A BPT Application: Semi-automatic Image Retrieval Tool

Shirin Ghanbari, John C. Woods, Simon M. Lucas,
School of Computer Science and Electronic Engineering, University of Essex, Colchester, United Kingdom
Email: {sghanb, woodjt, sml}@essex.ac.uk

Hamid R. Rabiee
Department of Computer Engineering, Sharif University of Technology, Tehran, Iran
Email: rabiee@sharif.edu

***Abstract*—This work presents a semi-automatic tool for content retrieval. In contrast to traditional content based image retrieval systems that work with entire images, the tool we have developed handles individual objects. The availability of a pool of pre-segmented objects found using region analysis allows the human behaviour of pre-segmentation to be replicated. To generate defined objects in the object pool, segmentation is performed using multi-dimensional Binary Partition Trees (BPTs). The tree structure uses colour, spatial frequency edge histograms to form semantically meaningful tree nodes. The BPTs can be intuitively browsed and are stored within XML documents for ease of access and analysis. To find an object a node from a query image is matched against the nodes of the BPT of the database image. These are matched according to a collection of MPEG-7 descriptors. Performance evaluation shows high quality segmentations and reliable retrieval results.**

***Index Terms*—Binary Partition Tree, segmentation, content retrieval, object extraction, MPEG-7**

I. INTRODUCTION

To date people looking for content have used text-based engines with moderate retrieval performance. The fact that they are in widespread use indicates a need exists. These engines rely on human operators to manually describe multimedia content through keywords, yielding uncertainty and noisy results. This leads to the so-called semantic gap; "… the lack of coincidence between the information that one can extract from visual data and the interpretation that the same data has for a user in a given situation" [1]. Clearly the human vision system has evolved over millennia and much prior art exists in the interpretation of what we see, thus it is extremely difficult to teach a machine; "while text is man's creation, images are a replica of what man has seen since birth" [2].

Traditional Content Based Image Retrieval (CBIR) systems that consider the entire image have been shown to be effective in multimedia databases. Along with their simplicity they have even been used for both experimental and commercial systems [3]. However, real-world images are complicated, and multiple objects are present that may lead to undesired retrievals. There are situations where users may wish to find a semantic object in the presence of other objects and there could also be a complicated background, such as an animal in long grass. The object could be at a different physical location in the image and also the background may have changed. If we wanted to find the image within an archive and the background features were dominant the results returned would be based on the statistics of the background and not the object of interest. Therefore it is more appropriate to work with small individual objects found using a pre-processing segmentation tool. Binary Partition Trees (BPT) [3] have proven to be reliable in representing and retrieving objects (or regions) included within an image.

The dictionary states that an object is anything that is visible or tangible and is relatively stable in form. This definition whilst useful does not fully define an object for retrieval. Our interpretation of an object consists of the following properties:

a) distinct from the background,
b) closed in boundary,
c) enclosed by other objects,
d) bounded in size,
e) represented by a finite set of statistics,
f) salient or semantic or both,
g) made of homogenous texture
h) holey,
i) identifiable to humankind,
j) part of another object,
k) themselves surrounded,
l) identifiable in properties,
m) stable,
n) tangible,
o) partial
p) solid

Essentially the BPT allows a database representation of images, documenting the merging order of homogeneous regions for manual or automatic retrieval. Leaf nodes represent the initial image partition, with the remaining nodes created by merging two child nodes to form a parent node according to their similarity. With this structure the tree can represent a set of regions at different scales of resolution, with which BPT users can actively select individual nodes to identify and segment their desired object(s). Our proposed multi-dimensional BPT generates high density partial objects with clearly defined boundaries using a combination of colour and spatial frequency. These complete objects can now be appropriately processed and matched with nodes from other images allowing a retrieval system to be formed. This tool allows us to work with a pool of smaller defined objects rather than a busy entire image, and importantly allows users to have more freedom in the type of query they input.

In particular, this paper justifies how segmentation can considerably enhance content based retrieval systems, and how effective multiple descriptors are in describing content; be it entire images or smaller regions.

The rest of this paper is organized as follows: Section II presents the generation of a two dimensional Binary Partition Tree. Section III discusses a semi-automatic retrieval system. Section IV presents test results and their analysis. Finally the paper is concluded in Section V.

II. BPT Object Segmentation

A key requirement in the generation of a BPT is the ability to accurately preserve boundaries within the generated nodes. To generate a BPT, two clear stages are required [4]; a pre-segmentation phase; where images are initially partitioned into thousands of small homogenous regions that may have no semantic meaning, and a region growing phase. The latter stage is an iterative process; where two children nodes are merged to form a parent node continuously until the root node representing the entire image is generated.

As part of the MPEG 7 standard [5], its colour descriptor is the most commonly employed low-level descriptor in BPT's [6] producing somewhat robust results. However colour on its own performs poorly in the presence of low saturation or high texture content. It would not be able yield reliable segmentations on real-world images that contain high spatial frequency and homogenous areas where the hue differs as a result of lighting variation. For example, imagine a photograph of a wolf taken at night; here the image is affected by illumination due to shadowing. Another typical example would be an animal camouflaged by its surroundings. With this in mind the authors in [7] generated trees incorporating spatial frequency.

To increase semantic meaning within the BPT nodes, spatial frequency or texture is adaptively considered alongside colour during the merging process reinforcing the boundary requirement. Furthermore, to use the full benefits of colour, the CIE L*a*b* colour space is used, as it has been shown to quantify colour differences as perceived by humans.

For texture, we look to capture energy at specific frequencies, which can be achieved through the wavelet transform. The wavelet transform is successively applied along the rows and columns of the image. This procedure results in the decomposition of the image into four distinct sub-bands (fig. 1): the lowest frequency, the Low Low (LL) band and the higher-frequency sub-bands; Low High (LH), High Low (HL) and High High (HH). In this four-band decomposition energy in the diagonal direction is negligible and high spatial frequency is mainly concentrated in the vertical and horizontal directions. It is within these bands that finer detail can be found.

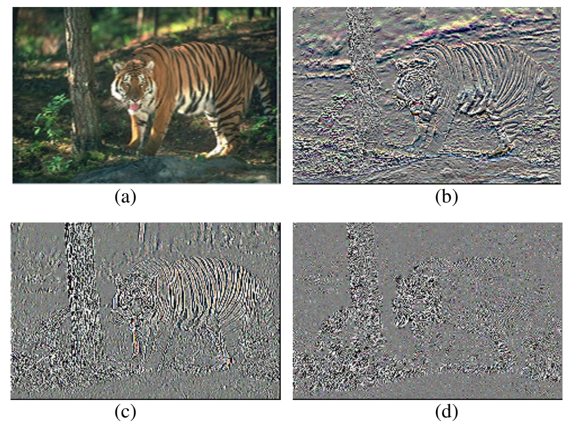


Figure 1. Wavelet Transform; (a) Low Low (LL) Band, (b) Low High (LH) Band (c) High Low (HL) Band, (d) High High (HH) Band

Fig. 1 illustrates the four bands; where clearly in the LL band the majority of the image content has been preserved. The finer detail manifests in the other remaining bands. The high frequency bands are shown in gray-scale and have been magnified by a factor of 16 for visualization purposes. From the sub-bands one can locate areas having significant levels of texture, for example the tiger's body (Fig. 1b), as well as the foliage and the tree in the background (Fig. 1c).

To obtain initial regions (or seeds), images are pre-segmented or partitioned using the Watershed [8] transform. It is applied to a gradient magnitude image resulting in the partition of the image into non-overlapping regions. A watershed region or catchment basin is defined as the region over which all points flow "downhill" to a common point. Although, the Watershed transform is an unsupervised method it is highly sensitive to gradient noise resulting in over-segmentation; even small noise can make a homogenous region 'break' into lots of small watersheds. However, compared to other pre-segmentation techniques such as K-means clustering or the mean shift algorithm, its regions preserve detailed object boundaries (again reinforcing our boundary). Fig. 2 illustrates the labeling of the Watershed transform, and clearly highlights the formation of numerous small regions.

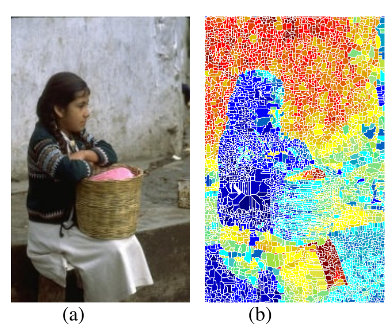


Figure 2. Watershed Transform; (a) Original image, (b) watershed applied

To rectify the over-segmentation an iterative region merging procedure follows. Here adjacent children nodes are constantly merged until the final parent node (the root node), is formed. Then by considering colour as well as texture, the merging order between two adjacent regions is calculated in two steps. Firstly, the mean colour distance, C_{ij}, between two adjacent region nodes i and j is evaluated as in [6], for the LL band. Then the region's texture energies (texture variance) are considered, by examining the region's corresponding LH and HL bands (the HH band can be avoided due to its low energy and its sensitivity to noise). The energies between adjacent region nodes are defined as:

$$E_{LH} = \left| LH_i - LH_j \right| \tag{1}$$

$$E_{HL} = \left| HL_i - HL_j \right| \tag{2}$$

where E is the energy contained in one of the wavelet sub-bands. From this the final merging cost D is defined as:

$$D_{ij} = C_{ij} \times \left(E_{LH} + E_{HL} \right) \tag{3}$$

When observing a scene, the human visual system segments the view into a series of discrete objects. This process is so efficient that a person is not usually confused, and observes a series of familiar objects. The precise mechanism the brain is employing remains a mystery but it is clear the boundary condition makes a large contribution to cognition. However, recognized by many [9] the ability to quantify this in a general way is an ill posed problem. We can analyze these segmentations subjectively or more accurately through an empirical discrepancy approach based on the density of the segmentations. In this work we use the object boundary to form a ground truth. The best match is the single node within the tree which best approximates the content inside the boundary. The segmentation is then quantified according to the percentage of pixels inside and outside the mask of the ground truth. These two metrics, intrinsic and extrinsic [10], represent under and over segmentation respectively and can be combined into a single metric of segmentation quality: the bi-trinsic quality measure [10]:

Bi-trinsic = Intrinsic x (100 - Extrinsic)/100 (4)

Fig. 3 and fig. 4 illustrates attempts to segment objects from their background; one from the colour-only based BPT and the other from the colour-texture BPT. By simply looking at the images, one can immediately see their differences in density. However, this may not be quite as easy in all cases and therefore the bi-trinsic measure is used. Fig. 3's overall bi-trinsic value for the colour based BPT and colour-texture model is 32.5 and 77.3 respectively and for fig. 4, it is equal to 72.7 and 80.09 (percent). In both examples, the colour-texture algorithm has been shown to perform well even under illumination changes. The algorithm has facilitated subjectively meaningful segmentations which are more amenable to browsing by constraining salient objects to individual branches within the BPT. These high density segmented objects are now ready for further processing such as content retrieval.

(a) (b) (c)

Figure 3. BPT algorithm comparison; (a) Original image, (b) Colour segment, (C) Colour-Texture segment

(a) (b) (c)

Figure 4. BPT algorithm comparison; (a) Original image, (b) Colour segment, (C) Colour-Texture segment

III. Application: Semi-automatic Content Retrieval Tool

The essence of a content-based retrieval system is to find images that are semantically related to the user's query from a database. Two methods are recognized for describing the content of images: using global features and using local features. In the global descriptor attributes are computed on the whole image, whereas in the local descriptor attributes are computed on regions of the image [11]. In the proposed semi-automatic system, the user selects a node from the image's BPT which initiates a search of the XML database. In this way it is the user who drives the search but within the confines of an automated retrieval system. If the search is refined the retrieval process becomes progressively more robust.

A. Node Description

Semantic concepts are complex and can be better described using a mixture of descriptors. Consequently, in representing or describing nodes within our BPT, a collection of MPEG-7 descriptors is implemented; each incorporating their unique influence. Other than texture variance and colour descriptors, edges constitute an important feature in representing content for both man and machine, were the human eye is normally sensitive to edge features. In MPEG-7 edges can be represented through an Edge Histogram Descriptor (EHD) ([5] and [12]). This histogram represents the frequency and the directionality of the brightness changes within images.

According to the MPEG-7 standard [5], the EHD represents the distribution of five types of edges; vertical, horizontal, 45-degree diagonal, 135-degree diagonal and non-directional edges. These edges are located locally within an image or sub-image. In our implementation each node represents a segment, where it is then sub-divided into 4x4 sub-images. Then the local edge distribution for each sub-image may be represented by a histogram. This results in a total of 80 (5x16) histogram bins, which are quantized and normalized accordingly.

For each image-block we may extract edge information including the existence of edges and their type. The predominant edge is determined and the histogram value of the corresponding edge is incremented by one. Since the EHD describes the distribution of non-directional, as well as non-edges and four directional edges, the extraction scheme is block-based. In this case the sub-image is further divided into non-overlapping square image-blocks (where the size depends on the resolution of the image) and the coefficients [12] for the edge categories are applied accordingly. [12] extends the histogram grouping the image blocks (and the corresponding bins). The extended bins are referred to as the global and semi-global edge histograms. In our node description, we also consider global information (adding an extra five bins) representing the edge distribution for the whole image space, in our case a node, within the EHD.

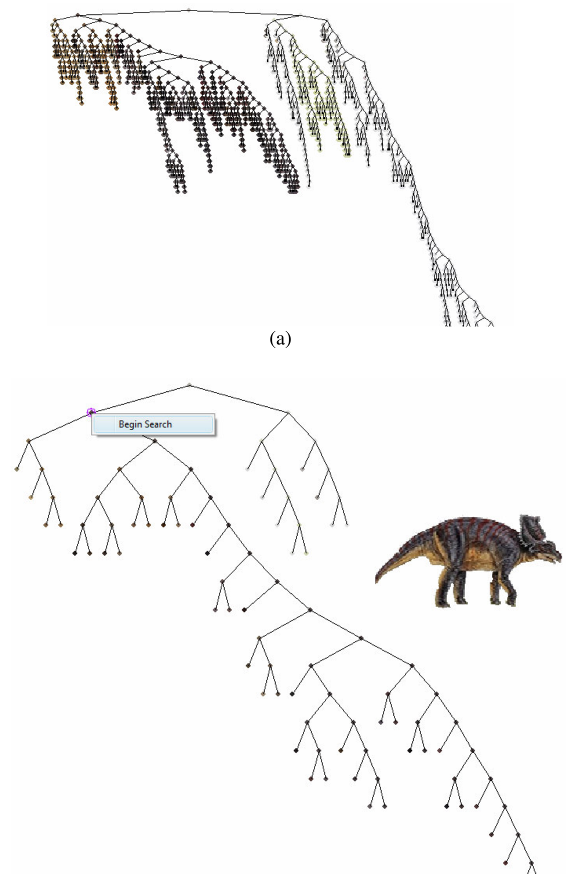
The EHD is not translational invariant and as a consequence if the objects have moved, false matches would be returned when searching the tree. To overcome this a boundary box is placed over the regions,. Furthermore, there are situations where regions are relatively small (e.g. 24 by 16 pixels), and subsequently it would not be appropriate to have a large block size. Instead we apply variable block sizes according to the size of the region (8x8, 4x4, 2x2).

To complete our object descriptions we draw upon another powerful feature descriptor, shape, where psychological experiments have shown considerable evidence that objects are primarily recognized by their shapes [13]. MPEG-7 discusses two types of shape representations, contour-based and region-based. Many can be time-consuming. Moment invariants [14] are widely used for contour-based shape description, as they comply with key requirements being invariant to translation, rotation and scale. In our implementation the boundary of the nodes are computed and the seven moment invariant coefficients [15] are applied accordingly to form a feature vector. The invariance of the moments are important and not their signs and consequently their absolute values are used.

B. Similaity Match

To manage complexity and storage, the BPT of the images (query and the database) can be simplified using region evolution [6]. In effect, the simplification or pruning process (Fig. 5) takes a BPT containing many hundreds of nodes and simplifies it to just a few tens, whilst still maintaining the majority of the semantic content.

After the pruning of nodes, comes the actual process of matching between the images in the database and the node from the query image. For each node comparison their absolute mean colour, texture variance, and average shape feature differences are computed. For the similarity matching of the EHD, the absolute distance between histograms is evaluated [14].



(a)

(b)

Figure 5. Semi-automatic tool; user selects query node, (a) BPT, (b) pruned BPT with query object selected by user

For content management there is a need to reference BPT nodes from a database of images. To achieve this, we store relevant statistical information from the pruned BPT within an eXtensible Markup Language (XML) document generated using CMarkup[1]. Then the values from these documents are automatically matched using a JDOM[2] parser thus simplifying the similarity matching process. In our semi-automatic tool, mean colour, size, area, colour variance, texture variance, EHD values and shape feature vector, as well as the label identifying the node are recorded within the XML file.

In combining these descriptors, there exists no single solution achieving optimum for all objectives at the same time [16] and hence we undertake a series of steps. Firstly, for each node descriptor (colour, texture, edge and shape) their n most similar nodes and their corresponding root image are recorded within separate lists. Then these are rank ordered and the top candidate is selected along with its corresponding image. Finally, these images are further ranked and otherwise combined

[1] C++ XML parser http://www.firstobject.com/

[2] Java XML parser http://www.jdom.org/

through a cost function [15]. The reason for a weighting is because not all images contain equal amounts of descriptor, e.g. an image may have little or no texture, and hence analysis would be biased.

C. Cost Function

The cost function associates a weight for each of the ranked nodes for each list (one for each descriptor), starting from the value 1 and incrementing accordingly. If a particular statistic is missing from a node's description then a large number is associated with that image. For each descriptor (Desc_n) a rank ordered list is formed with the image number ID (e.g. 109090) used as the index. Table 1 shows a simple scenario that is based on three rank ordered descriptors.

TABLE I.
EXAMPLE LIST OF RANKED ORDER IMAGES FOR EACH DESCRIPTOR

Weight	Desc_1	Desc_2	Desc_3
1	109090	160068	109090
2	291000	291000	160068
3	160068	109090	234324
4	234324	453434	376043
5	157055	376043	856454

To provide a final ranked ordered list the cost function is applied. For example, as tabulated in table 2, image number 109090 cost function would be equal to 5 (1+3+1) due to its occurrences in the table. Image 291000 has a value of 14 (2+2+10), as it is not referenced within one of the ranked lists (third column) an arbitrary value of 10 is applied. Similarly image 376043 does not occur in the first column, resulting with a high value of 19 (10+5+4). The first five similar images would therefore be:

TABLE II.
EXAMPLE OF RANK ORDERED IMAGES

	Image No.	Cost
1	109090	5
2	160068	6
3	291000	14
4	234324	17
5	376043	19

IV. EVALUATION AND ANAYLSIS

To demonstrate the semi-automatic system, a subset of the Corel database [17] containing 600 images in total (grouped into six classes each consisting of 100 images) was used as the query set in a simulated analysis. A retrieved image is considered a match if and only if it is in the same category as the query. During experimentation, as shown in Fig. 5 (b) the user clicks on their chosen query node and the semi-automatic tool begins its search.

Fig. 6 presents a number of query test images and their returned results (The test images shown are from each class and are shown based on their segmentation quality). In the first column, the node segments and their corresponding root images are shown. Then for each trial, the most similar and second most similar retrieved images are represented in the subsequent columns.

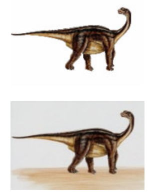
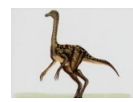
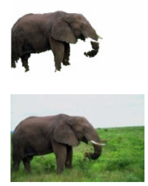
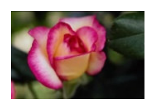
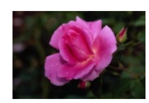
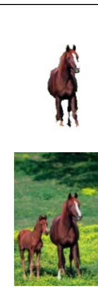
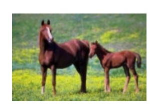
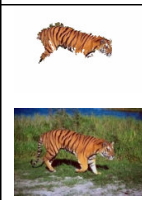
Category	Query Node and Image	Most similar image	Second most similar images
01			
02			
03			
04			
05			
06			

Figure 6. Retrieval results

Every image in the *sub-database* was tested as a query, and the retrieval ranks of all the rest images were recorded. To determine the precision of the retrieved images for N top matches (number of results per query image) the ratio of the number of retrieved *relevant* images (that are similar to the query images) to the number of all retrieved images (output images) is measured. We look upon the first five top matches.

To illustrate the advantage of using the BPT for image retrieval, table 3 compares the precision of recalling five images based on our semi-automatic node-based approach against evaluating and matching the mean colour of the entire image.

TABLE III.
PERFORMANCE EVALUATION

Class	Image-based (%)	Node-based (%)
01	36	39.6
02	99	65.6
03	59	55
04	44	89.9
05	21	44
06	19	36
Average	46.3	55.1

Having a wide range of images, within the database, increases the difficulty of the retrieval process. Moreover, the quality of the segmentation can dramatically affect retrieval results. If the query image does not produce defined boundaries then the foreground will be confused with the background and a collection of irrelevant images will be retrieved. This is the case for images that lack a dominant colour and do not contain much texture, and as depicted in fig. 7, an elephant is a good example of this. Also with poor segmentation shape matching is affected [18]. As the BPT is based on colour and texture there may still be situations where fragmented objects are generated. In fact elephants contain very little statistical information. However, as predicted flowers have performed well (as seen in table 3) as they are generally simple to retrieve being distinct in colour, texture and shape.

Also as shown in table 3 the retrieval performance for the tiger class is low. Although good segmentations can be achieved from this class, the colour and texture contained within the object is very much similar to that of its surrounding and the background of the images from the other classes.

Figure 7. An example query node with poor segmentation

Moreover, what is shown within table 3 is that our node/object-based approach provides better recalling results. Indicating that descriptions applied on entire images can also be effectively applied to the node domain due to the nature of the Binary Partition Tree.

V. CONCLUSION

This paper presents a semi-automatic tool for object recognition that can be applied to a content based image retrieval system. The Binary Partition Tree is used to generate object nodes with the aim of fulfilling our aforementioned properties of an object. These objects are indexed and matched through a collection of descriptors. The use of objects rather than the entire image increases the dynamic range of the difference measure aiding the short-listing of candidates from the database.

The colour-texture algorithm facilitates subjectively improved segmentations that are meaningful, and amenable to browsing with salient objects constrained to the individual branches within the BPT. By adding extra descriptors like the edge histogram and moment invariants, the similarity measure is further refined. The interactive nature of the tool allows greater utility to the user in selecting and assigning the query.

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Shirin Ghanbari received her B.Sc. in computer science with First class honors in 2001 and the M.Sc. degree in e-commerce with Distinctions in 2004, both from University of Essex, UK. She is currently a Ph.D. student and working on image/video segmentation and content retrieval, at the School of Computer Science and Electronic Engineering, University of Essex.

John C. Woods was born in a small fishing village near Colchester U.K. in 1964. He received the B.Eng. (hons.) degree (first class) in 1966 and the Ph.D. degree in 1999 from the University of Essex, Colchester, U.K.

He is a reader at the School of Computer Science and Electronic Engineering, University of Essex. Although his field of expertise is image processing, he has a wide range of interests including telecommunications, autonomous vehicles and robots, intelligent power control, networks and network pricing. During his career he has accumulated over 60 journal and conference publications and has been awarded grants in these areas.

Dr John Woods is a member of the Institute of Electrical and Electronics Engineers, Inc. (IEEE)

Hamid R. Rabiee received his BS and MS degrees in Electrical Engineering from CSULB, USA, his EEE degree in Electrical and Computer Engineering from USC, USA, and his PhD in Electrical and Computer Engineering from Purdue University, West Lafayette, USA in 1996. From 1993 to 1996 he was a Member of Technical Staff at AT&T Bell Laboratories. From 1996 to 1999 he worked as a Senior Software Engineer at Intel Corporation. He was also with PSU, OGI and OSU Universities as an Adjunct Professor of Electrical and Computer Engineering from 1996-2000. Since September 2000, he has joined Sharif University of Technology, Tehran, Iran.

He is the founder of Sharif University Advanced Information and Communication Technology Research Center (AICTC), Sharif University Advanced Technologies Incubator (SATI), and Sharif Digital Media Laboratory (DML). He is currently an Associate Professor of the Computer Engineering Department at Sharif University of Technology, an Adjunct Professor of Computer Science at UNB, Canada, and the Director of AICTC and DML Research Centers. He has been the initiator and director of national and international level projects in the context of UNDP International Open Source Network (IOSN) and Iran’s National ICT Development Plan.

Dr. Hamid Rabiee has received numerous awards and honors for his industrial, scientific and academic contributions. He has acted as chairman in a number of national and international conferences, and holds three patents. He is also a Senior Member of IEEE.

Simon M. Lucas (SMIEEE) is a Professor at the School of Computer Science and Electronic Engineering, University of Essex (UK). His main research interests are evolutionary computation, games, and pattern recognition, and he has published widely in these fields with over 130 peer-reviewed papers.

Professor Simon Lucas was chair of IAPR Technical Committee 5 on Benchmarking and Software (2002 - 2006) and is the inventor of the scanning n-tuple classifier, a fast and accurate OCR method. He was appointed inaugural chair of the IEEE CIS Games Technical Committee in July 2006, has chaired or co-chaired many international conferences, including the first IEEE Symposium on Computational Intelligence and Games in 2005. He is an associated editor of IEEE Transactions on Evolutionary Computation, and the Springer Journal of Memetic Computing. He was an invited keynote speaker or tutorial speaker at IEEE CEC 2007, IEEE WCCI 2008, IEEE CIG 2008, PPSN 2008, and IEEE CEC 2009. He leads the newly established Game Intelligence Group at the University of Essex.