Research Article

A Non-geographical Application of Spatial Information Systems in Pupillometry

Brett A Bryan
GISCA – The National Centre for Social Applications of GIS
University of Adelaide

Benjamin P Stone
Department of Psychology
University of Adelaide

Abstract
Spatial analysis and spatial information systems have great potential in many non-geographic domains. This paper presents an example of the utility of spatial analysis in a non-geographic domain. A technique of pupillometry using digital infrared video loosely coupled with a Spatial Information System and a spreadsheet is developed to accurately quantify pupil dilation magnitude and constriction onset latency for participants of different cognitive ability and under different cognitive loads. Spatio-temporal pupil dynamics of participants are recorded using digital infrared video. The pupil to iris area ratio is calculated for over 470,000 temporally sequenced de-interlaced video fields by automatic feature extraction using a combination of threshold analysis, spatial smoothing and areal filtering. Pupil dilation magnitudes and constriction onset latencies are calculated through post-processing in a spreadsheet. The study identifies inadequacies in current spatial analytical techniques for automatic feature extraction not necessarily evident in geographic applications. Issues impeding the employment of spatial analysis in non-geographic domains including the lack of a generic spatial referencing system are identified and discussed.

1 Introduction

Over recent years, the term spatial has proceeded to replace the term geographic amongst many aspects of the profession and science of spatial information. Part of the justification for the increased usage of the term Spatial Information Systems (SIS) rather than Geographic Information Systems (GIS) has been the realisation that geographic is semantically limited to phenomena pertaining to the earth. The term spatial on the other
hand, encapsulates a much broader suite of applications. Whilst countless studies attest to the wide utility of SIS in analysing geographic phenomena, SIS can also be useful for visualising and analysing the spatial characteristics (for example – area, distance and shape) of a wide variety of phenomena not pertaining to the earth. Nearly a decade and a half ago, Dangermond and Smith (1988, p 309) envisaged the wider application of spatial technologies to the mapping and visualisation of non-geographic domains:

It is possible that the wider availability of automated mapping technology will encourage users to map – in the cartographic or GIS sense – the human brain, the way in which the AIDS virus travels through the human body or the natural environment of bacteria at a scale of perhaps 10,000,000:1. Using this technology, users may begin to map the seeming aspatial worlds of human decision making or crowd phenomena, or more effectively map the multiple dimensions of time, space and self perception in which every human being exists.

Spatial information is used in a wide range of non-geographic applications that do not use the earth as a spatial reference point. Probably the largest usage of non-geographic but spatial information occurs in architectural and engineering design. Architects commonly create plans and scale drawings of buildings and other constructions that make use of distance, area and other inherently spatial calculations. Engineers and designers also routinely produce scale drawings of objects. In these and other similar fields, the integrity of the spatial dimensions of the object is important and influences the success of future activities which rely on the drawings. Commonly, features within these non-geographic but spatial representations are referenced to some arbitrary point or are relative to the object itself. Usually, the value of the spatial information in these applications is simply in creating an accurate scale representation of the object under study for visualisation and reference.

Visualisation of the spatial distribution of other non-geographic phenomena has been employed in the medical field. The BodyViewer software uses a spatial information system to map, on a human body, the frequency of different body parts affected by diseases and injuries (www.geohealth.com). Old (2001) used a SIS to visualise the structure of the information science discipline using author citation data that had been subject to Multidimensional Scaling. The Kohonen Self-Organizing Map neural network architecture and correspondence analysis are examples of other techniques used in the spatial visualisation of data from a wide range of phenomena.

Beyond visualisation, spatial analysis is being employed in the field of medical imaging in the form of automatic analysis of images of human and animal body parts from X-ray computed tomography (CT), magnetic resonance imaging (MRI), ultrasound and other technologies. Glasbey et al. (1996) and Glasbey and Robinson (1999) have reported techniques for the automatic detection of sheep lumbar tissue and calculation of bone volume in the automated search for abnormalities from medical images.

However, publication of the extension of spatial analysis and Spatial Information Systems to non-geographic problems in the GIS literature has been limited to date. In this paper we aim to demonstrate the wider utility of spatial analysis and SIS in quantifying spatial characteristics and metrics beyond the geographical realm. We present a very different, non-geographic application of SIS in the field of cognitive psychology. We loosely couple digital infrared video, a SIS, and a spreadsheet to create a pupillometer, and use it to quantify the spatio-temporal reflex dynamics of the human pupil under different experimental conditions.
This paper presents a method of pupillometry used as part of a broader study. The general hypothesis underlying the broader study is that pupil reflex dynamics are related to cognitive ability. In the experimental design, participants were asked to perform three tasks of increasing cognitive difficulty in a darkened room whilst being periodically exposed to a light stimulus. During the experiment, the pupil responses of participants were recorded using infrared digital video and the data imported into a SIS. The extent of the pupil in each de-interlaced field of each frame is extracted from the digital video using threshold analysis, the pupil extent is refined using a boundary smoothing algorithm and areal filtering, and the area of pupil is calculated using zonal operations, all within a SIS. Temporal sequences of pupil dynamics are analysed in a spreadsheet. The data produced by this technique are used to assess relationships between pupil dynamics and cognitive ability. Some background on the relationship between cognitive ability, the pupil reflex and pupillometry is provided initially, followed by a brief outline of the broader experimental design. The remainder of the paper describes and discusses the combination of digital infrared video with automatic feature extraction in a SIS in pupillometry and the implications for the extension of spatial analysis and SIS into non-geographic applications.

2 Cognitive Ability, the Pupil Reflex and Pupillometry

The search for biological correlates with intelligence has been an active field of research in cognitive psychology for some time (Brody 1992). Brain nerve conduction velocity (Reed and Jensen 1991), electroencephalogram (EEG), and event-related potentials (ERP) (see Deary 2000) are some of the measures of biological activity that have been used to investigate individual differences in intelligence as measured by psychometric test performance.

Associations have been found between human reflexes and measures of cognitive ability (Kimmel et al. 1967, Siddle and Glenn 1974, Smyth et al. 1999). Specifically, pupil reflexes have been related to a vast array of cognitive abilities including short-term memory (Kahneman and Beatty 1966, Peavler 1974), long-term memory (Kahneman and Beatty 1966), choice reaction time (Richer et al. 1983), language processing (Beatty and Wagoner 1978, Schluroff 1982, Hyönä et al. 1995, cited in Beatty and Lucero-Wagoner 2000), attention (Beatty 1982), mathematical task complexity (Mentz 1985, Henrich 1896, Roubinovitch 1900, Hess and Polt 1964, Boersma et al. 1970, Ahern and Beatty 1979, Schaefer et al. 1968, Steinhauser et al. 2000), and individual differences in cognitive ability tests (Boersma et al. 1970, Peavler 1974, Ahern and Beatty 1979). These studies have consistently found that greater pupillary dilation is observed when cognitive task difficulty is increased and pupil dynamics is claimed to generally reflect human information processing load (Beatty and Lucero-Wagoner 2000).

The magnitude of pupil dilation has been related to the difficulty of mathematical tasks being performed (Hess and Polt 1964, Schaefer et al. 1968, Bradshaw 1968, Ahern and Beatty 1979, Steinhauser et al. 2000) and differences in individual cognitive ability (Hess and Polt 1964, Peavler 1970, Ahern and Beatty 1979). Pupillary dilation latency has been related to the difficulty of mathematical tasks and inversely related to cognitive ability (Boersma et al. 1970). Evidence suggests that pupil constriction latency may also be related to mathematical task difficulty (Steinhauser et al. 2000), and therefore, may also be related to cognitive ability. The broader study by Stone et al. (in preparation)
investigates relationships between pupil dynamics under mathematical tasks of varying difficulty and cognitive ability as measured by psychometric tests.

Pupillometry was coined by Hess in 1965 to describe a new research field that has focused on the quantification of pupillary dynamics (Hess 1972). At the start of the twentieth century, German psychologists interested in pupil size made qualitative judgments on the extent of pupillary dilation during experimental tasks (Mentz 1895, Heinrich 1896, Roubinovitch 1900). In the 1960s the science of pupillometry advanced to encompass the quantitative measurement of the extent of pupil dilation. Hess and Polt (1964) used a ‘motor-animated camera’ to record the extent of participant’s pupil dilations at a rate of 2 images per second. These researchers then made a manual measurement of pupil size in each image.

Nguyen and Stark (1993) developed a pupillometer that utilised an infrared video camera and purpose-built software to capture and analyse the frames on an AT-386 computer programmed in Turbo-C. Their automatic feature extraction algorithms include auto-thresholding with masking. More recently, advanced technologies such as the IS-CAN, Inc., Model RK-406 pupillometer (used by Steinhauer et al. 2000) have enabled the fast (60 images per second), accurate, and automated assessment of pupil dynamics. However, these machines are uncommon and the price is extremely prohibitive to most research laboratories. Hence, the need for alternative strategies for the robust measurement of pupil dynamics is apparent.

3 Experimental Design Summary

Whilst providing full detail of the experimental and psychological detail of the overall study is beyond the scope of this paper, a summary is provided here for context. The major hypotheses to be tested by the data collected by the pupillometer are that increased cognitive task difficulty will elicit larger pupil dilation and longer light-evoked pupil constriction onset latencies. In addition, when occupied by mathematical tasks, a higher IQ group will, on average, have smaller pupil dilations and shorter light-evoked pupil constriction onset latencies than a lower IQ group.

Forty-eight university students and employees volunteered and were accepted to take part in the study. Experimental difficulties (discussed later) meant that it was only possible to complete analyses on 37 participants. All participants underwent psychometric and chronometric testing to assess cognitive ability. Pupillometric testing was then conducted to assess pupil reflexes under differing cognitive loads. Participants were secured in a head brace in a darkened room with a digital infrared video and red light stimulus situated directly in front of them (Figures 1 and 2).

Participants were assigned three mathematical tasks of varying difficulty in random order. These tasks consisted of a No Task condition, a paced series add 1 (Add 1) condition, and a paced series subtract 7 (Subtract 7) condition. The No Task condition was a control condition in which the participants were asked to stare at the camera and not think of anything. For the latter two tasks participants were assigned a randomly generated number between 250 and 1000 and were required to add 1 to, or subtract 7 from (respectively), this number sequentially (e.g. Subtract 7 – 357, 350, 343, 336 . . . ) approximately once every two seconds.

After two minutes in the darkened room participants were presented with a random number and the mathematical task was set randomly. Approximately five seconds later,
a sequence of 11 light flashes was presented lasting for one second each and separated by three-second intervals of darkness. This was repeated for all three tasks. The same procedure was utilised for each of the 15 cases used to assess the test/retest reliability of the pupil measure.

The above procedure was recorded using a Sony CVX-V18NSP closed-circuit camera with high power zoom lens and infrared night-shot capacity onto a Sony DVCAM
Digital Video Cassette Recorder (DSR-V10P). The camera emits an infrared light source during nightshot operation. A red (\(\lambda \approx 630\) nm) light emitting diode (LED) display was used as the light stimulus to elicit the pupillary light reflex.

4 Digital Video and SIS Pupillometry

The full method of conducting pupillometry using digital infrared video and automatic feature extraction in a SIS is described below. The method involves loosely coupled technologies integrated to provide an accurate measure of the spatio-temporal dynamics of the pupil under the differing experimental conditions. The process involves capturing and deinterlacing digital infrared video of the participants, automatically extracting and quantifying the pupil extent with a SIS and analyzing the data in a spreadsheet.

4.1 Capturing and Deinterlacing Digital Infrared Video

To induce the pupillary responses to light stimuli required in this study, dark experimental conditions are required. Infrared data capture was used for its ability to detect pupil dynamics well in both darkness and lighted conditions. In addition, human pupils generally have a high reflectance/emittance in the infrared spectrum compared to the iris which enhances the capacity for automatic feature detection. The nightshot function of the Sony video camera was used to capture pupillary responses of participants in the infrared spectrum.

The Australian Standard Phase Alternation by Line (PAL) video format was used at a rate of 25 frames per second, or one frame every 40 milliseconds (ms). In the PAL standard, each frame image is a composite of two image fields. Each field is a half picture, composed of alternate horizontal lines (Figure 3) captured every 20 ms. Fields are engineered so that each field presents every other alternate horizontal line when compared to the field immediately before it and two consecutive fields are interlaced to form a frame. Through this process of presenting 50 half pictures per second humans gain the perception of fluid motion in video and television images, whilst the amount of data required is minimised. This feature is used to enhance the temporal sampling resolution in this study.

Initially, digital infrared video data for each participant was imported from the camera through the Super Video port of a Silicon Graphics Indy R5000 using the

![Figure 3](image-url) An illustration of 4 fields, each field is a half picture displaying every alternate line captured every 20msec. Fields presented in temporal order to enhance the perception of fluid motion in moving pictures

© Blackwell Publishing Ltd. 2003
Pupillometry: A Non-geographical Application of SIS

491

The capture function in the Media Recorder (Version 1.2.0) software. The PAL format video was captured in SGI raw (uncompressed) format at half size (384 × 288 pixels), thereby reducing data handling and computation time with acceptable loss of spatial accuracy. The Media Recorder software was also used to both split and deinterlace the frames of the digital video, and save them as separate 3-band, 24-bit colour, Tagged Image File Format (TIFF) image files.

The 40 ms temporal sampling unit provided by the digital PAL format video was too coarse to accurately quantify pupil dynamics which operate in the order of hundreds of milliseconds. However, by deinterlacing the frames, a doubling of the temporal resolution of the data can be achieved with the tradeoff being a change in the dimensional ratio of the image (Figure 4). Using deinterlaced fields compresses the image along the Y axis such that each distance unit in the Y direction is equivalent to two distance units in the X direction. Thus, deinterlacing the frames has a major effect on the spatial integrity of the features in the image. Instead of appearing roughly circular, pupils appear as ellipses whose horizontal (or semi-major) axis is roughly twice as long as its vertical (or semi-minor) axis (Figure 4). However, this dimensional change is consistent across all frames for all participants and the effects are predictable. Hence, the tradeoff for a doubling in temporal resolution is acceptable.

The result of the splitting and de-interlacing process was, for each participant, a temporal series of TIFF images of around 320 kilobytes each, corresponding to the frames of the digital PAL video. Within each frame image, the two fields from each frame were stacked, with the top field preceding the bottom field by 20 ms (Figure 5).

Figure 4 Comparison of the circular pupil shape of the interlaced frame of the digital infrared video (left) with the elliptical pupil shape of the deinterlaced fields (right). Note the high pupil/iris contrast present in the infrared response.

© Blackwell Publishing Ltd. 2003
For each pupillometric test there was approximately two and a half minutes (3,750 TIFF frames, 7,500 fields) of data captured, requiring a total storage space of 1.2 gigabytes. A total of 63 tests were conducted and 157.5 minutes of video captured. These 63 included initial tests for each of the 48 participants, and retests of 15 participants taken to examine test-retest reliability of the pupillometric measure. In total, approximately 236,250 TIFF frames were captured (76.5 gigabytes of data) containing 472,500 stacked fields. The extent of the pupil needs to be extracted from each field and the spatial metrics of the pupil need to be quantified. The next few sections describe the automated technique devised to perform this task.

4.2 Programme and Data Structures

The de-interlaced TIFF frame images of the responses of each participant to the experimental conditions were analysed in a process of automatic feature extraction using ESRI’s ArcGIS 8.1 software. A macro programme called Extract was written in Arc Macro Language that automatically extracts the extent of the pupil from each field and calculates pupil area. The programme can be run in graphical mode which displays the result of every feature extraction for every field (used for diagnostics and troubleshooting), or in non-graphical mode which is significantly faster. The Extract program quantifies the iris diameter, pupil area, and the status of the light stimulus in each field of digital video.

The coordinate systems of the spatial data layers in the analysis are relative coordinate systems with no relation to actual distance measures. Each pixel and grid cell has a resolution of 1 distance unit and spatial metrics are measured based on this fundamental unit. Similarly, due to the experimental design where participants were secured in the head-brace and looked directly into the camera lens, each image was assumed to be orthogonal to the look angle of the camera and the radial distortions of the camera were assumed to be negligible. Hence, no spatial correction or projection was performed on the raw data.

Data structures were set up such that the TIFF files for each participant are stored in a separate folder on the computer hard drive. Extract is designed to analyse one

Figure 5 A TIFF image frame containing temporally stacked fields. The top field precedes the bottom by 20 ms, illustrated by the beginning of a blink in the bottom field.
participant at a time and run from the Arc command line prompt within the workspace of the participant under analysis. The Extract programme identifies all TIFF files within the folder and sets up a programmatic loop to cycle through and analyse each sequential TIFF file and field within each file.

4.3 Preprocessing and Setting the Analysis Environment

Initially, the red, green, and blue colour bands are extracted from the TIFF file and converted to ESRI grid format. The output grids have the same number of rows and columns as the input TIFF image, and the value of each output grid cell for each band is equal to the colour intensity value for the corresponding band in the TIFF image (an integer between 0 and 255). These image grids had to be shifted to a new origin (0, 0) to align perfectly with the TIFF image.

The first objective of the automated feature extraction process is to interactively create a user-defined analysis extent and mask to both enable feature extraction and to reduce processing time. These processing environments are set once for each participant at the beginning of the programme run. The first TIFF image in the series for each participant is presented to the user in a display window who is prompted to identify, using the mouse, the left, top, right, and bottom extent of a rectangle defining the general iris extent (Figure 6). The analysis extent for the top field is snapped to the TIFF image such that the rectangle aligns perfectly with pixel edges. An analysis extent is automatically created for the bottom field simply by subtracting 144 (half of the number

**Figure 6** Interactive user-specified analysis extent and mask. The user first identifies the extent of the rectangular analysis window, and then traces a mask polygon to restrict analysis to inside the iris area.
of image rows) from the Y units of the analysis extent of the top field. The cell size for all subsequent analysis is set to that of the image grids (1 distance unit). The display window is updated with both the top and bottom field masks (Figure 6) and the user is prompted to either continue or recreate the mask.

On continuing, the display window zooms into the analysis extent of the top field and the user is prompted to create an analysis mask. The user interactively traces a polygon around the inside of the iris (Figure 6) using the mouse and hits 9 when finished. A polygon coverage is created for the mask which is then converted to a grid with matching origin and extent of the analysis mask, and a cell size matching the image. A mask is also created for the bottom field by shifting a mask grid down by 144 units. The user is prompted to either recreate the mask or continue. This static analysis mask was successful in restricting the analysis to the iris area where the contrast in brightness between the pupil and iris was generally large thereby enhancing the automatic feature extraction of the pupil. Breaching of the mask area by the pupil was rare due to the experimental design which ensured the limited participant eye movement.

Calculation of the iris diameter is another fundamental step in pre-processing. It is assumed that the iris diameter of each participant remains constant under the different experimental conditions and hence, is only measured once for each participant. This is accomplished interactively with the user instructed to mouse-click on the left-most extreme of the iris, then on the right-most extreme (Figure 7). A simple equation is used to calculate the iris diameter as the distance in grid cells between these points.

4.4 Identifying Pupil Threshold Value

One final piece of pre-processing involves the interactive query of grid cell values. As is described below, the green band performed best for pupil extraction. After the iris width is calculated Extract enables the user to query the value of grid cells in and around the pupil area to guide the selection of the threshold value for feature extraction.

A number of techniques were trialled for efficiency in identifying the extent of the pupil including using all three image grids, and converting all three bands to brightness values. However, the identification of pupil area was best accomplished using the grid of the green band of the TIFF image (hereafter referred to as the green grid) alone which displayed greatest pupil/iris contrast. Typical grid values for the pupil are very similar to those of the sclera (the ‘whites’ of the eye) and eyelids (Figure 8). The analysis mask was able to restrict analysis to within the iris which successfully overcame the
problem presented by the similarity between values of the pupil and other parts of the eye area.

To derive an appropriate value threshold for distinguishing between pupil and iris, grid cell values were queried from several frames for each participant covering the full range of pupil dynamics. As the pupil constricts under the varying task conditions it tends to become less bright. Hence, to ensure accurate feature extraction under the full range of pupil dynamics, the threshold value needs to exceed, but only slightly, the highest surrounding iris values.

This value is then used in a threshold analysis to identify the extent of the pupil using an automated feature extraction process. The thresholds set varied between participants from 90 to 178 on a scale of 0 to 255; however, thresholds were most commonly set in the low 100s. Much of the variance in these threshold values can be explained by different exposure levels set to maximise picture quality on the Sony video camera.

4.5 Automatic Feature Extraction of Pupil Extent

After the pre-processing, setting the analysis environment, and determination of the value threshold, the process of automatic feature extraction begins. A primary loop is used to cycle through the TIFF image frames for the participant under analysis and a secondary loop is used to analyse both fields within each frame. Within each frame the top field is analysed first, then the bottom field. The following analysis is performed individually on each field.

The first task involves the collection of base data for later automatic determination of whether the light is on or not. This was accomplished by setting the analysis extent to the entire top field and calculating the mean value of the grid of the red band of the TIFF image (red grid) for all cells. When the light was on, the mean value of cells in the

Figure 8  Typical green grid values of features of the eye area. Green grid values for pupils are generally higher than for the iris (scale 0–255) when sensed using infrared video. However, pupil values are very similar to those produced by the sclera and eyelid. Also note the low value cells in the centre of the pupil caused by reflection of the light.
The analysis extent and mask are then set to the user-specified areas for the top field and a series of raster operations performed to identify the pupil extent. Firstly, threshold analysis is performed by setting all cells with values less than the threshold value to NODATA. The areas classified as pupil by threshold analysis tend to include multiple distinct zones and exhibit spatial irregularities such as irregular edges and holes or islands caused by reflection of the light in the pupil (Figures 8 and 9). A boundaryclean spatial smoothing function is used to eliminate the islands and smooth the edges of the zones classified as pupil area (Figure 9). The boundaryclean function uses an ‘expand and shrink’ method to remove these islands. First, every cell value is expanded to replace lower value neighbouring cells in all eight directions. If the new grid value is not surrounded on all eight sides by the same value, it is then shrunk back to its original value, otherwise the new value is retained (ESRI 2001). This was very successful in refining the threshold analysis to a solid elliptical shape and consistently enhanced the accuracy of pupil feature extraction (Figure 9).

Commonly, more than one contiguous area (or zone) was classified as pupil as the threshold analysis identifies all grid cells with values greater than the specified threshold value as pupil. If there are small clusters of non-pupil cells classified as pupil, such as areas of sclera, eyelid or small areas with higher values in the iris, the boundaryclean operation does not eliminate them. Erroneous zones tend to be much smaller in area than the actual pupil area and are removed using a process of areal filtering. Areal filtering involves identifying each contiguous zone classified as pupil using the regiongroup function and calculating the area of each zone using the zonalarea function. The area of the largest contiguous pupil zone is identified using the describe function and this becomes the final measure.
of pupil area. Areal filtering is used to set all cells not contiguous with the largest zone to NODATA, which leaves only the largest contiguous area of pupil (Figure 9).

Identifying and calculating pupil area for each field of each image frame is the fundamental feature extraction and analysis task performed in the Extract programme. Other secondary metrics are also calculated such as the pupil to iris fraction (described below). A series of values are then output to a Comma Separate Values (CSV) text file which can be directly imported into Microsoft Excel. Output values include frame and field number, time in milliseconds, mean redness, pupil area and pupil to iris fraction for each field. Spatio-temporal pupil dynamics were analysed further outside of the SIS using a spreadsheet.

After writing these output values for the top field of the first frame, the analysis extent and mask are switched to the bottom field and the same automatic feature extraction and analysis is performed and outputs written. The programme cycles through each field in every frame for each participant. A snapshot of every 50th field image (one per second) of the pupil feature extraction results is saved to disc for inspection and troubleshooting purposes. The snapshots enable refinement of pupil thresholds and assessment of the limitations with the methodology.

4.6 The Measure: The Pupil to Iris Fraction

Several studies have proposed a pupil to iris fraction to correct for differences in pupil size between participants (Fotiou et al. 2000, Lanting et al. 1990, Sacks and Smith 1989). Usually, a ratio of the radius of the pupil divided by the radius of the iris is used (Fotiou et al. 2000). Similarly, to calibrate a measure of relative pupil size that allows inter-individual comparisons to be made in this study, the ratio of the pupil area to iris area (P/I area ratio) is used as the pupil to iris fraction.

The calculation of the P/I area ratio is performed automatically in Extract. The area contained within the circumference of the iris is calculated from an initial measurement of the diameter of the iris made interactively by the user (see above). This estimation is performed only once under the assumption that iris area remains constant. A second assumption was made that the iris, as recorded in interlaced video, is circular, and that deinterlacing the frames changes the shape of the iris to an ellipse whose semi-major axis is twice as long as the semi-minor axis. Given these assumptions, the calculation used to define the ellipsoidal area of the iris in each field is given in Equation 1:

\[ A_i = \frac{\pi D^2}{8} \]  

where \( A_i \) = the ellipsoidal area of the iris and \( D \) = the diameter of the iris as entered interactively by the user. The P/I area ratio is simply the ratio of pupil area to iris area as calculated by these methods.

5 Post-processing and Analysis

5.1 Identification of the Light Stimulus

As mentioned above, the mean value of cells in the red grid was used to identify whether the light stimulus was on or off in each field. In fields where the light stimulus is on, the mean red grid cell value is approximately 10 units higher. Formal determination of the
light status was made from the red grid brightness values stored in the output CSV file using the Microsoft Excel spreadsheet. For each participant, the maximum mean brightness value from the 140 fields in the three-second light-off period between the presentation of the first and second light stimuli was calculated. The light stimulus was deemed to be ON for fields with mean redness values exceeding this maximum mean brightness value by more than 2 units, otherwise the light was deemed to be OFF. This proved to be a very accurate method of light identification through cross-checking the raw image data.

5.2 Calculating Mean Pre-Light Pupil Dilation
Hess (1972) has prescribed the use of a mean pupil dilation score generated from 20 sequential images. Pre-light pupil dilation was calculated using a standard measure of the mean pupil to iris fraction over the 20 field images that precede the presentation of each light stimulus using Microsoft Excel.

5.3 Calculating Pupil Constriction Onset Latency
To measure the time from presentation of the light stimulus to the beginning of pupil constriction or pupil constriction onset latency, it was necessary to define precisely when the pupil started to constrict. To automatically define pupil constriction onset, 20 field moving averages and standard deviations for P/I area ratio are calculated. A z-score is calculated for the P/I fraction in each field based on the average and standard deviation of the P/I fractions of the 20 preceding fields. When the P/I fraction had decreased by more than one standard deviation for nine consecutive fields or more, and the light stimulus was deemed to be on, the pupil was defined to have started constriction in the field the decrease was first detected. Calculation of the pupil constriction onset latency was a simple calculation of subtracting the time the light stimulus was presented from the time of constriction onset.

6 Example Results
As discussed above, the output or results of the combination of digital infrared video with the automatic pupil feature extraction is manifest as a table of numbers for each participant. The table of numbers includes a time stamp, mean field redness, and the P/I area ratio for each frame. When graphed, this data provides insight into the spatio-temporal pupil dynamics of each participant in response to the light stimulus and tempered by cognitive load (Figure 10). Post-processing in the spreadsheet identifies the light status for each frame and calculates the mean pupil dilation and constriction onset latency for each participant. In the broader study, the mean pupil dilation and constriction onset latency were summarised for each participant and used in the statistical comparison of pupil dynamics under different cognitive loads with cognitive ability.

7 Discussion
On the whole, the method of pupillometry outlined in this paper was very successful. The combination of digital infrared video and the automatic pupil feature extraction...
and analysis procedure in a SIS and spreadsheet provided an inexpensive, accurate and reliable pupillometry technique. The quantification of pupil dynamics using this technique provided a suitably rigorous output for the broader study of the relationship between the pupil dynamics and cognitive ability published elsewhere.

However, several factors resulted in error in the automatic feature extraction and quantification of pupil area. Error resulting from both the analytical process and human procedural-based problems made the automatic analysis of some or all of the data from some participants difficult or impossible. The major problem in the automatic analysis technique is the identification of pupils exhibiting a low pupil to iris contrast in infrared. Human procedural-based problems include moving pupils and ‘sleepy-eyes’. These are discussed below and solutions are suggested.

### 7.1 Sources of Analytical Error

Automatic pupil feature extraction was difficult for participants with relatively low contrast between the pupil and the iris. For most participants, the pupil appears brighter than the iris in infrared and automatic pupil feature extraction is successful. However, for six participants this clear distinction between pupil and iris brightness values could not be made (Figure 11). In addition, four participants had pupils which appear darker than the iris when viewed in infrared (Figure 11). Finally, some participants had bright pupils when dilated and on constriction would decrease in brightness to become similar

---

**Figure 10** Example graphical output of the automatic feature extraction process. The light status can clearly be seen in the oscillating high and low mean image redness value. Pupil dilation and constriction dynamics are illustrated by the P/I ratio and constriction onset latencies are reflected in the time lag between presentation of the light stimulus and constriction onset. Note the spike in P/I area ratio caused by periodic blinking. The data presented is the subtract 7 task for retest participant 7.
to, or even darker than, the iris. Whilst, in all of the above cases, the pupils were still clearly distinguishable with the human eye, the automatic feature extraction process used in the Extract programme resulted in serious errors when automatically analysed.

This difficulty in automatic feature extraction of low contrast pupils is a combination of shortcomings in the data, the analysis design, and the limitations of current spatial analytical techniques. Firstly, the data are captured in infrared under experimental conditions of total darkness (except when the light stimulus is on). A greater range of spectral sampling could well be used to detect differences between the pupil and the iris. Certainly, under lighted conditions, few people have pupils the same colour as their iris. If this distinction is detectable under lighted conditions there is a good possibility that it may also be detectable in darkness using combinations of different parts of the electromagnetic spectrum than were used in this study in a multi-spectral analysis. Further to this, spectral enhancement techniques and transforms also offer potential to increase pupil detectability in low contrast cases.

Secondly, the threshold analysis used in this study as the basis of automatic feature detection is simplistic. Although it works well in the majority of cases, a more sophisticated heuristic or numeric classification using all three bands of the infrared data, or if available, multi-spectral data as described above, could improve the classification accuracy of participants with low contrast pupils. Other techniques may also assist feature extraction including shape analysis as we know that the pupil is elliptical, and edge detection as the change in values at the iris/pupil interface will be greatest. It may also be possible to develop a dynamic classification algorithm where the threshold changes according to the size of the pupil and other intelligent, dynamic classification rules.

Thirdly, established analytical methods and tools routinely available in spatial information systems and image analysis software have not developed sufficiently to include algorithms capable of detecting from image data features that are distinguishable with the human eye, but are of low contrast with the surrounding environment. Developments in image analysis techniques need to mimic better the way humans detect features and patterns from images.

7.2 Human Procedural-Based Problems

During the experiment, movement and fidgeting by two participants made automatic pupil feature extraction difficult to assess accurately and prone to error. Movement of
the pupil in the order of more than around 0.5 cm through a combination of body or eye movement, was enough for the pupil to breach the analysis mask set at the beginning of the analysis. The result of this is an underestimate of pupil area. To properly evaluate these moving pupils the analysis mask would have to be dynamically adjusted to follow the eye movement of the participant. This is technically possible by comparing the centroids of the analysis mask and of the pupil area after analysis of each field and shifting the analysis mask by the distance of centroid separation after each iteration. However, this would add to the processing time significantly.

Another problem was that of ‘sleepy eyes’, which arose because three participants were unable to keep their eyelids open above their pupils. This obstruction of the pupil by the eyelid caused an overestimation of pupil area. Due to the similarity between pupil and eyelid image values (Figure 8) the area classified as pupil included large areas of eyelid which were difficult to mask out. Sampling different spectral regions with digital video could assist in the distinction between eyelid and pupil especially in the thermal infrared as it is possible that the two features may emit significantly different thermal responses.

### 7.3 Future Development

Work is currently underway to tightly couple and indeed integrate the technologies used in this study. The methodology presented here is based on ESRI’s ArcGIS software but is general enough to be implemented in most raster GIS, some of which are available at very low cost or free of charge. A major problem with the Extract programme was inefficient analysis. Data from each participant took over 24 computer hours to analyse on a Pentium III 600. However, tasks other than data analysis, such as library access, took up the vast majority of run time. Current work involves the development of non-proprietary softcopy pupillometry software which performs all the tasks described in the above process including importing and de-interlacing the digital infrared video, automatic feature extraction and analysis of pupillometric measures. It is expected that analysis times will be greatly reduced.

### 7.4 Implications for Spatial Analysis and Spatial Information Systems

Applications of spatial analysis, including the quantification of fundamental spatial metrics of objects such as length, distance, area and shape, to non-geographic phenomena are uncommon. One reason for this may be due to the requirement of assumptions made about the spatial integrity of the data. The widespread use of spatial information systems for geographic applications has been facilitated by developments in accurate spatial referencing systems including ellipsoid estimation, geodetic datums, projections and coordinate systems. Spatially accurate feature extraction from geographic image data has been facilitated by substantial development in geometric correction of sensor and topographic distortions. There has been less development to ensure the integrity of spatial information in non-geographic domains probably because of the potential diversity and limited generality of these domains. Without a sound spatial referencing system, the calculation of spatial metrics is dubious. Most non-geographic applications of spatial analysis have to make similar assumptions as this study as to the effect of geometric distortions on spatial calculations.

The lack of development of appropriate spatial referencing systems for non-geographic environments is a major obstacle for the extension of spatial analysis and
SIS into these domains. However, the mathematics behind the establishment of spatial referencing systems for the Earth and the geometric transformations of camera distortions are directly transferable to non-geographic domains. Although clearly not a trivial exercise, attention needs to be devoted to the creation of a generic spatial referencing methodology and geometric transformations applicable to a wide range of non-geographic domains to increase the benefits of spatial analysis in these domains.

Another obstacle to the extension of spatial analysis to non-geographic domains is the lack of appreciation of spatial issues amongst domain experts. A lack of appreciation of the potential utility of spatial analysis within a particular domain impedes the take-up of this analytical technology. Greater collaboration between the growing number of spatial scientists and non-geographic domain experts may remedy this.

8 Conclusions

This study presents a very different application within spatial information science – the loose coupling of digital infrared video with a SIS and spreadsheet to create a pupillometer. Digital infrared video provided a useful spatio-temporal data capture medium for pupillometry. De-interlacing the digital video was used to double the temporal sampling resolution of the data with an acceptable and predictable loss in spatial integrity of the data. The automatic pupil feature extraction technique employs interactive user-specified analysis limits, and combines threshold analysis with spatial smoothing and an areal filter, to successfully quantify pupil area and calculate the P/I area ratio. Image analysis was also able to identify the light status in each field. Post-processing in a spreadsheet was used to quantify pupil metrics including mean dilation magnitude and constriction onset latency figures for analysis in the broader study into the relationships between pupil dynamics and cognitive ability under varying cognitive loads. The method of pupillometry presented here illustrates and discusses some of the issues involved in the accurate and rigorous use of spatial analysis and SIS in a non-geographic domain.

Acknowledgements

The authors greatly appreciate the generosity of Mr. Iain Grierson of the Department of Soil and Water, The University of Adelaide, in lending the digital video equipment used in this study. The use of the computing resources at GISCA, the National Centre for Social Applications of GIS, is also greatly appreciated.

References


Reed T E and Jensen A R 1991 Arm nerve conduction velocity (NCV), brain NCV, reaction time, and intelligence. *Intelligence* 13: 33–47


Sacks B and Smith S 1989 People with Down’s syndrome can be distinguished on the basis of cholinergic dysfunction. *Journal of Neurology, Neurosurgery, and Psychiatry* 52: 1294–5

Schluroff M 1982 Pupil responses to grammatical complexity of sentences. *Brain and Language* 17: 133–45
Siddle D A T and Glenn S M 1974 Habituation of the orienting response to simple and complex stimuli. *American Journal of Mental Deficiency* 78: 688–93