

## VISUAL SPACE PERCEPTION MODEL IDENTIFICATION BY EVOLUTIONARY SEARCH

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### 1. Introduction

Implications of design decisions are difficult to oversee. This is particularly the case when design decisions affect perception related aspects of a design. Such properties are visual openness, visual privacy and spatial intimacy of spaces. Perceptual properties are difficult to assess systematically due to the soft nature of perception. Visual perception is a phenomenon where the geometric shape of a space is observed and interpreted by means of vision. Different shapes yield different visual perceptions. Until recently no models existed, which adequately describe this relationship and quantify the implications of spaces for visual perception. Subjectivity in assessment of spatial properties makes the perception modelling a challenging task. The search for optimal shape formations, which is an essential activity in architectural design, requires the ability to measure perception qualities of spaces. In architecture such perceptual aspects are generally relevant with respect to comfort and privacy related issues. In the domain of mechanical engineering such aspects are relevant for example in the design of a production facility, where visibility of certain areas for supervision is a design requirement.

A number of researches dealt with perceptual aspects of spaces [Do and Gross 1997, Turner et al. 2001, Franz et. al 2005]. Existing methods to assess perceptual qualities of spaces are not based on modelling visual perception. The methods used are generally based on isovist calculation or analyses of graph-theoretic design representations [Hillier et al. 1984]. Isovists, which were introduced by Benedict in 1979 [Benedict and Burnham 1981], are polygons, which enclose the volume visible from a location within a space. Isovist calculations do not consider certain characteristic properties of visual perception, so that the integrity of the results obtained by these methods as to perceptual assessment is challenged. In isovist-based methods all spatial directions are considered equally significant. This does not represent the phenomenon of the visual perception, in which the perception intensity diminishes for angles off the forward direction. That is, the visual awareness is concentrated in the central region of the field and diminishes towards peripheric regions. A second incompatibility of isovists with visual perception originates from cognitive aspects of space perception. The distances between a perception location and positions in a surrounding spatial shape vary. In space cognition this variation is apparently interpreted as a space with a certain perceptual property. The relation between retrieved distances and perceived spatial property must be considered non-linear. This is easily substantiated considering that distances which are very large, such as blackness of the night sky, can be accounted for together with the relatively proximate spatial shapes surrounding a perceiver. Isovist methods do not consider such probable non-linearity in distance interpretation in the assessment of a perceived spatial property. In the graph-theoretic representations design elements are represented as nodes and they are linked in a network structure. Graph properties, such as mean shortest path length, etc. can be

identified. Such graph analyses results are considered to be correlated with certain perceptual qualities [Turner et al. 2001]. Graphs identify visible locations only indirectly, via a network of related positions, and not directly in terms of physiological visibility. Both, Isovist and graph based approaches are not modelling the visual perception process. Due to sensitivity of these processes with respect to the constitution of the visual field, as well as the graded relevance of distance data, their ability to assess perceptual design qualities is limited.

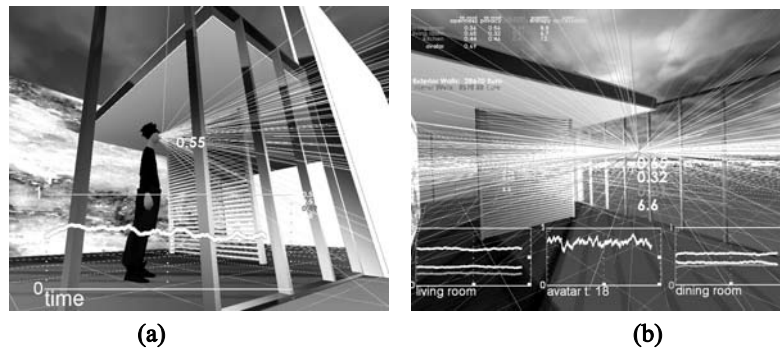
Different individuals often attribute different degrees of visual openness and privacy to the same space. This indicates that their perceptions are different. In particular we should assume they apply, consciously or unconsciously, different definitions of the relation between shape features and perceptual properties of a space. The existing methods mentioned above cannot be used to model such individual perceptual differences because they are not based on modelling visual space perception.

## 2. Modelling visual space perception

Recently, a novel probabilistic visual perception model was introduced [Bittermann and Ciftcioglu 2005]. It consists of a vision model and a cognition model as shown in figure 1. The vision model probes the space surrounding a perceiver in a probabilistic way and delivers distance data. The cognition model maps each distance datum to a perception sample. A number of such elemental perceptions are integrated in a real-time averaging process to form the perception outcome.

### 2.1 Modelling vision

Essential task of vision is continuous retrieval of information coming from positions surrounding the perception position. This process is modelled as a probabilistic sampling process, which is termed random direction distance sampling (RDDS). Figure 1 shows an RDDS implementation. In the Figure the measurement outcomes are plotted in graphical form. The model is initialized by continuous generation of sight lines in random directions. The vision model is a cyclopean model, which means the visual apparatus is represented with a single geometric point indicating the perception location.



**Figure 1. Modelling visual space perception by means of random direction distance sampling (RDDS). Field of forward vision (a); field of vision of 360o (b)**

Three uniform random numbers  $x_{source}$ ,  $y_{source}$ , and  $z_{source}$  are used as components of a 3-dimensional direction vector to model the visual field. To account for the greater perceptual awareness along the central direction of the visual field the probability for generating a sightline in a certain direction is defined via a 3-D Gaussian shaped probability density function given by (1).

$$\vec{F} = \begin{bmatrix} (x_{src} + m_x)\sqrt{\sigma_x} \\ (y_{src} + m_y)\sqrt{\sigma_y} \\ (z_{src} + m_z)\sqrt{\sigma_z} \end{bmatrix} \quad (1)$$

Here  $m_x$  and  $\sigma_x$  are the mean and the variance in the  $x$  direction and similar notations for the other directions. The visual field in this perception model is defined by the probabilistic distribution of the orientation of generated sightlines and it can be adjusted in real-time by means of modifying the parameters of the Gaussian normal distribution in the shape-filter. A number of sight lines form a field corresponding to the field of vision, so that the field has a greater density of sight lines in its center and a reduced density in its periphery. Any shape of visual field can be achieved by means of the parametric adjustment of the shape-filter. Through interaction with the spatial environment each sight line delivers an individual distance data-sample.

## 2.2 Modelling space cognition

The distance samples are continuously processed by means of a mapping function. The mapping function expresses the relation between distances and perception. Each distance sample is mapped to a particular degree of perception resulting in an elemental perception sample between zero and one. The mapping function is defined based on the definition of the spatial requirement to be measured [Bittermann and Ciftcioglu, 2005]. In this research, to assess visual openness, preliminarily a sigmoid function is used as mapping function given by (2). The variation of sigmoid is plotted in figure 2a.

$$S = \{1 + \exp[-m(x - I_c)]\}^{-1} \quad (2)$$

The variable  $x$  is the obtained distance between perception origin and point of intersection of sightline with the volume boundary involved. The parameter  $I_c$  represents the sigmoid shift, which is used to adapt the function. The parameter  $m$  represents the steepness of the sigmoid curve for  $S=0.5$ . In the visual openness measurement, if no geometric shape was intersected,  $S$  is considered to be unity assuming that the distance  $x$  extends to infinity. In visual privacy and spatial intimacy assessment, a Butterworth function that is given by (3) is used, where  $m$  is the steepness parameter and  $I_c$  is a parameter used to adapt the function.

$$S = [1 + (x/I_c)^m]^{-1} \quad (3)$$

The variation of the Butterworth function is shown in figure 2b.

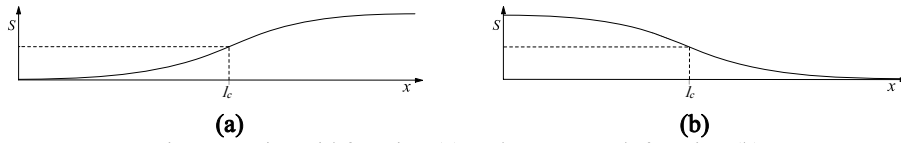


Figure 2. Sigmoid function (a) and Butterworth function (b)

In the visual privacy and spatial intimacy measurement, if no geometric shape was intersected,  $S$  is considered to be zero assuming that the distance  $x$  extends to infinity. The function parameters can be modified to adjust the measurement adaptation to match with different requirement definitions and measurement conditions. As an alternative to sigmoid and Butterworth functions, mapping functions based on fuzzy membership functions of fuzzy logic can be used, thereby matching the mapping functions in a more detailed way to any non-linearity in the definition of a distance-based perceptual space property. The mapped samples are analyzed by means of time-series analysis, namely exponential averaging. Exponential averaging identifies average signal-values by means of continuous weighting of signal values using a time constant  $\tau$ . The time constant represents the size of a time-window in which samples are averaged while the time window moves forward in time. This corresponds to continuous update of the average value, which is expressed by (4).

$$P_q = \omega P_{q-1} + (1 - \omega) S_q \quad (4)$$

Here  $\omega = 1 - 1/\tau$ ,  $P_q$  is the measurement outcome at the time-step  $q$  and  $S_q$  is the value of  $S$  in (2) and (3), at the time-step  $q$ . Contrasting with conventional averaging methods, in exponential averaging the average is updated at every measurement step in real-time in a computationally efficient and effective way [Ciftcioglu and Peeters 1995]. Further details on perception based measurement, the definitions of the perceptual properties, as well as results of implementation can be found in [Bittermann and Ciftcioglu 2005].

### 3. Systematic dealing with subjectivity

Different individuals often attribute different degrees of visual openness and privacy to the same space. This indicates that their perceptions are different. From the design viewpoint, the following question arises: *“How exactly do visual space perceptions differ among individuals and how can that be taken into account in design?”*. This is an interesting question because requirements for perceptual properties are generally expressed based on subjective definitions. In order to assess the satisfaction of design requirements, which include perceptual requirements of individuals, understanding of individual space perception is necessary. Assessment of requirement satisfaction is the major component in the search for optimal design configurations, which is an essential activity in design. With respect to the perception model presented in the previous section, we can assume that the model parameters in (1), (2) and (3) differ when modelling the perception of different individuals. In order to understand the differences among subjective visual space perception, the understanding of the specific constitution of the perception of an individual forms the basis. So the main question addressed in this research is: *“Which parameter settings of the measurement system most adequately model the perception of a person?”*.

#### 3.1 Systematic adaptation of the perception model

Goal of the perception model adaptation, which is the focus of this research, is to establish the appropriate model settings to match the perception model with perception statements. For this purpose a number of spatial assessments taken from a selection of scenes given by both model and person are collected and interpreted. Systematic finding of the appropriate parameter settings of the perception model is essentially an optimality search. The optimality to be found is to minimize the sum of the differences between model and subjective assessment for the collection of scenes. Since the vision is modelled by the random sight lines, the parametric expression of this model cannot be given. That is, although the statistical properties can be analyzed by the probabilistic computation methods using the probability density functions involved, these results cannot be incorporated into the perception assessment method being adopted. This is due to the individual sight line tracing for each sight line as a granulated constituent of the simulated vision where the perception assessment model accepts such discrete non-stationary random inputs. The non-stationarity is due to the variable visual perception due to the variable visual field. In order to be able to handle this nonstationarity of the random inputs, a randomized search method is used where the discrete nature of the optimization task is also conveniently taken care of. The method is genetic algorithm based optimisation. This method is able to deal with the probabilistic and discrete nature of the perception model. This is explained in the following section.

#### 3.2 Evolutionary Search

Evolutionary search is a methodology, which was developed in the domain of computational intelligence. Its general purpose is to search optimality in complex and voluminous search spaces. A search space is defined as the collection of all possible solutions, that is all possible attribute states which constitute possible solutions. A rather generic evolutionary search method are Genetic algorithms. Genetic algorithms (GA) are combinatorial optimization techniques inspired by the mechanism of evolution and natural genetics [Holland 1979, Goldberg 1989]. Their feature is the ability of parallel search of the state space for optimization, in contrast to the point-by-point search of conventional optimization. In GA, the set of possible solutions of the optimization problem is called *population*. In a population any individual is a string of symbols or bits, which are readily represented by a digital computer. The symbols are called *genes* and each string of genes is called *chromosome* so

that each chromosome represents a solution. During a parallel search process, the validity of each solution individual of the population is graded by some criterion called *fitness*. The fitness evaluation marks the end of the iteration and according to the evaluation results a new population is formed. In a natural way, in the consecutive population there are more individuals inclined to acceptable solutions than the ones in the preceding population. The initial preparation of the population is done randomly if there is no information on the location of the solution. Otherwise, initial approximate representation of the solution to the problem as string of symbols is performed that it greatly facilitates the search process. The ensuing population is prepared according to genetic rules and implemented by means of genetic operators. These operators are basically *reproduction*, *crossover*, and *mutation*. The genetic operators are applied on the parents, which were probabilistically selected based on their fitness, to generate new possible solutions called *offspring*. Obviously, selected parents are the best representative candidates for solution in the population. Afterwards, the individuals of the current population and their offspring form a population.

These basic concepts are implemented as follows. We assume that, the initial population is created randomly at the time  $t=0$ . Let  $P(t)$  be the population at time  $t$ , consisting of chromosomes the size of which is  $P$  as a constant scalar quantity. Crossover with an associated probability  $P_C$  recombines two chromosomes by cutting them at a random position and partially exchanging the genes of the chromosomes. Mutation, with an associated probability  $P_M$ , changes the values of the some randomly selected genes. The “*fitness*” of each newly formed chromosome is evaluated and chromosomes with a low fitness score are replaced with those having high scores. This process is called *reproduction*. By the end of the reproduction a new population is formed that it becomes population  $P(t+1)$  at the time  $t+1$ . Note that the reproduction ensures that the population size is maintained as constant. The application of GA requires genetic parameters, namely: population size, crossover probability and mutation probability. Each of these greatly influences the performance of the GA. More details on Genetic Search can be found in the literature [Holland 1979, Goldberg 1989].

#### 4. Implementation

In this work, the genetic search is implemented to find optimal parameter settings for the perception model. In particular parameters in (1), (2), and (3) are to be adjusted to yield minimum difference between modelled and subjective assessment. A design of a residence is used as assessment object. Visual openness is the perceptual property to be assessed. A number of representative scenes are chosen for assessment. Six virtual cameras are positioned and orientated differently in the VR environment as shown in figure 3.

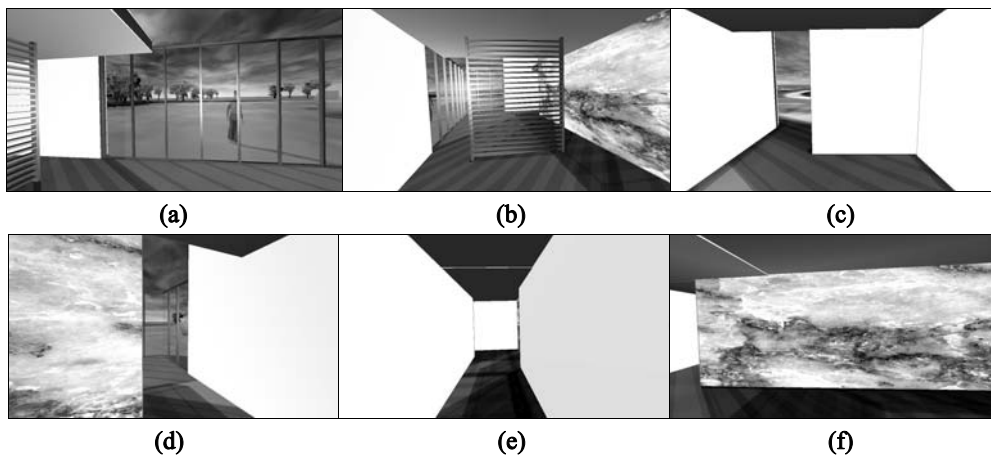
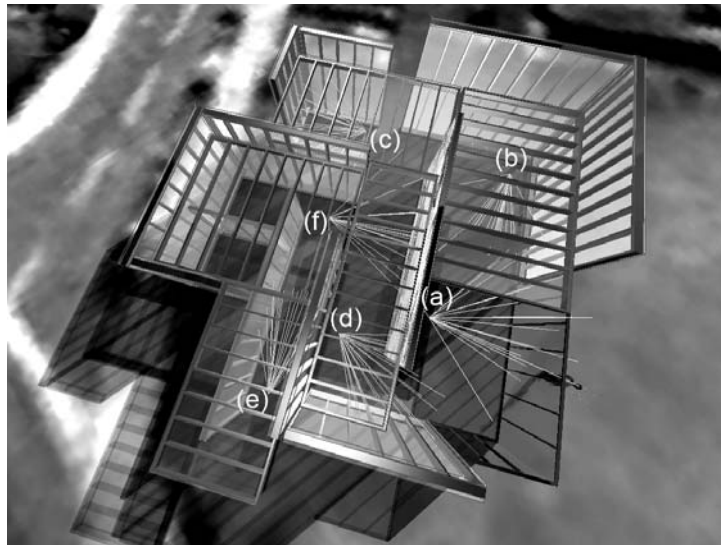


Figure 3. The six scenes, which are subject to visual openness assessment

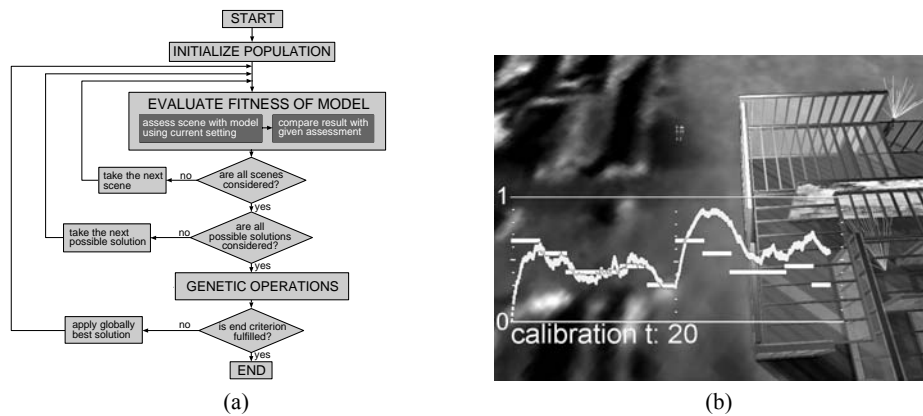
The six scenes, which are in the viewshed of these cameras are shown in figure 4. The scenes are sequentially presented individually to three test persons on a monitor. The persons are instructed to give their subjective assessment of the visual openness for each scene on a scale from zero to ten. In case of visual openness, ten signifies maximum and zero minimum visual openness. These statements are then normalized to values between zero and one for convenience in ensuing calculations.

The parameters of the perception model of (1),(2), which are to be adapted are  $\sigma_y$ ,  $m_z$  and  $l_c$ . The parameters  $\sigma_y$  and  $m_z$  are characteristic in the determination of the vision model. The other parameters of the vision model (1) are set to  $m_x=0$ ;  $\sigma_x=1$ ;  $m_y=0$ ; and  $\sigma_z=1$  to model a visual field of forward vision. Time constant  $\tau$  in (4) is set to  $\tau=20$ . The higher the time constant the greater the precision of the measurement, which is payed with increasing computational time for the adaptation process. The population size is set to 10 chromosomes. Crossover probability is set to 0.85 and mutation probability to 0.05. The adaptation process is executed. The genetic search is initialized by generating an initial population of chromosomes, with random values for the model parameters. The initial ranges for the random values of the perception model are  $0.2 \leq \sigma_y \leq 0.8$ ,  $1.5 \leq m_z \leq 5.0$ , and  $3.5 \leq l_c \leq 5.5$ .



**Figure 4. Overview of the scenes shown in figure 3**

A chromosome, which represents a particular random setting, is used as setting for the measurement system. For each of the selected scenes this model is positioned and oriented as the cameras from which the person made his/her subjective assessments. Sufficient time has to be given to the measurement system to establish the perceptual property after each transition condition, due to latency of exponential averaging. At that moment the absolute difference between the subjective statement and the measured value is obtained. After model assessment of all selected scenes the absolute differences between statements and measurements are summed up. The reciprocal value of this sum is interpreted as fitness, which is associated to the chromosome, which was applied to the perception model as a setting. This procedure is completed for all chromosomes in the population. After that, based on the associated fitness values of the chromosomes, they are genetically evolved to obtain the next generation of parameter settings. The process of fitness evaluation and genetic operation is repeated for a number of generations. The average fitness of the population increases steadily. After a number of generations the best chromosome which appeared in the search can be considered the optimal parameter setting, which represents the perception of the test person with minimal difference to his/her statements. Figure 5a shows the schematic representation of this process, and figure 5b shows a plot of a part of the fitness evaluation process.



**Figure 5. Schematic description of the visual perception model identification process by means of genetic optimization (a); plot of fitness evaluation process (b)**

The plot is to monitor the measurement given by the perception model and to compare with the statements. Horizontal lines in the plot of figure 5b show the statements of a person and the crooked line shows the measurement outcome given by the perception model. A model setting with a high fitness visually reflects in the plot as proximity between the horizontal lines and the measurement plot, as it is the case for example in the left half of the plot shown in the figure.

## 5. Results

The results obtained from the implementation described above are summarized in table 1.

**Table 1. Absolute Differences between measurements and statements of three test persons during the model optimization**

Generation	P1 best	P1 average	P2 best	P2 average	P3 best	P3 average
1	0.076	0.118	0.055	0.100	0.086	0.141
2	0.076	0.120	0.038	0.076	0.086	0.124
3	0.076	0.142	0.033	0.067	0.081	0.121
4	0.075	0.103	0.033	0.072	0.059	0.111
5	0.069	0.113	0.033	0.070	0.059	0.151
6	0.065	0.103	0.033	0.078	0.059	0.126
7	0.065	0.108	0.033	0.087	0.051	0.105
8	0.064	0.085	0.033	0.077	0.046	0.086
9	0.050	0.087	0.033	0.072	0.046	0.081
10	0.050	0.089	0.024	0.064	0.046	0.095
11	0.050	0.087	0.024	0.084	0.046	0.072
12	0.050	0.084	0.024	0.082	0.046	0.075
13	0.050	0.093	0.024	0.074	0.034	0.072
14	0.050	0.088	0.024	0.085	0.034	0.071
15	0.050	0.117	0.024	0.080	0.034	0.079

Table 1 shows the improvement of model fitness with each generation. The numbers give the absolute difference between measurements and the statements of the test person averaged over the 6 assessment positions. This is done for each testperson for the best and average solution of that population. After 15 generations the best solutions show an average difference of 0.050, 0.024, and 0.034, which means that the measurement outcomes differ about 5 per cent from the statements of the person. This is rather low, which indicates that the perception model, that was adapted in this research, is rather appropriate. Further elaboration on the goodness of the model are published in another work. The best solutions for

testperson 1, 2, and 3 after 15 generations are shown in table 2. The models given in table 2 are the characteristic models of visual openness perception for each test person.

**Table 2. Resulting openness perception models for three testpersons**

	P1	P2	P3
$\sigma_y$	0.76	0.40	0.41
$m_z$	3.33	1.92	2.15
$l_c$	4.42 m	4.54 m	3.98 m

## 6. Conclusions

A model is identified for human visual space perception. The model parameters are found to be varying from one individual person to other ones, as one should expect. However, the variations are not significantly different, so that the results can be averaged to obtain a satisfactory general model of human visual space perception. This can be done for specific groups of people, for example ethnic groups or a group of customers. Visual space perception modelling is an important asset in design, to accurately monitor the perceptual properties of spaces and to be able to search for optimal spatial shapes systematically, which satisfy perceptual design requirements. Additionally it is an important facility during collaborative architectural design processes, since it provides designers with a means to communicate on a common discussion platform; that is, it provides a design ontology for collaborative architectural design. Considering a number of test persons and test scenes, the perception model established indicated satisfactory accurate responses, which form sound evidence for the validity of the model. Based on this model, further investigations are being planned to investigate the other factors, which may play a role in human visual space perception, such as color and illumination.

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