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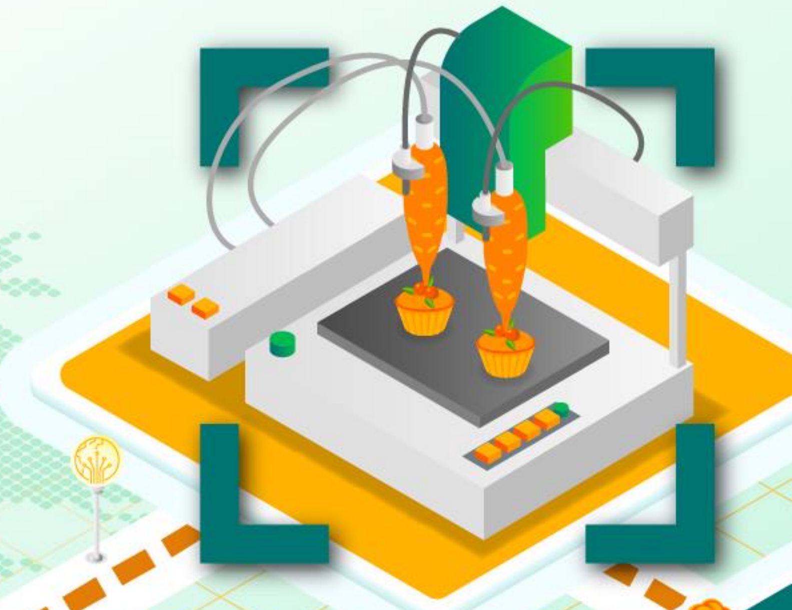

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PROCESS MAP GENERATION OF GEOMETRICALLY UNIFORM BEADS USING SUPPORT VECTOR MACHINE
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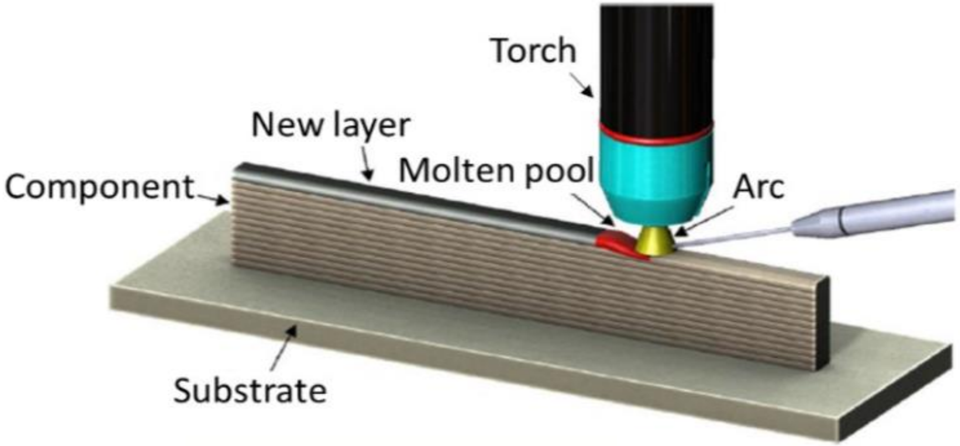
Wire Arc Additive Manufacturing (WAAM)

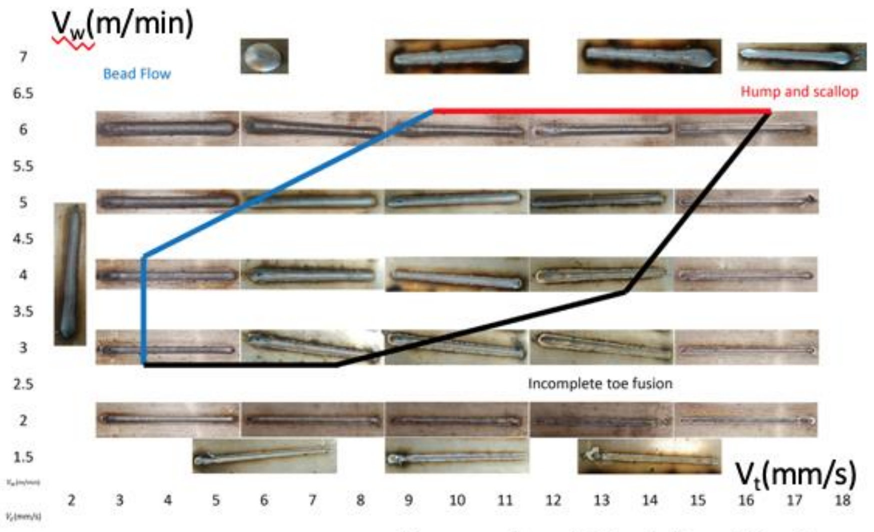
- WAAM is an arc-welding-based Direct Energy Deposition additive manufacturing technique.
- Adds overlapping beads layer by layer.
- Low equipment cost, low buy-to-fly ratio, high deposition rate, and friendly to the environment.



Typical Set up of WAAM

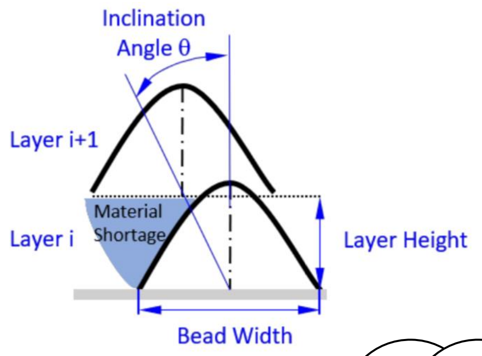
Implementation Challenge

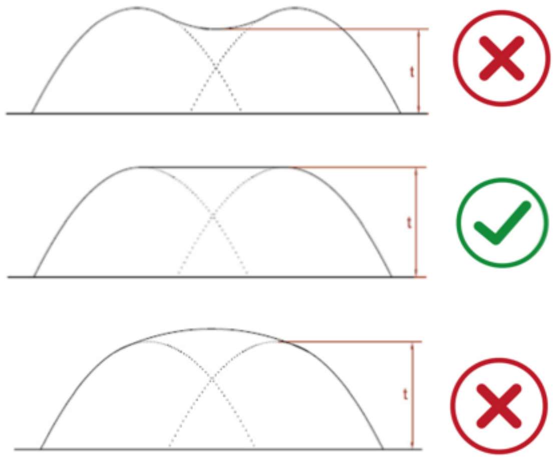
1. Process Parameters
   - Good bead formation
   - Material Dependent



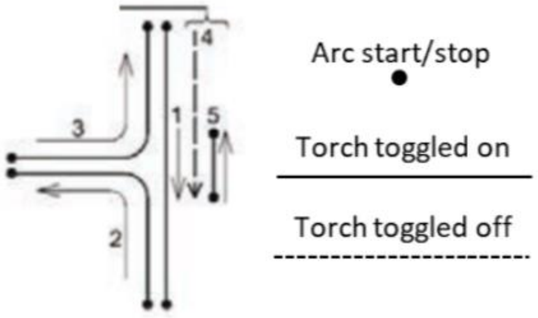
Key results of Single Bead Study

2. Bead Overlapping Profile





3. Build Strategy
   - Toolpaths
   - Stack up Errors
   - Residual Stress



Implementation Challenge

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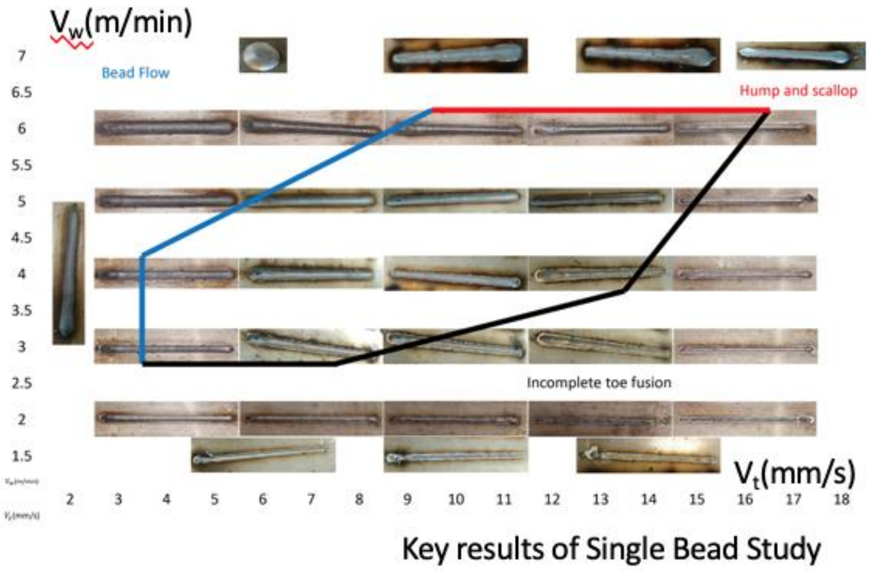


WAAM Process Map

- Material Specific Processes and very **time-consuming** to construct material-specific processes using trial and error.
  - Process map of one material does not scale to another material
  - Lack of a systematic method to quantify print beads defects
  - Impossible to print all different combinations of process parameters to model the bead accurately, as printing them is expensive and time-consuming

Goal

To develop a systematic methodology to generate a particular material process map based on bead uniformity.

Our Approach

Construct the process parameter map for WAAM based on the probability that a bead geometry is uniform using support vector machine.

Related Work on Process Map Generation

- Kenta Aoyagi et al. constructed a process map for the **powder bed fusion** AM process.
- They can predict the **process condition of fabricating a part with low pore density**.
- As functions of scan speeds and
  - current,
  - line energy,
  - area energy, and
  - energy density.

- Used material: CoCr alloy

Procedures for Process Parameter Map Generation

Inputs

- The Process parameters (torch speed, wire feed rate) and annotated labels

Machine Learning Model

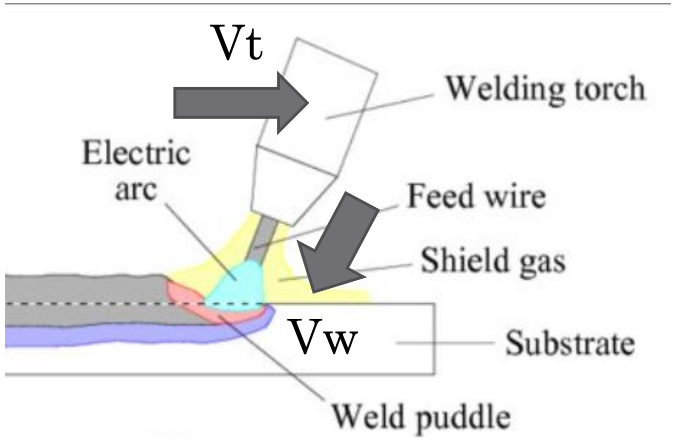
- Two-parameter sigmoid function based on SVM

Output

- Process Map based on probability that produces a good bead.

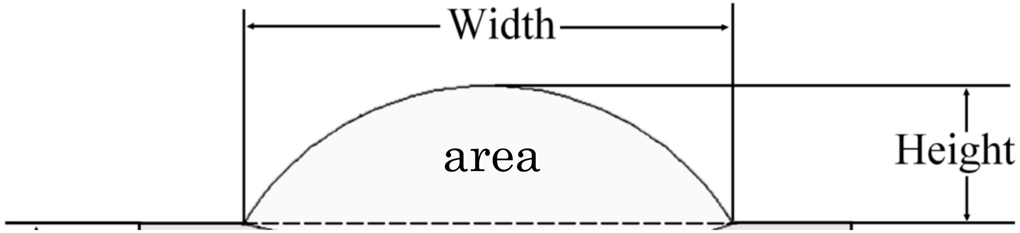
Inputs

- **Process Parameters**
  - Torch speed, Wire feed rate



- **Annotated Labelling**
  - Quantify uniformity via the bead RMSE width, height and area along the entire bead:

$$\mathrm{RMSE} = \frac{width_{RMSE} + height_{RMSE} + \sqrt{area_{RMSE}}}{3}$$

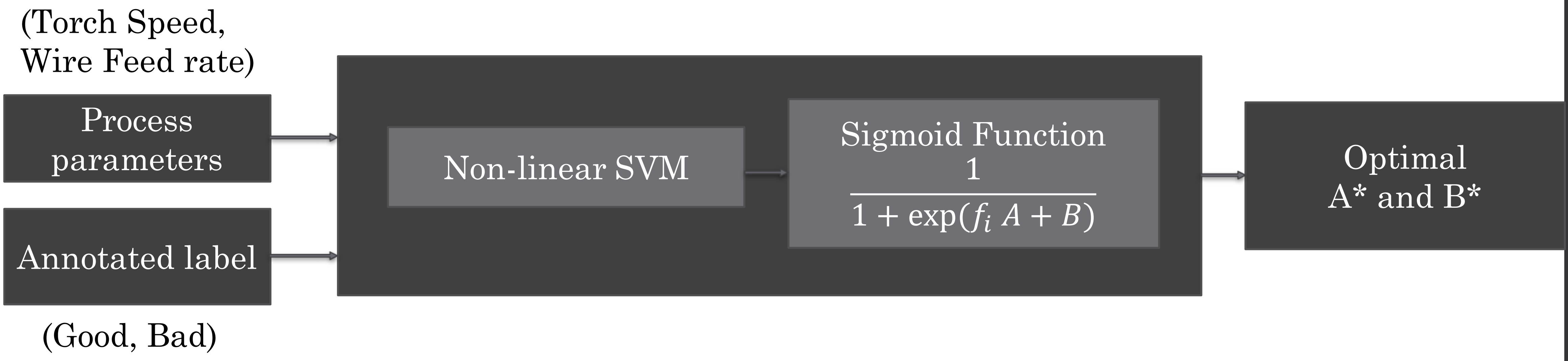


(Bad) RMSE $>$ Threshold

(Good) RMSE $\leq$ Threshold

Machine Learning Model

- **Training**
  - We train a two-parameter sigmoid function based on SVM.



A, B = Sigmoid parameters to be Trained

Output

- **Process Map Generation**
- We used the learned sigmoid function to obtain the probability for a particular set of process parameters to generate the process map.

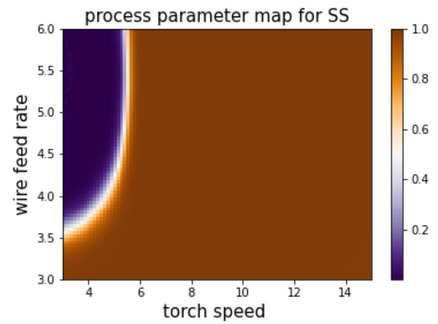
(Torch Speed, Wire Feed rate)

Process parameter

Learned Sigmoid Function

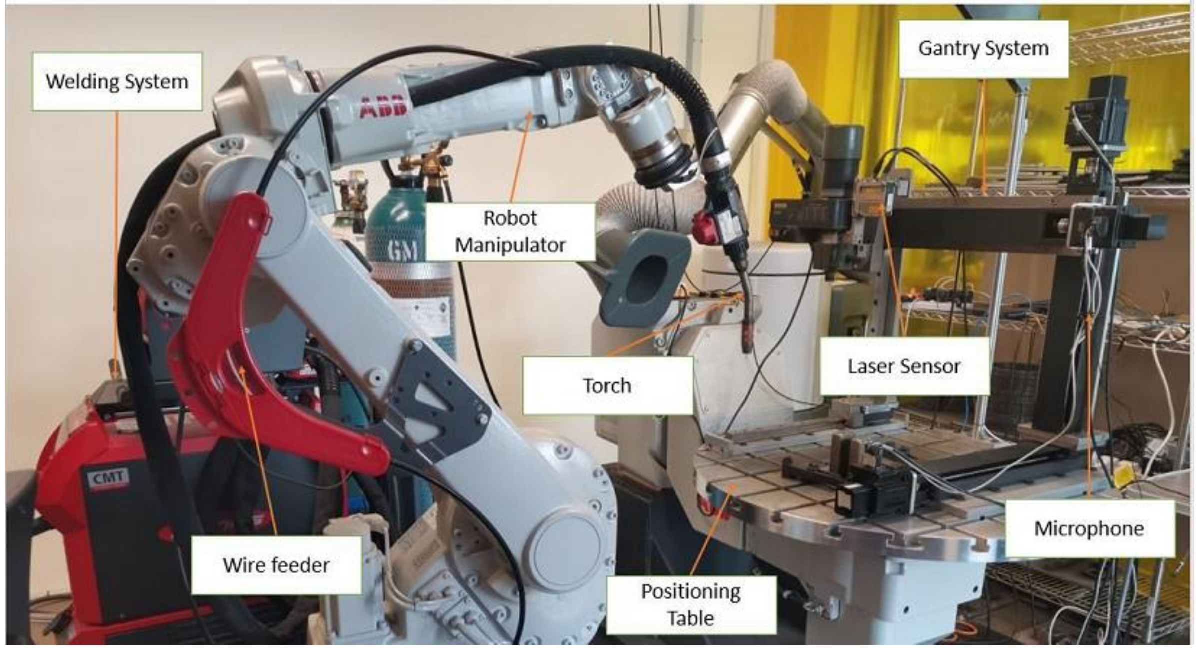
$$\frac{1}{1+\exp(f_i\ A^* + B^*)}$$

Probability (0-1)



High probability means set of process parameters can form a good bead and low probability means set of process parameters can form a bad bead

Experimental Setup



- **Data collection:**
  - Printed 50 bronze and 52 stainless steel beads.
  - Varied torch speed and wire feed rate to print beads of different qualities onto a substrate.

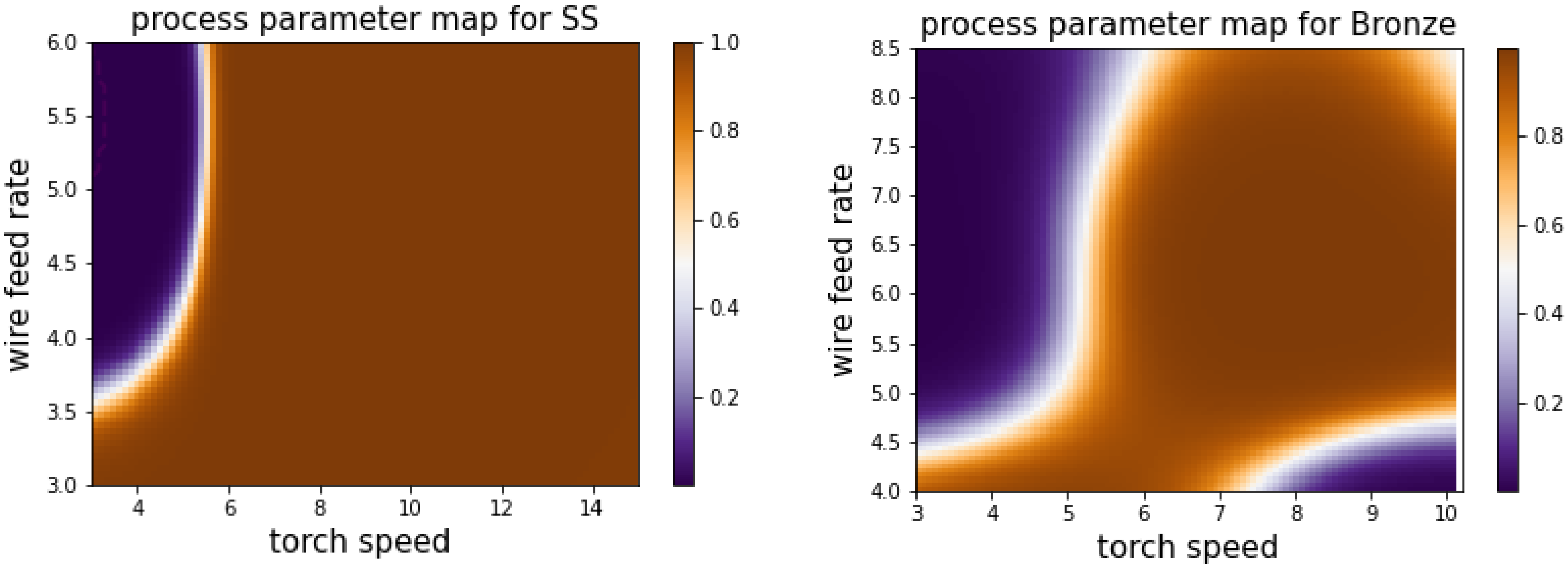
- **Dataset labelling**
  - Measured height, width and area: Moving 2D laser scanner
  - Threshold for defective beads:
    - Stainless steel : 0.4 mm
    - Bronze : 0.5 mm.

Material	Defective Beads (bad)	Non-Defective Beads (Good)
Bronze		
Stainless Steel		

defects

Results

- **Process Map Generation**
  - Based on its probability to produce a good bead

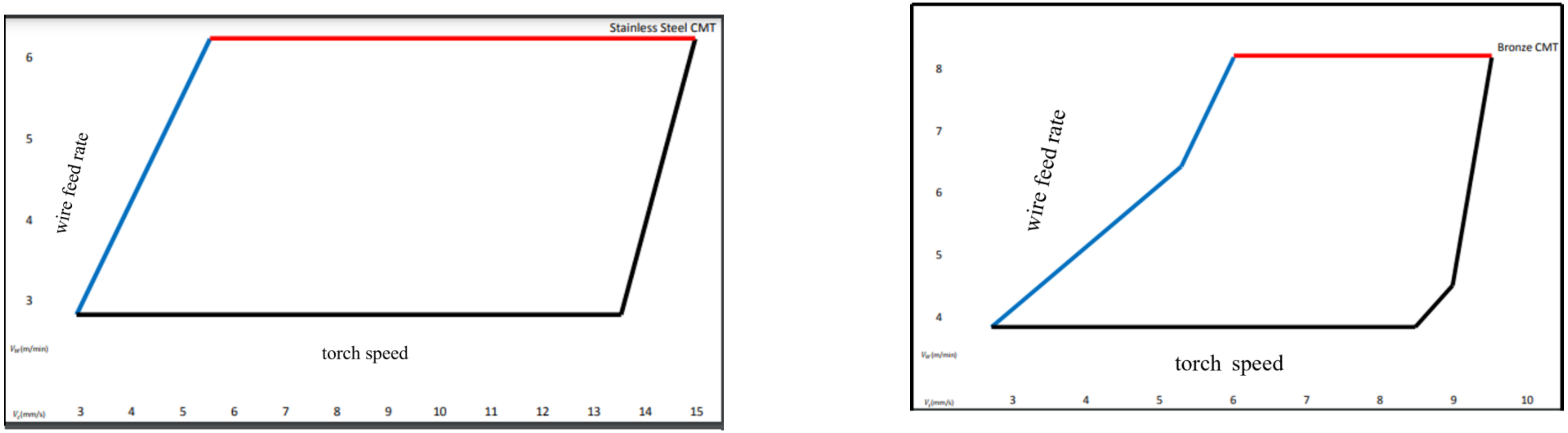


a b

Process parameter map generation using SVM for (a) Stainless steel (SS) and (b) Bronze

Results

- **Benchmarking with Manual Quantization**
  - A WAAM expert performs manual quantization of the process parameter map based on her experience.

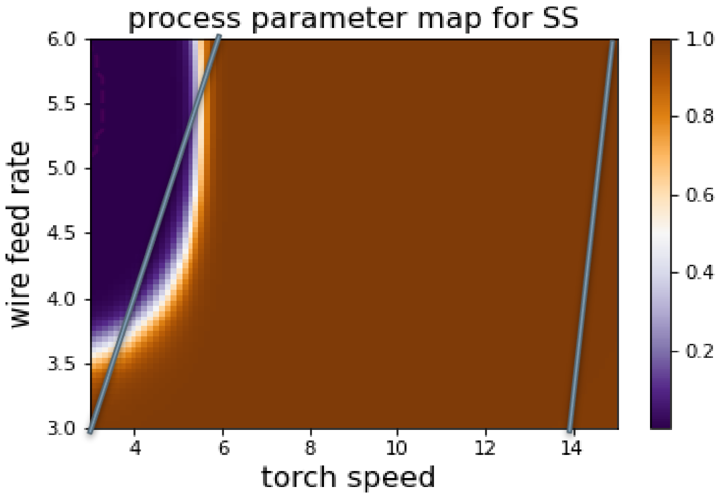


a b

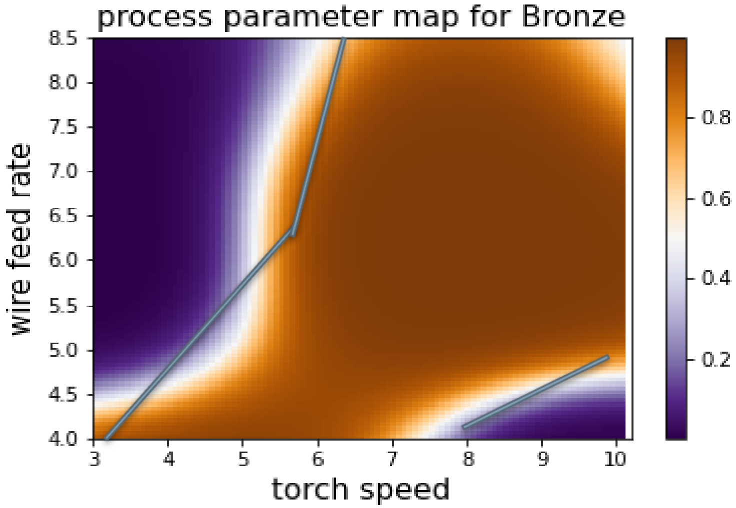
Expert manual quantization Process parameter map for (a) Stainless steel (SS) and (b) Bronze

Results

- We superimpose the two figures on each other.
- The process map for both stainless steel and bronze matches well based on the human quantization process=>process parameter map based on our approach is consistent with the current approach.
- We can predict the quality of the beads at the boundary region.



a



b

Comparison of two Process parameter maps for (a) Stainless steel (SS) and (b) Bronze

Results

- **Performance evaluation**
  - We quantify the performance of our SVM model based on the testing accuracy and confusion matrix.
  - We use eight combinations of features including those that we used to generate the process map.
  - We include also geometric parameters like the bead height (h), width (w), or area (A) for training and testing.

INPUT FEATURES (X)	TESTING ACCURACY (SS)	TESTING ACCURACY (B)
torch speed wire feed	92 %	**72 %**
torch speed wire feed height	92 %	**73 %**
torch speed wire feed width	92 %	**72%**
torch speed wire feed area	92 %	**69%**
torch speed wire feed height width	92 %	**76 %**
torch speed wire feed height area	92 %	**69%**
torch speed wire feed width area	92 %	**68%**
torch speed wire feed height width area	**92 %**	**72 %**

Conclusion

- **Objective:** Construct a process parameter map based on the uniformity of bead geometry using support vector machine.
- **Advantages:**
  - Predict the quality of beads based on their uniformity.
  - Give a mapping relationship between process parameters and final part qualities.
  - Reduce the number of experiments required to achieve a cost-effective and efficient development of AM parts over a wide range of materials.
  - Show machine learning can provide a practical methodology to optimize the process parameters of AM technologies.
- **Used material:** Stainless steel and Bronze
- **Label of dataset :** We propose label to measure the bead geometry based on the RMSE of its width, height, and area.
- **Corelation with human quantization approach:** Our proposed map co-relates with the human quantization approach.
- **Testing Accuracy :**
  - For stainless steel, testing accuracy is 92% for all input combinations
  - For Bronze, testing accuracy varies from 68% to 76%, depending on different combinations

THANK YOU

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Supplementary slides

- Based on our gantry measurement system resolution, the number of scan lines for each bead is 50 (for some beads, it is 49). Hence, we further segment each bead into 50 (or 49) segments for training and testing purposes.

Training and testing dataset

- The training dataset we used for stainless steel is n = 1950 (based on 39 beads), and the testing dataset is 650 (based on 13 beads).
- For bronze, the training dataset used is n = 1950 (39 beads), and the testing dataset is 539 (11 beads).
- The torch speed and wire feed rate range from [3,10] mm/s and [3,8] m/min respectively for bronze, and [3,15] mm/s and [3,6] m/min respectively for stainless steel.