

CALIBRATION OF A DIGITAL SINGLE LENS REFLEX (SLR) CAMERA USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT:

The use of non-metric digital cameras in close-range photogrammetric applications and machine vision has become a popular research agenda. Being an essential component of photogrammetric evaluation, camera calibration is a crucial stage for non-metric cameras. Therefore, accurate camera calibration and orientation procedures have become prerequisites for the extraction of precise and reliable 3D metric information from images. The lack of accurate inner orientation parameters can lead to unreliable results in the photogrammetric process. A camera can be well defined with its principal distance, principal point offset and lens distortion parameters. Different camera models have been formulated and used in close-range photogrammetry, but generally sensor orientation and calibration is performed with a perspective geometrical model by means of the bundle adjustment. In this study, a feed-forward network structure, learning the characteristics of the training data through the backpropagation learning algorithm, is employed to model the distortions measured for the Olympus E-510 SLR camera system that are later used in the geometric calibration process. It is intended to introduce an alternative process to be used at photogrammetric calibration stage. Experimental results for SLR camera with two focal length setting (14 and 42 mm) were estimated using standard calibration and neural network techniques. The modeling process with ANNs is described and the results are quantitatively analyzed. Results show the robustness of the ANN approach in this particular modeling problem and confirm its value as an alternative to conventional techniques.

1. INTRODUCTION

Last decade has witnessed an extensive use of digital non-metric SLR cameras for use in low cost applications in archaeology, architecture, cultural heritage and others. Increase in image resolution, the dropping prices, present facilities in storing/transferring images files and easy direct image acquisition (without digitizing films or paper prints) are the main reasons increasing the use of these instruments. Also, the use of low cost digital photogrammetric systems, such as Photo Modeler and 3D Mapper has contributed to the use of these "off the shelf" cameras among photogrammetrists and non photogrammetrists (Cardenal et. al., 2004).

Digital cameras have been widely used for close range photogrammetry and machine vision applications. For any photogrammetric application, the accuracy of the derived object data is mainly dependent on the accuracy of the camera calibration, amongst many other factors.

Camera calibration has always been an essential component of photogrammetric measurement, with self-calibration nowadays being an integral and routinely applied operation within photogrammetric triangulation, especially in high-accuracy close-range measurement. With the very rapid growth in adoption of off-the-shelf digital cameras for a host of new 3D measurement applications, however, there are many situations where the geometry of the image network will not support

robust recovery of camera parameters via on-the-job calibration. For this reason, stand-alone camera calibration has again emerged as an important issue in close-range photogrammetry, and it also remains a topic of research interest in computer vision (Remondino and Fraser, 2006).

A camera is considered calibrated if the principal distance, principal point offset and lens distortion parameters are known. In many applications, especially in computer vision (CV), only the focal length is recovered while for precise photogrammetric measurements all the calibration parameters are generally employed. Various algorithms for camera calibration have been reported over the years in the photogrammetry and CV literature. The algorithms are generally based on perspective or projective camera models, with the most popular approach being the well-known self calibrating bundle adjustment, which was first introduced to close-range photogrammetry in the early 1970s.

In the past decade, the artificial neural network approach, theoretically a sophisticated and robust method of pattern recognition and modeling, has been employed in many applications in diverse areas. It is generally agreed that artificial neural networks (ANNs) produce results with higher accuracies from fewer training samples (Hepner et al. 1990; Paola 1994; Foody 1995). An important characteristic of ANNs is their non-parametric nature, which assumes no a priori knowledge, particularly of the frequency distribution of the data. Because of

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their adaptability and their ability to produce high accurate result, their use has spread in the scientific community. ANNs have been successfully employed in many fields for solving complex modeling, prediction and simulation problems that are often represented by noisy and missing data. Neural networks have been used in a variety of studies in photogrammetry field (e.g. Lilienblum et al., 1996; Basri and Heipke, 2003; Civicioglu and Besdok, 2006).

This paper overviews the current and ANN approaches adopted for camera calibration in close-range photogrammetry, and discusses operational aspects for calibration. Also, the results of camera calibrations using two different algorithms are examined and discussed. Experimental results for SLR camera with two different lenses derived from the two calibration method, including an assessment of the effect and repeatability of the distortion variation, are presented and the effectiveness of the techniques is quantitatively analyzed.

2. PHOTOGRAMMETRIC CAMERA CALIBRATION

Different camera models have been formulated and used in close-range photogrammetry, but generally sensor orientation and calibration is performed with a perspective geometrical model by means of the bundle adjustment (Brown, 1971). A review of methods and models of the last 50 years is provided in Clarke & Fryer (1998). The basic mathematical model is provided by the non-linear collinearity equations, usually extended by correction terms (i.e. additional parameters or APs) for interior orientation (IO) and radial and decentering lens distortion (Fraser, 1997; Gruen & Beyer, 2001). The bundle adjustment provides a simultaneous determination of all system parameters along with estimates of the precision and reliability of the extracted calibration parameters. Also, correlations between the IO and exterior orientation (EO) parameters, and the object point coordinates, along with their determinability, can be quantified. A favorable network geometry is required, i.e. convergent and rotated images of a preferably 3D object should be acquired, with well distributed points throughout the image format. If the network is geometrically weak, correlations may lead to instabilities in the least-squares estimation. The use of inappropriate APs can also weaken the bundle adjustment solution, leading to over-parameterization, in particular in the case of minimally constrained adjustments (Fraser, 1982).

The self-calibrating bundle adjustment can be performed with or without object space constraints, which are usually in the form of known control points. A minimal constraint to define the network datum is always required, though this can be through implicit means such as inner constraint, free-network adjustment, or through an explicit minimal control point configuration (arbitrary or real). Calibration using a testfield is possible, though one of the merits of the self-calibrating bundle adjustment is that it does not require provision of any control point information. Recovery of calibration parameters from a single image (and a 3D testfield) is also possible via the collinearity model, though this spatial resection with APs is not widely adopted due to both the requirement for an accurate testfield and the lower accuracy calibration provided.

One of the traditional impediments to wider application of the self-calibrating bundle adjustment outside the photogrammetry community has been the perception that the computation of initial parameter approximations for the iterative least-squares solution is somehow 'difficult'. This is certainly no longer the

case, and in many respects was never the case. As will be referred to later, self-calibration via the bundle adjustment can be a fully automatic process requiring nothing more than images recorded in a suitable multi-station geometry, an initial guess of the focal length (and it can be a guess), and image identifiable coded targets which form the object point array.

2.1. The Additional Parameters (APs)

The most common set of APs employed to compensate for systematic errors in CCD cameras is the 8-term 'physical' model originally formulated by Brown (1971). This comprises interior orientation (IO) parameters of principal distance and principal point offset (x_p, y_p), as well as the three coefficients of radial and two of decentering distortion. The model can be extended by two further parameters to account for affinity and shear within the image plane, but such terms are rarely if ever significant in modern digital cameras. Numerous investigations of different sets of APs have been performed over the years (e.g. Abraham & Hau, 1997), yet this model still holds up as the optimal formulation for digital camera calibration.

The three APs used to model radial distortion Δr are generally expressed by the odd-order polynomial $\Delta r = K_1 r^3 + K_2 r^5 + K_3 r^7$, where r is the radial distance. The coefficients K_i are usually highly correlated, with most of the error signal generally being represented by the cubic term $K_1 r^3$. The K_2 and K_3 terms are typically included for photogrammetric (low distortion) and wide-angle lenses, and in higher-accuracy vision metrology applications. The commonly encountered third-order barrel distortion seen in consumer-grade lenses is accounted for by K_1 . (Fraser & Al-Ajlouni, 2006).

Decentering distortion is due to a lack of centering of lens elements along the optical axis. The decentering distortion parameters P_1 and P_2 (Brown 1971) are invariably coupled with x_p and y_p . Decentering distortion is usually an order of magnitude or more less than radial distortion and it also varies with focus, but to a much less extent. The projective coupling between P_1 and P_2 and the principal point offsets increases with increasing focal length and can be problematic for long focal length lenses. The extent of coupling can be diminished through both use of a 3D object point array and the adoption of higher convergence angles for the images.

3. MATHEMATICAL MODEL

The work with non-metric digital cameras for photogrammetric purposes is accompanied by the following problems:

- Defining the image co-ordinate system (non-metric cameras do not have fiducial marks).
- Defining the unknown elements of internal orientation (focal length and image co-ordinates of the principle point of the photograph).
- Maintaining the elements of internal orientation unchanged in time - usually when working with non-metric cameras, the elements of internal orientation get slightly changed after every single exposure.
- Defining the distortion of lens - the distortion with amateur cameras often amounts to considerable values and have substantial effect.

There are three basically different methods for solving the above mentioned problems known. These are laboratory

calibration (calibration in advance), calibration during processing, and self calibration methods. The first one was used in this study.

In accordance with the co-linearity condition, every object point, its image and the projection centre, should belong to one and same line, called ray. Mathematically this can be represented by means of the following three equations:

$$\begin{bmatrix} x_i \\ y_i \\ 0 \end{bmatrix} - \begin{bmatrix} x_0 \\ y_0 \\ f \end{bmatrix} = \lambda_i R \left\{ \begin{bmatrix} X_i \\ Y_i \\ Z_i \end{bmatrix} - \begin{bmatrix} X_0 \\ Y_0 \\ Z_0 \end{bmatrix} \right\} \quad (1)$$

where: $i = 1, 2, \dots, n$

- n : the number of measured image points,
- $(x_i, y_i, 0)^T$: image co-ordinates of point i ,
- $(x_0, y_0, f)^T$: the elements of internal orientation,
- λ_i : the scale factor,
- R : the rotation matrix, defining the spatial rotation of the geodetic coordinate system in relation to the image co-ordinate system. R is function of the three angles ω, φ, κ ,
- $(X_i, Y_i, Z_i)^T$: the geodetic co-ordinates of point i ,
- $(X_0, Y_0, Z_0)^T$: the geodetic co-ordinates of projection centre O .

It is not justifiable to render different scale factor for each i point. The scale factor could be eliminated by dividing the first and second equations from the system by the third one:

$$\begin{aligned} F_x &= x_i - x_0 + f \frac{m_{11}(X_i - X_0) + m_{12}(Y_i - Y_0) + m_{13}(Z_i - Z_0)}{m_{31}(X_i - X_0) + m_{32}(Y_i - Y_0) + m_{33}(Z_i - Z_0)} = 0 \\ F_y &= y_i - y_0 + f \frac{m_{21}(X_i - X_0) + m_{22}(Y_i - Y_0) + m_{23}(Z_i - Z_0)}{m_{31}(X_i - X_0) + m_{32}(Y_i - Y_0) + m_{33}(Z_i - Z_0)} = 0 \end{aligned} \quad (2)$$

where; m_{ij} terms are the elements of R matrix.

$$R = \begin{bmatrix} m_{11} & m_{12} & m_{13} \\ m_{21} & m_{22} & m_{23} \\ m_{31} & m_{32} & m_{33} \end{bmatrix} \quad (3)$$

A system of kind (2) could be composed for each measured image point i . This means that if the object is photographed by one stereo-pair, each point from the object would originate two systems of kind (2) or in total 4 equations, since each point is appeared on two photographs.

3.1. Additional Parameters in Mathematical Model

Lens distortions, as well as some other possible defects of the camera, are origin for systematic errors in image co-ordinates, because the images get drawn away from correct central projection. One of the conditions of the least squares adjustment is that the adjusted quantities should not contain systematic errors. With amateur cameras, as distinct to professional cameras, these defects may have significant values and hence may considerably disturb the processing.

If the lens distortion is known, the image co-ordinates may be adjusted before the bundle adjustment. This process is known as image refining. Even in case of some distortion, the refining is ineffective, because with non-metric cameras it gets changed in time. It is more effective for the image defects to be reduced by introduction of additional parameters into the mathematical instrument:

$$\begin{aligned} x - x_0 + \Delta x_p &= -f \frac{m_{11}(X_i - X_0) + m_{12}(Y_i - Y_0) + m_{13}(Z_i - Z_0)}{m_{31}(X_i - X_0) + m_{32}(Y_i - Y_0) + m_{33}(Z_i - Z_0)} \\ y - y_0 + \Delta y_p &= -f \frac{m_{21}(X_i - X_0) + m_{22}(Y_i - Y_0) + m_{23}(Z_i - Z_0)}{m_{31}(X_i - X_0) + m_{32}(Y_i - Y_0) + m_{33}(Z_i - Z_0)} \end{aligned} \quad (4)$$

where the additional parameters Δx_p and Δy_p are function of some unknowns and take part in adjustment together with the rest of unknowns.

4. CAMERA AND IMAGE ACQUISITION

The Olympus E510 digital SLR camera contains a 10 megapixel CCD sensor (3648×2736 pixel with approximately 5 μm pixel spacing) with a format size of 18.25 mm×13.7 mm. The camera system has two different lenses (14-42 mm and 40-150 mm).

In this study, in order to metric calibration of the digital camera a planar calibration testfield (Figure 1), which is a plate with regular grids, has been used. It has 144 circular coded targets on it. Four of these targets were used as control points. Using the calibration grid, 6 images were taken for each focal distance setting. In other words, 12 images were totally taken for two different lenses, including the ideal geometric conditions and network geometry.

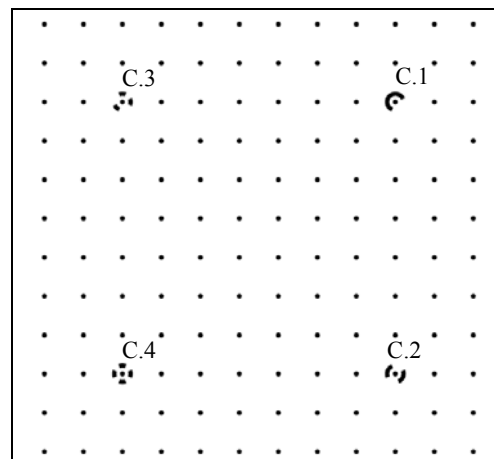


Figure 1. Calibration grid used in this study

A comparison between different methods was carried out using a grid and 12 images acquired with Olympus digital camera at an image resolution of 3648×2736 pixels. In all cases, the target images were automatically measured by intensity-weighted centroids (Trinder, 1989) using the PhotoModeler software by EOS system.

5. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANNs) are computational models that attempt to imitate the function of the human brain and the biological neural system. They are considered as heuristic algorithms, in that they can learn from experience through samples and subsequently applied to recognize new data. The robustness of ANNs rests on their ability to generalize and classify noisy or incomplete data. They also do not make any assumptions about the frequency distribution of the data. ANNs can also provide superior results for limited data compared to the conventional methods (Blamire, 1996; Foody, 1995). Artificial neural networks learn the characteristics of the training data typically in an iterative way by taking every single data into consideration; therefore, they are viewed as data-dependent models (Kavzoglu, 2001). Despite their significant advantages, they have the main drawback of having a poorly interpretable nature. Therefore, they are often called black-box methods.

Although various types of neural network models have been developed, the majority of applications in the literature have used the multi-layer perceptron (MLP) model trained with the back-propagation algorithm. The basic element of ANNs is the processing node that corresponds to the neuron of the human brain. Each processing node receives and sums a set of input values, and passes this sum through an activation function providing the output value of the node. The structure of MLP includes three types of layers: input, output and hidden layers (Figure 2). All inter-node connections have associated weights, which are usually randomized at the beginning of the training. When a value passes through an inter-connection, it is multiplied by the weight associated with that inter-connection.

The backpropagation learning, the most popular learning algorithm, is based on an iterative gradient decent strategy. After weight initialization, outputs are estimated for the input data presented to the network and then the difference (i.e. error) is estimated. New weights are calculated in a way that the error is minimized. The whole process is repeated until a user defined criterion is achieved.

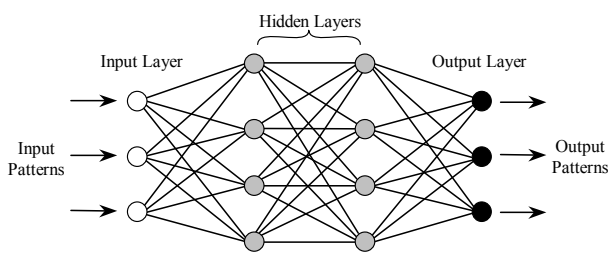


Figure 2. Generic structure of a MLP network

The use of ANNs is somehow complicated, due to problems encountered in their design and application. From the design perspective, the specification of the number and size of the hidden layer(s) is critical for the network’s capability to learn and generalize. A further difficulty in the use of MLPs is the choice of appropriate values for network parameters that have a major influence on the performance of the learning algorithm. It is often the case that a number of experiments are required to determine optimum parameter values. Therefore, a trial-and-error strategy is frequently employed to determine appropriate values for these parameters. It should be noted that all experiments were carried out considering the guidelines

suggested by (Kavzoglu and Mather, 2003) for designing the network structure and setting up the learning parameters.

6. RESULTS AND DISCUSSIONS

Two calibration processes were applied for selected lenses with 14 and 42 mm, determining the additional parameters. The calibration of the Olympus E510 digital camera was performed using Photomodeler (version 5) self calibration module, using several images of a plane grid supplied with the software. The results of calibration with 14 and 42 mm lenses are shown in Figures 3 and 4. In addition to this, 3D co-ordinates of the coded targets were calculated using conventional photogrammetric approach.

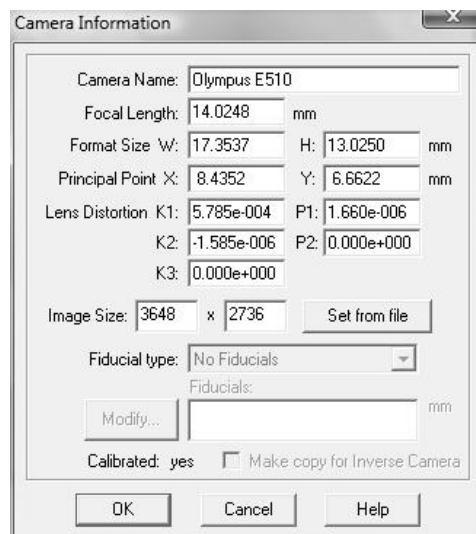


Figure 3. Calibration information for 14mm lens

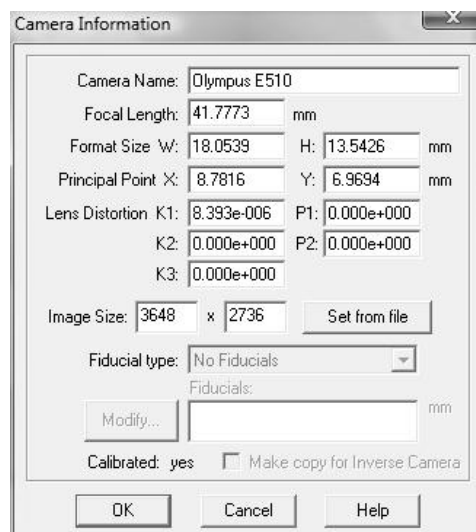


Figure 4. Calibration information for 42mm lens

Bundle adjustment with additional parameters was applied for 14 and 42mm focal distances using Photomodeler software. Then, the distortions were calculated for x- and y-coordinate directions for both settings that are shown in Figures 5 and 6.

Note that the estimated distortions were shown as vectors with a scale factor.

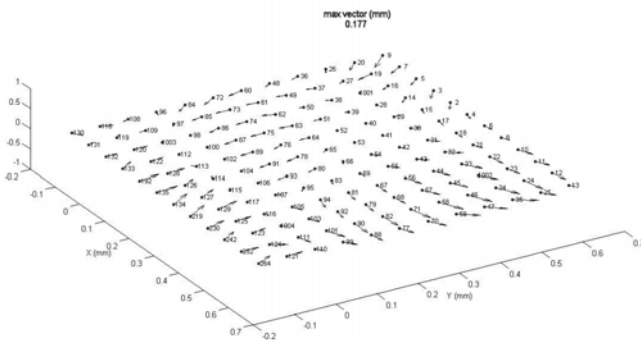


Figure 5. Distortions as 2D vectors estimated for 14mm lens

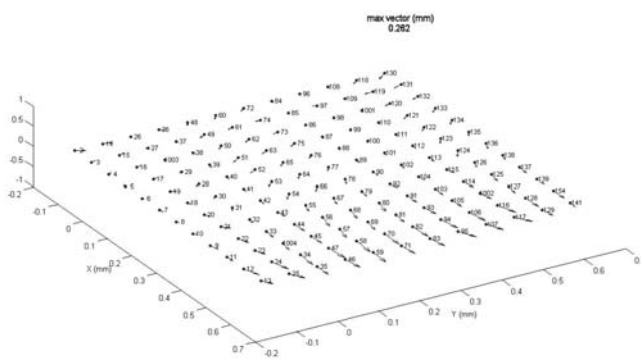


Figure 6. Distortions as 2D vectors estimated for 42mm lens

In the second stage of this study, distortions estimated through the bundle adjustment with additional parameters were taught to a MLP neural network using backpropagation with momentum learning algorithm. After several trials, it is decided that a single hidden layer with 10 neurons (or nodes) would be sufficient to learn the distortion characteristics of the camera. Distortions for the two focal distances were introduced to two separate networks with the same structure (2-10-2 where 2 shows the number of inputs, 10 shows the number of hidden layer nodes and the latter 2 indicates the outputs). 50 well-distributed control points on the grid were selected for training, 24 for validation and 70 for testing the network's performance. In the learning process, distortions of selected 50 points were introduced to the network and the process was stopped when the error on the validation set started to rise significantly.

Whilst the momentum was set to 0.6 throughout the learning, learning rate was systematically reduced from 0.3 to 0.05 to reach the global minimum in the error surface. Trained networks were tested on how well they learn the distortion surfaces in x- and y-directions. Distortion differences were estimated at each point and statistically analyzed (Table 1). It is clear from the figure the network trained for 42mm lens produced better results compared to those for 14mm lens. This could be easily derived from standard deviation and R-square values estimated for the distortions. It should be noted that the values presented in the table are in millimeter level.

Assuming that the distortions estimated through bundle adjustment with 6 images of the grid are the real distortions,

differences were estimated to determine the neural network performances. Differences were depicted on Figures 7 and 8. Further analyses show that the networks in fact create trend surfaces representing the complicated distortion surface. These surfaces are more complicated than a two or three-dimensional polynomial surfaces. Standard deviations estimated for network performances were about 30 micron that can be overall regarded as a successful modeling for complicated distortion surfaces.

Criteria	14mm		42mm	
	x	y	x	y
Minimum	-0.060	-0.072	-0.072	-0.061
Maximum	0.080	0.061	0.063	0.060
Standard Dev.	0.027	0.030	0.024	0.027
R-square	0.777	0.770	0.890	0.854

Table 1. Analysis of the performance of neural net learning for 14mm and 42mm lenses

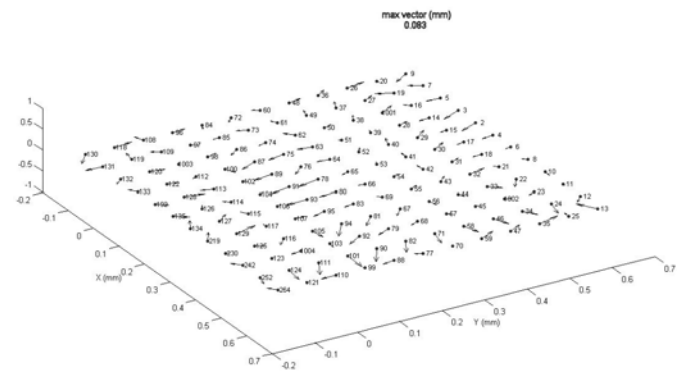


Figure 7. Distortion differences as 2D vectors showing the performance of the neural network trained for 14mm lens

Trained networks can be considered a distortion surface for the lenses and distortion for any required point on the grid can be easily estimated. Thus, a correction term estimated from the trained networks can be added to image coordinate estimations. Instead of a simple polynomial formulation, which has been a traditional way for representing distortions, a more complex representation of the distortion for any camera can be achieved with neural networks.

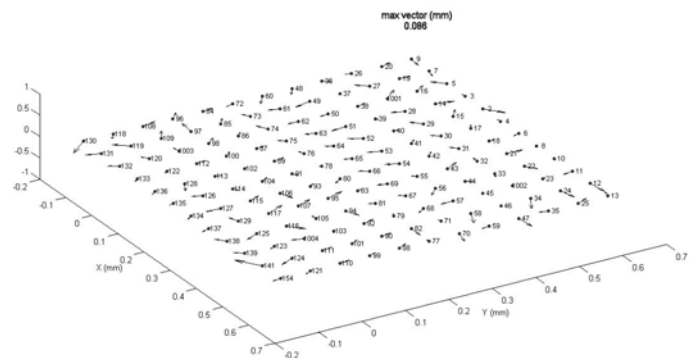


Figure 8. Distortion differences as 2D vectors showing the performance of the neural network trained for 42mm lens

7. CONCLUSIONS

With recent developments and achievements in digital photography and technology, digital cameras have become popular and used for variety of purposes. Calibration of these cameras has become an important issue and a research agenda in the scientific community. Camera calibration is regarded as an essential step in photogrammetric 3-D object restitution. Calibration parameters including focal length, principal point location and lens distortion are usually determined by a self-calibrating approach. In fact, calibration parameters are estimated by a bundle adjustment with additional parameters based on the collinearity equations, simultaneously with the object reconstruction. In the calibration of non-metric cameras, accurate determination of optical distortions due to lens (i.e. radial and tangential lens distortions) is of vital importance.

Low degree polynomials have been conventionally used to model the distortions, particularly for radial lens distortion. The use of polynomials can give inferior results for some particular cases and camera types. In this study, artificial neural networks, specifically a multi-layer perceptron, is suggested to model the distortions existing for an Olympus E510 digital SLR camera. The distortions estimated through bundle adjustment with additional parameters were used as inputs to neural networks. After training the networks with some intelligent approaches, network performance tested both graphically and statistically. Results show that distortions can be modeled with standard deviation of less than 30 micron. It is noticed that the trained networks are in fact complex trend surfaces formed by weights of the interconnections in the network.

Results produced in this study confirm the value of neural networks in this particular modeling problem (i.e. distortion modeling for a non-metric digital camera). Camera calibration is only one subject area in photogrammetry that neural network approach can be an alternative. They can be also employed in various photogrammetric applications.

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