

# FURTHER STUDIES ON VISUAL PERCEPTION FOR PERCEPTUAL ROBOTICS

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Abstract: Further studies on computer-based perception by vision modelling are described. The visual perception is mathematically modelled, where the model receives and interprets visual data from the environment. The perception is defined in probabilistic terms so that it is in the same way quantified. At the same time, the measurement of visual perception is made possible in real-time. Quantifying visual perception is essential for information gain calculation. Providing virtual environment with appropriate perception distribution is important for enhanced distance estimation in virtual reality. Computer experiments are carried out by means of a virtual agent in a virtual environment demonstrating the verification of the theoretical considerations being presented, and the far reaching implications of the studies are pointed out.

## 1 INTRODUCTION

Visual perception, although commonly articulated in various contexts, it is generally used to convey a cognition related idea or message in a quite fuzzy form and this may be satisfactory in many instances. Such usage of perception is common in daily life. However, in professional areas, like computer vision, robotics, or design, its demystification or precise description is necessary for proficient executions. Since the perception concept is soft and thereby elusive, there are certain difficulties to deal with it. For instance, how to quantify it or what are the parameters, which play role in visual perception. Visual perception is one of the important information sources playing role on human's behavior. Due to the diversity of existing approaches related to perception, which emerged in different scientific domains, we provide a comprehensive introduction to be explicit as to both, the objectives,

and the contribution of the present research.

Perception has been considered to be the reconstruction a 3-dimensional scene from 2-dimensional image information (Marr, 1982; Poggio, Torre et al., 1985; Bigun, 2006). This *image processing* approach attempts to mimic the neurological processes involved in vision, with the retinal image acquisition as starting event. However, modeling the sequence of brain processes is a formidable endeavor. This holds true even when advanced computational methods are applied for modeling of the individual brain-components' behavior (Arbib, 2003). The reason is the brain processes are complex.

Brain researchers trace visual signals as they are processed in the brain. A number of achievements are reported in the literature (Wiesel, 1982; Hubel, 1988; Hecht-Nielsen, 2006). However, due to complexity there is no consensus about the exact role of brain regions, sub-regions and individual

nerve-cells in vision, and how they should be modeled (Hecht-Nielsen, 2006; Taylor, 2006). The brain models are all different due to the different focus of attention that refers to uncountable number of modalities in the brain. Therefore they are inconclusive as to understanding of a particular brain process like perception on a common ground. As a state of the art, they try to form a firm clue for perception and attention beyond their verbal accounts. In modeling the human vision the involved brain process components as well as their interactions should be known with certainty if a deterministic approach, like the image processing approach, is to be successful. This is currently not the case. Well-known observations of visual effects, such as *depth from stereo disparity* (Prince, Pointon et al., 2002), *Gelb effect* (Cataliotti and Gilchrist, 1995), *Mach bands* (Ghosh, Sarkar et al., 2006), *gestalt principles* (Desolneux, Moisan et al., 2003), *depth from defocus* (Pentland, 1987) etc. reveal components of the vision process, that may be algorithmically mimicked. However, it is unclear how they interact in human vision to yield the mental act of perception. When we say that we perceived something, the meaning is that we can recall relevant properties of it. What we cannot remember, we cannot claim we perceived, although we may suspect that corresponding image information was on our retina. With this basic understanding it is important to note that the act of perceiving has a characteristic that is *uncertainty*: it is a common phenomenon that we overlook items in our environment, although they are visible to us, i.e., they are within our visual scope, and there is a possibility for their perception. This everyday experience has never been exactly explained. It is not obvious how some of the retinal image data does not yield the perception of the corresponding objects in our environment. Deterministic approaches do not explain this common phenomenon.

The psychology community established the probable “overlooking” of visible information experimentally (Rensink, O’Regan et al., 1997; O’Regan, Deubel et al., 2000), where it has been shown that people regularly miss information present in images. For the explanation of the phenomenon the concept of *visual attention* is used, which is a well-known concept in cognitive sciences (Treisman and Gelade, 1980; Posner and Petersen, 1990; Itti, Koch et al., 1998; Treisman, 2006). However, it remains unclear what attention exactly is, and how it can be modeled quantitatively. The works on attention mentioned above start their

investigation at a level, where basic visual comprehension of a scene must have already occurred. An observer can exercise his/her bias or preference for certain information within the visual scope only when he/she has already a perception about the scene, as to where potentially relevant items exist in the visible environment. This early phase, where we build an overview/initial comprehension of the environment is referred to as *early vision* in the literature, which is omitted in the works on attention mentioned above. While the early perception process is unknown, identification of attention in perception, that is due to a task specific bias, is limited. This means, without knowledge of the initial stage of perception its influence on later stages is uncertain, so that the later stages are not uniquely or precisely modeled and the attention concept is ill-defined. Since attention is ill-defined, ensuing perception is also merely ill-defined. Some examples of definitions on perception are “*Perception refers to the way in which we interpret the information gathered and processed by the senses,*” (Levine and Sheffner, 1981) and “*Visual perception is the process of acquiring knowledge about environmental objects and events by extracting information from the light they emit or reflect,*” (Palmer, 1999). Such verbal definitions are helpful to understand what perception is about; however they do not hint how to tackle the perception beyond qualitative inspirations. Although we all know what perception is apparently, there is no unified, commonly accepted definition of it.

As a summary of the previous part we note that visual perception and related concepts have not been exactly defined until now. Therefore, the perception phenomenon is not explained in detail and the perception has never been quantified, so that the introduction of human-like visual perception to machine-based system remains as a soft issue.

In the present paper a newly developed theory of perception is introduced. In this theory visual perception is put on a firm mathematical foundation. This is accomplished by means of the well-established probability theory. The work concentrates on the early stage of the human vision process, where an observer builds up an unbiased understanding of the environment, without involvement of task-specific bias. In this sense it is an underlying fundamental work, which may serve as basis for modeling later stages of perception, which may involve task specific bias. The probabilistic theory can be seen as a unifying theory as it unifies synergistic visual processes of human,

including physiological and neurological ones. Interestingly this is achieved without recourse to neuroscience and biology. It thereby bridges from the environmental stimulus to its mental realization.

Through the novel theory twofold gain is obtained. Firstly, the perception and related phenomena are understood in greater detail, and reflections about them are substantiated. Secondly, the theory can be effectively introduced into advanced implementations since perception can be quantified. It is foreseen that modeling human visual perception can be a significant step as the topic of perception is a place of common interest that is shared among a number of research domains, including cybernetics, brain research, virtual reality computer graphics, design and robotics (Ciftcioglu, Bittermann et al., 2006). Robot navigation is one of the major fields of study in autonomous robotics (Oriolio, Ulivi et al., 1998; Beetz, Arbuckle et al., 2001; Wang and Liu, 2004). In the present work, the human-like vision process is considered. This is a new approach in this domain, since the result is an autonomously moving robot with human-like navigation to some extent. Next to autonomous robotics, this belongs to an emerging robotics technology, which is known as perceptual robotics (Garcia-Martinez and Borrajo, 2000; Söffker, 2001; Burghart, Mikut et al., 2005; Ahle and Söffker, 2006; Ahle and Söffker, 2006). From the human-like behaviour viewpoint, perceptual robotics is fellow counterpart of emotional robotics, which is found in a number of applications in practice (Adams, Breazeal et al., 2000). Due to its merits, the perceptual robotics can also have various applications in practice.

From the introduction above, it should be emphasized that, the research presented here is about to demystify the concepts of perception and attention as to vision from their verbal description to a scientific formulation. Due to the complexity of the issue, so far such formulation is never achieved. This is accomplished by not dealing explicitly with the complexities of brain processes or neuroscience theories, about which more is unknown than known, but incorporating them into perception via probability. We derive a vision model, which is based on common human vision experience explaining the causal relationship between vision and perception at the very beginning of our vision process. Due to this very reason, the presented vision model precedes all above referenced works in the sense that, they can eventually be coupled to the output of the present model.

Probability theoretic perception model having been established, the perception outcome from the model is implemented in an avatar-robot in virtual reality. The perceptual approach for autonomous movement in robotics is important in several respects. On one hand, perception is very appropriate in a dynamic environment, where predefined trajectory or trajectory conditions like occasional obstacles or hindrances are duly taken care of. On the other hand, the approach can better deal with the complexity of environments by processing environmental information selectively.

The organization of the paper is as follows. Section two gives the description of the perception model developed in the framework of ongoing perceptual robotics research. Section three describes a robotics application. This is followed by discussion and conclusions.

## 2 A PROBABILISTIC THEORY OF VISUAL PERCEPTION

### 2.1 Perception process

We start with the basics of the perception process with a simple and special, yet fundamental orthogonal visual geometry. It is shown in figure 1.

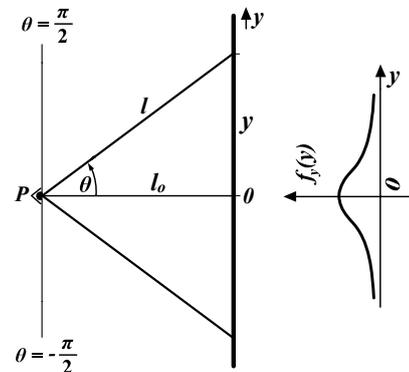


Figure 1: The geometry of visual perception from a top view, where  $P$  represents the position of eye, looking at a vertical plane with a distance  $l_o$  to the plane;  $f_j(y)$  is the probability density function in  $y$ -direction.

In figure 1, the observer is facing and looking at a vertical plane from the point denoted by  $P$ . By means of looking action the observer pays visual attention equally to all locations on the plane in the first instance. That is, the observer visually experiences all locations on the plane without any

preference for one region over another. Each point on the plane has its own distance within the observer's scope of sight which is represented as a cone. The cone has a solid angle denoted by  $\theta$ . The distance of a point on the plane and the observer is denoted by  $l$  and the distance between the observer and the plane is denoted by  $l_o$ . Since visual perception is associated with distance, it is straightforward to proceed to express the distance of visual perception  $l$  in terms of  $\theta$  and  $l_o$ . From figure 1, this is given by

$$l = \frac{l_o}{\cos(\theta)} \quad (1)$$

Since we consider that the observer pays visual attention equally to all locations on the plane in the first instance, the probability of getting attention for each point on the plane is the same so that the associated probability density function (pdf) is uniformly distributed. This positing ensures that there is no visual bias at the beginning of visual perception as to the differential visual resolution angle  $d\theta$ . Assuming the scope of sight is defined by the angle  $\theta = \pm \pi/2$ , the pdf  $f_\theta$  is given by

$$f_\theta = \frac{1}{\pi} \quad (2)$$

since  $\theta$  is a random variable, the distance  $x$  in (1) is also a random variable. The pdf  $f_l(l)$  of this random variable is computed as (Ciftcioglu, Bittermann et al.)

$$f_l(l) = \frac{2}{\pi} \frac{l_o}{l \sqrt{l^2 - l_o^2}} \quad (3)$$

for the interval  $l_o \leq l \leq \infty$ .

Considering that

$$\tan(\theta) = \frac{y}{l_o} \quad (4)$$

and by means of pdf calculation similar to that to obtain  $f_x(x)$  one can obtain  $f_y(y)$  as (Ciftcioglu, Bittermann et al.)

$$f_y(y) = \frac{l_o}{\pi(l_o^2 + y^2)} \quad (5)$$

for the interval  $-\infty \leq y \leq \infty$ . (9) and (11) are dual representation of the same phenomenon. The probability density functions  $f_l(l)$  and  $f_y(y)$  are defined as *attention* in the terminology of cognition.

By the help of the results given by (9) and (11) two essential applications in design and robotics are described in a previous research (Bittermann,

Sariyildiz et al.). In this research the fundamental orthogonal visual geometry is extended to a general visual geometry to explore the further properties of the perception phenomenon. In this geometry the earlier special geometry the orthogonality condition of the infinite plane is relaxed. This geometry is shown in figure 2 where the attentions at the points  $O$  and  $O'$  are subject to computation, with the same axiomatic foundation of the probabilistic theory, as before. Since the geometry is symmetrical with respect to  $x$  axis, we consider only the upper domain of the axis without loss of the generality.

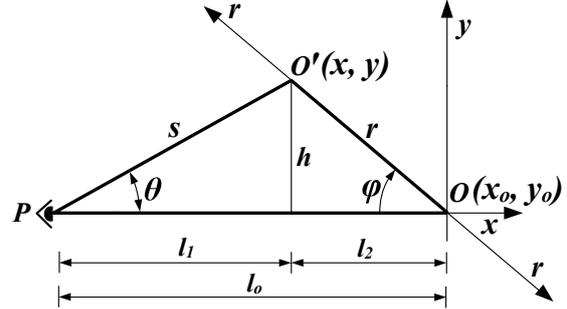


Figure 2: The geometry of visual perception where the observer has the position at point  $P$  with the orientation to the point  $O$ . The  $x, y$  coordinate system has the origin placed at  $O$  and the line defined by the points  $P$  and  $O$  coincides with the  $x$  axis for the computational convenience.

In figure 2, an observer at the point  $P$  is viewing an infinite plane whose intersection with the plane of page is the line passing from two point designated as  $O$  and  $O'$ .  $O$  represents the origin. The angle between  $OO'$  and  $OP$  is designated as  $\theta$ . The angle between  $OP$  and  $OO'$  is defined by  $\phi$ . The distance between  $P$  and  $O'$  is denoted by  $s$  and the distance of  $O'$  to the  $OP$  line is designated as  $h$ . The distance of  $O'$  to  $O$  is taken as a random variable and denoted by  $r$ . By means of looking action the observer pays visual attention equally in all directions within the scope of vision. That is, in the first instance, the observer visually experiences all locations on the plane without any preference for one region over another. Each point on the plane has its own distance within the observer's scope of sight which is represented as a cone. The cone has a solid angle denoted by  $\theta$ . The distance between a point on the plane and the observer is denoted by  $l$  and the distance between the observer and the plane is denoted by  $l_o$ . Since we consider that the observer pays visual attention equally for all directions within the scope of vision, the associated probability

density function (pdf) with respect to  $\theta$  is uniformly distributed. Positing this ensures that there is no visual bias at the beginning of visual perception as to the differential visual resolution angle  $d\theta$ . Assuming the scope of sight is defined by the angle  $\theta = +\pi/2$ , the pdf  $f_\theta$  is given by

$$f_\theta = \frac{1}{\pi/2} \quad (6)$$

Since  $\theta$  is a random variable, the distance  $r$  in (1) is also a random variable. The pdf  $f_r(r)$  of this random variable is computed as follows.

To find the pdf of the variable  $r$  denoted  $f_r(r)$  for a given  $r$  we consider the theorem on the *function of random variable* and, following Papoulis (Papoulis), we solve the equation

$$r = g(\theta) \quad (7)$$

for  $\theta$  in terms of  $r$ . If  $\theta_1, \theta_2, \dots, \theta_n, \dots$  are all its

$$r \operatorname{tg} \theta + r \operatorname{tg} \varphi = \frac{l_o \operatorname{tg} \varphi}{\sin \varphi} \operatorname{tg} \theta \quad (18)$$

$$\left( r - l_o \frac{\operatorname{tg} \varphi}{\sin \varphi} \right) \operatorname{tg} \theta = -r \operatorname{tg} \varphi \quad (19)$$

$$\operatorname{tg} \theta_1 = \frac{r \operatorname{tg} \varphi}{\frac{l_o \operatorname{tg} \varphi}{\sin \varphi} - r} \quad (20)$$

real roots,

$$r = g(\theta_1) = g(\theta_2) = \dots = g(\theta_n) = \dots$$

Then

$$f_r(r) = \frac{f_\theta(\theta_1)}{|g'(\theta_1)|} + \dots + \frac{f_\theta(\theta_2)}{|g'(\theta_2)|} + \dots + \frac{f_\theta(\theta_n)}{|g'(\theta_n)|} + \dots \quad (8)$$

Aiming to determine  $f_r(r)$  given by (8), from figure 2 we write

$$\operatorname{tg} \theta = \frac{h}{l_1} \quad l_1 = \frac{h}{\operatorname{tg} \theta} \quad (9)$$

$$\operatorname{tg} \varphi = \frac{h}{l_2} \quad l_2 = \frac{h}{\operatorname{tg} \varphi} \quad (10)$$

$$l_1 + l_2 = \frac{h}{\operatorname{tg} \theta} + \frac{h}{\operatorname{tg} \varphi} = l_o \quad (11)$$

From above, we solve  $h$ , which is

$$h = \frac{l_o}{\frac{1}{\operatorname{tg} \theta} + \frac{1}{\operatorname{tg} \varphi}} \quad (12)$$

From figure 2, we write

$$r(\varphi) = \frac{h}{\sin \varphi} \quad (13)$$

Using (12) in (13), we obtain

$$r(\varphi) = \frac{l_o}{\sin \varphi} \frac{1}{\frac{1}{\operatorname{tg} \theta} + \frac{1}{\operatorname{tg} \varphi}} = g(\theta) = \frac{l_o \operatorname{tg} \varphi}{\sin \varphi} \frac{\operatorname{tg} \theta}{\operatorname{tg} \theta + \operatorname{tg} \varphi} \quad (14)$$

We take the derivative w.r.t.  $\theta$ , which gives

$$g'(\theta) = \frac{l_o \operatorname{tg} \varphi}{\sin \varphi} \frac{\frac{1}{\cos^2 \theta} (\operatorname{tg} \theta + \operatorname{tg} \varphi) - \frac{1}{\cos^2 \theta} \operatorname{tg} \theta}{(\operatorname{tg} \theta + \operatorname{tg} \varphi)^2} \quad (15)$$

$$= \frac{l_o \operatorname{tg} \varphi}{\sin \varphi} \frac{\operatorname{tg} \varphi}{(\operatorname{tg} \theta + \operatorname{tg} \varphi)^2} \quad (16)$$

Substituting  $\operatorname{tg}(\theta)$  from (14) into (16) yields

$$\begin{aligned} g'(\theta_1) &= \frac{\sin \varphi}{l_o} \frac{1}{\sin^2 \theta} r^2 \\ &= \frac{\sin \varphi}{l_o} r^2 \frac{1 + \operatorname{tg}^2 \theta_1}{\operatorname{tg}^2 \theta_1} \\ &= \frac{\sin \varphi}{l_o} r^2 \left( 1 + \frac{1}{\operatorname{tg}^2 \theta_1} \right) \end{aligned} \quad (17)$$

Above,  $\operatorname{tg}(\theta_1)$  is computed from (14) as follows.

We apply the theorem of *function of random variable* (Papoulis):

$$f_r(r) = \frac{f_r(\theta_1)}{|g'(\theta_1)|} \quad (21)$$

$$f_r(r) = \frac{1}{\frac{\pi}{2} \sin \varphi r^2} \frac{l_o}{\left( 1 + \frac{1}{\operatorname{tg}^2 \theta_1} \right)} \quad (22)$$

where

$$\operatorname{tg} \theta_1 = \frac{r}{\frac{l_o}{\sin \varphi} - \frac{r}{\operatorname{tg} \varphi}} \quad (23)$$

Substitution of (23) into (22) gives

$$f_r(r) = \frac{1}{\frac{\pi}{2} |\sin \varphi|} \frac{l_o}{\left| r^2 + \left( \frac{l_o}{\sin \varphi} - \frac{r}{\operatorname{tg} \varphi} \right)^2 \right|} \quad (24)$$

or

$$f_r(r) = \frac{l_o}{\frac{\pi}{2}} \frac{\sin(\varphi)}{r^2 - 2l_o r \cos \varphi + l_o^2} \quad (25)$$

$$\text{for } 0 < r < \frac{l_o}{\cos(\varphi)}. \quad (26)$$

To show (25) is a pdf, we integrate it in the interval given by (26). The second degree equation at the denominator of (25) gives

$$b^2 - 4ac = -4l_o^2 \sin^2(\varphi)$$

where  $b=2l_or$  and  $a=1$  and  $c=l_o^2$ , so that  $b^2 < 4ac$  which means, for this the integral

$$I = \int_0^{l_o / \cos(\varphi)} f_r(r, \varphi) dr \quad (27)$$

gives (Korn and Korn)

$$I = \frac{1}{\pi/2} \operatorname{arctg} \left\{ \frac{r - l_o \cos(\varphi)}{l_o \sin(\varphi)} \right\} \Big|_0^{l_o / \cos(\varphi)} = 1 \quad (28)$$

as it should verify as pdf. Since attention is a scalar quantity per unit, it has to be the same for different geometries subjected to computation meaning that it is measured with the same units in both cases. In the same way we can say that since perception is a scalar quantity, the perceptions have to be correspondingly the same. Referring to both the orthogonal geometry and the general geometry, the density functions are shown in figure 3a. The same attention values at the origin  $O$  are denoted by  $p_o$ . Since the attentions are the same, for the perception comparison, the attention values have to be integrated within the same intervals in order to verify the same quantities at the same point. Figure 3b is the magnified portion of figure 3a in the vicinity of origin. In this magnified sketch the infinitesimally small distances  $dy$  and  $dr$  are indicated where the relation between  $dy$  and  $dr$  is given by  $dy = dr \sin(\varphi)$  or

$$dr = dy / \sin(\varphi) \quad (29)$$

and

$$f_r(r) dr = \frac{l_o}{\frac{\pi}{2}} \frac{\sin(\varphi)}{r^2 - 2l_o r \cos \varphi + l_o^2} dr \quad (30)$$

substitution of (29) into (30) yields

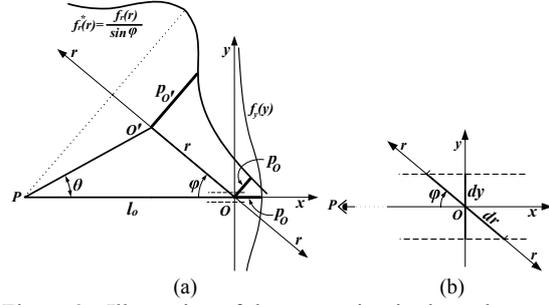


Figure 3: Illustration of the perception in the orthogonal geometry and the general geometry indicating the relationship between the infinitesimally small distances  $dy$  and  $dr$ . The geometry (a) and zoomed region at the origin (b).

$$f_r^*(r) = \frac{l_o}{\frac{\pi}{2}} \frac{1}{r^2 - 2l_o r \cos \varphi + l_o^2} \quad (31)$$

which is the attention for a general geometry. It boils down into the orthogonal geometry for all conditions; for a general position of  $O'$  within the visual scope, this is illustrated in figure 4 as this was already illustrated in figure 3 for the origin  $O$ .

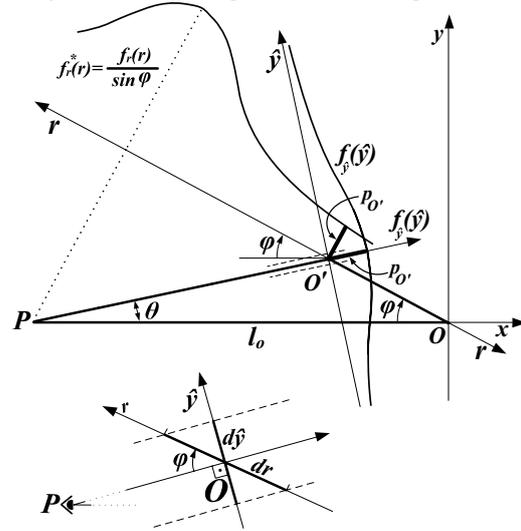


Figure 4. Illustration of the perception in the orthogonal geometry and the general geometry indicating the relationship between the infinitesimally small distances  $d\hat{y}$  and  $dr$ . This is the same as figure 3 but the zoomed region is at a general point denoted by  $O'$ .

The pdf has several interesting features. First, for  $\varphi = \pi/2$ , it boils down

$$f_y(r) = \frac{l_o}{\pi} \frac{1}{(r^2 + l_o^2)} \quad (32)$$

An interesting point is that when  $\varphi \rightarrow 0$  but  $r \neq 0$ . This means  $O'$  is on the gaze line from  $P$  to  $O$ . For the case  $O'$  is between  $P$  and  $O$ ,  $f_r(r)$  becomes

$$f_r(r) = \frac{l_o}{\pi} \frac{1}{(l_o - r)^2} \quad (33)$$

or otherwise

$$f_r(r) = \frac{l_o}{\pi} \frac{1}{(l_o + r)^2} \quad (34)$$

In (33) for  $r \rightarrow l_o$   $f_r(r) \rightarrow \infty$ . This case is similar to that in (3) where  $l \rightarrow l_o$   $f_l(l) \rightarrow \infty$ .

The variation of  $f_r^*(r, \varphi)$  is shown in figure 5 in a 3-dimensional plot where  $\varphi$  is a parameter.

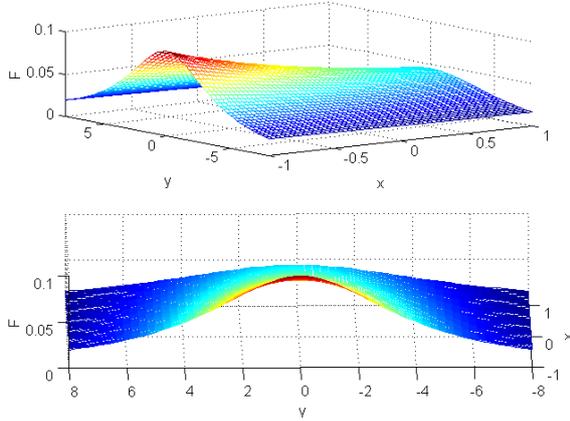


Figure 5: The variation of  $f_r^*(r, \varphi)$  is shown as a 3-dimensional plot for  $l_o=5$ .

The actual  $f_r(r)$  is obtained as the intersection of a vertical plane passing from the origin  $O$  and the surface. The analytical expression of this intersection is given by (25) and it is shown in figure 4 where  $\varphi$  is a parameter; for the upper plot  $\varphi = \pi/4$  and for the lower plot  $\varphi = \pi/2$ . The latter corresponds to the vertical cross section of the surface shown in figure 3 as lower plot.

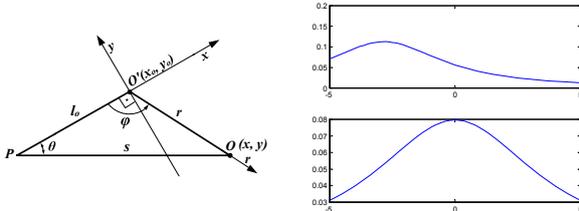


Figure 6: The pdf  $f_r(r, \varphi)$  where  $\varphi$  is a parameter; for the upper plot  $\varphi = \pi/4$  and for the lower plot  $\varphi = \pi/2$ .

The pdf in (25) indicates the attention variation along the line  $r$  in figure 2 where the observer faces the point  $O$ .

### 3 APPLICATION

Presently, the experiments have been done with the simulated measurement data since the multiresolutional filtering runs in a computationally efficient software platform which is different than the computer graphics platform of virtual reality. For the simulated measurement data, first the trajectory of the virtual agent is established by changing the system dynamics from the straight ahead mode to bending mode for a while, three times. Three bending modes are seen in figure 7 with the complete trajectory of the perceptual agent. The state variables vector is given by

$$X = [x, \dot{x}, y, \dot{y}, \omega]$$

where  $\omega$  is the angular rate and it is estimated during the move. When the robot moves in a straight line, the angular rate becomes zero.

In details, there are three lines plotted in figure 7. The green line represents the measurement data set. The black line is the extended Kalman filtering estimation at the highest resolution of the perception measurement data. The outcome of the multiresolutional fusion process is given with the blue line. The true trajectory is indicated in red. In this figure they cannot be explicitly distinguished. For explicit illustration of the experimental outcomes the same figure with a different zooming range and the zooming power are given in figures 8 and 9 for bending mode and 10 for a straight-ahead case. From the experiments it is seen that, the Kalman filtering is effective for estimation of the trajectory from perception measurement. Estimation is improved by the multiresolutional filtering. Estimations are relatively more accurate in the straight-ahead mode.

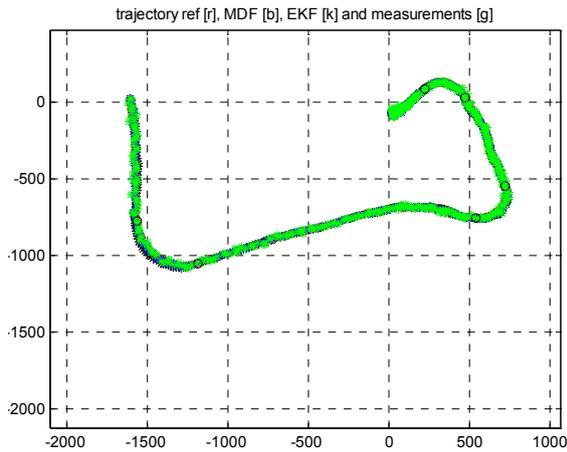


Figure 7: Robot trajectory, measurement, Kalman filtering and multiresolutional filtering estimation.

It is noteworthy to mention that, the multiresolutional approach presented here uses *calculated* measurements in the lower resolutions. In general case, each sub-resolution can have separate perceptual measurement from its own dedicated perceptual vision system for more accurate executions. The multiresolutional fusion can still be improved by the use of different data acquisition provisions which play the role of different sensors at each resolution level and to obtain independent information subject to fusion.

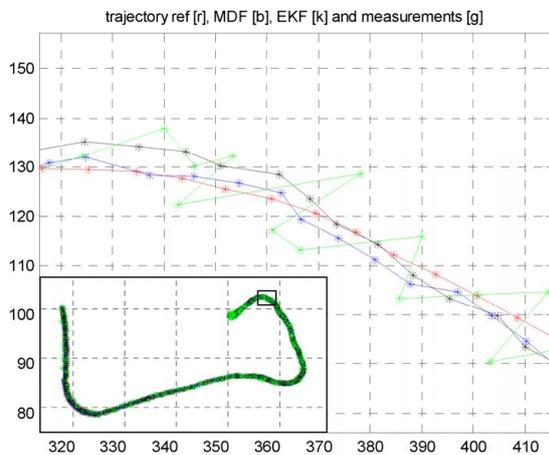


Figure 8: Enlarged Robot trajectory, measurement Kalman filtering and multiresolutional filtering estimation, in bending mode (light grey is for measurement, the smooth line is the trajectory).

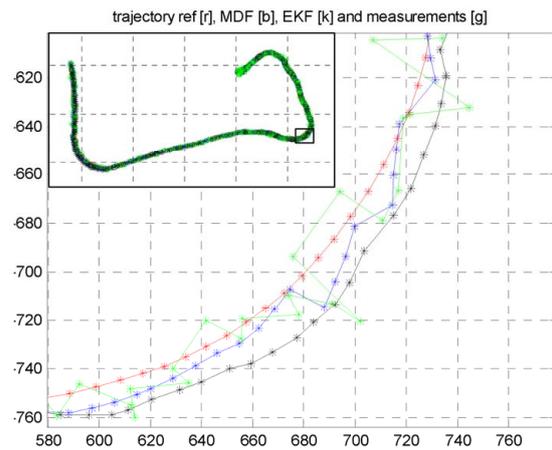


Figure 9: Enlarged Robot trajectory, measurement Kalman filtering and multiresolutional filtering estimation, in bending mode (light grey is for measurement, the smooth line is the trajectory).

## 4 DISCUSSION AND CONCLUSION

Although, visual perception is commonly articulated in various contexts, generally it is used to convey a cognition related idea or message in a quite fuzzy form and this may be satisfactory in many instances. Such usage of perception is common in daily life. However, in professional areas, like architectural design or robotics, its demystification or precise description is necessary for proficient executions. Since the perception concept is soft and thereby elusive, there are certain difficulties to deal with it. For instance, how to quantify it or what are the parameters, which play role in visual perception. The posing of this research is that perception is a very complex process including brain processes. In fact, the latter, i.e., the brain processes, about which our knowledge is highly limited, are final, and therefore they are most important. Due to this complexity a probabilistic approach for a visual perception theory is very much appealing, and the results obtained have direct implications which are in line with our common visual perception experiences, which we exercise every day.

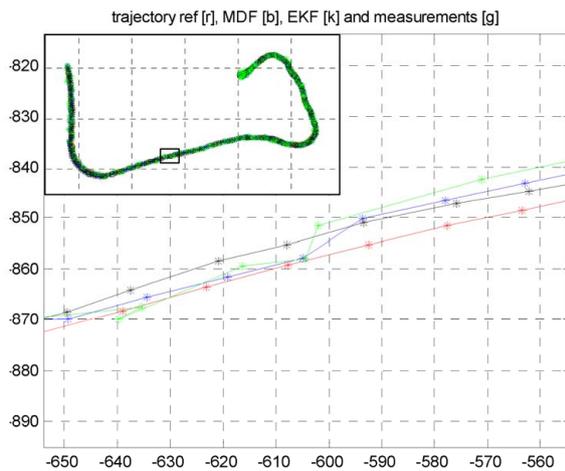


Figure 10: Enlarged Robot trajectory, measurement Kalman filtering and multiresolutional filtering estimation in straight-ahead mode (light grey is for measurement, the smooth line is the trajectory).

In this work a novel theory of visual perception is developed, which defines perception in probabilistic terms. The probabilistic approach is most appropriate, since it models the complexity of the brain processes, which are involved in perception and result in the characteristic uncertainty of perception, e.g., an object may be overlooked although it is visible. Based on the constant differential angle in human vision, which is the minimal angle humans can visually distinguish, vision is defined as the ability to see, that is, to receive information, which is transmitted via light, from different locations in the environment, which are located within different differential angles. This ability is modeled by a function of a random variable, namely the viewing direction, which has a uniform probability density for the direction, to model unbiased vision in the first instance. Hence vision is defined as probabilistic act. Based on vision, visual attention is defined as the corresponding probability density with respect to obtaining information from the environment. Finally, the visual perception is the intensity of attention, which is the integral of attention over a certain unit length, yielding a probability that the environmental information from a region in the environment is realized in the brain.

It is noteworthy to emphasize that perception is to be expressed in terms of intensity, which is the integral of a probability density. This is not surprising since perception, corresponding to its commonly understood status as a mental event, should be a dimensionless quantity, as opposed to a

concept, which involves a physical unit, namely a probability density over a unit length, like visual attention. The definitions are conforming to common perception experience by human. The simplicity of the theory in terms of understanding its result together with its explanatory power, indicates that a fundamental property of perception has been identified.

In this theory of perception a clear distinction is made between the act of *perceiving* and *seeing*. Namely, seeing is a definitive process, whereas perception is a probabilistic process. This distinction may be a key to understand many phenomena in perception, which are challenging to explain from a deterministic viewpoint. For example the theory explains the common experience, that human beings may overlook an object while searching for it, although such an overlooking is not justified, and it is difficult to explain the phenomenon. This can be understood from the viewpoint that vision is a probabilistic act, where there exists a chance that corresponding visual attention is not paid sufficiently for the region in the environment, which would provide the pursued information. An alternative explanation, which is offered by an information theoretic interpretation of the theory, is that through the integration of the visual attention over a certain domain some information may be lost, so that, although attention was paid to a certain item in the environment, pursued information is not obtained. The theory also explains how it is possible, that different individuals have different perceptions in the same environment. Although similar viewpoints in the same environment have similar visual attention with unbiased vision, the corresponding perception remains a phenomenon of probability, where a realization in the brain is not certain, although it may be likely.

The theory is verified by means of extensive computer experiments in virtual reality. From visual perception, other derivatives of it can be obtained, like visual openness perception, visual privacy, visual color perception etc. In this respect, we have focused on visual openness perception, where the change from visual perception to visual openness perception is accomplished via a mapping function and the work is reported in another publication (Ciftcioglu, Bittermann et al.). Such perception related experiments have been carried out by means of a virtual agent in virtual reality, where the agent is equipped with a human-like vision system (Ciftcioglu, Bittermann et al.).

Putting perception on a firm mathematical

foundation is a significant step with a number of far reaching implications. On one hand vision and perception are clearly defined, so that they are understood in greater detail, and reflections about them are substantiated. On the other hand tools are developed to employ perception in more precise terms in various cases and even to measure perception. Applications for perception measurement are architectural design, where they can be used to monitor implications of design decisions, and autonomous robotics, where the robot moves based on perception (Ciftcioglu, Bittermann et al.).

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