REAL-TIME FUSION OF VISIBLE AND THERMAL INFRARED IMAGES IN SURVEILLANCE APPLICATIONS ON SOC HARDWARE.



Konrad Moren, Thomas Perschke

Institute of Optronics, System Technologies and Image Exploitation (IOSB) Ettlingen Germany

konrad.moren@iosb,fraunhofer.de, thomas.perschke@iosb.fraunhofer.de

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Fusion of visible and thermal infrared images - Applications







http://www.dailymail.co.uk/sciencetech/article-2640869/Google-glass-war-US-military-reveals-augmented-reality-soldiers.html



https://www.bhphotovide o.com/c/product/1373861-REG/bosch_mic_9502_z30w qs_mic_ip_fusion_9000i.ht ml







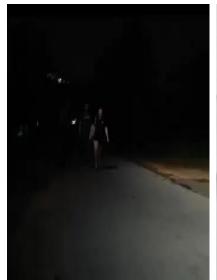
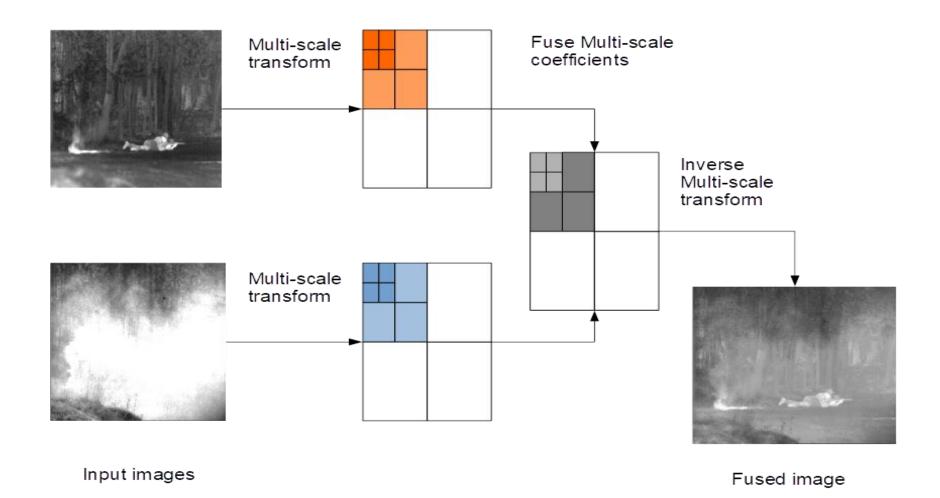


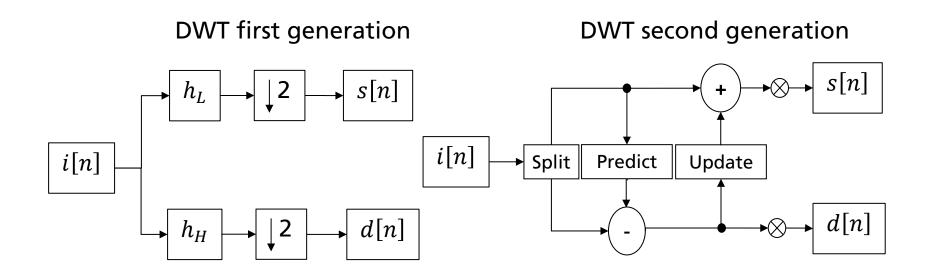


Image Fusion – Visual and IR Images



Multi-scale transformations

- Discrete Wavelet Transformation (DWT)
 - First generation wavelets DWT Mallat Scheme
 - Standard method used to create the multi-scale representation
 - Second generation wavelets DWT Lifting Scheme
 - Optimized method with reduced number of arithmetic operations



DWT Convolution

- 2D convolution with a low and a high pass (FIR) filters
- Filters are separable Decompose filtering into a vertical and horizontal
 1D-convolution

n	0	1	2	3	4
Low pass $h_L[n]$	0.06029	0.26684	-0.07822	-0.01686	0.0267
High pass $h_H[n]$	0.5575	0.2956	-0.0287	-0.0456	0

- Coefficients for the Cohen-Daubechies-Feauveau 9/7 wavelet
- Filters are symmetric :

•
$$s[n] = i[2n] \cdot h_L[0] + \sum_{k=1}^4 (i[2n+k] + i[2n-k]) \cdot h_L[k]$$

•
$$d[n] = i[2n+1] \cdot h_H[0] + \sum_{k=1}^{3} (i[2n+1+k] + i[2n+1-k]) \cdot h_H[k]$$

Complexity minimum effort : 23 MAD = 9 MUL + 14 ADD per output pixel pair (s[n], d[n])

DWT Lifting

- Lifting method reduces computational complexity of convolutions
- Convolution operation changed in series of lifting steps
 - Split, Update, Predict, Normalize
- Complexity, minimum effort: 14 MAD = 6 MUL + 8 ADD per output pixel pair (s[n], d[n])

n	0	1	2	3
α_n	1.58613	0.05298	0.88291	0.44351
$\boldsymbol{\beta}_n$	0.81289	0.61508	/	1

Split

$$s_0[n] = i[2n]$$

$$d_0[n] = i[2n+1]$$

Update, Predict

$$d_1[n] = d_0[n] - \alpha_0 \cdot (s_0[n+1] + s_0[n])$$

$$s_1[n] = s_0[n] - \alpha_1 \cdot (d_1[n] + d_1[n-1])$$

$$d_2[n] = d_1[n] - \alpha_2 \cdot (s_1[n+1] + s_1[n])$$

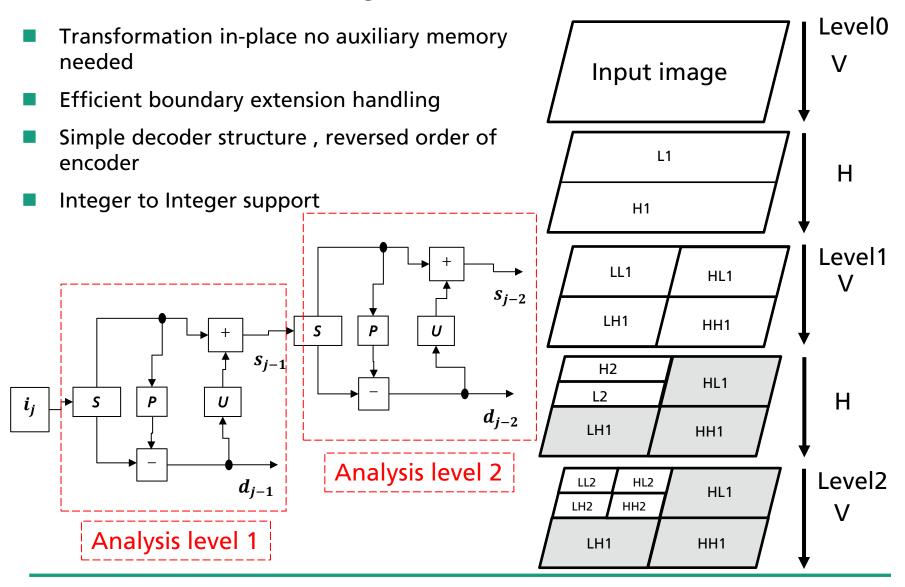
$$s_2[n] = s_1[n] + \alpha_3 \cdot (d_2[n] + d_2[n-1])$$

Normalize

$$s[n] = \beta_0 \cdot s_2[n]$$

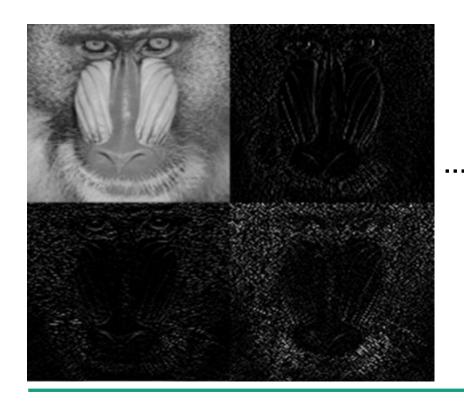
$$d[n] = \beta_1 \cdot d_2[n]$$

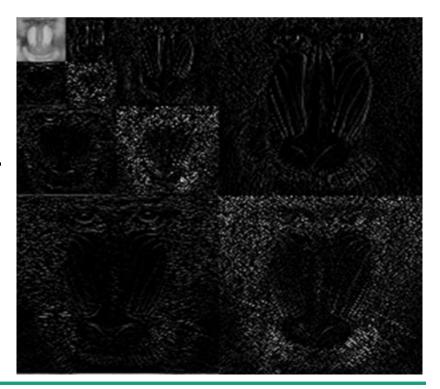
Multi-level DWT Lifting



Multi-level fusion

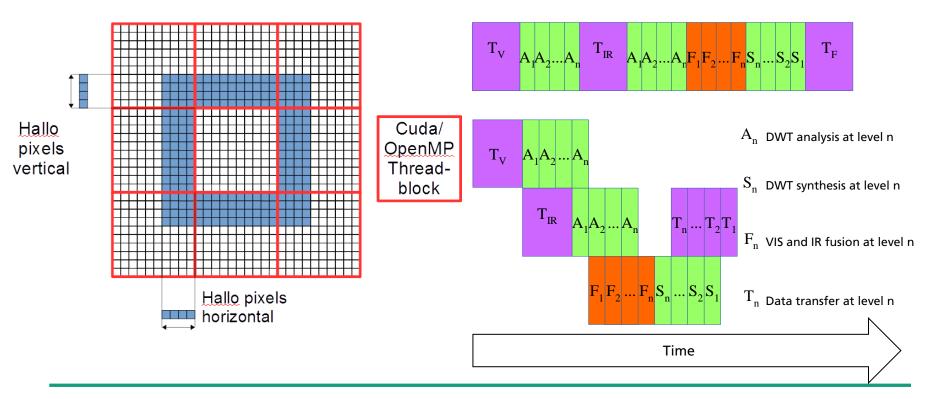
- Pixel-wise combine functions:
 - Average, Abs-max fusion $F_j[n] = Max(Abs((V_j[n] + IR_j[n]) * 0.5)))$
 - Fusion operators independent at different DWT analysis/synthesis levels





Data parallel, pipelined Fusion

- DWT- Lifting parallelized on CPU and GPU
 - Each output pixel pair computed independently
- Pipelined data transfers between I/O and CPU/GPU
 - Overlapped data transfers with computation

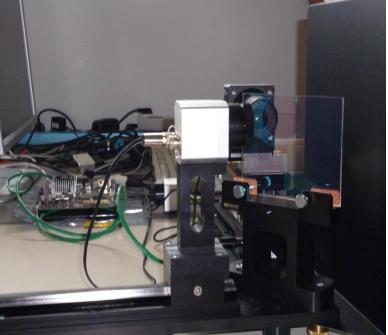


Evaluation - SoC Hardware

- Jetson TX2 NVidia
 - Programmable multi-core CPU / GPU
 - More than a 1 TFLOP/s of performance at 7.5Watt









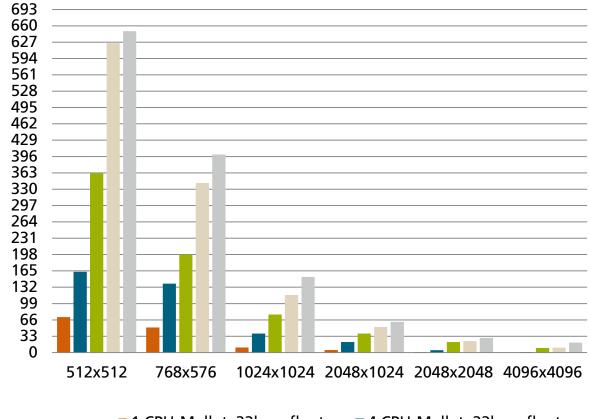


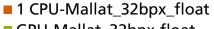
Results

DWT Encode+Decode without data transfers CPU/GPU [FPS]

Performance DWT:

- DWT-Lifting performance 1.41x better than DWT-Mallat
- GPU performance4.7x higher thanCPU
- Real-time (30 Hz)
 performance with
 GPU for Full-HD
 resolution





4 CPU-Mallat_32bpx_floatGPU-Lift_32bpx_float

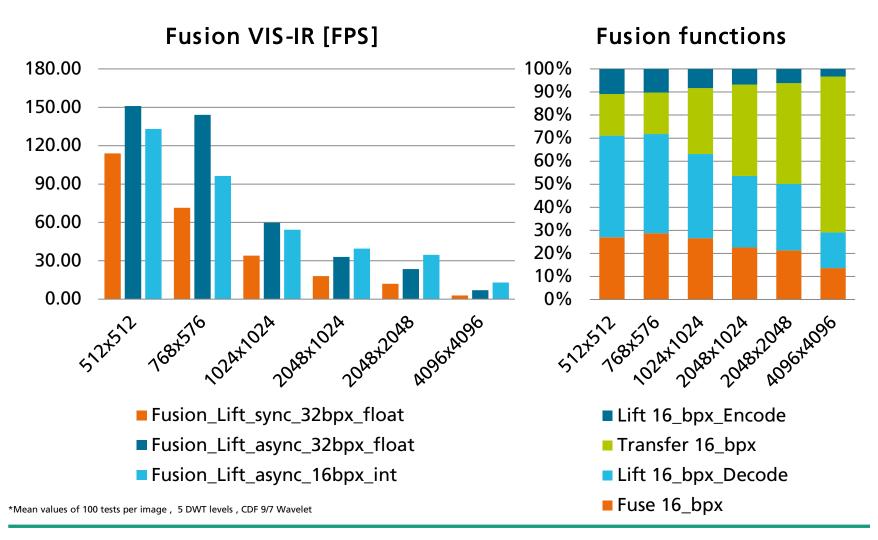
■ GPU-Mallat_32bpx-float

■ GPU-Lift_16bpx_int

*Mean values of 100 tests per image, 5 DWT levels, CDF 9/7 Wavelet



Results





Conclusion, Future work

- We show that the pipelined fusion method provides a real-time performance.
- The CPU is less suited than the GPU for a data-parallel DWT.
- The higher memory throughput of GPU is crucial for performance.
- The data transfers are bottleneck to further improve the performance.
- We plan to optimize the data transfers between I/O sensors and processing units.

Thanks for you attention! Questions?

