Abstract—Inspired by humans’ ability to perceive the surface texture of unfamiliar objects without relying on vision, the sense of touch can play a crucial role in robots exploring the environment, particularly in scenes where vision is difficult to apply, or occlusion is inevitable. Existing tactile surface reconstruction methods rely on external sensors or have strong prior assumptions, making the operation complex and limiting their application scenarios. This letter presents a framework for low-drift surface reconstruction through multiple tactile measurements, Tac2Structure. Compared with existing algorithms, the proposed method uses only a new vision-based tactile sensor without relying on external devices. Aiming at the difficulty that reconstruction accuracy is easily affected by the pressure at contact, we propose a correction algorithm to adapt it. The proposed method also reduces the accumulative errors that occur easily during global object surface reconstruction. Multi-frame tactile measurements can accurately reconstruct object surfaces by jointly using the point cloud registration algorithm, loop-closure detection algorithm based on deep learning, and pose graph optimization algorithm. Experiments verify that Tac2Structure can achieve millimeter-level accuracy in reconstructing the surface of objects, providing accurate tactile information for the robot to perceive the surrounding environment.

Index Terms—Force and tactile sensing, mapping, surface reconstruction.

I. INTRODUCTION

THE ability of robots to complete manipulation tasks strongly depends on accurate information about the contact object. Visual information is generally sufficient to perceive, track, or recognize objects in most scenes [1]. However, visual methods have many disadvantages, such as low accuracy and occlusion. Commonly used visual depth cameras usually have centimeter-level accuracy for depth measurements. In robot manipulation tasks, occlusion is inevitable when the robot is physically in contact with objects, causing visual methods to fail. To solve this problem, a novel image-based tactile sensor, such as Gelsight [2] or Gel Slim [3], is added to the end of the manipulator to sense the structural properties of the contact object, which can enhance the robot’s knowledge of the scene. This sensor finely senses the texture of the contact surface and outputs high-resolution images, which can be converted into 3D point clouds using a photometric stereo algorithm [4]. Inspired by the human reading Braille, which combines various pieces of information through multiple touches, robots can fuse multi-frame point clouds and reconstruct the surface of objects using the point cloud registration algorithm.

However, most current studies obtained the pose transformation of the sensor through external devices [5], [6] to improve the fusion accuracy, significantly limiting the application scenarios. Owing to the influence of sampling pressure [7], the reconstructed texture obtained by feature matching [8] lacks consistency in depth, which produces uneven fracture surface phenomena, leading to significantly reduced reconstruction accuracy. In addition, during the reconstruction of large-scale object surfaces whose scale is at least ten times the effective sampling area of the sensor, the accumulative error generated by multi-frame fusion is often unacceptable, seriously affecting the accuracy.

To solve these problems, we propose a novel framework called Tac2Structure for simultaneous sensor localization and object reconstruction.
surface reconstruction based on a tactile sensor only. First, we use the point cloud registration algorithm to estimate the pose transformation of the sensor between multi-sampled frames such that the global reconstruction process does not rely on external devices. Second, an adaptive pressure correction algorithm is proposed to enhance the consistency of the depth between frames and reduce the difficulty of the actual sampling operation. Finally, we utilize the loop-closure detection method based on deep learning and the pose graph optimization algorithm to reduce the accumulative error and improve accuracy.

To the best of our knowledge, this work is the first to achieve low-drift reconstruction of object surfaces without relying on external observation equipment. As shown in Fig. 1, the proposed algorithm can provide accurate surface texture information of the contact objects for the robot. It can enhance the cognitive ability of the robot for unknown objects and improve the robustness of the robot in performing tasks in unfamiliar scenes or scenes with visual occlusions. In general, the proposed algorithm makes the following contributions:

- Egomotion estimation: can accurately estimate the sensor’s egomotion without relying on the accurate observations provided by other external sensors.
- Pressure adaptive: can overcome the sensor’s inherent disadvantage of accuracy affected by the sampling pressure.
- Low-drift global reconstruction: can reduce the accumulative error and achieve millimeter-level accuracy.

II. RELATED WORK

Owing to the lack of tactile perception, traditional robots have difficulty accurately performing delicate tasks, such as interacting with humans and grasping or manipulating breakable objects. Furthermore, unacceptable operational errors may occur in complex and unfamiliar scenes or scenes with visual occlusions. To solve these problems, researchers have begun to add tactile sensors to the ends of robots to perceive objects better and improve their operational abilities [9], [10], [11], [12]. Image-based tactile sensors are gradually becoming mainstream tactile sensors owing to their advantages of high resolution and low cost.

Here, we use a tactile sensor similar to Gelsight [2], which uses a soft gel and built-in camera to collect high-resolution tactile signals. The image represents the raw data type of the output of the sensor. Because of the structure of the three LED sources separated inside the sensor, the image can be converted into a 3D point cloud using a photometric stereo algorithm [4].

Recently, several researchers have successfully utilized this sensor to assist robots in task performance. Ma et al. used the inverse FEM algorithm to estimate the force distribution on a contact surface [13]. Chaudhury et al. [14] and Dikhaile et al. [15] jointly used vision and tactile information to estimate the pose between the robot and object. The above research only employs the information of a single frame of tactile data, which implies that the potential of tactile sensors has still not been fully exploited. Our work combines multi-frame sensor data to construct a more accurate object surface texture. The studies by [5], [6] and [8] are related to this study.

Li et al. [8] first proposed the concept of a tactile map regarding the multi-frame tactile map registration problem as an image mosaicing problem. They registered multi-frame local tactile maps using feature-based matching techniques, assuming that tactile maps have the same scale and that there will be no out-of-plane rotation. To construct the global tactile map, they coarsely averaged the depth values of the overlapping areas between the frames. However, when pressed manually to sample, making the forces consistent requires a high sampling operation. Inconsistent forces reduce the accuracy of subsequent global tactile map construction. Because the fusion process only considers the $SE(2)$ pose transformation, it cannot be applied to surfaces with undulations, such as cylindrical surfaces. Because the incremental reconstruction process easily produces accumulated errors, this simple method is unsuitable for large-scale object surface reconstruction. Our method automatically adapts to the pressure without limiting the operation of the sampling process. During global tactile map construction, instead of being constrained to solve the pose transformation in 2D, our method directly solves it in 3D. Our method uses loop-closure detection and pose-graph optimization techniques for large-scale objects to mitigate the accumulative error, significantly reducing the non-negligible accumulated error during the reconstruction process.

In subsequent studies, Li et al. [5] and Bauza et al. [6] extended the tactile map concept to 3D scenes to reconstruct a 3D object’s surface. However, their methods strongly depend on the pose transformation of the tactile sensor provided by external devices, such as sensors on a robot arm with robot kinematics or a motion capture device. External equipment limits the application scenarios of the algorithm and makes the overall reconstruction system more expensive. Our method uses a point cloud
registration algorithm to estimate the tactile sensor egomotion between frames, which requires no additional equipment.

Our work is based on the famous simultaneous localization and mapping (SLAM) framework [16], [17], [18], [19]. Some of these algorithms use LiDAR information [16], and some use visual information [17], [18]. Although tactile images also belong to the visual information category, using only these images to reconstruct surface textures under the pure monocular Visual SLAM framework is challenging. This is because they can only build up-to-scale structures of the sensor pose and environment. Our method estimates the accurate scale of the surface texture from raw tactile image data based on the photometric stereo algorithm [4].

III. METHODS

The proposed low-drift surface reconstruction framework is shown in Fig. 2. By receiving multi-frame inputs from a tactile sensor, our framework can accurately estimate the egomotion of the sensor and reconstruct object surfaces with low drift. Our framework is composed of three key submodels.

- **Local tactile map construction**: In this module, given a tactile image, we output its corresponding local tactile map representing the shape of the local contact area. We use the multi-layer perceptron (MLP) model and 2D Poisson solver. We provide a practical toolbox to improve the efficiency of training dataset annotation. Section IV explains the detailed process.

- **Adaptive pressure correction**: We mitigate the pressure inconsistencies introduced by manual pressing based on statistical methods. The analysis of the depth error caused by the inconsistent pressure and adaptive correction algorithm are explained in Section V.

- **Global tactile map construction**: Given a series of corrected local tactile maps, we use the point cloud registration algorithm, loop-closure detection algorithm based on deep learning, and pose graph optimization technology to reconstruct the global tactile map. Section VI elaborates on the details of this content.

IV. LOCAL TACTILE MAP CONSTRUCTION

Similar to the work of Wang et al. [7], our method uses a multi-layer perceptron and Fast Poisson solver [20] to estimate the local 3D surface texture from the raw tactile image data. Given the focus and length of the letter, we refer readers to their work [7] for details on the network structure and data collection method.

After collecting datasets, the difficulty lies in labeling them, which needs to extract the center’s position and the circular area’s radius, as shown in Fig. 3(a). Most existing studies [7], [10], [21] extracted them using the Hough Circle Transform. However, in practice, the detection parameters must be adjusted repeatedly to adapt to different images, which is labor-intensive.

We implement a toolbox suitable for extracting the required circle parameters to label datasets more efficiently, as shown in Fig. 3(b). Our work is open source, and codes are available at.

![Image](https://github.com/ljy-zju/Tac2Structure.git)

\[1\] [Online]. Available: https://github.com/ljy-zju/Tac2Structure.git

![Fig. 3](Image)

(a) Imprint of pressed ball 
(b) Toolbox interface

Fig. 3. Training data labeling process. Different sliders of the toolbox can control the position and radius of the auxiliary circle of the contact circle between the ball and sensor. The position and radius information of the contact circle are obtained when the auxiliary one fits the actual one.

![Object Tactile images Local tactile maps](Image)

Fig. 4. Local tactile map construction results. From left to right: visual image, tactile images, and local tactile maps of 3D printed ‘ZJU’.

![Fig. 5](Image)

(a) Ground truth reconstruction result 
(b) Reconstruction result 
(c) Reconstruction result

Fig. 5. Analysis of gel structure of sensor surface. (a) is the side view of the sensor, which shows a certain spherical arc. (b) and (c) are the side and top views of the local tactile map made by pressing the sensor on a flat desk, respectively. The wine-colored part is the theoretical flat reconstruction result, while the colored part is the actual spherical arc.

The experimental section VII-A introduces the quantitative results of the local tactile map construction in detail. As shown in Fig. 4, we visualize some local tactile maps of the 3D printed ‘ZJU’ here.

V. ADAPTIVE PRESSURE CORRECTION ALGORITHM

A. Reconstruction Error Sources Analysis

1) **Arc-Shaped Sensor Surface**: The tactile sensor used here is shown in Fig. 5(a). The gel surface is a slight arc, which causes a deviation between the local tactile map construction result and the ground truth, as shown in Fig. 5(b) and (c). The result of the local reconstruction is essentially gel deformation, which is larger in the central region than in the other regions. Therefore, the local tactile map is characterized by a deep center and shallow periphery, reducing the accuracy of the reconstructed depth.

2) **Sampling Pressure Inconsistency**: According to Wang et al. [7], different pressures yield different degrees of gel deformation for the same object, even if the sensor surface is flat. Therefore, the shape reflected in the local tactile map does not conform to the real situation, indicating that the accuracy will be affected by accidental errors if the pressure cannot maintain consistency. We verify this phenomenon through a more detailed experiment: pressing the sensor on a flat desk using different

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forces and performing spherical fitting to the reconstructed local tactile maps (all in spherical arc shape) through RANSAC technology. As shown in Table I and Fig. 6, as the pressure increases, the fitted radius decreases, which implies that the depth deviation between the center and periphery becomes more obvious.

Therefore, during global tactile map reconstruction, the errors caused by 1) the arc-shaped sensor surface and 2) the inconsistency of pressure are coupled, further reducing the accuracy. The correction algorithm must consider both factors.

### B. Correction Algorithm

We innovatively propose a correction algorithm that can comprehensively reduce errors in the two aspects mentioned above. 1) Press the flat desk with a standard force to obtain the standard point cloud $P_s$. 2) Estimate the relative force magnitude coefficient $\alpha$ between each sampling force and standard force. 3) Generate the correction point cloud $P_{c_i}$ from the standard point cloud $P_s$ for each sampled point cloud $P_i$ and then use it to correct the depth of $P_i$.

Essentially, $P_s$ reflects the depth error distribution caused by the arc shape of the sensor surface under specific pressure. This distribution is further affected by unstable pressure during sampling. Therefore, it is necessary to estimate the relative magnitude $\alpha$ of the sampling pressure between each subsequent sample point cloud $P_i$ and $P_s$. $P_{c_i}$ is generated by adjusting the distribution of $P_s$ through $\alpha$, such that the correction algorithm can achieve a self-adaptive effect.

1) **Estimation of the Relative Magnitude of Pressure**: As shown in Fig. 7, we divide the sampling area $T$ into two main sub-regions with equal area, $C$ and $A$. We denote the depths of the central and surrounding areas as $d_c$ and $d_a$, respectively, and denote the deviation between them as $\Delta d$. We estimate the relative magnitude coefficient $\alpha$ as follows:

The depths of areas $C$ and $A$ are estimated by counting the mean depth of the points in their corresponding regions and are denoted as $\hat{d}_c$ and $\hat{d}_a$. The deviation between them is denoted as $\Delta \hat{d}$. This way, the depth deviation of the standard frame and each subsequent sampling frame are denoted as $\Delta d_c$ and $\Delta d_a$, respectively, representing the different deviation intensities caused by the inconsistency pressure. The relative magnitude coefficient $\alpha_i$ between the two frames is estimated as $\alpha_i = \frac{\Delta \hat{d}_i}{\Delta d_i}$.

It is worth mentioning that $\alpha_i$ must be estimated for each $P_i$ to improve the depth consistency during the entire sampling process. When $\alpha_i$ is greater than a threshold (1.1 in our experiments), which implies that the contact surface is possibly curved, we set $\alpha_i$ as the threshold to avoid an inappropriate, excessive correction. The only assumption is that the correlation between the depth deviation and pressure described in Section V-A2 is independent of the pressed object surface texture. Thus, the standard point cloud $P_s$ collected on the flat desk is suitable for correcting other objects.

2) **Depth Correction**: According to the correlation between the depth deviation and pressure $\Delta d \propto F$, we perform depth correction for each local tactile map according to (1)

\[
P_{s_i}^c = P_{s_i}^c \times \alpha_i
\]

where $P_{s_i}^c$ is the z component (depth distribution) of point cloud data $P_i$. First, we transform the depth distribution of $P_s$ by $\alpha_i$ to form $P_{c_i}$ with depth deviation $\Delta d_c$. The correction point cloud $P_{c_i}$ satisfies $\Delta d_{c_i} = \Delta d_c$, which implies that it has the same intensity of depth deviation as the local tactile map, $P_i$. Then, by subtracting the depth values of $P_i$ and $P_{c_i}$, depth correction is completed, making $\Delta \hat{d}_i = 0$.

### VI. GLOBAL TACTILE MAP CONSTRUCTION

This section details how our method fuses multi-frame pressure-corrected local tactile maps into a global tactile map to accurately reconstruct a large-scale object surface. We describe the point cloud preprocessing technique and the coarse-to-fine point cloud registration algorithm in Section VI-A and then elaborate on the loop-closure detection algorithm and the pose graph optimization algorithm in Section VI-B.

#### A. Point Cloud Preprocessing and Registration

Because of the high resolution of the image-based tactile sensor and the fact that only a small area of the sensor surface will be in contact with the object during sampling, the local tactile map is very dense with a low percentage of valid information, making the registration process lengthy and less robust.

In our case, before point cloud registration, the preprocessing operations include 1) voxel downsampling and 2) ROI (region of interest) extraction based on the pitch angle of the surface normal, defined as (3). Among them, voxel downsampling helps
improve the efficiency of the registration algorithm by properly setting the voxel size (0.3–0.4 mm in our experiments). By setting a threshold on the pitch angle (60–80° in our experiments), our ROI extraction module detects points with significant deformations and extracts a bounding box for them. The points inside the bounding box are used in the subsequent registration process to increase the robustness of the registration. As shown in Fig. 8, the preprocessing module can significantly improve the accuracy of the registration algorithm.

In the registration stage, we implement a coarse-to-fine point cloud registration algorithm based on Open3D, an open-source point cloud library [22]. We use the RANSAC algorithm based on FPFH [23] for rough global registration and then use the result as the initial value of the iteration for fine registration based on the point-to-plane ICP algorithm [24], [25].

While registering a sequence of local tactile maps, we estimate the transformation matrix between two adjacent frames by registering their point clouds. Then we use the result matrix to align them. Repeating this operation allows each local tactile map to be aligned to the same frame. In our case, the first frame is chosen as the base frame, where the position of the tactile sensor is the identity matrix.

B. Loop-Closure Detection and Pose Graph Optimization

Although the algorithm mentioned in Section VI-A can register a sequence of local tactile maps, it is essentially an odometry model with an inevitable accumulative error. When the object’s scale is much larger than the effective sampling area of the sensor, the accumulative error significantly reduces the accuracy of the final result. Loop-closure detection algorithms are often used in SLAM to address this problem [26], [27], [28]. Algorithms that rely on convolutional neural networks (CNN) for scene re-recognition and loop-closure detection have also been widely used [27], [28].

As there is both tactile image and map information during the global tactile map reconstruction, we use the ResNet152 neural network, pre-trained using the ImageNet dataset [29], without its last linear layer as the tactile image descriptor encoder. We determine whether loop-closure occurs based on the cosine similarity of the descriptor vectors defined by (2). X and Y are the descriptor vectors of two tactile images with N dimensions.

\[
S_{sim} = X \cdot Y = \sum_{i=0}^{N} X_i Y_i
\]  

Because of the limited size of the sampling area, if the distance between two candidate frames is too large, there will be no common area, which means that they are sampled from two different spots. Therefore, these frames may be false positive detection results. As shown in Fig. 9, by filtering out candidate frames whose distance is too close or too far comprehensively considering the efficiency and accuracy, the validity and accuracy of detection are improved, giving the subsequent pose graph optimization more reliable data association information.

The pose graph comprises nodes and edges, where the nodes represent the pose of each frame and the edges represent the relative transformation between two connected nodes. In our case, a pose graph is constructed during point cloud registration. We initialize the pose graph by setting the pose of the first frame as the identity matrix, coinciding with the world coordinate. During the process of point cloud registration, nodes and their adjacent edges in the pose graph are gradually added by the odometry described in Section VI-A whereas edges between non-adjacent nodes are added by loop-closure detection. Finally, we used the LM (Levenberg–Marquardt) method in the optimization stage to optimize the pose of each node. It is known to have better convergence than the commonly used GN (Gauss–Newton) method.

Overall, loop-closure detection and pose-graph optimization techniques reduce the accumulative error and ensure the accuracy of the surface reconstruction of large-scale objects.

VII. EXPERIMENTS

In this section, we elaborate on the experimental setup and analyze the result, which comprises four parts. First, in Section VII-A, to illustrate the accuracy of our local tactile map construction algorithm, we describe the training process of the MLP model and quantitatively evaluate it. Second, in Section VI-B, we define two indexes: 1) the reconstruction flatness of Fig. 9. Elimination process of false positive loop-closure detection. From the left to right: the original detection results based on CNN (the top 20% of cosine similarity ranking are retained), results after removing candidate frames that are too close, and final results after further removing the candidate frames that are too far.
flat objects and 2) the fitted radius of the local tactile map of a hemisphere. The first index is used to evaluate the effectiveness of the proposed pressure correction algorithm on flat surfaces. The second index validates the algorithm on a non-flat surface. Third, in Section VII-C, to illustrate the practicability and necessity of the proposed pose graph optimization method, we compare the results of three types of global tactile map construction methods: 1) Tac2S(Odometry), 2) Tac2S, and 3) MC2S (reconstructed by motion capture equipment). Finally, in Section VII-D, we conduct ablation experiments on the core functional modules involved in Tac2Structure and demonstrate the value and necessity of each part.

### A. Local Tactile Map Construction

1) Data Collection: To make the training data as useful and non-repetitive as possible, we collect 60 tactile images with a sphere of diameter 6 mm and one tactile image with nothing pressed to generate 150,000 vectors for training. Subsequently, a sphere with a diameter of 12 mm is used to collect the test data, and 50,000 vectors are collected.

2) Train: Our multi-layer perceptron model is trained on an Nvidia GTX1060 GPU with 6 GB of memory using the Adam optimizer in Pytorch. We set the learning rate to 0.00112, the batch size to 4000, and the total epoch to 400.

3) Evaluation: We design two performance indexes to evaluate the trained MLP model. First is the pitch and yaw angles of the surface normal, as in [2]. Second is the flatness of the reconstructed point cloud without pressing.

#### Pitch and yaw angles

The surface normal is defined in mathematical form as \( \mathbf{n} = (n_x, n_y, n_z) \), where \( n_x \) and \( n_y \) are the outputs of the perceptron model and \( n_z \) is the physical length of one pixel. The pitch and yaw angles of the surface normal are defined by (3):

\[
\begin{align*}
\text{pitch} &= \arctan \left( \frac{n_x}{n_{xy}} \right), \\
\text{yaw} &= \arctan \left( \frac{n_y}{n_x} \right) 
\end{align*}
\]

(3)

For all pixels in the nine test tactile images, we perform zero- intercept line fitting on the predicted value and ground truth of pitch and yaw, obtaining the slope \( a \) and the coefficient of determination \( R^2 \). As summarized in Table II, the mean value of \( a \) is approximately 1, and the mean value of \( R^2 \) is approximately 0.9, which indicates that the perceptron model can accurately estimate the gradient corresponding to each pixel.

#### Tactile-map flatness without pressing: The flatness is defined by the root mean square distance between all points and the theoretical plane \( Z = 0 \), as shown in (4)

\[
\text{flatness} = \frac{1}{n} \sum_{i=1}^{n} \| \mathbf{p}_i \cdot \mathbf{\hat{n}} + D \|_1 
\]

(4)

where \( \mathbf{p}_i \) is the \( i \)th point of the local tactile map, \( n \) is the number of points in the local tactile map, and \( \mathbf{\hat{n}} = (A, B, C) \). \( A, B, C \) and \( D \) are parameters in the planar equation \( (Ax + By + Cz + D = 0) \).

The flatness of the reconstruction point cloud of the non-pressing tactile image is calculated to be 0.1869 mm, which implies that our multi-layer perceptron can estimate the depth within millimeter-level accuracy.

### B. Tactile Map Depth Correction

We first evaluate the depth-correction algorithm on flat objects ‘ALLCCT’ and ‘Dragon–Phoenix.’ We compare the point cloud registration results (without loop-closure detection and pose graph optimization) of the sequential local tactile maps before and after correction. As shown in Fig. 10, unacceptable bending errors occur in the results before correction, while the results after correction have much better smoothness.

For quantitative comparison, we perform plane fitting on the reconstructed point cloud using RANSAC technology to obtain the parameters in the planar equation. The flatness is the same as that in (4). As shown in Table III, the flatness is significantly improved after correction, indicating that the proposed algorithm can solve the problems caused by the sensor surface appearance and pressure inconsistency.
TABLE III
FLATNESS BEFORE AND AFTER CORRECTION, UNIT: MM

| Object       | before correction | after correction | Ground truth |
|--------------|-------------------|------------------|--------------|
| Alligator    | 2.103             | 0.807            | 20           |
| Dragon–Phoenix| 1.614             | 0.723            | 20           |

TABLE IV
FITTED RADIUS BEFORE AND AFTER CORRECTION, UNIT: MM

| Fitted radius | before correction | after correction | Ground truth |
|---------------|-------------------|------------------|--------------|
| mean          | 17.922            | 20.569           | 20           |
| std           | 1.300             | 1.695            | —            |

Specifically, the motion capture system includes four optitrack cameras placed on the four vertices of a square area. Five markers are attached evenly to the tactile sensor. To stably accept the pose transformation of the tactile sensor during the reconstruction process, we ensure that the makers are always within the common field of view of the four optitrack cameras. We use the pose obtained by direct point cloud registration between the first and last frames as the true value (Q) and the odometry pose before and after optimization as the estimated value (P) to calculate the RPE, defined by (5). We only take the length of the translation vector of RPE as the final index, denoted as $\|\text{RPE}\|$. 

$$\text{RPE} = \left(\frac{Q_{1} - Q_{last}}{P_{1} - P_{last}}\right)^{-1}$$  \hspace{1cm} (5)

The flatness calculation method is consistent with that described in Section VII-B. The deviation between the reconstructed result and CAD model includes the mean value and standard deviation of the distance between them (unit: mm). It is calculated using the open-source software Cloud Compare [31].

The results are listed in Table V. In Tac2S(Odometry), $\|\text{RPE}\|$, the flatness and deviation are large. After optimization, all performances improve, indicating the effectiveness of the pose graph optimization algorithm. Because the accuracy of MC2S is slightly lower than Tac2S, we believe that the main reason is that optitrack only has millimeter-level accuracy, which is not sufficiently accurate for tactile reconstruction. Furthermore, the calibration between the optitrack and tactile sensor makes it difficult to achieve millimeter accuracy.

The experimental results verify the necessity and effectiveness of the pose graph optimization technology in our Tac2Structure framework, which can reduce the accumulative error and improve the accuracy of the global reconstruction.

D. Ablation Experiment

Finally, we take the ‘Dragon–Phoenix’ as the experimental subject and conduct an ablation experiment on the core functions of the proposed algorithm (depth correction and pose graph optimization). The results are presented in Table VI.

The depth-correction algorithm can significantly improve the flatness. In contrast, the pose graph optimization algorithm can reduce the accumulative error of odometry and improve the RPE. Combining the two algorithms can reduce the deviation between the reconstruction result and the CAD model. This table further shows that the entire algorithm system can reconstruct the object surfaces with millimeter-level accuracy.

To verify the effectiveness on the non-flat surface, we collect 100 tactile images on a 3D printed hemisphere with a known radius (20 mm) using different forces. We compare the fitted radius generated from spherical fitting (using the RANSAC technique) on the local tactile maps before and after correction. As shown in Table IV, the mean value of the radius after the correction operation is closer to the ground truth, verifying the validity of the algorithm on the curved surface.

C. Global Tactile Map Construction

We compare the global map construction results with and without optimization, named Tac2S and Tac2S(Odometry), respectively, on the ‘Dragon–Phoenix’ and ‘Coiling Dragon’ 3D printed pieces. As shown in Fig. 11, the accumulative error of the odometry is very obvious because of the large scale of the objects. Specifically, ‘Dragon–Phoenix’ and ‘Coiling Dragon’ are reconstructed from 55 and 45 local tactile maps, respectively, nearly 20–30 times larger than the sensor sampling area. After the pose graph optimization operation, the drift is significantly reduced, and the reconstruction result is closer to the actual situation of the object surface.

To quantify the improvement brought by optimization, we design three indexes: 1) the RPE, relative pose error of the first and last frames; 2) flatness (only for flat object ‘Dragon–Phoenix’); and 3) deviation between the reconstructed point cloud and object CAD model. To further illustrate the effectiveness of our algorithm, we use a motion capture device (optitrack [30]) to assist in reconstructing the surface texture of the object, as in [5], [6], named MC2S. The second and third indexes evaluate the results of MC2S.

To verify the effectiveness on the non-flat surface, we collect 100 tactile images on a 3D printed hemisphere with a known radius (20 mm) using different forces. We compare the fitted radius generated from spherical fitting (using the RANSAC technique) on the local tactile maps before and after correction. As shown in Table IV, the mean value of the radius after the correction operation is closer to the ground truth, verifying the validity of the algorithm on the curved surface.

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TABLE VI

| Depth correction | Pose graph optimization | RPE$_t$ | flatness | $\varepsilon_{\text{mean}}$ | $\varepsilon_{\text{std}}$ |
|------------------|-------------------------|--------|----------|-----------------|-----------------|
| X                | X                       | 7.291  | 1.614    | 5.380           | 5.136           |
| ✓                |                         | 3.247  | 0.723    | 0.456           | 0.370           |
| ✓                | ✓                       | 0.056  | 1.749    | 4.847           | 4.613           |
| ✓                | ✓                       | 0.049  | 0.651    | 0.416           | 0.352           |

VIII. CONCLUSION

We propose a low-drift framework, Tac2Structure, for the surface reconstruction of large-scale objects, relying only on an image-based tactile sensor. Our toolbox helps efficiently complete the annotation of the training dataset. Using the trained MLP model with a Fast Poisson solver, the tactile image can be accurately converted to a local tactile map. By jointly using the adaptive pressure correction algorithm and point cloud registration algorithm, our method constructs a global tactile map of an object. We use a deep learning-based loop-closure detection algorithm and a pose graph optimization algorithm for large-scale object surface reconstruction to reduce accumulative error and drift. In general, without additional observation equipment, our framework can achieve good accuracy, making the overall operation process simpler, cost cheaper, and applicable to wider application scenarios.

However, similar to the drawbacks of LiDAR odometry in SLAM, our framework fails in scenes without valid textures, making it difficult to reconstruct the surfaces of objects with sharp edges, such as cubes. Therefore, our next work is to design and implement a new framework for “Tactile-IMU” multi-sensor fusion object surface reconstruction. It will make the estimated egomotion of the tactile sensor more robust and accurate in these scenes, greatly expand the applicable scenes and significantly improve the algorithm’s modeling ability.

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