# CS448f: Image Processing For Photography and Vision 

Wavelets and Compression

## ImageStack Gotchas

- Image and Windows are pointer classes
- What's wrong with this code?

Image sharp = Load::apply("foo.jpg");
Image blurry = foo;
FastBlur::apply(blurry, 0, 5, 5);
Subtract::apply(sharp, blurry);

## ImageStack Gotchas

- Image and Windows are pointer classes
- What's wrong with this code?

Image sharp = Load::apply("foo.jpg");
Image blurry = foo.copy();
FastBlur::apply(blurry, 0, 5, 5);
Subtract::apply(sharp, blurry);

## ImageStack Gotchas

- Images own memory (via reference counting), Windows do not.
- What's wrong with this code?

```
class Foo {
    public:
    Foo(Window im) {
        Image temp(im);
        ... do some processing on temp ...
        patch = temp;
    };
    Window patch;
};
```


## ImageStack Gotchas

- Images own memory (via reference counting), Windows do not.
- What's wrong with this code?

```
class Foo {
    public:
    Foo(Window im) {
        Image temp(im);
        ... do some processing on temp ...
        patch = temp;
    };
    Image patch;
};
```


## Using Windows Wisely

```
float sig = 2;
Image pyramid = Upsample::apply(gray, 10, 1, 1);
// pyramid now contains }10\mathrm{ copies of the input
for(int i = 1; i < 10; i++) {
    Window level(pyramid, i, 0, 0, 1, pyramid.width, pyramid.height);
    FastBlur::apply(level, 0, sig, sig);
    sig *= 1.6;
}
// 'pyramid' now contains a Gaussian pyramid
for(int i = 0; i < 9; i++) {
    Window thisLevel(pyramid, i, 0, 0, 1, pyramid.width, pyramid.height);
    Window nextLevel(pyramid, i+1, 0, 0, 1, pyramid.width, pyramid.height);
    Subtract::apply(thisLevel, nextLevel);
}
// 'pyramid' now contains a Laplacian pyramid
// (except for the downsampling)
```


## The only time memory gets allocated

```
float sig = 2;
Image pyramid = Upsample::apply(gray, 10, 1, 1);
// pyramid now contains 10 copies of the input
for(int i = 1; i < 10; i++) {
    Window level(pyramid, i, 0, 0, 1, pyramid.width, pyramid.height);
    FastBlur::apply(level, 0, sig, sig);
    sig *= 1.6;
}
// 'pyramid' now contains a Gaussian pyramid
for(int i = 0; i < 9; i++) {
    Window thisLevel(pyramid, i, 0, 0, 1, pyramid.width, pyramid.height);
    Window nextLevel(pyramid, i+1, 0, 0, 1, pyramid.width, pyramid.height);
    Subtract::apply(thisLevel, nextLevel);
}
// 'pyramid' now contains a Laplacian pyramid
// (except for the downsampling)
```


## Select each layer and blur it

```
float sig = 2;
Image pyramid = Upsample::apply(gray, 10, 1, 1);
// pyramid now contains }10\mathrm{ copies of the input
for(int i = 1; i < 10; i++) {
    Window level(pyramid, i, 0, 0, 1, pyramid.width, pyramid.height);
    FastBlur::apply(level, 0, sig, sig);
    sig *= 1.6;
}
// 'pyramid' now contains a Gaussian pyramid
for(int i = 0; i < 9; i++) {
    Window thisLevel(pyramid, i, 0, 0, 1, pyramid.width, pyramid.height);
    Window nextLevel(pyramid, i+1, 0, 0, 1, pyramid.width, pyramid.height);
    Subtract::apply(thisLevel, nextLevel);
}
// 'pyramid' now contains a Laplacian pyramid
// (except for the downsampling)
```


## Take the difference between each layer and the next

```
float sig = 2;
Image pyramid = Upsample::apply(gray, 10, 1, 1);
// pyramid now contains }10\mathrm{ copies of the input
for(int i = 1; i < 10; i++) {
    Window level(pyramid, i, 0, 0, 1, pyramid.width, pyramid.height);
    FastBlur::apply(level, 0, sig, sig);
    sig *= 1.6;
}
// 'pyramid' now contains a Gaussian pyramid
for(int i = 0; i < 9; i++) {
    Window thisLevel(pyramid, i, 0, 0, 1, pyramid.width, pyramid.height);
    Window nextLevel(pyramid, i+1, 0, 0, 1, pyramid.width, pyramid.height);
    Subtract::apply(thisLevel, nextLevel);
}
// 'pyramid' now contains a Laplacian pyramid
// (except for the downsampling)
```


## Review: Laplacian Pyramids

- Make the coarse layer by downsampling



## Review: Laplacian Pyramids

- Make the fine layer by upsampling the coarse layer, and taking the difference with the original



## Review: Laplacian Pyramids

- Only store these


Fine


## Review: Laplacian Pyramids

- Reconstruct like so:



## Laplacian Pyramids and Redundancy

- The coarse layer has redundancy - it's blurry. We can store it at low resolution
- In linear algebra terms:
- coarse = Upsample(small)
$-\mathrm{c}=\mathrm{Us}$
$-c$ is a linear combination of the columns of $U$
- How many linearly independent dimensions does c have?


## Laplacian Pyramids and Redundancy

- The fine layer should be redundant too
- What constraint does the fine layer obey?
- How much of the fine layer should we actually need to store?


## Laplacian Pyramids and Redundancy

- The fine layer should be redundant too
- What constraint does the fine layer obey?
- How much of the fine layer should we actually need to store?
- Intuitively, should be $3 / 4$ n for $n$ pixels



## Laplacian Pyramids and Redundancy

- What constraint does the fine layer obey?
$\mathrm{f}=\mathrm{m}-\mathrm{c}$
$\mathrm{f}=\mathrm{m}-\mathrm{UDm}$
$K f=K m-K U D m$
if $K U D=K$
then $\mathrm{Kf}=0$

$$
\begin{aligned}
& m=\text { input image } \\
& c=\text { coarse } \\
& f=\text { fine } \\
& U=\text { upsampling } \\
& D=\text { downsampling } \\
& K=\text { some matrix }
\end{aligned}
$$

$$
K(\text { UD-I })=0
$$

K is the null-space (on the left) of UD-I
May be empty (no constraints)
May have lots of constraints. Hard to tell.

## Laplacian Pyramids and Redundancy

- What if we say DU = I
- i.e. upsampling then downsampling does nothing
- Then (UD) ${ }^{2}=(U D)(U D)=U(D U) D$
- $\mathrm{f}=\mathrm{m}$ - UDm
- UDf = UDm - UDUDm = UDm - UDm = 0
- f is in the null-space of UD
- Downsampling then upsampling the fine layer gives you a black image.


## DU = I

- How about nearest neighbor upsampling followed by rect downsampling?
- How about lanczos3 upsampling followed by lanczos3 downsampling?


## DU = I

- How about nearest neighbor upsampling followed by nearest neighbor downsampling?
- Yes, but this is a crappy downsampling filter $*$
- How about lanczos3 upsampling followed by lanczos3 downsampling?
- No :
- This is hard, if we continue down this rabbit hole we arrive at...


## Wavelets

- Yet another tool for:
- Image = coarse + fine
- So why should we care?
- They don't increase the amount of data like pyramids (memory efficient)
- They're simple to compute (time efficient)
- Like the Fourier transform, they're orthogonal
- They have no redundancy


## The Haar Wavelet

- Equivalent to nearest neighbor downsampling / upsampling.
- Take each pair of values and replace it with:
- The sum / 2
- The difference / 2
- The sums form the coarse layer
- The differences form the fine layer


## The 1D Haar Transform



## Equivalently...

- The coarse layer is produced by convolving with [1⁄2 $1 / 2$ ] (then subsampling)

- The fine layer is produced by convolving with $[-1 / 21 / 2]$ (then subsampling)



## DU = I

- In this case, D =



## DU = I

- Note each row is orthogonal



## DU = 1

- So Let $\mathrm{U}=\mathrm{D}^{\top}$. Now $\mathrm{DU}=\mathrm{DD}^{\top}=1$
- What kind of upsampling is U?



## Equivalently...

- The scaling function is the downsampling filter. It must be orthogonal to itself when shifted by 2 n .
- The wavelet function parameterizes what the downsampling throws away
- i.e. the null-space of UD (orthogonal to every row of UD)


## The 1D Inverse Haar Transform



## Recursive Haar Wavelet

- If you want a pyramid instead of a 2-level decomposition, just recurse and decompose the coarse layer again
$-O(n \log (n))$


## 2D Haar Wavelet Transform

- 1D Haar transform each row
- 1D Haar transform each column
- If we're doing a full recursive transform, we can:
- Do the full recursive transform in $X$, then the full recursive transform in $Y$ (standard order)
- Do a single 2D Haar transform, then recurse on the coarse layer (non-standard order)


## 2D Haar Wavelet Transform

- (demo)


## Problem with the Haar Wavelet

- Edges at a certain scale may exist in one of several levels, depending on their position.

| 10 | 10 | 10 | 10 | 10 | 0 | 0 | 0 | 0 | 0 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 10 | 10 | 5 | 0 | 0 | 0 | 0 | -5 | 0 | 0 |
| Averages (Coarse) |  |  |  |  | Differences (Fine) |  |  |  |  |
| 10 | 10 | 10 | 10 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 | 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Averages (Coarse) |  |  |  |  | Differences (Fine) |  |  |  |  |

## Better Wavelets

- Let's try to pick a better downsampling filter (scaling function) so that we don't miss edges like this
- Needs a wider support
- Still has to be orthogonal
- Tent: [ $1 / 41 / 21 / 4$ ]?



## Better Wavelets

- Lanczos3 downsampling filter:
[0.02 0.00-0.14 0.00 0.61 1.00 0.61 0.00-0.14 0.00 0.02]
- Dot product $=0.1987$
- not orthogonal to itself shifted


## Let's design one that works

- Scaling function = [a b c d]
- Orthogonal to shifted copy of itself
- If we want $\mathrm{DD}^{\top}=I$, then should be unit length...
$-[a b c d] \cdot[a b c d]=a^{2}+b^{2}+c^{2}+d^{2}=1$
- That's two constraints...


## more constraints

- Let's make the wavelet function use the same constants but wiggle: [a -b c-d]
- Just like the Haar, but 4 wide
- Wavelet function should parameterize what the scaling function loses, so should be orthogonal (even when shifted)
- [a b c d].[a -b c -d] $=a^{2}-b^{2}+c^{2}-d^{2}=0$
- [0 0 a b c d].[a -b c -d 0 0] = ac - bd = 0


## Wavelet function should also be orthogonal...

- [0 00 a -b c -d].[a -b c-d 00 ] $=a c+b d=0$
- Good, we already had this constraint, so we're not overconstrained


## The constraints

- $a c+b d=0$
- $a^{2}+b^{2}+c^{2}+d^{2}=1$
- $a^{2}-b^{2}+c^{2}-d^{2}=0$
- $a c-b d=0$
- Adding eqs 1 and 4 gives us $a=0$ or $c=0$, which we don't want...
- In fact, this ends up with Haar as the only solution


## Try again...

- Let's reverse the wavelet function
- Wavelet function = [d -c b -a]
- $a c+b d=0$
- $a^{2}+b^{2}+c^{2}+d^{2}=1$
- [a b c d].[d -c b-a] = ad -bc $+b d-a d=0$
- trivially true
- [0 0 a b c d].[d -c b -a 0 0] = ab - ba = 0
- also trivially true
- [a b c d 0 0].[0 0 d -c b-a] = cd - cd = 0
- Also trivially true


## Now we can add 2 more constraints

- Considerably more freedom to design
- Let's say the coarse image has to be the same brightness as the big image:

$$
a+b+c+d=1
$$

- And the fine layer has to not be effected by local brightness (details only):

$$
d-c+b-a=0
$$

## Solve:

- $a c+b d=0$
- $a^{2}+b^{2}+c^{2}+d^{2}=1$
- $a+b+c+d=1$
- $d-c+b-a=0$
- Let's ask the oracle...


## No Solutions

- Ok, let's relax U = D ${ }^{\top}$
- It's ok for the coarse layer to get brighter or darker, as long as DU = I still holds
- $a^{2}+b^{2}+c^{2}+d^{2}=1$
- $a+b+c+d^{\prime}=1$
- $a+b+c+d>0$


## Solve:

- $a c+b d=0$
- $a^{2}+b^{2}+c^{2}+d^{2}=1$
- $a+b+c+d>0$
- $d-c+b-a=0$
- We're one constraint short...


## Solve:

- $a c+b d=0$
- $a^{2}+b^{2}+c^{2}+d^{2}=1$
- $a+b+c+d>0$
- $d-c+b-a=0$
- We're one constraint short...
- Let's make the scaling function really smooth
- minimize: $a^{2}+(b-a)^{2}+(c-b)^{2}+(d-c)^{2}+d^{2}$
- or maximize: $a b+b c+c d$


## Solution!

- $a=0.482963$
- $b=0.836516$
- $c=0.224144$
- $d=-0.12941$


## Ingrid Daubechies Solved this Exactly

- $a=(1+\operatorname{sqrt}(3)) /(4 \operatorname{sqrt}(2))$
- $\mathrm{b}=(3+\operatorname{sqrt}(3)) /(4 \operatorname{sqrt}(2))$
- c = (3 - sqrt(3)) / (4 sqrt(2))
- $\mathrm{d}=(1-\operatorname{sqrt}(3)) /(4 \operatorname{sqrt}(2))$
- Scaling function $=[a b c d]$
- Wavelet function = [d -c b-a]
- The resulting wavelet is better than Haar, because the downsampling filter is smoother.



## Applications

- Compression
- Denoising


## Compression

- Idea: throw away small wavelet terms
- Algorithm:
- Take the wavelet transform
- Store only values with absolute value greater than some threshold
- To recontruct image, do inverse wavelet transform assuming the missing values are zero


## Compression

- ImageStack -load pic.jpg -daubechies
-eval "fabs(val) < 0.1 ? 0 : val"
-inversedaubechies -display


## Input:



## Daubechies Transform:

## Dropping coefficients below 0.01

30\% less data


## Dropping coefficients below 0.05

65\% less data


## Dropping coefficients below 0.1

## 82\% less data



## Dropping coefficients below 0.2

## 94\% less data



## Daubechies vs Haar at 65\% less data



## Daubechies vs Reducing Resolution



## Denoising

- Similar Idea: Wavelet Shrinkage
- Take wavelet coefficients and move them towards zero
- E.g.
- 0.3 -> 0.25
- -0.2 -> -0.15
-0.05 -> 0
- 0.02 -> 0


## Input vs Output



## Wavelet Shrinkage vs Bilateral



- Wavelet shrinkage much faster - Denoised at multiple scales at once



## Lifting Schemes

- Turns out there's a better way to derive orthogonal wavelet bases
- We've done enough math for today
- Next Time


## Edge-Avoiding Wavelets

- Laplacian Pyramid : Wavelets
- as Bilateral Pyramid : Edge-Avoiding Wavelets


## Projects

- Rest of Quarter:
- Project proposal, due 1 week after due date of assn3
- 1 Paper presentation on your chosen paper (20 minutes of slides, 15 minutes of class discussion)
- Final project demo (after thanksgiving break)
- Final project code due at end of quarter.
- Intent: rest of quarter is $50-75 \%$ of the workload of start of quarter.


## Project Ideas:

- http://cs448f.stanford.edu/

