Unsupervised Contour Tracking of Live Cells by Mechanical and Cycle Consistency Losses

What is the problem?

Tracking the dynamic changes in the contours of live cells is a critical step in understanding cellular behaviors, including stem cell function and cancer cell movement. Live cell contours are highly deformable and lack distinct visual features, making it difficult to track their movements accurately across video frames. Traditional methods like optical flow and point set tracking are unsuitable because they assume stable visual features, which cells do not exhibit due to their fluid nature. These existing methods also fail to maintain point correspondence between frames and cannot handle cell shape changes like expansion and contraction, leading to tracking inaccuracies.

What has been done earlier?

Optical Flow: This technique attempts to track pixels frame by frame, assuming consistent and identifiable visual features between frames. However, this assumption fails for live cells, which lack easily identifiable features, making it unsuitable for cellular contour tracking. Mechanical Model: This approach used segmentation masks and physical forces like torsion and spring forces to track the points on the contour. While it helped evade some issues of feature visibility, it ignored the raw image data, leading to inaccuracies in real-world scenarios, especially during cellular expansion or contraction. These methods either fixed the number of points or didn't consider the dense correspondence needed between consecutive frames for accurate tracking of contour movements.

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What are the remaining challenges? What novel solution proposed by the authors to solve the problem?

Cellular Fluidity: Cells exhibit complex and fluid shape changes, making it difficult to track their contours using traditional methods. Point Correspondence: Tracking systems need to accurately match each point on the cell's contour from one frame to the next, which becomes difficult due to the lack of distinct visual markers. Expansion and Contraction: As the cell shape changes, the number of tracking points can increase or decrease, requiring a method that can adapt to these changes dynamically. Manual Labeling Impracticality: Labeling each point on a cell's contour manually for training purposes is time-consuming and impractical, making supervised learning methods inefficient in this context.

The authors propose a **deep learning-based contour tracking** method that uses **unsupervised learning** through mechanical and cycle consistency losses, eliminating the need for manual labeling. The **mechanical loss** ensures realistic movement of contour points, while the **cycle consistency loss** tracks points consistently forward and backward. The model handles varying numbers of points to adapt to cell shape changes like expansion and contraction. By using **cross-attention**, the method fuses features from consecutive frames, achieving higher accuracy than previous approaches.

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