



**Biometrics Workshop, CVPR 2016**

# **A Polarimetric Thermal Database for Face Recognition Research**

**Shuowen (Sean) Hu, PhD**

**Nathaniel J. Short, PhD**

**Benjamin Riggan, PhD**

**Christopher Gorden**

**Kristan P. Gurton, PhD**

**Matthew Thielke**

**Prudhvi Gurram, PhD**

**Alex L. Chan, PhD**

**U.S. Army Research Laboratory**

**26 June, 2016**

**Objective:** Develop techniques exploiting multi-spectrum facial signatures for robust cross-spectrum face recognition in challenging scenarios (nighttime, extended range)

## **Significance:**

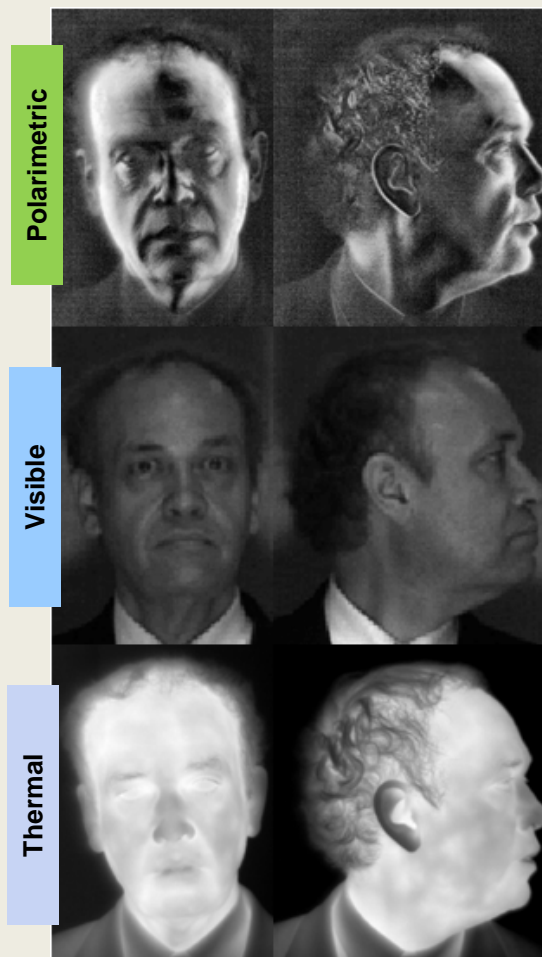
- Enable nighttime face recognition for surveillance and access control applications
- Recognize individuals in infrared images from a visible face watch list or database

## **Key technical challenges:**

- Substantial differences in infrared and visible face signatures due to phenomenology, especially for thermal infrared band
- Limited facial details at distance, non-frontal face poses

## **Community context:**

- Some work on NIR-to-visible and SWIR-to-visible recognition
- Limited work in thermal-to-visible face recognition (West Virginia U, Michigan State U, Karlsruhe Institute of Technology)
- No prior published work on polarimetric thermal based face recognition





# Polarimetric Face Recognition



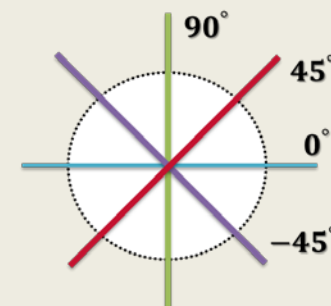
## Advantages:

Polarimetric LWIR provides key textural and geometric facial details not present in conventional thermal face signature

## Polarimetric characteristics:

- Measures emission intensity at different polarization-states
- Stokes vectors describe preferred polarization-state of captured light
- Degree of Linear Polarization (DoLP) used to approximate amount of linearly polarized light emitting from a source
- Provides information about surface texture and orientation of surface normal with respect to viewing angle

## Stokes Vector



$$S_0 = I_0 + I_{90}$$

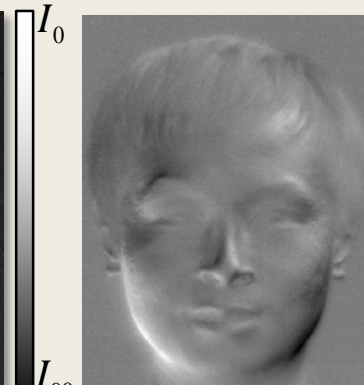
$$S_1 = I_0 - I_{90}$$

$$S_2 = I_{45} - I_{-45}$$

$$DoLP = \frac{\sqrt{S_1^2 + S_2^2}}{S_0}$$

## Conventional Thermal

## Polarimetric Images







# Composite Features



## Exploiting Polarization-state information for face recognition

- ❑ Stokes images contain complementary information about facial features
- ❑ Should be able to provide more information for cross-spectrum matching

Visible

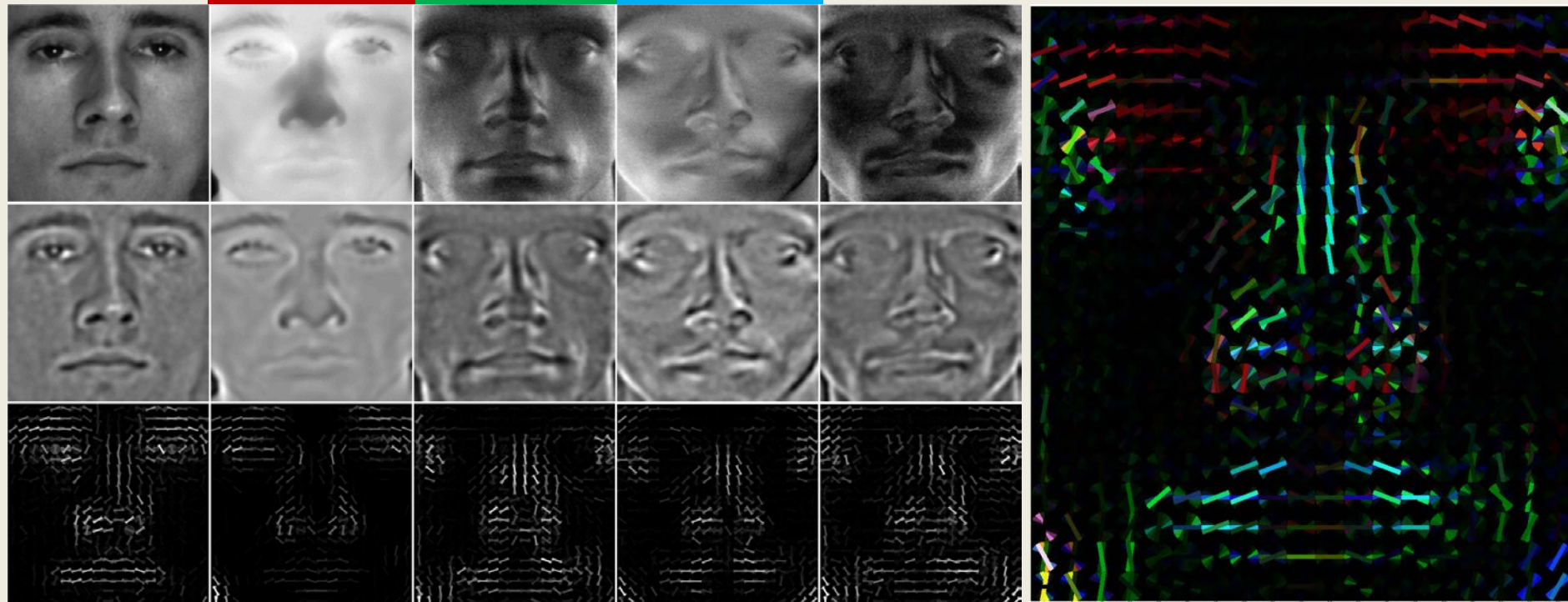
S0

S1

S2

DoLP

Composite





# Multi-Spectrum Face Dataset



## Collected multi-condition & multi-range polarimetric-thermal, conventional LWIR and visible face database

- First-of-its kind polarimetric face database
- Ranges: 2.5 m, 5 m, 7.5 m
- Conditions: baseline, expressions
- 60-subjects
- **Distributable to partners in government, industry and academia to facilitate research**
  - Database release agreement
  - Contact Sean (shuowen.hu.civ@mail.mil) and Matthew (matthew.d.thielke.civ@mail.mil)

### Polarimetric LWIR

- (Polaris Sensor Technologies)
- 640x480; 10.6° x 7.9° FOV
- 7.5-11.1  $\mu\text{m}$
- Cooled



### FLIR SC660 LWIR

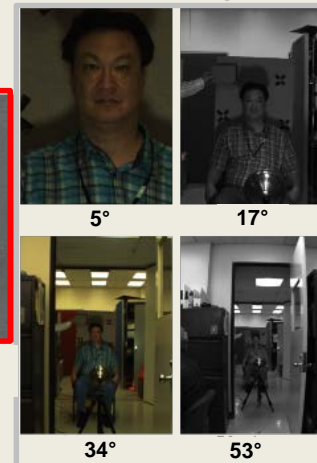
- 640x480
- 24° x 18° FOV
- 7.5-13  $\mu\text{m}$
- Uncooled

### Visible x4 (grayscale and color)

- 658x492, 5°, 17°, 34°, 53° FOV
- 400-920nm

### Sample Imagery at 5 m

#### Visible images



#### Conventional LWIR Image



#### Polarimetric LWIR Image



Degree of Linear Polarization  
(DoLP)

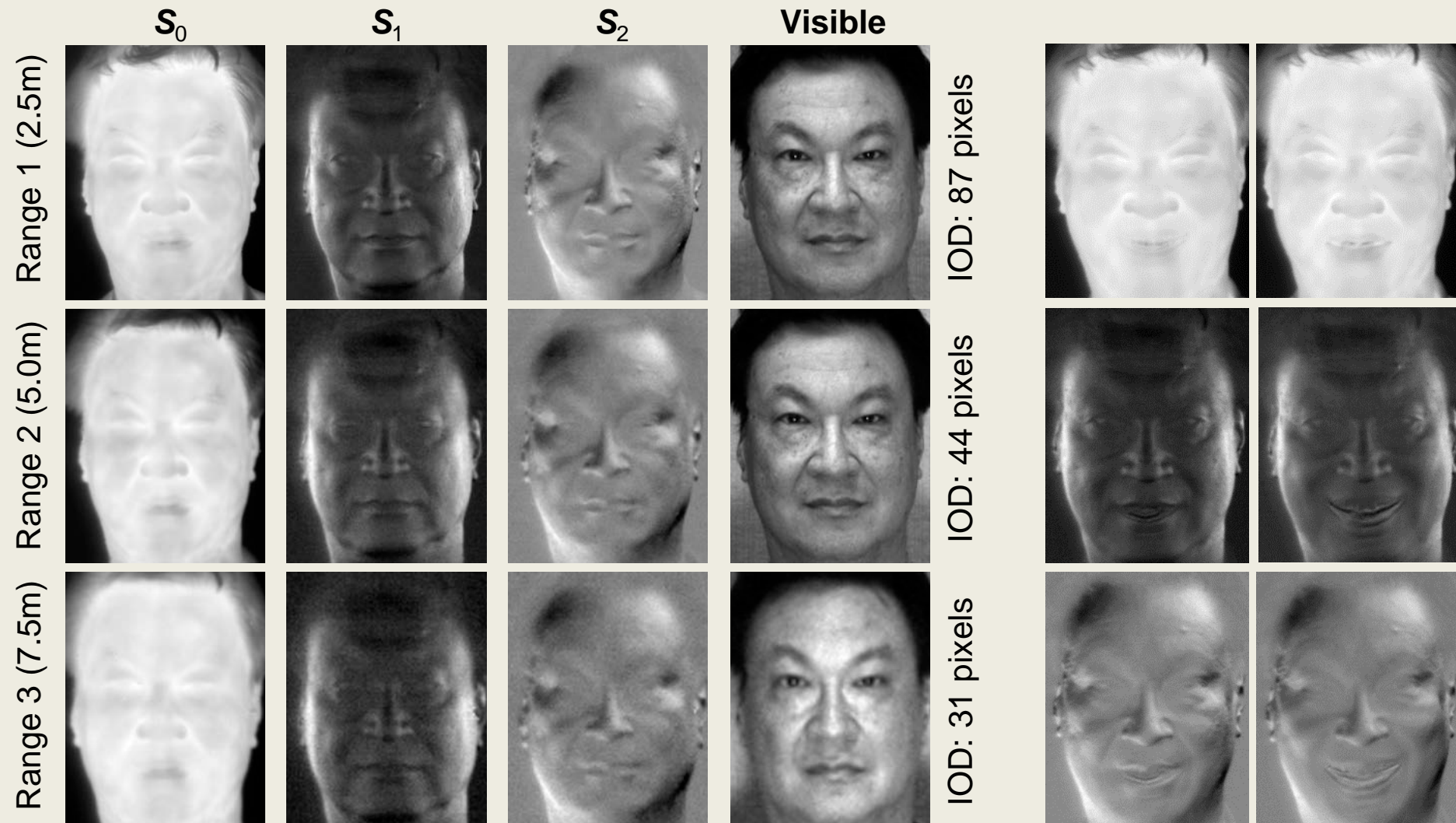


# Dataset Conditions



## Range

## Expression



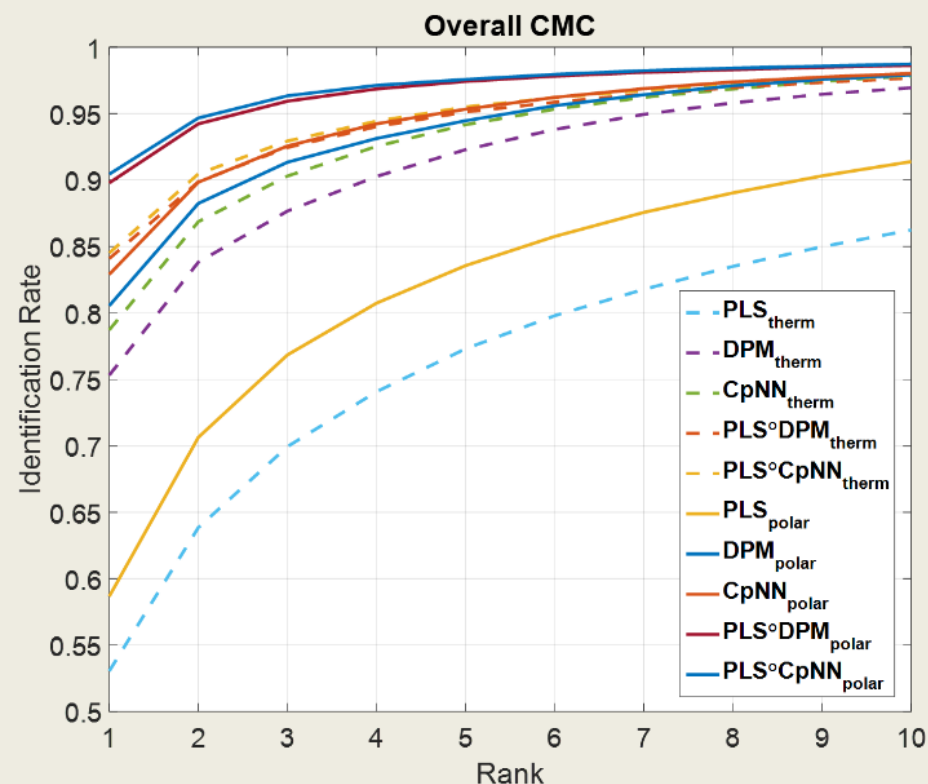




# Performance Benchmark



- Five techniques are used to assess **cross-spectrum** face recognition performance: partial least squares (PLS), deep perceptual mapping (DPM), coupled neural networks (CpNN), DPM followed by PLS (PLS $\circ$ DPM), and CpNN followed by PLS (PLS $\circ$ CpNN)
- Evaluated conventional thermal-to-visible face recognition performance (dashed lines), and polarimetric thermal-to-visible face recognition (solid lines) on a dataset of 60 subjects (25 for training, 35 for testing)



- ❖ Performance achieved on Range1-3 baseline data + Range 1 expressions:
  - 84.5% for thermal-to-visible using PLS $\circ$ CpNN
  - 90.5% for polarimetric thermal-to-visible using PLS $\circ$ CpNN
- ❖ Polarimetric thermal imagery provides additional facial details compared to conventional thermal imagery, improving recognition performance



# Performance Benchmark



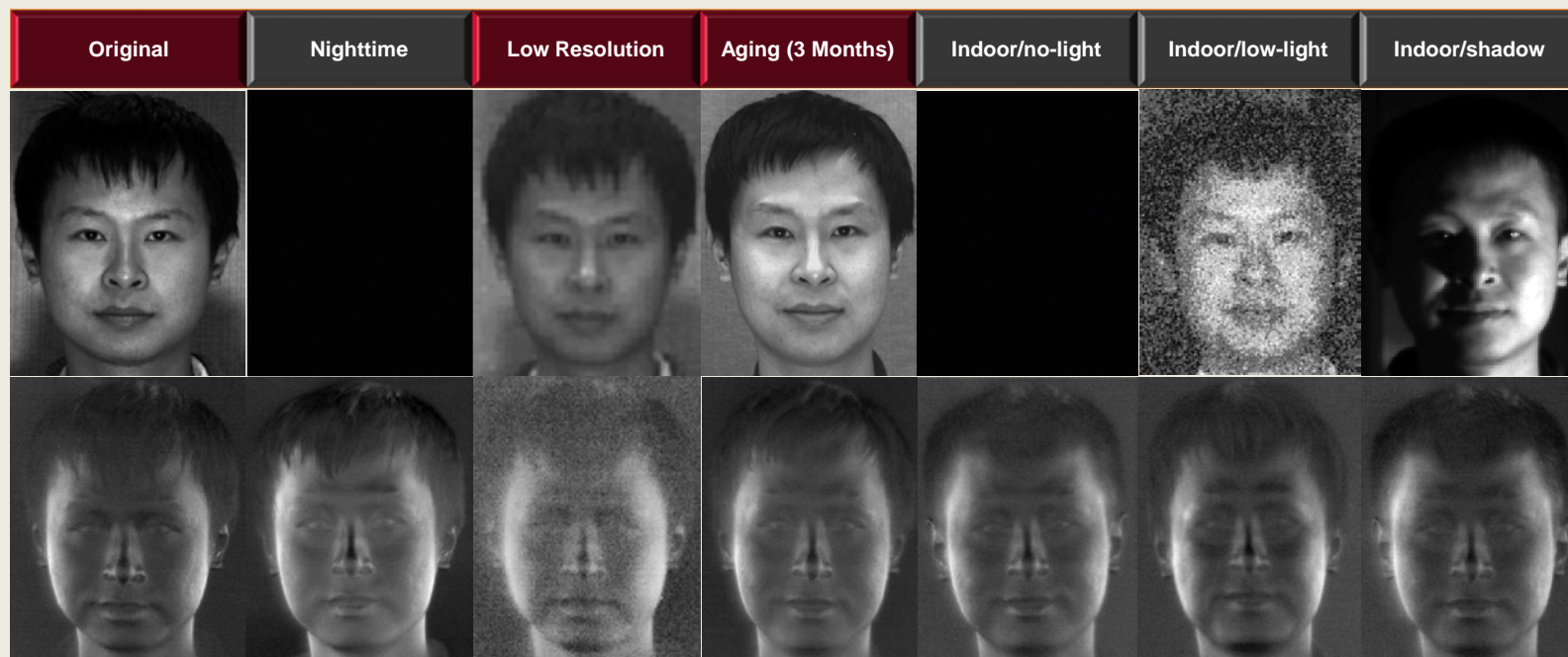
Scenario		Rank-1 Identification Rate				
	Probe	PLS	DPM	CpNN	PLS <sup>o</sup> DPM	PLS <sup>o</sup> CpNN
Overall	<i>Polar</i>	0.5867	0.8054	0.8290	0.8979	0.9045
	<i>Therm</i>	0.5305	0.7531	0.7872	0.8409	0.8452
Expressions	<i>Polar</i>	0.5658	0.8324	0.8597	0.9565	0.9559
	<i>Therm</i>	0.6276	0.7887	0.8213	0.8898	0.8907
Range 1 Baseline	<i>Polar</i>	0.7410	0.9092	0.9207	0.9646	0.9646
	<i>Therm</i>	0.6211	0.8778	0.9102	0.9417	0.9388
Range 2 Baseline	<i>Polar</i>	0.5570	0.8229	0.8489	0.9105	0.9187
	<i>Therm</i>	0.5197	0.7532	0.7904	0.8578	0.8586
Range 3 Baseline	<i>Polar</i>	0.3396	0.6033	0.6253	0.6445	0.6739
	<i>Therm</i>	0.3448	0.5219	0.5588	0.5768	0.6014

- Cross-spectrum feature mapping with DPM or CpNN combined with PLS significantly outperforms discriminative classifier alone
- More benefit from exploiting polarimetric information under more challenging conditions (e.g. long distance, expressions)



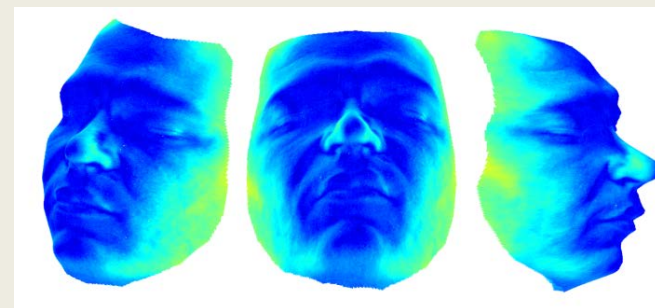


# Polarimetric-Thermal Advantages



## 3D Face Surface Reconstruction

- Potentially provide pose-invariance through frontalization
- Combine Stokes images by Fresnel relations to extract surface normals ( $\theta, \phi$ ) at each pixel, integrate surface normals to generate 3D surface
- Challenge:  $\pi$  ambiguity in azimuth angle  $\phi$





# Conclusion



- Polarization state information captures geometric and textural details unavailable in conventional thermal imagery
- First database containing polarimetric thermal facial imagery to be made available to academia and industry to facility multi-spectrum face recognition research