Thickness Estimation from Time of Flight data

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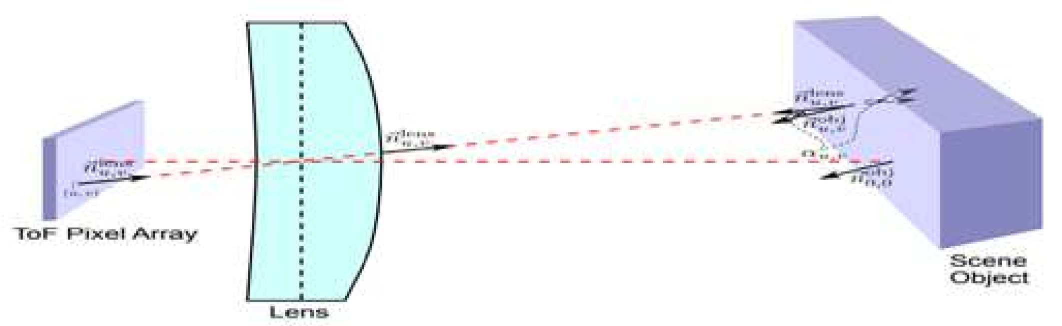
Introduction

- The thickness of a material can be estimated using the Material Impulse Response Function (MIRF) obtained from Time-of-Flight (ToF) measurements. The method typically involves analyzing the Fourier samples of MIRF.
- When light interacts with a material, especially materials with subsurface scattering phenomena, the MIRF is influenced by the thickness of the material. The Fourier samples of the MIRF capture the frequency content of the material's response to the incident light
- To estimate the thickness, a calibration process is often performed. This involves acquiring ToF measurements of the material at known thicknesses or using reference samples with known thicknesses. The MIRFs corresponding to these different thicknesses are then analyzed in the frequency domain
- The thickness estimation typically involves finding a correlation or relationship between the Fourier samples of the MIRF and the known thickness values from the calibration process. This correlation can be used to establish a mapping between the frequency content of the MIRF and the thickness of the material.
- Once the mapping is established, the Fourier samples of the MIRF obtained from ToF measurements of an unknown material can be analyzed, and the corresponding thickness can be estimated based on the established correlation

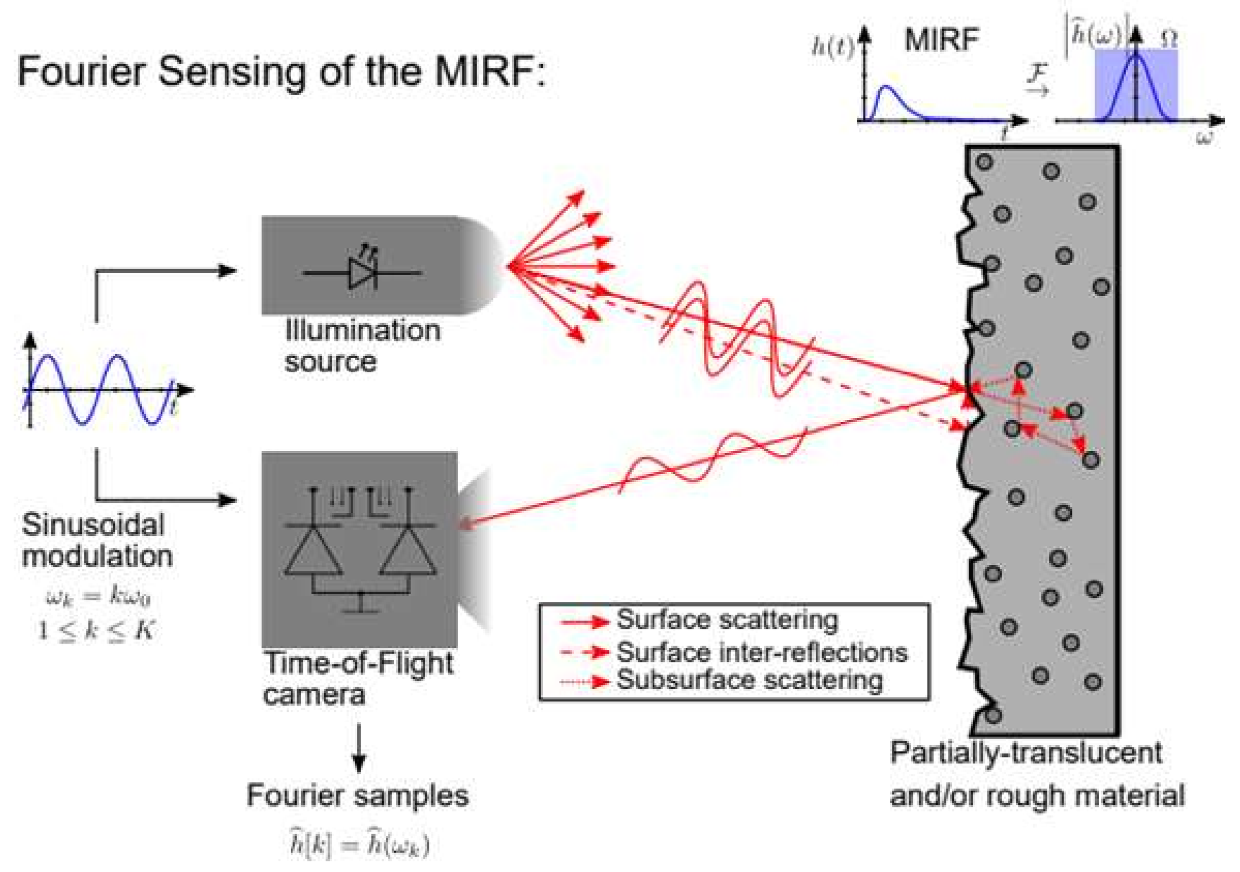
Data Processing

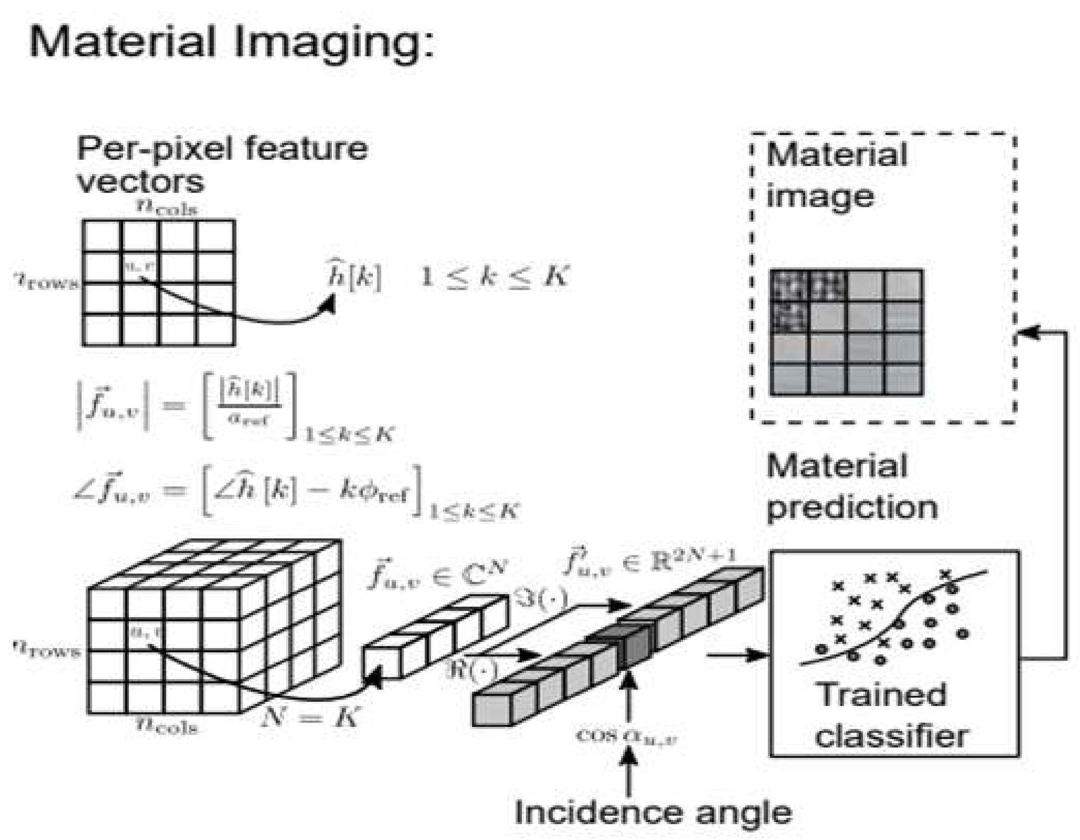
- There are two datasets available for thickness estimation:
  - Wax dataset with mirror background
  - Wax dataset with foam background
- Each data set consists of 9 features : 8 complex numbers and a cosine angle. These measurements are obtained at 8 different frequencies between 20 MHz to 160 MHz
- The complex numbers are further transformed to 16 entities in two different ways to study the behavior of correlation :
  - Separation of real and complex parts of the complex numbers
  - Amplitude and phase of the complex numbers

$$(\vec{f}_{u,v}, \cos\alpha_{u,v}) \longrightarrow \tilde{f}_{u,v} := \left[\Re\left(\vec{f}^{\top}_{u,v}\right), \cos\alpha_{(u,v)}, \Im\left(\vec{f}^{\top}_{u,v}\right)\right]^{\top}$$



Methodology





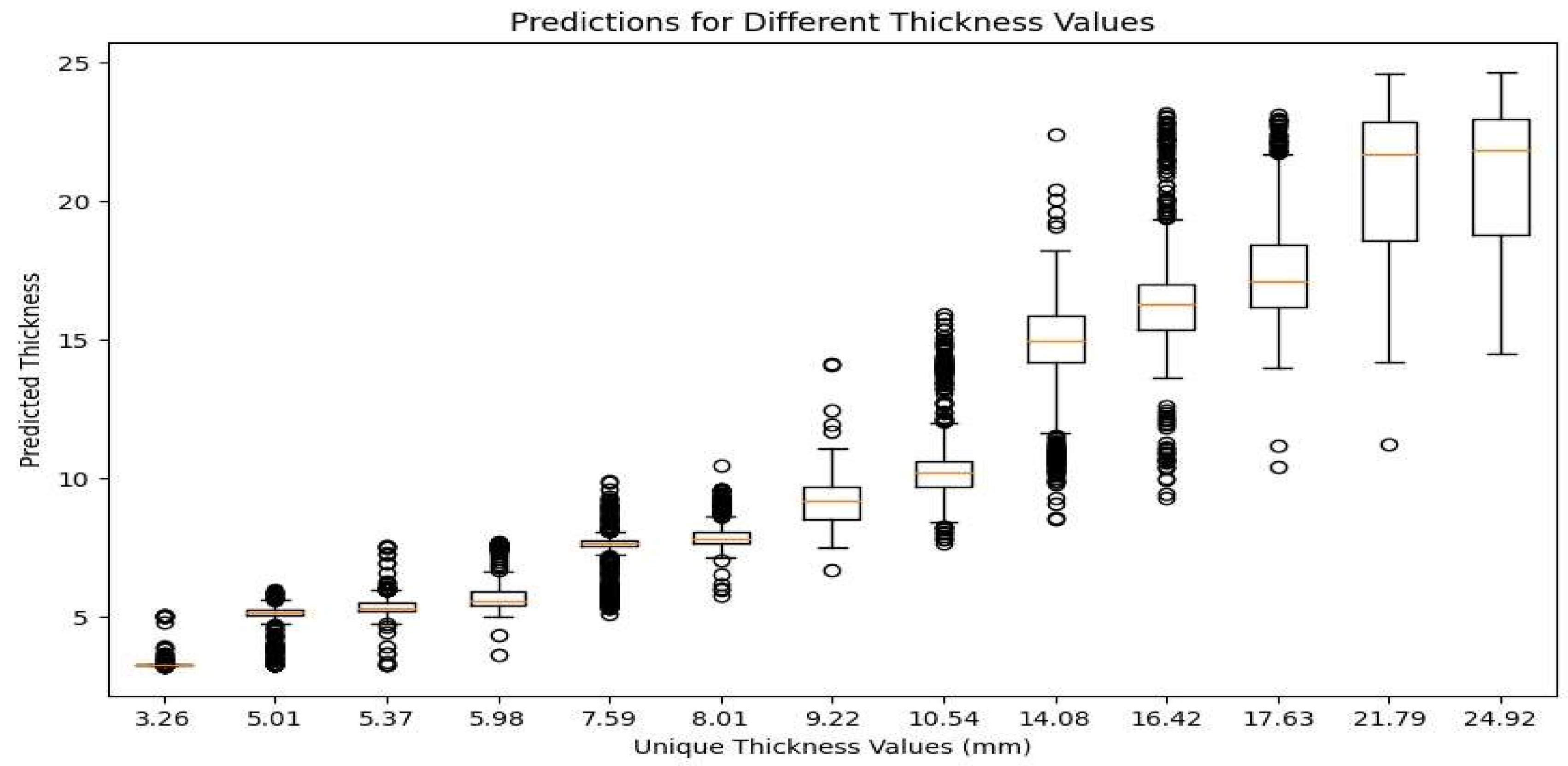
Ablation study

- Different architectures of Neural Networks are tried out and tested to study the correlation between various features :

1) Multilayer Perceptron (Base model)
2) Inception module with Conv1D layers
3) U-net architecture without inception module
4) U-net architecture with inception module
5) Transfer Learning on U-net architecture with inception module

Results

Wax data set with Foam background (Epochs = 50)					
Model	Criteria	Real & imaginary	Amplitude &Phase	Real & imaginary	Amplitude &Phase
		Metric = RMSE		Metric = MAE	
Multilayer Perceptron	With cosine angle	5.172	5.285	4.120	4.250
	Without cosine angle	5.142	5.035	4.030	3.943
Inception module with Conv1D layers	With cosine angle	1.509	1.559	0.935	0.943
	Without cosine angle	1.579	1.576	0.946	0.995
U-net without inception module	With cosine angle	1.508	1.550	0.904	0.901
	Without cosine angle	1.559	1.575	0.897	0.965
U-net with inception module	With cosine angle	1.498	1.519	0.896	0.877
	Without cosine angle	1.502	1.529	0.884	0.903



Conclusion

- Compared to the different models , U-net architecture with inception module performed better
- Also , in most of the cases , the error was less by usage of the real and imaginary parts separately instead of using amplitude and phase of the complex numbers
- Usage of Cosine angle in the features has shown better results
- Transfer Learning on U-net architecture with inception module has further decreased the error (RMSE - 1.488 , MAE - 0.864)

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