Fuzzy Vergence Control for an Active Binocular Vision System

Nikolaos Kyriakoulis, Antonios Gasteratos
Laboratory of Robotics and Automation,
Department of Production and Management Engineering,
School of Engineering,
Democritus University of Thrace,
University Campus Kimmeria, Greece, Xanthi - 67100
Email: [nkyriako,agaster]@pme.duth.gr

Spyridon G. Mouroutsos
Laboratory of Special Engineering,
Department of Electrical and Computer Engineering,
School of Engineering,
Democritus University of Thrace,
12 Vas. Sofias Str, Greece, Xanthi - 67100
Email: sgmour@ee.duth.gr

***Abstract*—Vergence control in binocular vision systems involves the adjustment of the angle between the two cameras' axes so that they are both fixated at the same point of interest. Vergence enables stereo vision systems to perceive depth and to acquire obstacle maps. Vergence movement is directly related to the binocular fusion. Additionally, the decision for convergence or divergence is extracted either by motion affine models or by mathematical ones. In this paper, a new method for extracting the cameras' movement direction, for verge or diverge, is presented. The movement decision is performed by a fuzzy control system, the inputs of which are the zero-mean normalized cross correlation (ZNCC) and the depth estimations at each time step. The suggested system can be used in any active binocular system and is computationally inexpensive. Moreover, the proposed system is independent to *a priori* camera calibration.**

I. INTRODUCTION

Binocular vision enables human and some animal species, mostly vertebrates, to perceive stereo. Stereopsis results to depth perception and, thus, to a deeper knowledge of the scene. Vergence control supports the above capacity by turning the eyes, so that they both are directed at the same point in the three-dimensional space. Humans possess the medial and lateral recti muscles to rotate their globes so that pair images are projected onto their fovea [1]. In a robot system the cameras play the role of the eyes, servo motors this of the muscles, and the optic sensors correspond to the fovea. A stereoscopic vision system, Fig.1, controls the vergence angle by initially having the target of interest at the image center.

Many techniques have been applied for controlling and calculating the vergence angle. Much effort is given to acquire better stereo correspondence. Stereo matching techniques deal with the problem of stereo correspondence and plenty of them have been realized for the control of the vergence angle. Normalized cross correlation (NCC), zero-mean normalized cross correlation (ZNCC) and sum of absolute differences (SAD) are the popular ones among the block matching methods [2],[3]. In most reported vergence control systems the disparity is extracted by one of the aforementioned similarity measures [4],[5],[6]. Disparity estimation with log-polar images [4] provides better results than with Cartesian ones. In [7] the cortically magnified visual cortex is used to match the entire image. Vergence control can also be achieved using disparity flux [8]. In addition, the responses of energy neurons can be used for vergence control and for disparity estimation [9]. The correct vergence angle can be reached by saccading to the target in the periphery map and subsequently by the cameras to be guided through the visual cortex [10]. Dense disparity estimation provides a deep analysis of the scene and is crucial to real-time operating systems. Dynamic vergence control for direct estimation of the disparity can be achieved with a robust binocular fusion computation [11]. Having acquired a disparity estimation, vital information can be extracted, such as depth, obstacle, and occlusion maps.

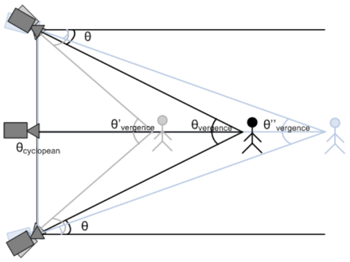


Fig. 1. The vergence angles in a stereoscopic vision system.

In this paper, a new method is apposed for controlling the vergence angle. All previous work has focused mostly on the optimal estimation of the 3D features between the stereo image pairs. We applied the proposed technique on a 4 dof robotic head mounted on a robot for bomb disposal [12]. The presented fuzzy system has two inputs, the similarity and the depth. The similarity method chosen for the vergence control is the zero-mean normalized cross correlation as it has exhibited smoother results and does not require camera calibration [13]. The current vergence angle is read directly on the encoders and the depth is calculated accordingly. The output of the fuzzy system is used as feedback for the vergence control.

II. MATHEMATICAL FORMULATION

A. Similarity Measure

The similarity method has an important role in vergence control. The similarity method should be able to provide accurate measures in low response times. For that purpose, a fusion index technique has been adopted as it exploits the fact that if a target is correctly verged, the stereo images are very similar. The images are binocularly fused, when the disparity between the images is low. The goal of the vergence control system is to maximize the similarity. The index of binocular fusion can be computed using the zero-mean normalized cross correlation (ZNCC) (1).

$$ZNCC = 1 - \frac{\sum (I_r(u,v) - \overline{I_r})(I_l(u,v) - \overline{I_l})}{\sqrt{\sum (I_r(u,v) - \overline{I_r})^2 \sum (I_l(u,v) - \overline{I_l})}^2} \quad (1)$$

where I_r and I_l are the right and left images, respectively. $\overline{I_r}$ and $\overline{I_l}$ represent the mean values of the right and left images, respectively. ZNCC is invariant to the illumination changes and its range is normalized into [0 1]. ZNCC was selected as it has the smoother performance, even in the most difficult scenes. This measure is fast, accurate and robust in environmental changes, as it compasses the correct vergence angle even with extremely low-resolution images, without making any topological rearrangement, such as log-polar mapping.

B. Depth Estimation

Stereo vision systems result to depth perception. The depth is calculated via triangulation of the 3D feature correspondence on the image pair. Moreover, when the camera angles are known, the vergence angle can be calculated geometrically, as well (see Fig.1). The mathematical equations for a symmetrical vergence system are:

$$Z = \frac{b}{2tan\theta} \quad (2)$$

and

$$\theta_{vergence} = 2\theta \quad (3)$$

where Z is the depth of the scene, and b is the baseline of the stereo head. $\theta_{vergence}$ is the vergence angle, while θ is the angle of one of the cameras. The above formulate are only valid for a parallel camera setup, i.e. zero cyclopean angle. An appropriate vergence angle leads to high similarity, i.e. either the stereo cameras are directed to the infinity or to the same object.

III. FUZZY VERGENCE SYSTEM

In Fig.2 the block diagram of the vergence control is illustrated. The control of the camera angles is done by a classic control scheme. The proposed fuzzy system calculates the feedback control signal. The images from the left and right cameras are used for the computation of the ZNCC and the readings of the encoders of the actuators of the camera angles are used for the computation of the depth (Z). Both ZNCC and Z are then fed into the fuzzy system. The output of the system is the amplitude and the sign of the angle applied to the actuators. The design of a fuzzy system is highly depended on the application and the experience of the designer. Therefore, building such a system, relies on previous experience and exhaustive experimentation. This approach was followed also for the proposed system, where five Gaussian membership functions (MFs) are used for both inputs and five trapezoid MFs for the output, as they found to be more appropriate for the desired task. Apart from the type of the MFs, important role to the fuzzy system plays the possible adjustment methods, such as the defuzzification and the aggregation one. In the proposed system the aggregation method was set to sum. Other aggregation methods such as the maximum, the minimum, and the probabilistic OR (probor), were tested, but the sum provided a smoother output value in our tests. The defuzzification method was set to centroid, as it covers the output range more efficiently. The centroid defuzzification method provides the center value between the interacted rules, so in some cases the uttermost values of the output are not fired, reducing so the efficient range. We also assessed other defuzzification methods, namely: bisector, middle of maximum, largest of maximum, and smallest of maximum. The results acquired by the centroid exceeded the ones of the other methods and, thus, the centroid one was selected.

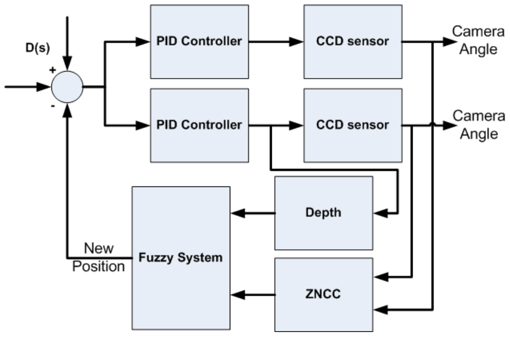


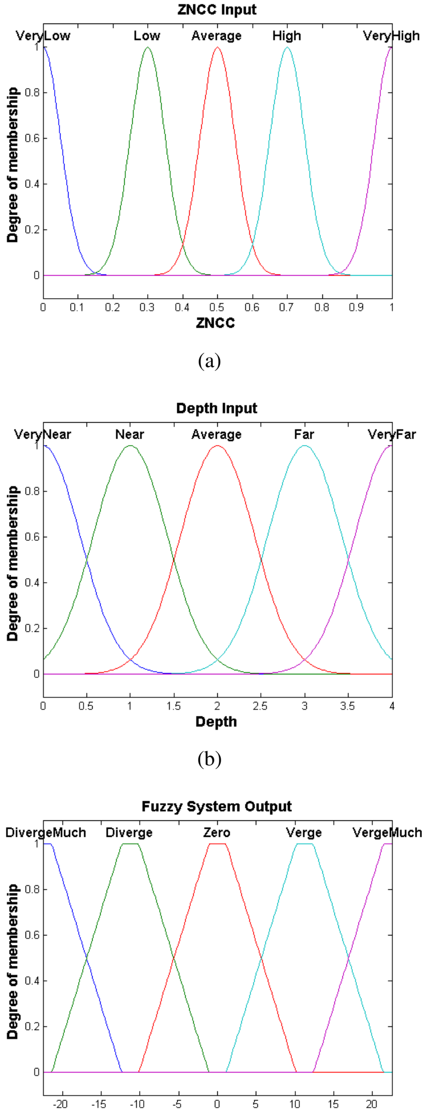
Fig. 2. Block diagram of the vergence system.

Key features to the design of a fuzzy system are the MFs and the rule base. In the fuzzy vergence system, apart from the first input, all MFs are normally distributed to their range. The first input (Fig.3(a)) is the similarity measure (ZNCC). The odd distribution of the MFs of the first input aims at distinguishing between the cases with a very high and a very low ZNCC. In the first cases, the system remains to the current state or makes small movements around the highest similarity point. On the other hand, in the cases with very low similarity the system covers big distances until it reaches a point with higher similarity. Three MFs are close to each other at the middle point, as the ZNCC in most cases varies in that range. By having a denser distribution of the MFs in that range, we have increased the system's efficiency. The second input (Fig.3(b)) is the depth and is set to be [0 4] meters, due to the nature of the application in hand. The output range was set to [-22.5 22.5] degrees. The minus sign implies the vergence while the plus sign the divergence movement. The membership functions are displayed in Fig.3 and the rules interaction is shown in Table I.

TABLE I
RULE BASE FOR THE FUZZY KALMAN SYSTEM

		ZNCC				
		Very Low	**Low**	**Average**	**High**	**Very High**
Depth	**Very Near**	DM	DM	D	D	Z
	Near	DM	D	D	D	Z
	Average	DM	D	D	Z	Z
	Far	VM	V	V	V	Z
	Very Far	VM	VM	V	V	Z

** DM=Diverge Much, D=Diverge, Z=Zero, V=Verge, VM=Verge Much*



(a)

(b)

(c)

Fig. 3. Membership functions of the fuzzy vergence system for (a) input 1, (b) input 2 and (c) output.

IV. EXPERIMENTAL RESULTS

The vergence control requires image processing, which possesses a high computational burden and demands the usage of certain instruction sets of a modern microprocessor. On the other hand, actuator control requires the operation system to be able to execute real-time tasks. This demand for high performance and real-time control has forced us to adopt a computer structure which meets the requirements for low latency. The interfaces used are CAN bus for the controllers and USB 2.0 for the cameras. In order to fully utilize the advantages and precision of the modern digital servo drives a tuning process for PID controllers was carried out, so that they could move the cameras simultaneously. The experimental setup, where the proposed vergence algorithm was assessed is the 4 dof robotic head shown in Fig.4.

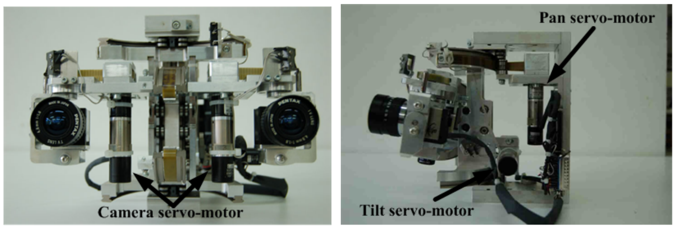
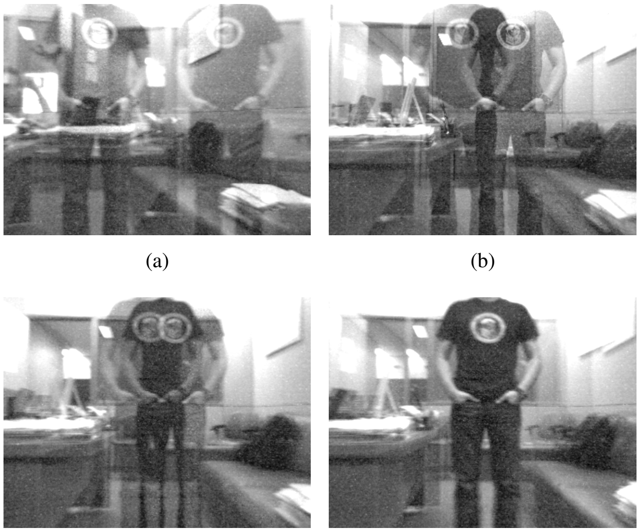


Fig. 4. The robotic head used for vergence control.

In order to evaluate the performance of the system we ran several tests. The tests include different vergence experiments. In every time step the ZNCC along with the depth were estimated. Extracting the vergence angle and the depth from the encoders, a new angle was exported by our fuzzy system, which was read by the PID controllers and finally it was reached by the servo motors. The new vergence angle was read from the motors' encoders and the new ZNCC was calculated. The process continues recursively as described above. The processing time of the fuzzy system in every time step is about 1.5 msec for a Pentium 4 PC, running at 1.8GHz. This capacity of fast processing enables it to operate in real-time. In the first experiment a human was put in a fixed position during the whole process. The distance from the robotic head was set randomly and as close to the cyclopean axis as possible. In the second experiment, some objects were put in front of the robotic head to a randomly selected position near to the cyclopean axis. In the last experiment a more difficult scene was selected, i.e. there were not a specific target for the stereo vision system and the system should aim to the infinity without any obstacle intruding directly into the field of view. In all experiments the system started from a random symmetrical vergence configuration and operated until the correct vergence one to be achieved. There was a restriction to the servo motors for not diverging further than the zero angle point. In case of violating the aforementioned restriction the system was programmed to return to its initial position. In the presented experiments the images are non rectified ones. Notwithstanding, the correct vergence angle was approximated after 4-5 iterations of the system. The visual results of the



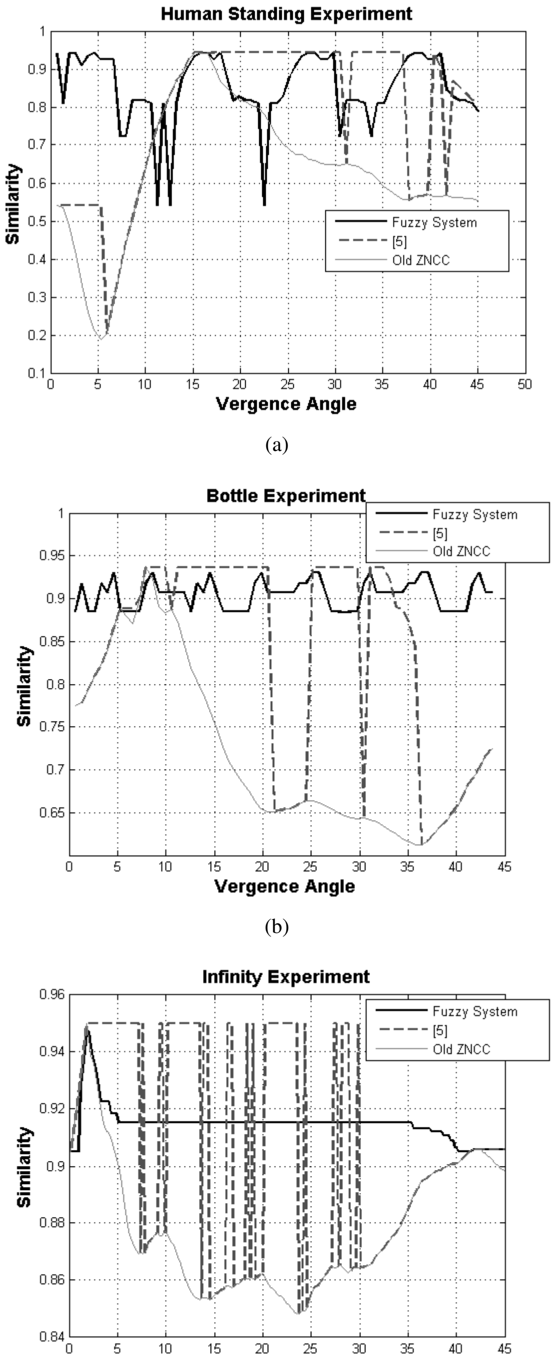
(a) (b)

(c) (d)

Fig. 5. The first measurement at the first vergence angle (a) and the consequent measurements at the respective vergence angles (b), (c), and (d).

fuzzy vergence system are demonstrated in Fig.5.

For further evaluating and examining the fuzzy vergence system, every measurement was stored. Thus, all the experiments are evaluated not only by their visual results, but also by the record of the actuators' encoders, concerning the maximization of the similarity and the time intervals needed. The acquired results of our system were compared with a known and used technique for controlling the vergence angle presented in [5]. The decision of verging or diverging is taken by examining the relation between the current and the previous correlation index values. The comparative results are shown in Fig.6. At the *x* axis lie the Vergence angle measurements, while their respective similarity ones lie at the *y* axis. The bold lines correspond to the fuzzy system's steady state output, while the dashed ones to the steady state output of the technique presented in [5]. The thin lines represent the computed similarity values at each time step before any correction has taken place. For demonstration reasons, the go-between ZNCC values are not illustrated, but only the final ones. Thus, for a vergence angle with an initial respective ZNCC, the diagrams in Fig.6 represent the final state achieved. From Table I, one can see that when a high ZNCC value is achieved, the system stands still. This is the reason of not reaching the highest possible similarity value. For example, in the Infinity experiment Fig.6(c), which had cluttered environment, and suffered from noise and occluded scenery, although the ZNCC values are quite high, the system responded accurately (the ZNCC is very high, about 0.92).



(a)

(b)

(c)

Fig. 6. The new ZNCC values acquired from the fuzzy system (bold lines) in relation with the old (thin lines) and with the [5] ones (dashed lines) for the examined situations.

The demonstrated results of all the experiments can be further improved by filtering the noise and by storing all history positions. In any new measurement a control will be made, with the form of a third input, whether the current or the old angle has higher similarity. Thus, the system will not reach a position with low similarity twice, but instead it will go to a higher similarity angle, reducing the iterations and the time intervals needed.

V. CONCLUSION

A new vergence control, which uses a fuzzy system, is proposed. The fuzzy system decides whether to converge or diverge, depending on the given similarity and depth.

The results show that the vergence direction was achieved during the whole process, while the amplitude of the exported vergence angle was the one which had provided the maximum similarity. In the cases where the opposite occurs is due to the restriction mentioned and to non rectified images. The fuzzy system responded efficiently to all the experiments, considering the noise involved to the image processing. Its fast response renders it appropriate for real-time operation. To conclude fuzzy systems are a promising vergence control method due to their low response times and the high efficiency.

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