

Content Based Image Retrieval in Digital Pathology

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Content Based Image Retrieval in Digital Pathology

Declan Kieran¹, Yinhai Wang¹, Danny Crookes², Peter Hamilton¹.

¹Bio-imaging & Informatics, Centre for Cancer Research & Cell Biology, Queens University Belfast.

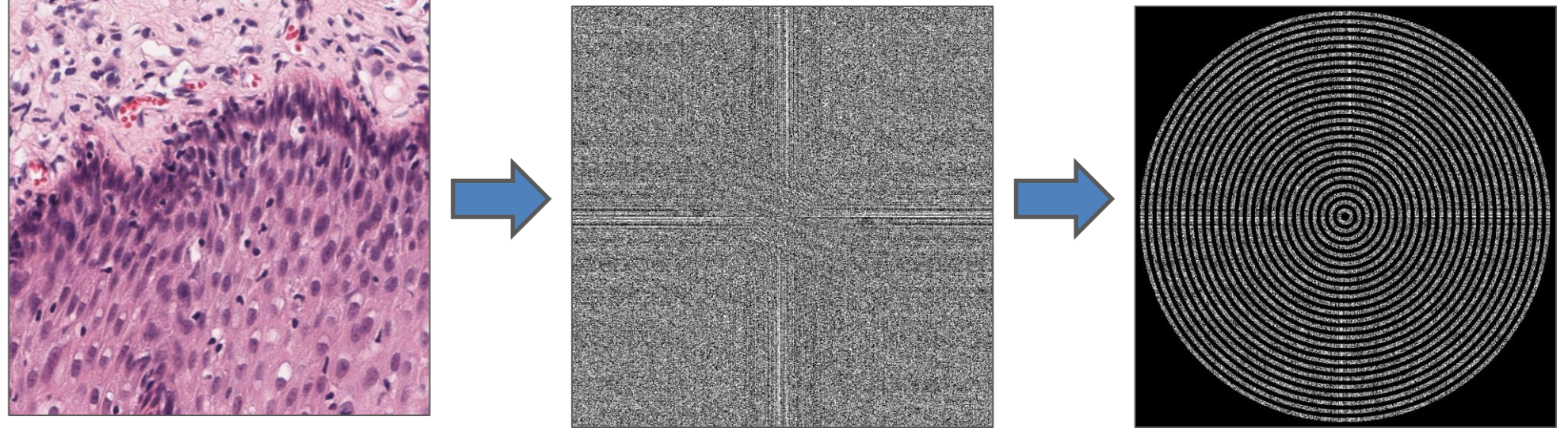
²Institute of Electronics, Communications and Information Technology, Queens University Belfast.

Overview

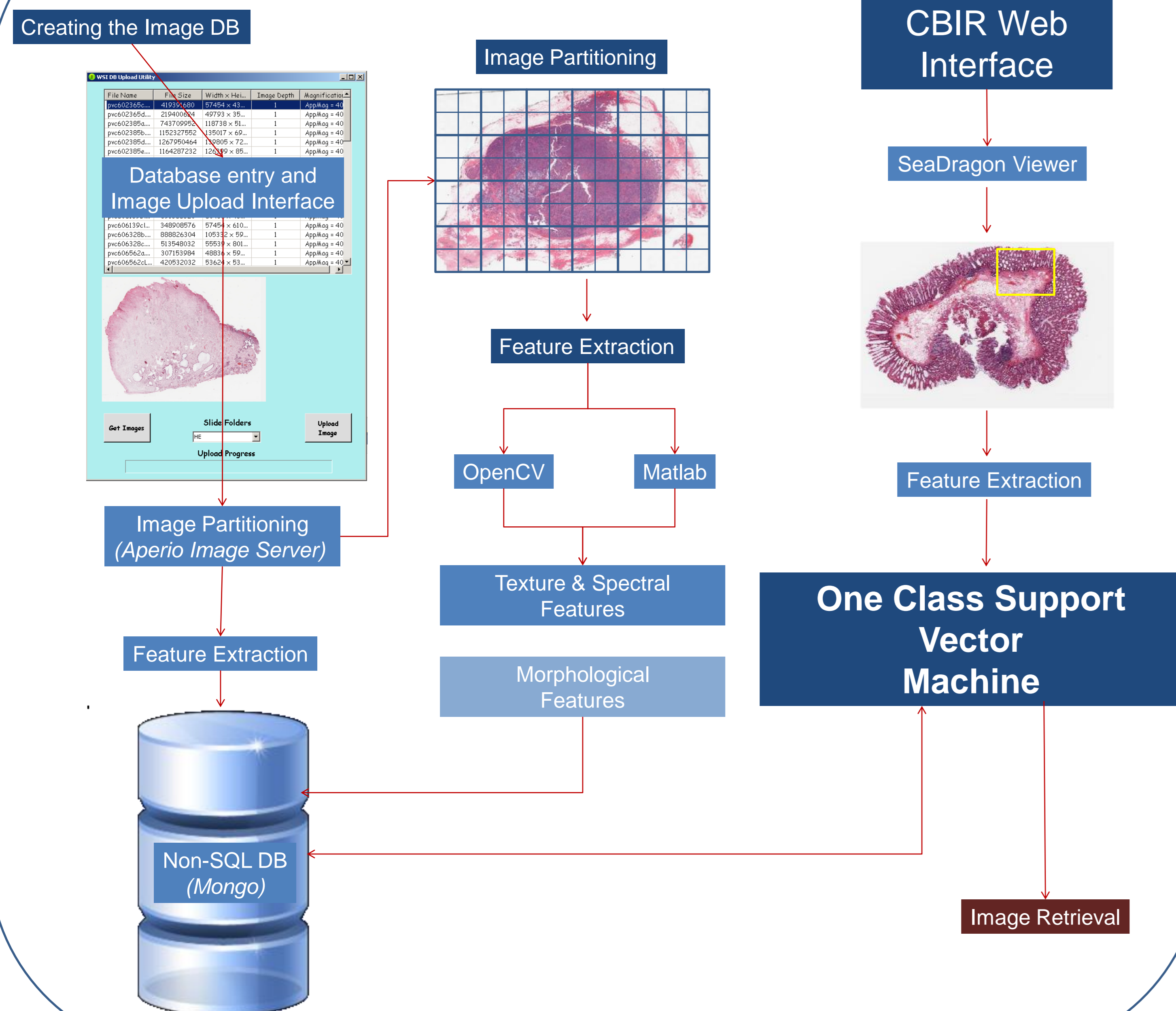
The proposed CBIR system works in the following way:

- i) An end-user is able to select a region of interest/concern from a candidate digital slide
- ii) A robust set of textural and spectral features are calculated on the selected region
- iii) This feature vector derived from the user-given image region is then trained to form a Support Vector using one-class Support Vector Machine (SVM) classification
- iv) A large set of virtual slides from a database is then queried
- v) Corresponding feature vectors for every region of the digital slides stored in the database are calculated
- vi) Pattern recognition is performed using the previous trained Support Vector and SVM for all feature vectors
- vii) The result from SVM, the so called decision value is then used as indication regarding how similar a region of an image in the database is to the candidate user selected region
- viii) Using the similarity metric, the top most similar images are retrieved from the archive.

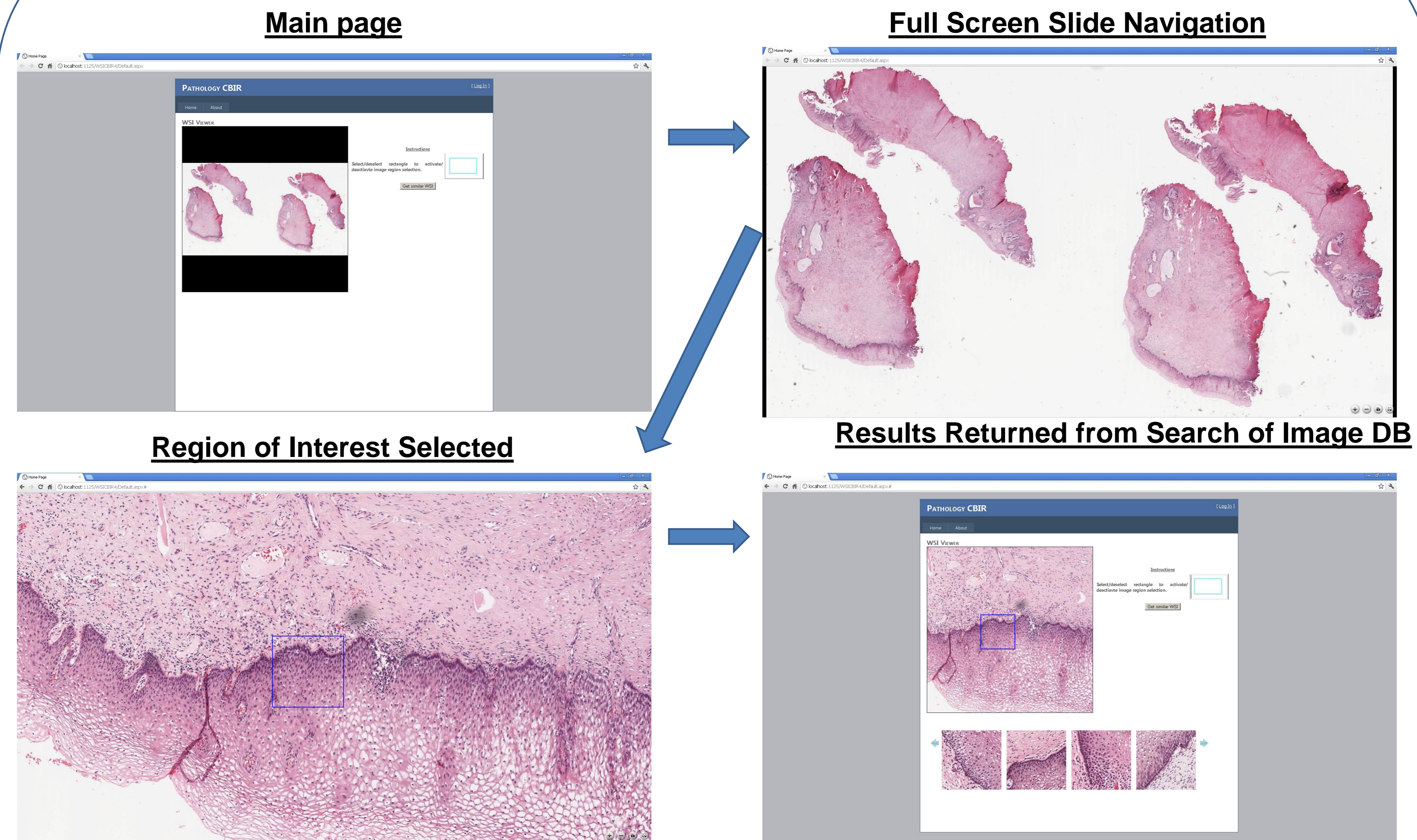
Features

Texture Measurements	2D Invariant Moments	Spectral Measurements of Texture
$m = \frac{1}{n} \sum_{i=1}^n x_i$	Normalised central moment $\rightarrow \eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\frac{p+q}{2}}}$, where $\gamma = \frac{p+q}{2} + 1$	2D Fourier Spectrum $\rightarrow F(u, v) = \int \int_{-\infty}^{\infty} f(x, y) e^{-j2\pi(ux+vy)} dx dy$
$\sigma = \left(\frac{1}{n-1} \sum_{i=1}^n (x_i - m)^2 \right)^{\frac{1}{2}}$	$\phi_1 = \eta_{20} + \eta_{02}$	2D Spectral Measures of Texture $\rightarrow S(r, \theta)$, where r is a radial direction and θ is a curve centred around the DC channel
$smoothness = 1 - 1/(1 + \sigma^2)$	$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2$	<ul style="list-style-type: none"> Below gives an illustration of how spectral measurements of texture are taken Using these spectral bands provides a mean of performing very fast pseudo-segmentation This allow for higher level measurements of structure and pattern to be taken by taking texture measurements directly from these spectral bands within the Fast Fourier Transform of a given image
$third\ moment = \sum_{i=1}^n (x_i - m)^3 p(x_i)$	$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$	
$uniformity = \sum_{i=1}^n p^2(x_i)$	$\phi_4 = (\eta_{30} - \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$	
$entropy = - \sum_{i=1}^n p(x_i) \log_2 p(x_i)$	$\phi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} - \eta_{12})[(\eta_{30} - \eta_{12})^2 - 3(\eta_{21} - \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{21} + \eta_{03})^2 - (\eta_{21} - \eta_{03})^2]$	
$skewness = \frac{E(x - m)^3}{\sigma^3}$	$\phi_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})$	
$kurtosis = \frac{E(x - m)^4}{\sigma^4}$	$\phi_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$	

System Architecture



CBIR Web Interface



Conclusions

CBIR has been shown to be feasible for WSI using texture and spectral feature measurements with a One Class SVM used as a classifier.

Further work needs to be developed to support high throughput analysis and evaluation on large image libraries. The computational complexity of working with such large imagery as well as the associated feature calculation is substantial.

It is clear the massively parallel nature of the problem can be exploited to provide a fast, real-time manageable CBIR system.