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# Self-Initialization and Recovery for Uninterrupted Tracking in Vision-Guided Micromanipulation

Liangjing Yang, Ishara Paranawithana, Kamal Youcef-Toumi, U-Xuan Tan, *Member, IEEE*

**Abstract—** In this paper, we propose a workflow algorithm for timely tracking of the tool tip during cell manipulation using a template-based approach augmented with low level feature detection. Doing so addresses the problem of adverse influences on template-based tracking during tool-cell interaction while maintaining an efficient track-servo framework. This consideration is important in developing autonomous robotic vision-guided micromanipulators. Our method facilitates vision-guided micromanipulation autonomously without manual interventions even during tool-cell interaction. This is done by decomposing the process to four scenarios that operate on their respective mode. The self-initializing mode is first used to localize and focus a region of interest (ROI) which the tip lies in. Once in focus, the tip is manipulated using a unified visual track-servo template-based approach. A reinitialization mechanism will be triggered to prevent tracking from being interrupted by partial cell occlusion of the tracking ROI. This mechanism uses the self-initializing concept combining motion cue and low-level feature detection to localize the needle tip. Following the reinitialization, we further recover tracking of the needle tip using a mechanism that updates the base template. This adaptive approach ensures uninterrupted tracking even when the cell is interacting with the tool and under deformation. Results demonstrated that with the newly incorporated mechanisms, the localized position improved from an error of more than 50% to less than 10% of the specimen size. When there is no specimen in the scene the new workflow shows no adverse effect on the localization through 270 tracked frames. By incorporating reinitialization and recovery to this workflow algorithm, we hope to initiate the first step towards uncalibrated autonomous vision-guided micromanipulation process.

## I. INTRODUCTION

Recent advancements in micromanipulation improve the usability, functionality, speed, accuracy, and repeatability in cell manipulation. The usability and functionality are enhanced through design-centric manipulation mechanisms [1, 2], intelligent image-guidance [3, 4] and intuitive operation interfaces [5, 6]. In addition, robotic vision-guided micromanipulators facilitate shorter operation time, higher precision, and better consistency [7].

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Liangjing Yang is with the Mechanical Engineering Department, Massachusetts Institute of Technology, Cambridge, Massachusetts (phone: +1-(617)258-6785; e-mail: [yanglj@mit.edu](mailto:yanglj@mit.edu)).

Ishara Paranawithana is with the Pillar of Engineering Product Development, Singapore University of Technology and Design, Singapore (e-mail: [ishara\\_paranawithana@sutd.edu.sg](mailto:ishara_paranawithana@sutd.edu.sg)).

Kamal Youcef-Toumi is with the Mechanical Engineering Department, Massachusetts Institute of Technology, Cambridge, Massachusetts (e-mail: [youcef@mit.edu](mailto:youcef@mit.edu)).

U-Xuan Tan is with the Pillar of Engineering Product Development, Singapore University of Technology and Design, Singapore (e-mail: [uxuan\\_tan@sutd.edu.sg](mailto:uxuan_tan@sutd.edu.sg)).

Effective visual tracking capabilities are paramount to the performance of a robotic vision-guided system during micromanipulation. Without timely tracking of the tool tip, motion control cease to function properly no matter how well they are designed. In developing an autonomous vision-guided micromanipulator, it is important to design a tracking algorithm that is adequately robust to ensure uninterrupted tracking and timely position feedback.

Template matching is effective in visually tracking the tool tip during vision-guided micromanipulation. This is especially true for cell manipulation where the end-effector is manipulated in a reasonably controlled environment [8]. This approach seeks matching region in every image frame of the motion with a base template and can be readily implemented for micromanipulation without worrying about rotation or scale invariant. This makes template-based tracking approaches advantageous for most vision-guided micromanipulation applications

Although template-based tracking is a popular approach for visual servo in micromanipulation [8, 9], its performance is adversely influenced during tool-cell contact and interaction. A template-based approach that uses a common base image for template matching assumes that the tracked region remains relatively unchanged in every frame. This is usually not the case when the tool tip comes close to or is in contact with the specimen. For effective vision-guided micromanipulation, an improved template-based approach for uninterrupted tracking even during tool-cell interaction is needed. We argue that it is this lack of effective visual tracking methods that results in the existing bottleneck for advancing autonomous vision-guided micromanipulation.

To address the mentioned needs, we propose a self-initializing and uninterrupted tracking framework which complements our previous work in robot-assisted micromanipulation [10, 11]. The research problem in this current work is to redesign template-based tracking approach to be robust against the influence of tool-specimen interaction in micromanipulation. This is done through combining low level feature extraction for self-initialization and timely template update for recovery.

In the next section, we discuss the limitations of existing related works to justify the motivation of this study. Section III explains the proposed method followed by results and discussion of the experiment in Section IV. Section V concludes this paper by summarizing the contributions and their significances including a brief comment of prospective development of this study.

## II. RELATED WORK AND LIMITATIONS

This section discusses existing work based on two themes. First, we survey current development on robotic vision-based micromanipulation to identify the challenges and needs in this application. Second, we review the limitations of existing systems, including our previous work, in the literature. This section aims to justify the aforesaid research problems through the needs and limitations of the existing work.

In the past decade, there has been extensive effort in the development of vision-guided micromanipulation. This includes pioneering work using direct visual servo method for micromanipulation by Sun and Nelson [8, 9]. The advantage of such approaches are that they generally do not require tedious calibration between the microscope camera and the micromanipulator unlike other calibrated vision-guided approaches [12-16]. An uncalibrated approach facilitates versatile deployment of vision-guided capability. It allows implementation of the workflow algorithm readily into the micromanipulation system easily without the need of calibration. There is no requirement to constrain the procedures in a calibrated setting.

Complying to this need to facilitate versatile deployment of vision-guided micromanipulation, we develop an uncalibrated vision-guided manipulation system through a unified visual track-servo framework [10]. It uses template matching not only to track the tool tip but also to infer its deviation from the focal plane. This is done through the similarity score-based depth compensation where changes in the similarity score between a focused base template and the matched region is used as the feedback for controlling the depth in the 3D workspace. With that, the tool tip can maintain its trajectory in focus even without calibration.

To enhance the ease of operation, we further minimized the need for manual locating and focusing of the tool tip by developing a vision-based workflow algorithm termed Detect-Focus-Track-Servo (DFTS) [11]. This is a self-initializing workflow that detect and focus the tool tip automatically. It subsequently applies the unified track-servo framework to perform vision-guided manipulation. The workflow of the DFTS is graphically summarized in Figure 1. Without the self-initializing part, the operation requires manual localization and focusing before a base template can be specified as shown in the Figure 1(a). Figure 1(b) depicts the automatic selection of the focused template. Finally, user is able to manipulate the tip on an interactive display using the track-servo framework as shown in Figure 1(c).

Combining visual tracking and servoing of the tool with automatic image-based detection of specimens potentially facilitates development in autonomous cell manipulation. Automatic tracking of the micropipette and blastomere is demonstrated in Preimplantation Genetic Diagnosis (PGD) [17]. Wang et al. uses image-based recognition of the embryo structure for automatic microinjection on immobilized zebrafish embryo [4].

Despite the development in vision-guided robotic micromanipulation systems, including our previous work [10,

11], the issue of uninterrupted tracking during tool-specimen interaction has not been investigated. This is important in applications like embryo biopsy or blastomere isolation where tool-specimen interaction is highly challenging for tracking. To pave the way for a fully autonomous vision-guided robotic micromanipulation systems in general cell manipulation, an uninterrupted tracking mechanism that provides timely position feedback is needed.

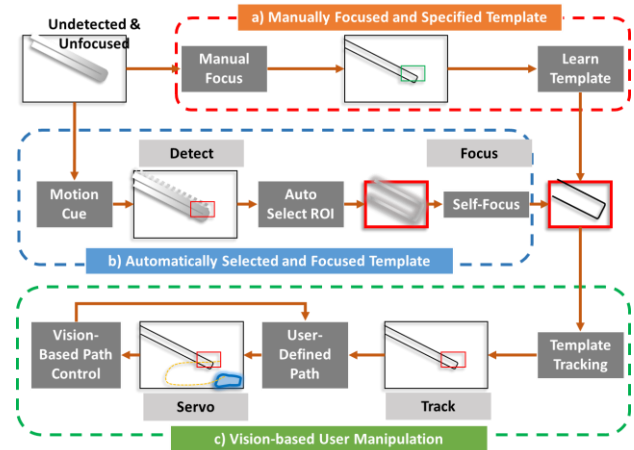


Figure 1. Graphical summary of the self-initialization and track-servo workflow in our previous work

## III. METHOD

### A. Overview

Our current work improves on the workflow of automated cell manipulation by combining our previous unified track-servo framework [10] and the self-initializing workflow algorithm [11] with further capabilities of reinitialization and recovery. This new workflow algorithm ensures timely tracking in vision-guided manipulation even during tool-cell interaction. This is done by classifying the operation modes to handle the respective scenarios using a hybrid tracking workflow that is robust against the influence of cell interacting with the tracking ROI. The following two subsections analyze the problem and outline our proposed solution.

#### 1) Problem with Visual Track-Servo

Template-based approach is an effective method to track the tool tip and perform visual servoing as the end-effector is manipulated in a reasonably controlled environment. As mentioned in the introduction, there are problems in this approach despite its strength. These problems are analyzed in this section prior to our discussion of the proposed solution.

To better structure the discussion, we classify four scenarios describing the tool position in relation to the specimen. The four scenarios are (A) Unfocused, (B) Distant, (C) In-Contact and (D) Interacting. These are illustrated in Figure 2.

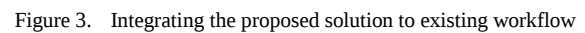
The tip may not be aligned with the cell in the focal plane as shown in Figure 2(a). Tracking is not possible without a focused vision of the tip. The tool has to be aligned with the specimen in the focal plane as shown in Figure 2(b) before

Figure 1 illustrates four configurations of an AFM tip relative to a cell surface, separated by a dashed line representing the focal plane. (a) Unfocused: The tip is positioned above the focal plane. (b) Distant: The tip is positioned below the focal plane. (c) In Contact: The tip is in direct contact with the cell surface at the focal plane. (d) Interacting: The tip is interacting with the cell surface at the focal plane. Labels include 'Tip', 'cell', and 'Focal Plane'.

The problem arises when the tip comes close to the cell, as shown in Figure 2(c). With the cell within the tracking ROI, base template cannot be matched with current ROI surrounding the tip hence disrupting the visual track-servo workflow. Certain applications, like cell biopsy, involve interaction and deformation of the specimen (Figure 2(d)) during the vision-guided micromanipulation process. The unpredictable dynamics involved in the scene further complicates the process of visual tracking and servoing.

However, to deal with the scenario where tip is in proximity with the cell, reinitialization of the tip is needed to relocalize the occluded ROI. When the tip is near the cell, this mode will be triggered to prevent tracking from being interrupted by the presence of cell in the tracking ROI. This is

We design a recovery mechanism to rectify the tracking uncertainty due to cell deformation during tool-specimen interaction. In this recovery mode, the system suspends motion cue detection and use the last updated tip coordinates to establish an ROI for subsequent template matching.



With the tip in focus, a window ROI is automatically specified as the base template for subsequent matching. The cross-correlation  $w_{cc}(u,v)$  at image coordinates  $(u, v)$  of the base template  $g(p,q)$  and an image  $f(p,q)$  in a particular frame

is expressed as

$$w_{cc}(u, v) = \sum_{p=0}^P \sum_{q=0}^Q g(p, q) f(p+u, q+v) \quad (1)$$

for a  $P \times Q$  patch and  $U \times V$  image. To account for intensity variation, we normalize  $w_{cc}(u, v)$  to obtain the coefficient

$$w_{ncc}(u, v) = \left( \sum_{p=0}^P \sum_{q=0}^Q \langle G \rangle \langle F \rangle \right) / \left[ \left( \sum_{p=0}^P \sum_{q=0}^Q \langle G \rangle^2 \right) \left( \sum_{p=0}^P \sum_{q=0}^Q \langle F \rangle^2 \right) \right]^{0.5}, \quad (2)$$

where  $\langle G \rangle = (g(p, q) - \bar{g})$  and  $\langle F \rangle = f(p+u, q+v) - \bar{f}(u, v)$ . Notation  $\bar{g}$  and  $\bar{f}$  represent the mean intensity value in the template and the window overlapping the patch, respectively. By obtaining the image coordinates and similarity score of the ROI, we can express the error signal as  $[\Delta u, \Delta v, \Delta w]$ . This unified approach enables uncalibrated 3D motion control.

TABLE I. PSEUDO-CODE FOR SELF-FOCUSING

| Variance Maximizing Algorithm for Self-Focusing                                     |
|-------------------------------------------------------------------------------------|
| 1. <b>initialize variables</b>                                                      |
| 2. $\Delta z := \Delta \sigma_{hist} := tol; \sigma_{hist} := \text{var}(H_{ROI});$ |
| 4. <b>while</b> $\Delta \sigma_{hist} \geq tol$                                     |
| 5. $\Delta \sigma_{hist} := \sigma_{hist} - \text{var}(H_{ROI});$                   |
| 6. $\Delta z := \Delta z * \text{sign}(\Delta \sigma_{hist});$                      |
| 7. $\sigma_{hist} := \text{var}(H_{ROI});$                                          |
| 8. <b>end loop</b>                                                                  |

a.  $\text{var}()$  is a function that returns the statistical variance; b.  $\text{sign}()$  extracts the sign

### C. Reinitialization and Recovery: (D/R)eLoCk

The main contribution of our current work is the incorporation of reinitialization and recovery mechanism into the existing workflow algorithm to enhance its robustness against tracking failures during cell occlusion or deformation. We denote the reinitialization and recovery mechanism as DeLoCk and ReLoCk, respectively.

#### 1) Detect-Localize-traCk: DeLoCk

The DeLoCk module is designed to reinitialize tracking whenever there is an occlusion in the tracking ROI by the specimen. The tracking performance of template matching deteriorates when the tracking ROI is occluded by the cell. This occurs when the tool approaches the specimen. To solve this problem, we make use of the self-initialization mechanism to relocalize the tip when it approaches the cell.

To automatically detect the need for reinitialization, a criterion has to be specified to trigger the DeLoCk mechanism when occlusion by specimen arises. Knowing the radius  $R_{roi}$  of the circle that circumscribes the ROI and the image coordinates  $(x_{roi}, y_{roi})$  of the ROI center. The extent to which the cell is occluding the tracking ROI can be given by

$$O_x = (R_{cell} + R_{roi}) - \left\| (x_{cell}, y_{cell})' - (x_{roi}, y_{roi})' \right\|, \quad (3)$$

where  $R_{cell}$  and  $(x_{cell}, y_{cell})$  are the nominal radius and the position of cell center in image coordinates.

As the cell is assumed to be in focus before the procedure, we can obtain  $(x_{cell}, y_{cell})$  and  $R_{cell}$  using a cell detection technique based on Hough transformation. This technique assumed cell to be almost circular and is applicable to PGD as demonstrated in a study for blastomere extraction [17].

When occlusion of the ROI by the cell is detected (i.e.  $O_x > 0$ ), the track-servo framework that maintains manipulation depth will be suspended. At the same time, reinitialization will be triggered to begin tracking using motion cue feature detection approach.

#### 2) Recover-Localize-traCk: ReLoCk

The ReLoCk mechanism is designed to recover tracking error during cell deformation. As discussed, deformation of the cell during tool-specimen interaction may result in false detection of the moving tip due to the sensitivity of the approach towards moving features. Therefore tracking the last location obtained by the motion cue detection before cell deformation occurs is a critical prerequisite for the recovery procedure.

In order to detect deformation, ReLoCk needs to be triggered automatically similar to that in DeLoCk. Like the case of DeLoCk, we formulate a criterion for this. Instead of extent of occlusion, we are interested in the extent of deformation. In our application the cell deformation can be estimated by

$$D_x = (R_{cell} + \Delta) - \left\| (x_{cell}, y_{cell})' - (x_{roi}, y_{roi})' \right\|, \quad (4)$$

where  $\Delta$  is a contact margin that is introduced to control the sensitivity in deformation detection. Assigning a positive  $\Delta$  makes the mechanism more sensitive and triggers recovery even before contact. Introducing this sensitivity-associating term to the equation allows fine tuning of the performance with easy-to-relate intuition about how readily a user expects the workflow algorithm to switch the tracking mode.

Once deformation is detected (i.e.  $D_x > 0$ ), the algorithm will update the tracking ROI with a new template before disabling DeLoCk. This is a simple heuristic approach that do not require complex prediction of the dynamics or prior assumptions about the specimen's material properties.

The process of recovery using ReLoCk is illustrated in Figure 4. In Figure 4(a), false detections due to cell deformation results in localization uncertainty. Based on Equation 4, DeLoCk is disabled (Figure 4(b)) while ReLoCk (Figure 4(c)) is activated. This adaptive template-based approach consequently recovers accurate track (Figure 4(d)).

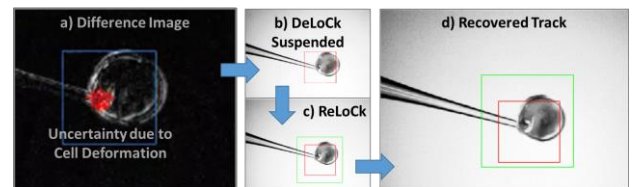


Figure 4. During cell deformation: (a) Tracking error; (b-d) Recovery

#### IV. RESULTS & DISCUSSION

##### A. Experiment and Setup

To evaluate the proposed workflow algorithm, microscope imaging during vision-guided micromanipulation is recorded and analyzed with our proposed method. This is done through a low-cost portable vision-guided micromanipulator system as shown in Figure 5. We use a portable system designed for micromanipulation and imaging in a more general setting to be inline with our long term design goal of a versatile system. In doing so, we hope to demonstrate our proposed method under a relatively more demanding conditions.

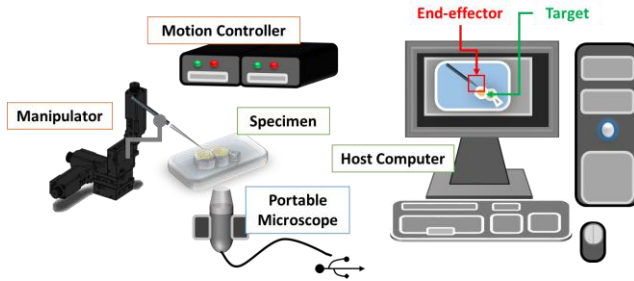


Figure 5. Setup of the vision-guided micromanipulation

Manipulation was carried out using a 3-axis Cartesian manipulator. Each axis of control (8MT173; Standa Ltd., Lithuania) has a resolution of 1.25  $\mu\text{m}$  per step. It is controlled using a multiaxis controller (8SMC4; Standa Ltd., Lithuania). The workspace is 20 x 20 x 20  $\text{mm}^3$ . A portable digital USB microscope with a 5-Megapixel CMOS image sensor (AM7013MZT Dino-Lite, AnMo Corp., Taiwan). Motion control, image processing, and user interface application are developed using LabVIEW Development Suite (National Instruments Inc., USA).

##### B. Robustness against Tracking Failures

To demonstrate the DeLoCk and ReLoCk mechanism, we visually tracked the tool tip of an image stream (493 frames) acquired during vision-guided micromanipulation. Figure 6 features four of the representative frames and a composite image with the frames superimposed to illustrate the displacement and deformation of the cell. In the next two subsections, we will demonstrate the DeLoCk and ReLoCk mechanism through visual inspection of the detected features in the difference images and the tracking display.

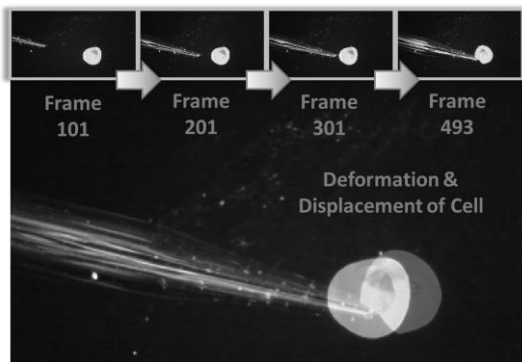


Figure 6. Manipulation of tool tip towards cell; superimposed image of the frames indicating both cell displacement and deformation

##### 1) Partial Occlusion

Figure 7. illustrates the effect of reinitialization against partial occlusion using the DeLoCk module. The enhancement of the moving tool tip and suppression of the background is also prominent from the Figure 7 (b). Such tracking is maintained by localization of the tip every frame because low level features can be detected from the difference image without have to match past frame. It is therefore robust against changing scene to guarantee uninterrupted tracking independent of previous frame as long as it is in motion.

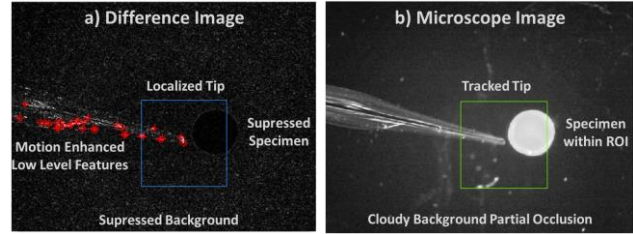


Figure 7. Effect of DeLoCk against partial occlusion; Red points denotes low level features

##### 2) Deformation in Specimen

The problem of cell deformation is demonstrated in Figure 8. Figure 8 (a) shows false detection of the tool tip as a result of cell deformation. This results in localization error and tracking failure. As shown in Figure 8 (b), template-based approach took over tracking to maintain accurate track. As annotated, we observed that motion cue detection erred in localizing the tool tip due to a false detection of the cell contour as the tool. Through visual inspection, we see that the recovered track, represented by a larger box, relocalized and rectified the tracking error.

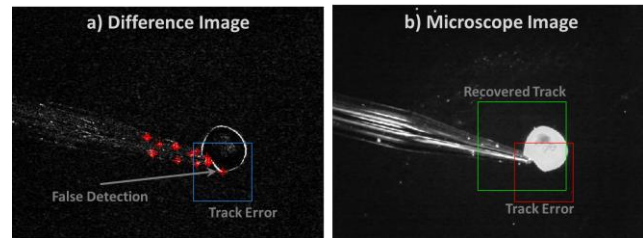


Figure 8. Tool-Specimen Interaction a) Tracking error b) Recovery; Red points denotes low level features; Large green and small red ROI denote updated template tracking and motion cue detection, respectively

Figure 9 demonstrates DeLoCk and ReLoCk by capturing tracking scene in scenario b) to d) defined in Figure 2. Reinitialization and recovery are both depicted. When tool tip is far away from the cell, both motion cue detection and template-based tracking approach are consistent in the localization as observed in Figure 9(a). In Figure 9(b) when cell is present in the vicinity of the tracking ROI, the template-based method could not localize accurately. However, DeLoCk managed to localized correctly until cell deformation in Figure 9(c), where the base template is updated via ReLoCk. It can be observed that tracking continues even under cell deformation.

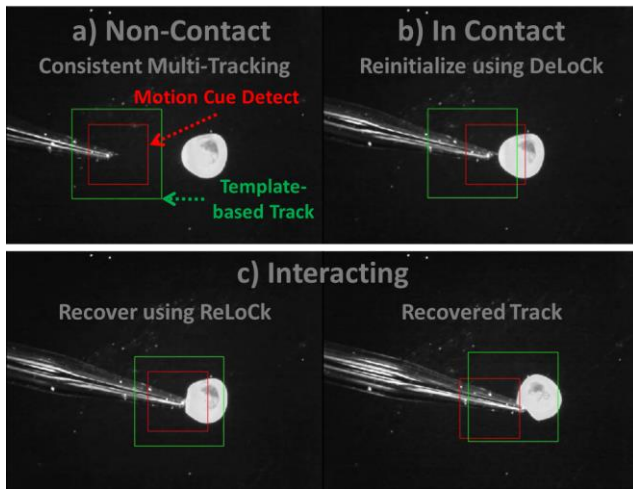


Figure 9. Results of DeLoCk and ReLoCk against occlusion and deformation; Large green and small red ROI denote updated template tracking and motion cue detection, respectively

### C. Localization Accuracy

#### 1) Comparison of Various Tracking Modes

To quantitatively evaluate the performance of DeLoCk and ReLoCk, we performed tracking with various approaches on a visually servoed path of the tool tip. Figure 10 is an illustration of the tracking results using methods including, fixed template matching, motion cue feature detection, and a hybrid workflow with recovery (D- & ReLoCk). These tracking results are overlaid onto a composite image superimposed with scenes in ten intervals within the 258 frames during the manipulation.

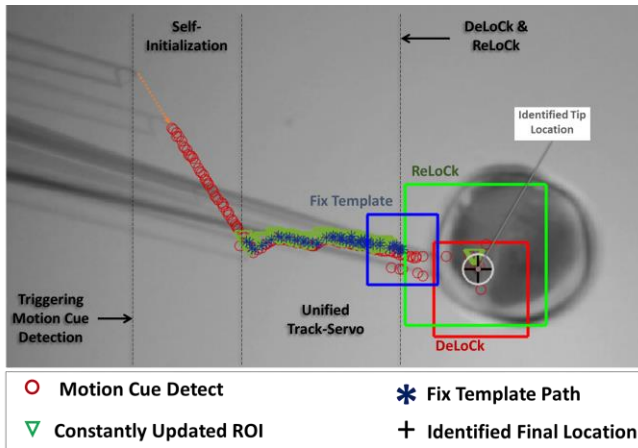


Figure 10. Composite image with overlays of motion history during tool-cell interaction; tracking labels are enhanced for annotation purpose in this particular image

Figure 11 is a close-up of the tracked path plotted in image coordinates after self-initialization. It can be observed that the localized final position is not accurate due to cell occlusion and deformation. Using a fixed template throughout the tracking, the error in localization is 47 pixels (= 0.59 mm). The localization errors are 12 pixels (= 0.15 mm) when tracked using motion cues detection without ReLoCk. When D- and ReLoCk are used, the error is 9 pixels (= 0.11 mm).

Under the adverse influence of specimen presence, using DeLoCk and ReLoCk reduces the localization error by more than five times. Normalizing the error by the size of the specimen (approximately 92 pixels in its longest dimension), the final localization error reduced from more than 50% to less than 10% of the specimen size.

Perfect visual localization under occlusion can be challenging, if not impossible. We do not exclude the potential fusion of other localization techniques even though the interest of this work is solely to investigate the robustness of our enhanced visual tracking approach to leverage previous work.

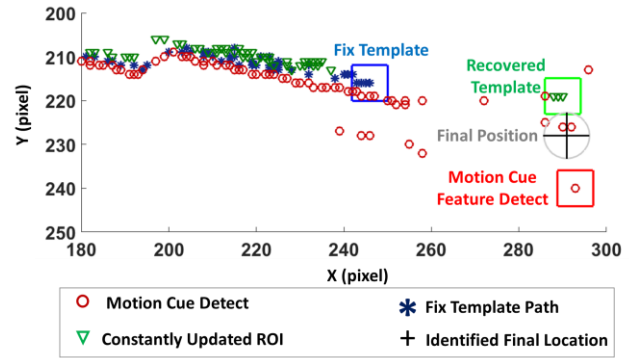


Figure 11. Tracking results using fix template, motion cue detection and recovery approach in the presence of cell

#### 2) Control Experiment in Absence of Specimen

While the previous section demonstrated the improvement in localization accuracy under the influence of cell occlusion or deformation, it is also important to investigate if there is any undesirable effect due to the incorporation of our new corrective mechanism. For this reason we designed a control experiment by repeating the same manipulation path while having the cell removed from the site. This control experiment allows us to track using the proposed mechanism and compared it with the original fix template matching approach without the influence of cell occlusion and deformation. The results are shown in Figure 12.

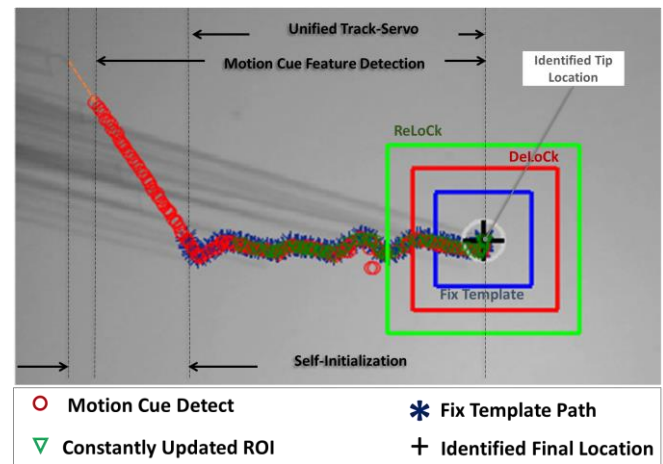


Figure 12. Composite image with overlays of motion history for the control experiment without specimen in the scene; tracking labels are enhanced for annotation purpose in this particular image

It can be observed that all tracking results have the same localization for the final position. This suggested that the three tracking approaches are generally consistent when not subjected to any adverse effect of the specimen in the scene. Nevertheless, the hybrid form of tracking is still essential as the unified track-servo framework is necessary for the manipulation of the tool trajectory in alignment to the specimen within the focal plane even though the method alone is not robust against cell occlusion and deformation.

The close-up visualization of the tracking history is presented in Figure 13. The tracking profile from the fix base template approach subjected to cell interaction is also overlaid in the graph to visualize the influence of cell occlusion and deformation. The localization results of the tip's final position are (312, 209), (313, 209), and (312, 209) for fix template matching, motion cue detection, and updated ROI template matching, respectively. The discrepancy is at most one pixels suggesting consistency in tracking when there is no negative influence from the tool-specimen interaction.

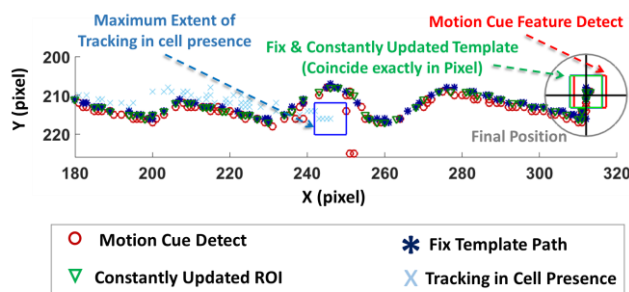


Figure 13. Tracking results using fix template, motion cue detection and recovery approach in the control experiment

## V. CONCLUSION AND FUTURE WORK

In this study, we demonstrated a tracking workflow that is robust during tool-cell interaction. This is achieved with the incorporation of two new mechanisms into our self-initializing vision-guided micromanipulation system namely, DeLoCk and ReLoCk. DeLoCk reinitializes during partial occlusion of the ROI and ReLoCk recovers tracking during false detection due to cell deformation. In the trial, DeLoCk and ReLoCk demonstrated successful tracking with improvement in localization from 50% error to less than 10% when under occlusion and deformation. This new workflow algorithm maintains uninterrupted tracking for visual servoing during tool-specimen interaction.

Future work includes gaining a better insight to design better heuristics that detect and recover from tracking failures to fully address the remaining possibility of error. This has been a common strategy for reducing uncertainty in other vision-based applications [19, 20]. Another aspect will be to investigate the feasibility of fusing tracking data from motion cue detection and the updated template matches to improve on the estimation of the tip position.

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