

In-situ additive manufacturing deposition trajectory monitoring and compensation with thermal camera

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ABSTRACT

Modern additive manufacturing systems still suffer from low fabrication accuracy and speed. This issue is particularly severe for thermal reaction bonding material extrusion systems, where the motion and the deposition processes are coupled. To enhance the deposition accuracy, this work established a method to use real-time in-situ thermal images to capture and compensate for the geometrical accuracy of the printed parts and establish the spatial and temporal relationship between the inaccuracy and the deposition trajectory commands. The paper derives an analytical slender condition to process the printing regions with low curvature while establishing deposition direction allocation methods to account for the trajectory regions with high curvature. Real-time thermal image localization is performed with key printing feature detection and calibration. The localized and calibrated thermal images are aligned with the defined deposition direction to acquire the deposition inaccuracies. With the deposition dynamics considered, the deposition inaccuracy is reduced via dynamic deposition rate compensation. The proposed thermal imaging and compensation techniques have been experimentally verified with a material extrusion experimental platform to illustrate its capabilities to alleviate the deposition inaccuracy during the corner regions.

1. Introduction

Additive manufacturing (AM) is increasingly adopted in aerospace, automotive, and medical applications [1] due to its flexibility and convenience in rapid prototyping [2] and the manufacturability of complex internal structures [3]. Despite its high-speed growth, modern AM still suffers from low precision, low product and process stability, lack of feedback, and insufficient data utilization [4,5]. Among the seven categories of AM [1], material extrusion (MEX) is a representative class widely used [6]. The MEX process is characterized by the strong coupling of the mechanical motion system and the deposition process [7]. The motion coupling leads to MEX having poor accuracy compared to other approaches [6,7] and poses challenges to the AM control systems. For improved printing accuracy, enhanced levels of monitoring and advanced control methods are needed.

Among various monitoring methods (e.g., acoustic, vibration, etc.), thermal monitoring plays a vital role in the AM processes, particularly in the thermal reaction bonding MEX process due to their distinctive heating and cooling cycles. In the MEX process, the filament is heated to

the liquid state, deposited from the nozzle, and then solidified in the environment [8]. The temperature distribution of deposited material in the MEX process contains real-time printing performance and deposition conditions, which significantly contribute to the possible printing defects (e.g., porosity, swelling) and printing geometrical accuracy. Besides, the thermal monitoring system has additional benefits due to its non-contact nature and rich spatial/temporal information. To exploit the information, various printing quality monitoring approaches for AM processes have been proposed. Tlegenov et al. [9] established a dynamic model for minimizing nozzle clogging by monitoring nozzle temperature. Zhang et al. [10] used the in-situ monitored surface temperature of the printing part to forecast the geometry in vat photopolymerization. Khanzadeh et al. [11,12] applied thermal monitoring to the melting pool for the prediction of internal structure anomalies (e.g., porosity and mini-cracks). Farshidianfar et al. [13] related real-time cooling rate and melt pool temperature with the microstructure change of the printed part. Thermal images of the printed layer were also used to analyze the thermal phase-changing process in bioprinting [14]. Caltanissetta et al. [15] presented an approach to detect temperature inhomogeneities in

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the printing part via thermal video imaging. Mazzarisi et al. [16] analyzed the relationship between the thermal gradient with the produced part's metallographic and microhardness. In addition, artificial intelligence (AI) algorithms are also widely used in thermal image processing. Li et al. [17] introduced a deep convolutional neural network model for feature extraction of thermal images. Li et al. [18] proposed a surface roughness prediction model with machine learning according to extruder temperature and some other printing parameters. Tian et al. [19] combined real-time captured thermal images with deep learning for in-situ porosity detection. However, the existing efforts have rarely tried to extract the deposited trajectory time-domain information from the thermal images, particularly in the MEX process, where a relatively long time-varying temperature history is readily available.

With the information from the monitoring system, the dynamic control of the deposition process and motion are key to the printing process [20]. The thermal image's benefit of its rich dynamic, spatial, and temporal information makes it a desirable candidate for control system feedback [21]. Wang et al. [22,23] utilized thermal imaging to build a regression model for surface temperature prediction and real-time layer printing time control. Li et al. [24] applied thermal monitoring to deposited filament for printing speed and temperature control. Salehi and Brandt [25] used a proportional, integral, and derivative (PID) controller to adjust the printer's laser power according to the temperature of the melting pool. Farshidianfar et al. [26] provided a closed-loop controller to manipulate the microstructure based on in-situ thermal images in the powder bed fusion process. However, most existing control methods exploiting the thermal images only adjust the printing parameters; they lack the capability to control the dynamic features during the deposition. These dynamic features are typically from the high-frequency portions of the motion and deposition (e.g., corners, vibration), whose deposition inaccuracy is commonly seen in MEX with motion/deposition coupling.

To close these gaps of dynamic feature monitoring and control in AM processes, this paper builds a real-time thermal monitoring and feedback control system to optimize the deposition trajectory, particularly for the deposition inaccuracy in the corner region. In particular, the proposed methodology provides the following main contributions:

- An analytical model of the dynamic relationship between deposition/motion trajectory and the printed path geometry of straight-line and corners is established;
- An in-situ thermal images automatic alignment strategy and its connection to the deposition trajectory time-domain signals are established;
- A method to generate deposition compensation trajectory accounting for both deposition inaccuracy and deposition dynamics is established.

The remainder of the paper is structured as follows: Section 2 proposes a model of the printed width calculation of straight-line and corners in MEX and discusses the method for actual deposition width extraction from thermal images. The error between the ideal and actual width is calculated and utilized as the feedback signal for generating the corresponding compensation trajectory. Section 3 shows the experiment details on hardware and software, so with the experiment processing. The comparison of 2D and 3D printed parts with a series of corners before and after compensation is illustrated, and the improvement of deposition inaccuracy is evaluated, followed by the conclusions in Section 4.

2. In-situ monitoring and deposition inaccuracy compensation method

2.1. Printed path geometry modeling and critical slender deposition condition

Considering the MEX process with a moving print head, assume the print head is moving along a given trajectory $x(t)$, $y(t)$ in a single layer with a deposition material flow rate $E(t)$. The printed layer height is assumed to be determined by the layer-to-layer distance, defined as h . The print head velocity $v(t)$ and the unit vector $e(t)$ representing the time-varying printing direction are defined as

$$v(t) = [x(t), y(t)]^T, \quad e(t) = \frac{v(t)}{|v(t)|}. \quad (1)$$

The printing direction $e(t)$ is constant when the trajectory is traveling straight, and is time-varying for curved printing paths. With these variables, the exact boundary (including the left and right boundary $x_l(t)$, $y_l(t)$ and $x_r(t)$, $y_r(t)$) of the printed path for an arbitrary curve can be established based on the simple law of mass conservation. To enable the later dynamic manipulation of the deposition process, a general time-varying flow rate $E(t)$ is assumed.

For the deposition along a straight line, the total deposited material Q from time t_0 to t_1 is given by

$$Q = \int_{t_0}^{t_1} E(t) dt = 2h \int_{t_0}^{t_1} |v(t)| w(t) dt, \quad (2)$$

where w is the half-width of the printed path. It is also assumed that steady-state initial and ending flow rates are E_0 and E_1 , respectively. Since Eq. (2) needs to be satisfied for all t , the printed path half-width w , without considering deposition delay and printed height variation, is thus derived as

$$w(t) = \frac{E(t)}{2h|v(t)|}. \quad (3)$$

Note that the printed path half-width is constant when the flow rate and the printing velocity are constant for the deposition along the straight line.

For more complex cases when the printed materials are deposited along a curved path, similar constitutive law can be derived from the curvature $\kappa(t)$ given by

$$\kappa = \frac{x'y'' - x''y'}{(x'^2 + y'^2)^{3/2}}, \quad (4)$$

where x' , x'' , y' and y'' are the first- and second-order curve derivatives of the x and y axis, respectively. Note that the curvature κ is positive for counterclockwise rotation in movement direction and is negative for clockwise movement.

Consider the deposition process at a particular time instant as shown in Fig. 1, S_l and S_r as the material deposition area on the left and right of the curve. Assuming the deposition process yields a slender curve (i.e., the major deposited material is perpendicular to the path center line), the incremental deposited area on the left and the right of the curve center line along a small curve length ds is calculated as

$$S_l(t) = w_l ds - \frac{1}{2} w_l^2 d\alpha = w_l \left(1 - \frac{w_l}{2} \kappa\right) ds, \quad (5)$$

$$S_r(t) = w_r ds + \frac{1}{2} w_r^2 d\alpha = w_r \left(1 + \frac{w_r}{2} \kappa\right) ds. \quad (6)$$

where $d\alpha$ is the incremental change of the printing direction (positive value indicates counterclockwise rotation, same as the sign of curvature κ). It is assumed that, along the printing direction $e(t)$, the material deposited on one side of the trajectory remains on that side, i.e.,

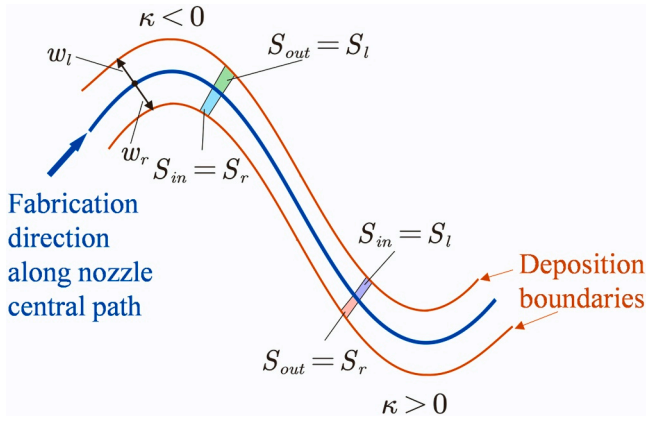


Fig. 1. Width calculation illustration for slender deposition path.

$$S_l = S_r = \frac{E}{2|v|h} ds. \quad (7)$$

Combining Eqs. (5) to (7), the left and right printed half width satisfies the following equations

$$\frac{\kappa}{2} w_l^2 - w_l + \frac{E}{2|v|h} = 0, \quad (8)$$

$$\frac{\kappa}{2} w_r^2 + w_r - \frac{E}{2|v|h} = 0. \quad (9)$$

The solutions to these two equations are

$$w_l(t) = \frac{1 - \sqrt{1 - \frac{\kappa E}{|v|h}}}{\kappa}, \quad (10)$$

$$w_r(t) = \frac{-1 + \sqrt{1 + \frac{\kappa E}{|v|h}}}{\kappa}. \quad (11)$$

Note that Eqs. (8) and (9) only have real solutions when

$$S_c(t) \triangleq \left| \frac{\kappa(t)E(t)}{|v(t)|h} \right| \leq 1. \quad (12)$$

This condition is defined as slender deposition condition. The slender deposition condition indicates that the deposition process is mainly along the perpendicular direction of the center line, such that the deposited line is a slender curve. However, this slender deposition condition may not always hold, particularly at corner regions where the curvatures are high. Around these regions, the slender deposition condition is typically violated. This indicates that the printing deposition direction can no longer be interpreted as perpendicular to the printing direction, and additional mathematical treatments are needed to correlate the deposition's spatial and temporal information.

2.2. Deposition direction allocation for high-curvature regions

To alleviate the issues of the high-curvature portions of the trajectory violating the slender deposition condition, a deposition direction allocation method (DDA) method is established to modify the assumed deposition direction, avoiding the possible intersection of the printed path boundaries. At normal regions of the trajectory where the curvature is small (satisfying slender deposition condition in Eq. (12)), the deposition direction is perpendicular to the printing direction. When curvature is large, an additional rotation angle $\phi(t)$ is introduced. The equivalent added curvature $\kappa_\phi(t)$ is defined as

$$\kappa_\phi(t) = \frac{d\phi}{ds} = \frac{d\phi}{dt} \frac{1}{v(t)}. \quad (13)$$

This rotation angle grants additional freedom to minimize the curvature for the slender deposition condition. Define the effective curvature as

$$\kappa_{eff}(t) = \kappa(t) + \kappa_\phi(t). \quad (14)$$

The slender deposition condition in Eq. (12) is modified to

$$S_c(t) \triangleq \left| \frac{\kappa_{eff}(t)E(t)}{|v(t)|h} \right| \leq 1. \quad (15)$$

On the other hand, the design of κ_ϕ in DDA is not completely free. It is expected to minimally change the normal regions that abide by the slender deposition condition. Define s_0 and s_1 are the representative curve length sufficiently far from the regions that need added curvature, while t_0 and t_1 are their corresponding time. The deposition direction orientation with and without DDA should be the same, i.e., the following spatial and temporal relationships should be satisfied:

$$\begin{aligned} \int_{s_0}^{s_1} \kappa(s) ds &= \int_{s_0}^{s_1} (\kappa(s) + \kappa_\phi(s)) ds, \\ \int_{t_0}^{t_1} \kappa(t) v(t) dt &= \int_{t_0}^{t_1} (\kappa(t) + \kappa_\phi(t)) v(t) dt. \end{aligned} \quad (16)$$

This condition can be achieved by the allocation of the high κ regions to its neighborhoods, as long as the high curvature regions are only consisting of a small portion within the entire trajectory. This is the fundamental concepts introduced by DDA.

The detailed iterative DDA implementation process is shown in Fig. 2. Zero additional curvature (i.e., $\kappa_\phi = 0$) is firstly assumed, while $S_c(t)$ along the entire trajectory is evaluated. The timespan where $S_c(t)$ continuously exhibiting larger than one absolute value is extracted. Define the first continuous timespan that violates Eq. (15) to be t_v , which start from $t_{v,0}$ and ends at $t_{v,1}$. The corresponding $\kappa_\phi(t)$ values when $t \in t_v$ are designed to enforce effective curvature $\kappa_{eff}(t)$ to satisfy Eq. (15). i.e.,

$$\kappa_\phi(t) = \begin{cases} \frac{|v(t)|h}{E(t)} - \kappa(t) & (\text{when } \kappa_{eff} > 0) \\ -\frac{|v(t)|h}{E(t)} - \kappa(t) & (\text{when } \kappa_{eff} < 0) \end{cases}. \quad (17)$$

The rotation angle error due to the introduction of $\kappa_\phi(t)$ is defined as $\Delta\Phi$ given by

$$\Delta\Phi = \int_{t \in t_v} \kappa_\phi(t) v(t) dt. \quad (18)$$

This additional rotation angle is designed to be redistributed to the neighborhood of t_v . To maintain the symmetry of the path, the value $\Delta\Phi$ is equally split to the past and future timespan, satisfying

$$\Delta\Phi_f = \Delta\Phi_p = \frac{1}{2} \Delta\Phi, \quad (19)$$

where $\Delta\Phi_f$ and $\Delta\Phi_p$ are the rotation angle introduced in the future and past timespan.

The allocations of $\Delta\Phi_f$ and $\Delta\Phi_p$ are performed in a discrete system with sampling time T_s , representations with defined future and past timespan to be $t_f = \{t_{f,1}, t_{f,2}, \dots, t_{f,N_f}\}$, and $t_p = \{t_{p,N_p}, t_{p,N_p-1}, \dots, t_{p,1}\}$, respectively. The element in t_f and t_p is defined as

$$\begin{aligned} t_{f,j} &= t_{v,1} + jT_s, \\ t_{p,j} &= t_{v,0} - jT_s. \end{aligned} \quad (20)$$

Define $\phi_f(t_{f,j})$ as the remaining rotation angle left for reallocation from $t_{f,j}$. From $t_{f,1}$ to t_{f,N_f} , this sequence of $\phi_f(t_{f,j})$ is strictly monotonically

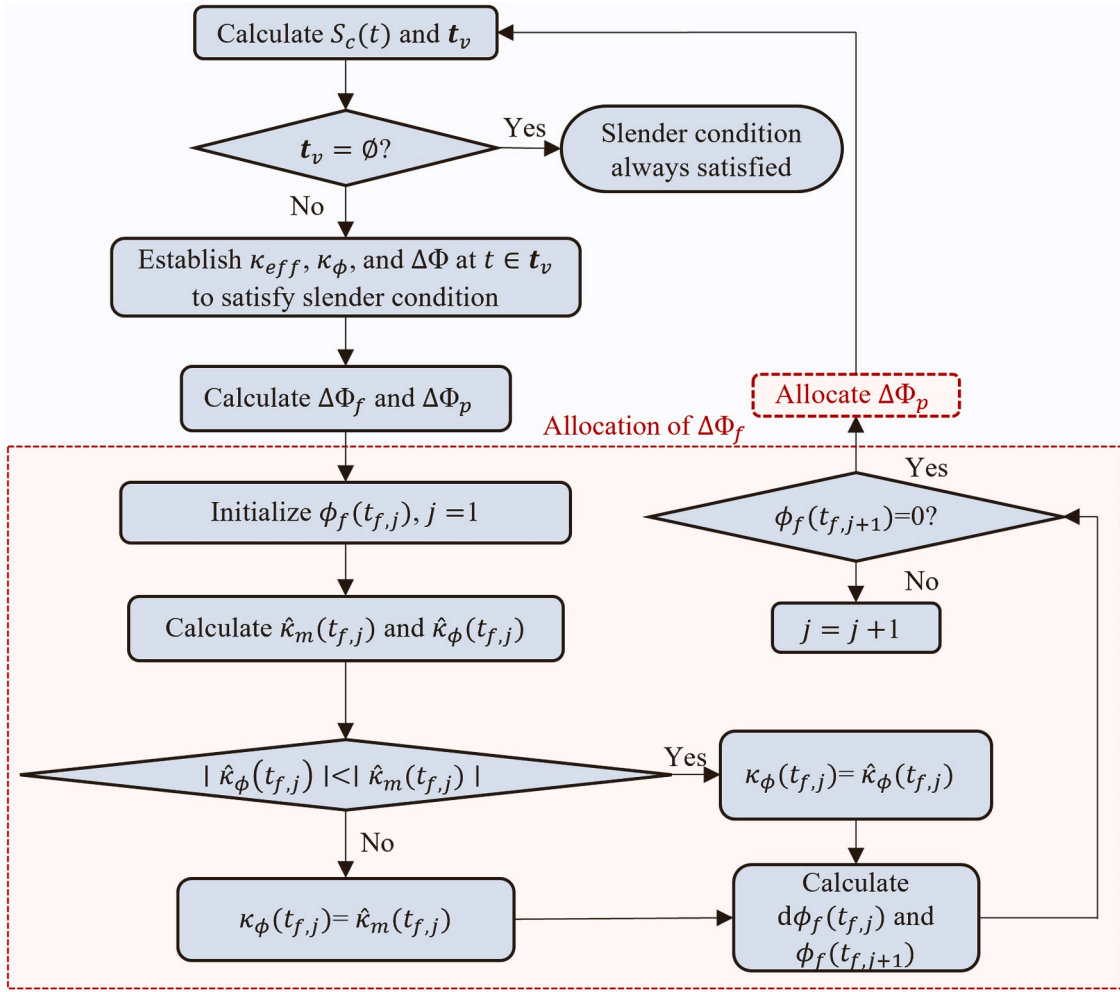


Fig. 2. Flow chart for deposition direction allocation avoiding slender condition violation.

increasing or decreasing to reach zero at t_{f,N_f} ; the direction depends on the sign of the initial condition $\phi_f(t_{f,1})$. This procedure is enforced by the relationship

$$\phi_f(t_{f,j+1}) = \phi_f(t_{f,j}) - d\phi_f(t_{f,j}), \quad (21)$$

where $\phi_f(t_{f,j})$ is the additional rotation angle caused by curvature reallocation at $t_{f,j}$ and is kept to be positive or negative for the entire t_f . Following the relationship between curvature and rotation angle in Eq. (13), $d\phi_f(t_{f,j})$ is calculated as

$$d\phi_f(t_{f,j}) = (\kappa(t_{f,j}) + \kappa_\phi(t_{f,j}))v(t_{f,j})T_s, \quad (22)$$

where $\kappa_\phi(t_{f,j})$ is the additional curvature caused by rotation angle reallocation at $t_{f,j}$. To determine the additional curvature $\kappa_\phi(t_{f,j})$, the method first calculates the maximum allowance of additional curvature $\hat{\kappa}_m(t_{f,j})$ at $t_{f,j}$ satisfying the slender condition, given by

$$\hat{\kappa}_m(t_{f,j}) = \begin{cases} \frac{|v(t_{f,j})|}{E(t_{f,j})}h - \kappa(t_{f,j}) & (\text{when } S_c(t_{f,j}) > 0) \\ -\frac{|v(t_{f,j})|}{E(t_{f,j})}h - \kappa(t_{f,j}) & (\text{when } S_c(t_{f,j}) < 0) \end{cases}. \quad (23)$$

The corresponding curvature $\hat{\kappa}_\phi(t_{f,j})$ candidate at $t_{f,j}$ is given by

$$\hat{\kappa}_\phi(t_{f,j}) = \frac{\phi_f(t_{f,j})}{T_s} \frac{1}{v(t_{f,j})}. \quad (24)$$

The candidate is then verified if it satisfies the maximum allowance defined in Eq. (23) (i.e., $|\hat{\kappa}_\phi(t_{f,j})| < |\hat{\kappa}_m(t_{f,j})|$). This verification further defines the actual $t_{f,j}$ applied in the curvature reallocation procedure with the following formula

$$\kappa_\phi(t_{f,j}) = \begin{cases} \hat{\kappa}_m(t_{f,j}) & (\text{when } |\hat{\kappa}_\phi(t_{f,j})| > |\hat{\kappa}_m(t_{f,j})|) \\ \hat{\kappa}_\phi(t_{f,j}) & (\text{when } |\hat{\kappa}_\phi(t_{f,j})| \leq |\hat{\kappa}_m(t_{f,j})|) \end{cases}. \quad (25)$$

With $t_{f,j}$ calculated, the corresponding effective rotation angle at $t_{f,j}$ is calculated as

$$\phi_{eff}(t_{f,j}) = \kappa_{eff}(t_{f,j})v(t_{f,j})T_s. \quad (26)$$

Now the additional rotation angle $d\phi_f(t_{f,j})$ allocated at $t_{f,j}$ and the residual additional rotation angle awaiting reallocation $\phi_f(t_{f,j+1})$ at the next time $t_{f,j+1}$ are calculated, following Eqs. (21) and (22). The operation is repeated until $\phi_f(t_{f,j+1}) = 0$ indicating that the reallocation of $\Delta\Phi_f$ in t_f is finished. This also defines the discrete steps needed for the reallocation process N_f .

The same reallocation method is operated for $\Delta\Phi_p$ in t_p with a similar process in the backward direction. When finishing reallocation in both t_f and t_p , the slender condition violation at t_v has been fully addressed. Note that this reallocation process only addresses one continuous

timespan that violates the slender condition; there typically still exists multiple similar continuous timespans, which can be recursively addressed by redefining t_v to the next violation. This recursive handling is repeated until $t_v = \emptyset$, indicating the curvature smoothing process is finished. This complete DDA process establishes the local deposition direction for arbitrary continuous trajectory. The results with and without the DDA process are illustrated in Fig. 3. It can be seen that the estimated boundary expands at the cornering regions with large κ and low velocities. Also, the primary deposition directions (marked in red) are continuously distributed in the neighborhood of the cornering regions without intersection due to the introduction of κ_{eff} .

2.3. Thermal image processing, stitching, and localization

With deposition direction defined, the thermal image could align the captured deposited path to its temporal deposition information. This process requires the thermal image calibration, stitching, and localization. Note that the thermal images typically have blurry boundaries (compared to conventional optical images) due to the heat flux. This causes additional challenges for its calibration. The thermal image distortion, similar to conventional optical images, is decomposed to radial distortion and distortion due to tilted camera alignment. The radial distortion is the camera's intrinsic parameter; it is conventionally addressed by applying Zhang's method [27], where the radial coefficients are identified with chessboard calibration images. The distortion due to tilted camera alignment is typically inevitable in AM monitoring process since the camera can only monitor the heat-affected regions from the side. This distortion can be addressed by homography transformation. Define a 2D generalized vector in the image coordinate frame and the ground coordinate frame to be $P^{(0)} = \{a^{(0)}, b^{(0)}, 1\}^T$ and $P^{(1)} = \{a^{(1)}, b^{(1)}, 1\}^T$ and a homography matrix H satisfying

$$P^{(1)} = HP^{(0)} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} P^{(0)}. \quad (27)$$

Since the homography matrix H has 8 degrees of freedom [28], at least four pairs of corresponding points are required to get its solution. As the MEX method contains plenty of dynamic features, the corner points'

position in thermal images and their corresponding corners in geometric printing trajectory are selected as the pairs for H matrix calculation. Note that as the thermal camera, which is attached to the nozzle is moving during the whole printing process, the H matrix is a function of time. For each thermal image, the H matrix might need to be recalculated, which is caused by the change of image capture conditions like the tilt angle of the thermal camera.

The conventional corner detection techniques, such as Harris, rely on significant gradient fluctuations in the image [29], which are unsuitable for thermal images with blurring edges due to heat flux. As the accumulation of heat at printing corners (usually caused by over-deposition in corners), feature extraction provides another way for corner point detection in thermal images. The feature extraction in thermal images in this work adopts the fast region-based convolutional neural networks (Fast R-CNN) model presented by Ren et al. [30] (with ResNet-50 as the backbone) while combining the Feature Pyramid Network (FPN) presented by Lin et al. [31] to enhance the feature detection robustness. The resultant detected feature boxes provide the thermal image corner estimations. Considering that the feature close to the edge of the image may be incomplete, those points whose distance to the image edge is less than 5% of the image size are removed. These detected corners are used to calibrate the thermal images as well as localize the thermal images with printed trajectory. The detected corners in the thermal image formulate the set of $P^{(0)}$ while the set of known physical points formulates the set of $P^{(1)}$, as Eq. (27) indicates. The homography transformation matrix H is thus calculated with least square algorithms. Solving H matrix requires at least four corners in an image to provide

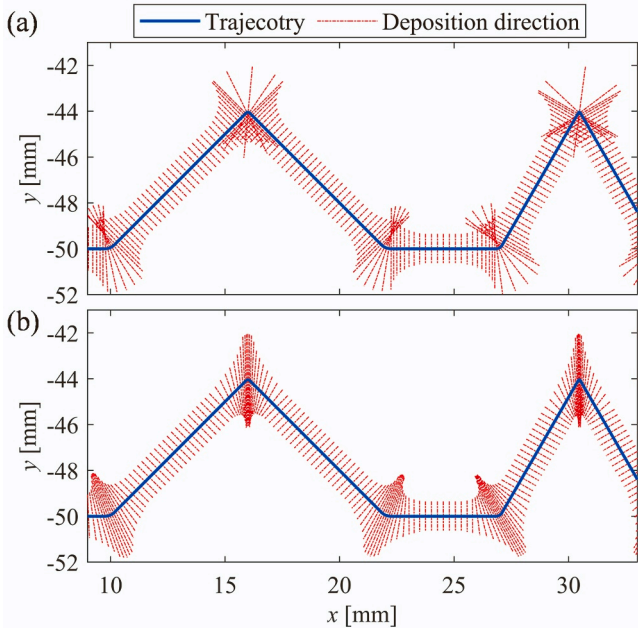


Fig. 3. The principal deposition directions (a) without and (b) with deposition direction allocation.

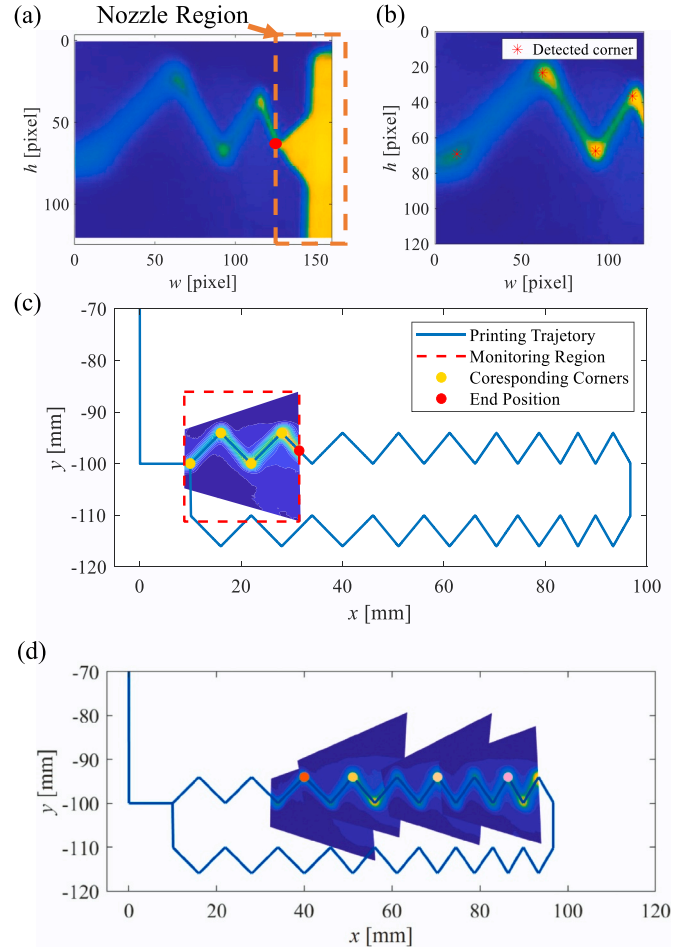


Fig. 4. Alignment of valid thermal image: (a) undistorted thermal image, (b) rich-information thermal image with the detected corner, (c) aligned result of the first thermal image, and (d) alignment of in-situ thermal images.

enough information. Fig. 4(b) shows the corner detection result of the first aligned thermal image after cropping to the rich information area, and Fig. 4(c) shows the localization result of the first aligned image.

Although the thermal camera is commanded to acquire the thermal image at a fixed rate, the actual image capture time instant has slight fluctuations and thus needs localization. The key to localization is the knowledge of the thermal image capture time instant. Define the i^{th} thermal image's true capture time, recorded time, and unknown time fluctuations to be $t_c(i)$, $t_r(i)$, $t_f(i)$, satisfying

$$t_c(i) = t_r(i) + t_f(i). \quad (28)$$

The fluctuations $t_f(0)$ is relatively small and thus $t_r(0)$ is typically used to estimate $t_c(0)$. Since the geometrical relationship between the thermal camera and printing nozzle is unchanged during the monitoring process, the nozzle position in the image frame is manually marked in the first aligned thermal image and defined as $P_N^{(0)} = \{a_N^{(0)}, b_N^{(0)}, a\}^T$. The nozzle position and the monitoring region of the i^{th} thermal image of the ground frame are defined as $P_{N,i}^{(1)} = \{a_{N,i}^{(1)}, b_{N,i}^{(1)}, 1\}^T$ and $R_i^{(1)}$, respectively. The recorded time $t_r(i)$ gives the approximated nozzle position $\hat{P}_{N,i}^{(1)}$ and expected monitoring region $R_i^{(1)}$ of the i^{th} thermal image. The corners in the i^{th} thermal image and in the trajectory within $R_i^{(1)}$ is detected, and they give the homography matrix $H(i)$ following Eq. (27). The actual nozzle position $P_{N,i}^{(1)}$ in the ground coordinate frame for the i^{th} thermal image is thus given by

$$P_{N,i}^{(1)} = H(i)P_N^{(0)}. \quad (29)$$

The calculated nozzle coordinate $P_{N,i}^{(1)}$, combined with the trajectory $x(t)$ and $y(t)$ in Eq. (1), is used to provide the estimation of the capture time instant, given by

$$\hat{t}_c(i) = \underset{t \in U(t_r(i), \delta t)}{\operatorname{argmin}} \left\{ \left\| \begin{pmatrix} x(t) \\ y(t) \end{pmatrix} - \begin{pmatrix} a_{N,i}^{(1)} \\ b_{N,i}^{(1)} \end{pmatrix} \right\|_2^2 \right\}. \quad (30)$$

where $U(t_r(i), \delta t)$ is the neighborhood of $t_r(i)$ with a small timespan δt . For typical thermal images, δt should be within 10 ms. Now capture time instant $t_c(i)$ of the i^{th} thermal image is accurately known, indicating that the localization of the thermal image is precisely aligned with the ground frame. Compared with the two-step calibration and localization method that calculates the calibration matrix and then does the alignment [32], the proposed method calibrates and localizes the thermal image with the trajectory simultaneously, which increases the computation efficiency and automation. The proposed method also eliminates the error of thermal image calibration caused by the image capture condition changing during printing (e.g., vibration, tilt angle change) as the H matrix is recalculated under a specific image capture condition. The resultant in-situ thermal images are shown in Fig. 4(d).

2.4. Deposition information extraction and dynamic deposition compensation method

With the DDA process and thermal image processing, the thermal-image-enabled dynamic deposition trajectory compensation (T-DDTC) method is established in this section. The deposition information at each sampling time at the trajectory $x(t)$, $y(t)$ is extracted along the critical deposition direction derived in Section 2.2 for each localized thermal image, as shown in Fig. 5(a). The contour with the threshold temperature T_c is applied to extract the left and right deposition half-width $w_l(T_c, t)$ and $w_r(T_c, t)$. Define the desirable printed path half-width to be $w_d(t)$ given by

$$w_d(t) = \frac{w_0}{\cos(\phi_{\text{eff}}(t))}, \quad (31)$$

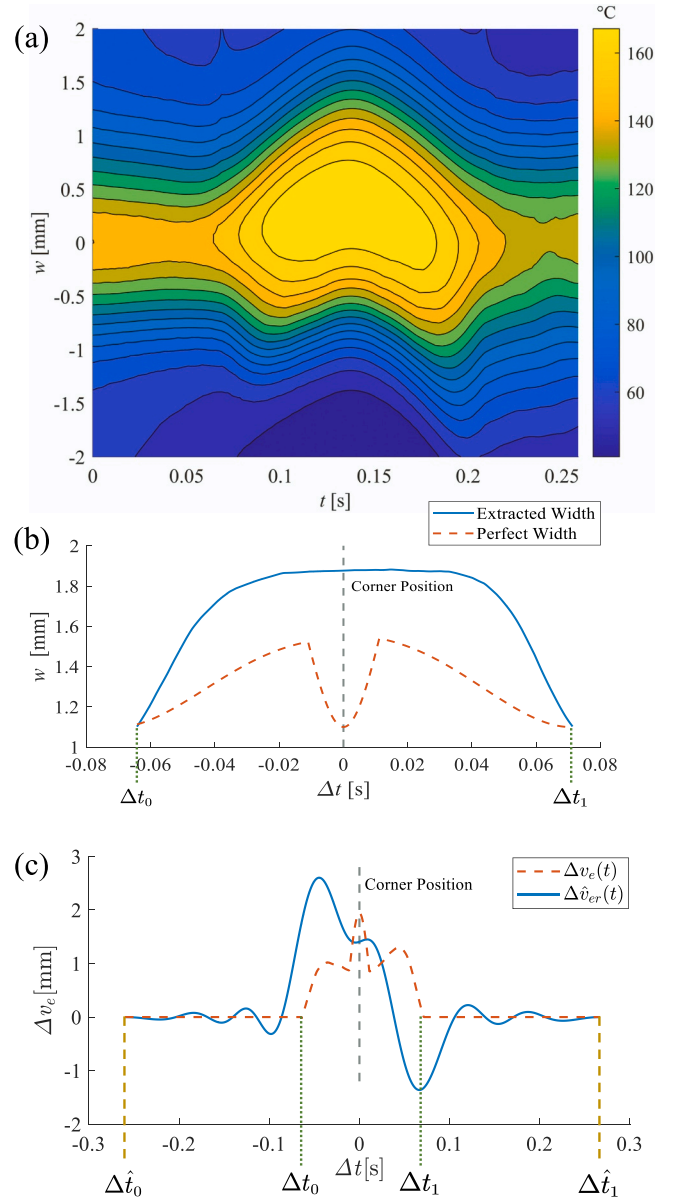


Fig. 5. Compensation trajectory generation process: (a) temperature distribution converted to the deposition direction and time, (b) extracted printed width and desirable printed width in a continuous timespan, and (c) deposition compensation sequence.

where $\phi_{\text{eff}}(t)$ is the effective rotation angle defined in Eq. (26) and w_0 is the theoretical width of a straight printed path. Correspondingly, the error of deposition width Δw is defined as

$$\Delta w = w_l(T_c, t) + w_r(T_c, t) - 2w_d(t). \quad (32)$$

Define ϵ as the maximum tolerable deposition inaccuracy; deposited regions satisfying $|\Delta w| \geq \epsilon$ indicates significant deposition inaccuracies that require compensation. Define Δt_0 and Δt_1 as starting and ending time of a continuous deposition inaccuracy timespan t_o , respectively. The extracted and perfect width in a continuous deposition inaccuracy timespan collected from Fig. 5(a) is shown in Fig. 5(b). According to the deposition inaccuracy Δw , the local deposition compensation rate is estimated to be

$$\Delta E(t) = K_e(w_l + w_r - 2w_d), \quad (33)$$

where K_e is a deposition correction gain.

To achieve desirable compensation results, the dynamic of the deposition process needs to be considered. This arises from the fact that there is typically a delay between the deposition signal and the actual deposition process. Define the deposition compensation reference command to be $\Delta E_r(t)$ and the actual deposition variation is $\Delta E_r(t)$. This input-output is researched by Bellini et al. [33] and Wu et al. [34], and their works adopt a first-order linear time-invariant (LTI) system representation $G(s)$ for its relationship, given by

$$\Delta E(s) = \frac{1}{\tau s + 1} \Delta E_r(s), \quad (34)$$

$G(s)$

where s is the Laplace variable; τ is the time constant; $\Delta E_r(s)$ and $\Delta E(s)$ are the Laplace transform of $\Delta E_r(t)$ and $\Delta E(t)$. Its time-domain representation is written as

$$\Delta E_r(t) = \Delta E(t) + \tau \frac{d\Delta E}{dt}. \quad (35)$$

Considering the dynamic of deposition, the compensation timespan is extended to $\hat{t}_o$, with starting and ending time at $\Delta \hat{t}_0$ and $\Delta \hat{t}_1$. The corresponding input deposition compensation velocity trajectory $v_{er}(\Delta t)$ is smoothened with an m order non-uniform rational basis spline (NURBS) as

$$\Delta \hat{v}_{er}(\Delta t) = \sum_{i=0}^n N_i(\Delta t) P_i, \quad (36)$$

where $\Delta t \in [\Delta \hat{t}_0, \Delta \hat{t}_1]$; $N_i(\Delta t)$ is the basis function; $P_i = \{\Delta t_i, \Delta V_i\}^T$ is the control point defining the pairs of compensation velocity at a particular time. To guarantee a smooth transition with the uncompensated regions, the final input deposition velocity $v_{ef}(\Delta t)$ satisfies

$$v_{ef}(\Delta t) = v_e(\Delta t) - \Delta v_{er}(\Delta t), \quad (37)$$

where $v_e(\Delta t)$ is the original input deposition velocity.

According to the filtered B-spline (FBS) approach proposed by Duan et al. [35], the transfer function $G(s)$ in Eq. (34) is applied to $N_i(\Delta t)$ to obtain the filter basis function $\tilde{N}_i(\Delta t)$.

Accordingly, the desired output deposition compensation velocity $\hat{v}_e(\Delta t)$ is calculated as

$$\Delta \hat{v}_e(\Delta t) = \sum_{i=0}^n \tilde{N}_i(\Delta t) P_i. \quad (38)$$

The control points $P_i = \{\Delta t_i, \Delta V_i\}^T$ are obtained by the minimum optimization with

$$\begin{aligned} P_i = \operatorname{argmin} \left\{ \left| \Delta \hat{v}_e(\Delta t) - v_e(\Delta t) \right|_2^2 \right\}, \\ \text{s.t. } \Delta V_{\min} \leq \Delta V_i \leq \Delta V_{\max}, \\ P_0 = (\Delta \hat{t}_0, 0), \\ P_n = (\Delta \hat{t}_1, 0) \end{aligned} \quad (39)$$

The range of ΔV_i is constrained considering origin deposition velocity and deposition dynamics with the minimum and maximum compensation velocity. Fig. 5(c) shows the calculated result of the desired input $\Delta \hat{v}_{er}(\Delta t)$ and perfect output $\Delta v_e(\Delta t)$ of deposition compensation velocity. Note that the generated deposition compensation sequences could be restored as a database and reused in further printing for similar trajectories. The application of the database saves needs of computation resources of the T-DDTC system. However, under different printing

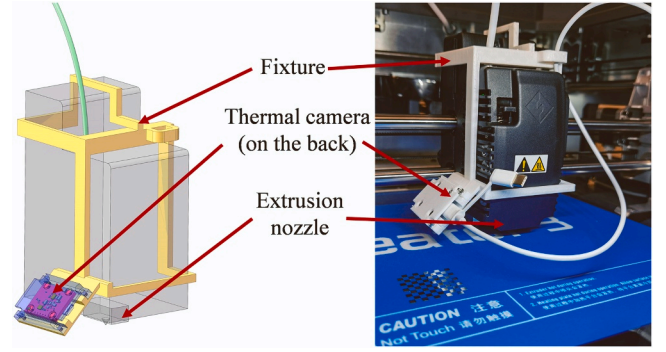


Fig. 6. Experimental MEX deposition nozzle with thermal camera [32].

conditions (like the change of viscosity and fluidity of printing materials, nozzle health conditions, the flatness of the base plate, or the previous layer), the deposition inaccuracy circumstance might deviate from the previously collected one. Therefore, if higher geometry accuracy is needed for the printing part, the real-time thermal monitoring and compensation system should be applied to the whole printing process.

3. Experiment Verification of Proposed Method

3.1. Experimental hardware setup

Fig. 6 shows the setup of the experiment. The Flashforge Creator 3 MEX printer is used for the experiments. The thermal camera (FLIR 3.5) is fixed on a printed lightweight fixture tightly installed on the printing nozzle and moves with the nozzle during printing. The installation of the thermal camera helps in capturing real-time deposition situations. The printing parameters and the camera specifications are specified in Table 1 and Table 2, respectively. Note that the thermal expansion of PLA in the targeted range is minimal: A 200 °C drop in temperature only causes 0.0041% 1D shrinkage. Therefore, the thermal expansion in the thermal image is omitted in this case.

The main testing trajectory includes different angles of corners (as illustrated in Fig. 7(a)) due to MEX process being typically rich in corner features. To further validate the efficiency of enhancing deposition accuracy during the layer-by-layer fabrication, the testing part consisting of 20 layers of the testing trajectory is designed, shown in Fig. 7(b). A baseplate is added to provide a flat and solid base for the main trajectory printing, despite the problem caused by the leveling of the print bed. The 3D printed parts with and without the proposed T-DDTC method are evaluated.

3.2. Thermal image processing and compensation trajectory generation

The first step in thermal image processing is corner detection. The images for corner detection model training are carefully annotated with one class (corner) using the mature and efficient image labeling manner [36]. There are total 69 annotated images with more than 200 features. The image dataset is packaged in the form of PASCAL VOC 2012 [37] and is randomly divided into train and test sets in a 1:1 ratio. The initial learning rate is set to be 0.01. The batch size for training is set to 2, and the epoch size is 15. The mean Average Precision (mAP) value of the model generated from each epoch is calculated according to the evaluation standard. The mAP of the final trained model selected is 99.5%, demonstrating high accuracy and precision. The monitoring system starts to capture and process thermal images after the beginning of main trajectory printing. The thermal images are first marked with the nozzle position and cropped, with the information-rich region remaining. With the pre-trained detection model, real-time captured images are sent for corner feature detection. The time interval of each thermal image is set to 0.125 s. The hardware of thermal image processing is an i5-12500H

Table 1

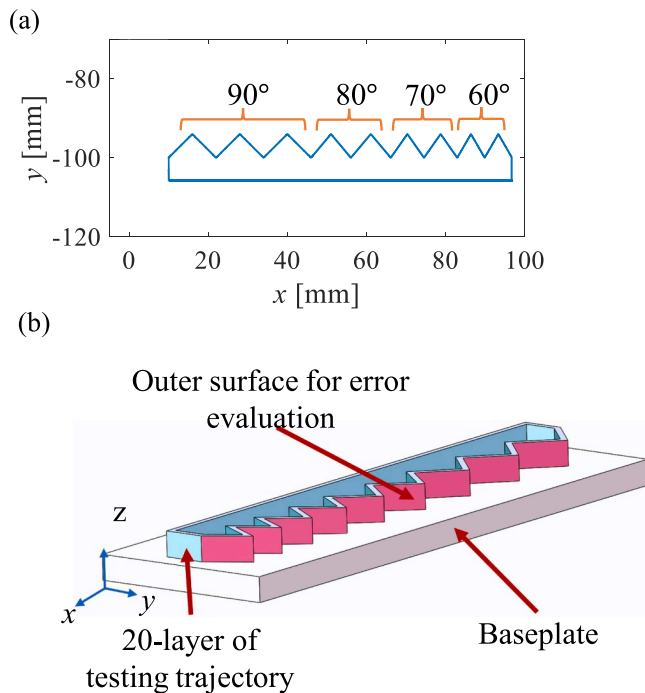
Printing parameters.

Printer name	Flashforge Creator 3
Printer maximum size	300×250×200 mm ³
Nozzle diameter	0.4 mm
Layer height	0.25 mm
Printing speed	20 mm/s
Acceleration	500 mm/s ²
Corner trajectory blending tolerance	0.05 mm
Printing material	PLA
Thermal expansion coefficient	41 μm/(m·K)
Nozzle temperature	230 °C
Print bed temperature	60 °C

Table 2

Thermal camera specifications.

Type	FLIR 3.5
Maximum frame rate	9 Hz
Minimum temperature	−10 °C
Maximum temperature	450 °C
Weight	0.9 g
Resolution	160 × 120
Thermal sensitivity	< 50 mK (0.050 °C)
Tilt angle	45°
Distance to the printing plane	14.5 mm

**Fig. 7.** (a) A 2D trajectory with different corners and (b) the 3D shape of the printed part.

CPU and a single NVIDIA GeForce RTX 2050 GPU.

With detected corners in thermal images, stitching, and localization, the deposited width extraction process in Sections 2.3 and 2.4 is performed. Note that only the thermal images with sufficient newly printed corners, whose temperature T_p satisfy $140^\circ\text{C} \leq T_p \leq 150^\circ\text{C}$, are further processed for monitoring accuracy. According to the monitored real deposited width, the deposition width error Δw is calculated according to Eqs. (31) and (32). The desired path width w_0 for a straight line in Eq. (31) is related to the feed deposit rate ratio α , and the relationship between them acquired by the experiment is expressed as $w_0 = K_{w\alpha}\alpha + b_w$, where the values of $K_{w\alpha}$ and b_w are experimentally identified [32]. The identification process included a series of experiments that printed a

one-layer straight line part in different α and measured the corresponding change of w_0 . The final identified result for $K_{w\alpha}$ and b_w is 3.44 mm and 0.67 mm, respectively. According to the deposition width error Δw , the local deposition inaccuracy rate $\Delta E(t)$ is calculated by Eq. (33). The deposition correction gain K_e is determined by experiment as $K_e = 1 + (150 - T_p)/15$, where T_p is the corner point temperature. For generating input deposition compensation velocity from $\Delta E(t)$, the time constant τ in Eq. (34) of the deposition dynamics for the used printer is identified. The identification process collected the step response of the deposition system of the MEX 3D printer. The identified result for τ is 0.0873 s [32]. The minimum and maximum compensation velocities in Eq. (40) have been set to $\Delta V_{\min} = -2\text{mm/s}$ and $\Delta V_{\max} = 4\text{mm/s}$, respectively. The time extension for the dynamic compensation (i.e., the time interval from Δt_0 to Δt_1 and from Δt_1 to Δt_2) is both set at 0.1 s. The calculated input compensated deposition velocity $v_{ef}(\Delta t)$ is sent to the printer for compensation.

3.3. Printing results and evaluation

To evaluate compensation accuracy, the parts with and without the proposed T-DDTC methods are 3D printed. The one-layer verification experiment is first conducted to illustrate the improvement of deposition accuracy in 2D. Fig. 8 shows the temperature distribution, extracted and desired width, and the deposition compensation sequence for different corners in the printing part. It is observed that the over-deposition problem is consistently shown across various corners, and the generated compensation sequences are similar. The computation time to generate the compensation sequence by T-DDTC for each corner is about 0.5 s, mainly from AI-based thermal image processing and the corresponding optimal compensation signal generation. The one-layer testing parts include 4 types of corners, so the total time consumption for generating the compensation sequence is about 2 s, while the printing takes about 10 s. As the compensation generation and the printing are executed simultaneously and printing time completely covers the compensation generation time, the total printing time is not affected by employing T-DDTC. Fig. 9 illustrates the printing result for different corners without and with compensation from the one-layer verification experiment. As the printed corners are smoothed out due to the deposition dynamics, to enhance the visual effects, Fig. 10 highlights the desired- and over-deposition area for the parts shown in Fig. 9. It is observed the printing result without compensation suffers over-deposition problems in corners while the result with compensation shrinks the over-deposition region significantly. For evaluating improvement in the over-deposition level for different corners, a 2D over-deposition index at the corner region O_E is introduced. The O_E at the corner region is defined as

$$O_E = \frac{A_o}{A_c}, \quad (40)$$

where A_o is the over-deposited area, and A_c is the perfect corner polytope area in a corner. The average over-deposition index for this print has dropped from 106.75% to 31.73%, indicating an enhancement in deposition accuracy.

After one-layer verification, the testing parts with and without compensation were printed, as shown in Fig. 11 (a) and (b). The testing parts share the same trajectory as the one-layer experiment. For the multi-layer testing parts, their external surface geometry accuracy is evaluated as the validation of T-DDTC. A Keyence LJ-V7300 2D laser profiler was applied to obtain the printing parts' external surface profiles with a z-axis sampling spacing of 0.5 mm. The measuring system setup is shown in Fig. 12. The deposition deviation e_t corresponding to each point $(x_t, y_t) \in P_t$, where P_t is a set of points representing the desirable external surface profile in a specific layer, is obtained after measuring. The coordinate (x_t, y_t) of each point in the set P_t is obtained from the CAD file of the printed part. The deposition deviation e_t with its

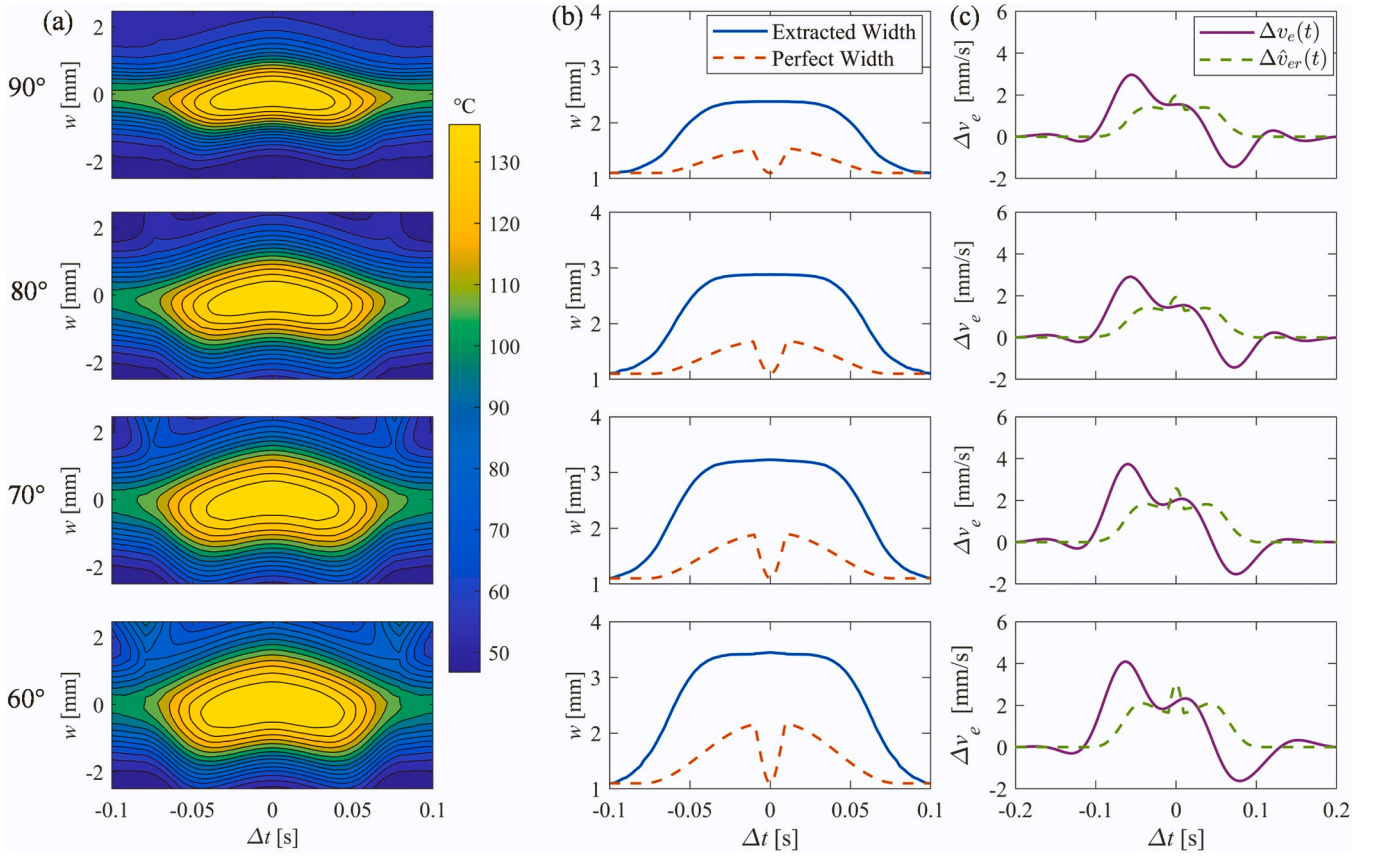


Fig. 8. (a) The temperature distribution, (b) extracted and desired width, and (c) deposition compensation sequence for different corners in the printed part.

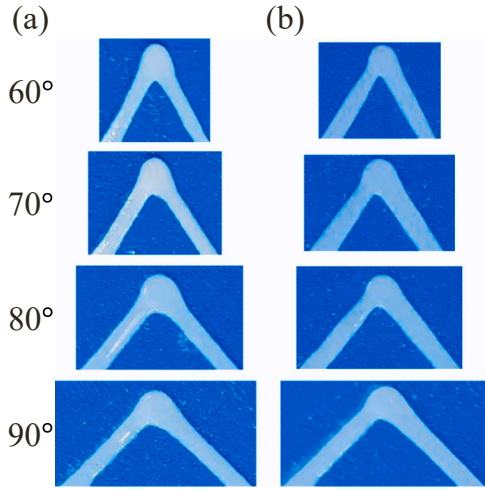


Fig. 9. The images of one-layer corners without (a) and with (b) proposed compensation.

corresponding (x_t, y_t) composite the element $(x_t, y_t, e_t) \in e_t$, where e_t is the error set. To calculate the error set that shows the difference between the desirable profile and the measured one, another point set P_m consisting of the points (x_m, y_m) representing the measuring profile of the same layer is defined. The deposition contour error e_t at a specific (x_t, y_t) is thus calculated as

$$e_t = \min_{(x_m, y_m) \in P_m} |(x_t, y_t) - (x_m, y_m)|_2. \quad (41)$$

The error set e_t for every layer with the sampled measuring profile was

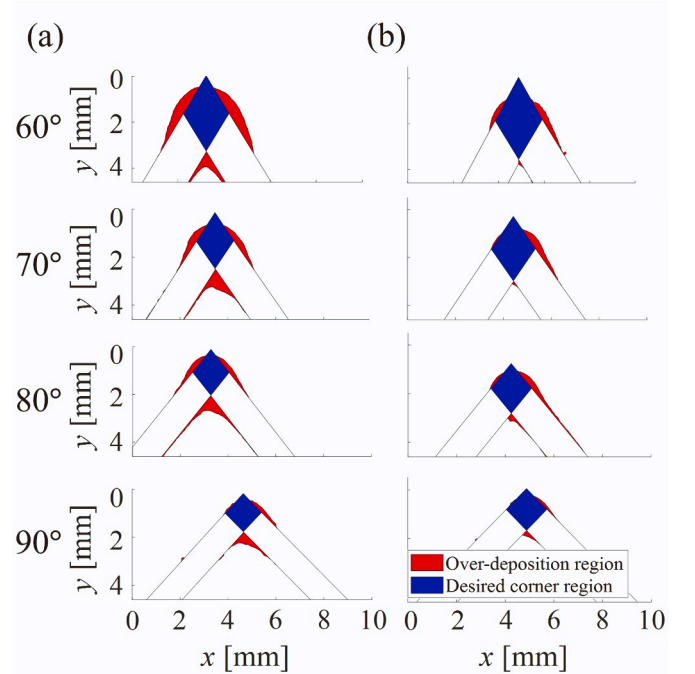


Fig. 10. The highlighted one-layer over- and desired-deposition region for corners without (a) and with (b) proposed compensation shown in Fig. 9.

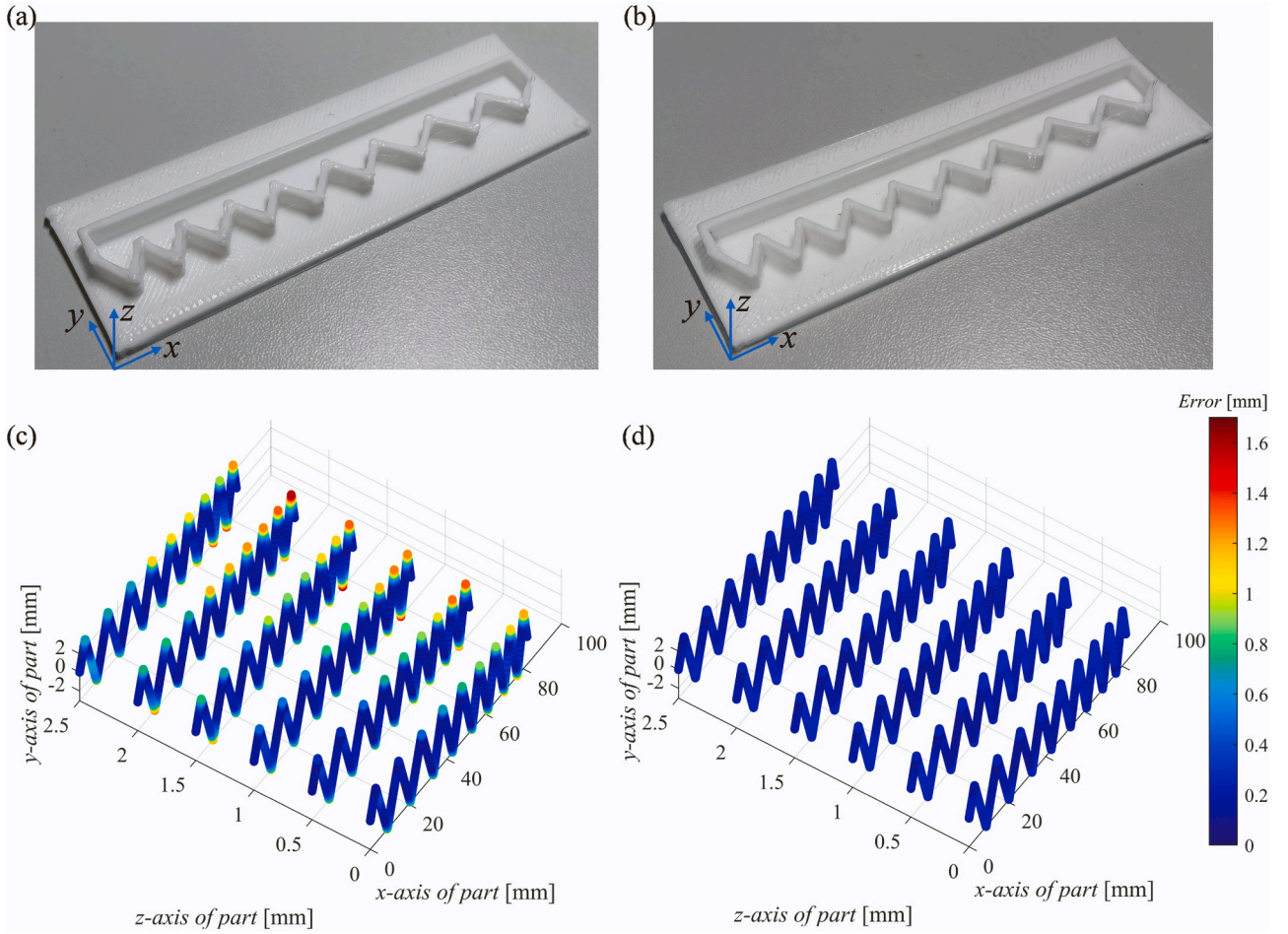


Fig. 11. The printed part (a) without and (b) with T-DDTC, along with its deposition contour error measurement (c) without and (d) with T-DDTC.

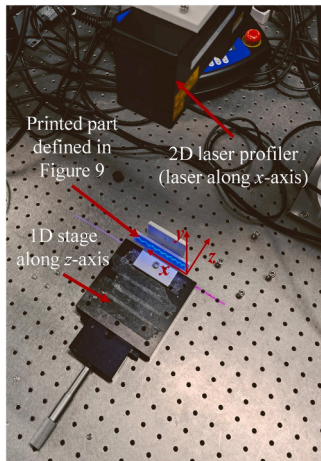


Fig. 12. Surface profile measurement setup with 2D laser profiler.

Table 3

The deposition deviation with and without T-DDTC.

	MAX	RMS
Conventional	1.6805 mm	0.4301 mm
T-DDTC	0.2468 mm	0.2017 mm
Error reduction	85.31%	53.10%

calculated, and the results for all of e_t belonging to the parts with and without compensation (shown in Fig. 11 (a) and (b)) are illustrated in Fig. 11 (c) and (d), respectively. After the monitoring and compensation system intervened, the maximum deviation is reduced from 1.6805 mm to 0.2468 mm, and the mean value is decreased from 0.4301 mm to 0.2017 mm, as shown in Table 3.

4. Conclusions

This paper proposed a thermal-image-enabled dynamic deposition trajectory compensation (T-DDTC) method for material extrusion process. It exploited the in-situ thermal image to extract the deposition trajectory as feedback. An analytical model describing the dynamic relationship between deposition/motion trajectory and the printed path geometry was established. A particular deposition slender condition was established for low-curvature trajectory regions. For the high-curvature trajectory regions, a deposition direction allocation algorithm was established to smoothly define the deposition direction to enable the alignment of the spatial deposition path to the time-domain deposition trajectory. The collected thermal images were sent to the systems to detect the key feature points with fast region-based convolutional neural networks and feature pyramid networks. The feature points help automatically localize the thermal image with the given trajectory. The alignment and the allocated deposition direction synergistically contribute to extracting the deposition inaccuracy at every instant during the process. With the deposition inaccuracy and the identified deposition dynamics, the deposition signal was compensated under a filtered basis framework to alleviate the inaccuracy. The proposed T-DDTC was validated in material extrusion experiments. A representative

part was printed with the conventional trajectory and the trajectory with the T-DDTC method. The deposition accuracy enhancement was verified with image-based deposition inaccuracy extraction and 2D laser profiler measurements.

CRedit authorship contribution statement

Yang Yuexin: Writing – original draft, Visualization, Software, Methodology, Data curation. **Chen Siqi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Duan Molong:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Liu Shuai:** Visualization, Validation, Software.

Declaration of Generative Artificial Intelligence (AI) and AI-Assisted Technologies in the Writing Process

The writing process only uses ChatGPT and Grammarly AI to perform grammar checks.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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