A fuzzy model for scene decomposition based on preattentive visual features

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ABSTRACT

Feature detectors in the early preattentive stage of the Human Visual System (HVS) are believed to cause regions of the viewing field to be identified as perceptually salient, attracting the attention of the viewer. It is anticipated that this characteristic of the HVS can be incorporated into a feature based fuzzy scene decomposition model, which will assist an image rendering system in the allocation of the highest levels of detail to the most conspicuous objects. Efficiency gains should occur, with minimal loss of perceptual image quality.

This paper describes the early stages of the development of this fuzzy model, for a small subset of commonly accepted visual features: colour, size, location, edges and depth cues. Previous researchers have used arbitrary feature relationship models in image processing systems, with some success. Our aim is to improve on these models by integrating present knowledge of visual feature relationships, with experimental results of our own, and to apply this model to the area of image synthesis.

Preliminary results from experiments with size features are presented, along with planned experimentation for other visual features. This work will have applications in the areas of scientific visualisation, vision simulation and entertainment.

Keywords: image generation, fuzzy systems, scene decomposition, preattentive visual features.

1. INTRODUCTION

The HVS is a strikingly complex mechanism that facilitates the visual comprehension of our surrounding world. Yet despite its complexity, research has made inroads into the processes that govern the allocation of visual attention. It is apparent from the tracking of eye movements that human subjects tend to regard specific regions of images, and that under closer analysis these regions contain consistent features that attract visual attention[5].

Psychophysical research has revealed that these same features contribute to a phenomenon named “popout”, whereby a spatially localised feature contrast may cause the area to become visually salient to the viewer[19]. A growing list of these features has been discovered, but little research has been carried out into characterising these features and their interrelationships [1,2]. Of the preattentive computer systems that have been developed, none contain a full model of preattentive feature relationships, but rather, have developed systems arbitrarily and modified them according to evaluation criteria [2,3,4]. It is envisaged that a fuzzy model of these features, based upon more rigorous psychophysical research, could be used to determine the perceptually important areas of a computer-generated image, bringing efficiency gains with minimal perceptual image degradation.

This paper first discusses eye movement research, and presents psychophysical theories on visual attention. Previous systems used in the areas of image processing and image synthesis will also be reviewed. We then present our progress in the development of a fuzzy model to extend present models of preattentive features, including planned psychophysical experimentation to characterise a subset of scene features and their relationships. Results are shown from a pilot study into the characterisation of the size feature, concluding with future work and expected application areas.

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2. VISUAL ATTENTION

2.1. Eye movement research

The processing ability of the HVS is limited, and is concentrated within a central area of 1° in visual angle, named the Fovea. In order to maintain a temporally and spatially continuous representation of our environment, the HVS must enact eye movements in order to bring the Fovea, and all its processing power, to bear upon important areas of the scene. These eye movements are called saccades and are enacted approximately every 100-500 msecs

Yarbus [5] researched various aspects of eye movements during the viewing of images. He noted that subjects would regard only certain regions of an image, despite an unrestricted viewing time. Results also showed that eye movements were remarkably consistent across viewers, especially when the context and the viewing task are the same, and that visual attention was drawn towards humans in the images, especially faces and hands. However, eye movements were modified by the nature of the viewing task. This last point is corroborated by research into the eye movements of trained and untrained personnel in the task of x-ray diagnosis. Gale [6] reports that trained personnel in inspection scenarios will have less fixations, with the eye movements being localised for longer at key locations in the viewing field.

It seems that the HVS has evolved particular eye movements aimed at reducing the uncertainty in the viewer's perception of their surrounding world [7]. Even though these eye movements have a definite task relationship, there is a noticeable relationship between certain underlying features in a viewed scene and the eye movements and fixations.

2.2. Present theories of visual attention

Hubel and Weisel's work on the physiological structure of the visual cortex revealed column-like structures in the monkey visual cortex that are sensitive to edge orientations, movement and colour[8, 9]. These structures are retinotopically arranged, ie. a displacement on the retina's surface has a direct correlate with a displacement along the columns, indicating that the visual cortex processes these features in parallel across the whole visual field.

These structures form the basis for present psychological feature-based visual attention models. The concept of a preattentive stage of vision, which processes features in parallel across the viewing field, has been proposed since the sixties[10]. This stage forms the first part of a number of two stage vision models[11, 12]. The preattentive stage is considered to process scene features in parallel, providing information to the attentive stage on where to apply object recognition and stimuli response resources. Treisman and Gelade's Feature Integration Theory (FIT) proposes a set of features maps which process the scene in parallel for the presence of edges, colour etc. These feature maps are then integrated together into a 'Master Map' [13,14], highlighting areas of interest within the visual field. These areas induce a perceptual phenomenon called "popout", attracting the attention of the viewer. A classic example of popout is an image containing one green circle (target) sitting in amongst a number of red circles (distractors). The green circle is easily seen (pops out) against the red circles due to a local hue feature contrast, no matter how many distractors are present.

However, recent experimentation indicates that this dichotomy between the preattentive and attentive stages of human vision is not as distinct as first thought[1]. Wolfe's guided search model [15, 16, 1] seeks to explain this by postulating that attentional mechanisms interact with the earlier preattentive stage, explaining our ability to carry out efficient searches in confusing multiple feature-laden scenes. In summary, the models indicate a definite stage of feature processing which will draw attention, but that there is a measure of interaction between early and late stages of vision.

2.3 Low level influences on eye movements

Wolfe[1] summarises the low-level preattentive features so far discovered that facilitate the phenomena of popout and efficient search:

- Colour contrast at the boundaries of different hued areas is one of the most obvious causes of popout and effortless texture segmentation. Colour is one of the strongest attractors of attention[7]. The level of contrast changes for different colours, artists use complementary colours (eg. orange and blue) to highlight areas of a painting[17, 18]. Opponent colours (eg. red and green) can also cause high levels of contrast due to the opponent encoding of colour in the HVS[18].

- Edges concentrated into regions attract attention[7]. An orientation difference of 15° can be preattentively detected against a uniformly oriented background of edges.

- Size differences can be preattentively perceived, and are considered to be almost identical to changes in spatial frequency. Size is also related to issues of scale, with groupings of smaller objects being perceived as one large object.

- Motion is considered the one of the strongest attractors of attention[7, 4, 2].

- Depth Cues; pictorial depth features, eg. lines drawn to show perspective, preattentively aids depth perception. Stereoscopic depth effects from binocular disparity are also preattentively discernible.

Other low-level features are: curvature, vernier offset, shape, global size and position, and the possibility of learned features. Some of these features have yet to be confirmed as being preattentive[1].

Some work has been carried out on the relationships of some of these features [20, 15, 19], but as yet there is no mention of a model which completely describes these features, their ordering and their relative weights[1, 2]. Our major aim is to construct a more complete fuzzy preattentive feature relationship model. The ultimate intention is to use this model to devise appropriate techniques for efficient image representation and generation.

3. PREVIOUS COMPUTATIONAL PREATTENTIVE SYSTEMS

Preattentive feature models have been applied to image compression [21, 2], where the systems allocate the highest number of bits-per-pixel to those regions deemed most important by the feature model. It has to be noted however, that the models use arbitrary integration schemes, not based explicitly upon psychophysical experimentation.

Koch's visual attention simulation system uses Gabor edge detectors, luminance and opponent colour processing to mimic the HVS's perceptual feature detection systems. However, they only state an efficiency basis for their feature integration scheme, mentioning that motion is given a five times larger weighting due to its perceptual importance[4].

Fuzzy preattentive feature systems have been successfully implemented in image processing [22, 23]. Hayasaka et. al.[22] have implemented a fuzzy model which segments an image based upon membership functions gained from a hue and luminance histogram. The regions with a similar hue, or in the absence of a saturated enough hue a similar luminance, are then compared to other intersecting regions. If the two regions have different hues then they are deemed to popout. They also process for the size feature by stating that the object's importance is directly related to its absolute size, in a similar fashion to Osberger[2]. However, they do not account for the effects of different hues, popout caused by size differences, and only carry out their calculations on a local basis.

Meyer's[25] perceptually based ray-tracer mimics the HVS colour opponency channels, with detail being removed from the colour channels and therefore producing efficiency gains with minimal perceptual loss of detail. Bolin and Meyer[26] have also exploited the HVS phenomena of masking to remove colour information in areas of high frequency detail in an image. The ray-tracer is able to quantise regions containing high frequency information, with minimal perceptual loss of detail.

Researchers such as Duchowski[24] have implemented foveated rendering systems. These systems track the movements of eyes, and degrade the peripheral regions of the image to match the loss of visual acuity that occurs in the periphery of human vision. This degradation produces rendering efficiency gains that are perceptually unnoticeable to the user of the system.

Xia et. al.[27], have implemented some perceptual factors in a polygon mesh optimisation system. They applied simple rules for the optimisation of the polygonal meshes, such as: projected edge size thresholds, placing higher levels of detail near the high contrast gradients of specular highlights and the retaining of high levels of detail near the silhouette of the polygonal mesh.

From the review of the systems shown here, we can see two major areas for new research. The first is the development of a more complete fuzzy model of preattentive features, which takes into account more than simple differences between features and weights them by an experimentally derived feature integration model. Secondly, to date nobody has applied a preattentive feature model to increasing image synthesis efficiency.

4. FRAMEWORK FOR THE DEVELOPMENT OF A FUZZY FEATURE-BASED SCENE DECOMPOSITION SYSTEM

4.1. Conceptual framework

The fuzzy preattentive feature model we are developing will be novelly applied to the enhancement of image synthesis efficiency. An overview of the general system architecture is shown in Figure 1. There are two main stages to the system. The first stage is a fuzzy decomposition process, which parses the scene description into separate perceptual objects, and calculates an importance value for that object, storing the value with the object's geometry information in an internal data structure. The second stage will take this internal data structure, and render a scene with varying levels of detail according to the importance values calculated by the scene decomposition system. This paper will concentrate on describing the structure of the proposed fuzzy decomposition system.

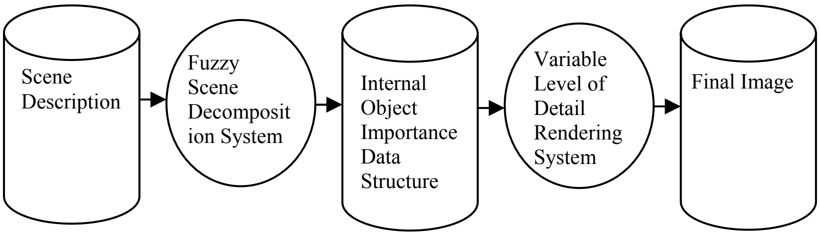

Figure 1. Schematic diagram of proposed feature-based rendering system.

4.2 Fuzzy decomposition of scene descriptions

Using object space attributes, we will parse a scene grammar to calculate an object's visual importance. The system will use scene geometry and attribute information, and so the overhead of image segmentation is reduced. However, a model will have to be developed which will allow the segmentation of the scene into separate objects, based on HVS principles. The grouping of these objects may be enforced by the modeling package used to produce the scene description, allowing user intervention in the process. This will be an area for later research, for now it is sufficient to assume that the scene grammar will be parsed into perceptual objects, ready for the feature-based importance calculations.

The system will use object centric calculations, similar to Osberger[2] and Hayasaka[3], where each object is compared to other objects close to it, and a peripheral area, as shown in Figure 2. The local region is the area of interaction between the object's boundary and its background. Here, the contributions of the intersections between the object in question and surrounding objects are calculated, local feature differences here may contribute to popout[19].

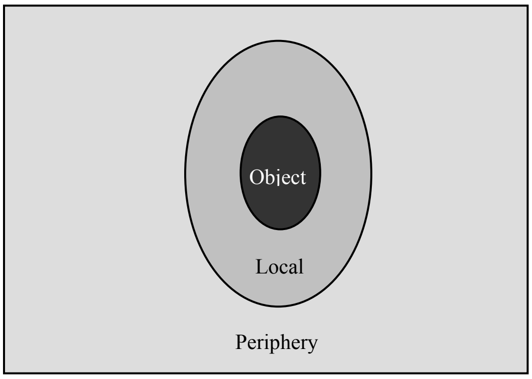

Figure 2. Diagram of importance calculation regions.

The periphery region is a novel concept, providing a broad computational measure of the influence of the whole scene. Drawing from Nothdurft's[19] research, it is anticipated that the variability of the background distractors within the feature dimension will affect the level of conspicuousness of the object being analysed. The measures used would involve the mean and variance of each feature dimension in the periphery, to broadly characterise whole scene influences on the local feature contrasts.

The feature processing rules will be incorporated into a fuzzy rule schema, as it enables a blurring of the truth of each feature variable, simulating human reasoning[29]. From a more pragmatic perspective, we also decided to use fuzzy theory due to its successful application to the area of pre-attentive features in image processing [3, 23]. The fuzzy system will extend Hayasaka's fuzzy model[3] by creating a hierarchical fuzzy rule system, with more sophisticated feature characterisations that will attempt to allow for the whole scene's features distributions, not just local contrasts. For example, the size fuzzy rule will not only take into account the absolute size of the object, but will look at local contrast and whole scene effects, as a measure of popout. We will also be extending the model to include depth effects, due to our work with 3d scene descriptions.

As our main goal is image synthesis efficiency, we expect that it is not necessary to implement the entire model, but that a subset of the rules may be implemented, in order to limit processing overheads: eg. hue, luminance and size. A new implication method may have to be developed to mimic the HVS weighted integration of image features.

We believe that an integration of principles used in image processing fields, and the popout research of psychologists, will produce a better model of scene feature based visual attention. Even though there have been comments on the lack of continuation of preattentive popout from simple test to real images[7], we believe that there are still some broad principles to be drawn from this area of psychophysical research, which can be applied to our fuzzy model. For example, we expect the features to obey a sigmoidal function when calculating importance from local feature contrast[19]. There will be a point of threshold where the object will very quickly become conspicuous, followed by a saturation point where an increase in feature contrast will not be registered as perceptually more conspicuous. We also expect that the interrelationships of these features will follow a similar function. The following is a prototype design framework for the fuzzy feature variables in the system, it is by no means complete, and may be modified to accommodate future psychophysical experimentation results.

4.3 Prototype fuzzy variables and rules

A small subset of important features has been chosen: hue, luminance, size, location, edges and depth cues, in order to ease the complexity of establishing a feature integration model. These match similar sets chosen by other researchers in the field[3, 2] with the exception of the novel use of depth cues. This subset of features suits our purposes, as they are relatively easy to calculate from object space geometry information. The following is a description of the qualitative rules we will attempt to encapsulate in the fuzzy system.

Hue

The hue attribute of the object will be used to calculate popout according to hue. Previous work indicates that MacAdam JND ellipses will be the preattentive threshold for contrast, yet this has been challenged[1]. We expect a saturation effect; a point where increases of hue feature contrast will produce no perceptual increase in popout. Researchers[17, 18] in the field of colour in art note that artists have used complementary hues (eg. orange and blue) to cause strong colour contrast, thereby attracting attention. They also note the strong contrast induced by opponent colours, eg. red on green. We believe that this will have an influence on the attention attracting ability of the contrast, so we propose a set of hue fuzzy membership functions, which are different for each of the six base hues: red, yellow, green, cyan, blue and magenta. This will involve the implementation of perceptual colour spaces for the rendering system[25]. A measure will also be taken of the variability of the hues used in the other objects in the scene. It is expected that high variation in the hues used in the rest of the scene will suppress any local colour contrast effects.

Luminance

The luminance of an object will be deduced from the luminance provided by the colour model and from information provided by the lighting model used by the rendering system. The lighting model is expected be used to deduce areas of high level specular highlights and the boundary of diffuse light fall off. Spotlight parameters could also be used to deduce the areas that will be brightly illuminated, and can thus be rendered in higher levels of detail. Again, overall scene values will be calculated to either enhance or suppress any local luminance popout.

Size

Along with the absolute size of an object, the size importance will be calculated from local differences, combined with a measure of the overall scene size variation. Similar to hue, this variation will either enhance or suppress the local size difference popout.

Edges

A number of rules govern edges, for example, popout occurs due to orientation differences[1, 13, 19]. However, this popout is only true for unnatural scenes. In natural scenes, concentrations of edges in regions attract attention[7], due to the high levels of information contained therein. A measure of edge concentration, with regards to the rest of the scene, will give an importance level for the region being examined.

Depth cues

The sharpness of edges is also a factor in attracting attention[7]. This may be modelled using depth of focus effects available in high quality rendering systems. It is anticipated that those objects in the scene which are in the correct focal depth will have an attracting effect due to their sharpness, in contrast to the other out of focus objects in the scene.

There is also issue of level of detail effects, related to the object's distance from the viewing point. This involves the foreground-background high level feature[2], where objects in the foreground are more attractive than those in the background.

Location

The location is a fuzzy variable calculated in terms of Euclidean distance from the centre of the screen, based upon the premise that the viewers will predominately look at the centre 25% of the screen[2].

4.4 Feature characterisation experiments.

A characterisation experiment will be carried out for each of the above features, to identify the parameters for each fuzzy membership function. Each of the above general rules will be characterised by either appropriate psychophysical experimentation, or the results of other visual attention researchers.

Our hypothesis is that the interactions between the features will be sigmoidal in nature, similar to the effect of local feature contrast. This will require a set of experiments to find the threshold whereby one feature difference becomes more salient than another feature difference. The features will be combined in pairs, with the addition of one extra feature to discern how the additional feature affects the scene importance calculations as a whole.

The next stage will be to evaluate the system at a number of different levels. Firstly, the fuzzy system needs to be evaluated for its prediction of object levels of importance and its scene decomposition, and whether this reflects HVS eye movements. We will also evaluate the system's ability to predict eye movements when viewing a synthesised scene. This will be carried out in two ways. The first level of evaluation will be to compare the system with results from Koch's[4] attention system and with Hayasaka's model[3]. The system's eye movement prediction ability will also be compared with eye movement recordings of synthesised scene viewing. To facilitate this evaluation process, a set of test scenes will be developed as an analog to test scenes used in the image processing community.

The next section will detail the results of a pilot study performed to characterise popout due to size feature differences.

5 PRELIMINARY SIZE FEATURE EXPERIMENTAL RESULTS

5.1 Experiment Goals

We performed a pilot study to ascertain the effectiveness of characterising popout with the size feature of an image. The aim was to begin with simple Mondrian like images progressing towards more realistic scenes. The intention is to note how variation of the scene's dimensions affects the visual prominence of targets.

These experiments extend Nothdurft's[19] work by seeking to characterise the size image feature, encapsulating the results into two fuzzy rules involving the local size difference and the whole image size differences. These new rules will be incorporated with a measure of the absolute size of the object, to form a more exact characterisation of the influence of the size feature on area conspicuousness in real images.

5.2 General experimental methodology

The experiments were performed in a CCIR Rec. 500[27] room with the images being displayed on a Sony PVM-2130QM Trinitron colour monitor. The monitor and room lighting specifications were: peak white luminance – 70.1 cd/m^2, inactive screen to peak ratio – 0.003, black screen to peak ratio – 0.002, contrast ratio – 0.012, average luminance of surrounding background – 10.41, overall illumination – low, background curtain chromaticity T_c – 2,883, duv – 0.0095.

The values were measured with a Nippon Denshoku NL-1 lumino meter. The experiment programs were written in OpenGL and Motif, running on an SGI O2/Irix 6.3, connected by an S-Video link to the Sony monitor.

Each viewer was seated in the room and asked to fixate on a cross in the centre of the screen. The images, unless mentioned otherwise, were displayed for 100msec, to prevent any unnecessary eye movements. Before each test image, the viewer was shown three screens to inform the subjects of the extreme values of the experiment: a large popout, small popout and zero popout image. These images were not changed for the extent of the experiment, to prevent any major biases being added to the subjective evaluation of the test images.

The viewer was then shown a randomised test image. The locations of the test image target were randomly assigned to one of four possible positions at a constant viewing eccentricity of 3°. For two seconds between each image, a neutral grey screen equivalent in luminance to the background of the test screen was displayed. Squares were used as objects, much like colour perception work with Mondrians, due to their utility in being arranged into other general shapes. The squares were arranged in an eight by eight grid, with each square being perturbed by 0.1° to confound vernier offset factors. However the squares remained roughly equidistant from each other. The squares were rendered in as fully saturated red as possible, at a luminance equal to the grey background of the display (10.41 cd/m$^{2)}$. This produced good foreground background differentiation, confounding the effect of smaller squares being regarded as "holes" in a grey screen. The size of the squares is stated in degrees of visual angle. The minimum size of any square was 0.5°, to avoid visual acuity problems.

Each subject was asked to subjectively evaluate the popout value of the test image target as being zero (no conspicuous target), small (target just perceptively prominent) and large (target obviously prominent). This was accomplished by pressing either the 0 (zero popout), 1 (small popout) or 2 (large popout) key on the keyboard provided.

5.3 Size experiment 1

Methodology

In the first experiment we aimed to gain preliminary results into the characterisation of the size popout fuzzy variable. It was anticipated from reading and small studies carried out previously, that the subjects would be able to characterise popout using the linguistic terms zero, small and large. In the first experiment the background distractor sizes were varied between 0.5° and 1.14°, by eight equal increments. The targets were varied in size from 0.5° to 2.26°, in eight equal increments according to a linear formula that ensured the targets and distractors did not overlap. A single target was shown on each test image, in a format similar to Figure 3.

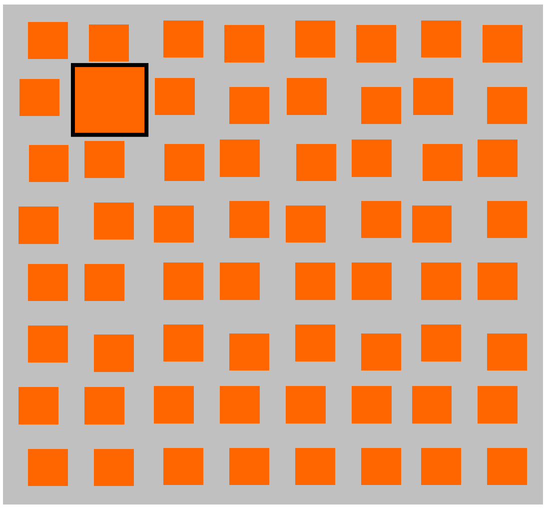

Figure 3. Example of a first size experiment test screen, with the target highlighted.

Four subjects, including the author, were involved, with ages ranging from 26 to 37, all had normal uncorrected vision with no major colour perception anomalies. The subjects were shown 43 combinations of target and distractor sizes, in three different locations, to super sample the size difference values. The experiment lasted for approximately one half-hour.

Hypotheses

We expected that the action of popout will be sigmoidal in relation to local area differences, with a threshold where popout will begin very quickly to appear and a point where it saturates to produce an object that is obvious. This should be reflected in the subjects' evaluation of popout into three definite categories: zero, small and large.

Results

The following diagrams, Figure 4-6 are histograms of the results from the experiment. They display the frequency distribution of the subjects' choices. As the amount of popout depended on both the size of the distractors and the size of the target, the two dimensions were reduced to one by normalisation, dividing the area difference between the target and distractors by the area of the distractors in the test image.

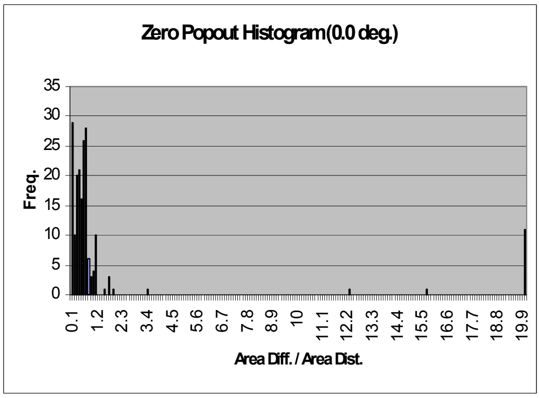

Figure 4.

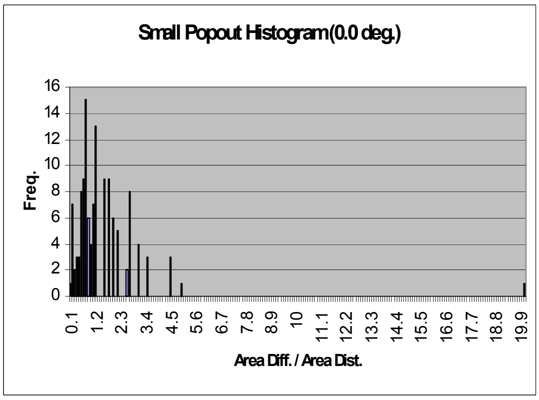

Figure 5.

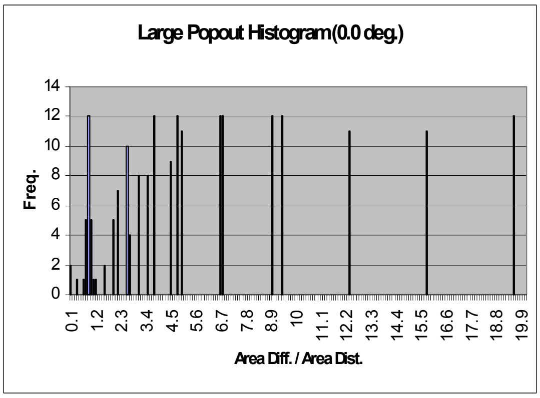

Figure 6.

Conclusions/Discussion

The three graphs show encouraging results for the subjective categorisation of popout into zero, small and large, with three peaks at differing positions on the domain of the graphs. The large popout graph does however show an anomalous peak around the same location as the small popout peak, indicating some confusion between the categorisation of some small and large popout images. The rest of the large graph shows a trapezoidal shape, indicating that people were easily able to discern the popout of an object past a certain area difference threshold. To date, we are limited by the lack of statistical power in the experiment, but the results indicate that people were reasonably consistent in their assessment of popout levels. Discussion with the subjects after the experiment yielded anecdotal evidence of the ease with which the subjects could discern these three levels, suggesting that zero, small and large are appropriate linguistic terms to be fuzzified, with regards to size difference popout.

5.4 Size experiment 2

Methodology

In the second experiment we varied the background distractors' size by a fixed magnitude, which was randomised in sign, allowing the background to randomly vary between two sizes. Due to time and subject number restrictions, we only tested for two magnitudes, 0.1° and 0.2°. The size of the distractors was again controlled by a linear function to prevent object overlap. The size of the distractors varied between 0.5° and 1.8°, with the targets varying in size from 0.6° to 1.1°. No test images contained targets the same size as the distractors, due to the variance of the background distractors. The rest of the second experiment's methodology remained consistent with the first experiment. Five subjects (including the author), aged between 23 and 37 performed this experiment. All had normal uncorrected vision, and no major colour perception anomalies. An example test screen is shown in Figure 7.

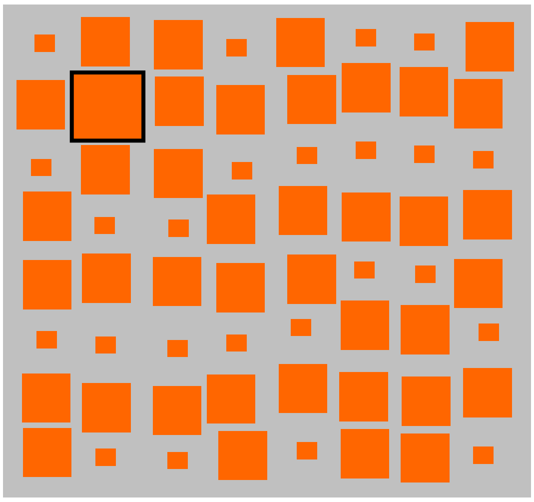

Figure 7. Example of a second size experiment test screen, with the target highlighted.

Hypotheses

We expected a similar result to Nothdurft[19] in that the popout effect would require a greater local size difference to occur in order to popout against a greater sized difference between background distractors. Therefore, we expected the previous first size experiment graphs to move across to the right, indicating a requirement for higher levels of local size difference to cause popout.

Results

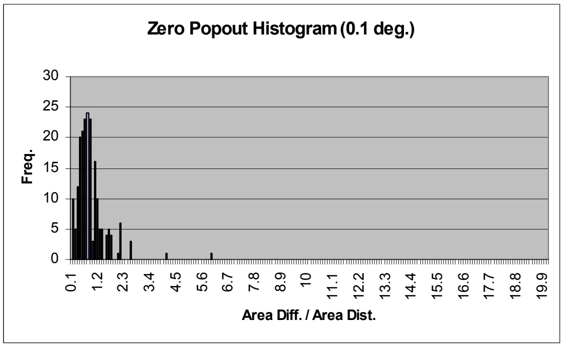

Figure 8.

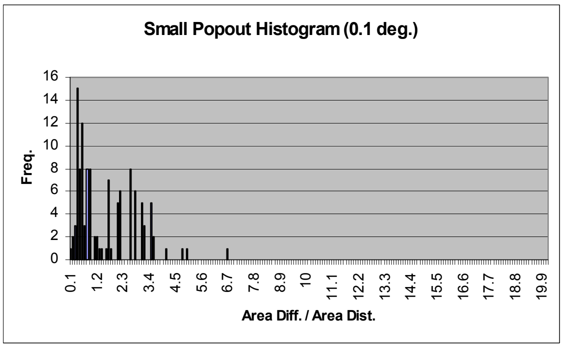

Figure 9.

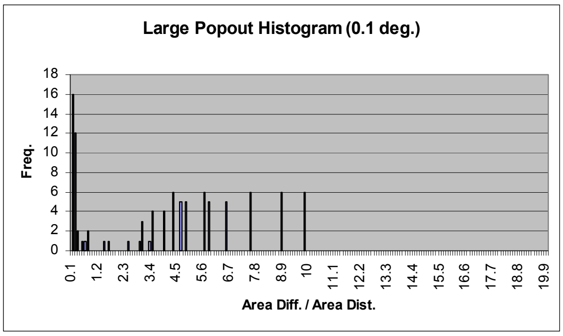

Figure 10.

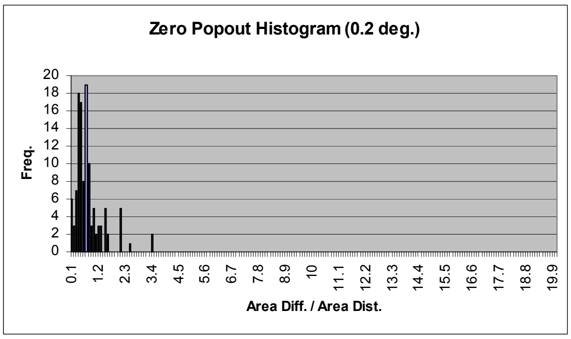

Figure 11.

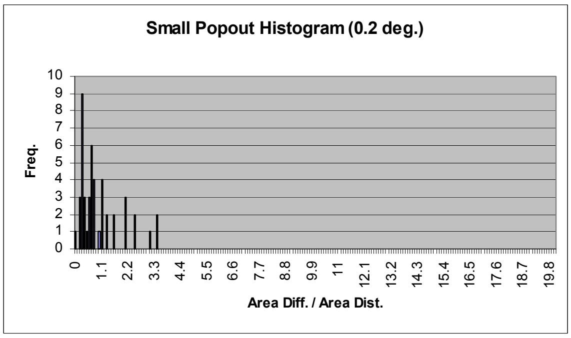

Figure 12.

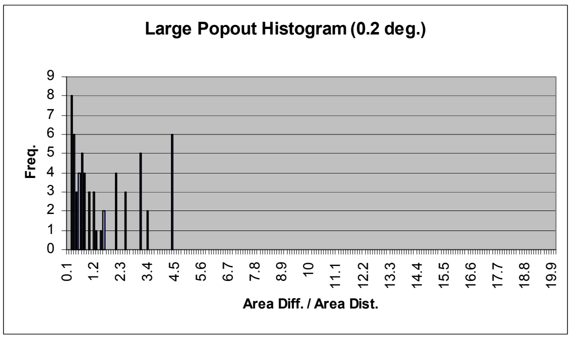

Figure 13.

Conclusions/Discussion

The results from the experiment differed from Nothdurft[19] in that the subjective point of change from target obscurity to conspicuousness was lost due to the noise of the background distractor differences, shown by the similarity of the positions of the peaks in Figures 11 and 12. There was still a point where the subjects were able to discern obvious popout, shown by the threshold in Figures 10 and 13 where the subjects only register large popout. In all the graphs there is a peak for target/distractor ratios of less than 2.0, signifying confusion on the part of the subjects in evaluating low levels of popout due to the size differences occurring in the background distractors. Instead of moving to the right as expected, the graphs contained peaks in the same location as the first size experiment. This incongruence with Nothdurft's results may be due to differences in methodology. His experiments were performed with hue, orientation and motion features, whereas our experiments endeavoured to characterise the size feature. The preliminary results here may indicate that the rules established by Nothdurft for hue, orientation and motion may not continue into the size feature, suggesting a reassessment of the rules of size popout with background distractor variations.

5. CONCLUSIONS AND FUTURE WORK

A conceptual framework for the development of a fuzzy scene decomposition system as a novel method for efficient image synthesis has been presented. A general experimental plan was also described, which it is anticipated will allow the fuzzy characterisation of chosen subset of preattentive features and their inter-relationships. A plan for the evaluation of the fuzzy decomposition system was also described in which its performance would be compared to already established feature systems and eye movement recordings.

A pilot study into the characterisation of the size feature was presented. The results of the study show a difficulty with changing the images into progressively more realistic scenes. We believed that the simplicity of the fuzzy rules would allow a characterisation of the size popout results. However, we met problems with the dichotomy between the low-level images of psychological research and the images generated in the image processing community. This makes the bottom-up creation of a fuzzy size popout model an unlikely path. For future work we will investigate the possibility of the use of real images with high frequency information removed, to allow the easier decomposition of the image into component feature dimensions. It is envisaged that such a simplified image would allow us to analyse images of a more realistic nature with some control of scene features, leading to a better characterisation of size popout.

Although our main aim is the development of efficient methods for image synthesis, it is expected that the finished model and rendering system will have many other applications including: image compression, virtual reality systems, entertainment systems and vision simulation.

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