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Predicting Features in Complex 3D Surfaces Using a Point Series Representation: A Case Study in Sheet Metal Forming

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Outline

Introduction

➢This paper presents an integrated framework for learning to predict geometry related features with respect to 3D surfaces.

➢The idea is to use a training set of known feature values to create a model founded on local 3D geometries associated with a given surfaces so that predictions with respect to a new "unseen" surfaces can be made.

➢The local geometries are represented using Point Series (PS) curves.

➢Two variations of PS technique are proposed: (i) discretised and (ii) real number.

➢To act as a focus for the work, we consider the prediction of "springback" resulting from sheet metal forming process, specifically Asymmetric Incremental Sheet Forming (AISF).

The Prediction Framework

➢The input to the proposed prediction framework is a grid representation of some 3D shape of interest.

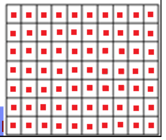
➢Each grid square is defined by its centre point in terms of x, y and z coordinate.

➢The number of grid squares required to represent a given shape will depend on the grid size d. Fewer grid squares will be generated if a larger d value is used.

➢A collection of local geometries can be defined (one per grid square).

➢Two alternative Point Series representation are considered : (i) Key Points and (ii) All Points.

➢Once a collection of point series curves have been generated, this model can be used for prediction process.



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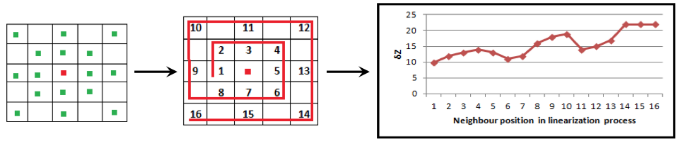
The Prediction Framework
Point Series Representation Technique

- The size of a neighbourhood can be simply described in terms of a Region Of Interest (ROI) surrounding each point $\mathbf{p}_i$ defined in terms of a $n \times n$ block of grid squares centred on $\mathbf{p}_i$.
- A straightforward spiral linearization was adopted.
- The number of points to be considered can include all points (n^2 -1) covered by a linearization or a selection of "key" points (((n-1)/2)X8).



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The Prediction Framework
Classification

- *k-NN* classification system is suggested to carry out the desired prediction.
- The *k* most similar pre-labelled curves were identified and the most similar (*k=1*) is selected according to the warping distance between two curves.
- The warping distance was obtained using the Dynamic Time Warping (DTW).
- DTW operates as follows:
- Given two point series $A_{|n|} = \{a_1, a_2,\ldots, a_n\}$ and $B_{|m|} = \{b_1, b_2,\ldots, b_m\}$.
- A matrix $R_{|nxm|}$ is defined.
- The value at each matrix element <i, j> (where $0 \le i < n$ and $0 \le j < m$) is the Euclidean distance between points a_i and b_j.
- Once the matrix elements have been computed the warping path $\mathbf{W}$ can be identified.

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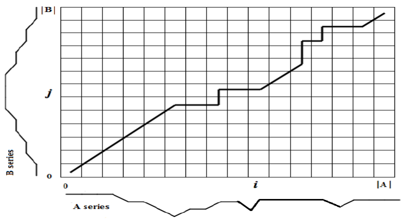
Dynamic Time Warping (DTW)

- $\mathbf{W}$ is the path from the bottom left corner of the matrix to the top right corner that links the matrix elements with the lowest values.
- The length of the warping path, $\mathbf{W}_\ell$, is the accumulated sum of the matrix element values:

$$\mathbf{W}_\ell = \sum_{k=1}^{k=|W|} W_k$$



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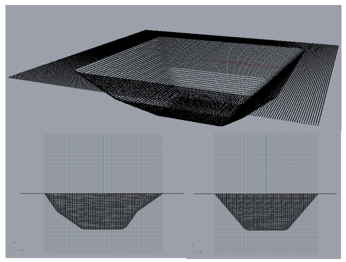
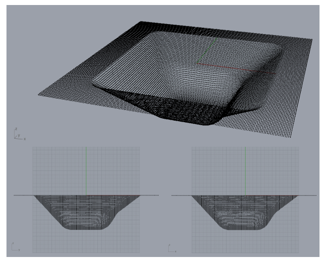
Evaluation

- Two sample surfaces (shapes) were considered, Gonzalo and Modified, both described flat topped pyramid shapes. Each was manufactured four times, twice using steel and twice using titanium (GS1, GS2, MS1, MS2, GT1, GT2, MT1 and MT2).



Gonzalo Pyramid



Modified Pyramid

Evaluation

- ➢ To determine best grid size
- ➢Key Points VS All Points
- ➢Neighbourhood Size
- ➢Generalization

Grid size

➢A range of grid sizes, d = {2.5, 5, 10, 15, 20} mm, were considered together with a 3x3 neighbourhood using the key point linearization.

	d=2.5		d=5		d=10		d=15		d=20	
	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC
GSV1	0.97	0.96	0.98	0.97	0.98	0.96	0.97	0.95	0.90	0.82
GSV2	**0.99**	0.94	0.98	0.89	0.97	0.84	0.96	0.64	0.96	0.78
GTV1	**0.99**	**0.97**	**1.00**	**1.00**	**0.99**	**0.98**	0.94	0.76	0.93	0.72
GTV2	**0.99**	0.96	0.99	0.99	**0.99**	0.97	**0.98**	0.93	0.96	**0.96**
MSV1	0.97	0.92	0.97	0.92	0.98	0.97	0.97	0.94	**0.97**	0.87
MSV2	0.96	0.94	0.98	0.97	0.98	0.93	0.97	0.92	0.92	0.71
MTV1	0.98	0.96	0.98	0.97	0.98	0.94	0.97	**0.96**	0.90	0.81
MTV2	0.97	0.96	0.96	0.94	0.93	0.90	**0.98**	0.94	0.82	0.73

3x3 neighbourhood using key point representation.

➢As the grid size increases the accuracy and AUC values start to decrease due to the coarseness of the representation.

Neighbourhood Size

➢Three values of n were considered, 3x3, 5x5 and 7x7 neighbourhood size.

	d=2.5		d=5		d=10		d=15		d=20	
	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC
GSV1	0.97	**0.96**	0.97	0.95	**0.98**	**0.97**	**1.00**	**1.00**	0.84	0.80
GSV2	**0.99**	0.94	0.97	0.89	0.96	0.75	0.94	0.64	0.92	0.73
GTV1	**0.99**	**0.96**	**0.99**	**0.99**	0.94	0.89	0.94	0.70	0.91	0.74
GTV2	**0.99**	**0.96**	**0.99**	0.98	0.96	0.85	0.95	0.90	**0.99**	**0.99**
MSV1	0.96	0.91	0.96	0.92	0.96	0.92	0.98	0.97	0.91	0.62
MSV2	0.96	0.94	0.96	0.94	0.97	0.91	0.97	0.93	0.92	0.64
MTV1	0.98	**0.96**	0.98	0.96	0.96	0.89	0.97	0.95	0.84	0.70
MTV2	0.97	**0.96**	0.96	0.94	0.93	0.92	0.96	0.93	**0.99**	0.98

5x5 neighbourhood using *Key* Point representation technique.

	d=2.5		d=5		d=10		d=15		d=20	
	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC
GSV1	0.98	**0.97**	**0.99**	0.98	0.94	0.92	0.87	0.70	0.78	0.33
GSV2	**0.99**	0.96	0.98	0.93	0.94	0.85	0.89	0.65	0.67	0.50
GTV1	0.98	0.93	**0.99**	**0.99**	0.87	0.77	0.79	0.57	**0.81**	**0.89**
GTV2	**0.99**	0.95	0.98	0.96	0.88	0.72	0.83	0.75	0.48	0.19
MSV1	0.96	0.92	0.97	0.95	**0.99**	**0.99**	0.89	0.81	0.75	0.67
MSV2	0.97	0.95	0.97	0.97	0.96	0.95	0.92	0.86	0.67	0.50
MTV1	0.98	0.95	0.98	0.97	0.92	0.72	**0.97**	**1.00**	0.70	0.47
MTV2	0.97	0.94	0.96	0.93	0.97	0.95	0.92	0.74	0.56	0.25

7x7 neighbourhood using *Key* Point representation technique.

➢There is no significant difference between the different neighbourhood sizes.

All Points versus Key Points

➢Three values of n were considered, 3x3, 5x5 and 7x7 neighbourhood size.

	d=2.5		d=5		d=10		d=15		d=20	
	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC
GSV1	0.97	**0.96**	0.97	0.95	**0.98**	**0.97**	**1.00**	**1.00**	0.84	0.80
GSV2	**0.99**	0.94	0.97	0.89	0.96	0.75	0.94	0.64	0.92	0.73
GTV1	**0.99**	**0.96**	**0.99**	**0.99**	0.94	0.89	0.94	0.70	0.91	0.74
GTV2	**0.99**	**0.96**	**0.99**	0.98	0.96	0.85	0.95	0.90	**0.99**	**0.99**
MSV1	0.96	0.91	0.96	0.92	0.96	0.92	0.98	0.97	0.91	0.62
MSV2	0.96	0.94	0.96	0.94	0.97	0.91	0.97	0.93	0.92	0.64
MTV1	0.98	**0.96**	0.98	0.96	0.96	0.89	0.97	0.95	0.84	0.70
MTV2	0.97	**0.96**	0.96	0.94	0.93	0.92	0.96	0.93	**0.99**	0.98

5x5 neighbourhood using *key* point representation technique.

	d=2.5		d=5		d=10		d=15		d=20	
	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC	Accuracy	AUC
GSV1	0.96	0.95	0.97	0.95	**0.98**	**0.97**	**1.00**	**1.00**	0.84	0.80
GSV2	**0.99**	0.94	0.98	0.90	0.96	0.75	0.94	0.64	0.92	0.73
GTV1	**0.99**	0.96	**0.99**	**0.99**	0.94	0.88	0.94	0.70	0.91	0.74
GTV2	**0.99**	0.96	**0.99**	0.98	0.96	0.85	0.95	0.90	0.98	**0.99**
MSV1	0.97	0.91	0.96	0.93	0.96	0.92	0.98	0.97	0.93	0.64
MSV2	0.96	0.94	0.96	0.94	0.96	0.92	0.98	0.96	0.90	0.64
MTV1	**0.99**	**0.97**	0.98	0.95	0.96	0.91	0.97	0.96	0.83	0.67
MTV2	0.98	**0.97**	0.96	0.94	0.93	0.92	0.98	0.96	**0.99**	0.98

5x5 neighbourhood using *all* point representation.

➢There is no significant difference between the Key Point and the All Point linearizations.

➢The Key Point linearization is more efficient than the All Point representation in terms of time complexity.

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Generalisation

- The main goal was to determine whether it is possible to generate a generally applicable classifier.
- Using classifier trained on one shape and tested on another.
- A best AUC value of 1.00 was obtained by using the proposed representation.
- Other alternatives (LGM, LDM and the combined LGM+LDM) performed badly in comparison with the PS representation.
- An effective generic classifier can be produced using the proposed PS representation.

		Train							
		GSV1	GSV2	GTV1	GTV2	MSV1	MSV2	MTV1	MTV2
Test GSV1	Point series		0.97	0.94	0.93	0.96	0.91	0.96	0.98
	LGM		0.66	0.59	0.70	0.44	0.52	0.48	0.52
	LDM		0.52	0.50	0.50	0.51	0.50	0.52	0.47
	LGM + LDM		0.94	0.76	0.81	0.80	0.89	0.75	0.70
GSV2	Point series	0.99		0.99	0.92	1.00	0.96	1.00	0.99
	LGM	0.62		0.68	0.74	0.60	0.53	0.67	0.61
	LDM	0.50		0.50	0.50	0.50	0.50	0.50	0.50
	LGM + LDM	0.72		0.78	0.83	0.81	0.90	0.78	0.74
GTV1	Point series	0.84	0.87		0.95	0.64	0.66	0.94	0.94
	LGM	0.65	0.74		0.75	0.69	0.67	0.69	0.67
	LDM	0.49	0.61		0.53	0.41	0.41	0.41	0.40
	LGM + LDM	0.70	0.89		0.80	0.80	0.89	0.73	0.72
GTV2	Point series	0.81	0.91	0.98		0.65	0.61	0.99	0.95
	LGM	0.66	0.81	0.72		0.70	0.63	0.68	0.65
	LDM	0.50	0.50	0.50		0.50	0.50	0.50	0.50
	LGM + LDM	0.74	0.97	0.79		0.83	0.93	0.79	0.74
MSV1	Point series	0.98	0.99	0.99	0.98		0.95	0.98	0.97
	LGM	0.61	0.57	0.70	0.76		0.82	0.76	0.77
	LDM	0.51	0.39	0.47	0.47		0.59	0.59	0.60
	LGM + LDM	0.66	0.89	0.74	0.76		0.92	0.74	0.75
MSV2	Point series	0.95	0.96	0.99	1.00	0.98		0.97	0.97
	LGM	0.65	0.75	0.72	0.77	0.80		0.70	0.73
	LDM	0.51	0.39	0.59	0.47	0.59		0.59	0.60
	LGM + LDM	0.77	0.95	0.78	0.83	0.84		0.77	0.73
MTV1	Point series	0.85	0.88	0.96	0.94	0.62	0.59		0.95
	LGM	0.62	0.74	0.72	0.71	0.75	0.73		0.76
	LDM	0.50	0.50	0.50	0.50	0.50	0.50		0.50
	LGM + LDM	0.74	0.93	0.76	0.81	0.80	0.91		0.71
MTV2	Point series	0.90	1.00	0.98	0.93	0.65	0.63	0.99	
	LGM	0.56	0.49	0.59	0.59	0.76	0.75	0.73	
	LDM	0.50	0.39	0.47	0.47	0.59	0.59	0.59	
	LGM + LDM	0.69	0.83	0.72	0.76	0.81	0.86	0.72	
Average (Point series)		0.90	0.94	0.98	0.95	0.79	0.76	0.98	0.96
Average (LGM)		0.56	0.64	0.69	0.69	0.74	0.73	0.72	0.64
Average (LDM)		0.50	0.50	0.47	0.50	0.52	0.53	0.50	0.51
Average (LGM + LDM)		0.81	0.79	0.79	0.83	0.78	0.81	0.81	0.77

AUC results for the generic classifier.

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Main Findings

- The experiments indicated that:
  - i. Smaller grid sizes tended to work better.
  - ii. The performance using 3X3, 5X5 and 7X7 neighbourhoods was almost the same.
  - iii. There was no significant difference in accuracy or AUC between the representations (all and key), however the key point representation offers runtime advantages.
  - iv. PS was able to produce a generic classifier.

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Conclusion and Future Work

- A new representation and supporting mechanism to predict feature values associated with 3D surfaces using a point series based approach has been proposed.
- The PS representation is founded on a *linearization* concept.
- The motivation for the work was springback prediction in sheet metal forming.
- Two 3D surfaces (shapes) were used to evaluate the mechanism.
- Excellent results were obtained, 100% in terms of AUC, indicating that the PS representation is able to capture general geometric information that can successfully be employed for prediction purposes.
- The ultimate goal is to build an intelligent process model that can predict springback errors, and suggest corrections, in the context of sheet metal forming.

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Tutorial | Time-Series with Matlab

Thank you :)

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