Using Blind Source Separation to Look Around Corners

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Introduction

- Passive Non-Line-of-Sight (NLoS) imaging aims to reconstruct a scene hidden from the camera's field of view by observing indirect light scattered off a wall.
- A drawback of many NLoS imaging methods is presence of clutter, or unwanted signals that impede the reconstruction of desired objects [1]. However, multispectral analysis has been shown to be a valuable tool in mitigating clutter and improving NLoS reconstructions [2].

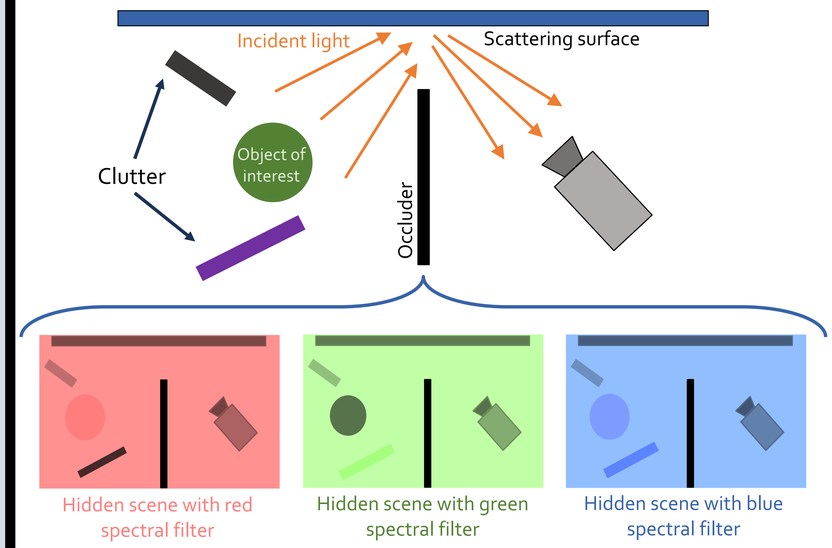


Fig 1: Multispectral NLoS imaging model.

What is Blind Source Separation (BSS) ?

- Blind Source Separation is a signal processing technique that attempts to separate a set of linearly mixed signals into the latent sources that make up these mixtures [3]. This is done based on the statistical independence or inherent structure of estimated sources [4].

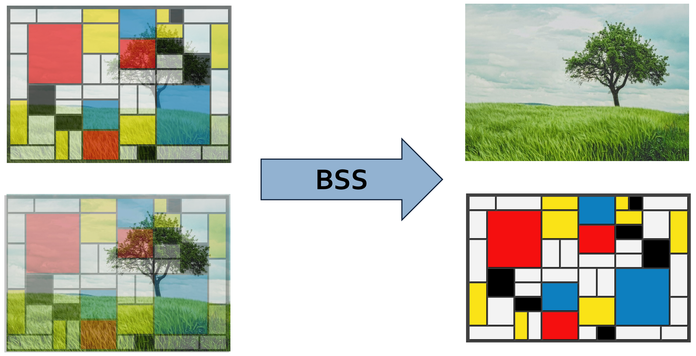


Fig 2: BSS can "unmix" linearly mixed signals.

Goals

- The goal of this project is to determine the contributions and limitations of BSS for multispectral NLoS imaging. We aim to use BSS to separate undesired clutter elements from the incident scene reconstructions.
- Theoretical and practical capabilities of different BSS algorithms were investigated using both simulations and real experiments

Methodology

- To test the theoretical limits of BSS, a computer-based NLoS imaging simulation was used to artificially generate multispectral observations of the incident and scattered light from the hidden scene.

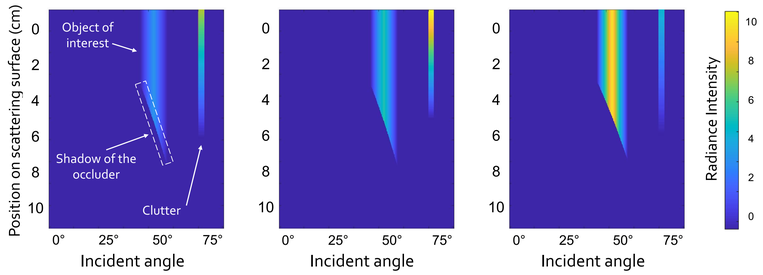
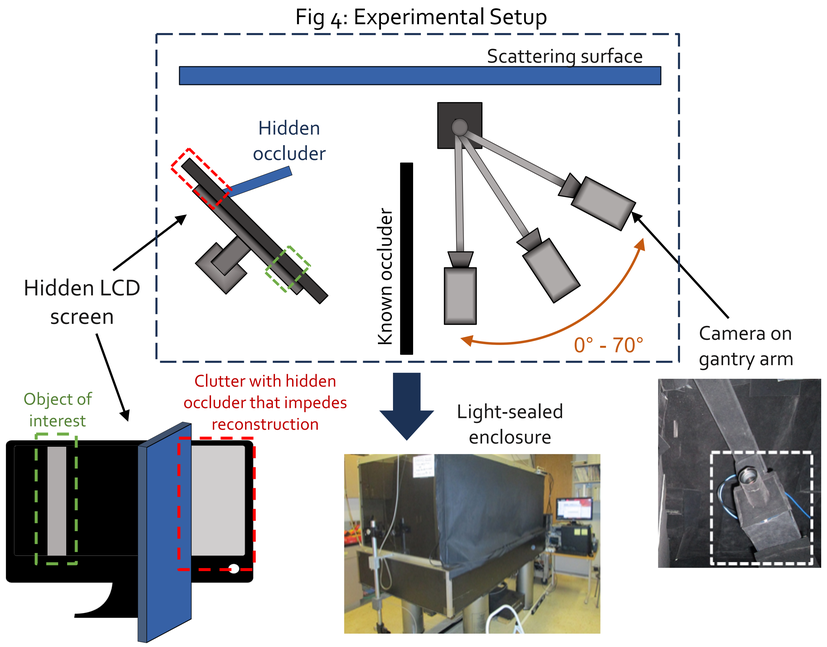


Fig 3: Artificially generated incident light as seen by the scattering surface for a range of incident angles and three different simulated spectral filters.

- Real experiments were performed using a camera inside a light-sealed enclosure to capture light scattered off a known surface. Multispectral observations of the hidden scene were generated with an LCD screen.

Fig 4: Experimental Setup



Results

- By expressing our multispectral measurements as linear mixtures of the object of interest and clutter source contributions, BSS algorithms can separate each component.

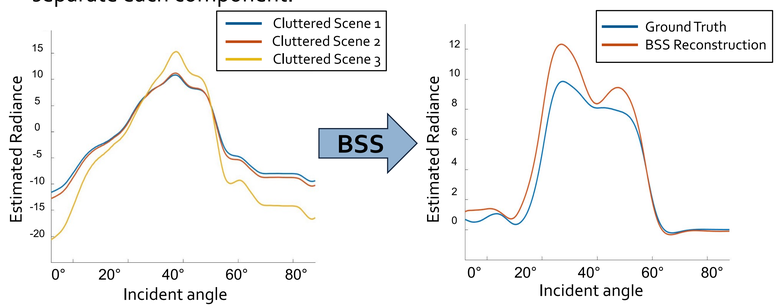


Fig 5: The curves on the right show hidden scene reconstructions from experimental data for three different spectral filters before applying BSS. The red curve on the left shows the BSS output corresponding to the object of interest.

- Performance was quantified by computing a normalized Mean Squared Error (MSE) between the ground truth and BSS reconstructions. The error in experimental results was evaluated for different clutter intensities and varying number of spectral filters.

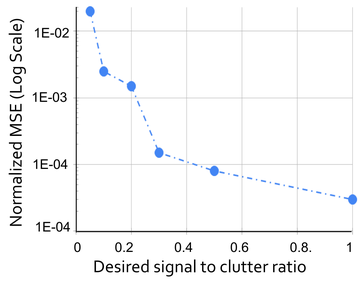


Fig 6: Error vs Signal to Clutter intensity

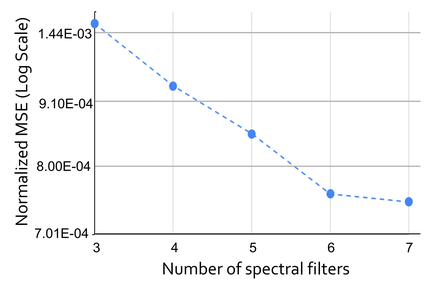


Fig 7: Error vs Number of Spectral Filters

Conclusion

- BSS yields good reconstructions of simple scenes, and accuracy improved with increasing signal to clutter ratio and larger number of spectral filters.
- However, both simulations and real experiments showed that BSS performance does not scale well with the complexity of the hidden scene.
- Overall, BSS was shown to be a good baseline method for multispectral NLoS imaging. Future work in this area might involve:
  - Extending the range of wavelengths in the multispectral observations into the infrared spectrum.
  - Performing measurements with real objects and color filters rather than using the LCD screen to generate them.
  - Further research into other clutter suppression algorithms.

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References

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