$\xrightarrow{\text{Desaturate}}$

Grayscale

Colorization

Definition 1: The inverse of desaturation.

Grayscale

Colorization

Definition 1: The inverse of desaturation.

Original

$\xleftarrow{\text{Colorize}}$

Grayscale

Colorization

Definition 1: The inverse of desaturation. (**Note: Impossible!**)

Original

$\xleftarrow{\text{Colorize}}$

Grayscale

Colorization

Definition 2: An inverse of desaturation, that...

Grayscale

Colorization

Definition 2: An inverse of desaturation, that...

Our Method

$\xleftarrow{\text{Colorize}}$

Grayscale

... is plausible and pleasing to a human observer.

Colorization

Definition 2: An inverse of desaturation, that...

Our Method

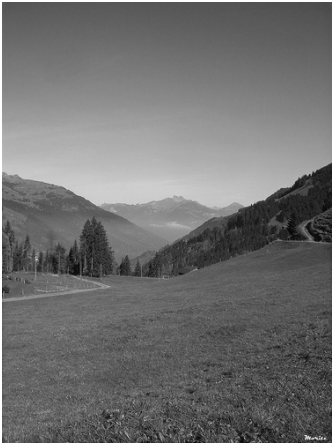
$\xleftarrow{\text{Colorize}}$

Grayscale

... is plausible and pleasing to a human observer.

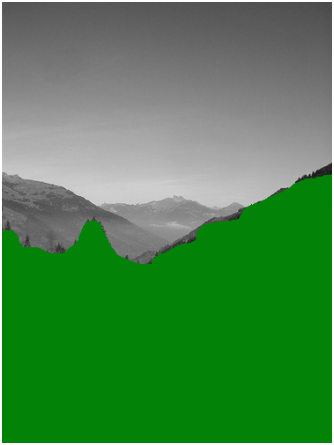
- Def. 1: Training + Quantitative Evaluation
- Def. 2: Qualitative Evaluation

Manual colorization



I thought I would give it a quick try...

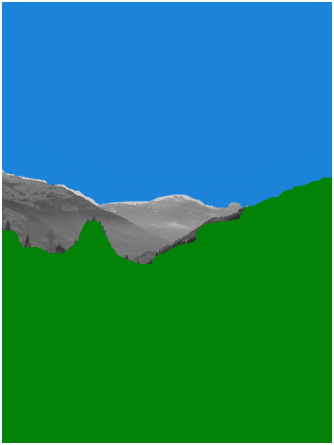
Manual colorization



Grass is green

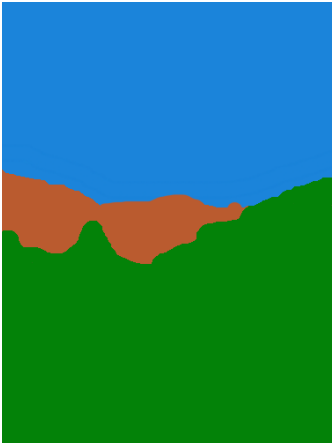
(low-level: grass texture / mid-level: tree recognition / high-level: scene understanding)

Manual colorization



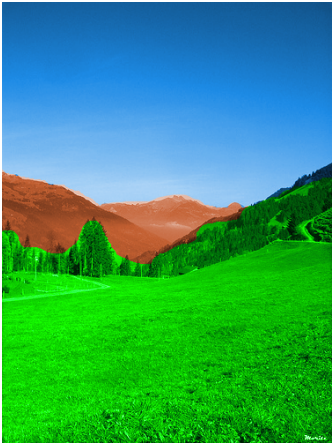
Sky is blue

Manual colorization



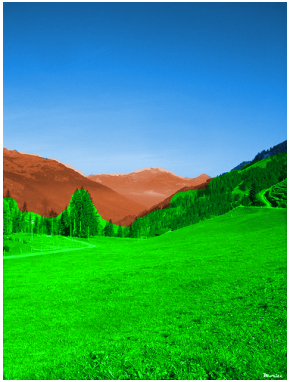
Mountains are... brown?

Manual colorization



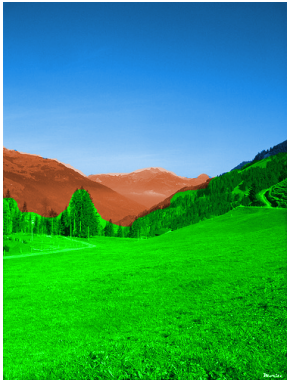
Use the original luminosity

Manual colorization

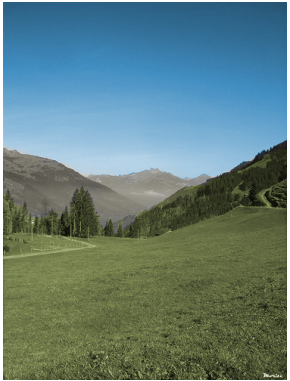


Manual ($\approx$ 15 s)

Manual colorization

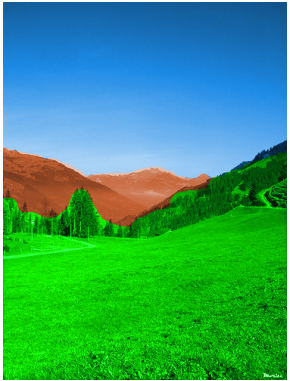


Manual ($\approx$ 15 s)

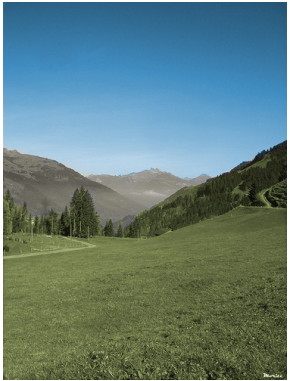


Manual ($\approx$ 3 min)

Manual colorization



Manual ($\approx$ 15 s)



Manual ($\approx$ 3 min)

Automatic (< 1 s)

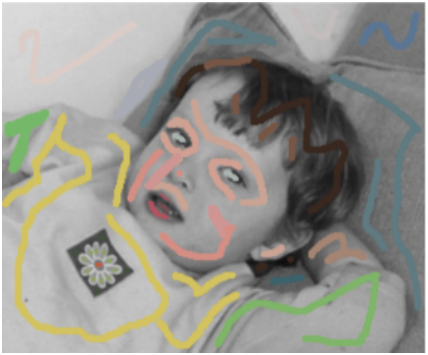
A brief history

The history of computer-aided colorization in 3 slides.

Method 1: Scribbles

Manual ——●—— Automatic

User-defined scribbles define colors. Algorithm fills it in.



Input

Output

Levin et al. (2004)

→ Levin et al. (2004); Huang et al. (2005); Qu et al. (2006); Luan et al. (2007)

Method 2: Transfer

Manual ——●—— Automatic

Reference image(s) is provided. Scribbles are automatically created from correspondences.

Reference

Input

Output

Charpiat et al. (2008)

→ Welsh et al. (2002); Irony et al. (2005); Charpiat et al. (2008); Morimoto et al. (2009); Chia et al. (2011)

Method 2: Transfer

Manual ——●——●——● Automatic

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Input

Output

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→ Welsh et al. (2002); Irony et al. (2005); Charpiat et al. (2008); Morimoto et al. (2009); Chia et al. (2011)

Method 3: Prediction

Manual ——●—— Automatic

Fully parametric prediction.

`colorize` () = 

Automatic colorization is gaining interest recently:

→ $\underbrace{\text{Deshpande et al., Cheng et al.}}_{\text{ICCV 2015}}$; $\underbrace{\text{Iizuka \& Simo-Serra et al.}}_{\text{SIGGRAPH 2016 (2pm, Ballroom E)}}$ $\underbrace{\text{Zhang et al., Larsson et al.}}_{\text{ECCV 2016}}$

Method 3: Prediction

Manual ——●—— Automatic

Fully parametric prediction.

`colorize_pixel`  $= (60, 87, 44)$

Automatic colorization is gaining interest recently:

→ Deshpande et al., Cheng et al.; Iizuka & Simo-Serra et al. Zhang et al., Larsson et al.

ICCV 2015 SIGGRAPH 2016 (2pm, Ballroom E) ECCV 2016

Model

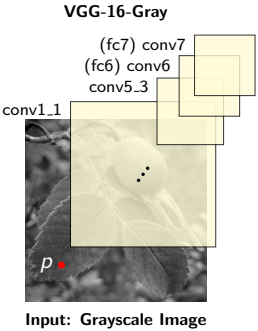
Design principles:

- Semantic knowledge

Model

Design principles:

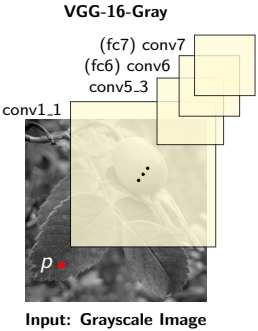
- Semantic knowledge $\rightarrow$ Leverage ImageNet-based classifier



Model

Design principles:

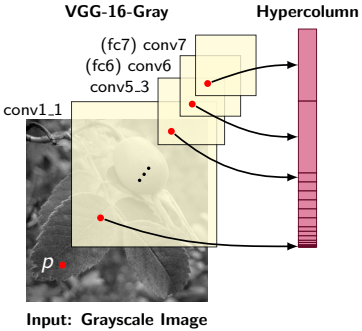
- Semantic knowledge $\rightarrow$ Leverage ImageNet-based classifier
- Low-level/high-level features



Model

Design principles:

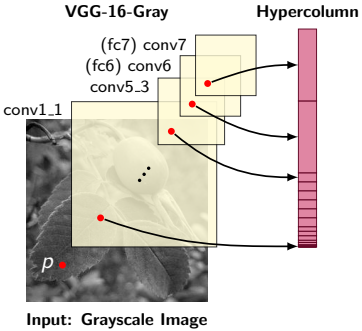
- Semantic knowledge $\rightarrow$ Leverage ImageNet-based classifier
- Low-level/high-level features $\rightarrow$ Zoom-out/Hypercolumn architecture



Model

Design principles:

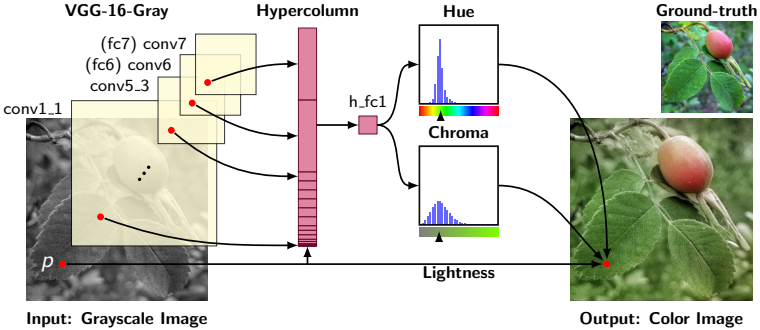
- Semantic knowledge $\rightarrow$ Leverage ImageNet-based classifier
- Low-level/high-level features $\rightarrow$ Zoom-out/Hypercolumn architecture
- Colorization not unique



Model

Design principles:

- Semantic knowledge $\rightarrow$ Leverage ImageNet-based classifier
- Low-level/high-level features $\rightarrow$ Zoom-out/Hypercolumn architecture
- Colorization not unique $\rightarrow$ Predict histograms



Instantiation

Going from histogram prediction to RGB:

- Sample

Instantiation

Going from histogram prediction to RGB:

- Sample
- Mode

Instantiation

Going from histogram prediction to RGB:

- Sample
- Mode
- Median

Instantiation

Going from histogram prediction to RGB:

- Sample
- Mode
- Median
- Expectation

Instantiation

Going from histogram prediction to RGB:

- Sample
- Mode
- Median $\leftarrow$ Chroma
- Expectation $\leftarrow$ Hue

Instantiation

Going from histogram prediction to RGB:

- Sample
- Mode
- Median $\leftarrow$ Chroma
- Expectation $\leftarrow$ Hue

The histogram representation is rich and flexible:

Instantiation

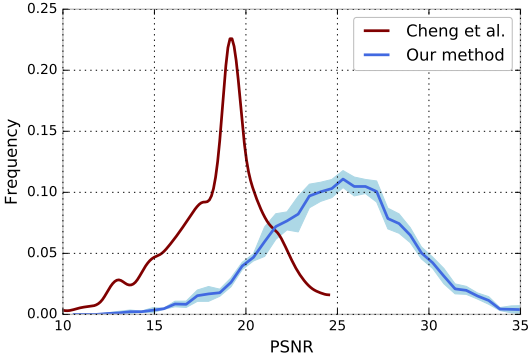
Going from histogram prediction to RGB:

- Sample
- Mode
- Median $\leftarrow$ Chroma
- Expectation $\leftarrow$ Hue

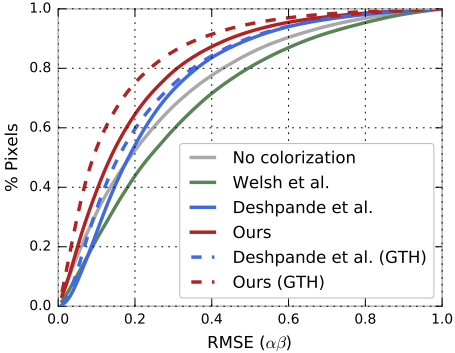
The histogram representation is rich and flexible:

Results

Significant improvement over state-of-the-art:



Cheng et al. (2015)

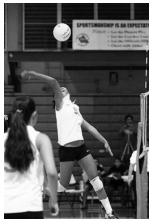


Deshpande et al. (2015)

Comparison

Model	AuC CMF non-rebal (%)	AuC CMF rebal (%)	VGG Top-1 Classification Accuracy (%)	Turk Labeled Real (%) mean	Turk Labeled Real (%) std
Ground Truth	100.00	100.00	68.32	50.00	–
Gray	89.14	58.01	52.69	–	–
Random	84.17	57.34	41.03	12.99	2.09
Dahl	90.42	58.92	48.72	18.31	2.01
Zhang et al.	91.57	65.12	56.56	25.16	2.26
Zhang et al. (rebal)	89.50	**67.29**	56.01	**32.25**	2.41
Ours	**91.70**	65.93	**59.36**	27.24	2.31

Table: Source: Zhang et al. (2016)



SCHOOL BUS
SPORTSMANSHIP IS AN EXPECTAT
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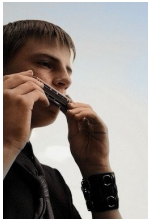
Photomatter.com



SCHOOL BUS
Beth Wade Photography
SPORTSMANSHIP IS AN EXPECTATION
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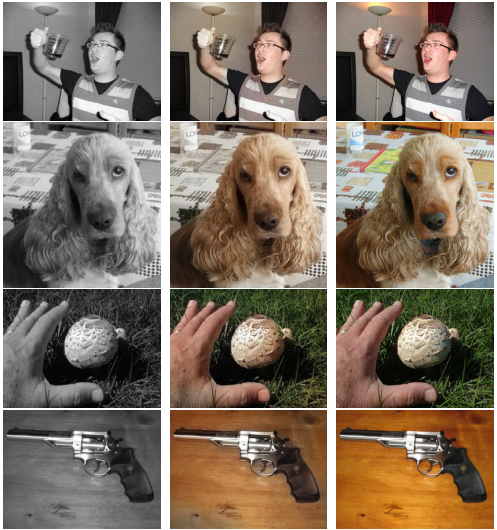
Examples



Input **Our Method** **Ground-truth**

Input **Our Method** **Ground-truth**

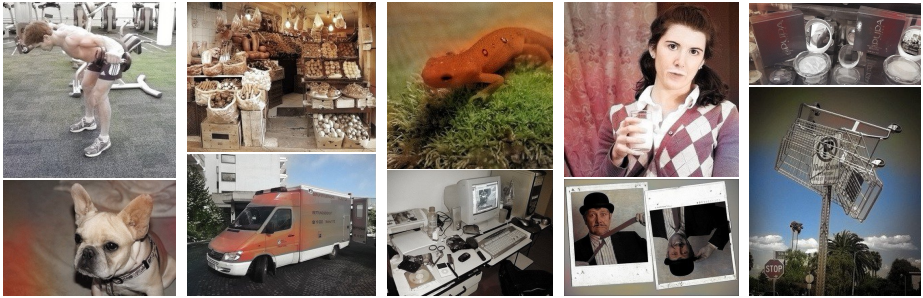


Figure: Failure modes.

Figure: B&W photographs.

Self-supervision (ongoing work)

Colorization as a means to learn visual representations:

1. Train colorization from scratch

Self-supervision (ongoing work)

Colorization as a means to learn visual representations:

1. Train colorization from scratch
2. Use network for segmentation, detection, style transfer, texture generation, etc.

Self-supervision (ongoing work)

Colorization as a means to learn visual representations:

1. Train colorization from scratch
2. Use network for segmentation, detection, style transfer, texture generation, etc.

Initialization	Architecture	X_{ImageNet}	Y_{ImageNet}	Color	mIU (%)
Classifier (ours)	VGG-16	✓	✓		64.0
Random	VGG-16				32.5
Classifier	AlexNet	✓	✓	✓	48.0
Random	AlexNet			✓	19.8

Table: **VOC 2012 segmentation validation set.**

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Random	VGG-16				32.5
Classifier	AlexNet	✓	✓	✓	48.0
BiGAN (Donahue et al.)	AlexNet	✓		✓	34.9
Inpainter (Deepak et al.)	AlexNet	✓		✓	29.7
Random	AlexNet			✓	19.8

Table: **VOC 2012 segmentation validation set.**

Self-supervision (ongoing work)

Colorization as a means to learn visual representations:

1. Train colorization from scratch
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Initialization	Architecture	X_{ImageNet}	Y_{ImageNet}	Color	mIU (%)
Classifier (ours)	VGG-16	✓	✓		64.0
Colorizer	VGG-16	✓			**50.2**
Random	VGG-16				32.5
Classifier	AlexNet	✓	✓	✓	48.0
BiGAN (Donahue et al.)	AlexNet	✓		✓	34.9
Inpainter (Deepak et al.)	AlexNet	✓		✓	29.7
Random	AlexNet			✓	19.8

Table: **VOC 2012 segmentation validation set.**

Questions?

Try it out yourself:
`http://colorize.ttic.edu`

References

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