Image Enhancement - An Emergent Pattern Formation Approach via Decentralised Multi-Agent Systems

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Abstract

A multi-agent framework inspired by natural and physical systems is presented for data discovery and image enhancement. The input image is represented as a topographic landscape upon which a large population of independent simple, reactive, mobile agents resides. The local landscape configuration presents stimuli to each agent, influencing agent behaviour and resulting in changes in agent orientation and movement. Individual agents deposit a trail as they move and leave specific marks in response to stimuli above a certain threshold. The parallel interactions of the agent population and the image landscape result in emergent patterns of trails and marks being generated, corresponding to global (population level) perception of the original image. The emergent patterns exhibit image feature extraction and represent an indirect processing of the input image. External environmental pressures may be applied to the emergent patterns to further amplify the feature extraction. The framework represents a decentralised approach to image enhancement which is extensible. Different types of agent may be developed to perform different image processing functions, or other problems whose definition and solution may be represented as spatial patterns. Results including binary image processing, greyscale enhancement, colour image processing and related spatial processing problems are presented.

Keywords: Image processing, Emergent pattern formation, multi-agent system, selection pressure

1. Introduction – Program Centric Vs Data Centric Processing.

Image processing is a major field of research and application of computing science. The classical data processing model used in computer science is the Input > Process > Output model. The sampling and storage of an image and subsequent representation as discrete arrays of data renders the image amenable to this processing model. Image processing tasks transform the input image in a processing stage, resulting in the output image. The processing may also be chained, i.e. the output of one image processing function may be used as the input stage for another processing stage. The processing stage typically consists of functions that serve to transform the data or highlight some desired feature within the data. The transformation of the input data to give the output results in the loss of the original input data. This fact is usually irrelevant, however, since the processing operations are performed on a copy of the input data. Although there are many different image processing techniques they all attempt to highlight particular aspects of the data contained within the image. These features commonly include: lines and edges, noise, gradient, shapes and rough estimates of background and foreground. Such transformations and processing are commonly referred to as low level image processing. High level image processing attempts to find more complex patterns and regularities within an image and can more accurately be described as image analysis, exemplar applications including: face detection, or the counting of objects within an image.

Low level image processing may be global or local in its nature. Global image processing transforms the entire image data, often depending on some statistical characteristics of the entire image, for example histogram equalisation or linear contrast stretch. Local image processing operations transform the individual pixels within an image, based on the single pixel data (point operations) or a localised window around each pixel (convolution operations). Conventionally image processing, like many other data processing operation, is ‘program-centric’: the output data result is a direct correspondence of the behaviour specified in the program code. Some feature of the data is considered in the processing stage and the direct decision of the program code results in the output. The code transforms the input data in such a way that the output data directly reflects some property of the program code. Consider the simple example of simple image thresholds on greyscale data in figure 1:

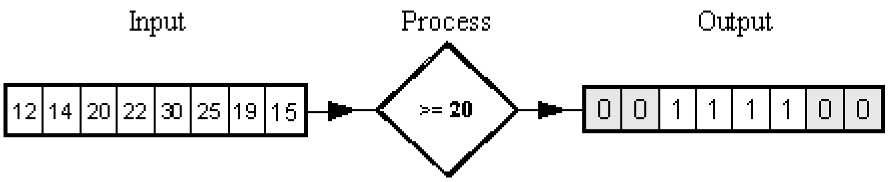


Figure 1: Direct, ‘program centric’ processing of input data in the classical data processing model. An example of simple image thresholding of pixel intensity, the threshold is >=20. Some aspect of the data (pixel intensity) is considered by the program to change its output.

The program-centric approach to data processing ensures that a single program can be used to process different data. Parameters may be varied (as in the threshold value ’20’ above) to give the program flexibility for different data sources. The program-centric approach implies a passive role for the data in its processing but this is not necessarily the case. Different properties of the data are also commonly used in programming to control the flow of the program code execution or control the iterative nature of program execution. For example, the threshold value in figure 1 may be calculated by the program automatically based upon, for instance, the average pixel intensity in the data image. The use of the actual data to control aspects of the program is usually limited, however, and strict data validation must be in place to ensure that the data is valid and within certain bounds. Invalid data may dramatically alter the behaviour of the program, effectively ‘derailing’ the execution of the code from its planned path. Modern programming languages (and teaching methods) usually place some restriction on the ability of data to directly control program behaviour and uses of techniques such as the Computed GOTO instruction, pointer arithmetic and self modifying program code are becoming less common with the increasing size of computer applications and the growing level of malicious threats to computer systems that exploit potential misuse of program flow.

For some applications, the spatial and distributed nature of the data presents difficulties with the serial architecture underlying the classical data processing model. Image processing is a suitable example – features within the data (image) cannot be described in terms of single data locations (pixels). Features are distributed across many pixels, in many different orientations – making perception of such features difficult when the data is presented in a linear manner to the processor. Nevertheless, a great many successful image processing applications exist that utilise the program-centric approach, commonly using the notion of overlapping windows of local data, and iteration of the processing, to effectively perceive the image features. If a data-centric approach were to be used for image processing function, how would it differ from a program-centric model?

A program-centric approach uses the *processor* (program) to process input data to give the resultant output data in a fairly linear manner. The complexity of the system is weighted towards the program. The algorithm controlling the program may be very complex in order to suitably process different data sources. Program-centric approaches may be characterised as centralised in their control and 'top-down' in terns of the program structure and development. A data-centric approach inverts the complexity weighting: The implication underlying a data-centric approach is that the complexity is stored in the patterns within the data. To make these patterns apparent (to perceive them); the configuration of the data may be used to *change the behaviour* of the very simple processors. The 'output' is read by the resulting pattern of behaviour of the processors. The result is seen in terms of the spatial and historical behaviour of the processors. A data-centric approach may be characterised as decentralised as no single processor is in 'control' of the data processing. It may also be described as asynchronous as the position and movement of the agents is more strongly influenced by the data rather than the program. The output behaviour emerges as a consequence of the interactions between the simple processors and the data and may be described as 'bottom-up' in terms of program behaviour.

The data-centric approach is commonly seen and exploited in natural and physical systems. These systems often contain features that are not readily apparent to the observer. The features may be visualised, however, when another (normally homogeneous) system is introduced that specifically interacts with the first system. The interactions between the two systems results in patterns of behaviour that render the previously unseen features visible. This rather abstract description can be more easily understood with examples of such systems.

Fingerprints consist or patterns of oil and amino acid residues deposited along friction ridge patterns in the skin. These patterns (the target system) are usually difficult to perceive, and on certain surfaces practically impossible. By introducing a homogeneous external physical system, such as fine particles of aluminium powder, chemicals that produce a fluorescence reaction, or cyanoacrylate fumes that condense on the friction ridge patterns, the interactions between the two systems render the print visible.

In Biological cell staining, the small dimensions of the cell samples (target system) make them appear almost transparent to the transmitted light through microscope optics. By applying a chemical stain (external homogenous system) to the cell, the two systems interact - different structures in the cell taking up the stain at different rates (due to the different structural properties of the cellular components). This interaction renders the cell visible under the microscope optics. Different external systems may also be used in microscopy to visualise previously unseen features: oblique light and polarising filters may be used to interact with the light transmitted through the cell sample to render the sample visible.

The above examples of data discovery in physical systems adopt a data-centric approach to render previously unseen features visible (the *behaviour* of one system is affected by the *content* of another), and they depend upon two factors being present. Firstly there must be a distinct interaction between the two physical systems and, secondly, the data in the target system must also contain content. If, for example, the stain used was not reactive with the target sample cells then no interaction would take place and the features would remain invisible. Secondly, if the target system did not contain actual content (for example if no cells were placed on the slide by mistake) then no interactions could take place and again no difference would be observed. Figure 2 contrasts the program-centric approach with a data-centric approach, influenced by the data discovery observed in physical systems.

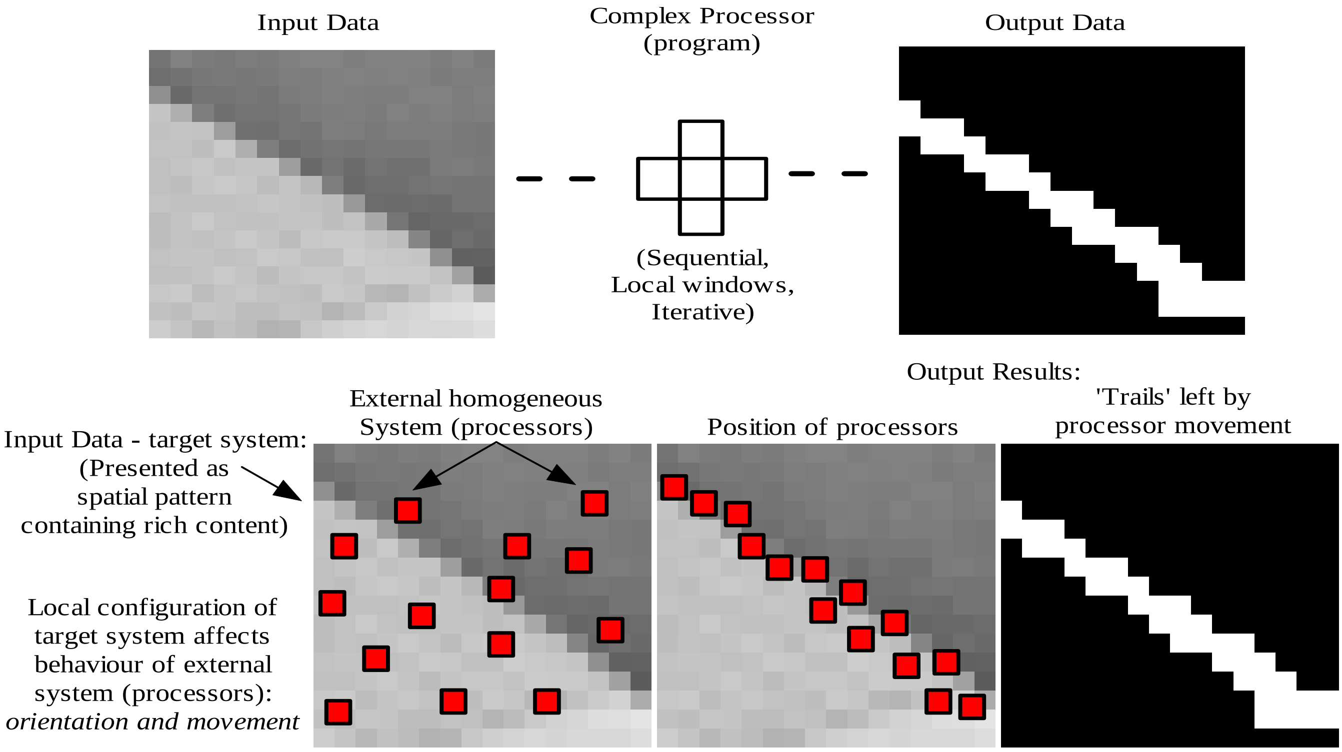


Figure 2: Program-centric and data-centric approaches.

The program-centric approach (top) - A complex processor is used to process the input data to give the result.

The data-centric approach (bottom) - The complex patterns of content within the data are used to affect the behaviour of an external system (exemplified as very simple processors). The interactions between the two systems provide the ‘result’ and the result is ‘read’ as the spatial distribution and historical behaviour of the processors.

This paper presents some results of taking a data-centric approach to image enhancement and data discovery. This approach is inspired by natural and physical systems, using emergent pattern formation to render previously unseen (or unclear) image features visible, and an external environmental selection pressure to further amplify the distinctions in the emergent patterns formed. The target system containing the data patterns to be discovered / enhanced is represented by a digitised image and the externally applied homogeneous system is represented by a population of simple reactive mobile agents. The framework developed for this research allows interactions between the target system and the external system and provides methods of applying the environmental selection pressure.

The remainder of this paper describes the system as follows: Section 2 describes the diverse previously related work of image processing inspired by natural and physical systems and introduces the research presented in this work in the context of previous research. Section 3 describes the framework used in this research. Sections 4, 5 and 6 describe parameterisation in terms of general framework settings, agent behaviours and parameterisation on real imagery respectively. Section 7 introduces the concept of applying external environmental selection pressures to the emergent patterns formed and discusses modifications to the default deposition and selection pressure schemes. Section 8 describes some exemplar image processing results on binary, greyscale, and colour images. Section 9 investigates applying the PixieDust framework to other problems that may be represented in terms of spatial patterns. Section 10 summarises the approach and results, drawing some conclusions and suggestions for further study.

2. Previous Work.

Although the majority of research into image processing methods has utilised the classical data processing model, there are numerous examples of approaches and techniques inspired by natural and physical systems. This research, however, is extremely diverse and is often centred on exploiting a particular existing technique, inspired by a particular natural system, for a new application. This section describes some examples of such techniques and seeks to draw together some of the overall similarities behind such approaches.

Cellular automata (CA), originally conceived by von-Neumann and Ulam to explore self-replication, are regular arrays of very simple processing elements. The processing elements operate as finite state machines and update their behaviour (usually in parallel and with identical update rules) according to their current state and the state of their local neighbours, from entries in a look-up table. The elements are arranged in regular n-dimensional arrays and the two dimensional configuration of cellular automata ideally matches the architecture of a digitised image. CA represent a discrete universe governed by simple rules, but exhibiting complex and often surprising emergent behaviour.

CA, particularly in their hardware implementation [1], provide a simple, fast and powerful approach to low-level (or ‘fine grained’) image processing. Significant difficulties in the CA approach arise in the design of suitable look-up tables to perform image processing tasks. Most early CA in early research into the field used binary states. In a binary state nine cell (including the current cell) neighbourhood CA, the number of possible entries (i.e. possible neighbourhood configurations) in the look-up table is 512. Increasing the number of states to cope with even modest colour ranges (for example 256 colours and a nine cell neighbourhood) dramatically increases the size of the table and the search for optimal entries (4.72 x 10^{21}). Sipper has explored the use of simple binary CA for low-level image processing; using evolutionary, non-uniform CA to aid the design of suitable look-up rules [2]. One method to reduce the complexity and size of look-up tables is to consider neighbourhood pixel values as relative to that of the current cell. A three state CA is then possible (less than, greater than, or the same), which significantly reduces the table size (6561 for 8 neighbourhood CA and 81 for four neighbourhood CA). This strategy, along with the use of a genetic algorithm to search for optimal look-up table entries was used to evolve a CA suitable for edge detection in greyscale images [3].

Toffoli noted that physical metaphors (masking, flooding etc.) are often used in image processing and suggests that fine-grained CA architectures are suitable to apply physically consistent instances of these metaphors, providing exemplar CA applications of image processing functions (blurring using simulated Brownian motion and texture recognition using a model based on phase-locked loops). He recognises, however, that the wide installed base, the very low cost of traditional von-Neumann architecture implementations, and the lack of programming methodologies for fine-grained systems currently places them at a disadvantage [4].

Data-centric approaches are also seen in the use of deformable geometric objects to perform image segmentation. These objects include so-called 'snakes' [5], a specific instance of deformable models [6]. These approaches use approximation and energy functions to minimise the energy of a deformable shape around the target data within the image. Historically, physical systems have also inspired the grassfire algorithm [7], versions of which are realised in various image skeletonisation algorithms. Watershed segmentation algorithms, the flooding - and later merging - of local minima basins in the image, are also inspired by phenomena seen in natural systems [8]. Other researchers have moved beyond physical systems as mere metaphor and attempted to utilise the physical domain to perform image processing. Grigorishin exploited electrostatic fields, generated by the boundaries of shapes, to perform image skeletonisation [9]. Adamatzky has explored the use of chemical reaction-diffusion systems to solve spatial problems, including image processing problems [10]. Rambidi suggests that reaction-diffusion systems and excitable media may be directly comparable in scope to traditional mathematical morphology image processing operators [11]. He describes the spatial chemical-based computers as 'instance machines' – computers whose architectures are specified by the configuration of the spatial problem that they are trying to solve. The output of instance machine computing devices is the final configuration pattern left at the end of the evolution of the system.

The direct use of physical systems to solve spatial image processing problems opens up vast possibilities for new research but it is not without its problems. Chemical reaction-diffusion systems (limited by the speed of wave propagation) operate very slowly compared to the switching speed of serial digital computers, but their massive parallelism suggests that such systems, or systems using similar principles, may provide significant advantages in large scale image processing.

Cellular automata and methods using real physical systems utilise the fine-grained physical rules to support higher level behaviour – the higher level behaviour showing image processing functionality. The process of designing look-up rules to result in suitable image processing functionality is difficult due to the size of look-up tables. If an evolutionary route is chosen to optimise look-up table entries it is also difficult to analyse the evolved entries to discover which entries are critical in providing the image processing functions. In recent years simple mobile multi-agent systems, originally inspired by models of social insect behaviour, have proven popular. Their popularity is perhaps because the underlying 'physics' of the agent universe is already a *given* and the designers of such systems can concentrate on directly developing agents that can perform the image processing.

It has long been observed that the population comprising an ant colony is able to find the shortest path from the colony to a food source. This behaviour was explained by Deneubourg [12] as a result of the ants depositing a pheromone trail as they moved and probabilistically following the concentration of pheromone when selecting new directions. The constant evaporation of pheromone over time ensures that shorter paths are more likely to persist (due to the shorter journey length along these paths, and so the likelihood of more frequent reinforcement), and a positive feedback cycle is initiated where stronger (shorter) paths are reinforced and weaker (longer) paths are not. Dorigo utilised this phenomenon as a metaheuristic for optimising path planning problems, most notably the Travelling Salesperson Problem [13]. Ramos and Almeida used a simple model of pheromone trail following for the global perception of image features [14] and speculated that ant-like agents may be used to perform image processing functions. Ramos has since extended his model to include variable sized agent populations and dynamic landscapes [15]. The Ant Colony Optimisation approach was modified by Zhuang [16] to consider all the features on an image as a perceptual graph. An ant population traversed this graph in an attempt to minimise the path cost in terms of different image features (corresponding to optimal edge detection and segmentation). An ant based approach was also considered by White to perform colour image segmentation using a foraging model [17] his segmentation approach was based on similarity between tagged regions and the later merging of similar regions.

Multi-agent approaches need not necessarily model the pheromone sensing features seen in 'strict' ant systems. Although the mobility of agents and small agent sizes do bring to mind the movement of ants, other systems used can have very different mechanisms of operation. Liu and Tang developed a reproducing agent population that clustered around image features and reproduced near sites of interest, achieving good results for image segmentation and edge enhancement [18]. Boucher used agents that were able to reproduce to extend feature segmentation regions in cell imaging. Adopting a region growing and merging approach to segmentation, the agents were able to track cellular features through a video sequence of cell movement [19]. Ballet et al. used mobile agents that followed the brightness of image gradients to perform image boundary detection. The agents collectively 'inscribed' their movements to a shared memory representing edges within the source image [20]. Rodin further developed this directional agent model (coupled with high level information about the structure of the images) to perform concentric ring detection in fish otolith images using a mechanism inspired by immune system selection to aid the problem of when to stop the algorithm [21]. The immune mechanisms used were based upon the proliferation response of the immune system. This enabled the population size to automatically adjust to the stimuli presented by the image. Initially, upon receiving stimulation by the image, the number of agents increased in response to the deposition of stimulant markers by the activated agents. As the population size increased, the consumption of the stimulants resulted in the destruction of non-activated agents, effectively regulating the population size and controlling the end point of the experiment. The mammalian immune system was also used to influence the development of a multi-agent system for the detection of road surfaces in aerial images [22]. McCoy used the immune system concept of negative selection (which may be naively stated as self/non-self recognition) to produce a population of agents that detected parts of an image that did not belong to the set of 'road features', resulting in the remaining features identified as the roads. Moving further away from 'strict' ant models, Adamatzky considered different versions of simple mobile particle based models and found that they were equivalent to CA and reaction-diffusion models of image processing [23]. Smolka also explicitly considered physical models of particle movement (the statistical summary of multiple experiments of single particles) influenced by heat equations and hidden Markov processes and was able to achieve good results in image contrast enhancement [24].

As noted above, the research literature contains diverse examples of image processing behaviour inspired by physical systems. As well as exploiting particular systems, some authors attempt to synthesise exactly what it is about natural systems that makes them suitable for influencing computer algorithms. Dorigo summarised the interim years of great interest in the ant colony optimisation field with a discussion of the importance of the environment (particularly the role of distance) in the models [25]. Physical distance between regions in the spatial system is also responsible for some of the effects observed in chemical based computing systems – differences in the spatial pattern being processed become apparent due to the different arrival times of propagating waves (travelling at identical speeds) because of the differences in the distances of the origin of the wavefronts. It is clear that environmental interactions play a significant part in the success of such models, both in terms of spatial configuration and external environmental 'forces' commonly seen in real natural systems. Any successful applications of physically inspired computing are likely to be weighted as much in favour of environmental behaviour, as the behaviour of the 'entities' comprising the system – whether they be CA cells, chemical waves or mobile agent.

The research presented in this paper uses simple reactive mobile agents, trail deposition and external environmental pressures. Despite this, it cannot be described as an 'ant colony' based system. The inspirations underlying this research have as more in common with purely physical systems as with living systems. The generation of emergent patterns using physical systems and their amplification by an external selection pressure are powerful data discovery and enhancement tools, and have long since been used in the physical and natural sciences for data discovery (as in the descriptions of cell staining and fingerprint enhancement). The basis for data discovery in physical systems is the mechanism by which the *content* of one system affects the *behaviour* of another. The resulting behaviour patterns of the second system can be used to render visible the hidden content in the first system. This is the approach used in this research to perform image enhancement.

3. PixieDust Multi-Agent Framework.

PixieDust is a multi-agent programming framework that has been created and developed by the authors to carry out research into image processing by simple, reactive multi-agent systems. Two systems interact (a digitised image and an agent population) to provide emergent pattern formation. The framework was specifically developed so that agents need not adhere to strict ant based models – any physical system may be simply modelled and be subject to external environmental influence. An input image is interpreted as a three dimensional topographic landscape upon which a population of simple mobile directional agents are located. The height of the landscape corresponds to pixel grey level intensity, zero (black) represents the lowest level and 255 (white) represents the highest level on the landscape. Colour images may be represented by having three different landscapes for each of the Red, Green and Blue colour channels (other colour models such as the HSI colour space can also be used). The agents can sense their local environment, typically a 3x3 window centred about their current location and the agents can move about the landscape. The agents sense and act in a local manner and the population is decentralised in terms of control. The framework is influenced by the stigmergy paradigm of indirect communication devised by Grasse to explain the complexity of termite building behaviour (see a summary in [26]), that has since been used as a model for communication in many different fields including some examples of human communication and robotics [27].

Agents are populated on the landscape in random positions with initially random orientations. The number of agents created is specified by the population parameter, *%p*, representing the population size as a proportion of the image area. Agents receive stimuli from their local landscape configuration, influencing the agents' behaviour. The agents are able to modify the landscape in three different ways: The deposition of a trail as the agents move forwards, the deposition of specific marks when an agent receives a stimulus that exceeds a particular threshold and the direct modification of landscape height by agents. The trail and mark deposition rates (*depT*, *depM*) can be specified as a parameter to the system and can be set to a simple model (fixed rate of deposition) or more complex models (for example, the rate of deposition may be influenced by the mean pixel level in the neighbourhood surrounding the agent).

The interaction between the population and the landscape, over time, produces a complex emergent global pattern produced by the agents' simple local behaviours. The sensitivity of the agents to the landscape may be adjusted using the parameter *sMin* so that, for example, the agent is only sensitive to variations above a certain value. A maximum sensitivity may also be specified (*sMax*), so that the agents may effectively ignore stimuli that are too strong. It is possible to specify a parameter, *pCD*, to provide a probability of an agent randomly changing direction. As this probability increases the behaviour of an agent moves from that of a guided walk to that of a pseudorandom walk. It is also possible to specify a parameter, *pTP*, to provide a probability of teleportation – a random jump to any unoccupied area of the image landscape. This parameter is used to ensure even coverage of the agent population over the entire image, since the mobile agent population needs to be significantly less than the image area for relatively unimpeded movement to occur.

The landscape may also be subjected to parallel environmental effects such as evaporation and diffusion. These effects can be applied to the trail patterns, specific marks or even the landscape data itself. The parallel environment effects can be used to amplify the emergent patterns formed by the agent behaviours by providing a selection pressure to the emergent patterns.

Agents inherit their basic behaviours from a prototype superclass and different agents may be created to serve different image processing functions. Agents operate in separate cognitive / motor modes. In the cognitive stage, the agent is able to sense its local environment on the image landscape and make a decision about its orientation in preparation for the motor stage. The motor stage then attempts to move the agent forwards in the current direction. Agents do not operate in a synchronous manner, although environmental selection pressures are implemented in a parallel synchronous manner. The algorithms controlling the agent behaviour have been made as simple as possible in order to ensure that any patterns formed are as a result of emergent behaviour and not as an artifact of the program complexity. Previous results using the PixieDust framework for the tasks of edge detection and impulse noise removal using different agent types have been presented in [28] and [29] respectively.

3.1 Framework Operation and Emergent Pattern Formation.

Different agent types are possible, each extending a base agent class that contains the necessary code to implement minimum agent functionality. The framework scheduler operates in the manner described below for all agent types and is illustrated in figure 3.

1. An image is loaded and represented as a three dimensional topographic landscape – landscape height corresponding to pixel intensity. The image represents the first (heterogeneous, or ‘content rich’) physical system, containing the data to be discovered and/or enhanced.
2. A population of mobile agents is created, residing on the landscape. The initial positions and directions of the agents are randomly chosen. The agent population represents the second (homogeneous) physical system.
3. The agent population and the landscape interact:
    - Agents sense their local environment based upon current position and orientation.
    - Local landscape configuration affects the agents’ choice of direction.
    - Agents attempt to move a step forwards in their current direction.
    - Agents deposit a trail as they move successfully forwards, incrementing the trail level at the new site.
    - Specific marks are also left if an agent receives a stimulus above a certain threshold. The mark level at the new site is incremented when the agent moves to the site.
4. Global emergent trail and mark patterns are produced by the population level summation of the individual interactions between the agents and their environment. The emergent patterns correspond to data discovery seen in two interacting physical systems. The trail and mark patterns grow by accretion from a zero level. The density of the trail and mark patterns affects their display: the greater the level, the greater the intensity.
5. Emergent patterns may be subject to external parallel environmental selection pressures.
6. Statistical data is gathered at every system step.
7. Stop conditions are evaluated. The stop conditions can be as simple as manual control or a fixed number of system steps.
8. More sophisticated stop conditions include the halting of the system when the emergent trail patterns match or exceed that of the original image, or if the contrast of the emergent trail pattern exceeds that of the original image by an amount set by the user.

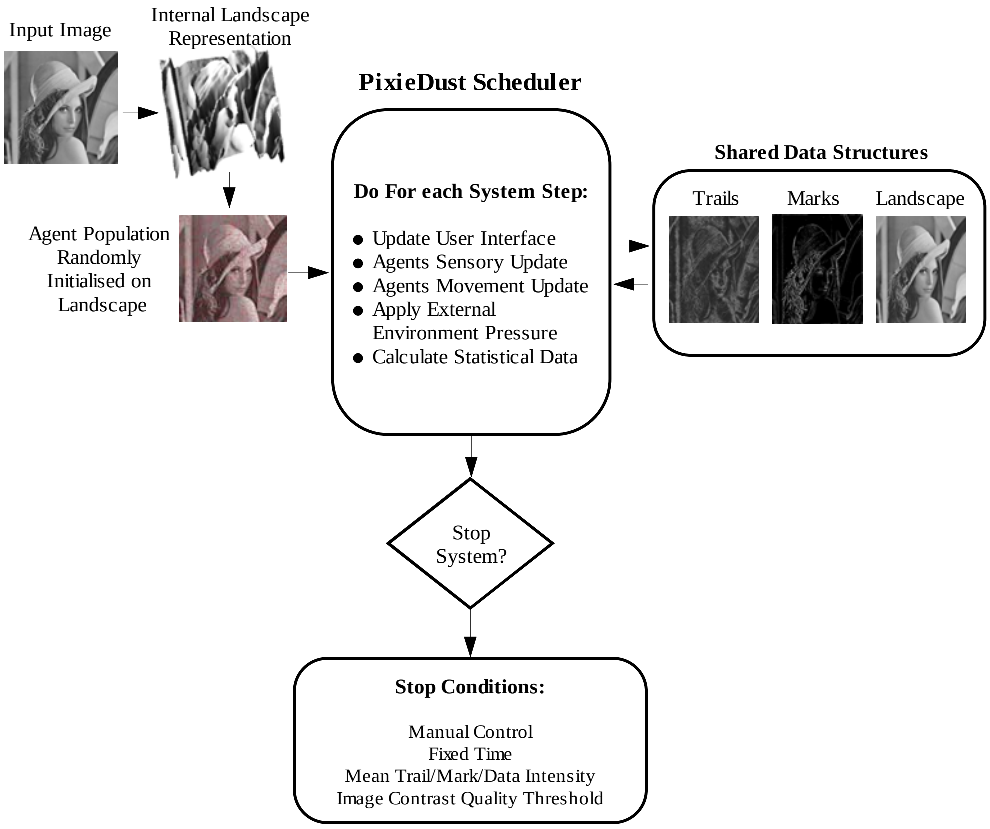


Figure 3: Schematic Diagram of PixieDust Scheduler and Data Structures.

The scheduler is implemented in a pseudo-parallel manner on a single processor machine. Within the time scale of one 'system step' the entire agent population carries out a sensory and movement step and the environment pressures are introduced to the emergent patterns. Parallel, decentralised and asynchronous behaviour is ensured by the stochastic nature of the framework, specifically: The initial random placement of the agents and the effect of random influences on agent position (pTP), agent direction (pCD) and agent-agent collisions. The stochastic behaviour of the framework might suggest that repeated experimental runs may differ in the output result. The large population sizes, experimental run time, and indeed the random influences on agent behaviour itself, act to converge the system behaviour so that different experimental runs do not differ significantly in their output. This may be likened to the effect of how repeated sampling using (for example) the normal distribution improves the perception of the shape of the distribution obtained from the samples.

For emergent pattern formation to take place, two criteria must be met – movement and information content of the environment. Movement of the agents is necessary since agents will only deposit trail when an agent successfully moves to a new cell. Movement is also necessary since the population size is likely to be much less than the landscape area size. Movement will therefore be necessary to position agents in areas of the landscape that are 'information rich'. Furthermore, movement will also help to amplify the emergent patterns produced by the agent population: Information rich areas will attract more agents and thus will have greater amounts of trail deposited at these locations.

Information content is necessary because the agents use the information content of the image to affect their choice of direction (the *stigmergy* paradigm). If the landscape has no varying content (a blank image) then no stimuli will be provided to the agent population and a uniform distribution of trail will be produced. This is akin to 'dusting' for a fingerprint that does not exist, or staining an empty microscope slide as discussed in section 2. The agents' cognitive response to the landscape configuration must be kept relatively simple in order to be able to trace back the effect of different behaviours on the emergent patterns formed.

4. Framework Parameterisation – 'Benign' Test Images.

There already exist a large number of framework parameters to optimise, even before considering additional parameters associated with specific agent behaviours. One difficulty in tuning parameters for image processing functions is the great many (for practical purposes, infinite) number of possible landscapes (images) that the agent population can populate. Even if the particular application limits the type of image to be processed (for example greyscale mammogram enhancement), there is still a massive scope for variability within the target images. When considering the two requirements for emergent pattern formation - movement and information content – it is possible to possible to configure a blank image with no varying information content (the 'empty microscope slide' configuration). Using a blank image it is possible to assess the effect of varying the framework parameters on the emergent trail formation. For a blank image presenting no stimuli, the ideal trail pattern would be a clear facsimile of the blank image.

4.1 Population Size (*%p*) and Emergent Trail Pattern.

As length and breadth vary with each target image, population size is expressed as a proportion of image area. What is the effect of increasing population size on the uniformity of the emergent pattern? Figure 4 shows a graph displaying global statistics for the emergent trail pattern when the population is placed upon a blank image, sized 200x200 pixels. Framework parameters used for the experiments used to generate the figures used in this paper are described in the appendix.

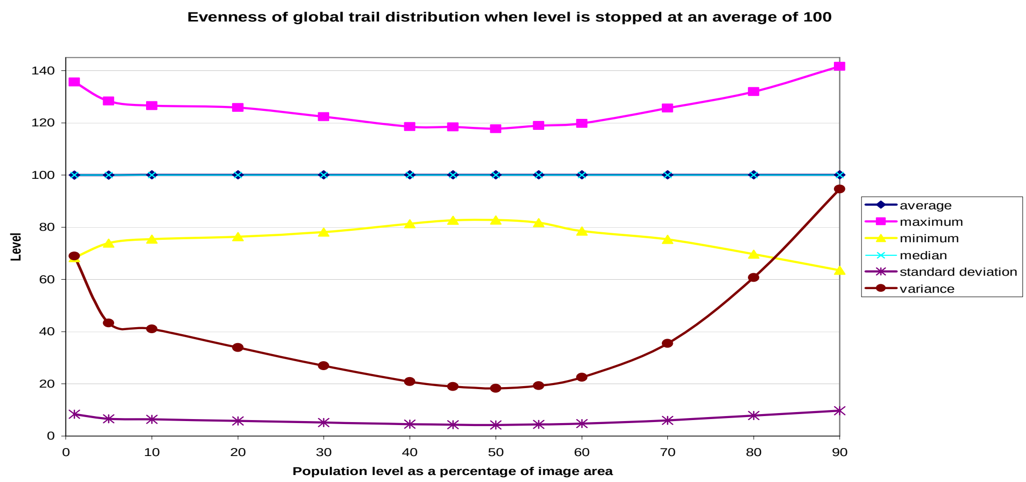
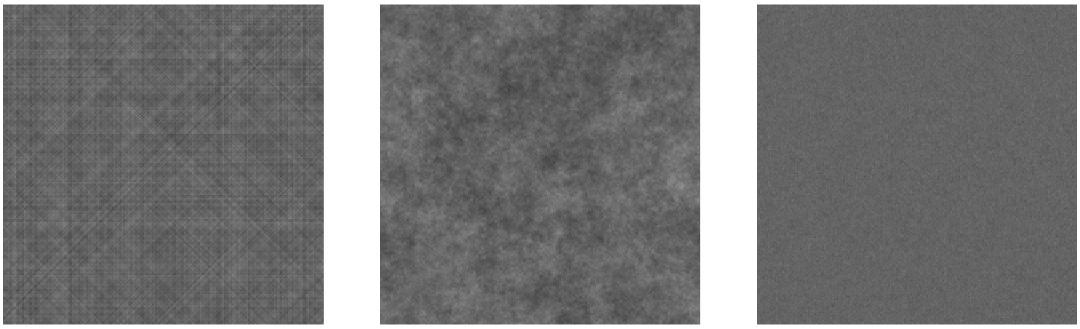


Figure 4: Population size parameterisation. The effect of increasing population sizes on the uniformity of the emergent trail pattern. For each population size the statistics were averaged over 5 runs.

Figure 4 shows that the variance of trail level is lowest at a population rate between 45 and 55 percent. Very low and very high population rates dramatically increased the variance. Low population sizes increased the variance due to the lower likelihood of agent-agent collisions (i.e. unsuccessful movements), resulting in ‘tramline’ like artifacts seen in figure 5a. The high variance seen in higher population rates is caused by too many agent-agent collisions, resulting in blotchy collision artifacts due to pockets of restricted movement (figure 5b). Figure 5c shows the trail pattern formed at a 50% population rate, minimising the trail level variance and providing the most even trail texture.



a) b) c)

Figure 5: Trail patterns produced by agent – landscape interactions: a) at population rate of 1%, b) 90%, c) 50%

If the agent population is to accurately perceive the image the emergent trail pattern must accurately reflect the input landscape image. Artifacts such as those seen in figure 5 (‘a’ and ‘b’) must be minimised. Figures 4 and 5 shows that population size is an important consideration in the evenness of the emergent trail pattern. The increasing frequency of agent collisions (unsuccessful moves forwards due to the chosen cell already being occupied) as population sizes increase can be seen in figure 6, a graph that plots the average number of successful and unsuccessful moves per system step.

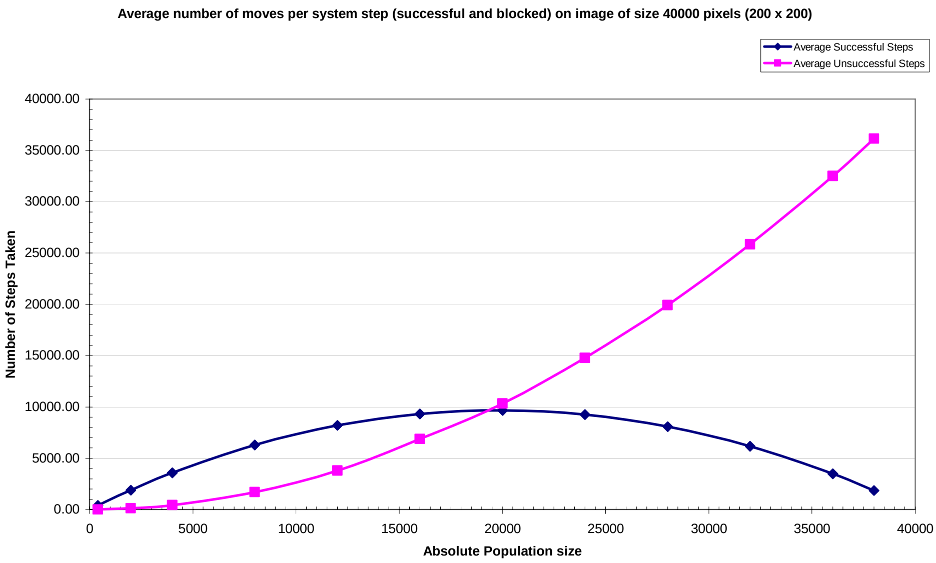


Figure 6: Graph illustrating the effect of population size on successful agent moves.

4.2 The effect of Random Changes of Direction and Position: pCD and pTP.

Artifacts arise in the global perception of the blank image due to lack of stimulation at low population levels and agent congestion at high population levels. Both of these problems may be reduced by adding random elements to the agents' choice of direction and position. The pCD parameter sets a probability (from zero to one) of a random direction change from the current direction to any of the other 7 remaining directions. The pTP parameter sets a probability of an agent randomly jumping to an unoccupied pixel anywhere on the image landscape. Empirical results show that increasing the pCD parameter reduces the trail level variance. The optimal pCD values lie between 0.1 and 0.3. Increasing the value above 0.3 only slightly decreases variance at the cost of longer computation time since if a random direction change is made, the current move forwards is abandoned until the next step. Increasing the pTP parameter also reduces the trail level variance – the optimum values lying between 0.01 and 0.1. At levels above 0.1 however, the trail level variance starts to increase. The pCD and pTP parameters are useful in reducing trail level variance on a blank image – an image providing no stimulation to the agents. Their effect may differ on images with real information content since these images are likely to have local regions of stimuli that attract agents, thereby increasing agent congestion at these points.

4.3 The Effect of Deposition Rate on Emergent Trail Patterns.

The trail deposition rate is the amount of trail laid down by an individual agent when it successfully moves forwards to occupy a new location. Intuitively, a lower trail deposition rate would be expected to provide a more even coverage of the emergent trail pattern. Experiments were performed to explore the effect of different deposition rates on a blank image. The experiments used a population size of 40% of the image area as this was at the lower end of the trail level variance. Both pTP and pCD were set to zero to avoid their influence on results. Figure 7 shows a graph that illustrates the effect of different deposition rates on the trail pattern standard deviation from the mean.

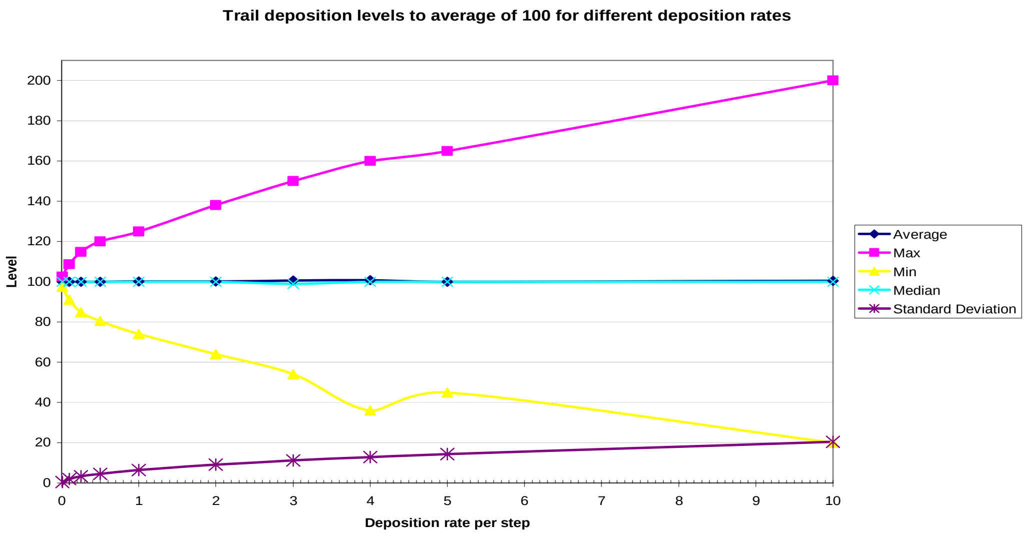


Figure 7: The effect of different trail deposition rates on emergent trail pattern standard deviation from the mean.

The graph clearly supports the intuition that lower deposition rates provide more even trail coverage. From an image processing perspective, the trail deviation from the mean value is seen in the grey level histogram frequency distribution produced in the emergent trail patterns. Figure 8 shows the grey level histograms from the emergent trail patterns at different deposition rates.

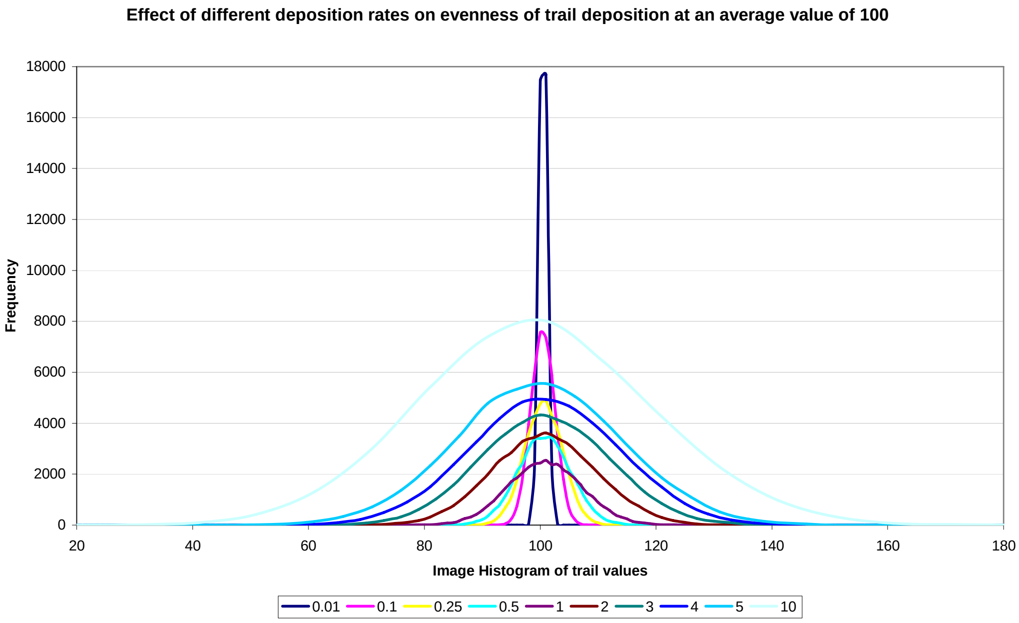
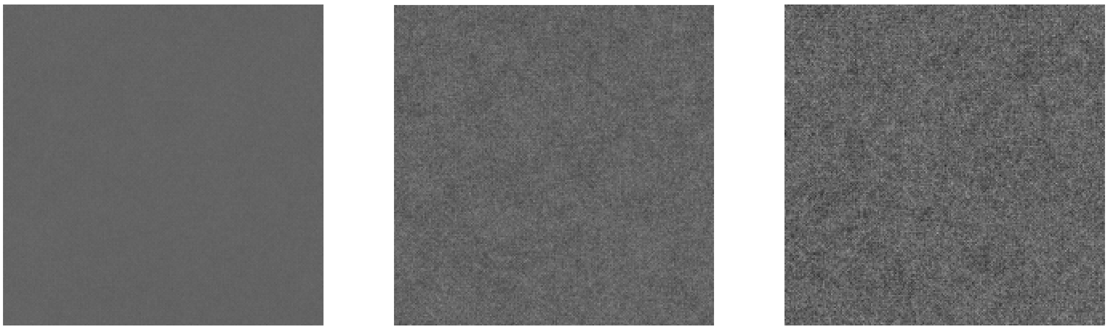


Figure 8: Grey level pixel frequency distribution histograms from emergent trail patterns at different deposition rates. Lower rates clearly show a closer distribution.

Figure 9 illustrates the effects of different deposition rates on the actual emergent trail patterns from the agent population's interaction with the blank image, again showing that lower deposition rates produce a more even trail pattern.



a) b) c)

Figure 9: Emergent trail patterns on blank image at different deposition rates: a) 0.1, b) 2, c) 5

Although lower deposition rates do increase the evenness of the emergent trail pattern, this is at the cost of computation time, since the smaller deposition rates will result in longer times for the global trail level increase to the desired level. A compromise value of between 0.1 and 0.5 provides even trail patterns and relatively short computation times.

5. Effect of Different Agent Cognitive Behaviours.

A blank image may be used to assess the effect of general framework parameters on the emergent trail patterns. This satisfies the parameterisation one of the two requirements for emergent pattern formation – movement. The other requirement, stimuli from the image landscape affecting behaviour, cannot be assessed with the blank image since no stimuli is provided by that landscape.

It was earlier mentioned that an almost infinite number of different possible image landscapes were possible. The same is true of possible agent behaviours. The criterion that agent behaviours must be simply specifiable (to examine the causes of emergent pattern formation) only slightly reduces the vast range of possible agent behaviours. Another restriction on possible agent behaviours is that of locality – the stimuli presented to each agent must be from the local neighbourhood around the agent. The result of the stimulus provided by the local configuration must be a change in the agent's current direction. The change in direction will be reflected (in images with real information content) as different levels of trail in different image areas.

There are a number of different properties of the local landscape that, from an image processing perspective, may be used to influence the agent's behaviour:

- Relative pixel intensity
- Absolute pixel intensity
- Gradient changes
- Line following
- Noise identification
- Uniformity identification

These properties will be suitable for different applications: gradient changes may provide suitable stimuli for agents developed to perform edge detection. Uniformity of the local neighbourhood may be suitable for agents developed for image segmentation purposes.

The differences in relative pixel intensity will be used to explore how differences in agent behaviour can affect the quality of the emergent trail pattern produced by the agent population's interaction with the environment. A simple agent was developed that is sensitive to, and attracted towards, pixel intensity. Each agent samples its local 3x3 neighbourhood in the current direction it is facing (one of eight compass points). The agent considers the difference between the pixels at the front-left (FL), front (F), and the front-right (FR) of its neighbourhood. If the agent receives a sufficiently large stimulus from either direction, the agent then rotates to face this direction and attempts to move forwards to this cell in the next motor stage. The simple algorithm governing the agent behaviour is shown by the following pseudocode in figure 10. The sensitivity parameters are omitted from the pseudocode for simplicity of reading.

Stage 1:

If (F > FL) and (F > FR)

Return (no change in direction).

Stage 2:

If (F < FL) and (F < FR)

Rotate left or right 45 degrees.

Return.

Stage 3:

If (FL < FR)

Rotate 45 degrees right.

Return.

Stage 4:

If (FR < FL)

Rotate 45 degrees left.

Return.

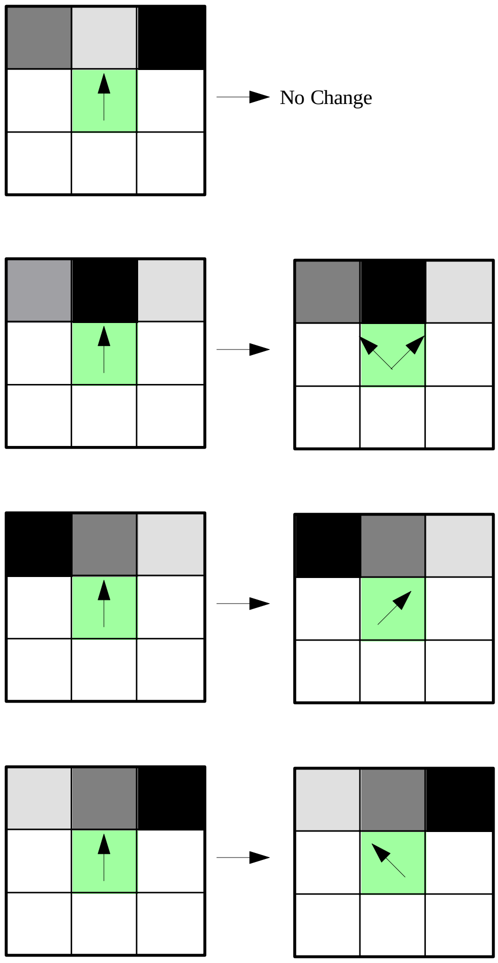
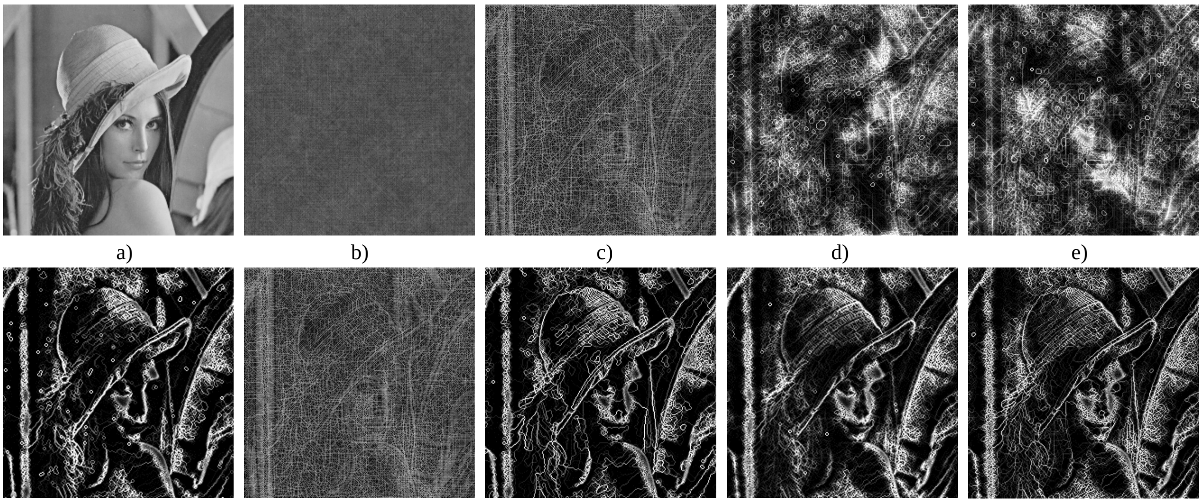


Figure 10: Simple light-attracted agent pseudocode and visualisation of agent behaviour. Green cell indicates current position. Arrow inside green cell indicates agent orientation.

As figure 10 illustrates, the cognitive abilities of this agent are very simple indeed and adhere to the locality requirements of emergent behaviour. The effect on the emergent trail pattern of switching on and off different stages of the algorithm can be seen in figure 11 on the following page. The agent population size was 10%. Both pTP and pCD were set to zero and the agents were set to their maximum sensitivity: sMin = 0, sMax = 255.



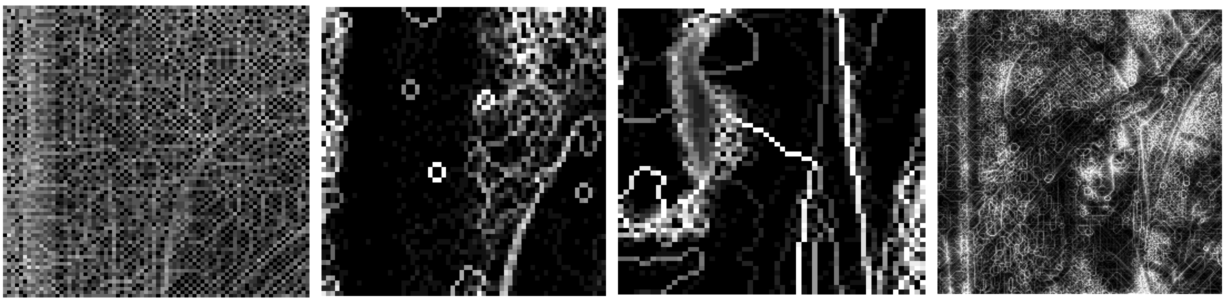
a) b) c) d) e)

f) g) h) i) j)

Figure 11: The effect of different agent behaviours on emergent trail patterns.

a) Original Lena image.
b) Stage 1 of the algorithm only.
c) Stage 2 only.
d) Stage 3 only.
e) Stage 4 only.
f) Stages 3 & 4 combined.
g) Stages 1 & 2 combined.
h) Stages 1, 3 & 4 combined.
i) Stages 2, 3 & 4 combined.
j) All four stages active.

Figure 11 demonstrates that different cognitive behaviours can have a dramatic impact upon the emergent trail patterns formed at the population level. The patterns differ in their perception of the original image and the presence and type of image artifacts formed during the pattern formation. Figure 12 illustrates some of the artifacts formed in more detail.



a) b) c) d)

Figure 12: Artifacts in emergent trail patterns:
a) Artifacts ("scratchy / tramlines") caused by too little stimulation.
b) Artifacts caused by agents becoming trapped in local cycles by the image configuration.
c) Artifacts caused by agents being drawn across straight channels by image configuration.
d) Artifacts caused by uneven agent sensory ability and hence uneven agent distribution across image.

5.1 Reduction of Trail Artifacts.

The presence of artifacts in the emergent trail pattern represents a problem for the use of simple agent populations for image processing functions. The ideal image processing algorithm would perfectly represent the general image and only highlight the relevant features required for a particular processing function. Artifacts are a common phenomenon in some image processing algorithms, particularly noticeable in image compression techniques. The artifacts seen in the emergent trail patterns arise due to a number of factors.

1. The sensitivity and directional capability of the agents:

    The agents in the above example are sensitive to *any* fluctuation in the image landscape gradient – no matter how small. This sensitivity results in agents responding to fluctuations that the human observer would not notice. As the response to the stimulus is a change in direction, certain local configurations of the landscape conspire to trap agents in a cycle of movement and rotation that results in small tight circular artifacts (Figure 12, b). This is also a consequence of the limitations of the agents' directional abilities. The eight way neighbourhood and the 45 degree rotations used (by this particular type of agent) result in the possibility of cyclic artifacts. The local configuration in this instance acts as a cyclic attractor, constraining the agent to repeat the same path.

2 The lack of stimulation to the agents:

    This effect was noted in the parameterisation of movement using the benign image and is also seen in figure 12 (a). The artifacts occur in this case due to the algorithm stages only considering a limited portion of the available local landscape configuration and results in scratch-like tramline artifacts. This may be remedied by considering more of the local landscape data in the cognitive stage.

3. Directional bias in the algorithm:

    If the algorithm used in the cognitive stage is biased in considering a particular direction over others, the resultant emergent trail pattern will also be biased in its distribution of trail. This can be seen in figure 12 (c and d). The straight line artifacts seen in 12c are a result of the combination of stages 1, 3 and 4 in the algorithm. The consideration of stage 1 however, takes precedent over stages 2 and 3 so straight paths are accentuated. The uneven trail pattern in 12d arise because the algorithm is only considering stage 3, thereby biasing the agent rotations to right hand 45 degree rotations. This affects the distribution of the agents into certain parts of the image. Large areas of the image become congested with agents, restricting their movement and resulting in an uneven trail distribution, even though the overall shape original image is perceived fairly well.

How then to minimise artifacts in the trail patterns? By observing the causes of artifact production it is possible to suggest some solutions in an attempt to ensure the emergence of an even global trail pattern.

1. Sensitivity:

    By decreasing the sensitivity of the agents to local fluctuations of gradient, relatively minor changes (that may not be noticeable to the observer) will not be amplified in the emergent trail pattern. Clearly the sensitivity must not be decreased to a point where important features are missed by the agents. The sensitivity of the agents will differ depending on the image processing application and may also be influenced by the presence of noise within the source digitised image.

2. Increasing the random element of movement:

    By setting the pCD parameter to provide a random element to the agent behaviours, the likelihood of agents becoming trapped in cyclic or straight line patterns is reduced. The pCD parameter may also help to alleviate the problem of random noise contamination of the source image, as random influence on agent direction may negate the erroneous stimuli presented by the noisy pixels.

By setting the pTP parameter to provide a random element to the agent position, the agents are less likely to become trapped in local congestion points that arise due to the higher concentration of agents to areas of interest in the image. The setting of the pTP parameter will also ensure that the entire image landscape is considered, and will help to ensure that the emergent trail pattern is not simply as a result of the initial agent distribution and direction.

3. Removing algorithm directional bias:

By ensuring that the algorithm behaves symmetrically in its evaluation of local landscape configuration, the agent distribution (and resultant trail pattern) will be free from bias due to the algorithm. This will result in an even trail distribution that more accurately reflects the source image.

4. The effect of population size on artifact production:

On the benign image, population size had an effect on trail artifacts. At very low population levels the combination of lack of landscape stimuli and the lack of directional influence by other agents resulted in 'tramline' like artifacts. At very high population levels, the density of the agent population ensured that very little free movement could occur without agent-agent collisions, resulting in blotchy artifacts in the emergent trail. On images with real content, changes in the landscape affects the agent's choice of direction. The example agent chosen is attracted to lighter areas of the image and lighter areas of the image have a higher influx of agents, with a relative lack of agent occupancy in darker areas of the image. This is desirable from an image processing perspective (since there will then be a discrepancy in the rates of trail deposition in lighter and darker areas), but the influx of agents may produce congestion in lighter areas and result in more agent-agent collisions, affecting the deposition rate. If a realistic perception of the original image is to be produced, the optimal population rate must be chosen.

6. Parameterisation on Images Containing Real Content.

Figure 11 illustrated how different cognitive behaviours of the agents resulted in differing emergent trail patterns. Whilst none of the patterns formed presented a realistic facsimile of the original image, figure 11j (all four sensory stages in place) did enable the agent population to collectively perceive the most important image features. The ultimate aim of image processing requires the system to accurately perceive an image, so that the desired features may then be extracted by the agents' interaction with the landscape. If the population cannot perceive the original landscape accurately, there is little hope for accurate processing to occur.

Parameterisation of the system on realistic imagery followed the same procedures as with the benign image to optimise the parameters of population size, random influences on position and direction, and deposition rate. The issue of sensitivity to landscape fluctuations (which could not occur in the benign image parameterisation) will first be considered.

6.1 Effect of Agent Sensitivity.

The sensitivity of the light attracted agent to gradient changes affects the choice of agent direction and ultimately will affect the distribution of agents throughout the image. If agents are too sensitive, they will respond to fluctuations that are not visible to the human eye, resulting in severe artifacts in the emergent trail pattern. Agents that are not sensitive enough to landscape changes will miss subtle cues to direct their movement into different parts of the image, resulting in a loss of detail and a 'washed out' perception of the image. This is shown in figure 13 that shows the effects of different sensitivity settings of the agent population.

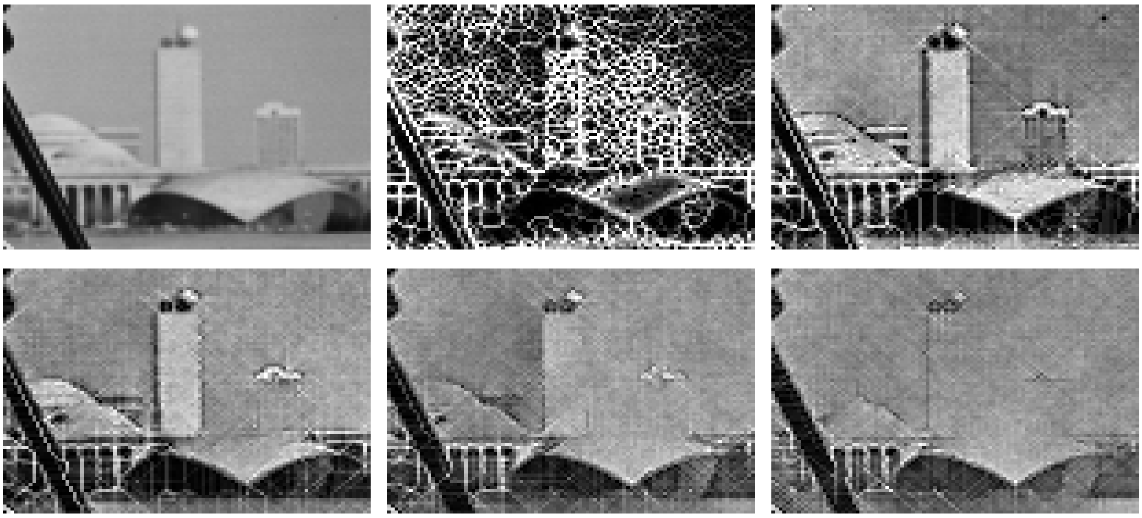


Figure 13: Effect of decreasing agent sensitivity - Enlargement of a portion of the Cameraman image (100 pixels wide and 80 pixels high) and emergent trail patterns. %p was 20.

Top Row, left to right: Original image, sMin=0, sMin=10

Bottom row, left to right: sMin=20, sMin=30, sMin=40

Figure 13 illustrates the effect of the sMin parameter on the perception of small features in the original image. Empirical results considered over a selection of standard test images suggest that the optimum sMin values lie between 20 and 40. One problem with the sMin sensitivity threshold is that it is a hard threshold function. Any value below the threshold will not be considered, even if it is only slightly below the threshold.

To remedy this, a method of softening the threshold was devised. The method involved setting a fixed threshold (for example 30, as this lies in the middle of the empirically discovered optimal range). Each agent then modulated this threshold before every cognitive step by sampling from the Gaussian distribution, with the mean value of the distribution set at the fixed threshold value. The sampled value was then added to the fixed threshold value, effectively modulating the threshold by randomly increasing or decreasing the fixed threshold. Experiments were performed to find the optimum standard deviation value (sigma) for the Gaussian distribution sample. The result of softening the sMin threshold value is shown in figure 14.

a) b) c) d)

Figure 14: Effect of randomly modulating the sensitivity parameter to soften the sensitivity threshold.
a) Original Image, b) Fixed sMin of 30, c) sMin 30 modulated by sigma 20, d) sMin 30 and sigma 20 further improved by decreasing the trail deposition rate to 0.2.

The emergent trail pattern seen in Figure 14d shows that the agent population is able to collectively perceive the original image (14a) to a very close approximation. It should be borne in mind that the figure in 14d is not a processed version of 14a but is simply a collectively accreted trail representing a historical record of movement by the population of independent agents across their habitat.

6.2 Effect of Population Size on Emergent Trail Patterns.

Population size affects the freedom of movement of the agents about the landscape. If the landscape is more densely populated, the opportunities for collision free movement are reduced. Figure 15 illustrates the effect of increasing population sizes on agent perception of the Cameraman test image. The sMin value was 20, pCD and pTP were zero. Trail deposition rate was set to 1 and the experiment was stopped when the mean trail level equalled that of the mean intensity of the original image.

a) b) c) d) e)

Figure 15: Effect of population size on the perception of the Cameraman image.
a) Original cameraman image, b) %p=10, c) %p=30, d) %p=50, e) %p=80.

Figure 15 illustrates how congestion affects movement, and hence trail deposition. At low population levels, the migration of agents into lighter areas (such as the white tower in the image) increases the deposition rate in those areas. As the population level increases, tramline artifacts caused by lack of stimulation at lower population levels are reduced. At higher still population levels, the increased congestion in light areas results in less successful movement and they appear darker. Ironically, the relative lack of congestion in the darker areas (for example the cameraman's coat) results in higher deposition rates in these areas. At higher population rates (50% of image area and above) a fundamental misperception of the original image starts to occur, inverting the actual intensity of the image. There is also a relationship between population size and agent sensitivity. At very high sensitivity to landscape fluctuations, the optimum population size is higher. As the sensitivity to image features decreases, the optimum population level also decreases. This is because greater agent sensitivity tends to result in more aggregation around image features. If the population size is too low, the aggregation will result in an uneven build up of trail pattern. If there is no random influence on agent position (pTP), the optimum range for population size is between 20 and 40% of the image area.

6.3 Effect of Random Influences on Position and Direction – pTP and pCD.

The effect of the pTP parameter is to reduce congestion in the landscape by randomly teleporting agents to an unoccupied area of the image landscape. The effect of increasing the pTP parameter can be seen in figure 16 below:

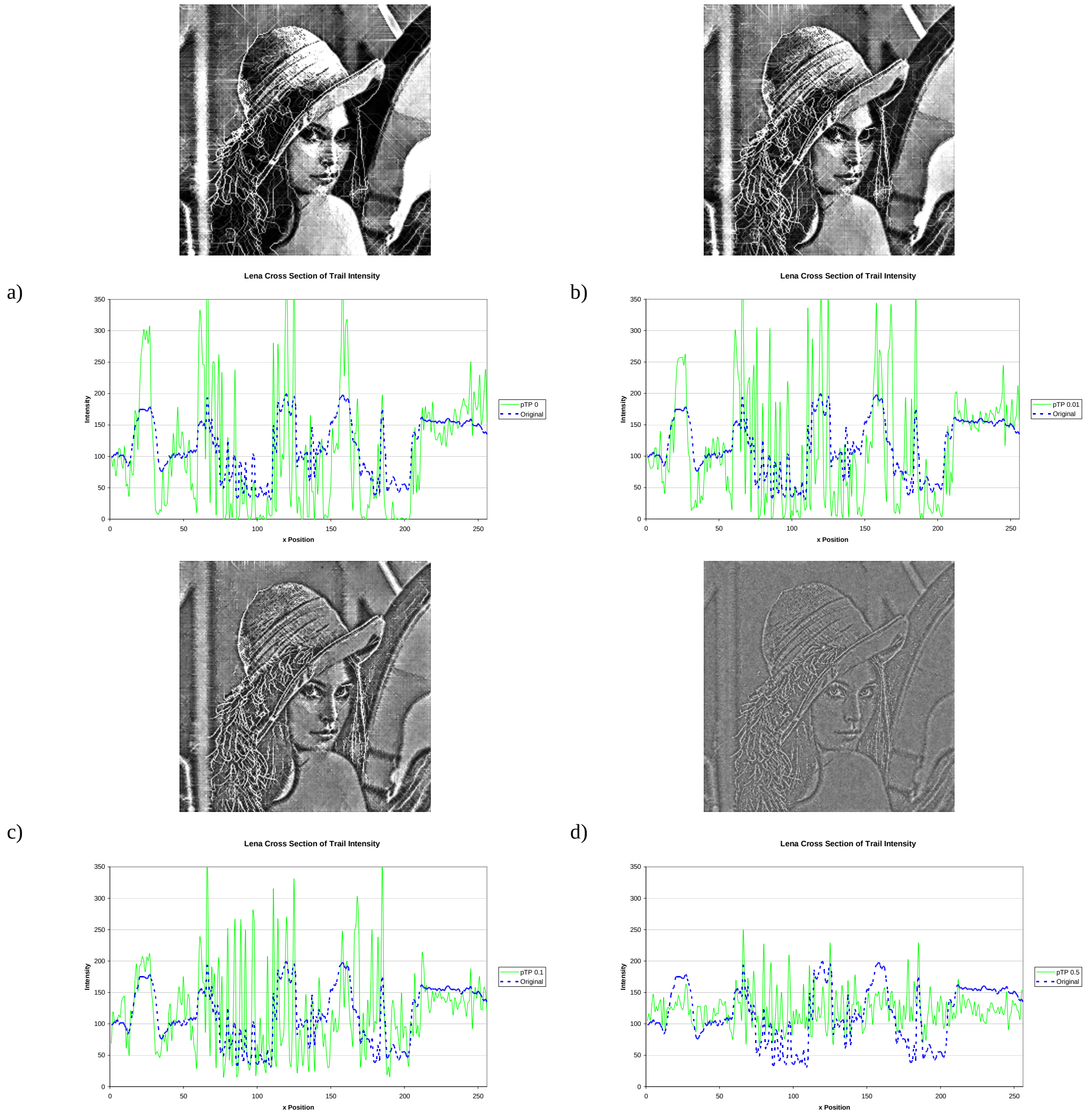


Figure 16: Effect of increasing pTP parameter on perception of the Lena image. Trail pattern and cross-section data.
a) pTP 0, b) pTP 0.01, c) pTP 0.1, d) pTP 0.5

The effect of reducing congestion in the image is to even out the distribution of trail across the image. The reduction of aggregation into lighter areas produces a ‘flattened’ perception of the original image, reducing the contrast in the trail pattern and elevating the mean level of the trail pattern. This can be seen in the cross-section data plot sampling across the image, and taken halfway down the image, that compares the emergent trail pattern intensity with the original image data (dotted line). The pTP parameter also impacts on the choice of population level and enables experiments with lower population levels to be used (%p 10). The effect of the pTP parameter is to ensure even image coverage that would otherwise not occur at low population levels.

The pCD parameter randomly selects a new direction for an agent and has a more subtle effect on the emergent trail pattern. The effect, as with the benign test image, is to reduce the visible presence of artifacts on the trail pattern.

6.4 Effect of Deposition Rate.

As with the benign test image parameterisation, decreasing the deposition rate results in a smoother build up of trail pattern and a more accurate, less noisy, perception of the original image, albeit at the expense of increased computation time. This can be seen by comparing the results seen in figures 14c (depT 1) and 14d (depT 0.2).

7. Application of External Environmental Selection Pressure to Emergent Patterns.

The patterns produced by the interaction of the agent population and their environment (a digitised image ‘landscape’) emerge as a result of simple, local rules to produce a global, population level perception of the original image features. The patterns are also *emergent* in the more literal meaning of the word: they emerge over time. The process is similar to the emergence of a photographic image when the light sensitive film is exposed to the target scene and later developed by developing chemicals. In photography, the interaction between the film and the scene to be captured is strictly controlled by the exposure time - the length of time in which the light sensitive film is exposed to the external light source. After chemical development, the photograph is then fixed by a separate chemical process to ensure that the captured image will persist over time.

The emergent pattern formation due to agent-environment interactions is a continuous dynamical process – as long as the agent population is stimulated by the landscape configuration, the trails left by their movement will continue to accrete. To continue the photography analogy, the ‘exposure time’ in the multi-agent system is the amount of time that the agents are exposed to the landscape stimuli. The sensitivity of the individual agents loosely corresponds to the sensitivity of the light sensitive particles in the camera film (or, perhaps more likely nowadays, CCD or CMOS sensor sensitivity in a digital camera). The deposition rate of the agents may correspond to the reaction speed of the film particles or the digital sensor pixel value quantisation level. The dynamical nature of the emergent pattern formation leaves the agent-environment interactions open to influence by an external selection pressure. Selection pressures in the natural world are environmental influences on a system that affect the persistence of some components of that system. Common selection pressures in physical systems are weather systems (wind, rain, erosion, and weathering). Living systems are subject to selection pressures too, the most common example being the well known maxim ‘survival of the fittest’: individuals in a system are subject to the external pressures of food availability, predation threats, reproduction opportunities, and - sometimes - luck. Selection pressures serve to amplify any minor distinctions in a system by their constant effects on the persistence of information.

The emergent trail and mark patterns are laid down by a process of accretion. The trail patterns correspond to a shared memory of agent occupation of pixel sites and the mark patterns are a map of points on the landscape where stimulation has occurred. More frequently visited sites have more dense trails. In the case of an agent that is attracted to lighter areas of an image, lighter areas will tend to be visited more frequently. This provides a discrepancy in the emergent trail pattern between lighter areas of the image and darker areas. Because the accretion of trails occurs in a continuous dynamical manner, this distinction between lighter and darker areas may be amplified by the application of a selection pressure.

One simple selection pressure to implement is the parallel erosion of trails. Every area of the landscape has its trail value decremented by a specific erosion rate. The frequency of erosion can be set by the user at every ‘*x*’ system steps. One system step occurs when all of the agents in the population have undergone one sensory (cognitive) and motor stage. Trails at frequently visited sites are more likely to persist over time, whereas trails at infrequently visited sites are less likely to persist. The result of applying this simple selection pressure can be seen in figure 17, showing the emergent trail pattern formed by the agent population stimulated by the original Lena image from figure 14a. Figure 17 illustrates the effect of increasing the erosion selection pressure rate on the persistence of the emergent trail patterns.

a) b) c)

Figure 17: Effects of applying a simple erosion selection pressure on emergent trail patterns. a) erosion rate of 0.01 per system step, b) erosion rate 0.05, c) erosion rate 0.1.

Figure 17 illustrates how selection pressure can be used as a mechanism to amplify differences present in the original image. The general tendency for agents to prefer lighter areas of the image is laid down in their trail movements. Applying the selection pressure to the emerging trail pattern further amplifies the distinction. The constant trail deposition of the agent population due to its movement provides an upward pressure on trail accretion. The selection pressure applies a constant braking effect on trail deposition, *pulling* the trail levels downwards and the discrepancy in trail deposition between lighter and darker areas is further stretched by the braking effect of the selection pressure.

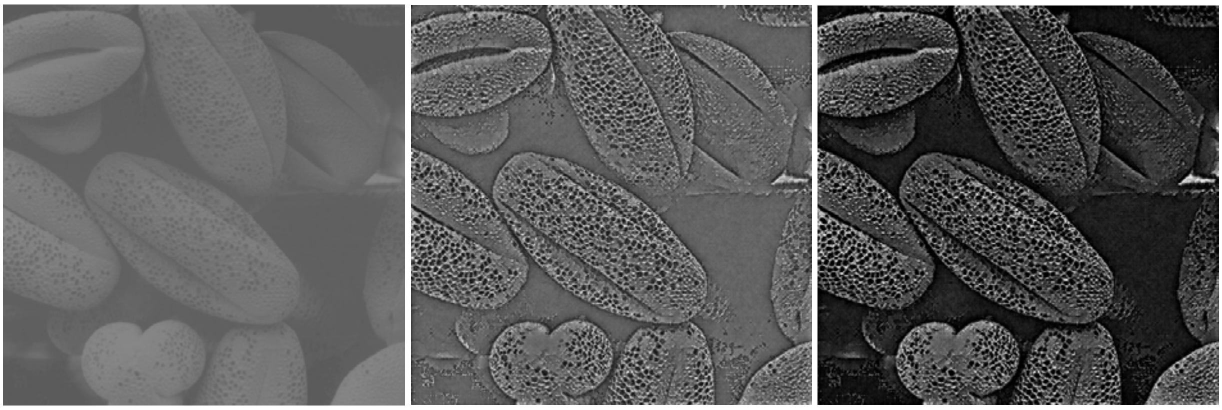
7.1 Modifications to the Deposition and Selection Pressure Models.

The emergent trail patterns formed as a result of agent/environment interactions have built up the trail level from a level of zero. Although the agent population is able to collectively perceive the original image at the population level, the resulting trail pattern can look artificial when compared to the original source image. Starting from a zero trail level also makes it more difficult to tune the parameters for different images since the different content of images will affect the migration to different areas of the image. The difficulty is caused because agents perceive their local surroundings in relative terms to their pixel neighbours, not taking into account the absolute height (pixel intensity) of their current position in the landscape. This makes the accurate perception of the image in figure 14d all the more surprising.

It is possible to initialise the trail pattern with a copy of the greyscale values of the original image to give the emergent trail pattern the initial ‘shape’ and height of the landscape. The agents still *perceive* the original relative values of the image data, but the trail pattern that emerges is added to a copy of the original image data. By initialising the trail with the original image values, the necessity for agent migration to different parts of the image is reduced, resulting in simpler parameterisation of population levels, pTP and pCD levels. The result of initiating the trail with the original image values in a system that is subject to a mild erosion selection pressure can be seen in figure 18 and illustrates how simple agent–environment dynamics can be used to perform useful image processing functions, in this case, contrast enhancement.

Figure 18: The effect of initialising the trail pattern with the original (left) greyscale values before further trail build-up occurs. The effect is a useful image processing behaviour – contrast enhancement (right).

An alternative to initialising the trail levels with the absolute image intensity values is to modify the deposition and/or erosion models to takes into account the absolute values of the local environment features. For example, the agent may deposit trail in direct proportion to the pixel intensity of its current site of occupancy, or the average pixel intensity in the 3x3 window surrounding the agent's current location. The erosion selection pressure may, for example, erode the trail in inverse proportion to the average pixel intensity at the agent's current location. This is analogous to evaporation of water by sunlight – water evaporates more quickly in well lit areas and more slowly in shaded areas. With the standard deposition models, the agents only respond to the landscape in terms of relative pixel intensity changes. The modifications to the deposition and erosion models allow some of the *absolute* features of the local landscape to influence the emergent patterns produced. This may be useful in certain applications where a reference to the original image is required. Figure 19 shows an example of a poorly exposed image (a), the emergent trail patterns formed with the standard deposition model, and (b), trail deposition directly proportional to the mean 3x3 window pixel intensity, and erosion inversely proportional to the mean 3x3 window pixel intensity.



a) b) c)

Figure 19: Effect of different deposition and erosion models. a) Original low contrast *pollen* image, b) Emergent trail pattern with standard (constant) deposition, c) Emergent trail pattern with deposition proportional to pixel intensity and erosion inversely proportional to pixel intensity.

8. Image Processing Applications of the PixieDust Framework.

This section describes some brief application results of the PixieDust framework for shape recovery, greyscale image enhancement and colour image enhancement. Examples using the framework for edge detection and noise detection and removal can be seen in [28] and [29].

8.1 Binary Shape Recovery from Noise Contaminated Images.

Many industrial applications require apparently binary simple image processing, locating objects in terms of foreground (object) and background (not objects). Conventional centralised approaches include simple and complex thresholding, smoothing and mathematical morphology operations. Binary thresholding of a greyscale input image can achieve reasonable performance when the input image is of high quality. If the input image is contaminated by noise, simple binary thresholds are not suitable. Smoothing the image before applying the threshold function can remove some of the noise component from the signal. Mathematical Morphology operators (opening and closing functions) can also be applied to the image after the threshold operation to remove any remaining small particles of noise.

A decentralised approach using the simple light attracted agent may also be employed to effectively resolve noise contaminated binary images into foreground and background. The light attracted agent previously described is centred in a 3x3 window and responds to stimuli by rotating in discrete steps of 45 degrees. This is in response to the discrete architecture of a digitised image. In some images that are heavily contaminated by noise, the noise component of the signal can be so strong that a window size of 3x3 is not large enough to effectively discern the original signal from that of the noise signal. It is possible to extend and enlarge the sensors of the light attracted agents so that they cover a larger area of the image landscape, and are more able to separate the signal from the background noise. As sensors larger than a single pixel will not be able to return a scalar pixel intensity value, the mean of the pixel intensity of the sensor window is returned. Figure 20 compares the architecture of the so-called ‘offset’ Pixie type from the conventional light attracted Pixie type. It is possible to have different offset widths and sensor widths. The offset value in figure 20 is three and the sensor width is 3. If a larger sensor value - say 5 - was used, the sensors would overlap slightly.

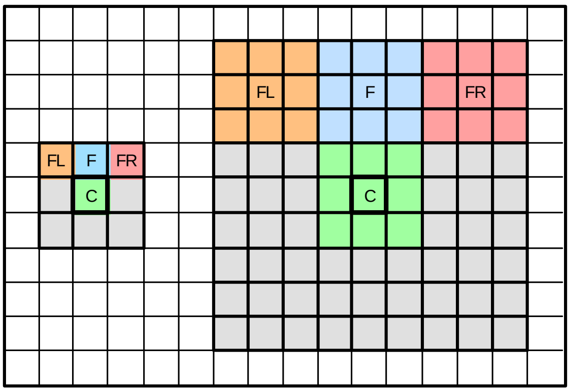


Figure 20: Comparison of the standard agent neighbourhood and the ‘offset’ type neighbourhood. This offset neighbourhood has sensor width of 3 and is offset from the current pixel location (‘C’) by 3 steps. The sensory area of the agent is now 81 pixels compared to nine pixels of the original agent. Each sensory segment returns the mean pixel intensity of the region covering the sensor.

For this application, offset light attractor agents were used and the agents deposit trail in direct proportion to the mean pixel intensity of a window surrounding the agent. If the noise contamination is very strong, the size of the window can be increased to reduce the effect of the noisy signal. The framework is able to correctly recover the object shape when the image is contaminated with either Gaussian additive noise or random impulse noise. Figure 21 shows some sample results using the framework for binary shape recovery.

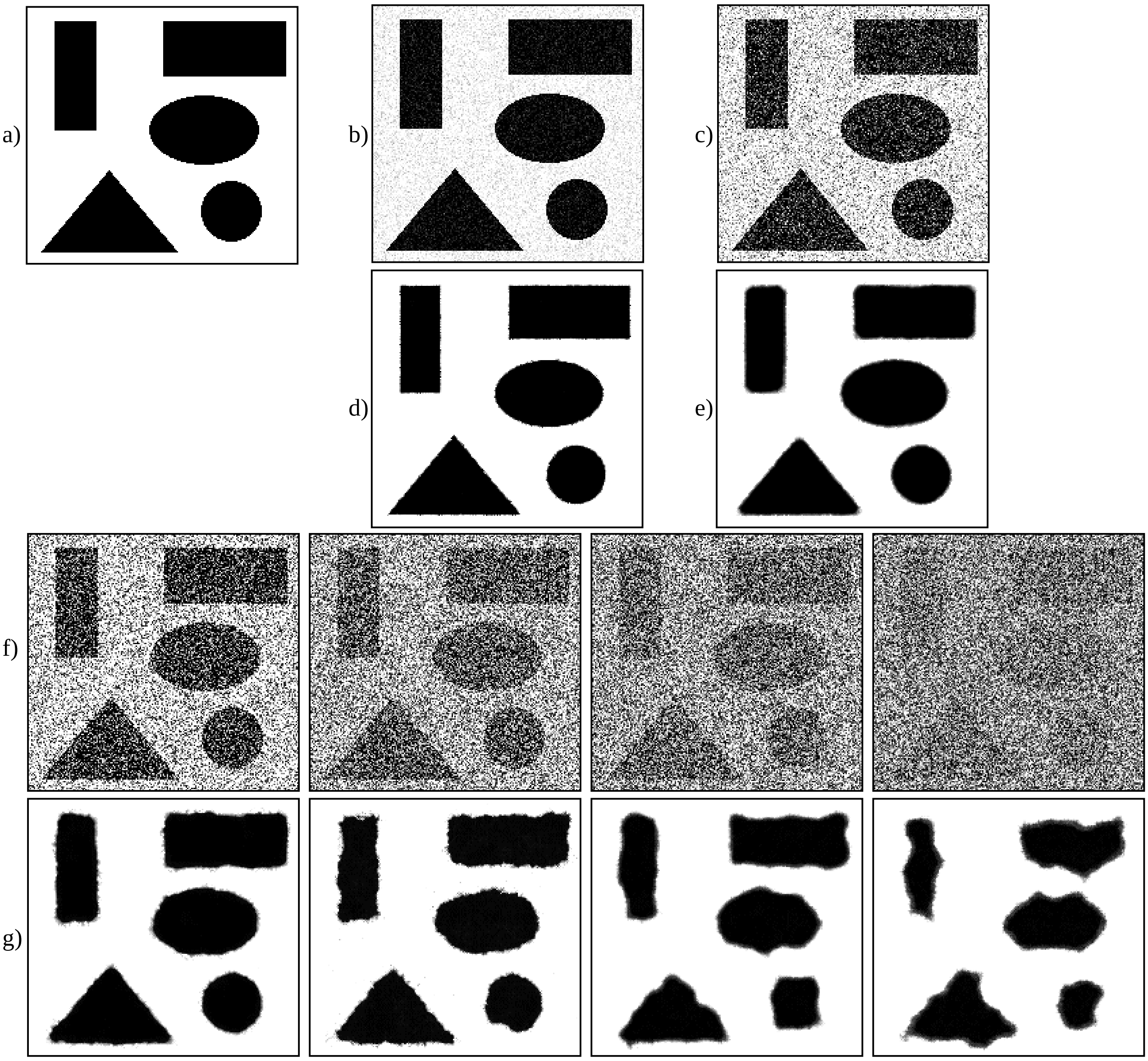


Figure 21: Binary shape recovery from noise contaminated images using simple, reactive multi-agent emergent pattern formation.
a) Original binary shapes image
b) Shapes image contaminated with Gaussian noise standard deviation 30
c) Shapes image contaminated with Gaussian noise standard deviation 99
d) Emergent trail pattern formation recovered from (b)
e) Emergent trail pattern formation recovered from (c)
f) Shapes image contaminated by random impulse noise (left to right): 50%, 70%, 80%, 90%
g) Emergent trail pattern formation recovered from the corresponding contaminated images directly above. Even at 90% noise, a reasonable facsimile of the original image is recovered.

8.2 Greyscale Image Contrast Enhancement.

It is possible to enable the agents to operate in sub-pixel space by moving from a discrete model of agent movement (discrete integer locations) and rotation angle (8 compass point positions) to a more flexible position (position stored as continuous variables) and rotation (360 degree possible rotation angle). The agents still occupy discrete pixel sites in the landscape but their movement is now at sub-pixel levels. The effect is to enhance the resolution of the emergent trail patterns and is particularly suitable for enhancing images with fine structures, such as vascular structures in medical imaging. Examples illustrating the continuous agent models using dark attracted agents (skull angiogram) and light attracted agents (retina) are shown in figure 22 below. The agent approach resolves the same amount of hidden detail as the histogram equalisation approach, but retains the realism of the original image that is lost in the histogram equalisation transformation.

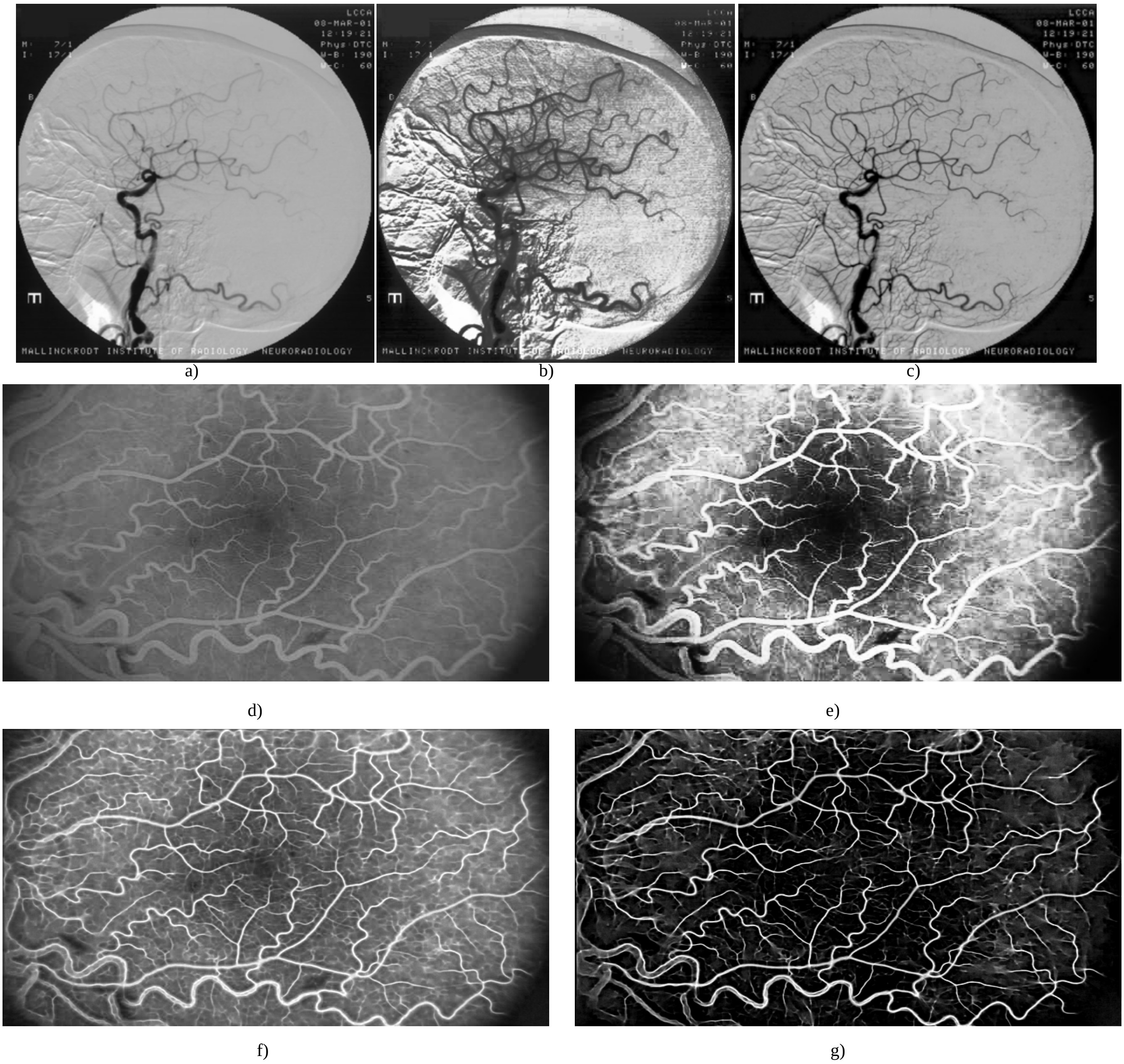


Figure 22: Greyscale contrast enhancement by agents with sub-pixel movement and variable rotation angle.

a) Original skull angiogram image, vessel visibility enhanced for x-ray visibility by introduction of high density contrast fluid.

b) Skull angiogram image enhanced by conventional histogram equalisation method.

c) Blood vessels enhanced by dark attracted agents migrating to darker areas in the image. Trail initialised with image values.

d) Original retina image, vessel visibility enhanced by fluorescein stain.

e) Retina image enhanced by conventional histogram equalisation.

f) Emergent trail pattern - enhancement by light attracted agents migrating to lighter areas of the image. Trail initialised with image values.

g) Emergent trail pattern formed by light attracted agents. Trail levels accreted from zero level.

8.3 Colour Image Enhancement.

The enhancement of colour images is more complex because colours cannot be represented as single scalar values. Each colour is a composite and its representation can vary depending upon the colour space used. RGB space (red, green and blue values) is a common representation because it is also commonly used in image capture and display devices. A single image landscape cannot be used to store the colour image, but the colour input image may be divided into its constituent channels and each channel used as a separate landscape (Figure 23). Each channel may then be populated with agents, and agent-landscape interactions commencing as before. Each separate landscape generates separate trail and mark patterns. The three separate trail patterns can then be recombined to give the output result.

Figure 23: Extracting scalar values from a composite RGB colour image. Original colour Lena image (left), and red, green and blue scalar landscape images.

Agents developed for colour image enhancement are as simple as those developed for greyscale enhancement, with minor alterations to place them in different colour channel landscapes. Selection pressures may be applied to each colour channel to amplify the emergent patterns. In some colour images, depending on the lighting conditions or the reflectance properties of the object, one colour channel may be dominant. In the case of figure 18, (and as suggested by the colour image itself) the red channel is more saturated than other channels. An automatic method of calculating agent sensitivity was developed that considers the mean intensity level for the channel that an agent resides in, the local window signal range and the local pixel intensity. The automatic sensitivity settings can be weighted for different applications and can be used, for example, to enhance darker areas of the image. Colour image processing using the PixieDust framework requires additional memory (to store the three separate landscape data, trail and mark fields and to store more agents since the population size has to be multiplied by three). This also increases computation time (in terms of *absolute* time, rather than the number of system steps), as each system step takes longer to complete).

Examples of using the framework for colour image enhancement can be seen in figure 24, with an emphasis on enhancing images taken in poor lighting conditions.

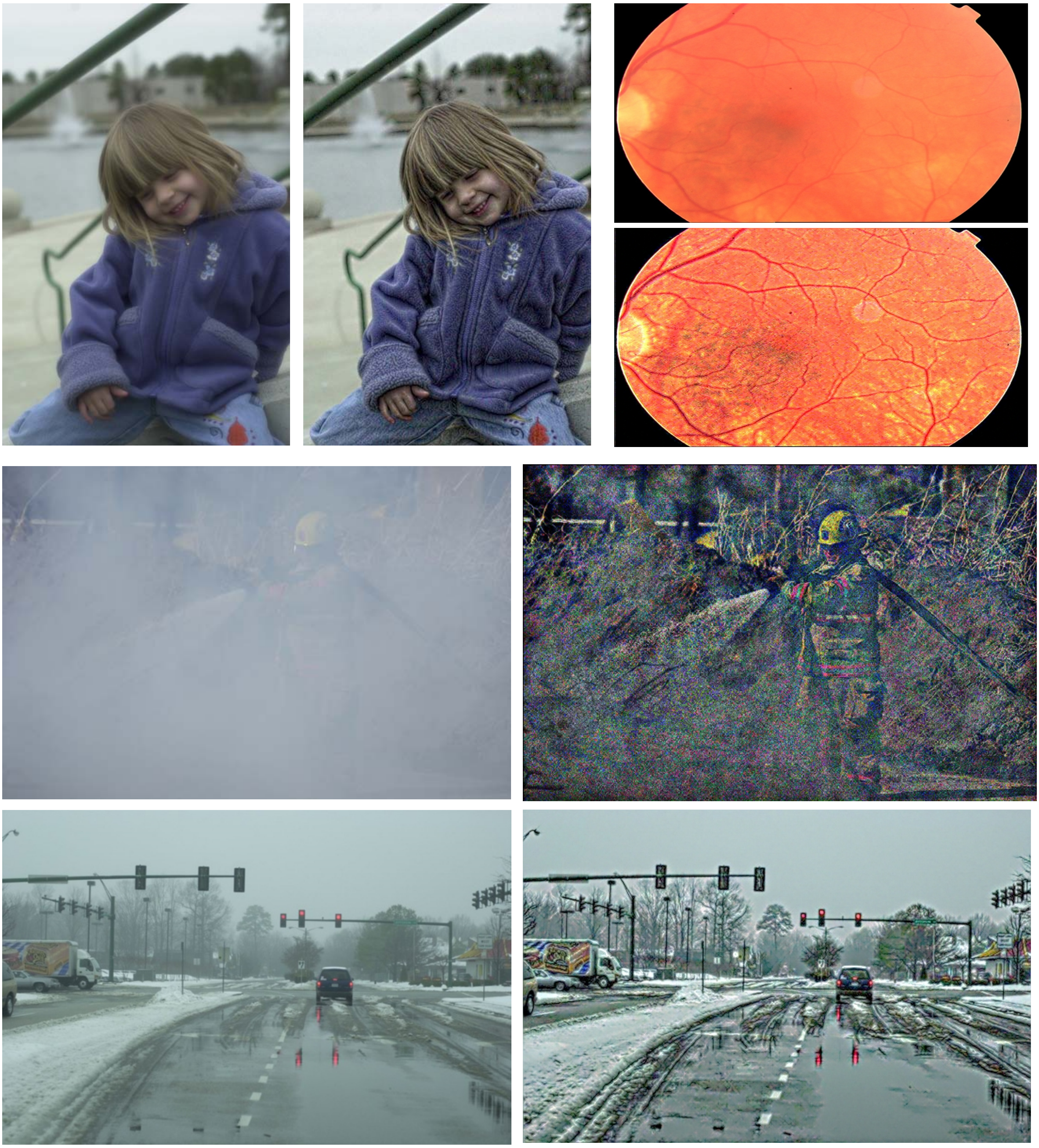


Figure 24: Colour image processing with the PixieDust framework.

Top row:

Original 'girl' image.
Sharpened girl image with richer colours and sharper texture.
Original Retina image
Enhanced retina image showing more detail of blood vessels and macula region.

Middle row:

Original forest fire image, taken in smoke and mist conditions.
Enhanced fire image, fireman and landscape detail are more clearly visible

Bottom row:

Original crossroads image taken in sleet weather
Enhanced crossroads image, more details are visible without over-enhancement.

(Original images reproduced from the NASA website: http://dragon.larc.nasa.gov/retinex/pao/news/)

8.4 Mammogram Mass Enhancement.

Mammograms are indirect photographic representations of breast tissue density. They are currently the widest used screening modality for breast cancers, due to the wide availability of x-ray film technology and it's relatively low cost. Mammograms are typically low contrast images and are particularly difficult to interpret when the breast tissue is glandular in content. This presents additional difficulties since dense glandular breast tissue is likely to be found in younger women who are unlikely to be at an age to be considered to participate in mass screening programmes. Dense breast tissue is also more closely associated with the development of some tumours. The aim of mammogram enhancement is to enhance the contrast between any suspicious masses and the surrounding background tissue. This is a difficult task as 'background' is difficult to define in terms of the mammogram. The background tissue may be of similar, or even higher, density than the target foreground. The strategy chosen for this emergent, multi-agent approach is as follows:

1. Select an agent with simple defined behaviours to generate the initial interactions with the landscape environment.
2. The interaction between the agent population and their environment results in emergent pattern formation.
3. These emergent patterns should discriminate (increase the contrast) between background tissue and contrast lesions.
4. Apply parallel environmental selection pressures to further amplify the contrast enhancement.

8.4.1 Selection of Initial Agent Behaviour and Initial Emergent Pattern Formation.

The agent type used is the simple light attracted agent described in section 5. The agents are initially placed on the landscape at random positions and each assigned a random direction. The behaviour of the agent in response to the local configuration of the landscape, specified in the pseudocode, influences each agent's choice of direction and the agent then attempts to move a single step in the current direction before repeating the sensory stage again. Every time the agent moves forwards in the current direction, a small amount of trail is deposited by the agent. If an agent is receives sufficient stimulus to make a change of direction, a specific mark is also laid down (separate to the movement trails) to represent exactly the point of stimulus. Unlike conventional image processing where the algorithm processes and modifies the actual image data, the PixieDust framework uses the input data to affect the behaviour of the agent population in order to render features in the image visible in the emergent trail patterns. Three resulting patterns of behaviour can therefore be seen, as shown in figure 25:

1. A pattern of agent distribution (Figure 25c) that is different from their initial random placement (Figure 25b) on the image landscape.
2. An emergent pattern of trail deposition (Figure 25d), created whenever the agent moves forwards.
3. An emergent pattern of mark deposition (Figure 25e), created in response to significant stimuli at certain image features.

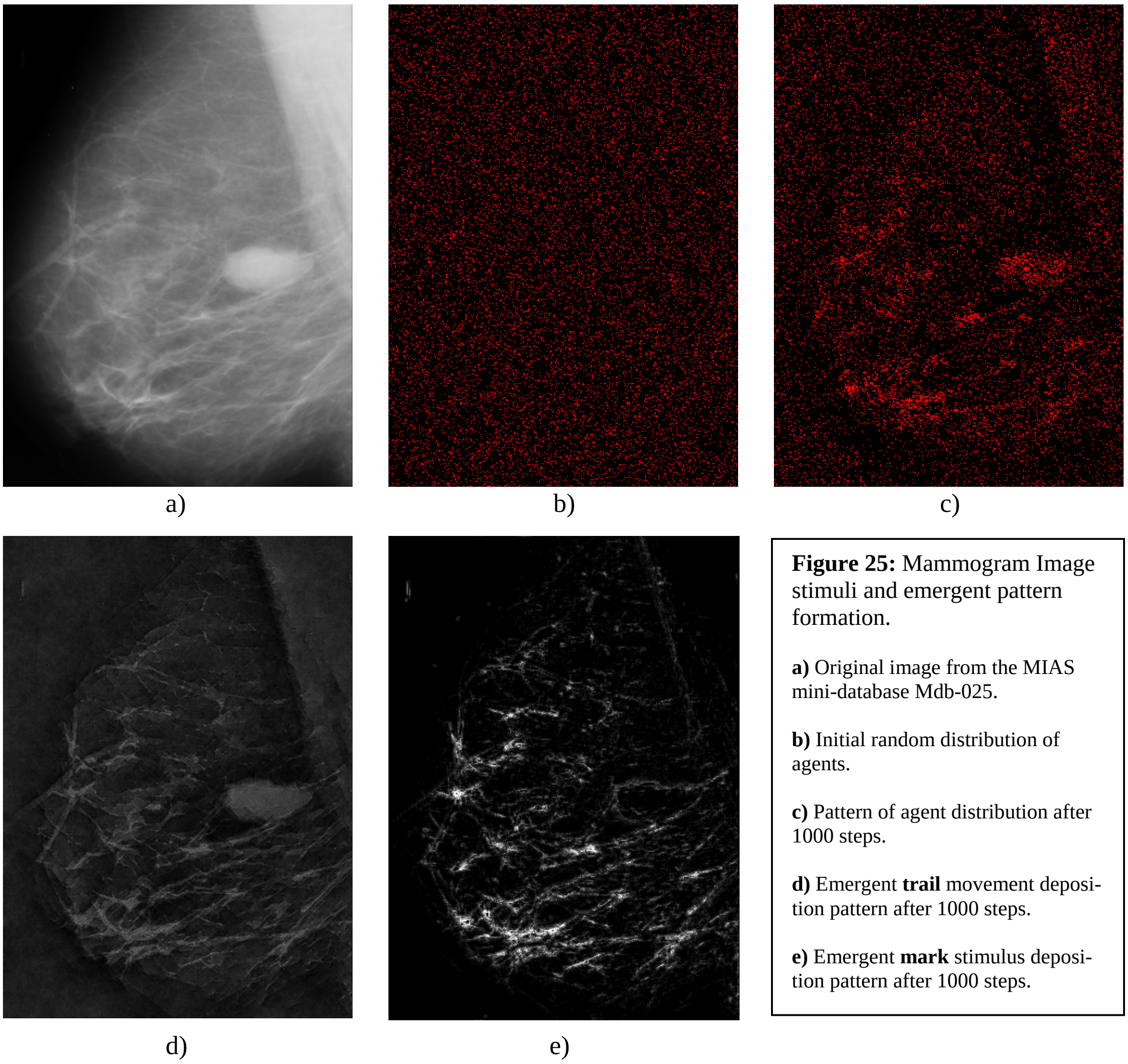


Figure 25: Mammogram Image stimuli and emergent pattern formation.

a) Original image from the MIAS mini-database Mdb-025.

b) Initial random distribution of agents.

c) Pattern of agent distribution after 1000 steps.

d) Emergent **trail** movement deposition pattern after 1000 steps.

e) Emergent **mark** stimulus deposition pattern after 1000 steps.

The patterns are an emergent phenomenon produced by the interaction of the entire population with the image landscape. The agents adhere to the tenets of emergent behaviour, namely: locality, simplicity, decentralised control and any emergent behaviour occurs at the population level. Individual agents can only perceive what is '*in front of their nose*', so to speak. At a population level, however, the entire pattern and features of the landscape are perceived.

8.4.2 Feature Discrimination and Contrast Enhancement in the Emergent Patterns.

The results shown in figure 25d and 25e show simple image enhancement taking place. Since the agents have a tendency to move (preference for) towards lighter areas in the image, the agents will aggregate in lighter areas of an image (25d). As there are more agents present within lighter areas, more trail will be deposited in those areas. Over time, the emergent pattern of trails will become correspondingly brighter in those areas, achieving a simple contrast enhancement effect. The emergent pattern of specific stimuli point marks shown in 25e illustrates some basic feature detection, namely edge detection, within the image landscape. It can be noted that the lesion region in the image shows high mark levels at the border of the lesion, but low levels within the lesion.

This is due to the comparatively even texture within the lesion region itself providing little stimuli for the agents.

8.4.3 Application of Selection Pressure.

The general tendency of a single agent's behaviour to move towards lighter areas of an image results in an emergent trail pattern that enhances the contrast between these lighter areas and the background tissues. As noted in the introduction, however, there are other areas of the mammogram, notably fibrous connective tissue, that are non-lesion areas (background). These areas are also light in appearance (i.e. high in pixel intensity). These areas are also enhanced during the emergent pattern formation, as shown in figure 25d. It is necessary to provide a mechanism that will enhance only the desired areas of the image, the lesion area itself. This moves the task from simple *image processing* towards image segmentation. Poli suggests [30] that any image processing function can be thought of as a filter since if we enhance one part of an image (foreground) from its background, we are effectively filtering out the background. If the removal of the background is absolute then segmentation has ultimately occurred.

The emergent pattern formation provides the enhancement of the lighter areas in the image. This can be considered as bringing the foreground (lesion and other light areas) *forwards*. A mechanism is required to move the background (non-lesion areas) *backwards*, to further enhance the contrast. The desired aim is also to place the bright structures that are not lesions in the background of the image. The emergent trail and mark patterns can be considered as a distributed shared memory of agent behaviours. In particular, the trail patterns show a memory of frequency of visits of all areas of the landscape. It is possible to apply an external selection pressure in the form of a parallel erosion of trail deposits in the environment. By eroding the trail pattern, we effectively shorten the period of time for which the trail pattern has a memory of agent movement.

There will be a certain rate of trail erosion that is sufficient to 'dampen down' the trail level in the background areas of the image whilst (because of a higher concentration of agents in these locations) enabling the lesion areas to maintain their accretion of trail.

A number of different strategies for erosion of the trail patterns are possible. The simplest strategy is standard erosion, constant across all areas of the landscape. More complex possibilities are possible such as eroding the trails in inverse proportion to the mean pixel intensity of a window surrounding each agent. It is also possible to adapt the *deposition* behaviour of the agents. At the simplest level the deposition is a standard amount configured at the start of each experiment. It is also possible to adjust the deposition to make it, for example, proportional to the mean pixel intensity, or proportional to the standard deviation from the mean intensity in the agent's local neighbourhood window. Different deposition and erosion strategies may be applied to enhance areas in images that have differing features.

The results in terms of image contrast enhancement of applying different selection pressures to the system and of also modifying the deposition models can be seen in Figure 26 based upon the original mammogram image Mdb025 shown in figure 25a.

a)

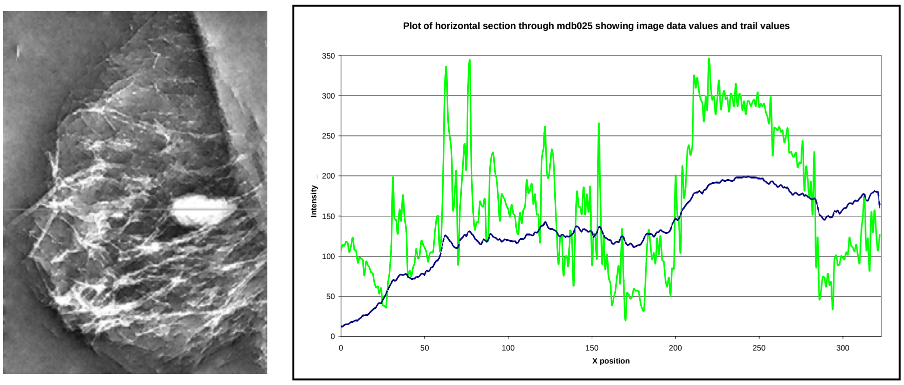
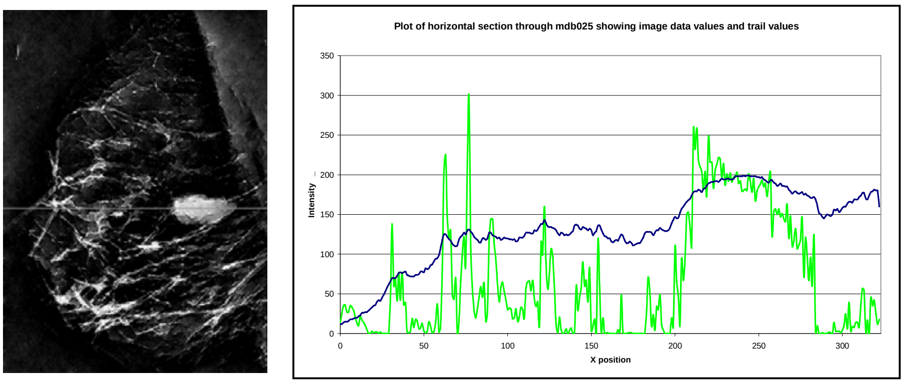


Figure 26: Selection pressure example images and cross section graphs.

a-e: The effects of adding a selection pressure in the form of trail erosion. At each time step trail is eroded in each cell. Original data is coloured blue, trail levels shown as green.

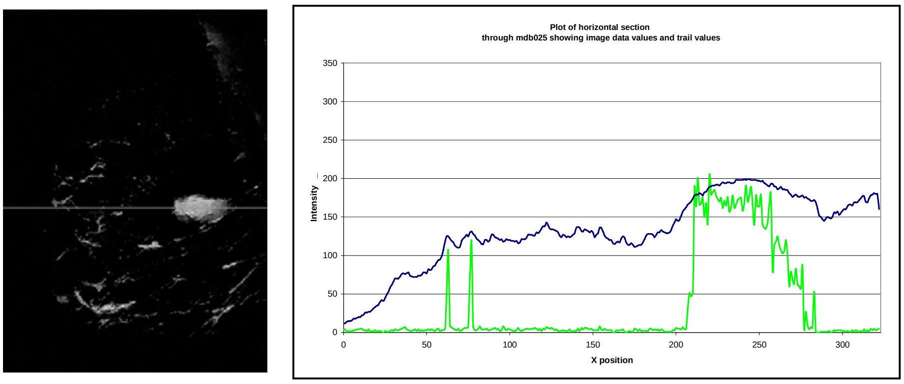
a) Trail pattern without any erosion applied. Some basic enhancement is already seen. The graph shows a cross section of data across the image at the point where y = 243 (indicated by faint horizontal line across lesion area). Blue line on graph shows pixel intensity level. Green line indicates trail height across the section.

b)



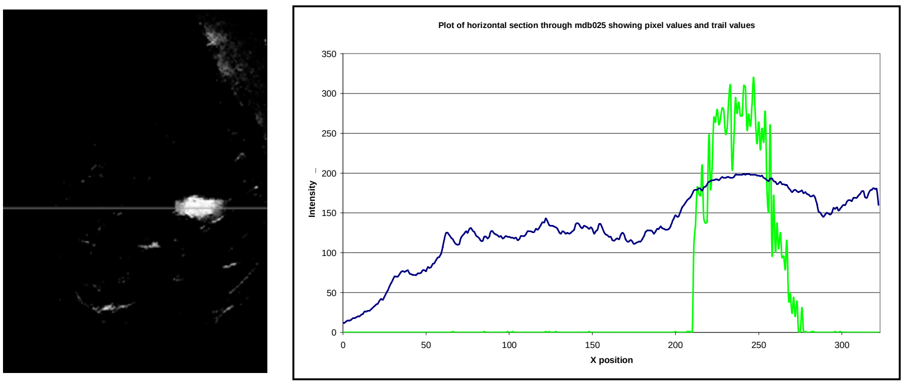
b) Erosion is applied at a constant rate throughout image. Image (shown as trail pattern) is clearer but other bright areas are still highlighted as can be seen in the trail level.

c)



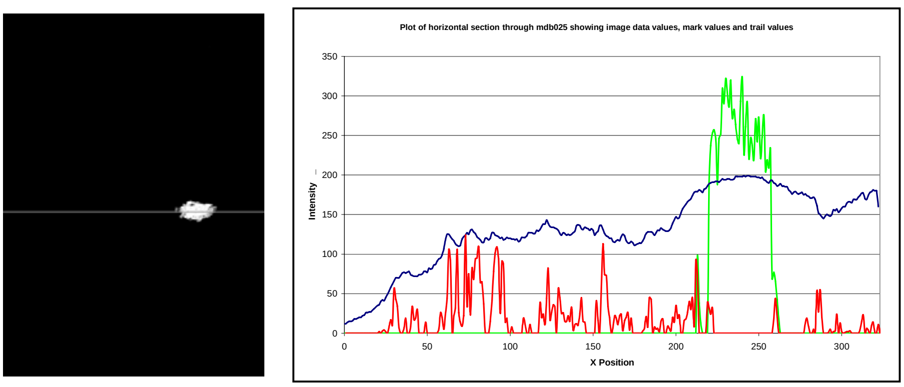
c) Erosion applied in inverse proportion to the average pixel intensity in a 3x3 window around each cell. More background areas have been suppressed. In the cross-section, only the lesion area and strong curvilinear structures are visible in the trail level.

d)



d) Erosion applied in inverse proportion to average pixel intensity as in ‘c’. Trail deposition for each agent is now proportional to the average pixel intensity of the 3x3 window of the current pixel at which the agent is currently located. Most background areas are now suppressed.

e)



e) As in ‘d’, deposition of trails is in proportion to the average pixel intensity at the agent’s current neighbourhood. Erosion is applied as in ‘d’ but extra erosion is later applied that is in direct proportion to the local neighbourhood mark level (seen in red), as in figure 25e. This removes the curvilinear lines corresponding to connective tissue of similar pixel intensity. Trail levels in the lesion area remain high because the mark levels in the same area are low, due to lack of stimulus by the relatively uniform lesion area.

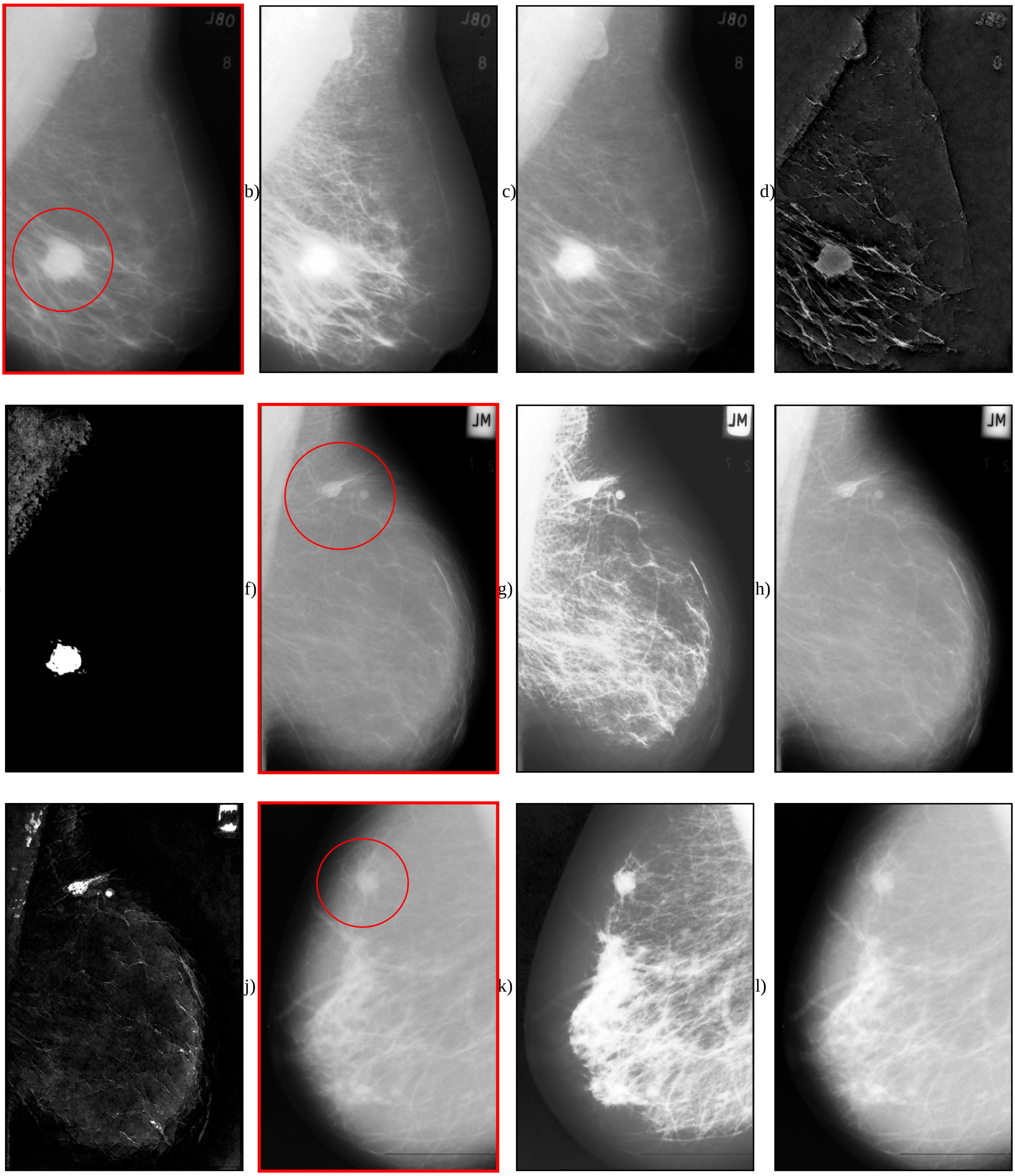
8.4.4 Enhancing Microcalcifications.

The enhancement of large masses is effective because they tend to contain an area within the centre of the mass that is relatively uniform in texture and intensity. This bright area will attract the light sensitive agents and the agents will deposit the trail at that location. The agents tend to stay within the mass area due to their ‘preference’ for the lighter parts of the image.

The eradication of curvilinear structures from the trail pattern is successful because those structures will tend to have a high mark level (due to their sudden changes in gradient) associated with them. By degrading the trail in direct proportion to the mark level, the thin bright edges will be degraded whereas the interior of the mass will remain relatively unchanged. The structure of microcalcifications, however, is almost the opposite to that of a larger mass. Microcalcifications consist of very small (as little as 0.1mm) particles of high density and are associated with sudden gradient changes within the image. Although the same light sensitive agents may be used to aggregate towards the microcalcifications, a different approach to the erosion and deposition of trail is necessary due to their different visual features.

Empirical results suggest that the most suitable deposition strategy to use in order to enhance microcalcifications is the laying down of trail in direct proportion to the standard deviation from the mean pixel intensity of each pixel neighbourhood. The erosion strategy should be simple erosion, i.e. the same amount eroded from every cell in the landscape. Another successful strategy is the method of initialising the trail field with a copy of the original image values, as described in section 7.1 . A simple erosion model may then be used to ‘wash’ the background away, whilst the agents (attracted to the ‘spikes’ of interest provided by microcalcifications) amplify the strong dense microcalcification signals.

Figures 27 and 28 illustrate some further results in mammogram mass enhancement and microcalcification enhancement using images taken from the MIAS mini mammogram database [31]. Some results using Histogram Equalisation and linear contrast stretching methods are included for comparison.



m)

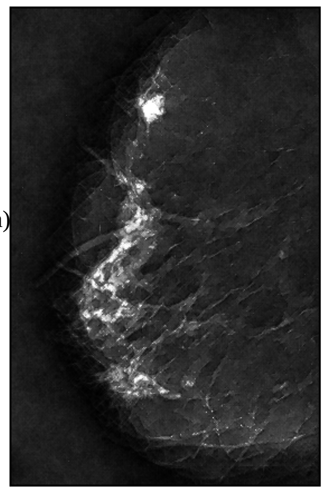


Figure 27: – Further Results: Tumour area highlighted with red circle

Platform: native x86 code from statically compiled Java. Intel Pentium mobile processor 1.8 GhZ.

From left to right:

a) Original MIAS image mdb028.
b) Histogram equalisation.
c) Histogram contrast stretch.
d) Emergent trail pattern with simple erosion.
e) Emergent trail pattern, erosion proportional to mark level and inversely proportional to pixel intensity.
f) MIAS image mdb132.
g) Histogram equalisation.
h) Histogram contrast stretch.
i) Emergent trail pattern, deposition proportional to pixel intensity,erosion inversely proportional to pixel intensity.
j) MIAS image mdb023.
k) Histogram equalisation.
l) Histogram contrast stretch.
m) Emergent trail pattern, erosion inversely proportional to pixel intensity and proportional to mark intensity.

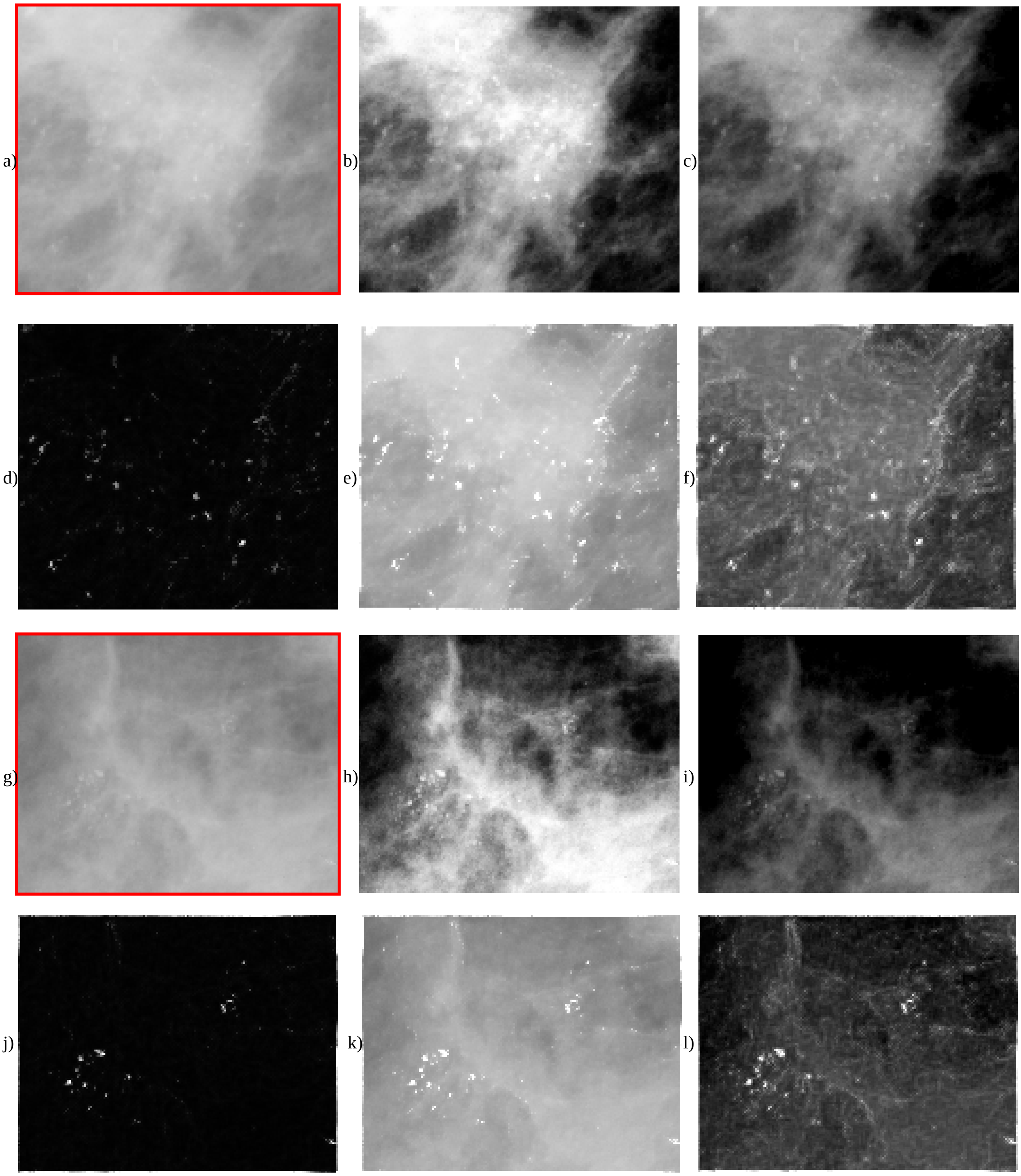


Figure 28: - Microcalcification enhancement results:

a) Original region of MIAS mdb209 image.
b) Histogram equalisation.
c) Histogram contrast stretch.
d) Emergent trail pattern, deposition proportional to pixel standard deviation, simple erosion.
e) Original region of mdb209 image with emergent trail pattern overlaid.
f) Emergent trail pattern, deposition and erosion as in (d). Trail initialised with copy of image intensity values.
g) Original region of MIAS mdb233 image.
h) Histogram equalisation.
i) Histogram contrast stretch.
j) Emergent trail pattern, deposition proportional to pixel standard deviation, simple erosion.
k) Original region of mdb233 image with emergent trail pattern overlaid.
l) Emergent trail pattern, deposition and erosion as in (j). Trail initialised with copy of image intensity values.

9. Applications to other Spatial Problems.

Image processing is but one example of a problem whose target data (source image) and solution (output image) may both be represented as a spatial pattern. Many other problems may be specified as spatial patterns. Path planning is one example. Many algorithms (usually data structure traversing, searching algorithms) exist to solve such problems, although such solutions do not directly use the spatial form of the problem in its solution. Babloyantz suggested that simple physical systems may be used to solve path planning algorithms, such as the shortest path through a maze [32]. Solutions to such problems inspired by physical systems have been developed using diffusion approaches [33]. In the diffusion approaches, wavefronts in excitable media or reaction-diffusion media are initiated at the exit of the maze, and the wavefront spreads throughout the maze covering all areas. It is then possible to find the shortest path through the maze from the start point by back-tracking the concentration gradient from the start point to the exit. Adamatzky provided both cellular automata and chemical hardware solutions to the shortest path problem [34] and Rambidi has also demonstrated a chemical based implementation [35]. A two stage software implementation of an algorithm has been suggested by Ito to solve shortest path problems using diffusing wavefronts [36]. All of the above solutions (software and unconventional hardware implementations) use a two stage approach: The first step is the propagation of the wave through the maze and the second 'backtracks' using the concentration of the now fixed wavefront to guide the correct path. If a modification to the input spatial pattern was introduced, the two stage algorithms would have to restart. The hardware implementations using reaction-diffusion media are somewhat cumbersome, often requiring time lapse video capture and some signal processing of the captured sequences.

A specific breed of agent was developed, extending the base agent class, to try and provide solutions to the shortest path problem. The agent simply tries to move forwards by sensing the concentration gradient of the mark field and orienting its direction to the strongest concentration, in a manner similar to bacterial chemotaxis. The input pattern is presented to the framework and a source of 'chemical' as a mark stimulus is deposited at the exit. The parallel selection pressure of the framework is used to diffuse the chemical mark from its initial point and the diffusing wavefront spreads throughout the maze. The chemical is deposited on the mark field and diffused at every system step. *At the same time,* a population of agents is instantiated at the start of the maze and moves throughout the maze, seeking the concentration gradient of the diffusing marks. As the agents move forwards, they leave a trail and this trail is also subject to a selection pressure (erosion at a small constant rate). As the agents move towards the source of chemical mark, the emerging trail pattern shows the strongest trails that persist against the erosion pressure. The solution to the shortest path can then be 'read' by the stable persistent trail pattern.

Even if the shortest path through the maze is changed (for example by 'unblocking' a wall), the system is able to adapt to the new configuration and the new shorter path subsequently emerges. The procedure and results are illustrated in figure 29.

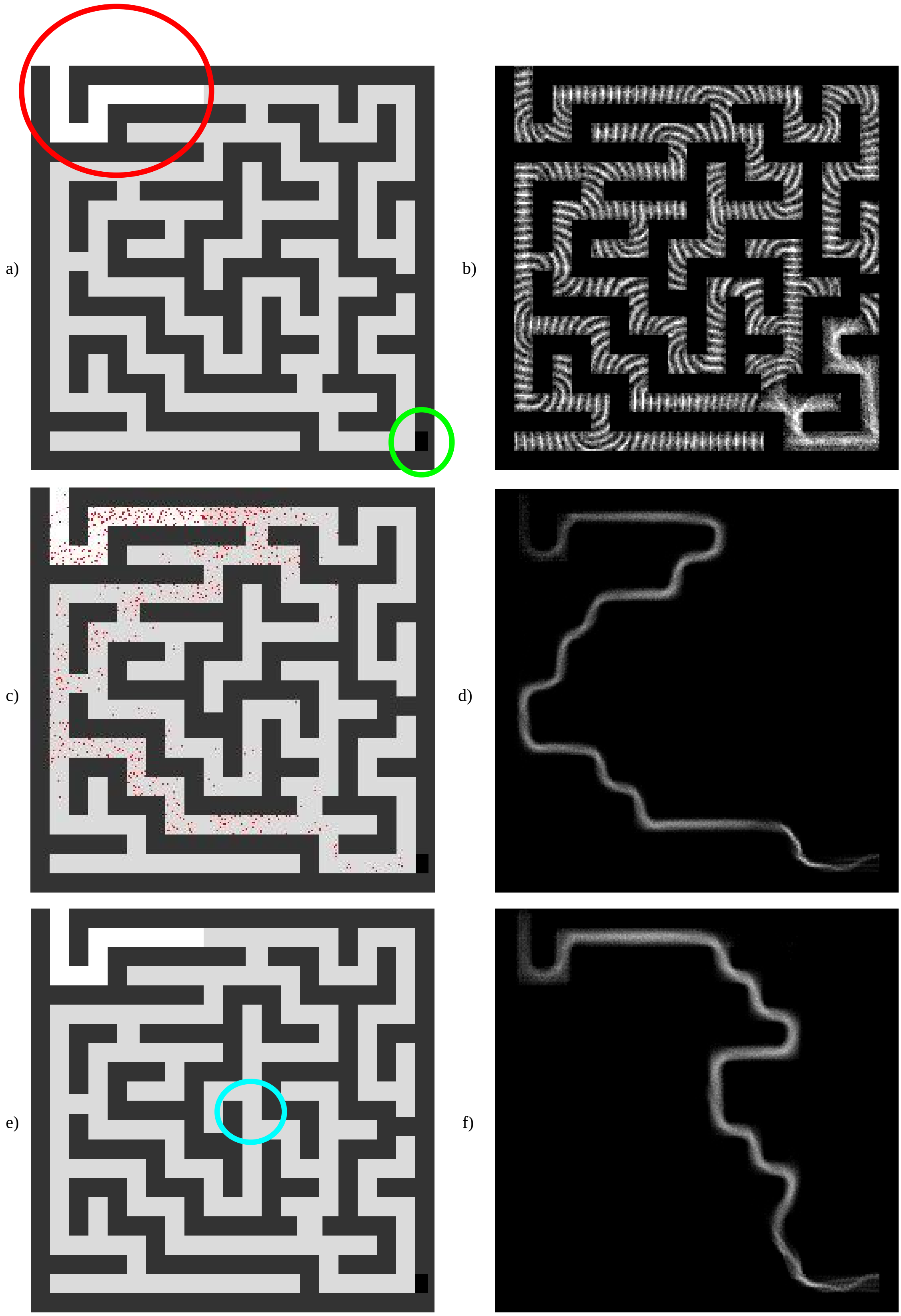


Figure 29: Applying the PixieDust multi-agent framework to a dynamic version of the shortest path problem:

Chemotactic agents attracted towards the strongest concentration of mark values are used as the basic agent behaviour.

a) Original maze pattern. Chemical diffusion source at exit in green circle. Agent start positions in red circle.
b) Pattern of the diffusing wavefront as it fills the maze from the exit outwards.
c) Distribution of chemotactic agents as they move from the start position, seeking the higher concentration of chemical.
d) Emergent trail pattern, subject to simple erosion pressure. The persistent trail displays the shortest path through the maze.
e) During the evolution of the system, a change to the maze is introduced: a wall is removed (blue circle) to give a new shorter path.
f) The diffusing wavefront continues to fill the maze, adapting to the shorter path, as does the agent population. The old shorter path disappears (due to the erosion pressure and the new shorter path persists).

10. Conclusions and Scope for Further Research.

We have presented an image-processing framework based upon a simple, reactive multi-agent system that does not process images in the same way as conventional image processing operators, but instead uses the image to provide stimuli to a population of mobile agents for emergent pattern formation to take place. The resulting emergent patterns represent an indirect processing of the input image. The inspiration behind the system is data discovery in physical systems where the behaviour of one system is influenced by the content of another, rendering previously unseen patterns visible. The emergent patterns formed are then amplified by the application of an external selection pressure.

Aside from the data-centric emphasis of this approach, the multi-agent system differs from that of other image processing methods in that the system relies on movement of the agents to generate distinctions between pixels. In a conventional image processing system (such as sliding window convolution operators or cellular automata methods), every pixel in the image is processed by the algorithm. The trail patterns (effectively a historical map of agent occupancy) provide a distinction between pixels of interest and background pixels. These distinctions can be further amplified by the external selection pressures. The system has been successfully applied to a wide range of image types and content and exemplar applications have been briefly described (binary shape reconstruction, greyscale contrast enhancement, colour image processing and adaptive solutions to spatial problems), and a more detailed investigation of mammogram enhancement has been described. Unlike the global histogram equalisation operator (HE) and linear contrast stretch, the system operates in a local fashion. This eliminates the 'washing out' of colours seen in HE in some images (e.g. Figure 22, k) and removes the need to blend together the separate windows used in adaptive HE techniques.

Many challenges remain for the use of emergent pattern formation in image processing applications. Artifact reduction is critically important for many applications, and care must be taken in the development of agent behaviours to minimise the production of image artifacts. Parameterisation of the system is constant for most mammogram images, however for images with very dense tissues, sensitivity of the agents needs to be increased to discern details in the very light areas. We are currently further developing the automatic sensitivity system for each agent that determines sensitivity depending on the local neighbourhood contrast and intensity. The system is also emergent in the literal sense – image result patterns take time to emerge (in a manner similar to photographic development processes), approximately 30 seconds with selection pressure amplification. The computation time reduces fairly linearly with more powerful PC platforms. When to stop the application is another challenge that will differ depending upon the application. Since the patterns emerge by a process of environmental stimulation and trail accretion, the agents would continue to build up the trail pattern forever unless a signal is sent to stop the system. Both simple and more complex solutions are possible: The computation may be stopped by either running the system for a fixed number of steps or halting the system when the output patterns reach a desired predefined contrast. The desired contrast required, of course, depends upon the application chosen.

Further research is currently taking place to by the authors to utilise the system for the solution of other problems that can be represented in terms of spatial patterns. Similarities to the trail output of the PixieDust system and that of the outputs (subjective perception) of the mammalian visual system, with respect to illusory perception, are also currently being explored.

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Appendix – Table of Experimental Parameters for Results Figures.

Figure	Image	%p	Agent Type	depT	depM	sMin	pCD	pTP	eroT	Stop Condition
4	Blank 200 x 200	1-90	Walking Pixie Attractor	0.5	NA	NA	0	0	NA	Mean trail >= 100
7	Blank 200 x 200	40	Walking Pixie Attractor	0.1 - 10	NA	NA	0	0	NA	Mean trail >= 100
11	Lena 256 x 256	10	Walking Pixie Attractor	1	NA	NA	0	0	NA	1000 Steps
13	Section of Cameraman (100 x 80)	20	Walking Pixie Attractor	1	NA	0-40	0	0	NA	Mean trail >= Original Image
14	Lena 256 x 256	20	Walking Pixie Attractor	0.2 - 1	NA	30 (14c, sigma 20)	0	0	NA	Mean trail >= Original Image
15	Cameraman 256 x 256	10-80	Walking Pixie Attractor	1	NA	20	0	0	NA	Mean trail >= Original Image
16	Lena 256 x 256	10	Walking Pixie Attractor	1	NA	10	0	0-0.5	NA	Mean trail >= Original Image
17	Lena 256 x 256	10	Walking Pixie Attractor	1	NA	10	0	0.1	0.01, 0.05, 0.1	1000 Steps
18	Lena 256 x 256	10	Walking Pixie Attractor	.2 (Init To Image)	NA	10	0.1	0.1	0.01	1000 Steps
19 b	Lena 256 x 256	10	Walking Pixie Attractor	1	NA	3	0.1	0.1	NA	Mean trail >= Original Image
19 c	Lena 256 x 256	10	Walking Pixie Attractor	Prop to 3x3 pixel intensity (weight 100)	NA	3	0.1	0.1	Inv Prop to 3x3 Pixel Intensity (weight 5)	1000 Steps
21 d,e	Multiple Shapes	10	Walking Pixie Attractor Offset	Prop to 9x9 Pixel Intensity (weight 100)	NA	10	0.1	0.1	Inv Prop to Pixel Intensity (weight 20)	5000 Steps
21 g	Multiple Shapes	10	Walking Pixie Attractor Offset	Prop to 13 x 13 Pixel Intensity (weight 100)	NA	30	0.1	0.1	Inv Prop to Pixel Intensity (weight 20)	8000 Steps
22 c	Cerebral Angiogram 650 x 652	10	Walking Pixie Dark Continuous Angle	-0.3 (Init to Image)	NA	3	0	0.01	-.001	1000 Steps
22 f	Retina 628 x 410	10	Walking Pixie Attractor Continuous Angle	0.3 (Init to Image)	NA	5	0	0.01	0.01	1500 Steps
22 g	Retina 628 x 410	10	Walking Pixie Attractor Continuous Angle	0.3	NA	5	0	0.01	0.001	1500 Steps
24	Colour Young Girl 390 x 600	30	Colour Walking Mix Pixie	0.5 / -0.2 (Init to Image)	NA	3	0.1	0.1	NA	1000 Steps
24	Colour Retina 598 x 448	30	Colour Walking Mix Pixie	0.5 / -0.2 (Init to Image)	NA	3	0.1	0.1	NA	1500 Steps
24	Colour Fireman 1000 x 656	30	Colour Walking Mix Pixie	0.5 / -0.2 (Init to Image)	NA	2	0.1	0.1	NA	2500 Steps
24	Colour Icy Crossroads 599 x 393	30	Colour Walking Mix Pixie	0.5 / -0.2 (Init to Image)	NA	3	0.1	0.1	NA	2000 Steps
25	MDB-025 Mammogram	10	Walking Pixie Attractor	0.5	1	5	0.3	0.001	NA	1000 Steps
26 a	MDB-025 Mammogram	10	Walking Pixie Attractor	1	NA	5	0.3	0.001	NA	1500 Steps
26 b	MDB-025	10	Walking Pixie Attractor	1	NA	5	0.3	0.001	0.05	1000 Steps
26 c	MDB-025	10	Walking Pixie Attractor	1	NA	5	0.3	0.001	Inv Prop to Pix Intensity 3x3 (weight 15)	1500 Steps
26 d	MDB-025	10	Walking Pixie Attractor	Prop to 3x3 Pixel Intensity (weight 100)	NA	5	0.3	0.001	Inv Prop to 3x3 Pixel Intensity (weight 50)	2000 Steps
26 e	MDB-025	10	Walking Pixie Attractor	Prop to 3x3 Pixel Intensity (weight 100)	1	5	.3	.001	Inv Prop to 3x3 pixel intensity (weight 50), Prop to 3x3 Mark level	2000 Steps
27 d	MDB-028	10	Walking Pixie Attractor	.5	NA	5	.3	.001	NA	1500 Steps
27 e	MDB-028	10	Walking Pixie Attractor	.5	NA	5	.3	.001	Inv Prop to 3x3 Pixel intensity (weight 5), Prop to Mark level (weight 20)	Manual
27 i	MDB-132	10	Walking Pixie Attractor	Prop to 3x3 pixel intensity (weight 100)	NA	5	.3	.001	Inv Prop to 3x3 Pixel Intensity (weight 5)	600 Steps
27 m	MDB-023	10	Walking Pixie Attractor	Prop to 3x3 pixel intensity (weight 100)	1	5	.3	.001	Inv Prop to 3x3 Pixel intensity, (weight 5) Prop to 3x3 mark intensity (weight 20)	Manual
28	MDB-209, MDB-213 Regions	10	Walking Pixie Attractor	Prop to 3x3 pixel standard deviation (weight 10)	NA	5	.3	.05	0.05	1500 Steps
29	Maze	1	Chemotactic Path Pixie	1	NA	0	0	0	0.05	1500 Steps