Ambient Environment Analysis by means of Perception

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1. Introduction
The theme of ambient intelligence (AmI) is getting a growing attention due to its importance in some practical applications, e.g. see Augusto and Shapiro (2007), Streiz, Kameas et al. (2007), Ramos, Augusto et al. (2008), Augusto and Nugent (2006). In this context perhaps security and utilitarian purposes take the important place. Ambient intelligence refers to electronic environments that are sensitive and responsive to the presence of people, and it can be implemented in various ways, satisfying the requirements of the application. The accomplishment to be attained is desirable by means of computational power, as it provides great flexibility in the execution Bhatt, Dylla et al. (2009). In this approach some model relationships between artefacts are defined as operational space, functional space and range space, and their characterizations are defined. Based on these characterizations also some design constraints are defined, so that demanded spatial relationships are guaranteed. The constraints involve semantic characterizations and spatial relationships among strictly spatial entities as well as other spatial artefacts. Furthermore, albeit being modeled qualitatively at a conceptual level, they also need to be validated against a quantitatively modeled work-in-progress design in addition to checking for the consistency of a designer’s requirements strictly. An example is seen in figure 1, where an ambient environment is considered consisting of sensors used to monitor the door and its functional space between two rooms. Figure 1a shows a situation where the door and its functional space are not fully covered by the range of two camera sensors, so that a requirement imposed on the environment, namely that the door in question must be supervised, is not satisfied. Figure 1b shows a situation where the door and its functional space are fully covered by the range of the camera sensors, so that the imposed requirement is fulfilled.

![Figure 1](image.png)

Although such algorithmic works are suitable for the intended goals, their assessment for degree of suitability remains undetermined. Namely the works assess consistency or inconsistency with requirements as a binary statement. Based on this view, the present work intends to make some steps forward along this line, in the sense of providing measured assessment about the degree of performance of designs with ambient intelligence. This is desirable in particular when optimal solutions are sought during a design process, for instance with respect to the ambient performance or with respect to the placement and orientation of sensors, or placement of a door, so that accurate assessment in terms of degree of performance is required for an effective process of reaching optimality.
2. Methodology

In this work ambient intelligence is treated within the computational intelligence concept, using the methods of this concept. Basically, these methods are used in the paradigm of perception, which is based on the probability theory, and the possibility theory in fuzzy logic, where the degree of surveillance of an object is aimed. It is noted that in the case of a human watching a scene, perception is modeled as a probabilistic event. That is, there is a chance to see an object, meaning the presence of the object is realized in mind, which implies a chance of overlooking the object, too. We can term this as the uncertainty of human vision, which is a result of the complex brain processing of visual stimulus (Rensink, O’Regan et al. 1997; Bittermann and Ciftcioglu 2008). Considering surveillance of a scene involving camera sensors it is noted that this consists of two phases. The first phase is camera sensing a scene, which is an event that is not probabilistic. However, the probabilistic nature of the human viewing a scene does not vanish in the surveillance situation. Namely, the human issue is exported to the second phase, where human is surveilling the scene on a screen. The human surveillance involves immersion, which is that the person has to interpret the camera image depicted on a screen as a three dimensional scene, as if he were actually viewing the scene from the camera viewpoint. Therefore, as an initial step, probability theoretic computations are used to simulate perception of objects from the sensor viewpoints, i.e. the degree to which an object is visually noticeable from the viewpoints is quantified as described in Ciftcioglu, Bittermann et al. (2006), Bittermann and Ciftcioglu (2008). This degree is given by a probability. Considering a basic geometric situation as shown in figure 2, for a visual scope $-\pi/4 \leq \theta \leq \pi/4$ the probability density characterizing perception of a plane is shown in figure 2b for $l_o=2$ and given by (1) Bittermann and Ciftcioglu (2008)

$$f(x) = \frac{2}{\pi (l_o + x)} \text{ for } -l_o \leq x \leq l_o$$

Figure 2: Figures taken from Bittermann and Ciftcioglu (2008): Plan view of the basic geometric situation of perception; $P$ represents the position of an observer viewing a plane from a distance $l_o$ (a); plot of the probability density function characterizing perception along x direction for $l_o=2$ (b).

For the purpose of measuring the degree of surveillance of an object in a room, consider the immersive perceptions of an observer via two camera sensors that are denoted as events $S_1$ and $S_2$. The associated probabilities respectively $P(S_1)$ and $P(S_2)$, are obtained by similar computations as given by (2) but for two dimensional space in the plan view or for three dimensional space where $\theta$ becomes solid angle $\Omega$. The scene subject to investigation in this research is shown in figure 3a. It is noted that the events $P(S_1)$ and $P(S_2)$ are not independent,
as they refer the perception of the same object. Therefore the probability of the union of events of perceiving the door space is computed by either 

\[ P(S_1 \cup S_2) = P(S_1) + P(S_2)[1 - P(S_1 \mid S_2)] \]

or alternatively 

\[ P(S_1 \cup S_2) = P(S_2) + P(S_1)[1 - P(S_2 \mid S_1)] . \]

The conditional probabilities \( P(S_1 \mid S_2) \) and \( P(S_2 \mid S_1) \) are shown in figures 3b and 3c as the perception of the white areas indicated by the letter \( B \) respectively. The integration of the probabilistic density function \( f_\theta(\theta) \) along one angle dimension, yielding \( P(S_1) \) and \( P(S_2) \) are shown respectively in figure 3d and 3e.

![Perception analysis via two camera sensors](image)

Figure 3: Perception analysis via two camera sensors \( S_1 \) and \( S_2 \) (a); conditional probabilities for either sensor (b and c); conversion from probabilistic to possibilistic perception (d,e,f)

Figure 3f shows the conversion of the probability of the union of events \( P(S_1 \cup S_2) \) into a possibility. This is done by combining the information coming from two sensors using possibility distribution. From the figure it is noted that \( P(S_1 \cup S_2) \) occupies a certain angle domain, spanning \( \theta_c \) and \( \theta_d \) of probability density function with \( \theta \), which is uniform. The probability density function has a possibilistic density counterpart, namely a triangular possibility density function, seen in figure 3f. It is noted that the possibility density shown in figure 3b is maximum at the place that corresponds to the expected value of the uniform probabilistic density w.r.t. \( \theta \). In an application in the paper, optimal sensor positions will be identified by means of evolutionary search, maximizing the possibility of perception of the door space.

References


