EFFICIENT MULTI-RESOLUTION FUSION FOR REMOTE SENSING DATA WITH LABEL UNCERTAINTY

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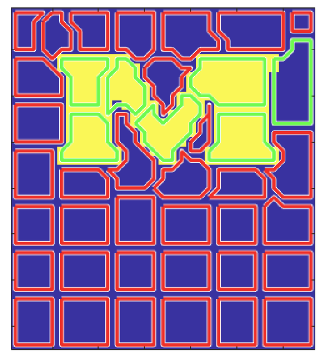
ROBOTICS

Multi-Resolution Sensor Fusion Challenges

- Optical sensors operate on various spatial, spectral, or temporal resolutions
- It is not always feasible to convert data to same resolution
- Standard supervised learning methods require accurate labels, which can be difficult to obtain

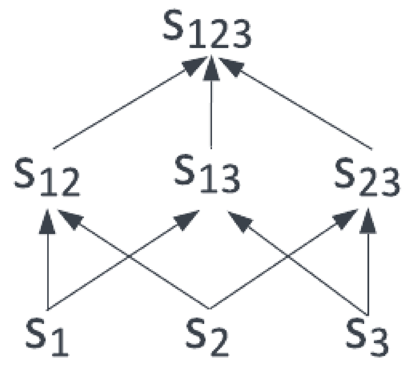
The MIMRF[1] Framework
Multiple Instance Multi-Resolution Fusion

Multiple Instance Learning (MIL)[2]
- Data is stored in "bags" labeled positive or negative depending on if it contains a target



MIL Bags; Red=Negative, Green=Positive

Fuzzy Measures (FM)
- Represents interactions of all subsets of fusion sources as a "weight"



Fuzzy Measure Structure for 3 sources (s_1, s_2, s_3)

Choquet Integral (CI)[3]
- Aggregation tool that uses fuzzy measure "weights" for complex, nonlinear fusion

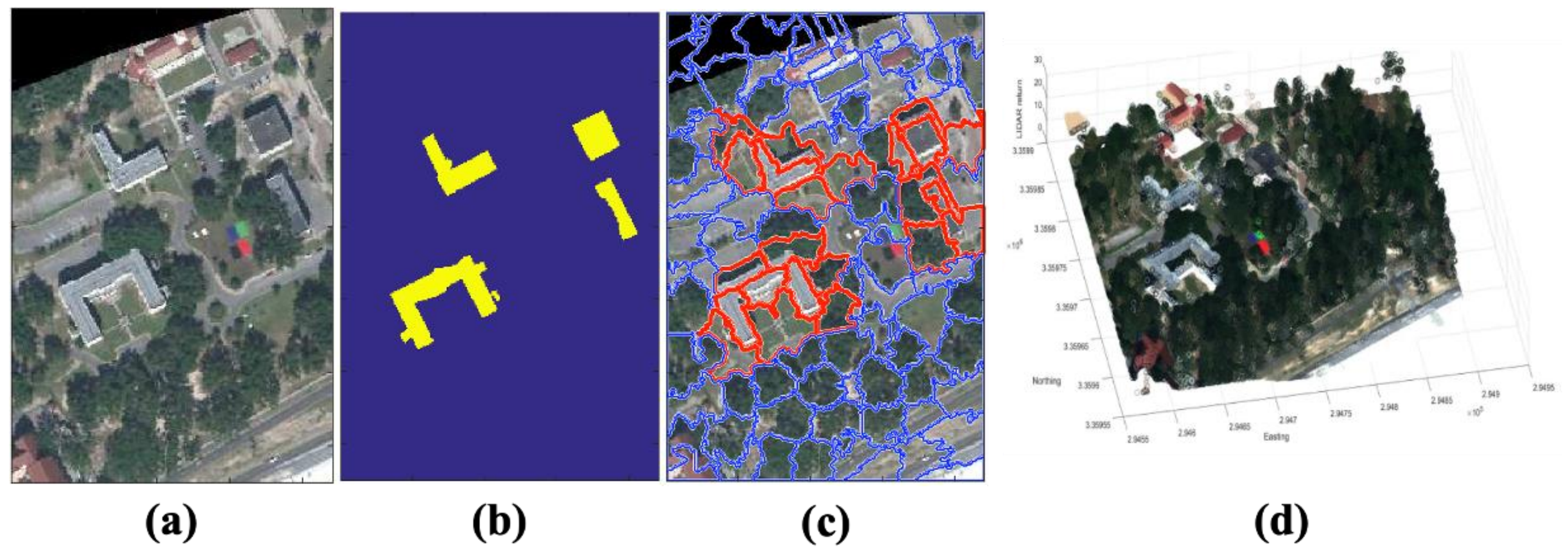
Genetic Algorithm
- Training data is given as labeled "bags" of data
- Fitness function encourages CI of points in negative bags to be 0 and positive bags to be 1
- Large and small-scale mutations of FMs computed to find FM with high fitness

MIMRF-BFM
Improving Efficiency with Binary Fuzzy Measures

Fuzzy Measures (FM)
- Maps 2^S -> [0, 1] for set of sources, *S*
- Training is computationally intense, with no guarantee of convergence

Binary Fuzzy Measures (BFM)
- **Maps 2^S -> {0, 1} for set of sources, *S***
- **Drastically reduces search space, genetic algorithm converges much faster**
- **Binary values make the FM more readable**

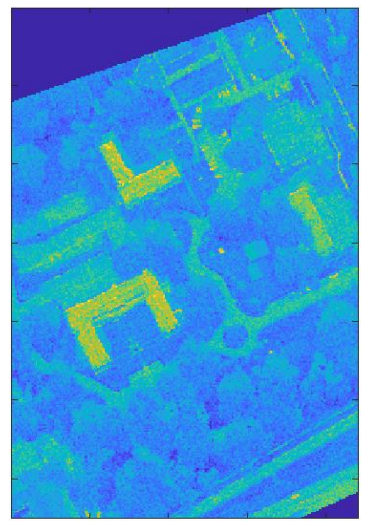
MUULF Gulfport Dataset[5] - Building Detection



(a) Hyperspectral imagery; (b) Ground truth for building detection; (c) Bag-level label map, where red superpixels are positive and blue are negative; (d) 3-D LiDAR point cloud

MIMRF-BFM Results

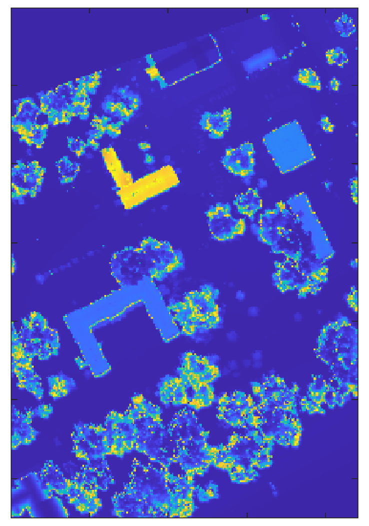
Source 1 (s_1)



Hyperspectral Adaptive Cosine Estimator

+

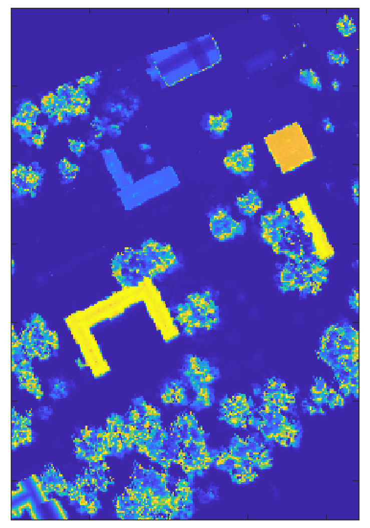
Source 2 (s_2)



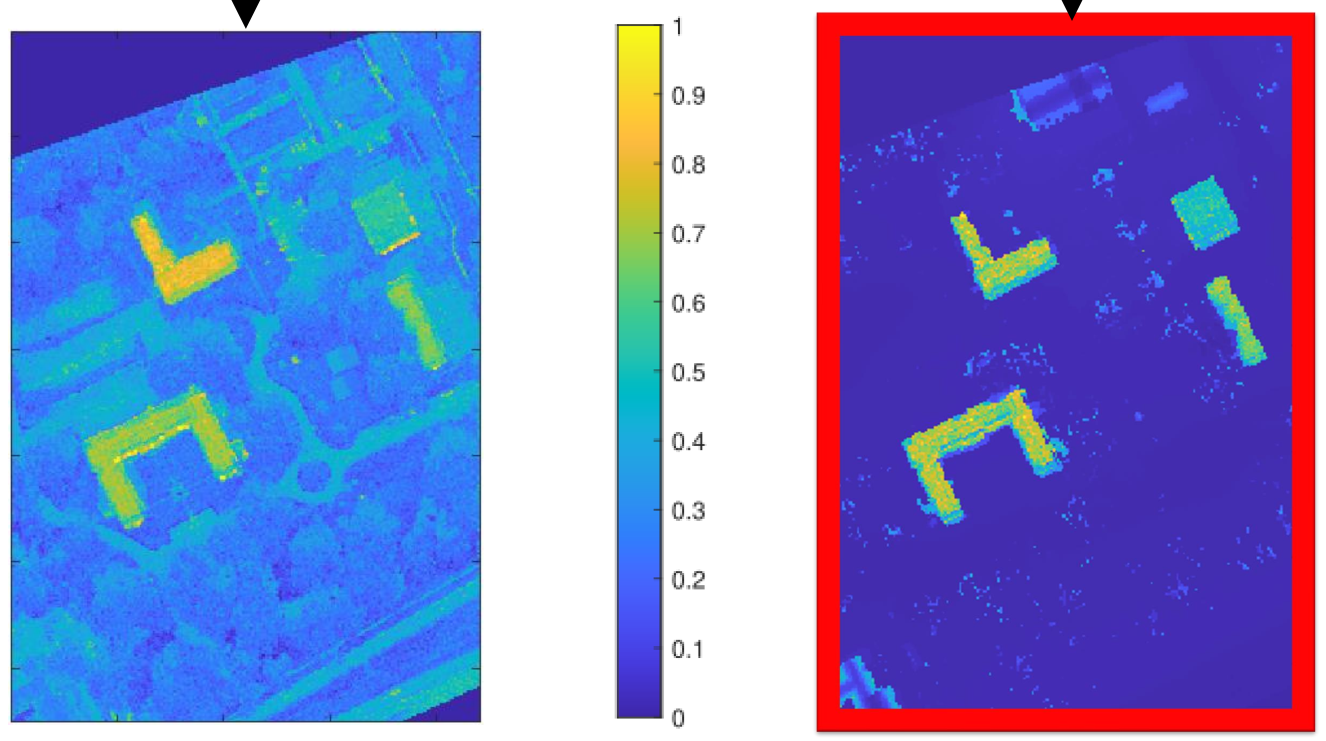
LiDAR Height Map 1 (raw data)

+

Source 3 (s_3)



LiDAR Height Map 2 (raw data)



MIMRF Result

Fuzzy Measure						
s_1	s_2	s_3	s_{12}	s_{13}	s_{23}	s_{123}
0.84	0.26	0.49	0.84	0.99	0.99	1

MIMRF-BFM (ours)

Binary Fuzzy Measure						
s_1	s_2	s_3	s_{12}	s_{13}	s_{23}	s_{123}
0	0	0	1	1	0	1

Experimental Analysis

Fusion Method	AUC ↑ / RMSE ↓ / PSNR ↑	
	Train 1 Test 2	Train 2 Test 1
ACE	0.906/0.362/8.839	0.952/0.346/9.214
LiDAR1	0.888/0.267/11.497	0.880/0.272/11.319
LiDAR2	0.850/0.273/11.243	0.839/0.280/11.053
Min	0.877/0.255/12.262	0.867/0.261/11.673
Max	0.916/0.434/7.333	0.932/0.422/7.501
Mean	0.941/0.310/10.492	0.953/0.302/10.400
SVM	0.892/0.415/7.637	0.958/0.285/7.637
mi-SVM	0.951/0.226/12.379	0.972/0.203/13.863
KNN	0.954/0.237/12.437	0.952/0.243/12.279
MICI Noisyor	0.943/0.377/8.621	0.946/0.326/9.030
MIMRF	**0.976**/0.310/10.314	**0.989**/0.254/10.635
MIMRF-BFM	0.974/**0.131/17.661**	0.973/**0.128/17.859**

Table 1. Comparison metrics between various fusion techniques; AUC = Area Under ROC curve; RMSE = Root Mean Squared Error from GT; PSNR = Peak Signal to Noise Ratio from GT

Fusion Method	Computation Time (s)			
	#6	#8	#10	#12
MIMRF	149.5(148.0)	772.1(442.1)	>5 hrs.	>5 hrs.
MIMRF-BFM	17.6(1.1)	92.1(5.1)	120.3(5.0)	772.4(15.9)

Table 2. Computation time for learning fuzzy measures for MIMRF and MIMRF-BFM when scaling number of sources to 6, 8, 10, and 12. Computation was capped at 5 hrs.

Discussion & Conclusion

- **MIMRF-BFM is an effective extension of MIMRF that significantly improves efficiency by decreasing fuzzy measure search space**
- **MIMRF-BFM excels at eliminating background noise, as shown by low RMSE and PSNR**
- **BFMs provide clear and explainable representation corresponding to the combination and (non-linear) interactions of sensor input sources**
- **This framework can be extended to other sensor modalities**

References & Acknowledgement

[1] X. Du and A. Zare, "Multiresolution multimodal sensor fusion for remote sensing data with label uncertainty," IEEE Transactions on Geoscience and Remote Sensing, vol. 58, no. 4, pp. 2755–2769, 2020.

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[3] G. Choquet, "Theory of capacities," in Annales de l'institut Fourier, 1954, vol. 5, pp. 131–295.

[4] X. Du, A. Zare, and D. T. Anderson, "Multiple instance Choquet integral with binary fuzzy measures for remote sensing classifier fusion with imprecise labels," in IEEE Symp. Comput. Intell., 2019, pp. 1154–1162.

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