Graph Cuts, MRFs and Graphcut Textures

CS448V — Computational Video Manipulation

April 2019

















Local

What makes this a "texture"?





Stochastic



Regular



Stochastic

Regular

Texture?

Textures are everywhere!









ere of a visual contreal neuron-the m













Graphcut Textures: Image and Video Synthesis Using Graph Cuts Kwatra et al. 2003

Graphcut Textures: Image and Video Synthesis Using Graph Cuts Kwatra et al. 2003







Capacity(S, T) = sum of edge weights (leaving) S



Max-flow Min-cut theorem



Max-flow Min-cut theorem



What is a flow?...

Max-flow Min-cut theorem







Many variants:

- directed/undirected
- with/without terminals
- multi-cut
- non integer weights
- negative weights

. . .



Many variants:

- directed/undirected
- with/without terminals
- multi-cut
- non integer weights
- negative weights

. . .



Many many applications!









we will use a similar trick...



Back to Graphcut Textures...






"Chernobyl harvest"

Where to place next patch?

Graph cuts to the rescue

Which pixels to use? Graph cuts to the rescue



Which pixels to use? Graph cuts to the rescue



Which pixels to use? Graph cuts to the rescue



M(s,t) = ||A(s) - B(s)|| + ||A(t) - B(t)||







1 from old 4 from new



1 from old 4 from new



1 from old 4 from new

1

Cut at most one edge!



1 from old 4 from new

1

Cut at most one edge! M should be a metric







Kept old seam



Updated seam



Removed seam







What might happen if we only connect a few pixels to B?

Minor detour: MRFs

Reminder: Markov property

Reminder: Markov property

"memoryless"

Reminder: Markov property

"memoryless"

For a discrete process: $P(X_n = x_n | X_n)$

$$X_{n-1} = x_{n-1}, \dots, X_0 = x_0$$
 = $P(X_n = x_n | X_{n-1} = x_{n-1})$

For a discrete process: $P(X_n = x_n | X_n)$



- **Reminder: Markov property**
 - "memoryless"

$$X_{n-1} = x_{n-1}, \dots, X_0 = x_0 = P(X_n = x_n | X_{n-1} = x_{n-1})$$

What about fields?

Reminder: Markov property

"memoryless"

For a discrete process: $P(X_n = x_n | X_n)$





$$X_{n-1} = x_{n-1}, \dots, X_0 = x_0 = P(X_n = x_n | X_{n-1} = x_{n-1})$$

What about fields?

two non-adjacent variables are conditionally independent given all other variables

Reminder: Markov property

"memoryless"

For a discrete process: $P(X_n = x_n | X_n)$





$$X_{n-1} = x_{n-1}, \dots, X_0 = x_0 = P(X_n = x_n | X_{n-1} = x_{n-1})$$

What about fields?

A variable is conditionally independent of all other variables given its neighbors

Reminder: Markov property

"memoryless"

For a discrete process: $P(X_n = x_n | X_n)$





$$X_{n-1} = x_{n-1}, \dots, X_0 = x_0 = P(X_n = x_n | X_{n-1} = x_{n-1})$$

What about fields?

two subsets are conditionally independent given a separating subset



What does it mean in our setting?

Where to place next patch?

Placing the next patch



Placing the next patch

• Random placement



Placing the next patch

- Random placement
- Entire patch matching


Placing the next patch

- Random placement
- Entire patch matching
- Sub-patch matching



Placing the next patch

- Random placement
- Entire patch matching
- Sub-patch matching

What would be the "right" thing to do, assuming no runtime constraints?



Results



describing the response of that neuron ht as a function of position—is perhap functional description of that neuron. seek a single conceptual and mathem escribe the wealth of simple-cell recept id neurophysiologically¹⁻³ and inferred especially if such a framework has the it helps us to understand the function leeper way. Whereas no generic most ussians (DOG), difference of offset (rivative of a Gaussian, higher derivati function, and so on—can be expected imple-cell receptive field, we noneth

errout nearon the the weath of simple-th describing the response of that neurophysiologically1-3 and nt as a function of position-is perhally if such a framework functional description of that neuron. us to understand the seek a single conceptual and mathr way. Whereas no gene scribe the wealth of simple-cell ians (DOG), difference of d neurophysiologically1-3 and ivative of a Ga response of the especially if such a framework functionnction of position-i t helps us to understand the funcional description of that eeper way. Whereas no generick a single conceptual and 1 ussians (DOG), difference of a function of position-is per ivative of a Gaussian, higher donal description of that neur he response od so on-can be a single conceptual and math escribing the response of that ne the wealth of simple-cell reas a function of position-is perbphysiologically1-3 and infe: actional description of that neurony if such a framework has ek a single conceptual and mathems to understand the fun ribe the wealth of simple-onceptual Whereas no generic neurophysiologically1-3 and th of simple), difference of offs pecially if such a frameworlogically1-3 Gaussian, higher deriv helps us to understand such a framewor so on-can be exp per way. Whereas us to understand the fun field, we nor



















Input





Image Quilting

Input



Graph cut

Graph cut



Rotation & Mirroring













Video synthesis





Spatio-temporally stationary



How should this affect patch search strategy?



Spatio-temporally stationary







+

Seam optimization

Per-pixel transition timing



Original



Original





Spatio-temporally stationary



Spatio-temporally stationary

Can search patches in time and space!



Spatio-temporally stationary



Robust results even for short sequences

Can search patches in time and space!



Can search patches in time and space!

Spatio-temporally stationary



Robust results even for short sequences

Input Resolution: 170 x 116 Output Resolution: 210 x 160



Original

Spatial Extension

Can make videos larger





Solution: explicitly force beginning and end to match



Solution: explicitly force beginning and end to match





• Textures are everywhere!





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• Add to your tool belt: Graph Cuts







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Graphcut Textures

Many things!

- Many things!
- E.g., image analogies

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- E.g., image analogies
 - Convert between different representations of an image



Unfiltered source (A)



Filtered source (A')



Unfiltered (B)



Filtered (B')



- Many things!
- E.g., image analogies
 - Convert between different representations of an image
 - Stylization



A



٠

A'





- Many things!
- E.g., image analogies
 - Convert between different representations of an image
 - Stylization
- We will discuss these applications later in the course (using more recent methods)



A



A'



