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Attention Guiding Visualization in Remote Sensing IIM Systems

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Zusammenfassung: *Aufmerksamkeitslenkende Visualisierung zur inhaltsbasierten Bildsuche in Fernerkundungsdatenbanken*. Obwohl erfolgreiche Algorithmen zur inhaltsbasierten Bildsuche entwickelt und implementiert worden sind, ist die Visualisierung der Abfrageergebnisse in Systemen der Bildsuche nicht an die menschliche kognitive Fähigkeit der visuellen Informationsprozessierung angepasst worden. Die wichtigsten Eigenschaften der visuellen Informationsprozessierung von Fernerkundungsbildern spiegeln sich in den Hauptfaktoren der visuellen Aufmerksamkeit wider: die Fähigkeit der schnellen Lokalisierung (wo) und der einfachen Dekodierung (was) von visualisierter Information, um Rückschlüsse ziehen zu können.

Die semantische Komponente dieser Faktoren ist wesentlicher Arbeitsgegenstand von Ingenieuren im Bereich der inhaltsbasierten Bildabfrage. Zusätzlich wird die visuelle Aufmerksamkeit von sensorischen Reizen gelenkt, welche Anwendern die Lokalisierung relevanter Information ermöglicht. Dieser Beitrag konzentriert sich auf die kognitiv-adäquate Visualisierung der Lokalität relevanter Information, um Anwender bei der schnellen Navigation in Richtung interessanter Information zu unterstützen. Die Unterstützung bei der Lenkung der Aufmerksamkeit auf die Lokalität relevanter Information führt zu einer Verminderung der beanspruchten kognitiven Kapazität, welche für die Prozessierung von Kontextinformation und der Entscheidungsfindung benötigt wird. Bei der Formulierung von adäquaten Gestaltungsprinzipien sind folglich Aspekte der neurokognitiven visuellen Informationsprozessierung und der Relevanz von Information bedeutend. Auf diesen Prinzipien basierend wird eine Methodik der Gestaltung von aufmerksamkeitslenkenden Visualisierungen entwickelt und angepasste Visualisierungen vorgestellt.

Die Anwendung eines rechnergestützten visuellen Aufmerksamkeitsmodells erlaubt die Evaluie-

Abstract: Although there has been successful work in developing image mining algorithms to extract information, the visualization of query results in Image Information Mining (IIM) systems is still not well adapted to the human cognitive skill of visual information processing.

The main value of processing remotely sensed images is reflected in basic factors of visual attention, i. e. the ability to promptly locate (where) and easily decode (what) geographic information for making inferences. The semantic component is reflected in the work of engineers in the field of Content-based Image Retrieval (CBIR). In addition, human visual attention is guided automatically by sensory stimulation affording users to know where relevant information is located.

This work concentrates on the cognitively adequate visualization of the location of relevant information to support users to navigate rapidly towards information of interest. Supporting users in directing their attention towards the location of relevant information reduces the cognitive workload retained for processing context information and decision making. Therefore, we consider neurocognitive foundations of visual information processing and theories of relevance to frame appropriate design principles. Based on these principles, we establish a design methodology for attention guiding visualization (AGV) and illustrate adapted visualizations. By applying a computed visual attention model, we evaluate proposed visualizations and relate results to upcoming research challenges for the effective visualization in remote sensing IIM systems.

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rung der Visualisierungen und offenbart zukünftige Herausforderungen für die Visualisierung von Informationen in Systemen der inhaltsbasierenden Bildsuche.

1 Introduction

This work focuses on the development, application, and evaluation of attention guiding visualization (AGV) on remotely sensed images with respect to visual cognition and relevance.

Image Information Mining (IIM) systems are increasingly in demand due to the rapid growth in the volume of remotely sensed imagery data. Using satellite images for land cover classification or managing ecosystems is no longer restricted to military or scientific experts. Missions like TerraSAR-X, coordinated by the German Aerospace Centre (DLR), that are realised in a public private partnership will allow the general public a spatiotemporal exploration of geographic phenomena on a very high level of detail. In order to derive semantic information from images there has been a large research effort in developing semantic concepts in visual databases and producing various solutions for the retrieval of earth observation data (Burl et al. 1999, Schröder et al. 2000, Ramachandran et al. 2000, Bretschneider & Kao 2002, Durba & King 2004, Aksoy et al. 2004). Various technical methods exclusively serve to bridge the semantic gap, i. e. linking the algorithmic extracted and clearly defined low-level features of a system with the neural and complex high-level semantic concepts that humans associate with images. The present configuration of IIM systems is therefore predominantly concentrated on developing techniques for the algorithmic search of information. Yet, in addition to the need of developing algorithms for pattern exploration, the results must be visualised effectively (Zhang et al. 2001b); i. e. supporting users to navigate their visual attention towards information of interest by making full use of their visual cognitive skills (Swienty 2005). Anyhow, Content-based Image Retrieval (CBIR) is characterised by the focus on the system's ability to retrieve information rather than by the human ability to visually detect relevant information. Assuming that CBIR "... addresses the problem of finding images relevant to the users' information needs ..." (Laaksonen et al. 2005, p. 127) and "... is characterized by the ability of the system to retrieve relevant images based on their semantic and visual contents rather than by using atomic attributes or keywords assigned to them" (Li & Narayanan 2004, p.673) implies that users are searching for the location of information by visually scanning the display. Exploring users have to cope with a plethora of displayed geographic information. Hence, success depends on the users ability to omit irrelevant sensory input to focus on the relevant information by directing the gaze towards objects of interest (Nobre et al. 2000, Itti 2003, Moore & Fallah 2004, Hafed & Clark 2002). Consequently, our main objective is to depict as much information as needed but as little as possible. Therefore, we propose an AGV serving the visual search of relevant information guided by perceptually salient characteristics.

The theoretical background of AGV is positioned in guidelines of usability engineering; i. e. a user's practical acceptability of a system highly depends on the basic pillar usefulness and its subcomponents, utility and usability (Nielsen 1993). Although there has been successful work in developing CBIR techniques for the retrieval of remotely sensed images (Vellaikal et al. 1995, Bretschneider et al. 2002, Aksoy 2006), the usefulness of IIM systems is still not achieved due to impairments of utility and usability. We consider the relevance of information as an element of utility and its cognitively adequate visualization as an element of usability (Reichenbacher & Swienty 2006). To enhance the utility, we separate irrelevant from relevant data by implementing relevance as a filter and embody relevance values as attributes of the selected objects (Reichenbacher 2005). These relevant objects and the surrounded context information are displayed in a visualization which is adapted to the human ability of visual attention to optimise the system's usability. An exploratory visualization must support users in keeping their focus on the task, with minimal distraction in operating the display (Shneiderman & Plaisant 2004). We argue that a combination of relevance filtering and a cognitively adequate visualization increases the overall usefulness of IIM systems and makes a substantial contribution to their practical acceptability.

2 Visual Processing of Image Data

Due to the novelty of IIM and its experimental stage in research (Zhang et al. 2001b, Li & Narayanan 2004) we emphasise that our approach is not bound to a specific remote sensing IIM prototype system. AGV is positioned in both image mining frameworks presented by (Zhang et al. 2001b); the function-driven framework (Datcu & Seidel 2005, Zaiane et al., 1998) and the information-driven framework (Zhang et al. 2001a). In the function-driven framework AGV plays an important role as a component of the pre-processing system and image mining system, affording to visually process image meaning and detect relevant patterns. In the information-driven framework AGV is a crucial element aiming at highlighting the role of information at different levels of representation. We consider AGV as a major technique of CBIR in remote sensing IIM systems. The implementation of attention guiding attributes accelerates the process of image processing and is therefore a major contribution to image understanding. AGV highlights the location (where) of information which is one of the components that humans process to comprehend the content (what) of images.

2.1 *Relevance and Visual Cognition*

'Relevance' is used to express the significance or importance and has a relative character. Saracevic (1996) classified such relations and differentiates between objective and subjective relevance. The objective relevance is reflected in the algorithmic determination of information. In the fields of communication and pragmatics the objective value is inapplicable and is replaced by the subjective relevance where the relevance of entities is determined by the user's judgement which can be influenced by interfering factors. For example, the result of a query could display a large amount of irrelevant information that deviates the user's gaze from relevant information. Subjective relevance includes the theory of cognitive relevance (Wilson & Sperber 2004) by applying relevance as an assessment criterion for processable stimuli; one basic aspect of AGV.

'Visual cognition' describes the processing of displayed information that is largely affected by factors of attention (Meador et al. 2002, Lezak et al. 2004). When processing complex visualizations in IIM systems users adopt a mechanism of visual attention to concentrate on relevant information while omitting competing irrelevant information; i. e. the capability of selective visual attention allowing humans to extract and recognise relevant information in visual scenes with high efficiency despite their complexity (Deco & Zihl 2001). In selective visual attention humans scan their visual environment where the quantity of information processed is in the range of 10^8–10^9 bits per second (Deco et al. 2002). Fig. 1a illustrates the basic cortical processing pathways and major cortical areas involved in attentional information processing.

(1) Early feature extraction carries sensory signals from the retina (RT) to higher brain areas via the primary visual cortex (V1). (2) The 'what' pathway is concerned with the identification and recognition of visual objects. The inferotemporal cortex

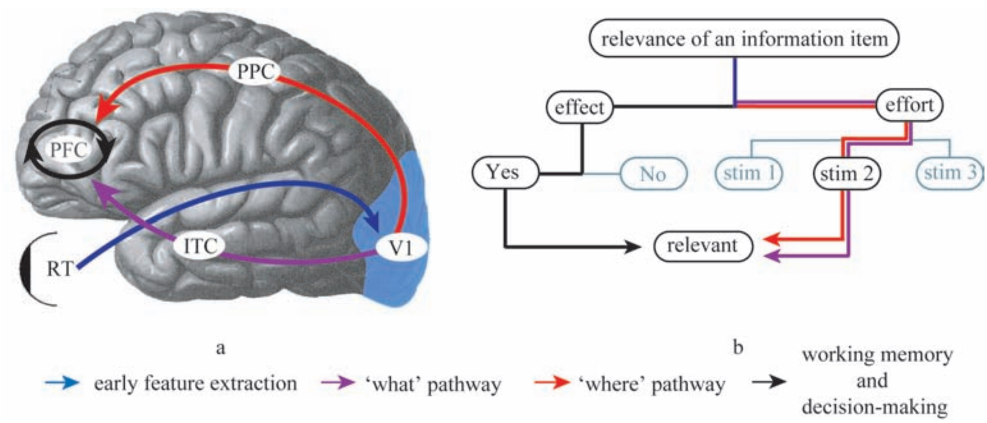

Fig. 1: (a) Major cortical pathways and areas of visual attention, (b) Cognitive relevance.

(ITC) deals with the identification of stimuli and pattern recognition (GRILL-SPECTOR & MALACH 2004). (3) The 'where' pathway is specialised in the spatial deployment of attention and localisation of attended stimuli. Neurons fire to the posterior parietal cortex (PPC) that contains a saliency representation of a visual scene (GOTTLIEB et al. 1998). (4) The prefrontal cortex (PFC) is important for converting sensory signals to motor output. This conversion takes place in the working memory (WM) system, deals with the updating, maintenance, monitoring, manipulation, and selection of stored information.

Fig. 1b depicts a cognitive relevance model by relating basic processing stages to appropriate pathways. According to the relevance theory (WILSON & SPERBER 2004), cognition is always geared to a maximisation of relevance. Two criteria effect and effort are responsible to evaluate the relevance of a stimulus. First, only a stimulus that is processed on the 'what' path (fast information decoding) and the 'where' path (fast object localisation) with little efforts is considered as relevant and will be further processed. The relevant stimulus has to attract the user's attention and conceal distractive irrelevant stimuli that deviates the gaze from the target. Second, only a stimulus that is processed via the PFC has an effect (triggers inferences) on further actions. Finally, only stimuli that unify both criteria, small effort and large effect, will be processed.

2.2 *Guiding Attention to Location*

It has been shown that in vision attention is controlled by knowledge (top-down) and sensory stimulation (bottom-up). The interaction of these factors controls where, how and to what humans pay attention in a visual environment to initiate cognitive control (CORBETTA & SHULMAN 2002). The development of AGV is bottom-up oriented and tends to accelerate the visual information processing by particularly providing neural responses along the 'where' pathway. We hypothesise that supporting a user in directing the attention to relevant information implicates a preservation of higher WM capacities that are needed for the semantic decoding of information. The design methodology of AGV adapts the visualization of relevant information to human capabilities of selective visual attention. The basic design approach follows the biological centre-surround mechanism, i. e. to suppress surrounded context information to focus on relevant information which optimises information transmission (VINJE & GALLANT 2000) and which can be regarded 'as the fundamental perceptual act of identifying objects' (WARE 2004, p. 196). This leads us to integrate the design principles into a visual hierarchy. Elementary design principles to establish a visual hierarchy are for instance (Krygier & Wood 2005): (1) Visual difference of colour, lightness or texture, (2) figure has more detail than ground and (3) sharp edges of figures separate them from less important figures.

Additionally, relevance values are encoded in the way that users can easily process the ranking order. Fig. 2 illustrates the possible use of visual elements in image processing techniques. The elements stem from graphical variables used in information visualization and recent findings on visual attention in cognitive neuroscience. We relate these attributes to graphical variables and derive their applicability to image processing techniques.

Visual attention guiding attributes

Amongst the number of stimuli to be processed some are reflexively extracted only because of local differences between this item and its surrounding without having any information about the target in advance. Such attention-guiding attributes and corresponding features were ranked by Wolfe & Horowitz (2004) who regard colour, motion, orientation, and size as undoubted attributes. In this work, we exclude motion, because we concentrate only on static attributes. However, motion plays a decisive role in attracting attention due to its shorter response time in visual search tasks compared to static attributes (Peterson & Dugas 1972).

Graphical and extended graphical variables

For designing visually discernible graphical signs that reflect differences in the data to be visualised, Bertin (1974) proposed a set of graphical variables such as size, orientation, colour (hue), and value (lightness), shape, and texture. We also consider the extended variables colour saturation, crispness, resolution, and transparency proposed by MacEachren (1995). Depending on the scale of measurement some of the graphical variables are more apt than others. Here, we deal with relevance values as an ordered set of relevance ranks. Bertin identifies texture, value, and size as ordered variables that allow the spontaneous decoding of order. MacEachren suggested that also colour

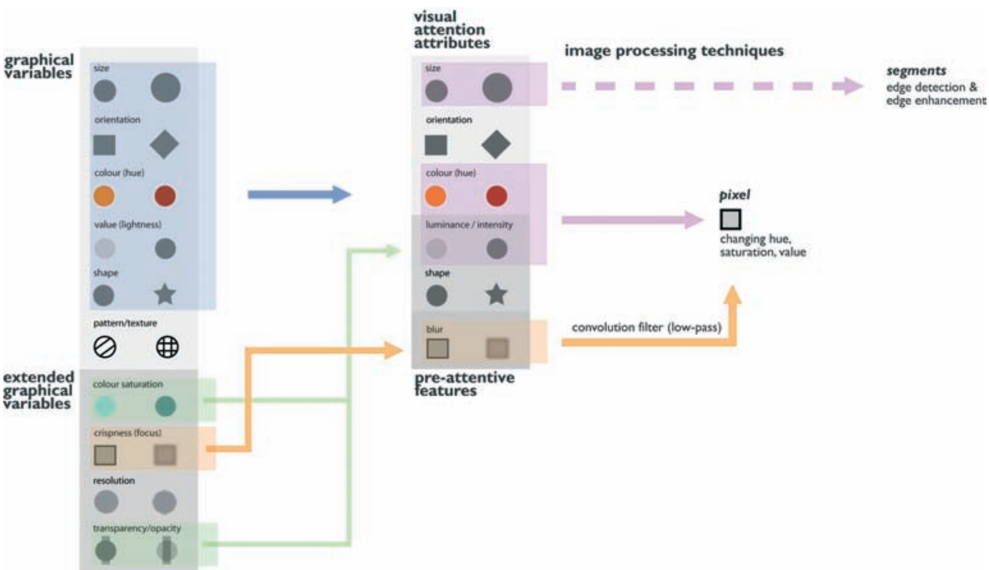

Fig. 2: Graphical variables for salient visualization in pixel-based remote sensing imagery.

hue could be used for visualising ordered data, if colours are used that form a sequence on the colour circle. He further proposes the use of colour saturation, transparency, and crispness for ordered values. Since the attribute shape is a graphical variable, we added it to the list of Wolfe & Horowitz (2004) who classified shape as a probable attribute to guide visual attention. The attribute luminance/intensity corresponds to the graphical variable value. Furthermore, we consider the extended graphical variables colour saturation and transparency to be correlated with value. The value is reflected in the luminance polarity ranked as a probable attribute. The attribute blur is not stated explicitly in the list of Wolfe & Horowitz but attested to serve for highlighting relevant objects by blurring distracting information (Kosara et al. 2002). We relate the size, orientation, colour, and shape to the mentioned graphical variables. With the exception of texture all graphical variables can be considered to guide a user's visual attention to the information of interest.

Image processing techniques

So far we have considered variables applicable to graphics. Here, we deal with pixels which implies that some of the variables are not applicable due to the intrinsic characteristics of the raster model. The variables orientation and shape cannot be used, because they are not variable in the raster model. The attribute size might be useful to highlight relevant objects in segment-based IIM systems. Wider edges make information to stand out against the thin edges of irrelevant information. This technique optimises the visual dissociation of objects from the background. The attribute blur is implemented to regulate the clarity of objects by using lowpass convolution filters. Objects that are in focus and sharp are extracted faster than smooth or blurred ones and the relevance order can be easily decoded. Note that attributes differ in their capability to encode relevance values. The effect of the variables blur, colour saturation, and transparency to visualise relevance orders are untested and may work for no more than two or three categories (MacEachren 1995). The attributes colour hue and luminance/intensity are used to regulate the saliency of objects by the changing hue, saturation and colour value of single pixels.

3 Implementation

The implementation of the proposed visualization method is demonstrated with two image information mining scenarios. The scenarios are based on an ESAR (German Aerospace Centre – X-SAR Sensor) scene from Mannheim, Germany. The pixel ground size is two meters. An unsupervised k-means clustering of the SAR scene was performed leading to four spectral clusters C1…C4, described by the assignment of image pixels to clusters $I \rightarrow C$. Based on these clusters, an interactive (supervised) training was performed to estimate the conditional probabilities $p(L|C_i)$ and $p(\neg L|C_i)$, which define the probability for the label L given cluster C_i. In our example, label L defines the label, which the user wants to detect in the image and $\neg L$ the alternative hypothesis, e. g. label L is street if the user wants to find streets and $\neg L$ means "not street". This is also a restriction, as we allow no other labels, which the user could detect. By giving positive or negative examples of the desired label L, the likelihood function $p(C_i|L)$ can be estimated, which, due to the Bayes Theorem, is proportional to the a posteriori function $p(L|C_i)$ (Datcu et al. 1998, Datcu & Seidel 2005). The example values for two simulated image information mining scenarios are shown in Tab. 1. For all clusters, example values for the a posteriori function $p(L|C_i)$ are listed. As label L we defined the information classes 'street' and 'forest', i. e. the user wants to detect streets and forests in the image database. In practical applications, the a posteriori probabilities are estimated by giving positive or negative examples of the desired label as for example seen in the values 0.9 for cluster 1 and 0.2 for cluster 4. The visualization method is implemented using the original

Tab. 1: Simulated information mining example: Listing of a posteriori probabilities for the two examples ''streets'' and ''forest''.

Class	$p(Street \mid C_i)$	$p(Street \mid C_i)$	$p(Forest \mid C_i)$	$p(-Forest \mid C_i)$
Cluster 1	0.9	0.1	0.2	0.8
Cluster 2	0.6	0.4	0.4	0.6
Cluster 3	0.4	0.6	0.9	0.1
Cluster 4	0.2	0.8	0.6	0.4

image I, the clusters C, and the a posteriori probabilities $p(L \mid C_i)$. We investigate the attention guiding attributes colour (hue, saturation, value), variable smoothing techniques (blur), and combinations of these.

Colour

The basic idea is to assign colours to probability values by applying a colour lookup table as shown in Tab. 2. The probabilities shown in Tab. 1 are classified into four probability classes (Tab. 2) and for each class a different colour is assigned based on varying the colour hue H, saturation S, and value V (colour indexing). Examples 1–5 list variations of the parameter hue, example 6 reflects the change of saturation, and example 7 corresponds to the variation of value. To compare these visualizations example 8

Tab. 2: Indexing of probabilities by colours (values according to the HSV colour space).

	$0 < p \leq 0.3$	$0.3 < p \leq 0.5$	$0.3 < p \leq 0.7$	$p > 0.7$
1	Yellow-Orange-Red			
	[17 100 100]	[12 100 100]	[6 100 100]	[3 100 100]
2	Orange-Red-Violet			
	[12 100 100]	[6 100 100]	[3 100 100]	[95 100 100]
3	Light blue-Dark blue-Violet			
	[50 100 100]	[60 100 100]	[67 100 100]	[75 100 100]
4	Yellow-Light green-Dark green			
	[17 100 100]	[24 100 100]	[31 100 100]	[39 100 100]
5	Light blue-Mid blue-Dark blue			
	[50 100 100]	[55 100 100]	[60 100 100]	[65 100 100]
6	Saturation change			
	[3 30 100]	[3 50 100]	[3 75 100]	[3 100 100]
7	Brightness change			
	[0 0 20]	[0 0 40]	[0 0 60]	[0 0 80]
8	Common visualization in IIM systems			
	[0 0 10]	[0 0 30]	[0 0 70]	[3 100 100]

shows the common way of visualization in IIM systems based on the transition from dark grey over bright grey to red.

Smoothing

In general, image smoothing is the convolution of a filter matrix F of size k with the original image I and usually involves a loss of information. Parameter k defines the magnitude of smoothing as a linear function depending on the a posteriori probabilities $k = a + b * p$, i. e. the original image I will be smoothed pixel-by-pixel with a varying mean filter depending on the a posteriori probability p. The linear equation implies that in pixels with low probability p the original image I will be more strongly smoothed. As the user is limited in the cognition of fine differences in the filter size, we applied an indexing of filter sizes similar to colour coding (Tab. 3), which corresponds to linear parameters $a = 1.04\text{e}02$ and $b = -1.22\text{e}02$ from the above-mentioned equation.

Tab. 3: Indexing of filter sizes k.

	$0 < p \leq 0.3$	$0.3 < p \leq 0.5$	$0.5 < p \leq 0.7$	$p > 0.7$
k	90	50	30	3

Combinations

The combination of colour indexing and variable smoothing combines the advantages of both visualization methods. The visualization of probabilities with colour is superimposed the smoothed original image. We generated the overlays of eight colourisations on the smoothed original image with transparencies of $t = 0.33$ and $t = 0.66$. The general case of a visualization V, which includes the transformation of the original image I by a function g (e. g. smoothing) and the visualization of probabilities by a function f, could be stated as follows:

$$V = [1 - t(p)] \cdot g(I, p) + t(p) \cdot f(C, p)$$

Additionally, this equation includes a functional relationship between the probability p and the transparency t, i. e. the transparency changes depending on the probabilities. Applying such a function would show more details of the less smoothed original image in pixels with higher probabilities and the colour coding in pixels with lower probabilities.

4 Evaluation

To approve the need for a salient and relevance-ranked visualization as a bottom-up component we evaluate the adapted visualizations with a computational visual attention model that is oriented towards neural mechanisms of human visual attention.

4.1 *The attention model*

The computational model has been successfully validated by experimental evidence in visual search tasks (Treisman & Gelade 1980) and proved to be appropriate to prognosticate human eye-movement data in map-design evaluation (Fabrikant et al. 2006). It is solely bottom-up guided and based on a multi-scale extraction of three pre-attentive features (colour hue, colour value, orientation contrast), i. e. the predicted gaze paths are directed to these features automatically. The circles illustrate eye fixations and arrows indicate the direction of gaze paths. The basic principle is the biological focussing character of visual neurons. In the centre of a visual scene neurons are highly sensitive, while they show a weak response in the concentric surrounded area. This mechanism is reflected in the computed difference between fine and coarse scales. Finally, the focus of attention highlights salient regions of a visualization in the attention map. For a detailed description see e. g. Itti & Koch (2001).

4.2 *Evaluation*

Fig. 3 to 5 depict the evaluation model outcomes that show the predicted locations that will attract gazes in our proposed visualizations. The yellow circles represent the locations of eye fixations (focus of attention) and

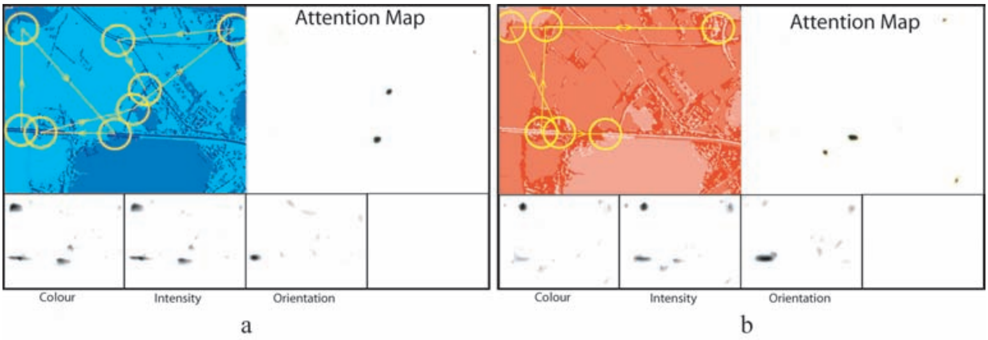

Fig. 3: (a) Image that was configured with the variable colour hue, (b) saturation.

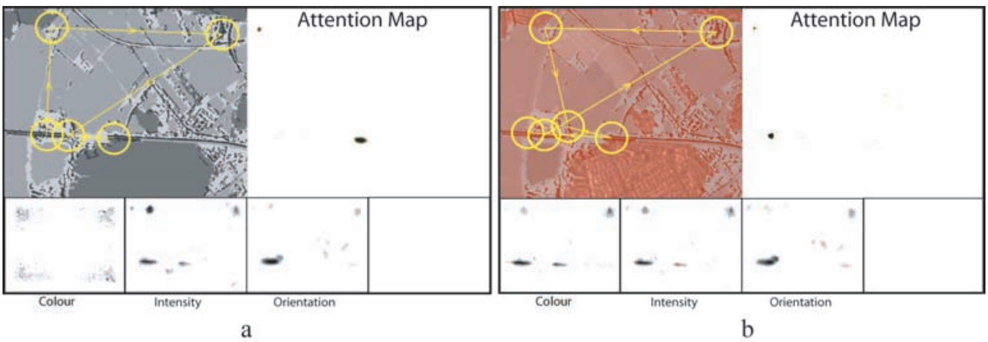

Fig. 4: (a) Image that was configured with the variable colour value, (b) colour value and blur.

the yellow arrows show the sequence and direction of eye scan paths. The light areas in the three conspicuity maps on the bottom indicate salient image locations related to colour (hue), intensity (value), and orientation contrasts. The most salient image locations of the image are represented by the areas in the attention map. Fig. 3a illustrates the configuration with the variable colour hue. The most relevant information (streets) appears in dark blue and was correctly located by the model except for the second fixation in the upper left corner of the image where high colour and intensity values deviated the gaze from the target. The street that horizontally crosses the image is located by the system within the first four fixations due to high salient image locations of colour, intensity, and orientation contrast.

Fig. 3b illustrates salient regions in the satellite image that are encoded with the variable saturation. Here, the information of interest (forest) appears in dark red and is fixated with the second and fourth eye fixation in the upper left corner (high colour and intensity contrast) and the third fixation in the lower left corner (high intensity and orientation contrast). Fig. 4a depicts the locations detected in the image where the relevant information is visualised with the variable colour value. The first fixation goes to the relevant information ('streets') because of high intensity and orientation contrast. The second focus of interest is deviated to the upper left and upper right corner attracted by high intensity contrasts. The scan path finally returns next to the starting point.

The variable colour saturation combined with blur was tested in Fig. 4b. Due to high salient image locations of colour, intensity and orientation the location of interest

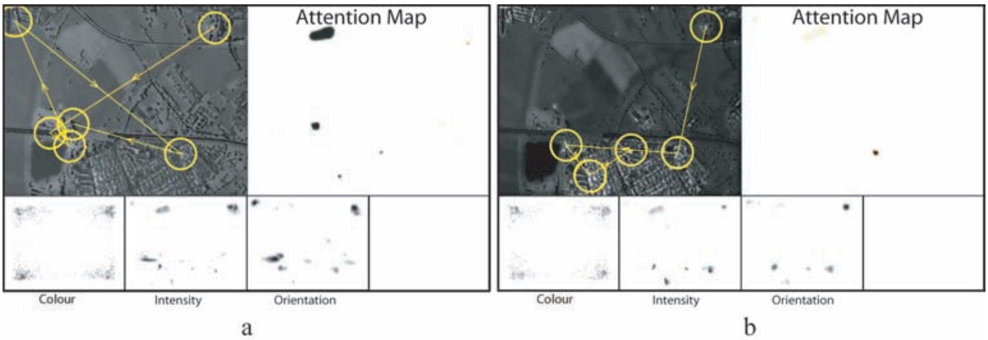

Fig. 5: (a) Image that was configured with the variables transparency and blur, (b) blur.

(streets) is rapidly detected. Salient regions in the upper left and right corner then deviate the gaze from the target. Finally, the last three fixations scan the street in short sequences. Fig. 5 depict the fixations and scan paths to the relevant information (streets) highlighted by the combined variables transparency and blur (Fig. 5a) and blur (Fig. 5b). Only one location was detected correctly in Fig. 5a. Gazes in Fig. 5b completely fail to detect streets in the image.

5 Conclusion

The evaluation allows drawing several conclusions. Following the proposed design principles have led to a partially better visual processing of relevant information. The visualizations with the variables colour hue, colour saturation, colour value, and the combination of colour saturation and blur are appropriate to detect structures depending on the adjacent cluster visualization. In Fig. 3a, 3b, 4a the relevant information was detected due to high differences in contrast of colour, intensity and orientation to neighbouring clusters in the image. For example dark red forests are detected because of the co-location of bright red streets. Accordingly, changing hue, saturation, and colour values of pixels is a useful technique to support the visual detection of salient information. The variable blur (Fig. 5a, b) is not favourable for a fast detection of information. Both visualizations contain too many distractive salient locations with high intensity and orientation contrasts.

As shown in Fig. 3 and 4 the pixel-based visualization of relevant information is suitable to a limited extent. While areas can easily be located, linear structures are often interrupted by distractive information and hardly to be perceived as a whole structure. Thus, in pixel-based IIM systems AGV has limited capabilities for highlighting relevant linear information. However, it is an appropriate technique to highlight areal structures and to depict a set of relevance ranks due to the use of ordered variables.

6 Outlook

Due to several limitations of pixel-based remote sensing IIM systems that compromise a system's practical acceptability we suggest further research in the following aspects:

(1) The proposed visualizations are in principal universal and independent of the sensor type, the viewing geometry, the spectral and spatial resolution. Still, results may differ, as for example images from active sensors like SAR are noisy due to the speckle effect. Thus, isolated, very bright pixels caused by the speckle effect could act as distractors. Speckle denoising may reduce the distractive influence of these pixels. Besides, as we suppose correct a posteriori probabilities and perfect clustering (i. e. all spectral clusters are directly related to information classes) we have to focus on the visualization

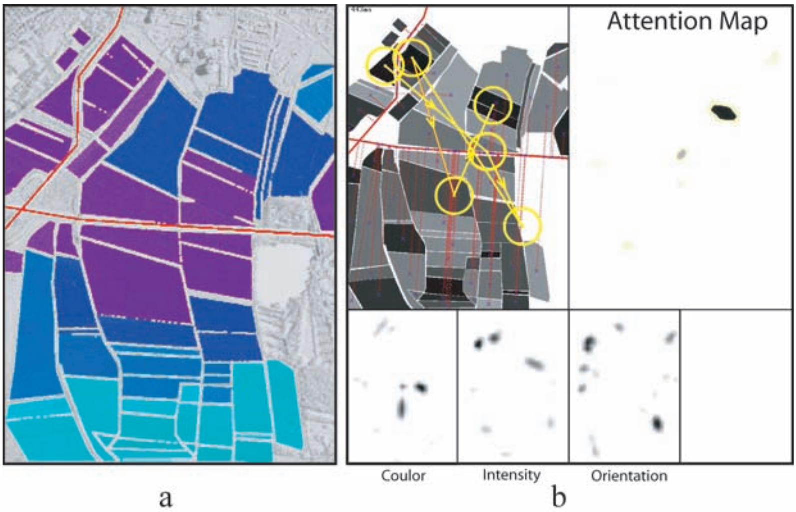

Fig. 6: (a) Possible AGV in a segment-based system, (b) AGV with graphics in a segment-based system.

of inaccurate probabilities and false clustering. Visualizations should avoid the suppressing of information in regions with low probabilities, since this information could be needed for the correct estimation of the a posteriori probabilities. Therefore, methods like masking or strong smoothing should not be applied.

(2) We did not consider the application of vector graphics. In Fig. 6 we presumed that a user searches for specific fields that are located at intervals of x meters to a certain type of street. The model indicates that there is evidence that AGV in segment-based systems is very effective. Since segments provide homogeneity, segment-based images have less distractive stimuli and relevance values can be easier decoded. Although the computational classification of relevance values and the extraction of relevant fields is successful the visualization lacks of missing context information. Colour value is not very appropriate to visualise the result, because it conceals relevant context information that users need for visual spatial navigation. The combination of the variable blur and different sizes of segment contours may be more appropriate. To outline, the variety of attention-guiding attributes can be more versatilely and effectively implemented to segments than to single pixels.

(3) It is quite problematic to categorise features only in relation to their salient pop-out effect and their efficiency in search tasks. Wolfe & Horowitz (2004) point out that their listed attributes 'might' guide the deployment of attention. Some searches for targets can be efficient even though no feature represents the focal information (Theeuwes & Kooi 1994) and others noted to be processed attentively are not fully appropriate to efficient search (Wolfe & DiMase 2003).

(4) The presented findings are exclusively related to the visualization of the location of information. As described, visual attention is also guided by top-down factors. Additional studies analysing the human gaze path of decoding semantic information from satellite images will generate findings that optimise information processing via the ventral what pathway. Due to the focus on static attributes we recommend further research to test the capability of dynamic attributes for the visual processing of remotely sensed images. There is clear evidence that dynamic attributes are highly appropriate to attract attention particularly in corners of a display (Bartram et al. 2003, Ware 2004).

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