Neal Wadhwa

December 10, 2012

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Processing is on uncompressed video



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- Uncompressed videos uses huge amounts of space.
- 1080p at 30 FPS is one gigabyte per second
- Lots of algorithms are easy to parallelize due to independence of processing in space or time.

DSP based method to magnify subtle motions

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- Here are some cool examples of motion magnification.

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Try to parallelize and see how far we can get

▶ 1. Spatially decompose each frame.

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- > 2. Temporally process each pixel in each decomposition level

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- Every stage is easy to parallelize individually

- ▶ 1. Spatially decompose each frame.
- > 2. Temporally process each pixel in each decomposition level
- 3. Reconstruct each frame
- Every stage is easy to parallelize individually
- Serial algorithm takes several hours on high resolution videos.

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Say you have frames F_1, \ldots, F_n

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Decompose each frame into different spatial bands

$$F_i \rightarrow (D_{i,1},\ldots,D_{i,k})$$

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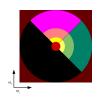
Transform is invertible.

 Create decomposition for every frame



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 Create decomposition for every frame





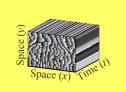
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 Create decomposition for every frame

Levels





 Orientations

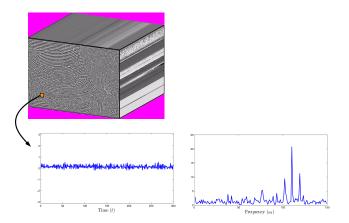
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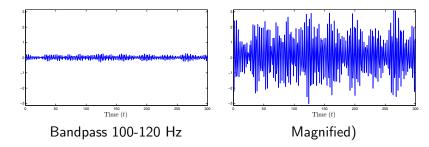
Outline of Algorithm

> For every pixel in every level, values contain motion signal



Outline of Algorithm

- Bandpass from 100 Hz to 120Hz
- Add bandpassed signal to original signal

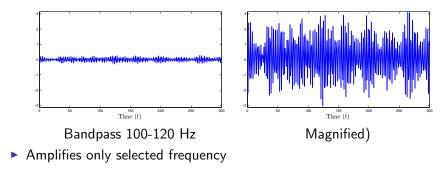


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Easy to Parallelize

Parallelize spatial decomposition over frames



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Parallelize temporal filtering over pixels.

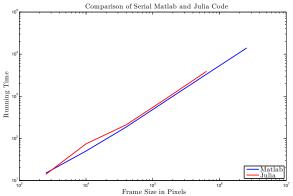
Easy to Parallelize

- Parallelize spatial decomposition over frames
- Parallelize temporal filtering over pixels.
- Difficulty lies in how to store data over cores.

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Relatively easy to port code to Julia

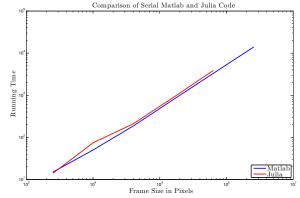
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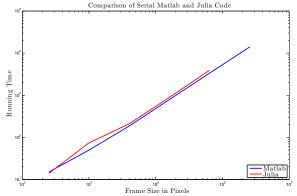
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Julia is slightly slower, but comparable.

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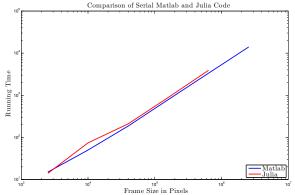


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- Julia is slightly slower, but comparable.
- Not surprising since main processing occurs in ffts (in libfftw).
- Uses 400 GB at largest problem size, 1600×1600×300.

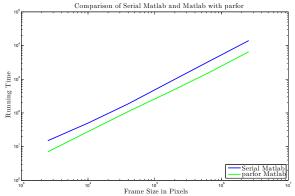
Matlab Parfor

Parfor gives factor of two improvement when used with 12 cores.

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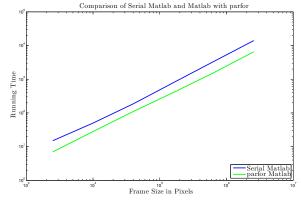
> Parfor processing on frames and on temporal processing



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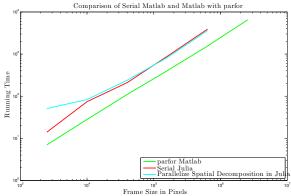
Only 2x improvement

Parllelize the spatial decomposition and reconstruction in Julia

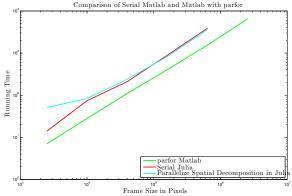
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Parllelize the spatial decomposition and reconstruction in Julia

> Faster than serial Julia for large problem size.

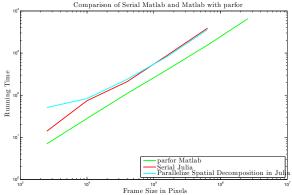


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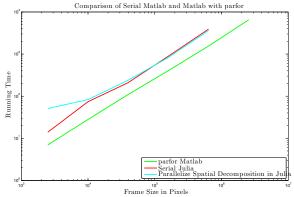
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- ▶ In serial code, temporal processing uses 14% of time.

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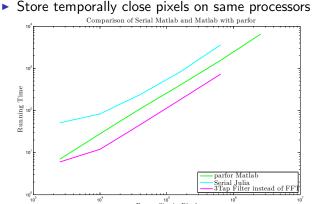


- The spatial decomposition is extremely fast, but reordered data for temporal filtering is very, very slow.
- ▶ In serial code, temporal processing uses 14% of time.
- In parallel code, temporal processing uses 50% of time.

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Frame Size in Pixels

- Makes temporal processing more local to avoid communication overhead.
- Store temporally close pixels on same processors Comparison of Serial Matlab and Matlab with parfor 10 10 Running Time ā. 10 parfor Matlab Serial Julia 3Tap Filter instead of F 105 10 Frame Size in Pixels

> 2.5x faster than Matlab, 5x faster than serial Julia

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Matlab parfor fails to capitalize on this