UNIVERSITÉ LAVAL

Automatic IRNDT Inspection Applying Sparse PCA-based Clustering

Bardia Yousefi
Hossein Memarzadeh Sharifipour*
Clemente Ibarra-Castanedo
Xavier P. V. Maldague

Canada Research Chair in Multipolar Infrared : MiViM
Computer vision and systems laboratory, Department of Electrical and Computer Engineering,
Laval University, Quebec city, Canada

*Departement of Computer Science, Laval University, Quebec City, Canada

MIVIM
Multipolar Infrared Vision

OUTLINE

INTRODUCTION

CLUSTERING

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CONCLUSION

INTRODUCTION

- Thermography

Infrared Non-Destructive Testing (IRNDT) provides thermographic images in the region of interest which usually involves defects.

Active thermography is a vast field including non-destructive and non-contact inspection techniques which have many applications in different industries

Applications

- Non-destructive Testing (NDT)
- Medical analysis (Computer Aid Diagnosis/Detection-CAD)
- Arts and Archaeology
- Geology
- Target detection
- *etc*

INTRODUCTION

- Segmentation by clustering

Clustering approaches have been proposed for countless applications in different research areas of such as pattern recognition and data-mining.

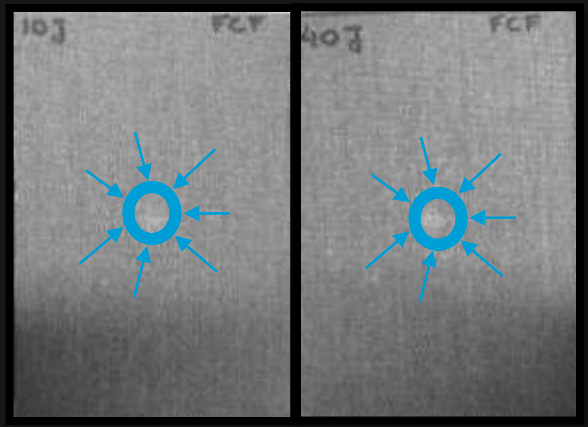
Here the application of clustering in **segmentation of defects** is investigated.

Automatic defect detection helps to make our IRNDT system works:

- Faster
- More accurate
- More robust

Segmentation in Industrial, Art, and Archaeology Applications

Impacted on the composite

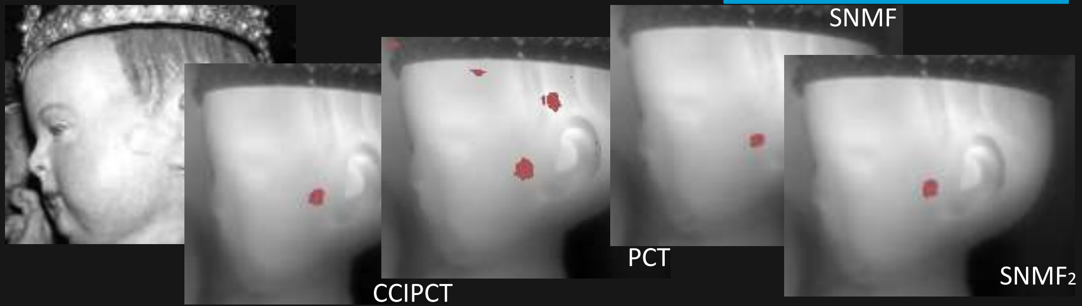


Fresco

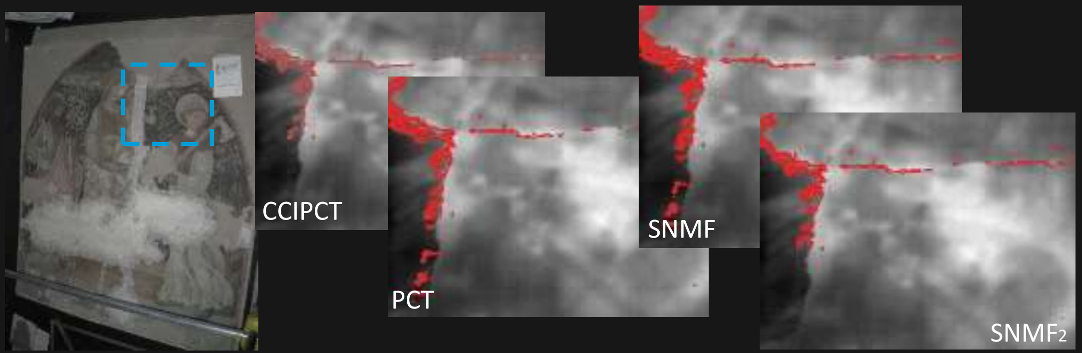
Polychromatic wooden statue

INTRODUCTION
- Real examples of Segmentation

Application in Art and Archaeology



Polychromatic wooden statue[1]



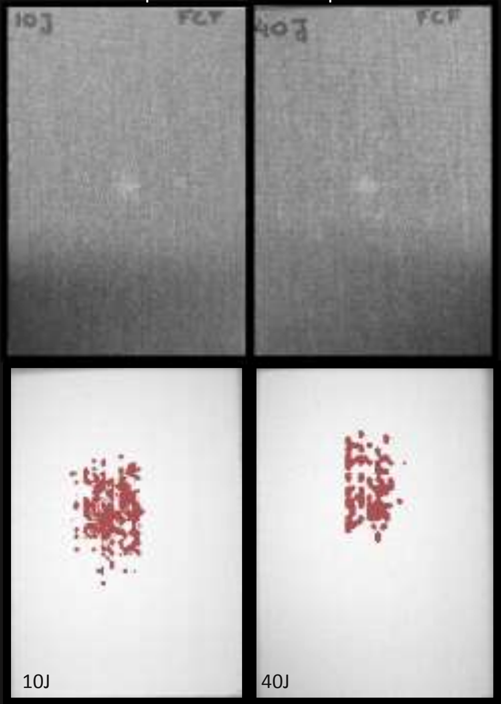
Fresco[1]

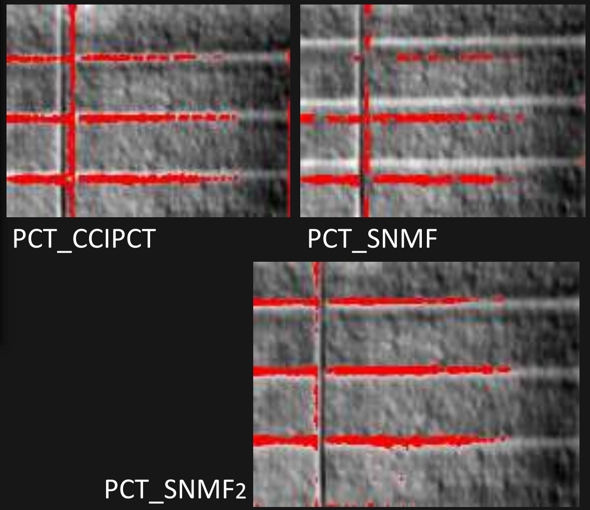
Principal Component Thermography (PCT)
Candid Covariance-Free Incremental Principal Component Thermography (CCIPCT)
Negative Matrix Factorization by gradient-descent-based multiplicative rules (SNMF)
Standard NMF by Non-negative least squares (NNLS) active-set algorithm ($SNMF_2$)

1. Bardia Yousefi, Stefano Sfarra, Xavier P. V. Maldague, ***"Quantitative assessment in thermal image segmentation for artistic objects"***, Optical Metrology SPIE 2017- Munich, Germany

Application in Industries

Impacted on the composite

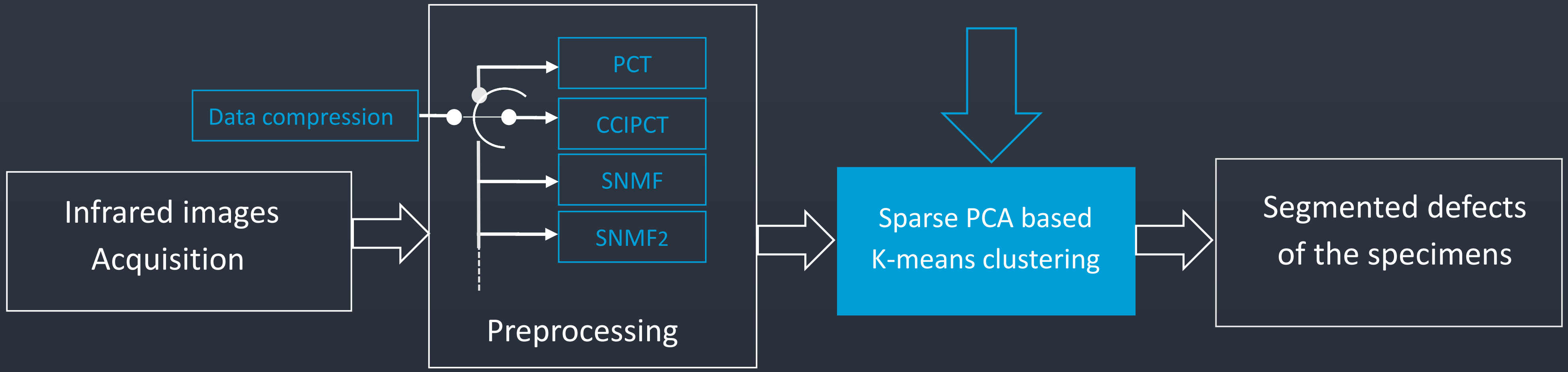




These are the data analyzed under a collaboration between MIVIM and Italy

CLUSTERING

- Our contribution



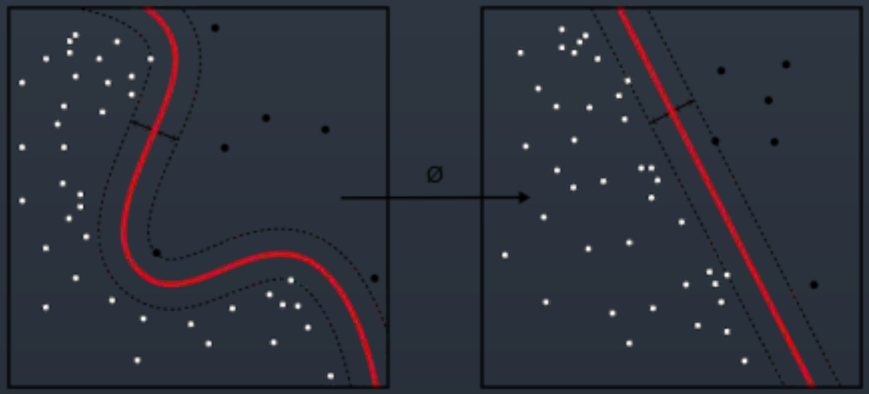
A good Clustering approach

A good clustering approach is a powerful tool which uses in data-analysis and dataming. It provides numerous applications in different field.

CLUSTERING

- Kernel and Data transformation

- Kernel methods clustering transform the data to kernel subspace to perform the clustering
- Principal Component Analysis (PCA) is one of the famous kernel methods and frequently used in different applications*
- We consider Sparse Principal Component Analysis (SPCA) based clustering and wish to have better performance in noisy condition**
- SPCA is not a linear transform like PCA**,***



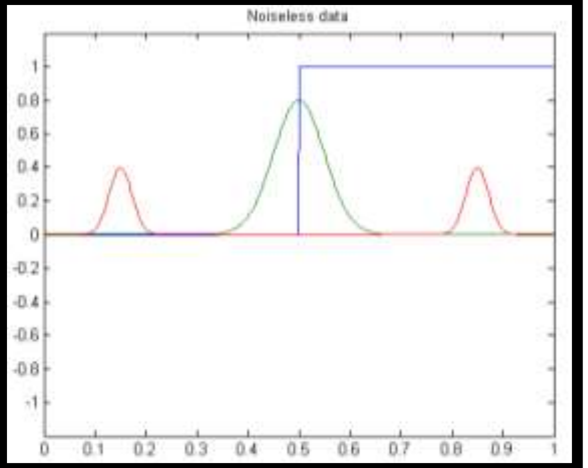
https://github.com/nicolaspanel/node-svm

*Chris Ding and Xiaofeng He. K-means clustering via principal component analysis. In Proceedings of the twenty-first international conference on Machine learning, page 29. ACM, 2004.
**Sanparith Marukatat. Sparse kernel pca by kernel k-means and preimage reconstruction algorithms. In Pacific Rim International Conference on Artificial Intelligence, pages 454–463. Springer, 2006.
***Karl Sjostrand, Line Harder Clemmensen, Rasmus Larsen, and Bjarne Ersbøll. Spasm: A matlab toolbox for sparse statistical modeling. Journal of Statistical Software Accepted for publication, 2012.

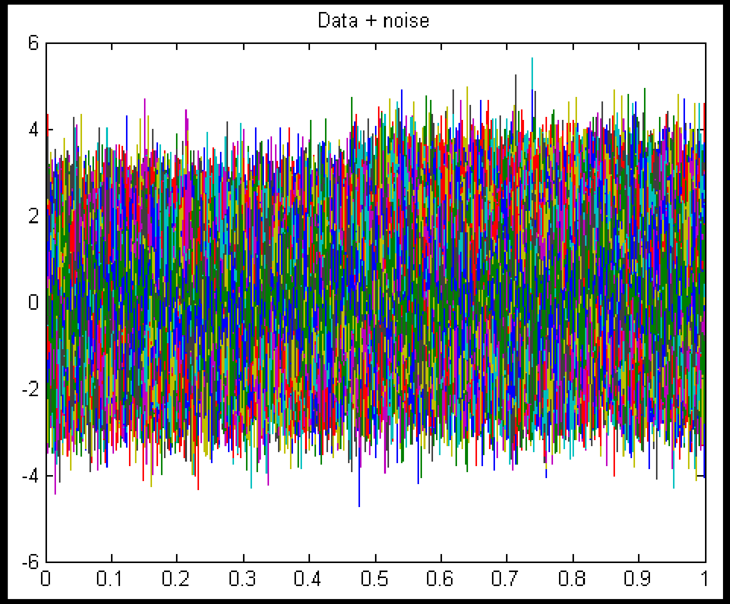
CLUSTERING

- Why Sparse PCA (one example)

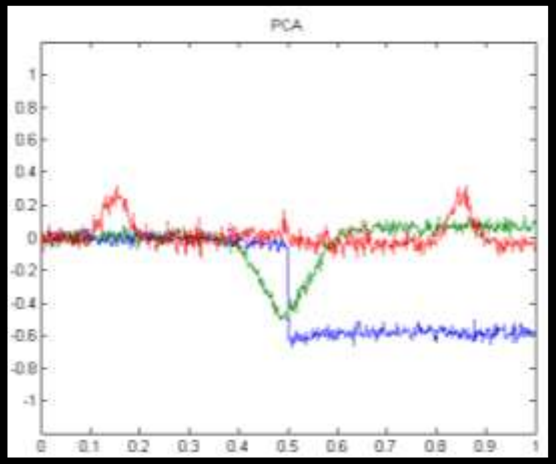
Mixing three different signals



Adding the noise to the mixure

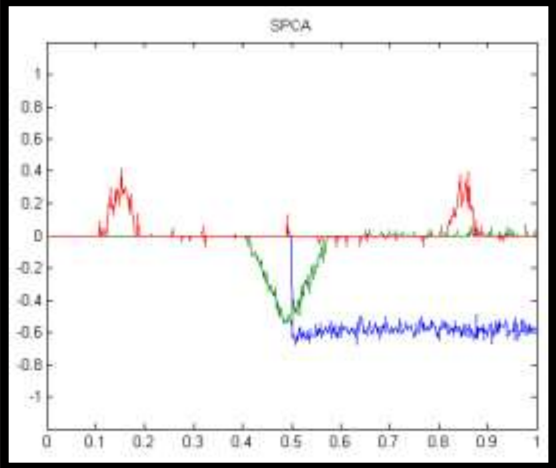


Decomposing the mixure by PCA



Better SNR performance

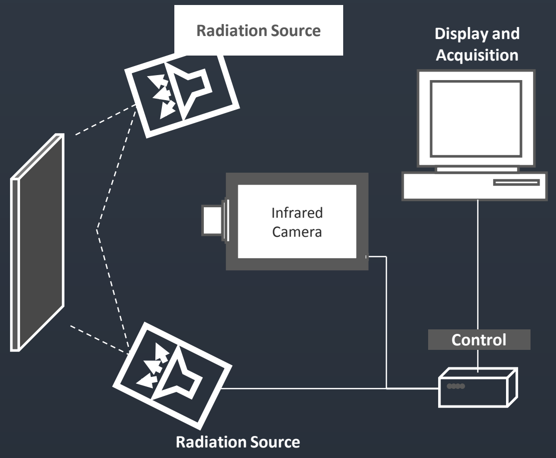
Decomposing the mixure by SPCA



Karl Sjostrand, Line Harder Clemmensen, Rasmus Larsen, and Bjarne Ersbøll. Spasm: A matlab toolbox for sparse statistical modeling. Journal of Statistical Software Accepted for publication, 2012.

RESULTS

- To benchmark the approach we are using Infrared non destructive testing (IRNDT) dataset.
- We used our approach in color (HSV) base segmentation form to segment the defects in the samples.
- Three different samples used under active thermography acquisition.
- The inspection was conducted from the front side of the specimen CFRP (CFRP having the depths range from 0.2 to 1 mm, Plexiglas form 1 to 3.5 mm, and Aluminium from 3.5 to 4.5 mm). Plexiglas and Aluminum having the depth range of 1-3.5 mm and 3-4.5 mm, respectively.*
- Two photographic flashes were used: Balcar FX 60, 5 ms thermal pulse, 6.4 kJ/flash. The infrared camera is a mid-wave infrared (MWIR) cooled by liquide nitrogen (320 * 256 pixels).



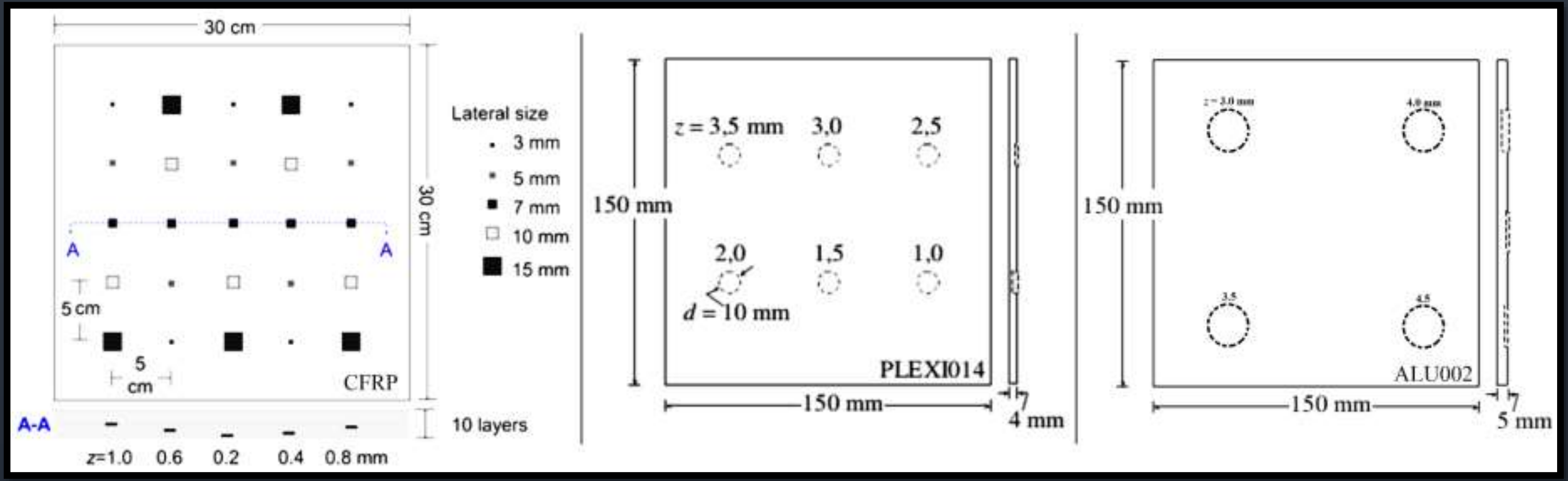
Scheme of the experimental setup

* Clemente Ibarra-Castanedo and Xavier P Maldague. Defect depth retrieval from pulsed phase thermographic data on plexiglas and aluminum samples. In Defense and Security, pages 348–356. International Society for Optics and Photonics, 2004.

RESULTS

- NDT samples

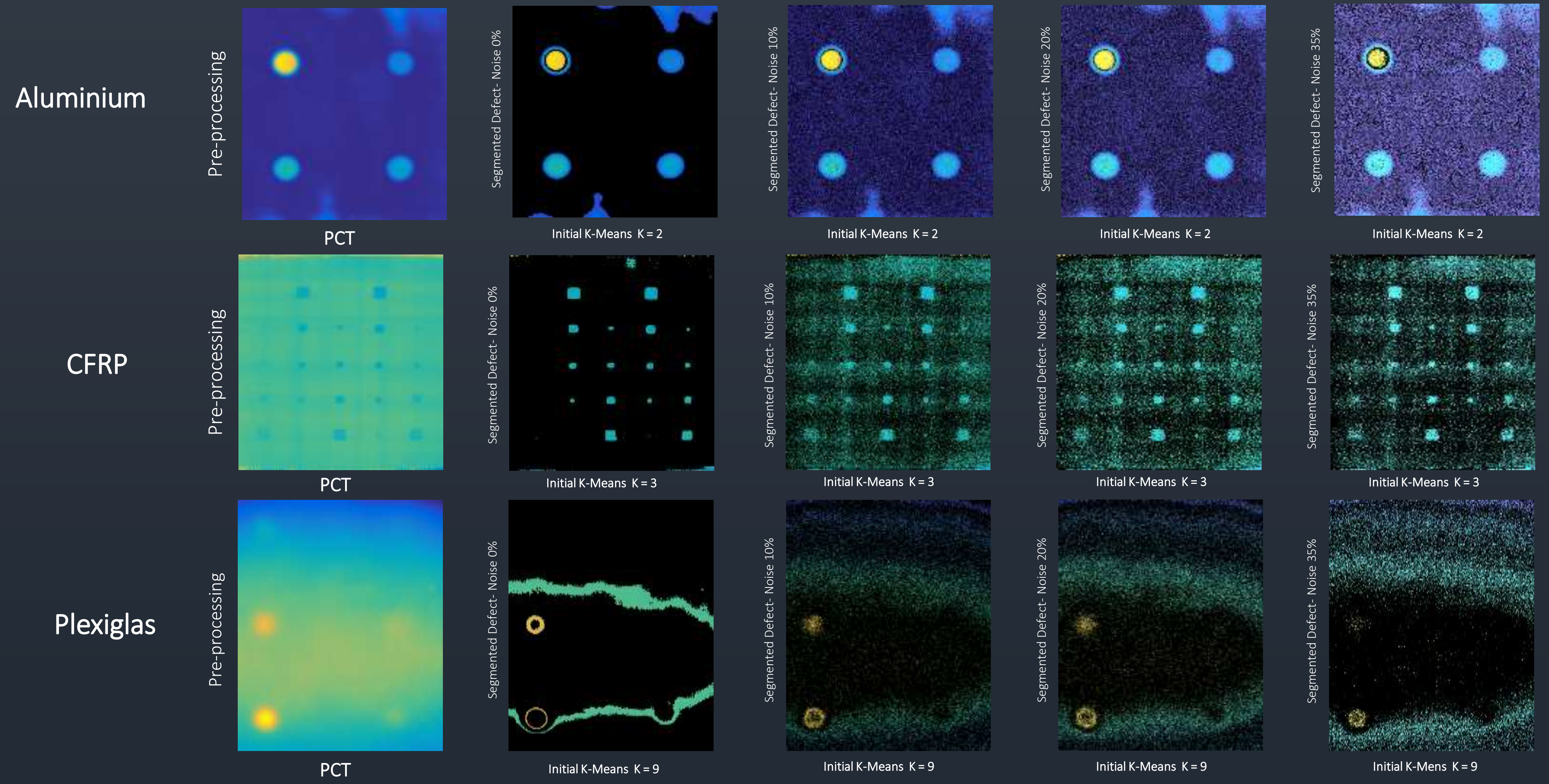
- NDT samples to test our clustering method by finding the artificial defects.



CFRP Plexiglas Aluminum

RESULTS

- Results of NDT samples



RESULTS

- Quantitative Results of NDT samples

Increasing in defect detection

Defect measuring Accuracy - ALUMINUM																							
Level of Noise to data			0			5			10			15			20			25			30		
Segmentation methods	Pre-processing	Overall Defect size-GT	ACC	FP	FN	ACC	FP	FN	ACC	FP	FN	ACC	FP	FN	ACC	FP	FN	ACC	FP	FN	ACC	FP	FN
SPCA K-means	PCT	24797	19911	1055	4886	23755	17933	1042	24072	44770	725	24230	1.05E+05	567	243333	2.06E+05	464	24182	3.24E+05	613	23822	4.259E+05	975
	CCIPCT	24797	8281	1.11E+05	16516	8812	1.65E+05	15985	7374	1.64E+05	17423	9236	2.29E+05	15561	7028	1.71E+05	17769	7252	1.61E+05	17545	6288	1.42E+05	18509
PCA K-Medoids	PCT	24797	19751	1055	5046	23295	19023	1502	23848	45990	949	23987	1.06E+05	810	24330	2.00E+05	467	24132	3.00E+05	665	23888	3.95E+05	909
	CCIPCT	24797	12515	75375	12282	7349	1.14E+05	17448	7579	1.17E+05	17218	7649	1.19E+05	17148	8016	1.22E+05	16781	8971	1.27E+05	15826	9388	1.30E+05	15409
SPCA K-Medoids	PCT	24797	20038	1055	4759	22905	15906	1892	23436	44044	1361	23558	1.15E+05	1239	23591	2.34E+05	1206	23436	3.45E+05	1361	23318	4.07E+05	1479
	CCIPCT	24797	8284	1.11E+05	16513	10073	1.30E+05	14724	9223	1.73E+05	15574	6927	1.56E+05	17870	9757	2.25E+05	15040	10429	2.23E+05	14368	9528	1.99E+05	15269

Defect measuring Accuracy - CFRP																							
Level of Noise to data			0			5			10			15			20			25			30		
Segmentation methods	Pre-processing	Overall Defect size-GT	ACC	FP	FN	ACC	FP	FN	ACC	FP	FN	ACC	FP	FN	ACC	FP	FN	ACC	FP	FN	ACC	FP	FN
SPCA K-means	PCT	8286	5694	3633	2592	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	80	8220	2.09E+05	66	8214	2.09E+05	72	8189	1.91E+05	97	8240	1.93E+05	46
	CCIPCT	8286	2045	6393	6241	2557	61955	5729	2472	71129	5814	3012	1.12E+05	5274	2793	1.12E+05	5493	3669	1.39E+05	4617	3458	1.22E+05	4828
PCA K-Medoids	PCT	8286	5330	2464	2956	7771	1.91E+05	515	8134	1.98E+05	152	8052	1.24E+05	234	8044	1.35E+05	242	8148	1.61E+05	138	8020	1.13E+05	266
	CCIPCT	8286	1756	22355	6530	1950	42413	6336	1919	36424	6367	2150	49414	6136	2258	60664	6028	2136	49920	6150	2214	53133	6072
SPCA K-Medoids	PCT	8286	7942	37176	344	8035	1.34E+05	251	7795	97949	491	7862	1.30E+05	424	7579	80272	707	7785	93932	501	7785	93932	501
	CCIPCT	8286	1937	6393	6349	2095	55109	6191	2049	58235	6237	1770	62081	6516	2731	71910	5555	920	58598	7366	1821	53158	6465

Increasing in defect detection

Defect measuring Accuracy – Plexiglas																							
Level of Noise to data			0			5			10			15			20								
Segmentation methods	Pre-processing	Overall Defect size-GT	ACC	FP	FN	ACC	FP	FN	ACC	FP	FN	ACC	FP	FN	ACC	FP	FN	ACC					
SPCA K-means	PCT	7858	3649	69432	4209	6467	2.1415e+05	1391	6434	2.4706e+05	1424	6622	2.9597e+05	1236	7079	3.3144e+05	779	6876	3.3357e+05	982	6712	3.3851e+05	1146
	CCIPCT	7858	4614	10697	3244	5148	93817	2710	5099	1.1325e+05	2759	6009	1.6113e+05	1849	5612	1.7008e+05	2246	5245	1.7395e+05	2613	5511	1.7301e+05	2347
PCA K-Medoids	PCT	7858	5330	2464	2956	7771	1.91E+05	515	8134	1.98E+05	152	8052	1.24E+05	234	8044	1.35E+05	242	8148	1.61E+05	138	8020	1.13E+05	266
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SPCA K-Medoids	PCT	7858	3996	1.00E+05	3862	4078	1.61E+05	3780	4311	1.72E+05	3547	4966	1.75E+05	2892	3938	1.98E+05	3920	4708	2.23E+05	3150	3875	2.06E+05	3985
	CCIPCT	7858	6086	81771	1772	6238	1.67E+05	1620	6765	2.04E+05	1093	6979	2.49E+05	879	6166	2.02E+05	1692	5653	1.92E+05	2205	4845	1.50E+05	3013

For CFRP after 15% Noise the defect detection performance decreased (Smaller defects noise are more effective)

Increasing in defect detection

RESULTS

- Computational time

Computational load of Defect measurement*					
Specimens	Segmentation methods	Spatial resolution of IR-image	Clustering (s)	PCT (s)	CCIPCT (s)
CFRP	HSV-SPCA K-means	613*537	3.24	3.51	5.51
Aluminum	HSV-SPCA K-means	580*518	2.72	8.21	16.38
PLXIGLASS	HSV-SPCA K-means	404*537	2.58	6.59	12.09

Infrared dataset and acquisition parameters					
Specimens	**Sampling rate (f_s)**	**Duration (t_{acq})**	**Time step(D_t)**	**Truncation window ($\omega(t)$)**	**Total Number of frames**
CFRP	157 Hz	6.37 s	0.025s	6.37 s	250
Aluminum	39.25 Hz	6.37 s	0.025s	6.37 s	250
PLXIGLASS	39.25 Hz	6.37 s	0.025s	6.37 s	250

* The analysis of thermographic process has been done with a PC (Intel(R) Core(TM) i7 CPU, 930, 2.80GHz, RAM 12.00GB, 64 bit Operating System) and processing of thermal data has been conducted using MATLAB computer program.

CONCLUSIONS

- A SPCA based clustering method has been described.
- The strength of SPCA compare to PCA is briefly explained.
- Three NDT samples (Aluminum, CFRP, and Plexiglas) were used for benchmarking.
- SPCA based clustering showed good response using the Gaussian noise.
- CFRP showed lower accuracy for our approach after 15% additive Gaussian noise because of smaller defect size.

Future Work:

- Further investigate to test the approach for more samples and applications to verify its performance
- Further analysis to use more kernel approaches

THANK YOU

This research is done under Canada Research Chair in Multipolar Infrared : MiViM at Computer vision and systems laboratory (CVSL), Department of Electrical and Computer Engineering, Laval University, Quebec city, Canada

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