CAMERA PLACEMENT FOR NETWORK DESIGN IN VISION METROLOGY BASED ON FUZZY INFERENCE SYSTEM !

M. Saadat-Seresht[a,*], F. Samdzadegan[a], A. Azizi[a], M. Hahn[b]

[a]Dept. of Surveying and Geomatics, Faculty of Engineering, University of Tehran, Tehran, Iran – (samadz-aazizi@ut.ac.ir, mostofi_n@yahoo.com

[b]Dept. of Geomatics, Computer Science and Mathematics, Stuttgart University of Applied Sciences, Stuttgart, Germany - michael.hahn@hft-stuttgart.de

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ABSTRACT

For measuring complex industrial objects using vision metrology systems, automatic optimum network design is a real challenge. In the absence of given or simulated 3D CAD models of the objects and the workspace, the complexity of objects introduces several uncertainty factors into the camera placement decision making process. These uncertainty factors include the vision constraints such as visibility, accessibility and camera-object distance.

For more complex objects, visibility is vastly influenced by hidden areas, the incidence angle of a target and the camera orientation. Mutual dependency of these factors increases the difficulty of camera placement. Further these factors directly influence the mensuration quality, in particular, precision and reliability. If an a priori 3D CAD model of the object is available, the aforementioned ambiguities can be tackled. However, a 3D model is often not available which makes the camera placement problem a nondeterministic process. An answer to this problem is to develop a fuzzy logic inference approach for camera placement and network design. The idea is to deal with the vision constraints in a fuzzy manner.

In this paper a novel method based on fuzzy logic reasoning strategy is proposed for the camera placement. The system is designed to make use of human type reasoning strategy by incorporating appropriate rules.The paper reports on the results achieved by testing the fuzzy based camera placement approach on simulated and real objects. The results indicate that this new conceptual approach has a remarkable strength for automatic sensor placement in vision metrology.

1. INTRODUCTION

Close range photogrammetry or vision metrology has demonstrated its capability as a precise measurement technique for 3D object acquisition with lots of applications (Atkinson, 1998; Fraser, 2001; Ganci and Handley, 1989). Users appreciate vision metrology as a technique with high flexibility, considerable accuracy, relatively low cost, and a high level of automation compared to other optical and mechanical methods. Automation in vision metrology systems has shown fast progress, e.g. regarding efficient self-calibration models, exterior orientation devices, coded target measurements, image matching algorithms and others (Hattori et al., 2002). So far less attention is paid to automatic network design which should be a first step in various vision metrology projects.

This paper focuses on intelligent network design based on fuzzy inference systems (FIS) and proposes a concept for automated camera placement. Many researchers in both fields of photogrammetry (e.g. Mason, 1995; Fritsch and Crosilla, 1990; Olague and Mohr, 1998) and machine vision (e.g. Sakane et al., 1992; Cowan and Kovesi, 1988) have carried out investigations on network design or sensor (camera) placement. Our aim is deriving accurate coordinates of some object points by a network of multi-image convergent camera stations. In contrast to Olague and Mohr (1998) and Mason (1995) we aim at a strategy of local improvement rather than looking for a global network design. We not expect that a 3D simulated model is available. Most unique for this research is that for the first time fuzzy inference in introduced for camera placement.

Figure 1 illustrates the concept of the proposed network design process. A primary or draft network design can be performed by users maybe even in the field. The output of this first step is a network with, for example, ten or more images. These images may allow to measures a high quota, e.g. of 95% of object points with good quality but for the remaining this is not guaranteed. The loop in Figure 1 indicates the iterations which

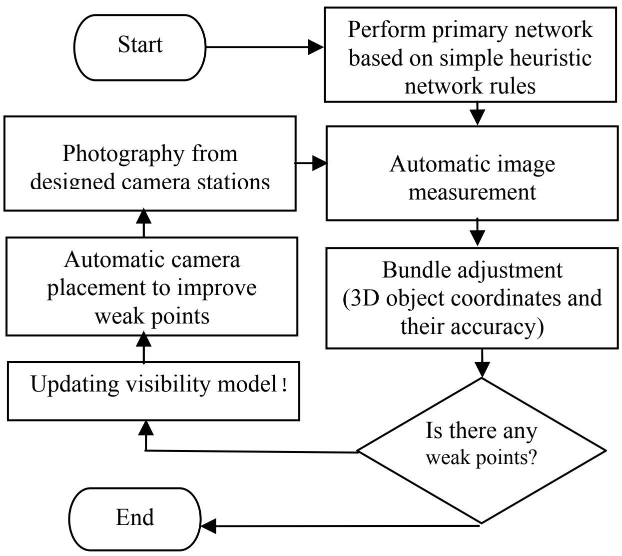

Figure 1. Proposed network design process

have to be carried out to make sure that all points can be measured with satisfying quality. Each iteration includes an update of the visibility model of object points followed by camera placement using the fuzzy inference system based on the updated visibility model.

2. MODELING VISION CONSTRAINTS

Sensor placement in computer vision (Cowan and Kovesi, 1988) has to deal with satisfying some vision constraints as well as with optimization of accuracy and cost criteria (Fraser, 1984). To prepare for fuzzy modelling of vision constraints in our approach, vision constraints are divided into three classes (Figure 2).

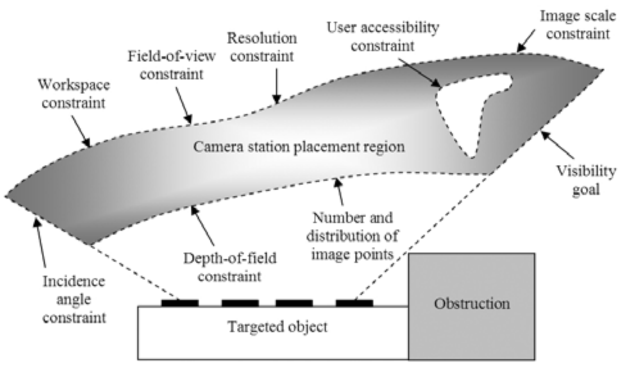

Figure 2. Vision constraints for camera placement (motivated by the work of Mason (1995))

Range Related Constraints are a class of constraints which limit the distance between object points and camera stations including image resolution, image scale, field of view, and workspace upper limits, depth of field and number and distribution of image points for the lower limit.

Visibility Related Constraints: The visibility of an object point from a camera station is a complex interrelated matter that depends on radiometric and geometric constraints. Radiometric constraints with constant "point to image quality" are easily satisfied in presence of retro-reflective targets and special flashing equipment. Geometric constraints include an incidence angle constraint, workspace obstructions, camera field of view, and position and situation of the camera station (Figure 3).

Accessibility Related Constraints depend on camera position accessibility, the workspace constraint, and object and obstructions inside. In addition to positional accessibility of camera, time accessibility is might have to be taken into account.

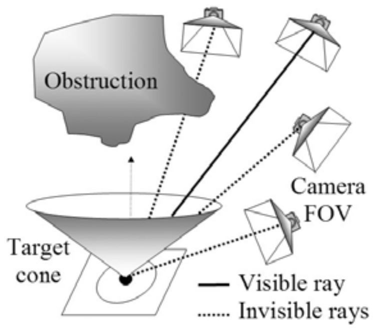

Figure 3. Visibility is a function of the target cone, camera FOV, and hidden areas

As already mentioned, a given or simulated model of the object and workspace is not assumed. Based on a high number of images of object and workspace in the primary network taken from different directions, target visibility is predictable by studying the corresponding image point observations and camera accessibility is predictable taking closeness to existing camera stations into account.

2.1 Visibility Prediction Modelling (VPM)

VPM concept is based on two principals: 1) Visibility of each direction toward a point is constant and does not depend on distance. 2) Visibility of a direction is the same as the visibility of its immediate vicinity directions for a point. The first principal causes to simplify the modelling by defining a visibility prediction sphere (VPS) and second principal is a basic for predicting hidden area in unknown directions by using known directions.

As illustrated in Figure 3, modelling of target visibility can be done by sequentially. This implies considering the effects of the camera field of view, target incidence angle, and hidden area constraints on the visibility of all rays between the target and related camera stations. In our modelling a fuzzy visibility index v between 0 (perfectly invisible) and 1 (perfectly visible) is assigned to each ray. A corresponding visualisation is shown in Figure 4.

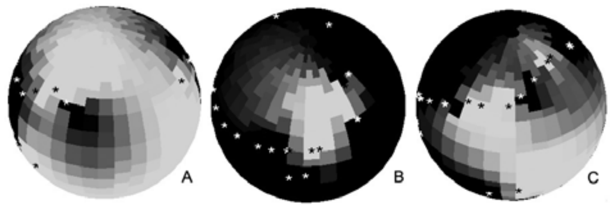

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Figure 4. Three examples of visibility prediction on VPS. The black and white stars are visible and invisible rays correspondingly which predict visible (bright) and invisible (dark) areas.

2.2 Accessibility Prediction Modelling (APM)

Briefly, APM concept is based on closeness to the positions of existing camera stations. In other words, a point closer to these positions probably has a higher accessibility. A proper way to model this concept is using analytical function like as Butterworth function which is a low pass frequency filter in signal processing (Gonzalez, 1993). In Equation 1, D_0 is the accessible vicinity radius around existing camera stations. n is the fuzzy behaviour factor that controls the width of fuzzy boundary between accessible and unknown transit areas. Usually n is less than 4 especially when camera stations are far from each other. D_0 is specified depending on object and workspace conditions and is usually about half of the average density of camera positions.

$$W = \frac{1}{1 + (\frac{D_{\min}}{D_0})^{2n}} \tag{1}$$

As a general rule, in the open workspaces with low obstructions a high value for D_0 and a low value for n are proper. Notably, a bad setting of these parameters leads to have a very unreal large or small accessible area definition. In the next section we briefly describe a fuzzy inference system for camera placement which aims at satisfying the accuracy of a weak points as well as vision constraints in an optimal way.

3. FUZZY INFERENCE SYSTEM (FIS) FOR CAMERA PLACEMENT

Since there are several interrelated vision constraints and most of them are highly uncertain, the camera placement is a subject that fits well to the ideas of fuzzy inference systems (FIS). It is noted that the efficiency of the FIS method depends significantly on properly formulated rules and their parameters (MATLAB, 2001).

Figure 5 shows the flowchart of the developed FIS for camera placement. Input and output of the FIS are normalized values. Input is a vector of constraint indicators and of distance and the output includes distance variation, rotation variation, a descriptor for enforcing camera position towards closest existing camera stations to satisfy accessibility constraints and another descriptor for enforcing camera situation toward the most effective direction for improving precision. Both descriptors are applied to the camera position and situation before the next iteration us carried out. To select an optimum estimate, the iteratively found estimates are evaluated with a criterion based on accuracy and constraints violation. The process leads to an optimal and stable state for camera placement after a significant number of iteration.

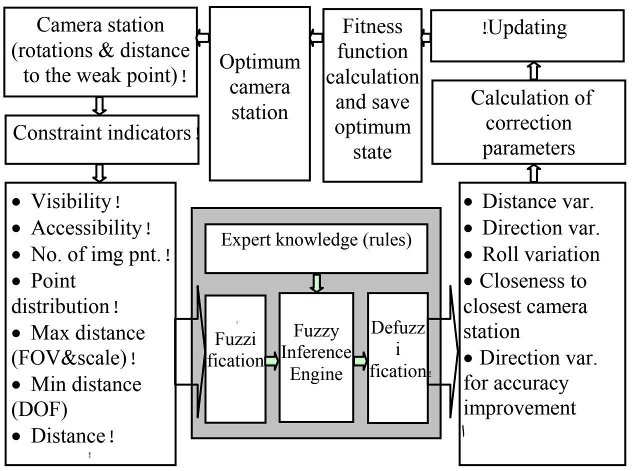

Figure 5: Camera placement flowchart by fuzzy inference system

4. EVALUATION OF PROPOSED METHOD

The presented concepts and algorithms are implemented in MATLAB code. For the experiments an ancient church illustrated in Figure 6 is selected. Excavations and restoration for this church are almost finished as can be seen in Figure 6. The object has a fairly complex shape with hidden areas. It rises from a deep pit and photographs had to be taken either from outside or the bottom of the pit. These conditions restrict modelling of the target visibility and camera accessibility. The photographs are taken with a DCS420 digital camera under incident solar radiation. The Vision Metrology software Australis (Fraser, 1999) was used for point measurement, but due to low quality of images most measurement had to eb carried out manually. Figure 6 shows a sample of the network comprising 215 object points and 57 images. The accuracy fulfilment for the above network through camera placement using 3D CAD model was not prosecuted. Instead out FIS based method for placing optimal camera stations without 3D CAD model requirement was tested.

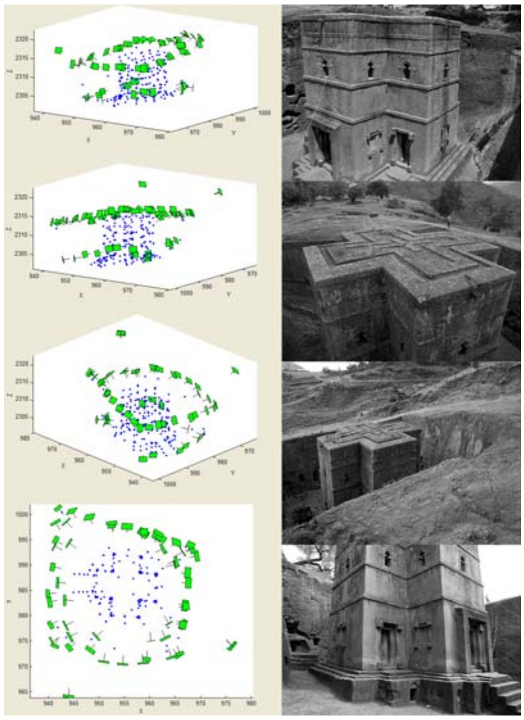

Figure 6: Object (ancient church) and photogrammetric network with several points of view

4.1 System Building and Adjusting

Since the proposed method is based on two main stages including constraint modelling and camera placement, at the first step the 3D coordinates of object points and their precision as well as exterior orientation of camera stations including camera self calibration is carried out with the Australis software. The second step was VPS determination for each object point to predict the visibility of every direction toward each object point (Figure 7.Up). To model the camera accessibility, we considered the parameters Do=5m and no=0.5 (Figure 7.Down).

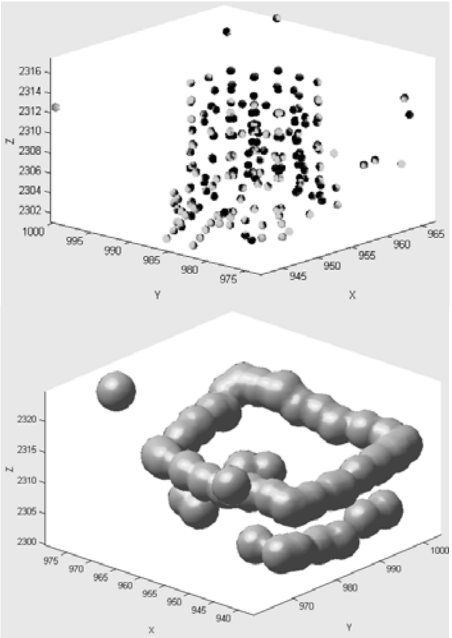

Figure 7: Up is VPS as target visibility model in which bright area of each sphere is the visible directions. Down is model of fuzzy accessible area for camera positions

In the second main stage it builds, adjusts and examines a fuzzy inference system including 14 fuzzy rules with equal weights, 8 inputs and 5 outputs implemented by using the fuzzy toolbox of MATLAB. The normalized membership functions of input and output parameters of FIS are provided using the trial and error method in order to place camera optimally and efficiently. To do this, the effect of each input parameter on all output parameters is studied through their rules and membership functions. The fuzzy operator setting in the FIS is as following: 'min' for fuzzy AND, 'max' for fuzzy OR, 'min' for implication, 'sum' for aggregation, and 'centroid' for defuzzification.

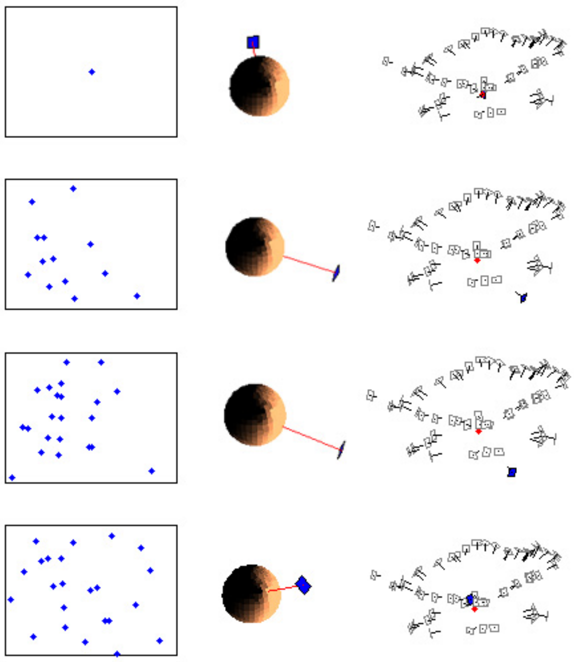

Figure 8: four states of camera placement optimization by proposed FIS

4.2 System Experiment

The FIS is utilized to optimally design a camera station around a weak point. To optimize our design, it is necessary to define a fitness function in the design process (Figure 7) in order to compare states and select the best one with highest fitness function value. To define an optimization criterion, a fitness function F (0<F<1) is computed as relation 1 in which *d, p, v, a, m,* and *u* are constraints of distribution and number of image points, visibility, accessibility, their average, and accuracy enhancement factor respectively. All these parameters are normalized to the range between zero and one.

$$F = \frac{w \times m + u}{w + 1} \qquad m = \frac{d + p + v + a}{4} \qquad (Ć)$$

w is the weight parameter which balances the attention to constraint satisfaction versus accuracy enhancement and equal with the number of unsatisfied constraints plus one. At first that usually any constraint is satisfied, $w = 5$ so the attention to satisfy all constraints is five times more than accuracy enhancement. When FIS satisfies constraints one by one, the attention is gradually decreased till FIS satisfies all constraints e.g. $w = 1$. It means accuracy enhancement and constraint satisfaction has same importance for FIS and if accuracy has been enhanced significantly, it is enough to stop the loop and consider the last state as the optimal final answer. To find weather a constraint has been satisfied, it should be defined a satisfaction threshold for each one. Satisfaction threshold is the difficulty or importance level of satisfying constraint. In our tests, we set thresholds 0.6, 0.6, 0.7, and 0.6 for *d, p, v,* and *a* correspondingly.

To study the optimization process, Figure 8 illustrates the four states of camera placement. Left column shows the progress of satisfying the number and distribution of image points into camera format border. The visibility constraint that is satisfied through above iterations is illustrated in middle column. Right column displays the position and situation of designed camera station which moves toward existing camera stations to satisfy accessibility constraint.

5. CONCLUSIONS

Based on the assumption that no simulated 3D model of object and workspace is available a fuzzy based camera placement concept is proposed using vision constraints. Incidence angle, visibility and accessibility constraints are introduced in a fuzzy inference system due to their high level of uncertainty. The developed fuzzy inference system (FIS) automatically designs a multi image convergent photogrammetric network based on the fuzzy model of vision constraints. The fuzzy rules of our FIS control three parameters of distance, direction and rotation. This method optimizes the camera station in cases of a high conflict among vision constraints and accuracy. Experimental investigations are carried out to examine our FIS with a real world example. Steps of camera placement by our FIS are discussed in the paper and illustrate the FIS process and results. The results demonstrate the efficiency and capability of our fuzzy inference system in camera placement.

The presented new ideas on photogrammetric network design can be further developed by extending the 4D search space (3 rotations and distance) of the FIS to a more comprehensive FIS based on rules in 6D search space with 3 degrees of rotation and 3 degrees for the position.

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