Hindawi Publishing Corporation
EURASIP Journal on Image and Video Processing
Volume 2007, Article ID 76204, 14 pages
doi:10.1155/2007/76204

Research Article

Transforming 3D Coloured Pixels into Musical Instrument Notes for Vision Substitution Applications

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Received 15 January 2007; Accepted 23 May 2007

Recommended by Dimitrios Tzovaras

The goal of the See ColOr project is to achieve a noninvasive mobility aid for blind users that will use the auditory pathway to represent in real-time frontal image scenes. We present and discuss here two image processing methods that were experimented in this work: image simplification by means of segmentation, and guiding the focus of attention through the computation of visual saliency. A mean shift segmentation technique gave the best results, but for real-time constraints we simply implemented an image quantification method based on the HSL colour system. More particularly, we have developed two prototypes which transform HSL coloured pixels into spatialised classical instrument sounds lasting for 300 ms. Hue is sonified by the timbre of a musical instrument, saturation is one of four possible notes, and luminosity is represented by bass when luminosity is rather dark and singing voice when it is relatively bright. The first prototype is devoted to static images on the computer screen, while the second has been built up on a stereoscopic camera which estimates depth by triangulation. In the audio encoding, distance to objects was quantified into four duration levels. Six participants with their eyes covered by a dark tissue were trained to associate colours with musical instruments and then asked to determine on several pictures, objects with specific shapes and colours. In order to simplify the protocol of experiments, we used a tactile tablet, which took the place of the camera. Overall, colour was helpful for the interpretation of image scenes. Moreover, preliminary results with the second prototype consisting in the recognition of coloured balloons were very encouraging. Image processing techniques such as saliency could accelerate in the future the interpretation of sonified image scenes.

1. INTRODUCTION

Echolocation is a mode of perception used spontaneously by many blind people. It consists in perceiving the environment by generating sounds and then listening to the corresponding echoes. Reverberations of various types of sound, such as slapping of the fingers, murmured words, whistles, noise of the steps, or sounds from a cane are commonly used. In this work we present *See ColOr* (*Seeing Colours* with an *Orchestra*), which is a multidisciplinary project at the cross-road of computer vision, audio processing and pattern recognition. The long-term goal is to achieve a noninvasive mobility aid for blind users that will use the auditory pathway to represent in real-time frontal image scenes. Ideally, our targeted system will allow visually impaired or blind subjects having already seen to build coherent mental images of their environment. Typical coloured objects (signposts, mailboxes, bus stops, cars, buildings, sky, trees, etc.) will be represented by sound sources in a three-dimensional sound space that will reflect the spatial position of the objects. Targeted applications are the search for objects that are of particular use for blind users, the manipulation of objects, and the navigation in an unknown environment.

Spatialisation is the principle which consists of virtually creating a three-dimensional auditive environment, where sound sources can be positioned all around the listener. These environments can be simulated by means of loudspeakers or headphones. Among the precursors in the field, Ruff and Perret led a series of experiments on the space perception of auditive patterns [1]. Patterns were transmitted through a 10×10 matrix of loudspeakers separated by 10 cm and located at a distance of 30 cm from the listener. Patterns were represented on the auditory display by sinusoidal waves on the corresponding loudspeakers. The experiments showed that 42% of the participants identified 6 simple geometrical patterns correctly (segment of lines, squares, etc.). However, orientation was much more difficult to determine precisely. Other experiments carried out later by Lakatos taught that subjects recognised with 60–90% accuracy ten alphanumeric characters [2].

Hollander carried out a series of comparative experiments between several spatialisation techniques [3]. He achieved a study, similar to that of Perret and Ruff, where each loudspeaker was virtually synthesised by a pair of *head related transfer functions* (HRTFs). In practice, the simulation of the spatialised environment was obtained by reproducing the perceptive process of sound source localisation. Specifically, to give the impression that a sound source was positioned at a given place, it was filtered through the pair of HRTFs corresponding to the position of the source in space, before being sent to the listener. For all the experiment participants, customised HRTF filters were determined by special measures. The author concluded that for an auditory display composed of 4×4 virtual loudspeakers, the participants found much more difficulty in the correct identification of simple patterns (20–43%, versus 60–90%). However, the author noticed that the percentage of correct answers increased, as the number of virtual loudspeakers increased.

1.1. Novel aspects of the See ColOr approach

Our See ColOr prototype for visual substitution presents a novelty compared to systems presented in the literature (cf. Section 2). More particularly, we propose the encoding of colours by musical instrument sounds, in order to emphasise coloured objects and textures that will contribute to build consistent mental images of the environment. Note also that at the perceptual level, colour is helpful to group the pixels of a monocoloured object into a coherent entity. Think for instance when one looks on the ground and it "sounds" green, it will be very likely to be grass. The key idea behind See ColOr is to represent a pixel of an image as a sound source located at a particular azimuth and elevation angle. Depth is also an important parameter that we estimate by triangulation using stereo-vision. Each emitted sound is assigned to a musical instrument, depending on the colour of the pixel. We advocate the view that under the same illumination an object must be rendered by the same combination of sounds, whatever its position in the sonified window. This is why location is perceived by sound spatialisation and the "identity" of a particular object resides in its particular sound timbre.

In this work, the purpose is to investigate whether individuals can learn associations between colours and musical instrument sounds and also to find out whether colour is beneficial to experiment participants. To the best of our knowledge this is the first study in the context of visual substitution for real-time navigation in which colour is supplied to the user as musical instrument sounds. We created two different prototypes; the first is based on the sonification of a subwindow of the image scene represented on the screen of a laptop, while the second is related to the sonification of a subwindow of the image captured by a stereoscopic camera providing depth. In the following sections, we present several techniques for image simplification, audio encoding without spatialisation, 3D spatialisation, and several experiments related to colour followed by the conclusion.

2. REAL TIME NAVIGATION PROTOTYPES FOR THE BLIND

Several systems have been proposed for visual substitution by the auditory pathway in the context of real-time navigation [4–8]. Systems developed for the analysis of static images during long intervals of time are not taken into account here; for a review see [9]. The "K Sonar-Cane" combines a cane and a torch with ultrasounds [4]. With such a device, it is possible to perceive the environment by listening to a sound coding the distance and to some extent the texture of the objects which return an echo. The sound image is always centered on the axis pointed by the sonar. Scanning with that cane only produces a one-dimensional response (as if using a regular cane with enhanced and variable range) that does not take colour into account.

TheVoice is a system where an image is represented by 64 columns of 64 pixels [5]. Every image is processed from left to right and each column is listened for about 15 ms. Specifically, every pixel in a column is represented by a sinusoidal wave with a distinct frequency. High frequencies are at the top of the column and low frequencies are at the bottom. Overall, a column is represented by a superposition of sinusoidal waves with their respective amplitudes depending on the luminance of the pixels. This head-centric coding does not keep a constant pitch for a given object when one nods the head because of elevation change. In addition, interpreting the resulting signal is not obvious and requires extensive training.

Capelle et al. proposed the implementation of a crude model of the primary visual system [6]. The implemented device provides two resolution levels corresponding to an artificial central retina and an artificial peripheral retina, as in the real visual system. The auditory representation of an image is similar to that used in *TheVoice* with distinct sinusoidal waves for each pixel in a column. Experiments carried out with 24 blindfolded sighted subjects revealed that after a period of time not exceeding one hour, subjects identified simple patterns such as horizontal lines, squares, and letters.

A more musical model was introduced by Cronly-Dillon et al. [7]. First, the complexity of an image is reduced by applying several algorithms (segmentation, edge detection, etc.). After processing, the image contains only black pixels. Pixels in a column define a chord, while horizontal lines are played sequentially, as a melody. When a processed image presents too complex objects, the system can apply segmentation algorithms to these complex objects and to obtain basic patterns such as squares, circles, and polygons. Experiments carried out with normal and (elderly) blind persons showed that in many cases a satisfactory mental image was obtained. Nevertheless, this sonification model requires a very strong concentration from the subjects and thus is a source of mental fatigue.

Gonzalez-Mora et al. have been working on a prototype for the blind in the Virtual Acoustic Space Project [8]. They have developed a device which captures the form and the volume of the space in front of the blind person's head and sends this information, in the form of a sound map through headphones in real-time. Their original contribution was to apply the spatialisation of sound in the three-dimensional space with the use of HRTFs. As a result, the sound is perceived as coming from somewhere in front of the user. The first device they achieved was capable of producing a virtual acoustic space of $17 \times 9 \times 8$ gray-level pixels covering a distance of up to 4.5 meters.

3. IMAGE SIMPLIFICATION AND SALIENCY

Since the amount of information collected by the camera on the facing scene is very large, sonifying a scene as it stands would create a cacophony. In this case the blind user, overwhelmed by all the sounds, would not understand the environment and would not be guided efficiently. Thus, the acquired data needs to be filtered and its amount reduced. To achieve this, we present and discuss here two methods that were experimented in this work: image simplification by means of segmentation, and guiding the focus of attention (FOA) through the computation of visual saliency.

3.1. Image simplification

To guide the sonification and reduce the amount of information given by the stereo camera, it was felt that a cartoon-like picture would be easier to sonify and understand. To this purpose we experimented and compared three different segmentation methods on the acquired images: a *split-and-merge* method based on *quadtrees*, and two clustering methods, *k-means*, and the kernel-based *mean shift*. These methods have been chosen because of their algorithmic simplicity or reported accuracy. Furthermore, they all directly perform in a colour space, which is a relevant point in a project where we want to sonify colours.

3.1.1. Methods

Image segmentation is a very wide and well documented research area. To decide which methods could be of interest in our case, we have chosen them according to the following constraints:

(1) speed: the segmentation has to run in real-time;
(2) automation: the number of parameters to set has to be negligible, if not zero;
(3) coherence: one region must be part of one and only one object; further an object should not be divided into too many different regions.

Split-and-merge methods [10] are simple to implement, do not have many parameters, and are computationally efficient. The method we have decided to use here is simply based on the division of the picture in *quadtrees*.

K-means [11, 12] is a classical classification technique. It groups the data based on features into K number of groups ($K > 0$). Each group, or cluster, is defined by its gravity center, called centroid. The gathering is done by minimizing the distance between data and the corresponding cluster centroid.

Mean shift [13, 14] is a procedure that detects modes in any statistical distribution. Based on the *CIE* $L^*u^*v^*$ colour space and the $\{x, y\}$ coordinates of the pixels, the resulting segmentation is visually consistent. For instance, the method presented by DeCarlo and Santella [15], based on a hierarchical mean shift segmentation, generally gives coherent visual results. More particularly, regions that really have different colours usually stay dissociated.

3.1.2. Results and discussion

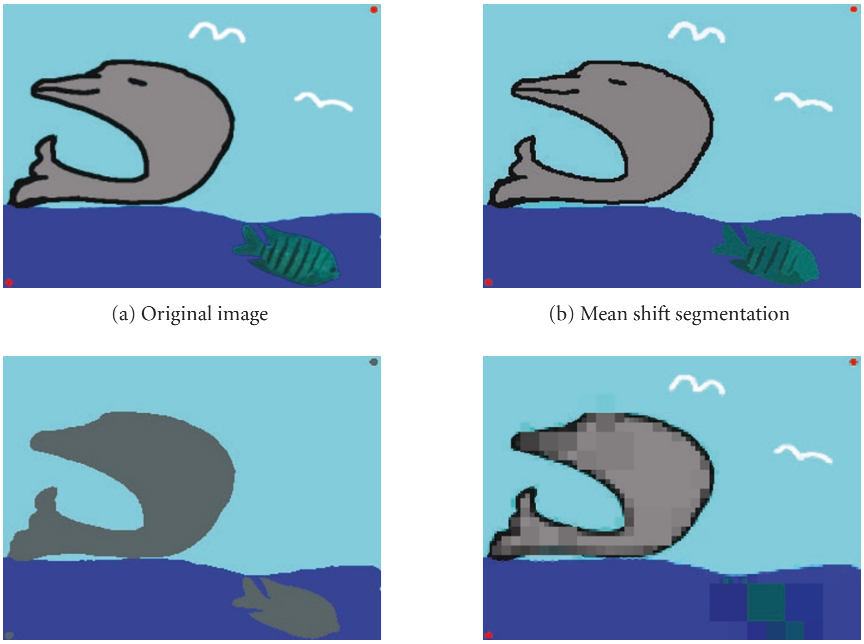
We have applied these methods on the set of images used for the experiment described in Section 6.1. Figures 1, 2, and 3 show the results of the different methods on some of these 320×240 pictures.

Results were analysed according to three different criteria: the computing time, the resulting number of regions, and a consistency measure defined as the mean size of regions. These results are summarised in Table 1.

The quadtree method is fast and only depends on a homogeneity criteria, for example, a threshold on the variance of colours in the studied area, but it creates rectangular regions. This is inadequate in our context since object edges are not respected. The blind user would be confused by such *Picasso's* world, if everything around him would sound like having straight and rectangular edges.

One of the problems with the k-means method is the number of regions it provides. The number of classes is exactly k, but this does not mean that only k regions are segmented. On the contrary, many small regions are spread all over the image. Another flaw is the dependence on the first positions of centroids; if they are first placed close to a local minima, the convergence time will be small. On the contrary, when their positions are far from minima, the convergence time can reach a few minutes. Last but not least, the final clustering depends too much both on the original position of centroids, as it can be seen on Figure 4, and on the chosen distance function, as Figure 5 shows it.

As for mean shift, the results seem visually interesting: the image is clearly simplified, while very few information on the objects is lost. We however noticed two problems. First, the choice of parameters is not straightforward, because in order to get the best results one has to give one parameter for each dimension of the feature space. This problem can be solved at the cost of losing precision, by setting a common parameter for all dimensions. The major problem lies with the computing time. Even if mean shift is not always the slowest of all three segmentation algorithms that were compared, it depends too much on the parameters chosen, the higher the parameters value, the longer the computing time, and never takes less than 1 second to compute. Indeed, in our case, we have to perform all image processing steps in less than a third of a second, so that our system can respond at a 3 Hz frequency. Results obtained in terms of speed and added complexity with respect to quality were not concluding enough to pursue the idea of simplifying images. As a consequence, the solution that finally consists in performing a simple vector quantization in colour space to decrease the number of colours to be sonified is seriously considered (cf. Section 4).



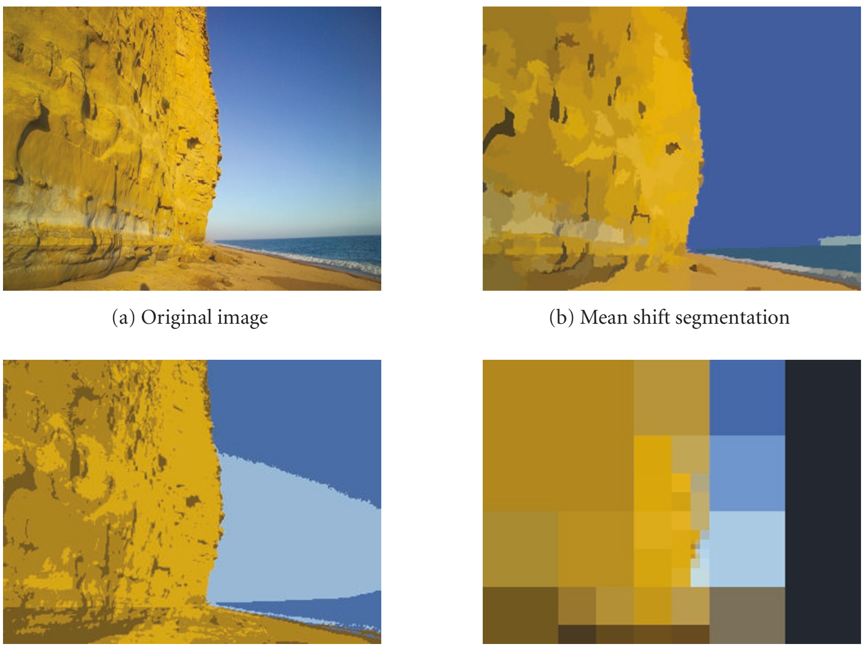
(a) Original image

(b) Mean shift segmentation

(c) K-means segmentation

(d) Quadtree segmentation

FIGURE 1: Examples of the results of the three segmentation methods on a children computer drawing.



(a) Original image

(b) Mean shift segmentation

(c) K-means segmentation

(d) Quadtree segmentation

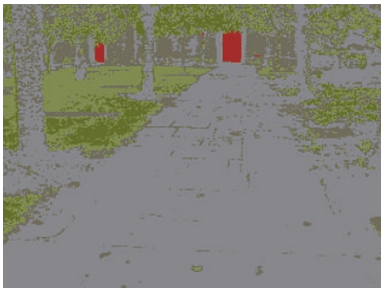
FIGURE 2: Examples of the results of the three segmentation methods on a real photography.

3.2. *Focus of attention*

As explained before, the system does not sonify the whole scene to avoid cacophony, which leads to misunderstanding. Since only a small window will be actually sonified, the risk of missing important parts of the scene is not negligible. For this reason an alarm system is being developed. It is based on the mechanism of visual saliency, that will be summarised in the next paragraphs. This mechanism allows detection of parts of the scene that would usually attract the

(a) Original image

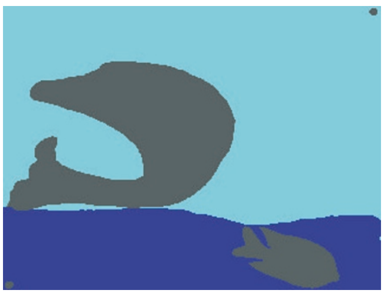
(b) Mean shift segmentation



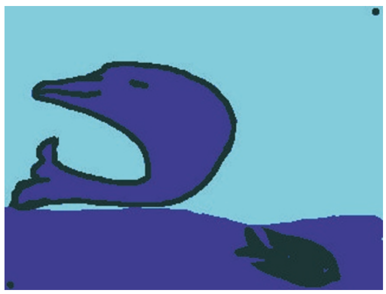
(c) K-means segmentation

(d) Quadtree segmentation

Figure 3: Examples of the results of the three segmentation methods on a churchyard photography.



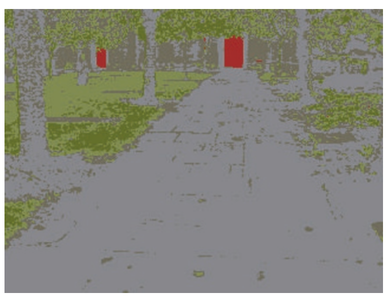
(a)



(b)

Figure 4: Different centroid positions lead to different K-means clusterings.

(a) Euclidean distance



(b) Cosine distance

Figure 5: Clusterings obtained by changing the distance function.

Table 1: Analysis of segmentation results on a set of 320×240 pictures.

	Number of regions	Regions mean size (in pixels)	Computing time (s)
Mean shift	237	324.7	4.5
K-means	2561	30.0	3.8
Quadtree	783	98.1	2.3

visual attention of sighted people. Once the program has detected such saliencies, a new sound will indicate to the blind user that another part of the scene is noteworthy.

3.2.1. Visual saliency

Saliency is a visual mechanism linked to the emergence of a figure over a background [16]. During the preattentive phase of the visual perception, our attention firstly stops on elements that arise from our visual environment, and finally focus the cognitive processes only on these elements. Different factors enter into account during this process, both physical and cognitive. Physical factors are mainly based on contrasts (lightness, colours), singularity in a set of objects or in an object itself [17], or cohesion and structuration of the scene. We are only interested in these physical factors: blind users will use their own cognitive abilities to understand the surroundings, given their personal impressions, particular knowledge of this environment (e.g., is the user inside or outside?), and the sonified colours.

Amongst the existing frameworks of visual attention and saliency, four different methods have been considered. They can be grouped in two categories. In the first one are approaches based on conspicuity maps [18, 19] and entropy [20] which provide accurate salient regions at the cost of high complexity. In the second category are methods based on differences of Gaussians (DoG) [21] and the speeded up robust features (SURF) [22]. They provide less accurate results but are of lower algorithmic complexity. The constraints on the viability of the See ColOr system (at least 3 Hz frequency answer's rate), led to the choice of the SURF method as a starting point. Moreover, the accuracy of the detected point is not a strong constraint: once the blind user has pointed towards this specific location with the stereoscopic camera, his own cognitive system will take over.

3.2.2. SURF's interest points

In this approach, interest points are determined as the maxima of the Hessian determinant distribution computed on the grey-level picture. For each point $\mathbf{x} = (x, y)$ of the picture, its Hessian determinant at scale σ is approximated as follows:

$$\det \left| \mathcal{H}_{\text{approx}}(\mathbf{x}, \sigma) \right| = D_{xx,\sigma} D_{yy,\sigma} - (c_\sigma \cdot D_{xy,\sigma}), \quad (1)$$

where $D_{xx,\sigma}$, $D_{yy,\sigma}$, and $D_{xy,\sigma}$ are box filter approximations for Gaussian second-order derivatives at scale σ and c_σ is a correction constant, depending on the current scale and the size of box filters.

The computation of the Hessian determinant is stored on a different layer for each scale. The combination of these layers is a three-dimensional image, on which is applied a non-maxima suppression in a $3 \times 3 \times 3$ neighbourhood. The maxima are then interpolated in scale and image space, and interest points are extracted from this new three-dimensional picture.

3.2.3. SURFing colours

Most methods that detect saliency over a colour domain are time consuming, and fast methods such as SURF only work on intensity values, that is, grey-level pictures. We have thus adapted the original SURF algorithm so that it operates in colour space, keeping in mind that speed is a strong constraint. Our approach, where we combine the salient points of each intensity colour plane, is a first step to a more sophisticated colour version of SURF.

The sonification part of See ColOr is working in HSL (cf. Section 4). We therefore attempted to map the camera colour space, that is, RGB, into HSL. This was found to create many problems due to the cyclic dimension of hue, from 0° to 360°. This is why we compute the SURF's interest points in the original RGB colour space on each colour plane. We then combine these three conspicuity planes into a final one: all detected points are present in this final plane, and whenever a point is detected in more than one colour plane, its final strength increases according to the SURF strength from each colour.

To decide which salient point is the most interesting, we look for the part of the scene containing the densest group of interest points. First we search for the 2 strongest interest points $\mathbf{p} = (x_p, y_p, s_p) \in S_I$, where $\{x_p, y_p\}$ are the pixel coordinates, s_p the strength computed by the SURF method, and S_I the set of interest points detected on the image I. A group of density G_c centered on $\mathbf{c}$—one of the strongest interest points of saliency s_c—is defined as follows:

$$G_c = \{\mathbf{p} \in S_I \mid d(\mathbf{c}, \mathbf{p}) < m \cdot s_c + n \cdot s_p\}, \quad (2)$$

where m, n are positive coefficients—respectively set to 1 and 0 in our current experimentation—used to define the influence area of the salient points and $d(\mathbf{c}, \mathbf{p})$ the distance of point $\mathbf{p}$ to the group's center $\mathbf{c}$. In our case, we have chosen the squared Euclidean distance. Figure 6 shows how, given a set of detected saliencies, we group them.

Here, we obtain two groups of points that can be indicated to the user. The chosen group is the densest one, according to the density measure A_{G_c}/W_{G_c}, where $A_{G_c} = \bigcup_{\mathbf{p} \in G_c} C_{\mathbf{p}}$—$C_{\mathbf{p}}$ being the circle area centered in $\mathbf{p}$, of radius s_p—and $W_{G_c} = \sum_{\mathbf{p} \in G_c} s_p$ are, respectively, the surface and the weight of the density group G_c. Finally, the center of gravity of this density group is proposed to the blind user as an interesting object in the scene.

We give here a description of the scenario which tells the system where to look when a salient point is found. First, the saliencies are computed. The strongest relevant area is sonified using a specific sound, and spatialised to indicate its exact position to the user, while the other ones are kept in the

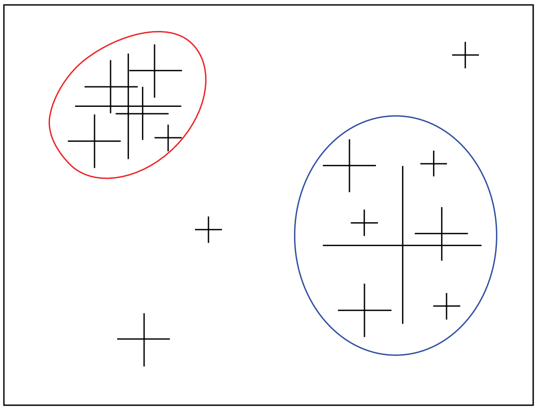


FIGURE 6: Detected dense groups of salience. A cross indicates a point of interest, and its size depends on the point's strength given by the SURF method.

system memory. The number of memorised areas is to be defined later, when further experiments with blind users will be achieved. Whenever the user's point of view changes, the scenario restarts, combining the new list of detected saliencies with the previous ones, keeping only the strongest salient areas. In addition, the spatialisation of previous saliencies has to take into account the user's movement to focus the attention on an updated geographic area.

Spatialised alarm sounds would be different than musical instrument sounds that are currently used for colour encoding (cf. Section 4). For instance we could imagine sounds of percussions or sounds used for earcons. Furthermore, the saliency submodule would be activated by the user on demand with the use of a special device button.

3.2.4. *Results and discussion*

We performed this method on pictures taken by a stereoscopic colour camera. Figures 7(a) to 7(f) and 7(g) to 7(l) show the results, compared to the original SURF computation.

Crosses are centered where a point of interest is detected, and their size depends on the strength of the point of interest. On Figures 7(c) and 7(i), blue crosses are the remaining points of interest, and the white cross is the point that will be sent to the See ColOr sonification system, as an alarm.

The next step will be the use of the disparity information given by the stereo camera. This additional information will be useful for the computation of saliency. For example, this could help in the choice of the point of interest's area of influence, or to dissociate salient points close in the image plane but distant depth. Moreover, we can then give more importance to close objects and to objects getting closer, and ignore leaving or distant ones.

4. FLAT AUDIO ENCODING

This section illustrates audio encoding without 3D sound spatialisation. Colour systems are defined by three distinct variables. For instance, the RGB cube is an additive colour model defined by mixing red, green, and blue channels. We used the eight colours defined on the vertex of the RGB cube (red, green, blue, yellow, cyan, purple, black, and white). In practice a pixel in the RGB cube was approximated with the colour corresponding to the nearest vertex. Our eight colours were played on two octaves: Do, Sol, Si, Re, Mi, Fa, La, Do. Note that each colour is both associated with an instrument and a unique note. An important drawback of this model was that similar colours at the human perceptual level could result considerably further on the RGB cube and thus generated perceptually distant instrument sounds. Therefore, after preliminary experiments associating colours and instrument sounds we decided to discard the RGB model.

The second colour system we studied for audio encoding was HSV. The first variable represents hue from red to purple (red, orange, yellow, green, cyan, blue, purple), the second one is saturation which represents the purity of the related colour and the third variable represents luminosity. HSV is a nonlinear deformation of the RGB cube; it is also much more intuitive and it mimics the painter way of thinking. Usually, the artist adjusts the purity of the colour, in order to create different nuances. We decided to render hue with instrument timbre, because it is well accepted in the musical community that the colour of music lives in the timbre of performing instruments. This association has been clearly done for centuries. For instance, think about the brilliant connotation of the Te Deum composed by Charpentier in the seventeenth century (the well-known Eurovision jingle, before important sport events). Moreover, as sound frequency is a good perceptual feature, we decided to use it for the saturation variable. Finally, luminosity was represented by double bass when luminosity is rather dark and a singing voice when it is relatively bright.

The HSL colour system also called HLS or HSI is very similar to HSV. In practice, HSV is represented by a cone (the radial variable is H), while HSL is a symmetric double cone. Advantages of HSL are that it is symmetrical to lightness and darkness, which is not the case with HSV. In HSL, the saturation component always goes from fully saturated colour to the equivalent gray (in HSV, with V at maximum, it goes from saturated colour to white, which may be considered counterintuitive). The luminosity in HSL always spans the entire range from black through the chosen hue to white (in HSV, the V component only goes half that way, from black to the chosen hue). The symmetry of HSL represents an advantage with respect to HSV and is clearly more intuitive.

The audio encoding of hue corresponds to a process of quantification. As shown by Table 2, the hue variable H is quantified for seven colours.

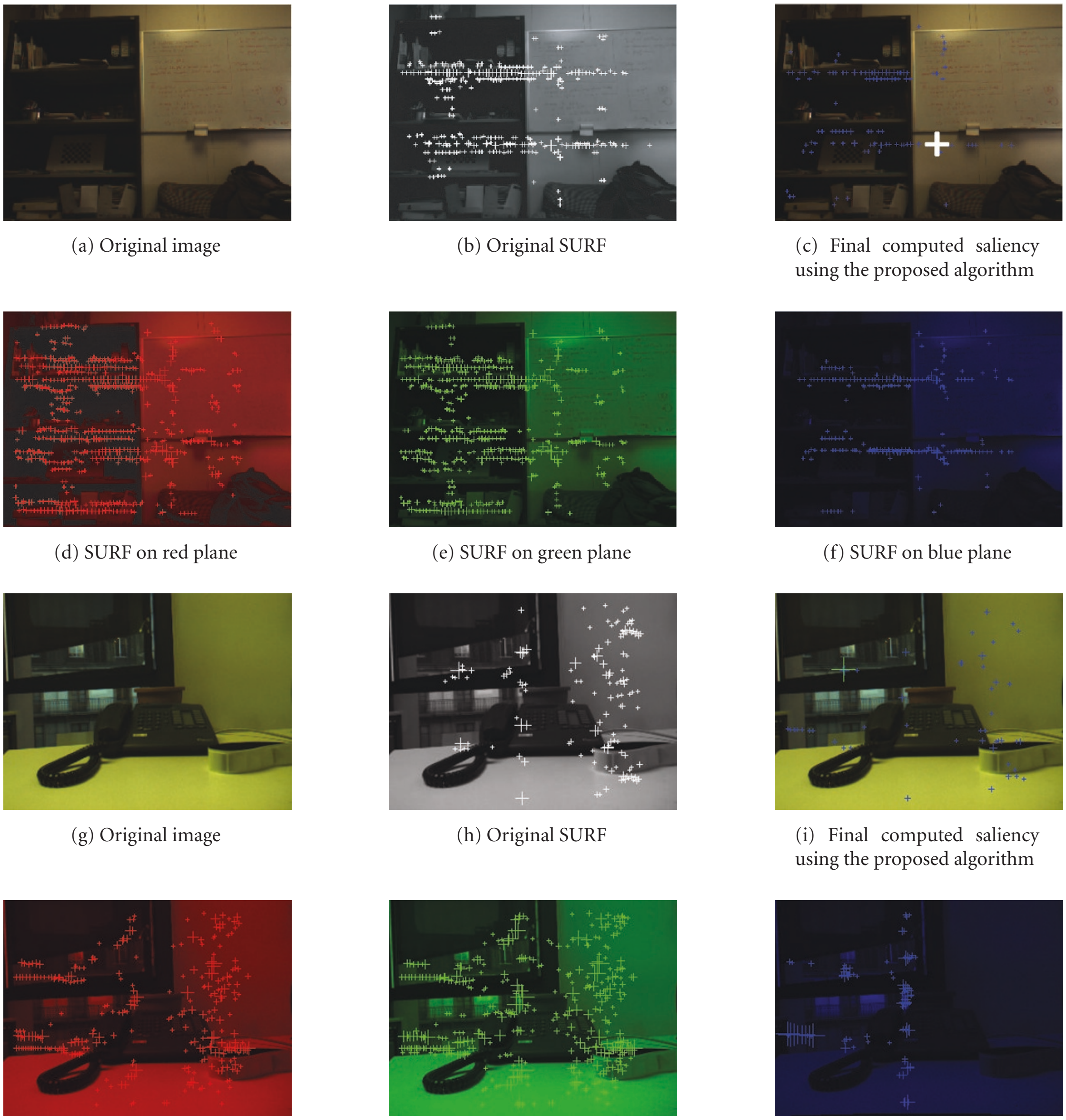
More particularly, the audio representation h_h of a hue pixel value h is

$$h_h = g \cdot h_a + (1 - g) \cdot h_b \tag{3}$$

with g representing the gain defined by

$$g = \frac{h_b - H}{h_b - h_a} \tag{4}$$

with $h_a \leq H \leq h_b$ and h_a, h_b representing two successive hue values among red, orange, yellow, green, cyan, blue, and



(a) Original image (b) Original SURF (c) Final computed saliency using the proposed algorithm

(d) SURF on red plane (e) SURF on green plane (f) SURF on blue plane

(g) Original image (h) Original SURF (i) Final computed saliency using the proposed algorithm

(j) SURF on red plane (k) SURF on green plane (l) SURF on blue plane

Figure 7: Examples of the results of the detection of coloured salient points.

purple (the successor of purple is red). In that manner the transition between two successive hues is smooth. For instance, when h is yellow, then $h = h_a$, thus $g = 1$ and $(1 - g) = 0$; as a consequence, the resulting sound mix is only pizzicato violin. When h goes toward the hue value of green, which is the successor of yellow on the hue axis, the gain value g of the term h_a decreases, whereas the gain term of h_b $(1 - g)$ increases, thus we progressively hear the flute appearing in the audio mix.

Once h_h has been determined, the second variable S of HSL corresponding to saturation is quantified into four possible notes, according to Table 3.

Luminosity denoted as L is the third variable of HSL. When luminosity is rather dark, h_h is additionally mixed with double bass using the four notes depicted in Table 4, while Table 5 illustrates the quantification of bright luminosity by a singing voice.

Note that the audio mixing of the sounds representing hue and luminosity is very similar to that described in (3). In this way, when luminosity is close to zero and thus the perceived colour is black, we hear in the final audio mix the double bass without the hue component. Similarly, when luminosity is close to one, the perceived colour is white and thus we hear the singing voice. Note that with luminosity at its half level, the final mix contains just the hue component.

Pixel depth is encoded by sound duration. For the time being, we quantify four depth levels; from one meter to four meters, every meter. Pixel depth farther than three meters

Table 2: Quantification of the hue variable by sounds of musical instruments.

Hue value (H)	Instrument
Red ($0 \le H < 1/12$)	Oboe
Orange ($1/12 \le H < 1/6$)	Viola
Yellow ($1/6 \le H < 1/3$)	Pizzicato violin
Green ($1/3 \le H < 1/2$)	Flute
Cyan ($1/2 \le H < 2/3$)	Trumpet
Blue ($2/3 \le H < 5/6$)	Piano
Purple ($5/6 \le H < 1$)	Saxophone

Table 3: Quantification of saturation by musical instrument notes.

Saturation (S)	Note
$0 \le S < 0.25$	Do
$0.25 \le S < 0.5$	Sol
$0.5 \le S < 0.75$	Sib
$0.75 \le S \le 1$	Mi

Table 4: Quantification of luminosity by double bass.

Luminosity (L)	Double bass note
$0 \le L < 0.125$	Do
$0.125 \le L < 0.25$	Sol
$0.25 \le L < 0.375$	Sib
$0.375 \le L \le 0.5$	Mi

Table 5: Quantification of luminosity by a singing voice.

Luminosity (L)	Voice note
$0.5 \le L < 0.625$	Do
$0.625 \le L < 0.75$	Sol
$0.75 \le L < 0.875$	Sib
$0.875 \le L \le 1$	Mi

is considered at infinity. The time duration of a sound of a pixel at infinity is 300 ms (the goal being real-time navigation, it would be unfeasible to use longer sounds), while sounds representing pixels of undetermined depth is 90 ms. Table 6 shows the correspondence between sound duration and the encoded depth of pixels. As a result, a window with all pixels at a close depth level will sound faster than a window having all its pixels at infinity.

In order to estimate profundity, we use a stereoscopic camera having an epipolar configuration (SRI International: http://www.videredesign.com). The key elements of the depth estimation algorithm are the enhancement of edge information by first computing a Laplacian-of-Gaussian feature on each image, then summing the absolute value of differences over a small window (area correlation). The maximum correlation is found for each pixel in the left image over a search area from 8 to 64 pixels. Finally, a confidence

Table 6: The encoding of depth (D) by sound duration.

Depth [m]	Sound duration (ms)
Undetermined	90
$0 \le D < 1$	160
$1 \le D < 2$	207
$2 \le D < 3$	254
$3 \le D < \infty$	300

measure based on edge energy, and a left/right match consistency check is calculated requiring that the same corresponding points are determined when the left and right images are swapped. Typical configurations for which depth is undetermined are homogeneous surfaces and occlusions.

5. 3D SOUND SPATIALISATION

Sounds emitted by loudspeakers at a reasonable distance from the listener can be approximated by plane waves. Our purpose is to reproduce a 3D soundfield in order to recreate as closely as possible the perception of localised sound sources. Ambisonic is a method for 3D sound production [23–26], based on the construction of the desired wave field by using several loudspeakers. Specifically, the key idea behind ambisonic is the reconstruction of plane waves with the use of a limited number of spherical harmonics.

For the sake of simplicity let us describe a two-dimensional case of a plane wave. Suppose that the plane wave is arriving at an angle ψ with respect to the x-axis and that the listening point is at a distance r with an angle ϕ with respect to the x-axis. The plane wave S_ψ is defined as

$$S_\psi = P_\psi e^{ikr\cos(\phi-\psi)}; \tag{5}$$

where P_ψ is the pressure of the plane wave and k is the wave number or $2\pi/\lambda$ (with λ the wavelength).

With the use of cylindrical Bessel functions $J_m(\cdot)$, (5) becomes [26]

$$S_\psi = P_\psi\Bigg(J_0(kr) + \sum_{m=1}^{\infty} 2i^m J_m(kr)\big(\cos(m\psi)\cos(m\phi) + \sin(m\psi)\cos(m\phi)\big)\Bigg). \tag{6}$$

In practice, the plane wave cannot be reproduced exactly, as the number of terms goes to infinity. Note that ambisonic can provide a higher level of localisation due to its ability to include more information about the soundfield than stereo or Dolby surround can include. In practice, the three-dimensional soundfield is approximated to a specific order, corresponding to the order of spherical harmonics. For instance, zeroth order corresponds to mono and first order is the prevailing form in use in the past, denoted as the B-format, which represents the pressure (omnidirectional component) and the three orthogonal gradient pressure components, corresponding to the three spatial directions.

In the See ColOr project, sound spatialisation is achieved by means of a virtual ambisonic procedure of order two [27]. Personalised HRTFs make it possible to correctly perceive directional sound sources with the use of a headphone. A loudspeaker at a particular position is a sound source, thus by means of HRTFs it is possible to simulate on a headphone the loudspeakers of an ambisonic architecture. The advantage of the virtual loudspeaker approach is that HRTFs are measured only for the positions corresponding to the loudspeakers, instead of requiring numerous measurements spanning space in azimuth and elevation.

6. PROTOTYPES AND EXPERIMENTS

Our first prototype is based on a sonified 17×9 subwindow pointed by the mouse on the screen which is sonified via a virtual ambisonic audio rendering system. In fact, the sound generated by a pixel is a monaural sound that is encoded into 9 ambisonic channels; with parameters depending on azimuth and elevation angles. Then, the encoded ambisonic signals are decoded for loudspeakers placed in a virtual cube layout. Finally, the physical sound is generated for headphones with the use of HRTF functions related to the directions of virtual loudspeakers. The HRTF functions we use, are those included in the CIPIC database [28]. The orchestra used for the sonification is that described in Section 4, without depth rendering. The maximal time latency for generating a 17×9 sonified subwindow is 80 ms with the use of Matlab on a Pentium 4 at 3.0 GHz. During the experiments individuals used the original pictures without any segmentation processing.

For the second prototype we used a stereoscopic colour camera with an algorithm for distance calculation (cf. Section 4). The resolution of images is 320×240 pixels with a maximum frame rate of 30 images per second. Depth estimation is based on epipolar geometry and the camera must be calibrated. Note that typical exposure time and gain parameters, as well as red and blue channels have very different values for indoor and outdoor environments. The major drawback of the depth determination algorithm is its unreliability when texture or edges are missing. The sonified subwindow is a row of 25 pixels located at the centre of the image. For the time being, we just take into account the left/right sound spatialisation. This prototype uses the first prototype audio encoding with the addition of depth rendering by time sound duration.

6.1. Tablet experiments

The purpose of this study was to investigate whether individuals can learn associations between colours and musical instrument sounds. Several experiments have been carried out by participants having their eyes enclosed by a dark tissue, and listening to the sounds via headphones [23]. In order to simplify the experiments, we used the T3 tactile tablet from the Royal National College for the Blind (UK) (http://www.rncb.ac.uk). Essentially, this device allows to point on a picture with the finger and to obtain the coordinates of the contact point. Moreover, we put on the T3 tablet a special paper with images including detected edges represented by palpable roughness. Figure 8 shows the T3 tablet.

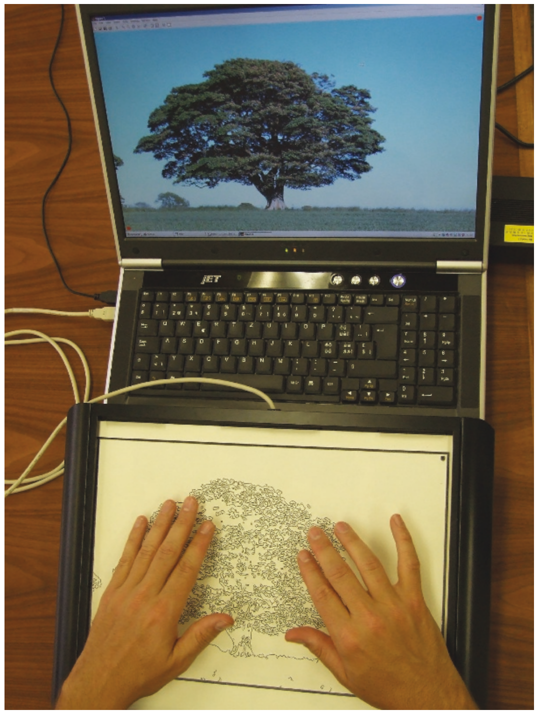


Figure 8: Experiments with the T3 tactile tablet.

Six participants were trained to associate colours with musical instruments and then asked to determine on several pictures, objects with specific shapes and colours. For each participant the training phase lasted 45 minutes. The training phase started with images of coloured rectangles of varying saturation values and constant luminosity. Then, training was pursued with coloured rectangles of constant saturation and varying luminosity. After fifteen minutes, we asked the participant to listen to distinct parts of images, such as sky, grass, ground, and so forth. After another 20 minutes, the tester eyes were enclosed by a dark tissue and the training was performed with the tactile tablet showing real pictures. In particular, participants were asked to identify colours under the touched regions; when wrong, participants were corrected.

At the end of the training phase, a small test for scoring the performance of the participants was achieved. On the 15 heard sounds, the average number of correct colours among the six participants was 8.1 (standard deviation: 3.4). It is worth noting that the best score was reached by a musician who found 13 correct answers. Afterwards, participants were asked to explore and identify the major components of the pictures shown in Figures 1(a) and 9.

Regarding the children draw picture illustrated in Figure 9, all participants interpreted the major colours as the sky, the sea, and the sun; clouds were more difficult to infer (two individuals); instead of ducks, all the subjects found an island with yellow sand or a ship.

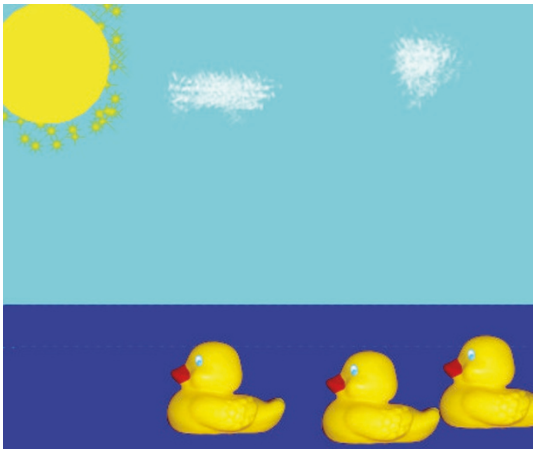


Figure 9: An elementary picture to be explored and interpreted in the experiments.

Figure 10: A real picture to be explored and interpreted in the experiments.

For the picture depicted in Figure 1(a) all participants interpreted the major colours as the sky and the sea; an individual said that the dolphin is a "jumping animal," another said that it was a fish and the others determined a boat or a "round shape;" only a person found birds and no one could identify the small fish.

On the interpretation of real images, such as the picture shown in Figure 10, four participants correctly identified the tree with the grass and the sky. A participant qualified the tree as a strange dark object and finally, the last individual inferred a nuclear explosion!

Concerning Figure 2(a), all subjects found major colours (blue and yellow); however no one made the distinction between the sky and the sea. Moreover, no one identified the yellow cliff, though a large yellow region was always described.

The last assignment was to find a red door in Figure 3(a). All participants found one of the red doors in a time range between 4 and 9 minutes.

Figure 11: A prototype showing a stereoscopic camera mounted on the head of a participant to an experiment (note that small head phones are not visible in the picture).

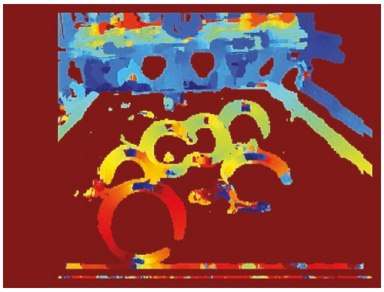
6.2. *Preliminary experiments with a stereoscopic camera*

The second prototype was tested by an individual with eyes enclosed by a dark tissue. That person is very familiar to musical instruments and in addition he has learned the colour encoding for much more time than the six participants of the previous series of experiments. The experiment consisted in recognizing coloured balloons. More particularly, our experimenter was on a chair in front of a desk and he knew that he had on his left side many balloons having seven possible colours: red, orange, green, yellow, blue, pink, and white. His task consisted in grabbing balloons and trying to recognise their colours. Figure 11 illustrates the participant to this experiment.

Figure 12 illustrates a typical distance estimation for balloons on a desk. Note that many depth points are undetermined, especially on the desk (brown colour). Moreover, close balloons are represented in red, orange, and yellow, while more distant points are green, cyan, and blue.

In this indoor experiment, the difficulty was that light reflections on the balloons created many white areas. During a training phase of 15 minutes the participant had his eyes uncovered with the stereoscopic camera mounted on his head. Then, the eyes of our experimenter were covered and he was told to grasp and explore each balloon for some time before giving an answer. On the 15 balloons (red: 3; orange: 2; green: 3; yellow: 2; blue: 2; pink: 1; white: 2), all the colours were correctly recognised. After the experiment we asked the participant which colour was the most difficult. He said that the difference between red and orange balloons was very small. In fact, for orange balloons more viola was present in the audio mixing than for red balloons. Moreover, the difference between pink and red balloons was the oboe note, which is higher for red and also the luminosity of pink corresponding to a brighter component encoded by the singing voice. The participant said that the easiest colours were those of blue balloons with very clear piano attack.

(a) Original image



(b) Depth map

Figure 12: A typical view of balloons with a corresponding depth map.

6.3. Discussion

The first experiment concerning the recognition of 15 colours corresponding to 15 sounds exhibited that correct answers were given in a little bit more than half of the times, on average. Therefore, roughly speaking our group gave correct answers for five colours out of nine. That is clearly better than black and white identification. Thus, this experiment demonstrated that learning all colours is possible, but difficult in a short training time. We have yet to precisely evaluate how long it will take to reach a perfect recognition rate. It is worth noting that learning Braille is also complicated and requires a long period of training. Accordingly, the training phase with musical instrument sounds should be repeated a reasonable number of sessions.

The second experiment with children's drawings demonstrated that the most important components of the pictures, such as the sky, the sea, and the sun were identified. Sometimes our participants were not completely sure, but with logical reasoning they inferred that if the top of the pictures is cyan and if the bottom is blue, then the bottom is the sea and the top is the sky. Moreover, if something at the top of Figure 9 is yellow and round shaped, this must be the sun. Another interesting observation is the difficulty to identify the three ducks. In fact, our common sense tells us that something yellow would be more likely to be the sand of an island or a yellow ship. Yellow ducks on the sea represent an unusual situation which is never considered by our participants.

The third experiment was performed with two real pictures. It is worth noting that Figure 10 has three major components (sky, grass, and tree), with a limited perspective view. Consequently, almost our participants gave a correct sketch of that picture. On the contrary, Figure 2(a) presents a noticeable perspective; as a result, the context of the picture was not determined by our six participants, although several individuals correctly identified the most important colours.

The fourth experiment consisted in finding one of the red doors of Figure 3(a). All the people were successful, however the elapsed time was quite long. The first reason is that with A3 paper format on the T3 tablet, it takes a long time to explore the picture with a small subwindow of size 17×9 pixels. Moreover, the image scene is complicated with a high degree of perspective. This is a typical situation where higher-level functions such as saliency (cf. Section 3) would accelerate the user search.

Five participants out of six said that colour was helpful for the interpretation of pictures. In fact, when one tries to identify a picture component, the presence of colour in the audio representation limits the number of possible interpretations. Finally, the experiments emphasised perspective as a major drawback for the understanding of two-dimensional figures.

When successful, participants formed an adequate mental map of typical static pictures in a time interval between five and ten minutes. This could appear quite long for real life situations; however, no saliency mechanism was provided and most importantly the participants to our experiments were acquainted to the colour encoding for only one training session.

7. CONCLUSION AND FUTURE WORK

We presented the current state of the See ColOr project which aims at providing a mobility aid for visually impaired individuals. Two image processing methods were experimented in this work: image simplification by means of segmentation, and guiding the focus of attention through the computation of visual saliency. Because of real-time constraints, image simplification in our two prototypes was achieved by colour quantification of the HSL colour system translated into musical instrument sounds. With only a training session, the experiments on static pictures revealed that our participants were capable to learn five out of nine principal colours, on average. We will investigate how learning improves with time. To this purpose, we plan to collaborate with psychologists, in order to define an appropriate protocol aiming at quantifying the learning rate over several training sessions. As a first element of answer to this question of learning rate, note that one of the experiment participants has used the prototype many times and has gradually learned the audio representation of colour. Without any doubt, after several training sessions this person recognises colours better than what he had learned during the first training session.

Furthermore, colour was helpful for the interpretation of image scenes, as it lessened ambiguity. These experiments also demonstrated that the exploration time of pictures is quite long, probably because the sonified subwindow is small and should not expand too much for reasons related to the limits of human audio channel capacity. Thus, the image processing techniques presented here such as the determination of salient points could reveal crucial for real-time navigation. Preliminary results with the stereoscopic camera prototype and an individual who is very familiar with the audio encoding has demonstrated excellent performance in colour recognition. It was noticed that light reflections on smooth surfaces such as balloons made recognition much more difficult, but contrary to robots which could be easily misled, our brains can reach superior performance.

In the future, we would like to replace the actual depth encoding by appropriate echoes. The main reason is that it is natural for a visually impaired person to estimate distance to obstacles by echo-locating sound reflections generated by her cane, or by slapping her fingers. In our next depth encoding, a close object will sound without echoes, while something placed far away will be perceived much more reverberated. Note also that the saliency will be used as an alarm system. While the user is focused on a particular zone of the scene, the system will tell him that another part deserves his attention. To decide on which salient point the user should point, the system will detect the area where the salient points are stronger and denser.

ACKNOWLEDGMENTS

The authors would like to gratefully acknowledge the support of the Hasler Foundation, who funded this research. Moreover, the authors would like to acknowledge the valuable insights and observations contributed by the following individuals who participated in the experiments: Guillaume Chanel, Joëlle Heldt, Julien Kronegg, Thierry Pun, Romana Rytsar, Fedor Thonnessen.

REFERENCES

[1] R. M. Ruff and E. Perret, "Auditory spatial pattern perception aided by visual choices," *Psychological Research*, vol. 38, no. 4, pp. 369–377, 1976.

[2] S. Lakatos, "Recognition of complex auditory-spatial patterns," *Perception*, vol. 22, no. 3, pp. 363–374, 1993.

[3] A. Hollander, "An exploration of virtual auditory shape perception," M.S. thesis, University of Washington, Seattle, Wash, USA, 1994.

[4] L. Kay, "A sonar aid to enhance spatial perception of the blind: engineering design and evaluation," *The Radio and Electronic Engineer*, vol. 44, no. 11, pp. 605–627, 1974.

[5] P. B. L. Meijer, "An experimental system for auditory image representations," *IEEE Transactions on Biomedical Engineering*, vol. 39, no. 2, pp. 112–121, 1992.

[6] C. Capelle, C. Trullemans, P. Arno, and C. Veraart, "A real-time experimental prototype for enhancement of vision rehabilitation using auditory substitution," *IEEE Transactions on Biomedical Engineering*, vol. 45, no. 10, pp. 1279–1293, 1998.

[7] J. Cronly-Dillon, K. Persaud, and R. P. F. Gregory, "The perception of visual images encoded in musical form: a study in cross-modality information transfer," *Proceedings of the Royal Society B*, vol. 266, no. 1436, pp. 2427–2433, 1999.

[8] J. L. Gonzalez-Mora, A. Rodriguez-Hernandez, L. F. Rodriguez-Ramos, L. Dfaz-Saco, and N. Sosa, "Development of a new space perception system for blind people, based on the creation of a virtual acoustic space," in *Proceedings of International Work-Conference on Artificial and Natural Neural Networks (IWANN '99)*, vol. 2, pp. 321–330, Alicante, Spain, June 1999.

[9] P. Roth, *Représentation multimodale d'images digitales dans des systèmes informatiques multimédias pour utilisateurs non-voyants*, Ph.D. thesis, Computer Vision and Multimedia Laboratory, University of Geneva, Geneva, Switzerland, 2002.

[10] S. L. Horowitz and T. Pavlidis, "Picture segmentation by a directed split and merge procedure," in *Computer Methods in Image Analysis*, pp. 101–111, IEEE Press, New York, NY, USA, 1977.

[11] E. Forgy, "Cluster analysis of multivariate data: efficiency versus interpretability of classifications," *Biometrics*, vol. 21, no. 3, pp. 768–769, 1965.

[12] J. McQueen, "Some methods for classification and analysis of multivariate observations," in *Proceedings of the 5th Berkeley Symposium on Mathematical Statistics and Probability*, vol. 1, pp. 281–297, Berkeley, Calif, USA, 1967.

[13] K. Fukunaga, *Introduction to Statistical Pattern Recognition*, Academic Press Professional, San Diego, Calif, USA, 2nd edition, 1990.

[14] Y. Cheng, "Mean shift, mode seeking, and clustering," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 17, no. 8, pp. 790–799, 1995.

[15] D. DeCarlo and A. Santella, "Stylization and abstraction of photographs," in *Proceedings of the 29th Annual Conference on Computer Graphics and Interactive Techniques (SIGGRAPH '02)*, pp. 769–776, San Antonio, Tex, USA, July 2002.

[16] F. Landragin, "Saillance physique et saillance cognitive," *Corela*, vol. 2, no. 2, 2004.

[17] D. D. Hoffman and M. Singh, "Salience of visual parts," *Cognition*, vol. 63, no. 1, pp. 29–78, 1997.

[18] R. Milanese, *Detecting salient regions in an image: from biological evidence to computer implementations*, Ph.D. thesis, University of Geneva, Geneva, Switzerland, 1993.

[19] L. Itti, C. Koch, and E. Niebur, "A model of saliency-based visual attention for rapid scene analysis," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 20, no. 11, pp. 1254–1259, 1998.

[20] T. Kadir and M. Brady, "Scale, saliency and image description," *International Journal of Computer Vision*, vol. 45, no. 2, pp. 83–105, 2001.

[21] D. G. Lowe, "Object recognition from local scale-invariant features," in *Proceedings of the 7th IEEE International Conference on Computer Vision (ICCV '99)*, vol. 2, pp. 1150–1157, Kerkyra, Greece, September 1999.

[22] H. Bay, T. Tuytelaars, and L. van Gool, "SURF: speeded up robust features," in *Proceedings of the 9th European Conference on Computer Vision (ECCV '06)*, pp. 404–417, Graz, Austria, May 2006.

[23] M. A. Gerzon, "Design of ambisonic decoders for multispeaker surround sound," *Journal of the Audio Engineering Society*, vol. 25, p. 1064, 1977.

[24] J. S. Bamford, "An analysis of ambisonic sound systems of first and second order," M.S. thesis, University of Waterloo, Waterloo, Ontario, Canada, 1995.

[25] D. G. Malham and A. Myatt, "3-D sound spatialization using ambisonic techniques," *Computer Music Journal*, vol. 19, no. 4, pp. 58–70, 1995.

[26] J. Daniel, *Acoustic field representation, application to the transmission and the reproduction of complex sound environments in*

a multimedia context, Ph.D. thesis, University of Paris 6, Paris, France, 2000.

[27] G. Bologna and M. Vinckenbosch, "Eye tracking in coloured image scenes represented by ambisonic fields of musical instrument sounds," in *Proceedings of the 1st International Work-Conference on the Interplay Between Natural and Artificial Computation (IWINAC '05)*, pp. 327–337, Las Palmas, Spain, June 2005.

[28] V. R. Algazi, R. O. Duda, D. P. Thompson, and C. Avendano, "The CIPIC HRTF database," in *Proceedings of IEEE Workshop on the Applications of Signal Processing to Audio and Acoustics (WASPAA '01)*, pp. 99–102, New Platz, NY, USA, October 2001.