

Autonomous Tumour Cell Classification from Texture analysis of the Spatial organisation of the Intracellular Cytoskeleton in Confocal images

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Background

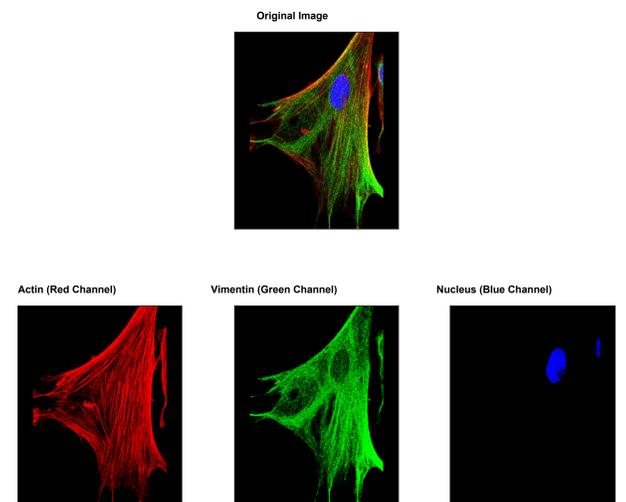
The metastatic dissemination of cancer cells in the body is the major cause of cancer death. How normal cells transform to motile, metastasising cells is not well understood. In this work we analyse a cell model representing the different stages of oncogenic cell transformation; A normal, primary cell type from a healthy individual, an Immortalised variant, an Oncogene-expressing variant, and a metastasising variant of the normal cell type.

Previous work was able to use machine learning algorithms to differentiate between a normal and a metastasising cancer cell based on image histogram features. However, distinguishing between the Immortalised Variant and the Oncogene-expressing Variant was found to be unreliable. Further, the global nature of these features did not offer sufficient transparency from a biological standpoint.

In this work texture feature maps, of both Actin and Vimentin, are developed that accounts for local spatial variations across cells. The spatial aspect of this analysis may further facilitate knowledge discovery with respect to the causes of metastasis.

Methods

- Haralick Feature Extraction [1]**
 - Form GLCM (Gray Level Co-Occurrence Matrix) (Fig.1) for each channel.
 - GLCM encodes the frequency that one gray level occurs with a specific spatial relation (angle and distance) to another gray level
 - Features, such as homogeneity, extracted from GLCM are dependent on the spatial relation used
- Invariant Feature Extraction as proposed in [2]**
 - Obtain GLCMs for 7 spatial relations (4 rotations (0,45,90,135°) and 3 offsets (1,2 and 3 pixel offsets)).
 - Extract Haralick features, f_n , from each GLCM and form Symmetric matrix F .
 - Compute Eigenvalues of Symmetric Matrix, .
 - Sum the first 3 Eigenvalues to obtain a single invariant feature from each Symmetric Matrix.
- Texture Maps**
 - Split all images into 100 pixel image grids.
 - Obtain features of each image grid.
 - Scatter plot Energy vs Homogeneity (Fig.3).
 - Select mapping points on each curve.
 - Map each grid to closest curve point and assign specific value.
 - Form texture maps of the whole image using the assigned values (Fig.4-7).



X \ Y	1	2	3	4	5	6	7	8
1	442956	24460	101	0	4	0	0	0
2	24460	52370	4966	151	10	0	0	0
3	101	4966	7344	1332	54	1	0	0
4	0	151	1332	1320	335	22	0	0
5	4	10	54	335	380	96	5	0
6	0	0	1	22	96	52	7	0
7	0	0	0	0	5	7	16	2
8	0	0	0	0	0	0	2	0

Figure 1. Example of Gray Level Co-Occurrence Matrix. Each grid represents how often a pixel with intensity value X appears next to a pixel with intensity value Y.

$$\mathbf{f} = [f_1, f_2, \dots, f_{k-1}, f_k]$$

$$\mathbf{F} = \begin{pmatrix} f_1 & f_2 & \dots & f_{m-1} & f_m \\ f_2 & \dots & \dots & f_m & f_1 \\ \dots & \dots & \dots & \dots & \dots \\ f_{m-1} & f_m & \dots & \dots & \dots \\ f_m & f_1 & \dots & \dots & f_{m-1} \end{pmatrix}$$

X \ Y	1	2	3	4	5	6	7	8	9	10	11	12
1	1.37	1.55	0.86	1.6	2.16	2.85	1.87	3.03	3.25	4.51	2.8	4.8
2	1.55	0.86	1.6	2.16	2.85	1.87	3.03	3.25	4.51	2.8	4.8	1.37
3	0.86	1.6	2.16	2.85	1.87	3.03	3.25	4.51	2.8	4.8	1.37	1.55
4	1.6	2.16	2.85	1.87	3.03	3.25	4.51	2.8	4.8	1.37	1.55	0.86
5	2.16	2.85	1.87	3.03	3.25	4.51	2.8	4.8	1.37	1.55	0.86	1.6
6	2.85	1.87	3.03	3.25	4.51	2.8	4.8	1.37	1.55	0.86	1.6	2.16
7	1.87	3.03	3.25	4.51	2.8	4.8	1.37	1.55	0.86	1.6	2.16	2.85
8	3.03	3.25	4.51	2.8	4.8	1.37	1.55	0.86	1.6	2.16	2.85	1.87
9	3.25	4.51	2.8	4.8	1.37	1.55	0.86	1.6	2.16	2.85	1.87	3.03
10	4.51	2.8	4.8	1.37	1.55	0.86	1.6	2.16	2.85	1.87	3.03	3.25
11	2.8	4.8	1.37	1.55	0.86	1.6	2.16	2.85	1.87	3.03	3.25	4.51
12	4.8	1.37	1.55	0.86	1.6	2.16	2.85	1.87	3.03	3.25	4.51	2.8

Figure 2. Symmetric Feature Matrix for a single feature.

Results

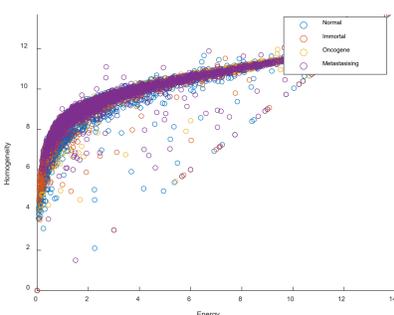


Figure 3. Homogeneity vs Energy feature curves.

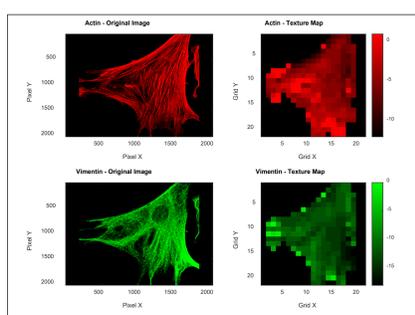


Figure 4. Texture Maps of a Primary Cell.

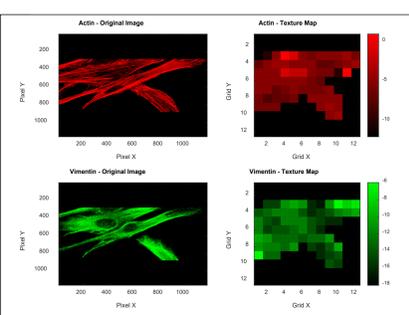


Figure 5. Texture Maps of an immortalised Variant.

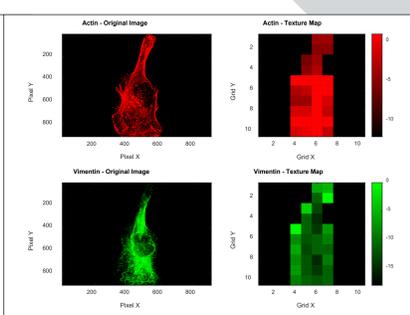


Figure 6. Texture Maps of an Oncogene Expressing Variant.

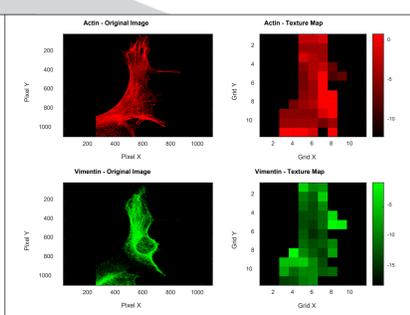


Figure 7. Texture Maps of a Metastasing Cell.

Summary and Conclusions

- Invariant texture features are extracted from Actin and Vimentin images of four cell lines.
- Global measures of texture showed no discrimination between cell lines.
- Development of texture maps based on the combination of two texture features (Energy and Homogeneity) .
- In general it was found that normal cells showed lower levels of homogeneity and energy compared to metastasising cells.
- Future work will concentrate on a machine learning approach to investigate correlations between cell lines and higher dimensional feature vectors maps that combines information from Actin, Vimentin and further texture features into a single analysis.

References

- [1]R. Haralick, K. Shanmugam and I. Dinstein, "Textural Features for Image Classification", *IEEE Transactions on Systems, Man, and Cybernetics*, vol. -3, no. 6, pp. 610-621, 1973. Available: 10.1109/tsmc.1973.4309314.
- [2]L. Putzu and C. Di Ruberto, "Rotation Invariant Co-occurrence Matrix Features", *Image Analysis and Processing - ICIAP 2017*, pp. 391-401, 2017. Available: 10.1007/978-3-319-68560-1_35

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