Visual Guidance of Robotic Wheelchair

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Abstract :

Most of the research effort in the visual guidance of autonomous robotic wheelchairs have been devoted to road edge detection. However, less attention has been paid to the after-detection process, especially the physical interpretation of what had been detected. In fact, there is a wide gap between the scene model built based on image processing algorithms and the physical model of the environment where the robotic wheelchair progresses. In this paper, we investigate the interaction between the scene model and the world model, and we propose a visual control scheme for robot guidance that minimizes the model error induced by processing raw image data. The involved control system includes the fuzzy approach at two levels: a fuzzy perception system which detects efficiently the road edges from the perception-domain image, and a fuzzy control system which uses the knowledge base information and the scene model to control the robot motion. On the other hand, the fuzzy control system is finely tuned through feed-backing mean square errors between the scene model parameters and the knowledge-base data. Hence, a road configuration from a preprocessed image is compared with a fuzzy template made from the fuzzy membership function based on the knowledge base module. Finally, the fuzzy controller as tuned is used to home the robot on the planned path. This paper shows the principle of this system and the simulation experiment results confirming the feasibility of the approach.

Keywords: Fuzzy Control, Vision System, Road Edge Detection, Visual Navigation, Robotic wheelchair.

Introduction :

The problem of guiding autonomously a robotic wheelchair in a real environment has attracted many researchers during the last decade [1], [2], [3], [4]. This problem is concerned with the quality of information provided by mounted sensors which are in reality not perfect. In fact, the quality of edge detection is limited by the raw contents of the image and the edge detecting programs processing this image. As a human being, an experimenter knows there is an edge because he is using knowledge in addition to what is contained in the image. How to use such knowledge on the real world in the process of general edge detection is a huge topic that is still under investigation. For example, if the program knows an edge is that of a road and it is likely that it will continue on the other side of a tree branch, then it may have a chance to detect the edge of each and every visible part of a road behind a tree; otherwise, some small and not so obvious pieces of the edge may remain undetected. Consequently, an edge detector may be tailored to take advantage of the domain knowledge. Accordingly, fuzzy logic allows us to take into account the sensor imperfections. On the other hand, using fuzzy measures we can introduce a confidence degree on every source and in between sources. Several techniques of data fusion have been proposed to improve the precision of information often perturbed by additive noise, and to reduce the incoherence rate [5], [6]. Furthermore, the choice of any technique is strongly dependent on the environment, sources of information and real time needs. Under such circumstances, we have previously proposed a modular vision system for outdoor autonomous robotic wheelchair navigation [7]. This system uses a visual servoing in which the control incorporates directly the visual feedback in order to guide the robot by detecting the road edges from the image space. One of the most important module in the system is the knowledge base module which uses the acquired and predicted data to construct a scene model. This model is the main product of the vision system since it reflects the perception of the road edges necessary to a robust and secure guidance. We have noticed experimentally that, relying simply on this model is not sufficient since its derivation was based on an analytical approach. Accordingly, the resulting analytical model involves approximations and simplifications to ensure a solution. Here, we introduce a fuzzy system to control the robot motion by considering the scene model parameters as fuzzy variables. The fuzzy parameters such as membership functions of the involved fuzzy variables are consequently tuned according to the knowledge base information.

VISUAL AND SERVOING SYSTEM :

The main objective of our project is to come up with a robotic wheelchair completely autonomous relying mostly on visual information in an unstructured environment in which conditions vary drastically. One way to solve this is to use a dynamic vision system to ensure the road following, obstacle avoidance or even scene recognition. The basic configuration of the developed visual servoing technique is depicted in figure 1. The approach is specified in terms of regulation in the image frame of the camera. Our application involves the motion control and specifically robotic wheelchair guidance through roadways. This task requires a reliable road edge extraction algorithm which is ensured by the fuzzy perception system. The parameters of the visually perceived features constitute the elements of the state vector which enables to elaborate a fuzzy control model based on the state space representation. This representation is based on the 2D model of both the robot and the perceived scene. It takes into account the visual features of the scene and the modeling of the robotic wheelchair. To realize a servoing technique, the knowledge base establishes a predicted scene model which should be taken as a reference. Hence, $\underline{R}_f$* represents a reference target image to be reached in the image space, $\underline{P}_i$ the perceived information, K the gain vector, $\underline{I}_s$ the system input parameters, and finally $\underline{O}_s$ the outputs characterizing the behavior of the robot.

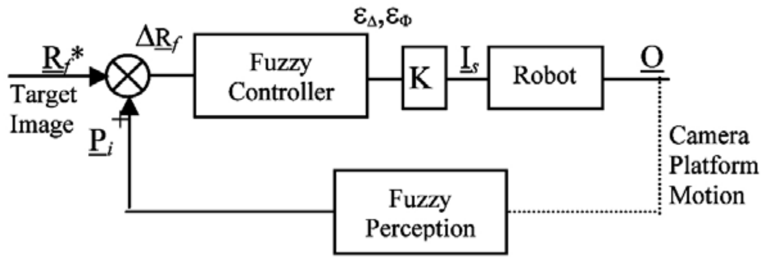

Figure (1) : Visual Servoing System

The fuzzy controller uses as input the mean square errors between the parameters of the perceived scene model and those of the corresponding predicted model. The prediction is performed in collaboration between the scene prediction module, the environment map and the knowledge base [8]. To minimize the matching error, a fine tuning of the fuzzy system through feed-backing the mean square errors is performed. Consequently, the knowledge-based control of the robotic wheelchair motion is considered as a hierarchical process involving road edge perception and guidance along a planned path. Most of the processing time is spent with the fuzzy perception module which is based mostly on image transforms. This module operates in two modes: the initial phase which includes all the processing applied to the first image acquired in order to initiate the navigation, and the continuous following mode which handles the processing of subsequent images taken at the end of each blind distance. This distance is linearly proportional to the total processing time. Moreover, the navigation security increases as the blind distance decreases.

FUZZY EDGE PERCEPTION SYSTEM :

The perception of the road edges constitutes the most essential feature for the autonomous navigation of the robot. The main idea in our approach is to extract the edges from the perception-domain image. This domain is defined by applying a mapping function on the gradient orientation image. The parameters of the mapping function enabled us to enhance and detect the edges having a specific orientation on the image plane. A prior rough knowledge of the road edge orientation makes it easy to detect it even under uneven conditions. In our work [9],[10], the problem of road edge detection is viewed as a phenomenon of perceiving gradient direction levels and then tracing the locus of the vectors which correspond to dominant linear features. We have noticed experimentally that the dominant characteristic of the road edge was its direction since it varies very slowly through the sequence of the input images. Moreover, it is less sensitive to noise than the amplitude of the edge, thus making the fuzzy road edge perception more practical. Accordingly, in order to enhance pixels belonging to the desired intervals of both road edges, we apply a mapping function on the orientation image. This mapping represents a perception of such phenomenon as edge dominance around a predicted direction. Consequently, the detection of the road edges requires a bi-level thresholding around the dominant directions. To determine the thresholds we proceed by measuring the fuzziness of the orientation image using the Yager's measure[11]. Thus; the minimization of this measure enables to determine the appropriate thresholds levels [12], [13]. The detection of the road edges permits the establishment of the scene model $\mathcal{M}_S$ as illustrated by figure 2.

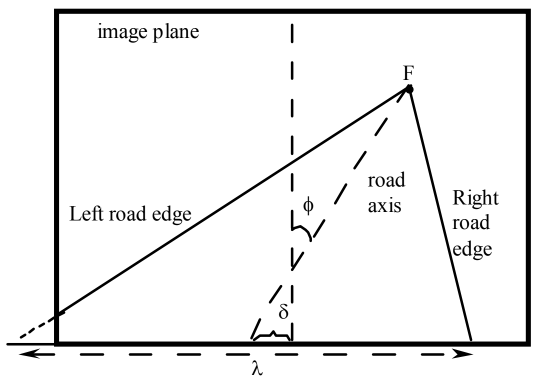

Figure (2) : The Scene Model Parameters.

According to this configuration, we express the theoretical aspects of the scene modeling. The output scene model composed of a right and a left road edge may be described by four parameters $\mathcal{M}_S$ (F,ϕ,δ,λ) as shown figure 2.

The physical parameters Δ and Φ (relative to δ and ϕ of the scene model) necessary to the robot guidance are determined by the vision system and involved with an uncertainty. Consequently, these parameters may be considered as fuzzy variables, and a fuzzy control system is then hooked in the visual servoing system [9].

THE FUZZY CONTROL SYSTEM :

The scene is described by the mathematical model $\mathcal{M}_S$ (F,ϕ,δ,λ). It seems convenient to take care of the fuzzy variables involved in the model through introducing a fuzzy system [6, 11]. A rule base is established by the operator according to a prior knowledge. Nevertheless, the fuzzy parameters such as membership functions of the involved fuzzy variables must be tuned according to the knowledge base information; i.e., predicted data samples. The vanishing point F is defined by its Cartesian coordinates (x_v, y_v). Moreover, fuzziness of variables F, ϕ, δ and λ is expressed by membership functions established by the operator as illustrated by figure 3. The fuzzy system inputs are as follows:

- Inputs 1 and 2 are x and y that specifies F.
- Input 3 and input 5 define the fuzzy variables λ and δ respectively.
- Input 4 stands for angle ϕ. Its universe of discourse is variation $\Delta\phi$ around a central value ϕ_0.

The universes of discourse of x, y, δ, and λ are normalized to 1 in order to accommodate any situation. The fuzzy system is then tuned using data of the knowledge base, according to a gradient descent algorithm scheme. Because of the feed-forward structure of the fuzzy systems, the back-propagation algorithm can be used in the same way as for feed-forward multi-layer neural networks. [3].

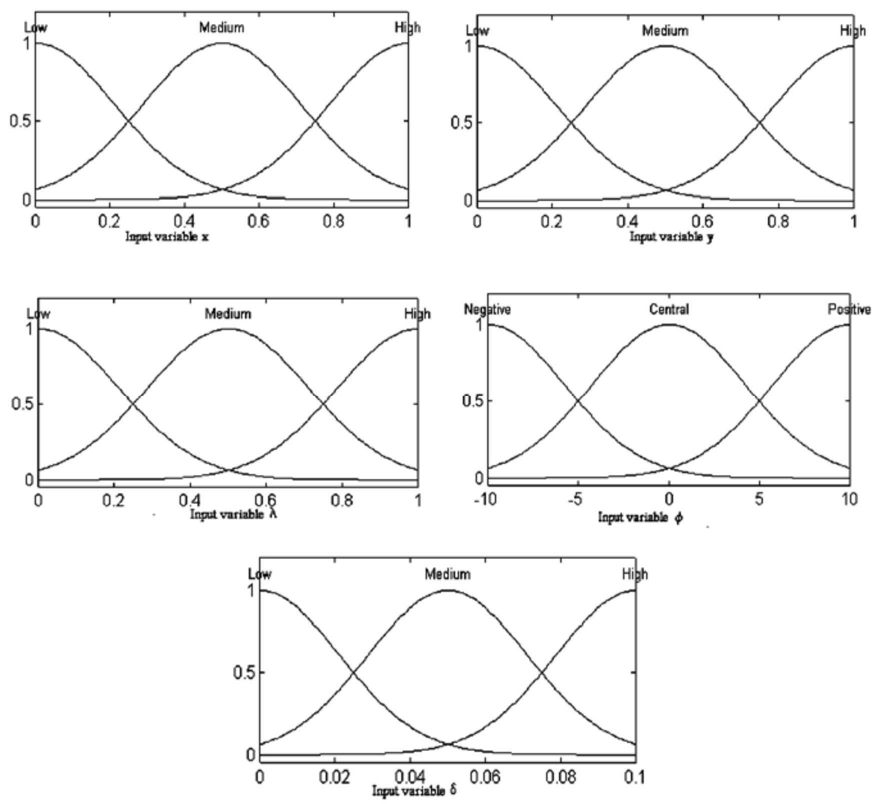

Figure (3) : Membership plots of variables F (x and y), λ, ϕ, and δ respectively

The established rules are expressed by the following form:

R_1: If x_1 is A_1 ... AND x_k is A_k AND..... THEN $y_1 = S_{11}$

R_j: If x_1 is A_m ... AND x_k is A_n AND..... THEN $y_i = S_{ij}$

S_{ij} represents the fuzzy singleton of output i in the j-th rule. Hence, the output is expressed by the following:

$$y_i = \frac{\sum_j \prod_k \mu_{jk}(x_k).S_{ij}}{\sum_j \prod_k \mu_{jk}(x_k)}$$

Where we designate the outputs, the fuzzy rules, and the inputs by the indices i,j, and k, respectively. And $\mu_{jk}(x_k)$ is the membership grade of the input k in the j-th fuzzy rule. To derive the above model, the following fuzzy operations are used:

- The max-product inference scheme is used for evaluating the overall output fuzzy set.
- The output fuzzy sets are distinct singletons.
- The centroid defuzzification scheme is used to produce a single numerical output from the resulting output fuzzy set.

The membership functions are Gaussian functions:

$$\mu_{jk}(x_k) = \exp\left(- \frac{\left| x_k - m_{jk} \right|^2}{2\sigma_{jk}^2} \right)$$

Where m_{jk} and σ_{jk} are the mean and standard deviation, respectively.

The error measure of interest is the sum squared errors between the desired parameter T provided by the knowledge base at any instant, and that produced by the fuzzy system (y) over all the training pairs (Y^p,T^p). This error is given as follows:

$$E = \frac{1}{2}\sum_p \sum_i \left(t_i^p - y_i^p \right)^2$$

Where y_i^p is the i^{th} output generated by the fuzzy system for the p^{th} input.

The back-propagation algorithm is used to adjust the fuzzy system parameters such that the error E is minimized: This is done by the following:

$$\frac{\partial E}{\partial S_{ij}} = \eta_s \frac{\partial E}{\partial y} \cdot \frac{\partial y}{\partial S_{ij}}$$

$$\frac{\partial E}{\partial m_{jk}} = \eta_m \frac{\partial E}{\partial y} \cdot \frac{\partial y}{\partial \mu_{jk}} \cdot \frac{\partial \mu_{jk}}{\partial m_{jk}}$$

$$\frac{\partial E}{\partial \sigma_{jk}} = \eta_\sigma \frac{\partial E}{\partial y} \cdot \frac{\partial y}{\partial \mu_{jk}} \cdot \frac{\partial \mu_{jk}}{\partial \sigma_{jk}}$$

Performing the above partial derivatives, we obtain:

$$\Delta S_{ij} = \eta_s.(t_i - y_i).\Phi_j$$
$$\Delta m_{jk} = \eta_m.\sum_i (t_i - y_i)(S_{ij} - y_i).\Phi_j.\frac{(x_k - m_{jk})}{\sigma_{jk}^2}$$
$$\Delta \sigma_{jk} = \eta_\sigma.\sum_i (t_i - y_i)(S_{ij} - y_i).\Phi_j.\frac{(x_k - m_{jk})^2}{\sigma_{jk}^3}$$

Where: $$\Phi_j = \frac{\prod_k \mu_{jk}(x_k)}{\sum_j \prod_k \mu_{jk}(x_k)}$$

which represents the normalized activation of rule j and η_s , η_m and η_σ denote the learning rates of the respective fuzzy parameters. The determination of the normalized activation Φ_j can be regarded as a procedure for selecting suitable features. The self-tuning architecture of the fuzzy system is given by figure 4.

The predicted model $\mathcal{M}_p$ produced by the knowledge base is used by the geometrical reasoning module in order to obtain a 3-D interpretation necessary to the pilot module. This interpretation reflects the predicted orientation error Φ_p and the predicted shift error Δ_p. On the other hand, the fuzzy perception system provides the measured scene model $\mathcal{M}_s$. The fuzzy systems are constructed and tuned so to match the system model of the knowledge base (predicted) with the system model $\mathcal{M}_s$ (measured). The Fuzzy systems 1 and 2 tune the control variables Φ and Δ by back propagating the mean square errors between $\mathcal{M}_s$ and $\mathcal{M}_p$. The iteration process of the controller halts when the estimated error reaches its minimal acceptable value generally prefixed by the operator.

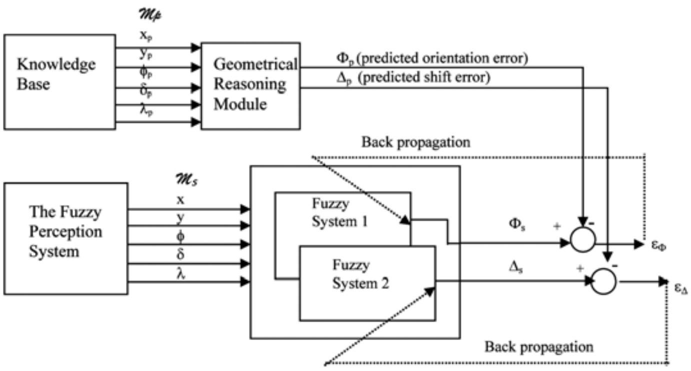

Figure (4) : Tuning schema of the fuzzy system through feed-backing mean square errors ε_Δ and ε_Ψ.

The error variations through the tuning process are shown by figure 5. Up to 100 epochs, the overall fuzzy system is supposed well tuned and ε_Ψ and ε_Δ reach $\varepsilon_{\Psi min}= 2.10^{-3}$ and $\varepsilon_{\Delta min}= 10^{-5}$ respectively. The resulting membership functions after fine tuning using back propagation are illustrated by figure 6.

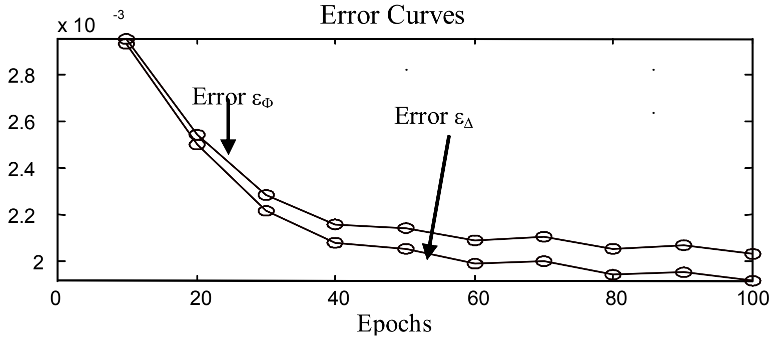

Figure (5) : Tuning process through error curves

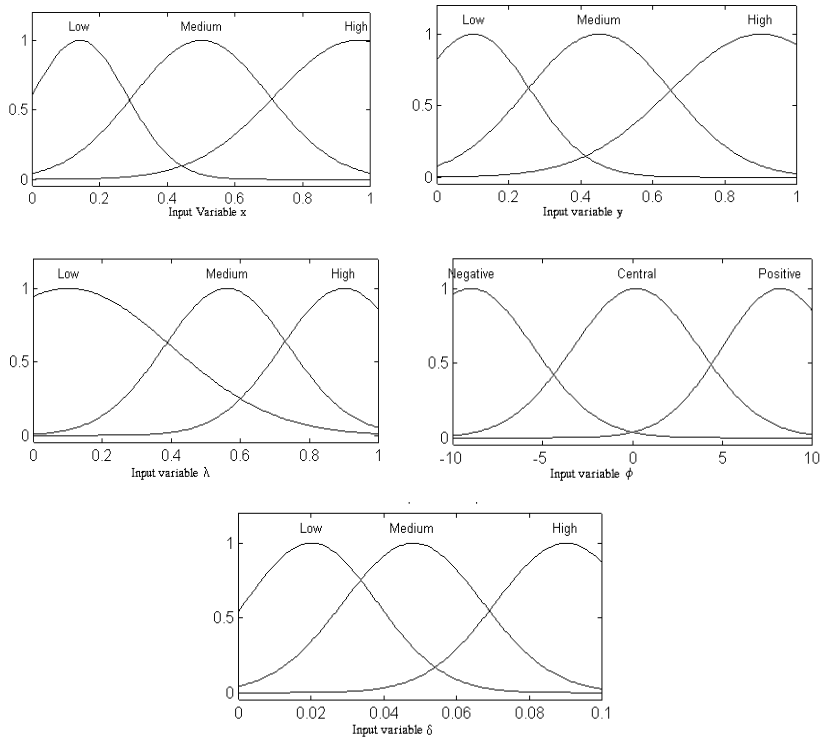

Figure (6) : Membership functions after fine tuning using back-propagation.

This controller is supposed to generate control values Φ and Δ with a high degree of accuracy even in presence of uncertain measured model parameters. The rule base is constructed by the expert (upon a prior knowledge). In general, there are 3^5 possible rules. For illustration, only relevant rules are chosen so to infer output control values Φ and Δ. As shown in figures 7 and 8 for the normalized outputs Δ and Φ respectively. These surface views are very useful especially during the calibration phase since they enable to determine easily the different parameters minimizing the output guidance parameters. One may easily notice from figure 7 that minimizing the parameter Δ would correspond to x=y=0.5 (which corresponds to a vanishing point centered on the image plane) with δ approaching zero. The same conditions would be true for minimizing Φ but with ϕ approaching zero (see figure 8).

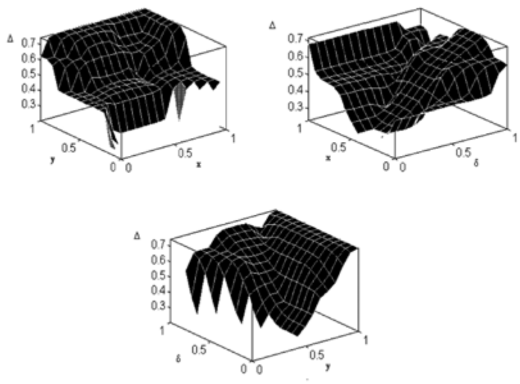

Figure (7) : Some Surface views of normalized output Δ produced by the fuzzy controller.

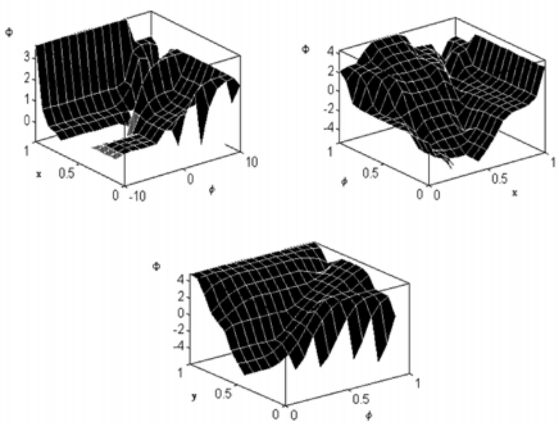

Figure (8) : Some surface views of output Φ produced by the fuzzy controller.

More, with the help of the used data structures and the representation of the membership functions in continuous, we obtain a *O(n)* calculation (with n the number of fuzzy partitions) that fit the sense of the real time objective fixed.

Experimental Results :

In order to evaluate the effectiveness of this approach, a series of 250 images (indoor and outdoor scenes) were tested. These images taken by a CCD camera are 256x256 in size with 256 gray levels. In case no vanishing point F_i is found, the supervisor identifies this situation as a complete failure and asks for a modification of the parameters of the camera-robot configuration. These relations may also be used for the calibration of the camera. Using the Parameters of the robot-camera configuration and considering a set of 8 images describing a real trajectory in the robot environment, the parameters of the scene model $\mathcal{M}_s$ and world model $\mathcal{M}_p$ were given by the fuzzy controller .

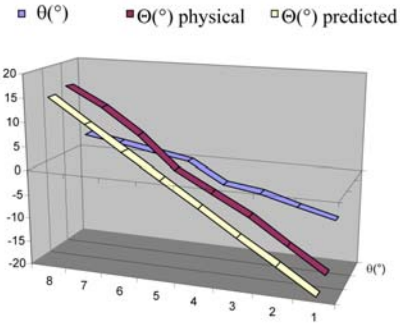

Figure (9) : error estimation on Θ

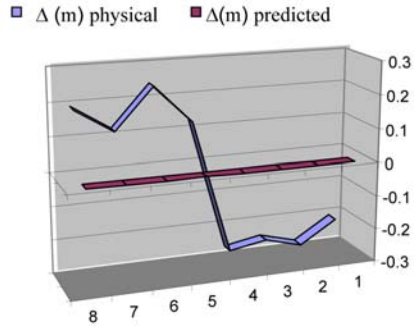

Figure (10) : error estimation on Δ

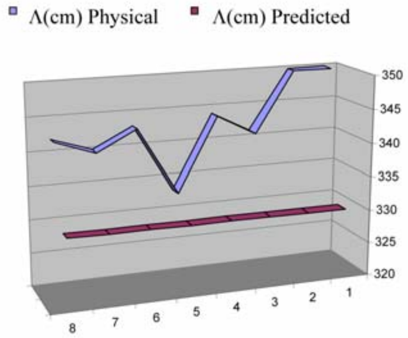

Figure (11): error estimation on Λ

The error on orientation parameter Θ were evaluated to be less than 5.31% as shown on figure 9. Another set of 8 images were chosen were the road axis shift error Δ is predicted to be zero; the fuzzy controller minimizes the error down to 2.7% (see Figure 10). Finally, for the road width Λ Figure 11 shows the results on 8 images where the road width is predicted to be 3.3m, the error on that assumption is about 6.06%.

Conclusion :

In this paper a scheme is proposed for the control of robotic wheelchair motion using visual guidance. The involved control system includes the fuzzy approach at two levels: a fuzzy perception system which detects efficiently the road edges from the perception-domain image, and a fuzzy control system which uses the knowledge base data and the scene model to produce an efficient control model with minimized errors for guiding the robot. The efficiency of the proposed scheme leads to the enhancement of the ability and the adaptability of the robotic wheelchair guidance in real complex environment. This has been show through the encouraging practical results obtained.

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قيادة كرسي آلي بالرؤية الحاسوبية

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الملخص :

إن معظم البحوث التي نشرت في مجال قيادة الكرسي الآلي بالرؤية الحاسوبية ترتكز أهميتها على اكتشاف حافتي المسار. بينما نجد أن قليل من تلك الأعمال تتطرق لما بعد تحديد المسار مثل الترجمة الفيزيائية لما تم اكتشافه من خلال الصورة. في الواقع هناك فرق شاسع بين نموذج الصورة المبني على خوارزميات تحليل الصور و النموذج الفيزيائي لمحيط الذي يتحرك فيه الكرسي الآلي. في هذا البحث تطرقنا إلى التفاعل بين نموذج الصورة و نموذج المحيط، و نقترح نظام تحكم مرئي لقيادة الكرسي الآلي حيث يمكن تخفيض الخطأ الذي يحدث في النموذج المبني على خوارزميات تحليل الصور إلى الحد الأدنى. يحتوي هذا النظام على مبدأ المنطق الضبابي على مستويين: نظام إدراك ضبابي لاكتشاف بطريقة فعالة حافتي المسار من الصورة الطبيعية، و نظام تحكم ضبابي الذي يستخدم قاعدة المعرفة و نموذج الصورة للتحكم في حركة الكرسي. من جانب آخر، نظام التحكم الضبابي يتوافق بطريقة دقيقة مع مردود متوسط مربع الخطأ بين نموذج الصورة و معلومات قاعدة المعرفة. لذلك نقارن هيئة المسار المستنتجة من الصورة مع مجموعة من الهيئات الضبابية المؤلفة من قاعدة المعرفة. أخيرا، يستخدم نظام التحكم الضبابي المتوافق لتوجيه الكرسي الآلي نحو المسار المبرمج. نبين في هذه الورقة مبدأ النظام الضبابي المقترح والنتائج التي تؤكد فعاليته في قيادة الكرسي.