TIAM+

extending the Tool for Integrative Analysis of Motility
https://github.com/r-medina/TIAM-

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Task

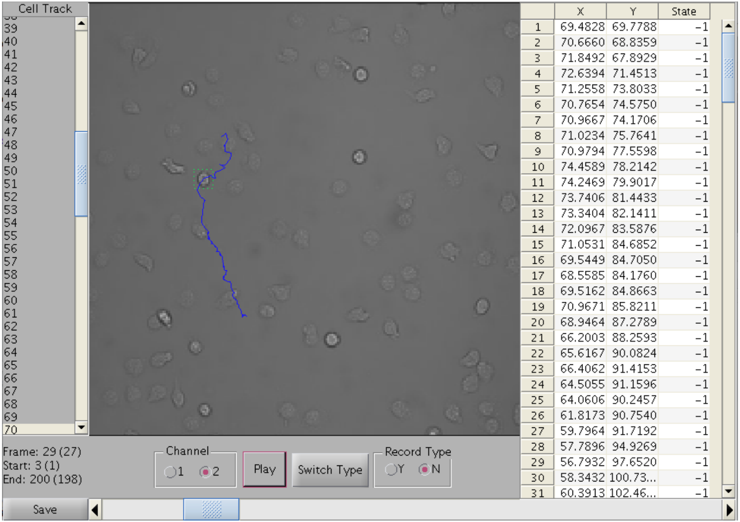
Using data from Vivek Mayya and Willie Neiswanger's TIAM tool, which performs detection and tracking of cells from multi-channel time lapse microscopy videos, build an algorithm that will classify track segments. Two initial decisions:

- 2 classes
- supervised

First tasks:

- collect supervised data
- engineer/discover useful features for segmented trajectory classification

GUI


Cell Track
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69
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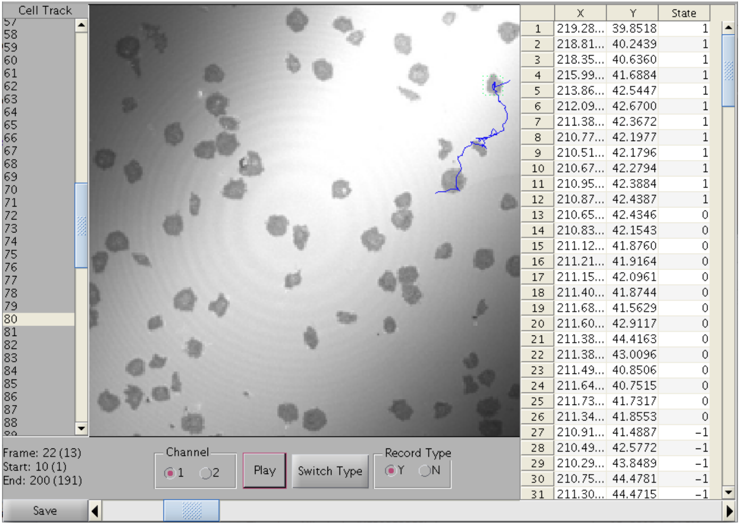
X Y State
1 69.4828 69.7788 -1
2 70.6660 68.8359 -1
3 71.8492 67.8929 -1
4 72.6394 71.4513 -1
5 71.2558 73.8033 -1
6 70.7654 74.5750 -1
7 70.9667 74.1706 -1
8 71.0234 75.7641 -1
9 70.9794 77.5598 -1
10 74.4589 78.2142 -1
11 74.2469 79.9017 -1
12 73.7406 81.4433 -1
13 73.3404 82.1411 -1
14 72.0967 83.5876 -1
15 71.0531 84.6852 -1
16 69.5449 84.7050 -1
17 68.5585 84.1760 -1
18 69.5162 84.8663 -1
19 70.9671 85.8211 -1
20 68.9464 87.2789 -1
21 66.2003 88.2593 -1
22 65.6167 90.0824 -1
23 66.4062 91.4153 -1
24 64.5055 91.1596 -1
25 64.0606 90.2457 -1
26 61.8173 90.7540 -1
27 59.7964 91.7192 -1
28 57.7896 94.9269 -1
29 56.7932 97.6520 -1
30 58.3432 100.73... -1
31 60.3913 102.46... -1
Frame: 29 (27)
Start: 3 (1)
End: 200 (198)
Channel
1 2
Play
Switch Type
Record Type
Y N
Save

GUI


Cell Track
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78
79
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87
88
Frame: 22 (13)
Start: 10 (1)
End: 200 (191)
Save
Channel
1
2
Play
Switch Type
Record Type
Y
N
X Y State
1 219.28... 39.8518 1
2 218.81... 40.2439 1
3 218.35... 40.6360 1
4 215.99... 41.6884 1
5 213.86... 42.5447 1
6 212.09... 42.6700 1
7 211.38... 42.3672 1
8 210.77... 42.1977 1
9 210.51... 42.1796 1
10 210.67... 42.2794 1
11 210.95... 42.3884 1
12 210.87... 42.4387 1
13 210.65... 42.4346 0
14 210.83... 42.1543 0
15 211.12... 41.8760 0
16 211.21... 41.9164 0
17 211.15... 42.0961 0
18 211.40... 41.8744 0
19 211.68... 41.5629 0
20 211.60... 42.9117 0
21 211.38... 44.4163 0
22 211.38... 43.0096 0
23 211.49... 40.8506 0
24 211.64... 40.7515 0
25 211.73... 41.7317 0
26 211.34... 41.8553 0
27 210.91... 41.4887 −1
28 210.49... 42.5772 −1
29 210.29... 43.8489 −1
30 210.75... 44.4781 −1
31 211.30... 44.4715 −1

Features

Helmuth *et al.* paper titled "A novel supervised trajectory segmentation algorithm identifies distinct types of human adenovirus motion in host cells" offers a methodology (features and procedure) for classifying segments of cell tracks. The features for some trajectory part P_j of l_w steps are:

- Net displacement
- Straightness
- Bending
- Efficiency
- Asymmetry
- Point position skewness
- Point Position kurtosis

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- Net displacement:
$$p_1 = \|\vec{x}_{j+l_w} - \vec{x}_j\|$$
- Straightness
- Bending
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Features

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- Net displacement
- Straightness:

$$p_2 = \frac{1}{l_w - 1} \sum_{i=j}^{j+l_w-2} \cos \beta_i$$

- Bending
- Efficiency
- Asymmetry
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- Net displacement
- Straightness
- Bending:

$$p_3 = \frac{1}{l_w - 1} \sum_{i=j}^{j+l_w-2} \sin \beta_i$$

- Efficiency
- Asymmetry
- Point position skewness
- Point Position kurtosis

Features

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- Net displacement
- Straightness
- Bending
- Efficiency:

$$p_4 = \frac{\|\vec{x}_{j+l_w} - \vec{x}_j\|^2}{l_w \sum_{i=j}^{j+l_w-1} \vec{s}_i^2}$$

  where $\vec{s}_i$ is the "step" from $\vec{x}_i$ to $\vec{x}_{i+1}$
- Asymmetry
- Point position skewness
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- Net displacement
- Straightness
- Bending
- Efficiency
- Asymmetry:
$$p_5 = -\log\left(1 - \frac{(\lambda_1 - \lambda_2)^2}{2(\lambda_1 + \lambda_2)^2}\right)$$
where λ_1 and λ_2 are the eigenvalues of R, the 2D radius of gyration tensor of the set of all points in P_j
- Point position skewness
- Point Position kurtosis

Features

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- Net displacement
- Straightness
- Bending
- Efficiency
- Asymmetry
- Point position skewness:

$$p_6 = \frac{\sqrt{l_w + 1}\sum_{i=j}^{j+l_w}(x_i - \langle x_i \rangle)^3}{\left(\sum_{i=j}^{j+l_w}(x_i - \langle x_i \rangle)^2\right)^{3/2}}$$

- Point Position kurtosis:

$$p_7 = \frac{\sqrt{l_w + 1}\sum_{i=j}^{j+l_w}(x_i - \langle x_i \rangle)^4}{\left(\sum_{i=j}^{j+l_w}(x_i - \langle x_i \rangle)^2\right)^{2}}$$

where x_i is the projection of the points in P_j onto the dominant eigenvector $\vec{v}$ of R: $x_i = \vec{x}_i \cdot \vec{v}$.

Features

Other features we're considering:

- Mean-squared displacement (MSD):

$$MSD(\Delta t) = \langle \{(x(t+\Delta t)) - (x(t))\}^2 + \{(x(t+\Delta t)) - (x(t))\}^2 \rangle$$

- Diffusion coefficient: taken from the initial slope of the MSD for a given track segment
- Feature developed by Simson *e al.* to detect temporary confinement:

$$L = \begin{cases} -\log(\Psi) - 1 & \Psi \leq 0.1 \\ 0 & \Psi > 0.1 \end{cases}$$

  where $\log \Psi = 0.2048 - 2.5117 Dt/R^2$ and D is the diffusion coefficient, t is some period of time, and R is the maximum distance the particle travelled during that time.

Algorithm

Helmuth *et al.* propose using a support vector machine (SVM) learning model—we intend to do the same.