A transfer learning based geometric position-driven machining error prediction method for different working conditions

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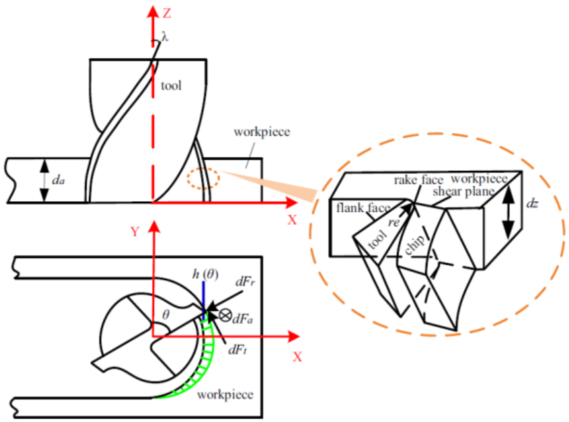
Outline

- **Background**
- **Methodology**
- **Experiment**
- **Result and Analysis**
- **Conclusion and Future Work**

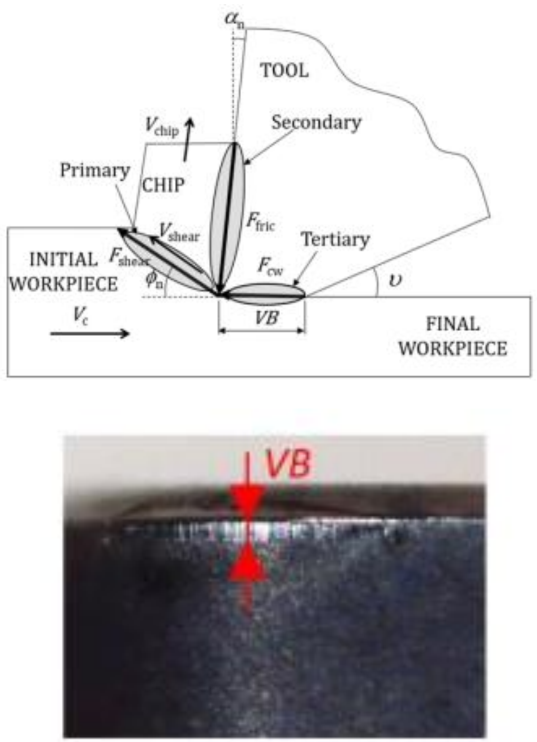
Background (Mechanism Modeling)



$$\begin{cases} dF_{tk}(\theta) = [K_{tc}h_k(\theta) + K_{te}]dz \\ dF_{rk}(\theta) = [K_{rc}h_k(\theta) + K_{re}]dz \\ dF_{ak}(\theta) = [K_{ac}h_k(\theta) + K_{ae}]dz \end{cases}$$

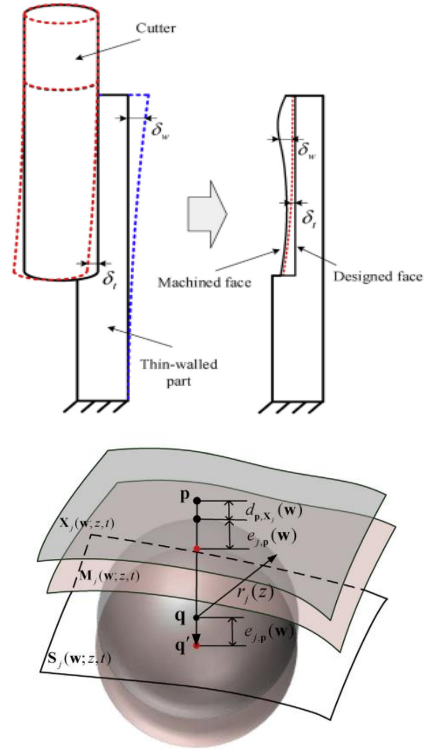
Cutting force

Zhou et al. MTM 2015



Tool wear

I. Urresti et al, CIRP 2021

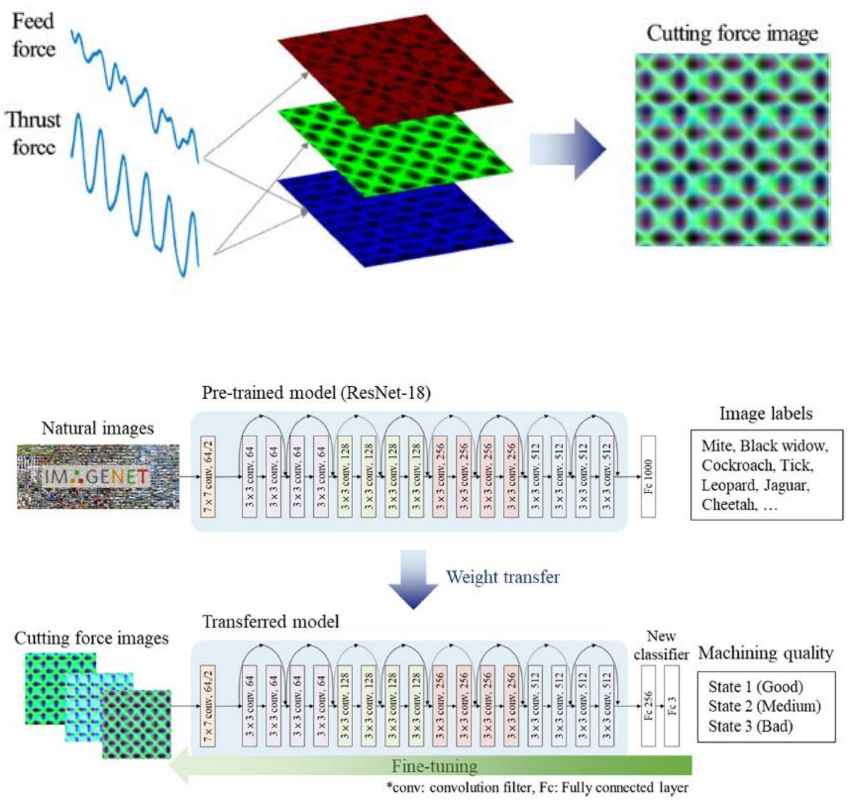


Tool & workpiece deformation

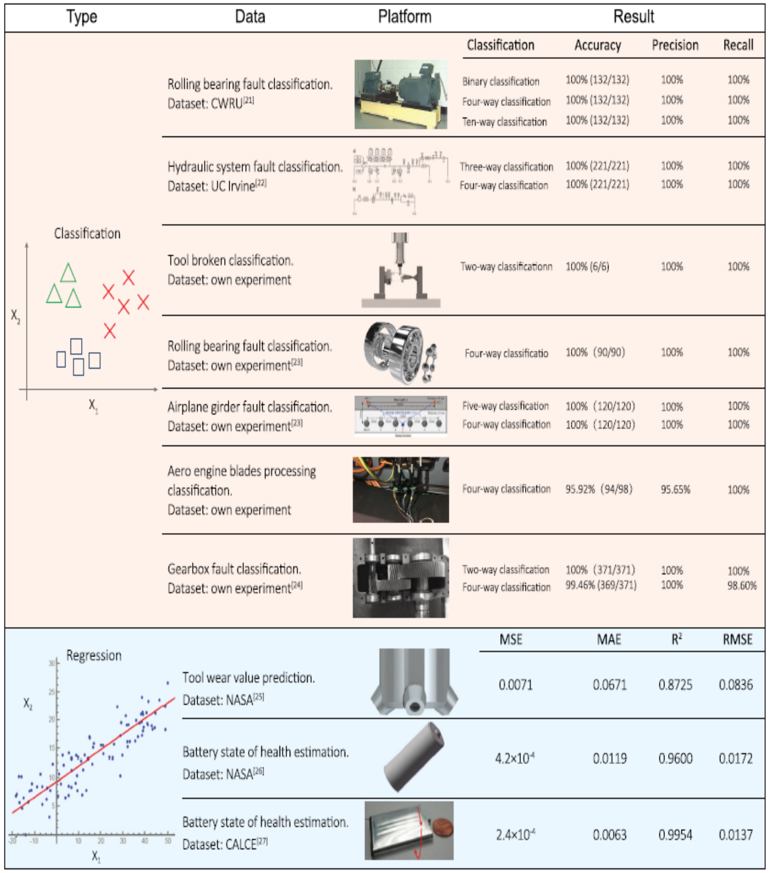
Li Z L et al, PE 2019

Modeling is difficult and model accuracy is low

Background (Data-Driven)



Yunhan Kim et al, JIM 2021



Type	Data	Platform	Result: Classification	Accuracy	Precision	Recall
Classification	Rolling bearing fault classification. Dataset: CWRU[21]		Binary classification	100% (132/132)	100%	100%
			Four-way classification	100% (132/132)	100%	100%
			Ten-way classification	100% (132/132)	100%	100%
	Hydraulic system fault classification. Dataset: UC Irvine[22]		Three-way classification	100% (221/221)	100%	100%
			Four-way classification	100% (221/221)	100%	100%
	Tool broken classification. Dataset: own experiment		Two-way classificationn	100% (6/6)	100%	100%
	Rolling bearing fault classification. Dataset: own experiment[23]		Four-way classificatio	100% (90/90)	100%	100%
	Airplane girder fault classification. Dataset: own experiment[23]		Five-way classification	100% (120/120)	100%	100%
			Four-way classification	100% (120/120)	100%	100%
	Aero engine blades processing classification. Dataset: own experiment		Four-way classification	95.92% (94/98)	95.65%	100%
	Gearbox fault classification. Dataset: own experiment[24]		Two-way classification	100% (371/371)	100%	100%
			Four-way classification	99.46% (369/371)	100%	98.60%
Regression			MSE	MAE	R^2	RMSE
	Tool wear value prediction. Dataset: NASA[25]		0.0071	0.0671	0.8725	0.0836
	Battery state of health estimation. Dataset: NASA[26]		4.2×10^{-4}	0.0119	0.9600	0.0172
	Battery state of health estimation. Dataset: CALCE[27]		2.4×10^{-4}	0.0063	0.9954	0.0137

Ye Yuan et al, National Science Review 2020

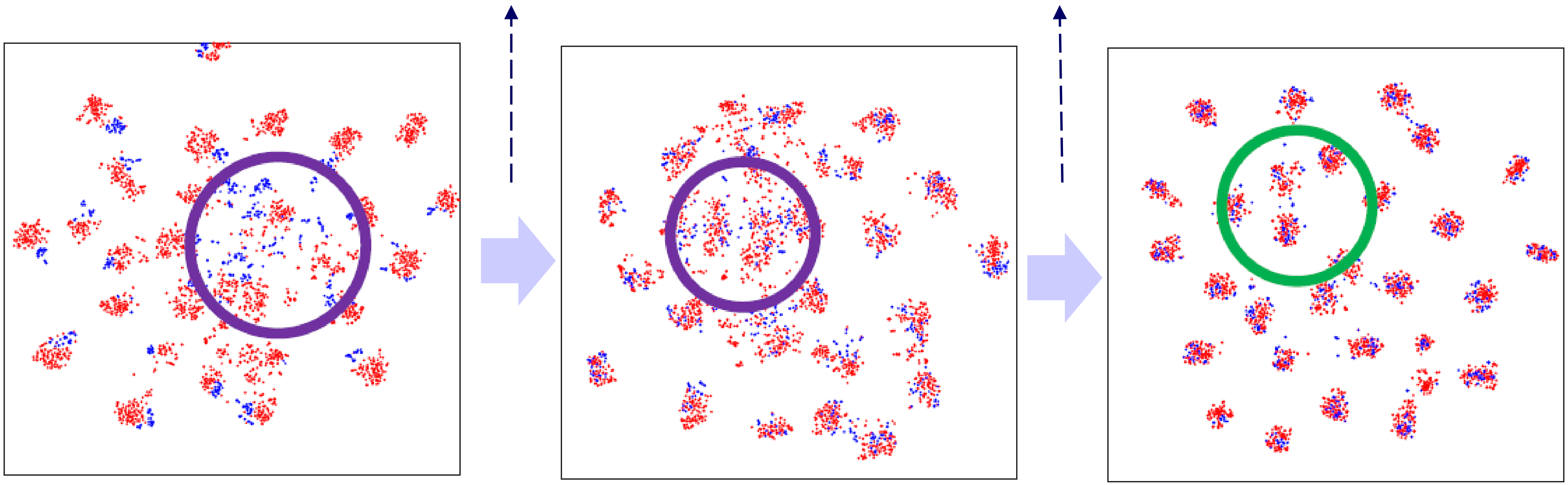
The generalization ability of the new scene is weak

Background

Why transfer learning?→Different distribution (Domain Adaption)

Marginal distribution adaption

Conditional distribution adaption



$P(x) \neq Q(x)$
$P(y|x) \neq Q(y|x)$

$P(x) \approx Q(x)$
$P(y|x) \neq Q(y|x)$

$P(x) \approx Q(x)$
$P(y|x) \approx Q(y|x)$

Background

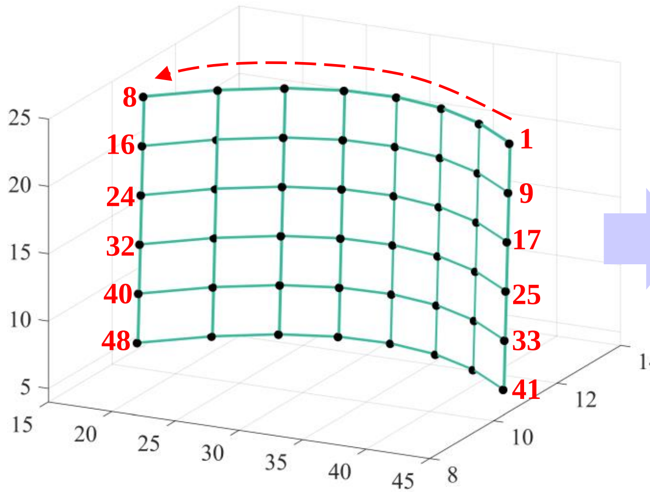
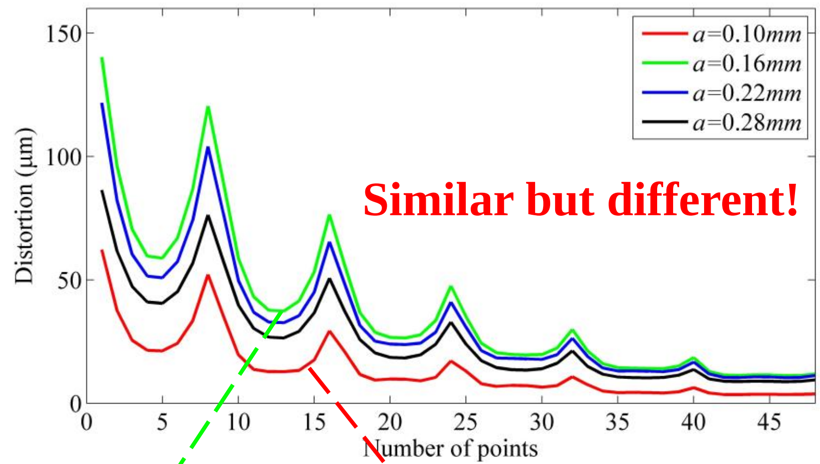
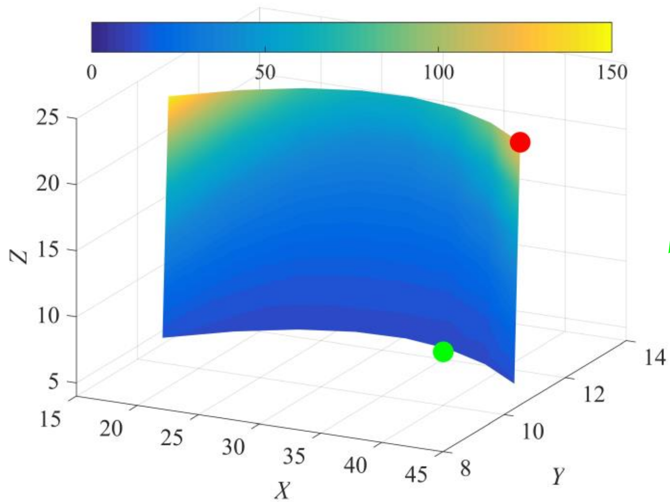


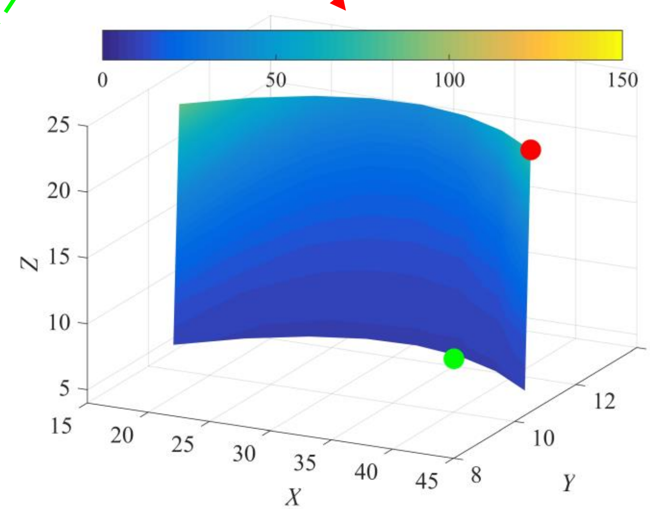
Diagram of measuring point position on surface



Distortion curves



The distortion field represented by the **green curve**



The distortion field represented by the **red curve**

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Methodology

Algorithm 1 TrAdaBoost.R2

Input: Source domain dataset χ^S with sample number n and target domain dataset χ^T with sample number m, the maximum number of iterations N, a base learner, and the initial weight of each sample $w_i^1 = 1/(n+m)$, $1 \le i \le (n+m)$;

For $e = 1, \cdots, N$

Step1. Train the learner to get a mapping relation: $f_e(x_i)$: $\chi \to \mathbb{R}$;

Step2. Calculate the training loss of each sample and obtain:

$$E_e = \max_{j=n+1}^{n+m} \left\| y_j - f_e(X_j) \right\| \quad where \ \ n+1 \le j \le n+m,$$

$$e_i^e = \left\| \frac{y_i - f_e(X_i)}{E_e} \right\| \quad where \ \ n+1 \le i \le n+m$$

Step3. Calculate the weighted sum of sample weights: $\varepsilon_e = \sum_{i=n+1}^{n+m} e_i w_i^e$,

If $\varepsilon_e \ge 0.5$, then terminate the iteration and let $N = e-1$

Step4. Calculation $\beta_e = \varepsilon_e / (1-\varepsilon_e)$, $\beta_s = 1/(1+\sqrt{2\ln n / N})$

Step5. Update the sample weight: $w_i^{e+1} = \begin{cases} \dfrac{w_i^e \beta_s^{e_i^e}}{Z_e} & 1 \le i \le n \\ \dfrac{w_i^e \beta_e^{-e_i^e}}{Z_e} & n+1 \le i \le n+m \end{cases}$

Where Z_e is the normalized constant, which satisfies $\sum_{i=1}^{n+m} w_i^{e+1} = 1$.

Output: The final mapping function $f_f(x)$ is the weighted summation expression of the learner $f_e(x)$. For the mapping function that meets the corner standard $\left\lceil \frac{N}{2} \right\rceil \le e \le N$, it is weighted as the coefficient $\ln(1/\beta_e)$.

①Set **uniform** sample weight

↓

②Training base model

↓

③Obtain the **maximum prediction error**

↓

④Calculate the weighted sum of the weights

↓

⑤Compute **two coefficients** β_e, β_s

↓

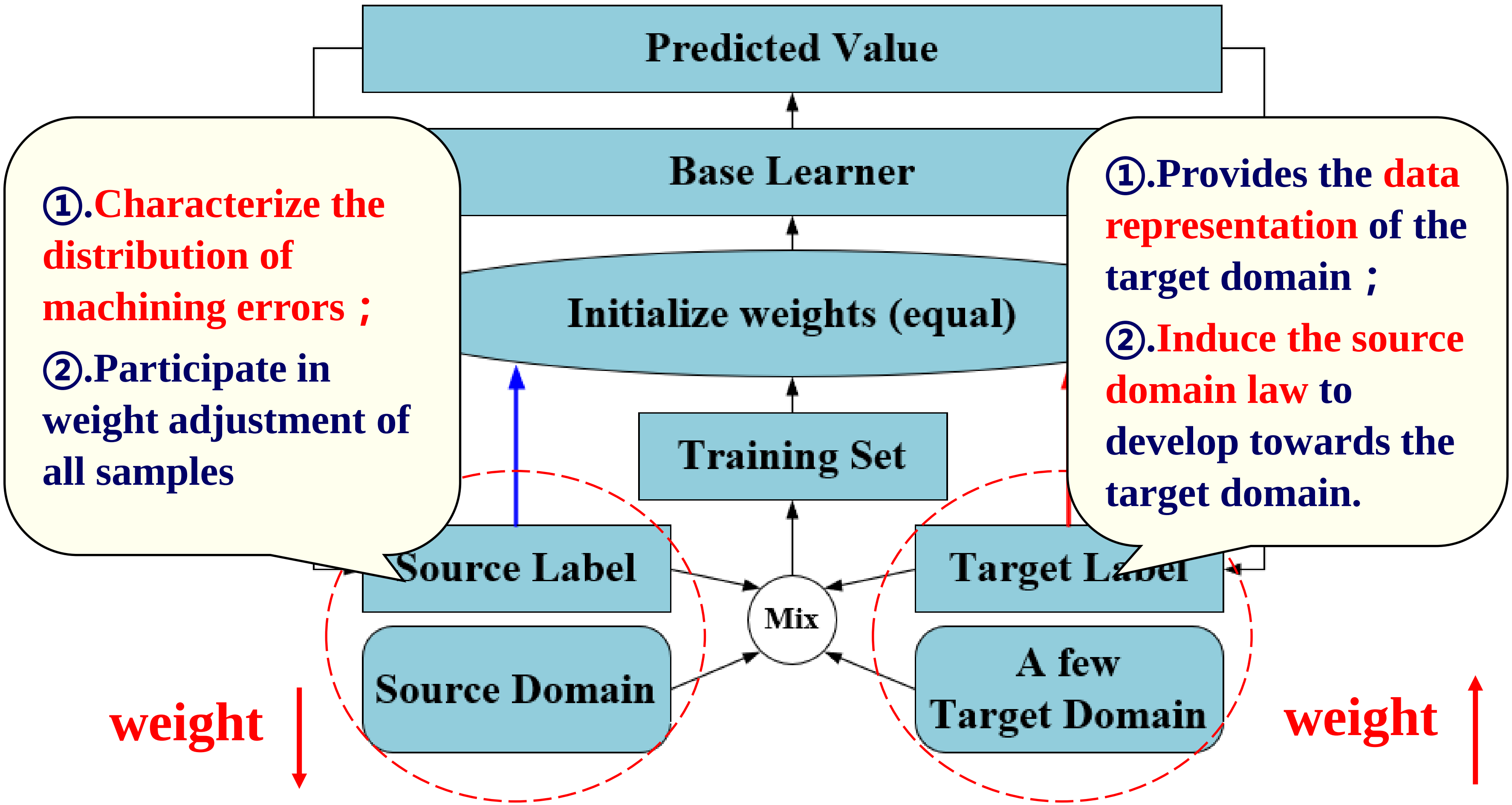
⑥Updata the sample weight

↓

⑦Learner weighted representation

D. Pardoe and P. Stone, "Boosting for regression transfer," ICML 2010 - Proceedings, 27th Int. Conf. Mach. Learn., no. June, pp. 863–870, 2010.

Methodology



Flow chart of the regression prediction with adaptive weights

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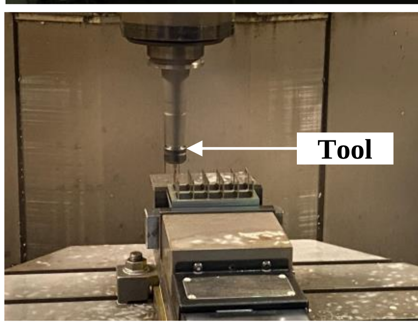
Experiment

◆ Milling experiment



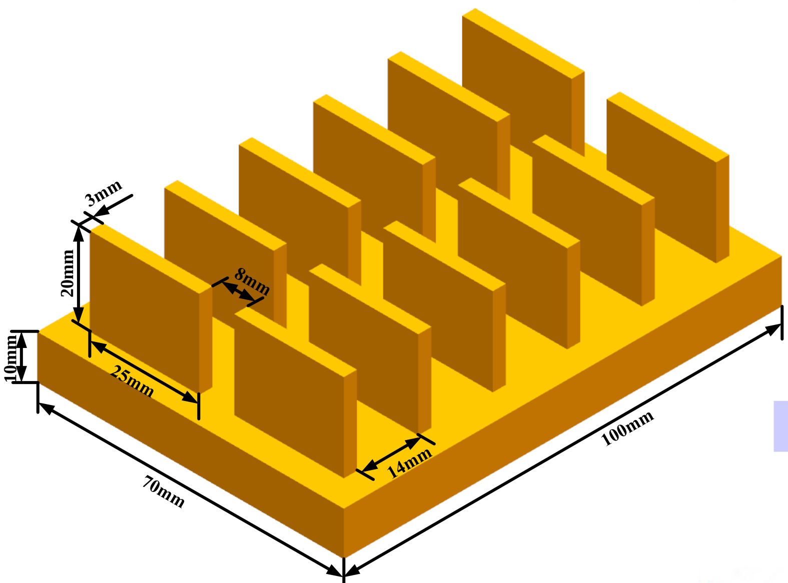
Rough & Semi-finish	**SHANHELE 6×6DX4TX50L**
Finish	**SHANHELE 4×4DX4TX50L**

◆ Processing parameters

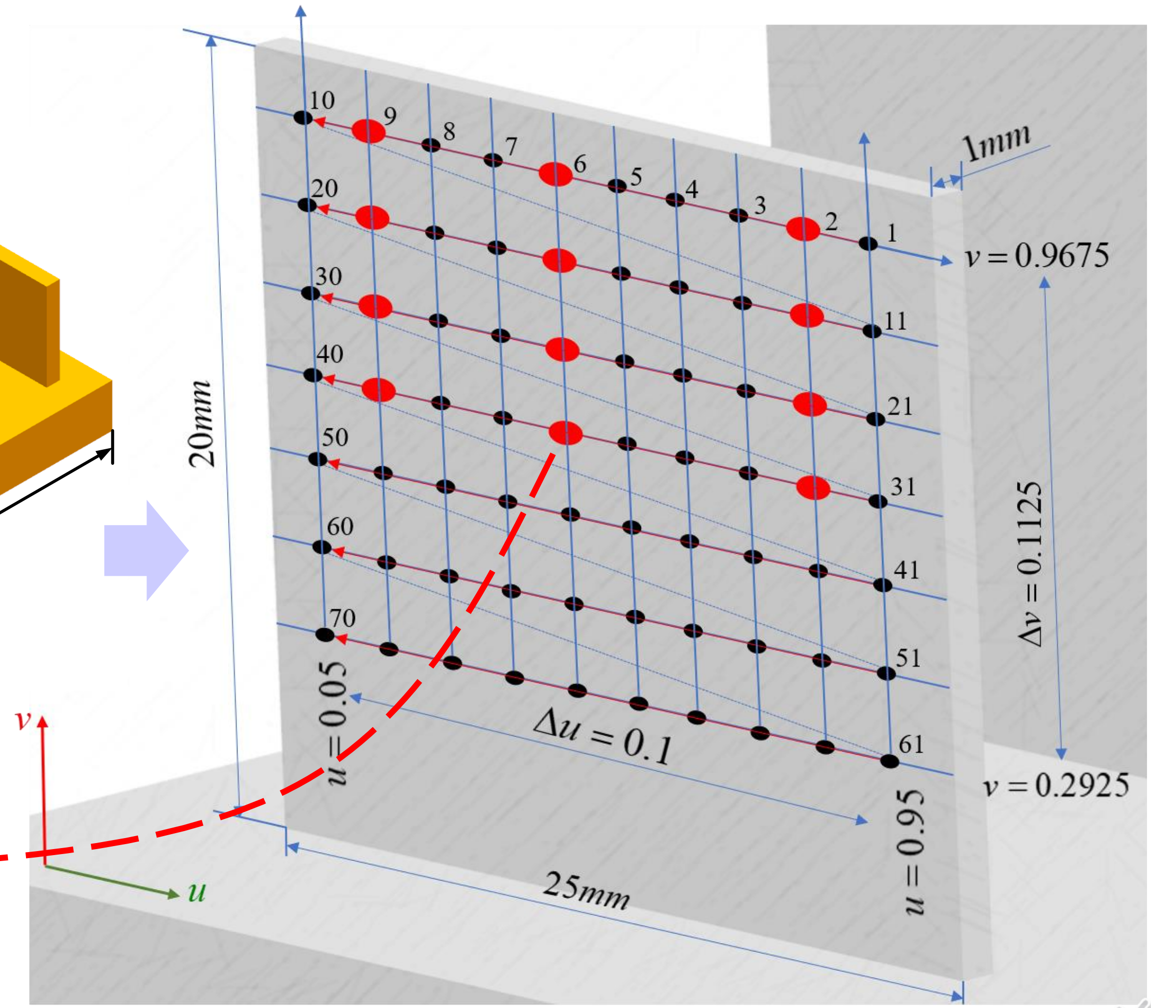
	No.	***Allowance (mm)***	***Feed per tooth (mm)***	***Cutting speed (m/min)***
Source	S1	0.16	0.05	40
	S2	0.18	0.05	50
	S3	0.16	0.08	55
	S4	0.18	0.08	40
	S5	0.20	0.05	55
	S6	0.20	0.08	40
	S7	0.14	0.04	35
	S8	0.22	0.09	60
Target	T1	0.16	0.07	50
	T2	0.18	0.07	55
	T3	0.20	0.07	50
	T4	0.17	0.06	45

Experiment

◆ The positions and path of each sampling point



The original workpiece



Induction points

The workpiece after processing

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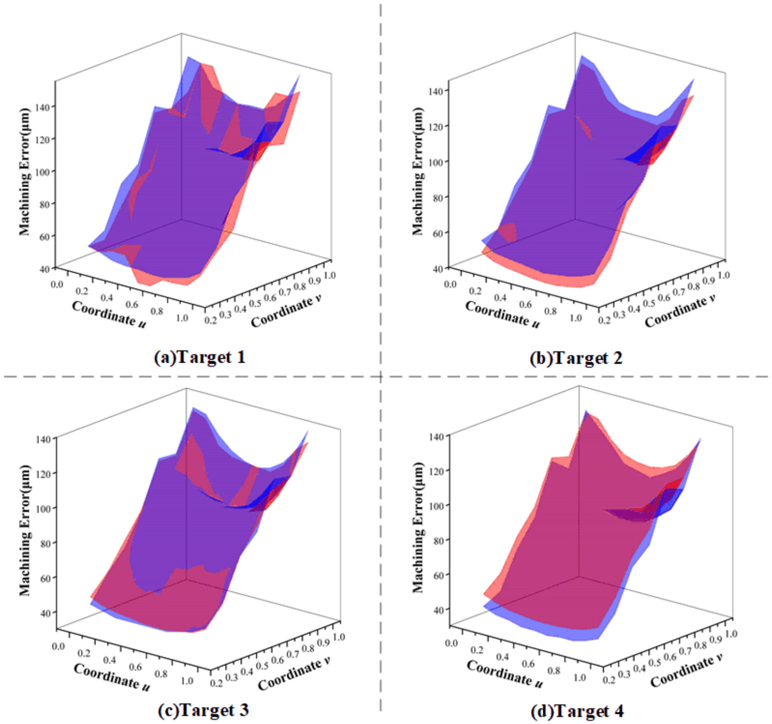
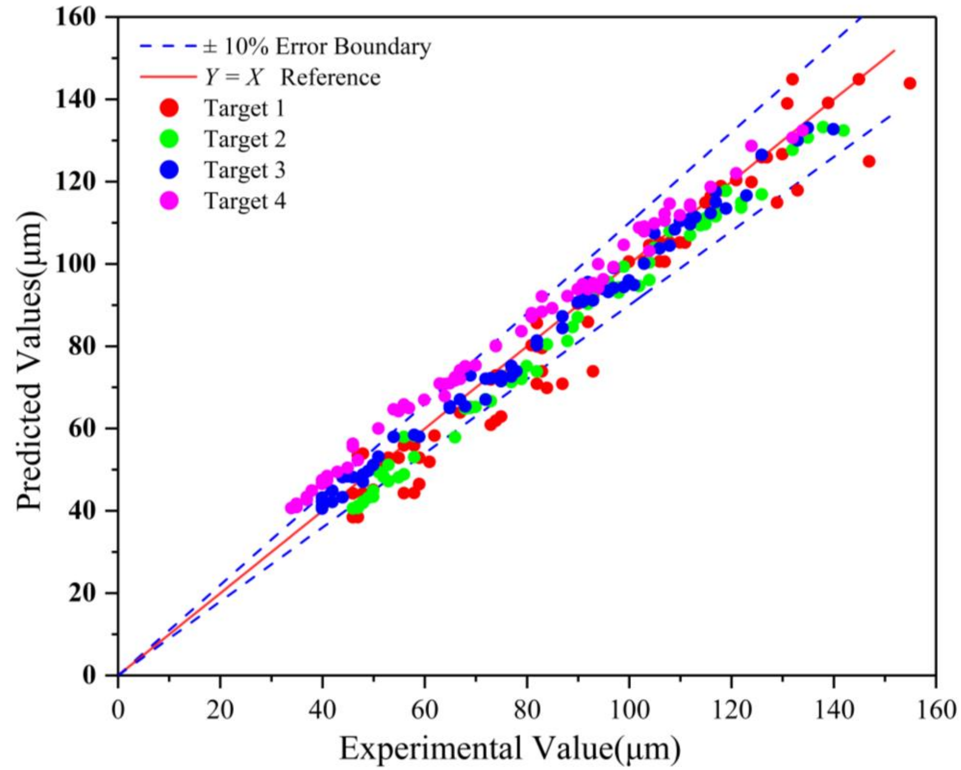
Result and Analysis

◆ The prediction accuracy of the proposed method



Distribution of experimental and predicted machining errors of T-shaped thin plates in target domain



Comparison of experimental and predicted machining error values

Result and Analysis

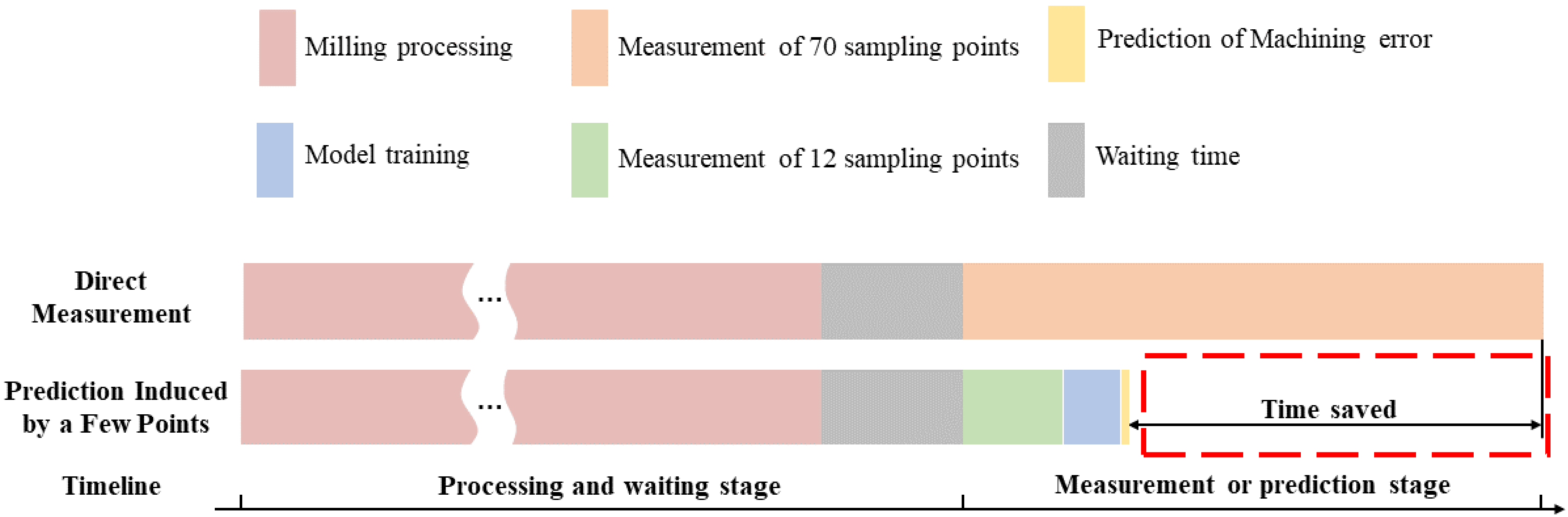
◆ Accuracy comparison of different methods

	GPR		SVR		**This Paper**	
	R^2	RMSE (μm)	R^2	RMSE (μm)	R^2	RMSE (μm)
T1	0.79	13.55	0.66	17.26	**0.94**	**7.55**
T2	0.90	8.47	0.79	12.13	**0.97**	**4.90**
T3	0.94	6.59	0.82	11.89	**0.99**	**2.69**
T4	0.90	8.79	0.77	13.33	**0.95**	**6.13**
Avg.	0.88	9.35	0.76	13.65	**0.96**	**5.32**

Sklearn is used to train GPR and SVR models. RBF is selected as the kernel function of the two models. Both models are automatically optimized under the default configuration.

Result and Analysis

◆ Evaluation of the efficiency of this method



Time/ sampling point ≈4.3s.

Train & Test time

Direct Measurement: 4.3×70=301s

This Method: 4.3×12+13.36+0.0217=64.9817s

78%

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Conclusion and Future Work

◆ Conclusion

- **A sample-based transfer learning method driven by geometric position was Proposed.**
- **The proposed model can predict the machining errors under different working conditions.**
- **This method can reduce the reliance on time-consuming and expensive measurements, and improve the efficiency of obtaining machining errors.**

Conclusion and Future Work

◆ Future Work

- The influence of the position of the induction points on the prediction results will be studied.
- The prediction effect of the model on the machining errors of the workpiece with similar geometrical configuration but different scales will be studied.
- The prediction of machining errors with larger differences will be studied, such as different materials, different tools, and different machine tools .
- The knowledge transfer and knowledge generalization in the manufacturing field will be deeply studied, and more complex experimental scenes will be promoted.

Conclusion and Future Work

◆ Acknowledgement

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Thanks for listening！

Question？

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