# Texture Based Classification of Topographic Objects

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## 1. Introduction

Geographical data is being generated at an ever-increasing rate by organisations involved with remote sensing, surveying and mapping. To capture semantic content of this data manually is expensive and so to address this issue, research carried out by our group, the Intelligent and Graphical Systems group of the Department of Computer Science, involves the capture and automatic structuring of data for various kinds of graphical information system. If this task can be automated, it will increase the availability of data and decrease its cost.

The goal of the systems currently in place is the recognition and classification of geographical features solely from vector data sets that have been captured through manual digitisation. Modifying the existing classification systems to deal with raster image data (such as remotely sensed images) is desirable for two reasons:

- Most captured data is initially in a raster data format and must be converted to vector formats
- The raster data can contain useful semantic information (such as colour, texture etc.) that is lost in the conversion

We propose to extend the application and effectiveness of our existing software by incorporating semantic information derived from raster data into our existing vector models.

This work can be decomposed into several elements:

- Geometric rectification – align the two data sets.
- Object extraction – which is relatively simple due to data sets being aligned.
- Calculate feature vector – to be used in classification.
- Classification – classify objects with appropriate feature code.

## 2. Geometric rectification

The first step in the process is the alignment of the vector and raster image data sets. This allows us to identify the part of the raster image that corresponds to any polygon in the vector data. The process involves choosing *ground control points* (GCPs). The GCPs determine a first order polynomial *geometric transformation* (Equation 1) where (x, y) represents a point in the original image and (x', y') a point in the rectified image. *Bilinear interpolation* is used to calculate the intensity values of the output-rectified image.

$$x' = a_0 + a_1x + a_2y \qquad (1)$$
$$y' = b_0 + b_1x + b_2y$$

Calculating the *root-mean-square error* (RMSE) (Equation 2) is used to see which GCPs exhibit the greatest error and remove them.

$$RMSE = [(x' - x)^2 + (y' - y)^2]^{0.5} \qquad (2)$$

### 3. Object extraction

For a given polygon in the vector data we extract the part of the raster image that corresponds to that polygon.

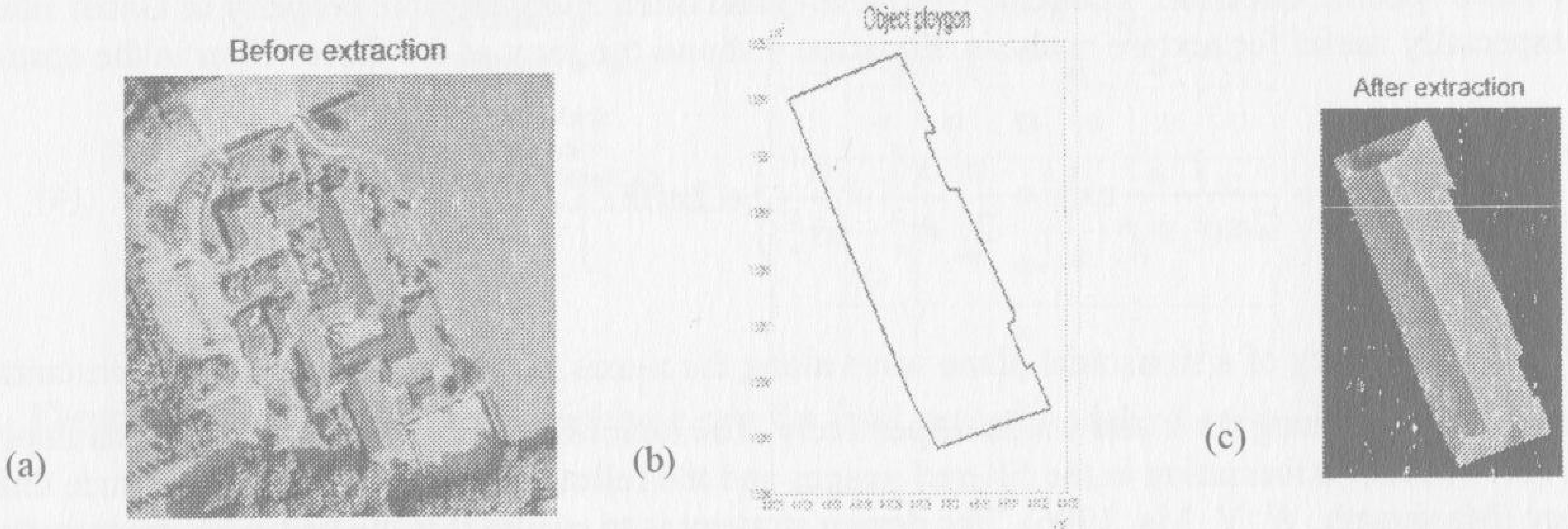


**Figure 1.** (a) Raster image before extraction. (b) Polygon corresponding to building located in centre of raster image. (c) Raster image with building extracted. (Sample data from Ordnance Survey, Southampton)

Figure 1 shows an example of the extraction process. The output image is significantly smaller then the input image. This is achieved by finding the minimum and maximum x and y values of the polygon creating another polygon. The image is then cropped with this polygon. This is essential for computation to be done in reasonable time.

### 4. Calculate feature vector

Texture is a repetitive pattern in which elements or primitives (pixel groups) are arranged according to a placement rule. A feature vector is a series of numbers, derived using the rule, that describe the texture. Taking the extracted object we measure its texture using standard models. All these models were redefined so they measure the texture of the object alone and not the background, with the object capable of varying in shape and size. This is achieved using the assumption that the object does not contain the pixel value zero and setting all background pixel values to zero. This is a reasonable assumption because all aerial photographs are taken at daytime in good light. We also make the assumption that all objects can be orientated at any angle so all texture measures must be rotation invariant. This research is concentrated on three different measures of texture: Co-occurrence matrices, Gabor filters and Gaussian Markov random fields.

#### 4.1. Grey level co-occurrence matrices

*Second-order statistics* have been shown to simulate the human perception of texture (Julesz, B, 1973). Haralick (Haralick, R.M. 1973) was the first to suggest the use of co-occurrence matrices to model these *second-order statistics,* which has become one of the most widely known and used texture models.

$$F_i^{MDMO} = \frac{1}{|\Delta|}\sum_{d\in\Delta}\frac{1}{|\Theta|}\sum_{\theta\in\Theta} f_i(d,\theta) \qquad (3)$$

There is no known rigorous optimal method for selecting displacement d and orientation θ for co-occurrence matrices. The mean displacement and mean orientation (MDMO) approach is used (Soh, Leen-Kiat. Tsatsoulis, Costas. 1999). This approach normalizes the feature vector over different displacement and angles (Equation 3) and is rotation invariant. $F_i$ represents a particular texture feature. Values 0°, 45°, 90° and 135° were selected for θ and values 1, 2, 4, 8 were selected for d. It was decided not to use larger displacements (a common practice) due to the small pixel width of the objects, which can be as small as 25 pixels. *Second-order-statistics* containing the value zero (background) are not included in calculations. The texture features used are energy, contrast, entropy, correlation and maximum probability. Classification is performed using a Euclidean distance.

### 4.2. Gabor filters

Gabor filters have been successfully applied to many imaging and many multidimensional signal-processing applications. Gabor filters are a group of wavelets, with each wavelet capturing energy at a specific frequency and a specific direction. The scale (frequency) and orientation tuneable property of Gabor filter makes it especially useful for texture analysis. Equation 4 shows the form of the Gabor filter in the spatial domain.

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)+2\pi jWx\right] \tag{4}$$

Where $W$ is the frequency of a sinusoidal plane wave along the x-axis, $\sigma_x$ and $\sigma_y$ are the space constants of the gaussian envelope along the x and y axis respectively. The nonorthogonality of Gabor wavelets implies that there is redundant information in the filtered images and the following strategy is used to reduce this redundancy (Manjunath, W. Y. Ma, 1996). The design strategy is to ensure that the half-peak magnitude support of the filter response in the frequency spectrum touch each other as shown in Figure 2.

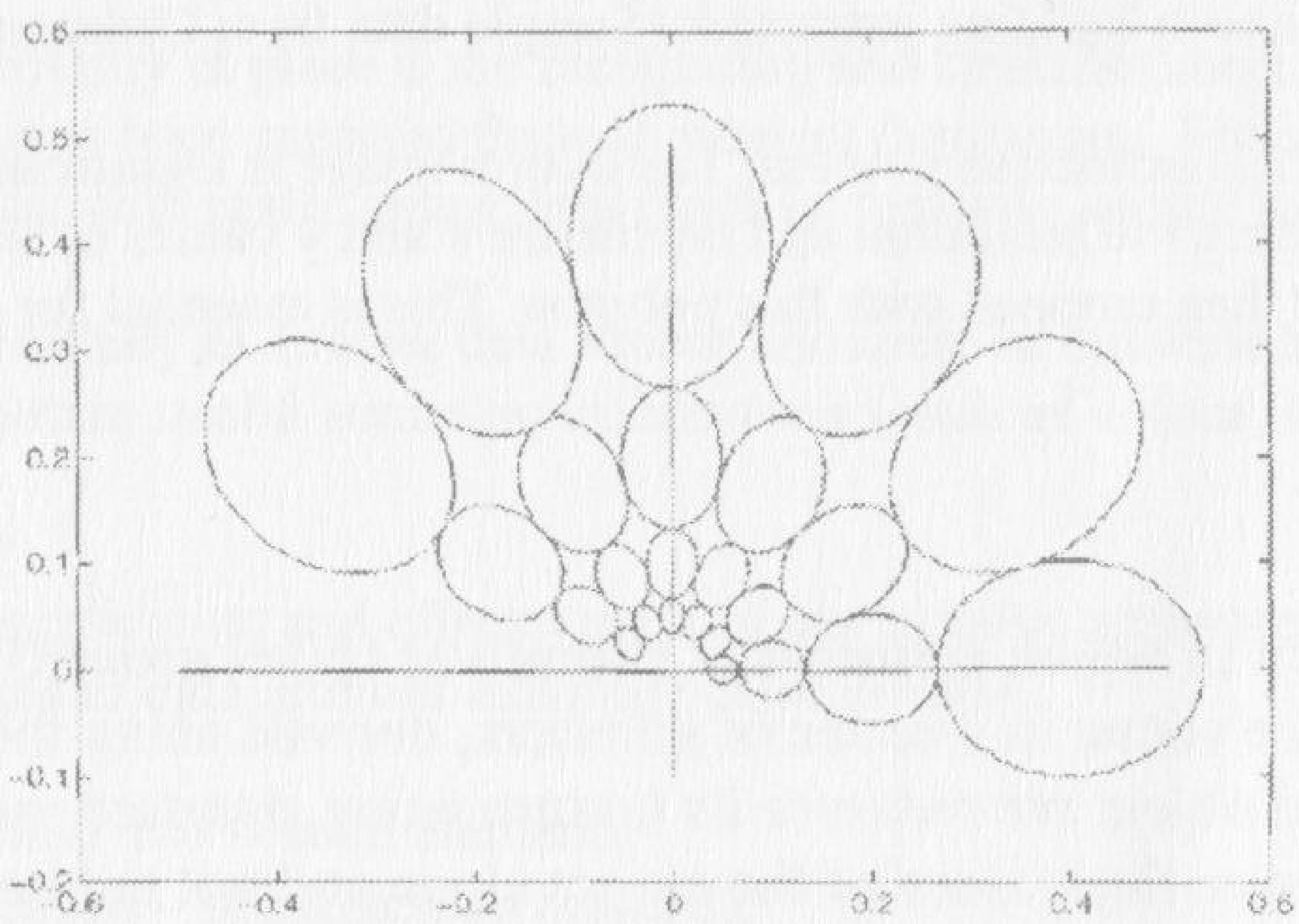

**Figure 2.** The contours indicate the half-peak magnitude of the filter responses in the Gabor Filter bank. The filter parameters used are $U_h = 0.4$, $U_l = 0.05$, S = 4 and K = 4.

Smaller filter kernels were achieved using values $U_h = 1$, $U_l = 0.4$. Ensure the filter kernel does not go outside the object boundary. I have shown that when the filter kernel is allowed to pass the boundary of the object (equivalent to zero padding) classification tends to favour objects of similar shape. The mean and standard deviation of filtered images energy represent our feature vector (Zhang and Lu, 2000). A simple circular shift on the feature map is used to solve the rotation variant problem associated with Gabor filters (Zhang and Lu, 2000). Classification is performed using Euclidean distance.

### 4.3. Gaussian Markov random fields (GMRFs)

GRMFs have been shown to perform well in texture classification. In the GRMF model, the texture is represented by a set of zero mean observations.

$$y(s), s \in \Omega, \Omega = \{s = (i,j) : 0 \le i, j \le M-1\} \tag{5}$$

for MxM lattice. The r GRMF model assume the observation abbey the following equation,

$$y(s) = \sum_{r \in N_s} \theta_r y(s+r) + e(s) \tag{6}$$

where $N_s$ is a neighbour set dependent on the order and type of model used, θ is the GRMF parameter for neighbourhood r and e(s) a stationary Gaussian noise sequence. The GMRF parameters for a given texture are calculated using a least squares method and these represent our feature vector. Traditional GRMF features are not rotation invariant. It was found that to achieve rotation invariance, the neighbour set should circularly symmetric in all directions as shown in Figure 3(Porter, R. and Canagarajah, N.). A third order neighbourhood is used in our tests and Euclidean distance is used for classification. The neighbourhood must not be allowed to pass outside the boundary of the object.

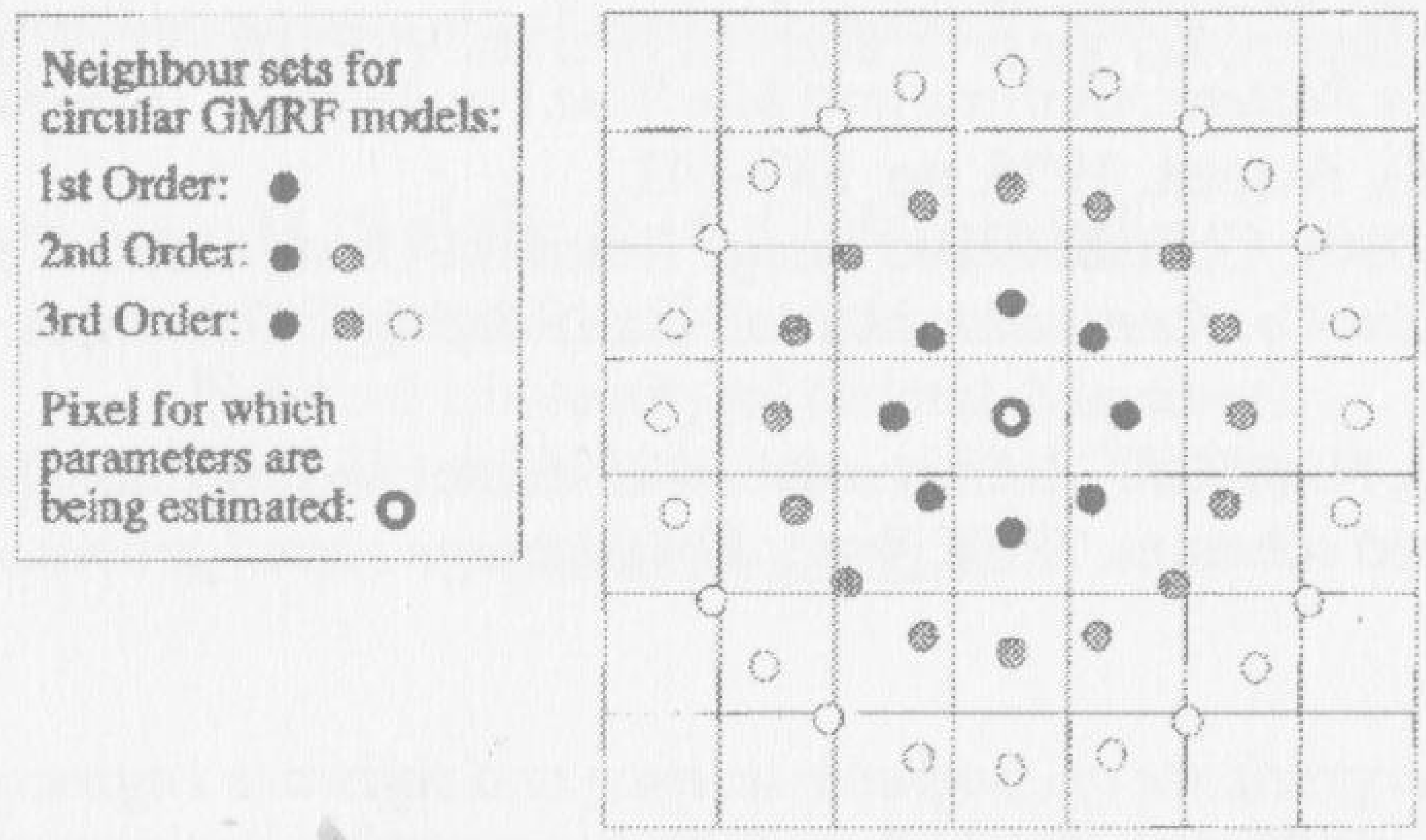


**Figure 3.** Circular symmetric neighbour sets for first, second and third order circular GRMF models

## 5. Results

We have limited the task to identifying roads and buildings. A breakdown of results is shown in Table 1. It must be stressed that these are just preliminary results based on measuring the Euclidean distance between two samples directly. A nearest neighbour classifier and Bayesian classifier will be implemented by the end of the project in March, which should improve results.

| *Texture model* | *Percentage of buildings classified correctly* | *Percentage of roads classified correctly* |
|---|---|---|
| Grey level co-occurrence matrices | 11% | 9% |
| Gabor Wavelets | 62% | 33% |
| Gaussian Markov random fields | 20% | 15% |

**Table 1.** Preliminary results using a Euclidean distance classifier

## 6. Conclusions

Using existing models of texture, we have applied them to this novel problem. Existing models of texture assume to input image only contains the texture to be measured, as opposed to our problem where the input image contains the texture to be measured and background, with the textured object capable of varying in shape and size. We have successfully created software to overcome this problem. Another problem encountered is that existing models were previously mostly tested on input images of larger size (64x64 pixels or greater). Three models were implemented with varying classification accuracy. Gabor filters achieve the greatest classification accuracy of all the models tested.

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**Biography**

*Padraig Corcoran is an undergraduate of computer science and software engineering in the National University of Ireland Maynooth. He is in final year of this four year degree course. This paper is the result of an internship he had with the National Institute for Regional and Spatial Analysis (NIRSA) at NUI Maynooth in summer 2003 and his final year project, due for completion in March 2004.*