# Implementation and testing the pose computation 

## (POSCOM) SYSTEM

## by

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## Abstract

This thesis describes the research part contributing to pose computation for accurate part positioning and reliable camera based robot workcell calibration. The pose computation technique presented here involves (1) the detection and recognition of artificial targets placed on the robot end-effector, on the fixture, and around the robot workspace; and (2) the computation of the camera pose (position and orientation) with respect to the targets using stereo triangulation. The artificial targets used for pose computation are designed for simplicity and distinctiveness so that they can be easily detected and used for pose computation. The major contribution of this technique is the use of passive vision with simple but distinctive targets for fast pose computation. Unlike many other pose computation techniques, this is based on detecting simple and unique targets. The process of target preparation and detection is described along with the formulation of stereo triangulation and pose computation. Results of target detection and stereo pose computation are also presented.

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## 1. INTRODUCTION

### 1.1 General Overview

Industrial robots have been successfully employed in industry to perform a variety of tasks from welding and spray painting to material handling. However they have limited to applications which do not require very accurate robot positioning and compliant motion. Robot calibration and accurate positioning of the robot end-effector and parts within its workspace are required to allow successful execution of high accuracy robot tasks. Hence, robot and workpiece information is required, so that inaccuracies, disturbances and variations in part size (or dimensions) and position and robot kinematics (and possibly robot dynamics) can be determined and accounted for. The pose information needed for robot calibration can be obtained using many alternatives, ranging from the simple three-point-touch technique for calibration to 3-D vision sensing. In the recent years, a variety of low-cost vision sensors have appeared. With the recent advances in computer technology (in terms of increasing computing speed and expanding memory sizes) as well as the advances in solid-state technology (in terms of enhanced sensitivity and resolution and improved signal-to-noise ratios), it is becoming technically and commercially possible to use these sensors in industrial applications that require accurate and reliable 3-D measurements. It is believed that efficient algorithms need to be developed to make effective use of these sensors and to enrich the industrial robot with the required intelligence to significantly improve their performance.

### 1.2 Research statement and motivation

This project presents the research part contributing to the development of a sensor-integrated robotic system for automotive-body-in-white assembly using simple and low-cost off-the-shelf) vision sensors.

The pose computation technique measures the camera pose with respect to artificial targets fixed at specific locations around the robot workspace and also fixed on the end-effector and programmable fixture. The objective is to use these targets to achieve fast and accurate pose measurements. The artificial targets are designed for ease of detection and simplicity of the pose computation. Target detection is based not only on the geometry of the targets, but also on the invariance of the reflectance ratio boundaries of the targets. This technique promises to yield fast and simple target detection, simple formulation for stereo triangulation and accurate pose measurements, as will be described below in full detail.

### 1.3 Thesis Outline

This thesis is divided into 6 chapters and two appendixes. This chapter provides a general overview of the current work, motivations, research objectives, and the thesis outline.

Chapter 2 starts with a brief description of the camera pose computation, and presents a literature review of pose computation and stereo vision, along with the possible combination of the two.

In Chapter 3 an overview of the pose computation system and its possible application to robot cell calibration is described. The chapter starts with presenting a general configuration of the robot cell and artificial targets, and continues by describing the different levels of pose computation and workcell calibration among the different robotic cell components.

The process of designing and detecting artificial targets is presented in Chapter 4. After a brief description of targets, along with their design criteria, the algorithms for detecting these features are presented along with experimental results from testing of the feature detection technique.

Chapter 5, titled "Stereo vision geometric calibration", basically presents ways of creating a calibration of the stereo vision system and describes the stereo matching of image pairs in order to get the location ( $x, y$ and $z$ coordinate) and orientation of target.

Chapter 6 summarizes the work and gives its main conclusions and recommendations for future research.

## 2. LITERATURE SURVEY

### 2.1 Vision for 3-D Measurements

In vision based robot calibration, pose computation is a crucial step for determining the camera pose with respect to a known inertial frame, and the pose of the robot end-effector with respect to the camera or another reference frame. Pose computation is also very important in positioning parts and objects so that the execution of tasks such as assembly or welding can be carried out with the required speed and accuracy. On the other hand, range sensing has become a vital tool to various robotic applications requiring accurate and reliable 3-D measurements. Since it is proposed to employ stereo vision for pose computation, a literature review of both topics is presented along with the possible combination of stereo ranging and pose computation.

### 2.2 Stereo Ranging

Range sensing deals with the measurement of the distance from a reference point to objects in the scene [Jarvis, 1993]. Stereo vision is one of the most prominent ranging methods, and it is most promising and practical due to its potentially high speed and high accuracy levels. The main purpose of stereo vision analysis is to recover range (depth) information of objects in a three-dimensional (3-D) scene based on an image pair taken from two distinct views. In stereo vision, depth information is obtained from triangulation of corresponding points in the stereo image pair. Significant research has
been done on stereo vision, and new stereo vision systems are still appearing [Marshall, 1992; Ross, 1993]. Further, new applications are emerging which range from automatic inspection [Marshall, 1992] and autonomous navigation of mobile robots [Bien, 1991; Kriegman, 1989], robot calibration [Bennett, 1991; Zhuang, 1991] to robot controlling system [Lantos, 1997]. The advantage of using stereo vision in industrial applications is availability, affordability and high performance of today's CCD video cameras, in addition to the ever increasing and improving computer technology in terms of speed, memory sizes and software development.

Stereo matching (correspondence between the stereo images) is a key step in stereo vision analysis. There exist two general types of stereo matching: intensity based or area-based matching [Hannah, 1989; Luo, 1995] and feature-based matching [Li, 1994; Tubaro, 1992; Venkateswar, 1995]. Feature-based stereo matching is a practical method where the speed and reliability of range finding in stereo vision depends to a great extent on the speed of feature extraction and that of establishing correspondence between the image features. The features used in the matching procedure often consist of points [Bien, 1991], edges and line segments [Brint, 1990; Marapane 1990], combinations of points and edges [Goldgof, 1992; Lee, 1994], or a hierarchy consisting of lines, vertices, edges and/or surfaces [Venkateswar, 1995]. However, although these local features are usually sparsely and irregularly distributed over the images but result in accurate depth measurement. In contrast, brightness-based processing is global and results in dense disparity maps, but such maps are difficult to achieve, particularly in passive systems. However, the features considered in most stereo vision systems and feature recognition systems are often local, very plain, and highly invariant, but not very
distinct, making the correspondence task quite challenging. Hence, new techniques have recently appeared that combine both intensity- and feature-based matching [Cochran, 1992]. Others have attempted to incorporate luminance characteristics in feature-based matching [Tubaro, 1992] to integrate shape from shading techniques [Cryer, 1993] or to use disparity map along epipolar lines [Fielding, 1997]. Other advanced techniques have also appeared to solve the feature -based matching problem, by using the paradigm of prediction and verification of hypotheses [Bensrhair, 1991] or by employing relational features and searching relational graphs [Li, 1994; Parlaktuna, 1994]. Recently, a Bayaesian estimation technique was developed [Scharstein, 1998] that outperforms the techniques based on area-based matching and also the use of matching probability and compatibility coeficients for stereo matching is presented [Do, 1998].

### 2.3 Pose Computation

Pose computation may be regarded as determining the transformation matrix (involving three rotations and three translations) between the sensor(s) and a scene coordinate frames, given a set of corresponding image and object features and the intrinsic properties and parameters of the imaging devices (e.g. CCD cameras). The corresponding features represent the 3-D scene or object information (data relative to a known reference frame) and the image information (e.g. 2-D projective data obtained from intensity images or 3-D range data).

Most research described in the literature on pose computation has focused on solving the inverse perspective projection problem using monocular vision, where the
image data consist of features such as lines and points extracted from intensity images. The inverse projection tries to obtain 3-D information from 2-D image features by applying inverse perspective transformation on these image features back to 3-D space. Significant work was reported on solving this problem with applications to object or target localization in monocular vision [Ferri, 1993; Haralick, 1989; Liu, 1990; Jacobs, 1997]. Relatively little work was done on solving the pose estimation and computation problem from range data in 3-D vision.

One major challenge associated with the inverse projection problem is establishing the correspondence between 3-D scene features and their projected image features. Generally, researchers assume that the environment is confined, and the recognition of objects of interest is complete, and the correspondences between image features and object/scene features have been obtained. However, that is not the case when dealing with a real scene or manufacturing environment. Therefore, special targets, which are more distinct than points and lines, have been used to facilitate this correspondence problem. What follows is a description of the inverse projection problem and its solution using simple features such as points and lines. The pose computation problem using specialized artificial targets will also be discussed.

### 2.3.1 Pose Computation by Inverse Projection and Using SImple Primitives

As described earlier, most research work on pose computation has focused on solving the inverse projection problem, where the image (projected) data consist of
brightness features obtained from intensity images. Kanade, [1981] solved analytically the inverse orthographic projection problem. The orthographic projection is a sufficiently close approximation to the perspective projection in cases when the depth of the viewed object(s) is much smaller than the distance from the camera lens (i.e. the imaged surfaces are almost parallel to the image plane). However, human and camera vision can be more correctly and accurately model using the perspective projections, thus more emphasis was placed on solving the inverse perspective projection (IPP) problem.

Many different techniques have been developed for solving the pose computation problem. Many techniques attempted to find a finite number of solutions using a minimum number of point features or straight-line segments. Haralick, [1989] derived a variety of relations that govern the perspective projection using various geometric features such as points, lines and angles extracted from brightness images. Huttenlocher and UlIman, [1990] showed that the three-point had a simple solution for orthographic projections. Fischler and Bolies, [1981] showed that there might be as many as four solutions if three corresponding points were used and that solving the IPP problem required in general six point correspondences. They also proposed an analytic formulation for a unique solution using four coplanar points. An analytic solution was also proposed by Horaud, [1989] for four non-coplanar points. Similarly, Horaud, [1987] proposed analytic procedures for solving the IPP problem using three non-coplanar lines and later also Horaud, [1997] presents in detail an iterative paraperspective pose computation method for both non-coplanar and coplanar points. Dhome, [1989] gave a method for determining all the solutions using three arbitrary lines, and Sumi, [1997] proposed a new method to recognize 3D objects using segment-based stereo vision.

In many other cases, all available corresponding features, which are more than the required minimum, are used to solve the IPP problem using some optimization techniques. Roberts, [1965] proposed a classic solution in a model-based context using a minimum square-error technique for finding the transformation between the model points and the observed image points. Similarly, [Lowe, 1987; 1991] presented an elegant leastsquares technique (requiring up to six pairs of image and model points) to iteratively solve for the viewpoint and object parameters from point-to-point and line-to-line correspondences. Haralick, [1989] classified the pose estimation problem into four different estimation problems from corresponding point data. They presented closedform least-squares solutions to the over-constrained 2-D-2-D and 3-D-3-D pose estimation problems, they also gave a globally convergent iterative technique for the 2-D perspective projection (2D-PP)-3-D pose estimation problem and presented a simplified linear solution to the 2D-PP-2D-PP pose estimation problem. Liu, [1990] proposed a linear algorithm using eight or more line correspondences and a non-linear algorithm using three or more line correspondences, where line correspondences were given or derived from point correspondences. This method provided a solution for the rotation matrix and translation vector separately. Finally, there are some issues related to numerical and iterative solutions that are seldom addressed but are critical to obtain a reliable solution. These issues include the selection of the starting pose for convergence, the stability of the solution, and the efficiency of the solution in terms of computations.

Other techniques used more complex primitives than points and line segments. For example, Faugeras and Hebert, [1986] presented a method for object position computation based on surface primitives extracted from 3-D range data. Haralick, [1989]
solved the IPP problem using rectangles. Richetin, [1991] solved the IPP problem using zero-curvature contour points for the localization of objects modeled by generalized cylinders. Ferri, [1993] presented analytic procedures for the perspective inversion using straight-line segments (four coplanar lines or three orthogonal line segments), as well as circular arcs and quadrics of revolution. Phong, [1995] presented a technique for optimally estimating the object 3-D poses (in terms of transformations between the camera and the object coordinate frames) from point and/or line correspondences. Recently Choy, [1997] extracted the depth information using an improved triangulation method based on stereo vision angles.

### 2.3.2 Pose Computation Using Artificial Targets

Simple features such as points and line drawings may not be very practical in some applications due to possible ambiguities in the correspondence between scene and image features. Therefore, special targets, which are more distinct and unique than points and lines, have been used to simplify the correspondence problem and to improve the pose computation process. Some of these targets consisted of light spots of LED patterns arranged in a specific array, and they were employed in space applications and teleoperation in nuclear and hazardous sites. Other targets, which consisted of contrastbased patterns, have also been conceived and used for pose computation, but were mostly limited to applications of autonomous vehicle navigation. Most pose computation techniques, which use such artificial targets may be regarded as model-based techniques where targets are modeled in advance and used later for on-line computation.

Numerous techniques using different types of artificial features have been reported in the literature of pose computation. In the eighties, Fukui, [1981] used a diamond-shape planar marker with known dimension to compute the camera pose with respect to the mark by relating the length of the vertical and horizontal diagonals in the image plane and the actual diagonals. Matas, [1997] placed special design pattems on the object that allowed to solve the pose computation problem easily. Magee, [1984] used a sphere marked with horizontal and vertical great circles and obtained the camera pose with respect to the sphere by computing the closest distance between the sphere's projected center and points on the projected great circles of the sphere. Abidi, [1990] used patterns of light spots, called light targets, for autonomous location of mating elements in space manipulation applications. Abidi and Chandra, [1990; 1995] also proposed a pose estimation technique based on the volume measurement of tetrahedra composed of feature-point triplets (extracted from an arbitrary quadrangular target) and the lens center of the vision system. Wang, [1993] used targets similar to bar codes for autonomous vehicle navigation. The targets consisted of two rectangular stripes of equal width and were separated by a distance equal to their width. The stripes or bars were black on a white background or vice versa. The targets were placed on a vertical plane, with their long edges being vertical. The target depth (with respect to the camera) was assumed to be constant, and the camera's optical axis and the horizontal axis of the image plane were kept horizontal and parallel to the ground. This technique proved to be reliable, accurate, fast and practical in vehicle navigation application. However, it suffered from the restricting assumptions about the scene structure and targets poses, hence could not be useful in more general applications.

Other techniques based on artificial targets were commonly used in indoor environments. Sugihara, [1988] used targets and landmarks such as vertical edges of scene objects to determine the camera position, thus avoiding sophisticated image processing. His method was based on the assumption that the scene map and that the points where vertical edges occurred were given, and the camera's optical axis was parallel to the ground. A possible location of the camera was given by a correct correspondence between the edges in the images and those given in the map through an exhaustive search. Onoguchi [1990] used stereo vision for creating a multi-information local map for the navigation of a vehicle. That stereo vision system was limited to the recognition of circles, lines and ellipses and their combinations in order to obtain the relevant depth information for navigation. Environment knowledge is built in the teaching stage which is done off-line through an operator.

### 2.3.3 Shading and Brightness Information

Most of the pose computation techniques described have solely relied on simple geometric features to compute the viewpoint and viewing parameters even when contrast based features were used. Shading and photometric properties have also been considered within the shape-from-shading paradigm for shape reconstruction, based on general object independent constraints [Horn, 1985]. However, these techniques have not been widely used and successfully applied for pose computation. Solving the pose computation problem using shading and photometric properties is a difficult and ill-posed one. It is not practical due to the high sensitivity of brightness-intensities to disturbances
in the object poses and lighting conditions and due mainly to interreflections. However, the shading information and brightness feature properties, if effectively exploited, can be used in the correspondence part of the pose computation problem and the identification of the objects in the scene, as well as the estimation of the object pose. Although the feature identification and correspondence step can effectively use shading and image brightness information, accurate pose computation can only rely on the geometric properties of the extracted features.

In this work, stereo triangulation of specialized targets and markers to compute the camera pose (in 3-D) with respect to the observed targets or vice versa. These artificial targets have distinct features and can be quickly and accurately located in the stereo image pair. The pose computation technique employs a simple-feature based stereo matching which takes advantage of the prior knowledge about the targets' geometric and photometric properties to obtain reliable feature matching, thus providing direct and accurate 3-D pose information. The stereo vision also provides constraints that eliminate the need to solve the inverse projection problem.

## 3. Overview of the Pose Computation System

The pose computation module will consist of detecting special targets in the stereo image pairs, then computing the positions and orientations of these targets with respect to the camera coordinate frame, or vice versa. These targets are dark rectangular regions on bright backgrounds (or vice versa), all regions having well-defined reflectances. These targets can be either attached to the robot end effector, the programmable fixture, or fixed at specific locations around the robot workspace. These targets are designed to have simple geometries that make their detection and reconstruction easy, fast and accurate (to the sub-pixel level). Hence, they will yield fast and very accurate pose measurements. The pose information will then be fed to the calibration module, which will determine a more accurate and correct model of the robot cell, including the robots, programmable fixture and workpiece. Figure 3.1 presents the configuration of the robot workcell and the tentative locations of the targets used for pose measurements. Figure 3.2 shows the different levels of pose computation and workcell calibration among the different robotic cell components (i.e. in terms of targets fixed to these different robotic cell components).

The proposed pose computation system is novel due to the following characteristics:

- This pose computation technique uses a passive vision system that does not require special lighting, extraction of object features, or the reconstruction of object shapes from images. Instead, it relies on the detection of simple, yet unique targets, which are conveniently placed and fixed around the robot workspace.
- The target detection is simple, potentially fast and robust, hence is very practical and is likely to work effectively in the industry.
- This system will be able to cover a large volume of the workspace (between $1 \mathrm{~m}^{3}$ and $2 \mathrm{~m}^{3}$ ) at large stand-off distance in the range of 1.0 to 2.0 m , which are significantly large compared to typically short stand-off distance in laser-based sensors (e.g. 20 to 40 cm ).


Figure 3.1 Configuration of robot cell and artificial targets used for pose computation
[source: EIMaraghy, 1997]

This system has a number of advantages, as well as technical and economic benefits. First, it is passive, flexible and practical, and it uses inexpensive components. It also observes a larger workspace volume than most conventional and commercial vision sensors. Second, this system can improve the quality of manufactured products and significantly reduce their cost. For example. industrial robots have been used quite extensively in the automotive industry, but they have not been used in a flexible and efficient way.


Figure 3.2 Schematics of the different robot workcell calibration steps
[source: ElMaraghy, 1997]

They could not adapt to changes and disturbances in the scene, hence resulting in a poor and inaccurate task execution, leading to low quality production. The proposed vision system would be an effective tool for industrial robots to become flexible, to be able to adjust to uncertainties and disturbances and to compensate for geometric and dimensional deviations of the parts. Besides the improved product quality, this system would significantly help reduce the number of assemblies or subassemblies that need to be rejected or reworked, resulting in substantial cost savings.

## 4. Artificial Feature Detection and Identification

This section describes the process of detecting specialized artificial targets placed around the robotic workcell, which will be used for pose computation. These targets are described, along with their design criteria and their brightness calibration (in terms of their reflectance ratios). The algorithms for detecting these features are then presented, along with some experimental results from the testing of the feature detection technique.

### 4.1 Artificial Target Description

Artificial targets are used to provide a reference pose (position and orientation) in the coordinate system in which the robot operates. By observing a single (monocular) or stereo (2 images) projection of a target or a mark, the robot should be able to determine its pose (position and orientation) in the coordinate system. The shape and characteristics of the target itself should yield enough information when it is imaged. Generally, a mathematical relationship between the target, its projection, and the camera has to be established to derive the pose computation information even from a monocular image. The use of a specifically designed target as the object of interest will greatly simplify the task of recognition and interpretation. Hence, the process of target conception and design is as important and critical as that of target detection and recognition.

Target design is constrained by the following factors concerning the application at hand:

- The target should be simple in shape so that it will be easy to install. For example, planar targets take less space and are much easier to install than three-dimensional targets.
- The target should be detectable under a variety of lighting conditions. Hence, it should have a reasonable size and not contain any fine details, since fine details may not be clearly seen from a large distance by the vision system.
- Since the robot workspace is cluttered with objects and parts, the machine vision system can easily confuse the target with other objects in the scene/robot workspace if the target is not highly distinguishable. Therefore, the system has to rely on the uniqueness of the target to effectively identify it and to reject the background.
- The system must satisfy certain accuracy requirements and must use inexpensive components.

The "flat target", consists of a pattem of rectangular stripes placed on a flat surface, and arranged in a way similar to the bar-code concept. These stripes are rectangles with known and well-specified reflectance, and with fixed and well-defined widths and separated by well-defined distances. The flat target model is similar to that used by Wang, [1993], but is more elaborate as it incorporates the brightness properties of the target regions, and is detected and used for pose computation in a different yet a more general and elaborate way (i.e. in 3-D). A sketch of a flat target is shown in Figure 4.1. Without any loss of generality, the target's bars are selected to be darker than the surrounding area, but the concept of their detection is independent of that order. Note again that the functional regions of the target are the stripes and the region separating
them. The areas surrounding the stripes are not as functional in terms of the target geometry, but are also important for computing the brightness ratio and detecting the targets as well as preventing the bars and targets from merging with the background.


Figure 4.1 Sketches of a flat target (i): (a) target appearance; (b) target properties to be detected; (c) target graph used for modeling and reconstruction.

In Figure 4.1, (i) denotes the target ID, and that $R_{1}^{(i)}$ is the reflectance of the two stripe region, while $\mathbf{R}_{2}^{(i)}$ is that of the regions separating the stripes and surrounding them. The target attributes are the eight vertices, which are the intersections of two sets of parallel lines.

The targets designed here are simple and unique. The simplicity of these targets stems from their simple rectangular shape. Their uniqueness is manifested on one hand by the unique geometry (i.e. the combination of the three bars for the flat target) and, on the other hand, by the fixed, yet well defined reflectance ratios at the boundaries of the targets regions. In fact, the geometry of the target is very important since it relates directly to the pose computation process. As for the uniqueness of the brightness characteristics, the brightness ratios are invariant to changes in scene lighting and
viewing parameters. The simple and unique characteristics of these targets make their detection and identification simple and quite easy, and most important reliable and robust against lighting variations. The target data, in terms of the number of targets, their shapes, and their brightness ratio characteristics, are stored as part of the priori knowledge of the robot workcell to be used by the vision system.

### 4.2 Target Modeling and Calibration. Equipment used

One way of creating a large number of targets with the same and extremely simple geometry was by using different shades of gray for each target created. In a given image each pixel has an associated row/column address and a gray-level value which can be retrieved for further analysis. If an 8 -bit representation is used, values range between 0 (black) and 255 (white). For the "flat targets" a combination between white (255) and shades of gray starting with 0 (black), $15,31, \ldots .255$ was created. The white (255) was used as background for the two rectangular stripes that forms the "flat target". The rectangular stripes were created in different shades of gray starting with 0 which is black for the first target and always increasing the gray level with 16 for the following targets. This resulted in 17 targets. The other approach in modeling targets was using a certain level of gray for the background and different levels of gray than the background for the functional areas of targets. For the background the 127 gray, and for the rectangular stripes grays from 0 (black) to 111 in increments of 16 were used. The resulting number of targets to be tested was 17 using the first approach, and 7 more targets using the second approach. To create the targets Power Point (97) was used which has the capability of controlling the gray levels and also the dimensions of the targets. As
dimensions the unit of one inch was used for the width of rectangular stripes and the gap between them, the length of the rectangular stripes being the double of the width.
a)

b)


Figure 4.2 Examples of target design.
a) Targets created on white background.
b) Targets created on gray (127) background.

Using these 24 targets, brightness measurements were done and the results stored in a database to be used later for matching. This information consists mainly of brightness information in terms of brightness ratios at the boundaries of the target regions. Brightness is defined as the amount of radiant energy (light) which an imaging system receives per unit apparent area. Brightness is equivalent to irradiance which can also be defined as the amount of incident radiant energy per unit area of the receiving surface [Horn, 1986]. This brightness ratio information is obtained interactively by selecting points at the boundaries of the targets, then reading the brightness gradient and the brightness ratio at each selected point. The user-selected points do not always fall on the exact target edge. Hence a small routine is added to determine the actual edge point
before computing the gradient and brightness ratio. A number of points is selected at the boundaries of each target region, then the value of the brightness ratios and the standard deviation is computed. The standard deviation value is used to select the tolerance value for labeling a detected edge as a target edge.

The first set of targets was made by printing the rectangular regions with gray shades on white paper using a laser printer HP LaserJet $4 / 4 \mathrm{M}$. After conducting measurements and actually testing these targets for the recognizability by the Poscom system the conclusion was that the resolution of maximum 600 DPI given by this printer is not good enough to create reliable targets.

The second set of targets was made by using Conica 812, resulting in prints characterized by 3600 DPI. For each target and each camera measurements were done using different camera settings, camera modes ( $\gamma=1$ or $\gamma=0.45$ ), and positions. The detection of targets relies on the brightness-related information collected from the images. The criteria in deciding how many and which targets out of the 24 test targets will be considered to be used at once in the system was based on the brightness ratios and the requirement that the brightness fields that are characteristic to each target not to intersect each other, so that targets are not going to be confused with each other.

For each case and each camera a number of 16 probes were taken along the edges of the functional regions of the targets. The recorded information that was recorded includes the minimum brightness, maximum brightness, the ratio of these two, as well as the gradient magnitude.


Figure 4.3 The format of table and data recorded

Figure 4.3 shows the table that was used for recording each of the measurements for each target. These measurements were collected in a database and were used later on for target matching. Measurements are included in the Appendix A.

The calibration measurements were done using a pair of converging black-andwhite CCD cameras and an image processing software.

Cameras. Two identical PULNiX black-and-white CCD cameras (model TM-7CN) are used along with a Matrox frame grabber to acquire intensity images of the scene. This camera type contains a $1 / 2^{\prime \prime}$ interline transfer imager with a resolution of $768(\mathrm{H}) \times 494(\mathrm{~V})$ sensor cells and excellent low light sensitivity. It is also equipped with back panel switches to adjust the gamma mode (1.0/0.45), the capture and transfer mode
(Frame/Field), and the gain control mode (AGC/MGC) as well as the gain constant for for the MGC. As a short explanation of the terms above, it should be mentioned that the video signal is proportional to the scene brightness to the power gamma.

The gamma $=1$ (linear) mode gives a linear relationship between the scene brightness and the video signal (converted to image intensities). This mode is meant to be used in machine vision applications where the image intensities are assumed to be proportional to the scene brightness. The gamma $\mathbf{=} 0.45$ results in a video signal that is approximately proportional to the scene brightness to the power 0.45 (can be regarded as the square root of the scene brightness), and is designed for surveillance applications where the video signal is directly fed to a CRT-type video monitor, which in turn displays the signal with a 2.2 power factor. Frame mode is the standard interlace mode of horizontal line transfer. For each frame, the odd lines are first transferred, then the second field when the even lines of video are transferred. This mode is used for normal operations and for integration applications. The field mode of operation works as follows: during each transfer, two adjacent lines are combined together and then shifted out. This is used in applications that involve shuttering because, during shuttering, the camera's sensitivity is reduced due to the reduction of integration time. Automatic gain control (AGC) is the feature that allows to condition the video signal depending on the scene brightness by increasing the resulted image brightness readings, but one of the disadvantages is that the effect of noise may be increased.

Image processing software. The software used is Image Workframe (IWF). This is a PC-based software used for image analysis and developing computer vision applications.


Figure 4.4 Image Workframe (IWF) Image processing software. Basic tools.

This software offers a wide selection of basic tools, as presented in figure 4.4. Subselections expand with each choice: for example, after selecting 'Capture' there are choices for getting of a live image (Live or Input device-0), capturing a single frame/field to a buffer (Snap), transferring the image from frame buffer to memory (Copy) or getting multiple video inputs (Stereo). The program also offers image statistics functions such as 'Read Pixel' which gives an average image intensity in a 3 by 3 patch around a selected pixel, or 'Histogram' which leads to the gray palette manager that allows to manipulate the lookup table. An image histogram is displayed along with the possibility to view the effects of thresholding. When selecting 'Threshold', and applying the threshold value to
the image, the original brightness values are destroyed and a thresholded image is created. The 'Sobel edge' operator is a first order differential operator which performs edge detection. After thresholding the differential image, and performing a thinning operation, a one-pixel-wide edge appears.

Besides the basic tools presented above, the IWF software also has more complicated functions that starts with brightness ratio measurements at the edges in any direction ('TargtTesting'), capturing one ('CaptureImage') or more than one (stereo) images ('CaptureStereo'), and ends with pattem recognition in one ('FindPattrenl') or two ('FindPattren2') images.


Figure 4.5 Image Workframe (IWF) Calibration tools.
In Table 4.1 each column represents the average brightness ratios resulting from measurements carried out under different conditions. However, for targets with the
rectangular strips of very light gray (gray level bigger than 223), the contrast between the background and the rectangles is very low, and the brightness ratio is unusable.

| Target | Target | Target | Target | Target | Target | Target | Targot | Target | Target | Target | Target | Target | Target |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 2 | 3 | 4 | 8 | 8 | 7 | 8 | 0 | 10 | 11 | 12 | 13 | 14 |
| 0.149 | 0.157 | 0.190 | 0.233 | 0.280 | 0.338 | 0.348 | 0.407 | 0.470 | 0.560 | 0.583 | 0.672 | 0.727 | 0.811 |
| 0.142 | 0.157 | 0.186 | 0.226 | 0.282 | 0.332 | 0.334 | 0.403 | 0.455 | 0.568 | 0.574 | 0.680 | 0.725 | 0.806 |
| 0.142 | 0.163 | 0.183 | 0.239 | 0.272 | 0.320 | 0.329 | 0.385 | 0.455 | 0.562 | 0.562 | 0.677 | 0.738 | 0.802 |
| 0.144 | 0.161 | 0.180 | 0.223 | 0.259 | 0.320 | 0.354 | 0.377 | 0.461 | 0.558 | 0.563 | 0.676 | 0.732 | 0.809 |
| 0.140 | 0.166 | 0.178 | 0.216 | 0.257 | 0.316 | 0.346 | 0.390 | 0.452 | 0.557 | 0.553 | 0.688 | 0.742 | 0.806 |
| 0.142 | 0.177 | 0.181 | 0.219 | 0.248 | 0.322 | 0.328 | 0.398 | 0.486 | 0.560 | 0.562 | 0.666 | 0.743 | 0.799 |
| 0.137 | 0.159 | 0.179 | 0.216 | 0.250 | 0.328 | 0.329 | 0.409 | 0.486 | 0.564 | 0.562 | 0.857 | 0.741 | 0.809 |
| 0.137 | 0.165 | 0.175 | 0.214 | 0.257 | 0.328 | 0.316 | 0.394 | 0.480 | 0.556 | 0.565 | 0.662 | 0.730 | 0.806 |
| 0.134 | 0.158 | 0.181 | 0.220 | 0.260 | 0.332 | 0.336 | 0.416 | 0.468 | 0.568 | 0.570 | 0.654 | 0.725 | 0.808 |
| 0.136 | 0.176 | 0.177 | 0.228 | 0.255 | 0.329 | 0.333 | 0.409 | 0.465 | 0.563 | 0.588 | 0.684 | 0.717 | 0.805 |
| 0.148 | 0.169 | 0.194 | 0.222 | 0.266 | 0.330 | 0.348 | 0.415 | 0.452 | 0.557 | 0.573 | 0.660 | 0.716 | 0.811 |
| 0.147 | 0.155 | 0.190 | 0.240 | 0.284 | 0.329 | 0.358 | 0.401 | 0.481 | 0.553 | 0.580 | 0.668 | 0.705 | 0.812 |
| 0.148 | 0.163 | 0.186 | 0.237 | 0.261 | 0.332 | 0.341 | 0.396 | 0.471 | 0.550 | 0.579 | 0.672 | 0.718 | 0.807 |
| 0.143 | 0.157 | 0.182 | 0.224 | 0.265 | 0.320 | 0.333 | 0.413 | 0.483 | 0.563 | 0.577 | 0.683 | 0.718 | 0.800 |
| 0.145 | 0.160 | 0.180 | 0.220 | 0.259 | 0.325 | 0.330 | 0.405 | 0.481 | 0.582 | 0.576 | 0.680 | 0.724 | 0.817 |
| 0.145 | 0.166 | 0.178 | 0.222 | 0.253 | 0.324 | 0.323 | 0.390 | 0.462 | 0.572 | 0.576 | 0.680 | 0.731 | 0.814 |

Table 4.I Brightness ratio averages for camera A.
Seven targets can be used by the system at the same time. The brightness ratios for the selected seven targets are presented in Figure 4.6.


Figure 4.6 Brightness ratios resulted from measurements done with camera A.

The same set of measurements was done for the second camera. The results are represented in Table 4.2 and Figure 4.7.

| $\begin{array}{\|c} \text { Target } \\ 1 \end{array}$ | $\begin{gathered} \text { Targen } \\ 2 \end{gathered}$ | $\begin{array}{\|c\|} \hline \text { Trorget } \\ 3 \end{array}$ | $4$ | $\begin{array}{\|c} \hline \text { Target } \\ 5 \end{array}$ | $\begin{gathered} \text { Target } \\ 6 \end{gathered}$ | $\begin{array}{\|c\|} \hline \text { Target } \\ 7 \end{array}$ | $\begin{gathered} \hline \text { Target } \\ 8 \end{gathered}$ | $\begin{array}{\|c\|} \hline \text { Target } \\ 0 \end{array}$ | $\begin{gathered} \hline \text { Target } \\ \hline 10 \\ \hline \end{gathered}$ | $\begin{array}{\|c\|} \hline \text { Targot } \\ \hline 11 \end{array}$ | $\begin{gathered} \text { Target } \\ 12 \\ \hline \end{gathered}$ | $\begin{gathered} \text { Targex } \\ 13 \end{gathered}$ | $14$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 0.154 | 0.184 | 0.199 | 0.221 | 0.262 | 0.320 | 0.340 | 0.397 | 0.477 | 0.557 | 0.599 | 0.717 | 0.751 | 0.831 |
| 0.147 | 0.188 | 0.182 | 0.224 | 0.263 | 0.318 | 0.34 | 0.39 | 0.465 | 0.573 | 0.586 | 0.698 | 0.747 | 0.820 |
| 0.142 | 0.173 | 0.185 | 0.220 | 0.270 | 0.337 | 0.333 | 0.390 | 0.459 | 0.559 | 0.572 | 0.696 | 0.749 | 0.819 |
| 0.134 | 0.164 | 0.183 | 0.224 | 0.272 | 0.326 | 0.342 | 0.383 | 0.454 | 0.542 | 0.568 | 0.702 | 0.748 | 0.811 |
| 0.139 | 0.163 | 0.188 | 0.219 | 0.27 | 0.32 | 0.332 | 0.381 | 0.454 | 0.556 | 0.575 | 0.701 | 0.758 | 0.818 |
| 0.133 | 0.159 | 0.197 | 0.211 | 0.285 | 0.33 | 0.314 | 0.418 | 0.475 | 0.557 | 0.570 | 0.693 | 0.762 | 0.826 |
| 0.161 | 0.161 | 0.210 | 0.205 | 0.270 | 0.325 | 0.319 | 0.443 | 0.487 | 0.562 | 0.575 | 0.678 | 0.755 | 0.833 |
| 0.160 | 0.169 | 0.197 | 0.204 | 0.273 | 0.326 | 0.315 | 0.423 | 0.480 | 0.562 | 0.571 | 0.688 | 0.747 | 0.823 |
| 0.156 | 0.179 | 0.180 | 0.204 | 0.257 | 0.323 | 0.321 | 0.388 | 0.481 | 0.549 | 0.600 | 0.691 | 0.753 | 0.819 |
| 0.164 | 0.187 | 0.188 | 0.198 | 0.263 | 0.322 | 0.321 | 0.379 | 0.465 | 0.558 | 0.602 | 0.686 | 0.737 | 0.822 |
| 0.161 | 0.173 | 0.190 | 0.210 | 0.260 | 0.317 | 0.323 | 0.402 | 0.471 | 0.550 | 0.607 | 0.698 | 0.728 | 0.821 |
| 0.154 | 0.173 | 0.201 | 0.213 | 0.266 | 0.316 | 0.350 | 0.401 | 0.467 | 0.562 | 0.589 | 0.707 | 0.724 | 0.823 |
| 0.148 | 0.175 | 0.194 | 0.212 | 0.269 | 0.328 | 0.343 | 0.400 | 0.450 | 0.545 | 0.598 | 0.713 | 0.738 | 0.822 |
| 0.145 | 0.160 | 0.197 | 0.215 | 0.271 | 0.332 | 0.353 | 0.397 | 0.445 | 0.542 | 0.604 | 0.704 | 0.743 | 0.821 |
| 0.151 | 0.168 | 0.198 | 0.215 | 0.275 | 0.328 | 0.347 | 0.398 | 0.445 | 0.548 | 0.601 | 0.689 | 0.747 | 0.823 |
| 0.147 | 0.167 | 0.198 | 0.214 | 0.272 | 0.327 | 0.337 | 0.392 | 0.451 | 0.544 | 0.615 | 0.709 | 0.754 | 0.822 |

Table 4.2 Brightness ratio averages for camera B


Figure4.7 Brightness ratios resulted from measurements done with camera B

After deciding which targets and how many of them to use at once, the measurements done with camera A and camera B were compared (Table 4.3).

| A | Target 1(A) | Target 4(A) | Target (B) | Target 8(A) | Target 10(A) | Target 12(A) | Target 14(A) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| min (br. Ratio) | 0.118 | 0.183 | 0.298 | 0.353 | 0.53 | 0.622 | 0.758 |
| max (br. Ratio) | 0.165 | 0.266 | 0.368 | 0.485 | 0.606 | 0.744 | 0.847 |
| Avr. (br. Ratio) | 0.143 | 0.225 | 0.326 | 0.400 | 0.562 | 0.671 | 0.807 |
| 8 | Target 1(B) | Target 4(B) | Target ( ${ }^{\text {( }}$ ) | Target B(A) | Target 10(B) | Target 12(B) | Target 14(3) |
| min (br. Ratio) | 0.12 | 0.183 | 0.309 | 0.365 | 0.488 | 0.635 | 0.79 |
| max (br. Ratio) | 0.196 | 0.246 | 0.32 | 0.485 | 0.61 | 0.752 | 0.849 |
| Avr. (br. Ratio) | 0.150 | 0.213 | 0.346 | 0.399 | 0.554 | 0.698 | 0.822 |
| overall min. | 0.118 | 0.183 | 0.298 | 0.353 | 0.488 | 0.622 | 0.758 |
| overall max. | 0.196 | 0.266 | 0.368 | 0.485 | 0.61 | 0.752 | 0.849 |
| overall avr. | 0.146 | 0.218 | 0.336 | 0.400 | 0.558 | 0.686 | 0.816 |
| Gradient ( A and B ) | $\begin{array}{\|c\|} \hline \text { Min. GR (1) } \\ 145.829 \end{array}$ | $\begin{gathered} \text { Min. GR (4) } \\ 147.497 \end{gathered}$ | $\begin{gathered} \text { Min. GR (6) } \\ 119.096 \end{gathered}$ | $\begin{gathered} \hline \text { Min. GR (8) } \\ 119.574 \end{gathered}$ | $\begin{array}{\|c\|} \hline \text { Min. GR (10) } \\ 64.722 \end{array}$ | $\begin{array}{\|c\|} \hline \text { Min. GR (12) } \\ 21.889 \end{array}$ | $\begin{array}{\|c\|} \hline \text { Min. GR (14) } \\ 14.283 \end{array}$ |

Table 4.3 Summary or measurement results for the $A$ and $B$ cameras.

The results of the measurements suggest that the system can handle seven targets at once without confusing them.

Another set of measurements was done to find the effects of target lamination/plastification. A comparation was made among the measurements resulted in testing a plain target, target covered with reflectant tape and target covered with mate or nonreflectant tape. It was concluded that covering the surface of targets using eighter shiny or mate tape has an effect of slightly reducing the brightness of the images by an approx. 2-3\%. Test results are annexed. One inconvenience of covering targets with reflectance tape is that incident lighting is uncontrollably reflected, resulting in a negative effect on recognition.

These targets are only experimental, and they should be made of, or printed on, flat rigid plastic material.

### 4.3 Target Detection

The concept of target detection is based on the invariance of the reflectance ratio in neighboring smooth surface patches [Nayar, 1993]. Unlike classical segmentation techniques (e.g. edge detection or thresholding), the proposed method uses the brightness information, otherwise often wasted, to quickly and reliably identify the targets. This results in reliable stereo matching and pose computation.

The target detection algorithm consists of two steps: a coarse search and fine search routines. The coarse search step aims at identifying seed points of the target edges, by scanning for high gradient points. The coarse search step aims at identifying seed points of the target edges, by scanning for high gradient points. This search process scans the image along a scan lines oriented at specified directions, typically horizontally, and labeling points of maximum gradient within a $N \times 1$ window, where $\mathbf{N}$ is the typical edge width. If the labeled edge point matches the brightness properties of the modeled target edges, then it will be considered as a seed point from which the fine search process takes over. Otherwise, that edge point is ignored and the search continues.

When a seed point is found, the fine search process starts along the tangent of this seed edge point, looking for similar edge points on either of its sides. Similar edge points should have the same brightness ratio, the same gradient value at the edge point, and the same edge orientation. The seed point and the detected neighboring points are then grouped and fitted (using a least-square fit) into a straight line segment, which is then
labeled with its slope (in image coordinates), y-intercept value, end points, brightness attributes and its target-model association, referred to as target index.

Once the image is completely scanned, all the labeled line segments present are then grouped based on similarity of brightness information to reconstruct the targets in the image. That is accomplished by organizing the detected lines into a graph structure representing the targets. In this process, the line segments with the same target-model and brightness attributes are first grouped, then sub-categorizing them based on parallelism, i.e. dividing them into a maximum of two sets of parallel lines. The graph is then constructed with vertices representing the nodes of the graph and the line segmenting the arcs connecting the graph nodes.

### 4.4 Experimentation of Target Detection

The robustness of target detection method was investigated against illumination variation, shadows, and target changes in orientation.

### 4.4.1 Illumination Variation

The illumination at a point on a surface is the luminous flux incident on an infinitesimal element of the surface centered at the given point divided by area of the surface element. The illumination at a point on a surface due to a point source of light is proportional to the luminous intensity of the source in the direction of surface point and to the cosine of the angle between this direction and the surface normal direction. It is inversely proportional to the square of the distance between the surface point and the source. Luminous flux is the radiant power evaluated according its capacity to produce
visual sensation. In the process of image formation the lens plays a major role. The lens is characterized by its f-number (aperture) which is the ratio of its focal length to the diameter of lens. Aperture allows the control of the amount of light that passes through the lens. To check the effects of illumination variation the aperture of the cameras used in this study was changed, and the system's ability to recognize the target was observed. The aperture change has an influence on the brightness that is defined as the amount of radiant energy (light) which an imaging system receives per unit apparent area. Brightness is also equivalent to irradiance, which can also be defined as the amount of incident radiant energy per unit area of the receiving surface.

Two examples were chosen to illustrate how well the program recognizes the target. The first example the target recognition under good illumination conditions Figure 4.8.


Figure 4.8 Testing the effects of illumination changes. Recognition of target with favorable illumination.


Figure 4.9 Testing the effects of illumination changes. Recognition of target when illumination is low.

It was observed and concluded that the target recognition program performs well even under unfavorable illumination conditions. This good feature results from the fact that the recognition algorithm is based on the brightness ratio values at edges which do not change even when illumination conditions are altered.

### 4.4.2 Shadowing

Shadow is considered as an area of the target that does not have the features that are used in target recognition. Features used in target recognition are the geometry of the target and the well-defined reflectance ratios at the boundaries of target regions. To create shadows on the target strips of paper with different reflectance than the functional regions of target were used.

Figure 4.10 shows that the target was successfully recognized when strips of paper covered part of it.


Fig. 4.10 Testing the target for shadows.

It is concluded that if functional areas of the target are not fully covered, then the target is recognized well, but if, for example, an edge is totally hidden and can not be used for recognition then the target is not recognized. This can be explained with the fact that in the recognition process edge points are grouped in line segments, and collinear line segments are combined into a line that is labeled with the target index.

### 4.4.3 Changes in Orientation

The target recognition system is extremely sensitive to the changes in orientation. The tests that were done in this respect show that the target recognition can not be
completely reliable. Figures 4.11 and 4.12 show the most frequent problem in recognition. Having the same conditions (lighting, camera settings, and aperture) and only some small change in orientation of target can influence the recognition process in an undesired way.

In Figure 4.11 the target is perfectly recognized. Around the two rectangular stripes the recognized edge points are shown. Also the lines are correctly recognized and grouped. The recognition of the target is successful.


Figure 4.11 Successful recognition of target.

In Figure 4.12, the conditions that were used to get the image were the same as in Figure 4.11. The edge points and the lines are recognized well, but an error occurs in the grouping of the lines. Although this case is fairly straightforward, the target is not recognized well; instead of one two targets are accepted.


Figure 4.12 Error that occurred most often in the recognition (1).


Figure 4.13 Error that occurred most often in the recognition (2).
Another problem often occurring is when besides the actual target a second target is accepted as target, which cannot create any usable output in terms of industrial applications.

In the case of Fig. 4.13, the problem is that one of the targets noted "Trgt 0 " in the figure should not be accepted by the system as target. The edge points are recognized well, the lines are also grouped well but an error appears and an extra target is accepted.

Considering these problems, the target recognition software should be improved before recommending its use for applications where the orientation of targets changes a lot. In this study as targets are fixed on the fixture their orientation will not change; the only thing open to change is their position.

## 5. Pose Computation

### 5.1 Stereo Vision Geometric Calibration

Three dimensional vision applications, such as robot vision, require modeling of the relationship between the two-dimensional images and the three-dimensional world. Camera calibration is a process, which accurately models this relationship. The problem of camera calibration is to compute the camera intrinsic and extrinsic parameters based on a number of points whose object coordinates in the $(x, y, z)$ coordinate system are measured and whose image coordinates $f$, and $g$ are known. The extrinsic parameters give information regarding the camera position and orientation with respect to the world coordinate system, while the intrinsic parameters include focal length, scale factors to go from pixels to units of length, as well as values expressing the different types of possible lens distortions. The term "camera calibration" refers to finding values of these parameters for a given camera setup so that the coordinates $\mathbf{x}, \mathbf{y}$, and $\mathbf{z}$ can be calculated. In this area there has been much previous work. The techniques proposed to solve this problem range from simple linear equation solving to complex non-linear optimization approaches. An optimized two-step calibration algorithm is developed by Bacakoglu [1997], that starts with a linear calibration and based on these results constructs the homogeneous 4X4 transformation matrix. Another camera calibration method is the three-step camera calibration method [Bacakoglu, 1997] which first approximates the calibration parameters using the linear least-squares method then finds the optimal
rotation matrix from the calibration parameters and as last step a nonlinear optimization is performed to handle lens distortion. An extension of the two-step calibration is the four-step calibration procedure [Heikkila, 1997] which ads a step to compensate for distortion caused by circular features, and a step for correcting the distorted image coordinates. Han [1992] presents a method of calculating the viewing parameters of a camera using a specially designed circular pattem,

To find the calibration and lens correction coefficients, the calibration algorithm provided by Sensor Adaptive Machines Inc. (SAMI) [56] was used. The provided routine is very easy to implement and requires no prior knowledge of the focal lengths of the cameras, the distance between them, or their relative angular orientation. To use it a table containing a large number of $x, y, z$, values and the corresponding pixel locations in each image was created for approximately 100 samples taken uniformly throughout the volume to be calibrated. A short description of the algorithm [56] used by this calibration routine given the following camera model mapping ( $x, y, z$ ) to undistorted pixel ( $f, g$ ):

$$
\begin{equation*}
f(u)=\frac{a(0) \cdot x+a(1) \cdot y+a(2) \cdot z+a(3)}{a(8) \cdot x+a(9) \cdot y+a(10) \cdot z+1} \tag{5.1}
\end{equation*}
$$

$$
\begin{equation*}
f(u)=f+D(f)(d f, o r d e r, f, g) \tag{5.2}
\end{equation*}
$$

$$
\begin{equation*}
g(u)=\frac{a(4) \cdot x+a(5) \cdot y+a(6) \cdot z+a(7)}{a(8) \cdot x+a(9) \cdot y+a(10) \cdot z+1} \tag{5.3}
\end{equation*}
$$

$$
\begin{equation*}
g(u)=g+D(g)(d g, o r d e r, f, g) \tag{5.4}
\end{equation*}
$$

- (f,g) is frame buffer pixel coordinate(column,row) with arbitrary origin.
- ( $x, y, z$ ) is world coordinate ie(mm).
- $a(k) k=0 . . .10$ are unknown camera parameters.
- $D(f)(d f, o r d e r, f, g)$ is a polynomial lens distortion model in $f$ with a set of (order +1 )(order +2 )/2 parameters,df.
- $D(g)(d g, o r d e r, f, g)$ is a polynomial lens distortion model in, $g$, with a set of (order +1 )(order +2 )/2 parameters,dg.

A third order lens distortion model, for example, has the following form:
$D(d, 3, f, g)=d(0)+d(1) f+d(3) f^{2}+d(4) f g+d(5) g^{2}+d(6) f^{3}+d(7) f^{2} g+d(8) f^{2}+d(9) g^{3}$
This algorithm finds the set of parameters, a (k), df and dg that minimizes the least squared error.

The solution is determined in stages:

1. Find the $a(k)$ parameters based on the set of $(x(i), y(i), z(i))$ and $(f(i), g(i)) i=1 \ldots n$
2. With the $a(k)$ parameters and $(x(i), y(i), z(i))$ find $F(i), G(i)$ using $x y z \_f g$ model above; compute difference( $\mathrm{DF}(\mathrm{i}), \mathrm{DG}(\mathrm{I})$ ) as $(\mathrm{F}(\mathrm{i})-\mathrm{f}(\mathrm{i}), \mathrm{G}(\mathrm{i})-\mathrm{g}(\mathrm{i}))$
3. Estimate lens distortion parameters df and dg, from difference ( $\mathrm{DF}(\mathrm{i}), \mathrm{DG}(\mathrm{i})$ )
4. Compute new pixel coordinates, ( $\mathrm{FF}(\mathrm{i}), \mathrm{GG}(\mathrm{i}))$ as $[\mathrm{f}(\mathrm{i})+\mathrm{D}(\mathrm{f})(\mathrm{df}, 3, \mathrm{f}(\mathrm{i}), \mathrm{g}(\mathrm{i}))$,

$$
g(i)+D(g)(d g, 3, f(i), g(i)))
$$

5. Iterate a second time: repeat step 1 , but use ( $\mathrm{FF}(\mathrm{i}), \mathrm{GG}(\mathrm{i})$ )
6. Repeat steps 2,3 and 4.

### 5.2 Collecting the calibration data

To collect the world coordinates $\mathrm{x}, \mathrm{y}, \mathrm{z}$, and the corresponding pixel locations in the images resulting from camera A and camera B besides the two cameras, the Poscom image processing software and a measuring device was used.

The steps in collecting the calibration data included:

1. Recognizing the target using the target recognition algorithm based on the brightness ratios of targets.
2. Collecting the pixel locations of targets in image $A$ and image $B$.
3. Finding the $x, y$ and $z$ coordinates of target.

### 5.2.1 Target recognition

The target recognition algorithm has as output the pixel location of the center of the target $P_{0}$ so the corresponding $x, y$ and $z$ had to be measured. The center location of target was found difficult to find, by measurements so, for the data collection purposes, the pixel locations of the four external comers $\mathrm{P}_{1}, \mathrm{P}_{2}, \mathrm{P}_{3}$ and $\mathrm{P}_{4}$ and the corresponding $\mathbf{x}, \mathbf{y}, \mathbf{z}$ coordinates were considered. The target recognition program when used for the stereo images, first activates image $\mathbf{A}$ and finds the target and corresponding target data (pixel locations of comers), then activates image $B$ and repeats the entire process to get the target data.

### 5.2.2 Collecting the plxel locations

To get the resulting target data in a file that can be used later in a spreadsheet or for further calculations, two small functions were written which store these data in an ASCII file. These functions were needed due to the fact that the same recognition algorithm was repeated two times, first for image $\mathbf{A}$ and second for image $\mathbf{B}$ and the target data resulting from testing the image A was overwritten by the target data resulting from testing image B. The functions are as follows:

- 'collectpoints 10 '
- 'coilectpoints2()'

```
void collectpoints1 ()
{
FILE *fin, *fout;
    char buffer[100];
    fin=fopen("pointdata.dat", "r");
            fout-fopen("pixel_location.dat", "w");
    while( (fgets(buffer, 100, fin)) != NULL)
    {
        //fgets(buffer, 90, fin);
        fprintf(fout, "%s", buffer);
        }
fclose(fin);
fclose(fout);
}
```

void collectpoints20

```
{
FILE *fin, *fout;
char buffer[100];
fin=fopen("pointdata.dat", "r");
    fout=fopen('pixel_location.dat", "a");
while( (fgets(buffer, 100, fin)) != NULL)
    fprintf(fout, "%s", buffer);
fclose(fin);
fclose(fout);
}
```


### 5.2.3 Collecting the $x, y, z$ coordinates

To collect the $x, y, z$ coordinates of the target in the scene which correspond to the $\mathrm{f}, \mathrm{g}$ pixel locations in the images resulted from both cameras it was considered that depending on the instrument used for the measurements there are at least three ways that this measurement can be taken:

- Using a ruler that has 1 mm divisions,
- Using a vernier,
- Using the CMM machine.

Each coordinate finding technique (using a ruler, vernier or CMM) has its own advantages and disadvantages that are going to be discussed later. For all three ways of measuring $x, y, z$ coordinates the cameras were positioned side by side at different heights ( $\mathbf{z}$ coordinates), and the targets positioned in the common field of view of cameras.

Data collection using a ruler. In this case the measuring device is a ruler with 1 mm divisions. The center of the coordinate system is situated at the level of cameras at a center point between them. Graph paper glued to the work plane was used to help in measuring. The advantages of this method are the really inexpensive measuring device and that it can be done everywhere without any special setup. The accuracy due to the measuring device (ruler) is 1 mm , but due to human interpretation error it can be much lower.

Data collection using a vernier. The setup for the measurements is the same as in case of measuring with a ruler. As instruments of measurement the following were used:

- Mitutoyo vernier (digital), with a resolution of $1 / 50$, measures up to 15 cm .
- Kanon vernier (analog), with a resolution of $1 / 50$, measures up to 60 cm .

As the flat target measured had no features like comers or walls, a block of $60 \times 60 \times 10 \mathrm{~mm}$ glued to the workplan at a well-defined position with respect to the cameras coordinate system was used so that its surfaces were used to help doing measurements.

This way of data collection is time consuming and even though the precision of the vernier is higher than the precision of the rulers the resulting data do not necessarily present a better resolution.

Collecting data with CMM. CMMs are machines that give physical representations of a three dimensional rectilinear Cartesian coordinate system.

The components of a coordinate measuring system are shown in Figure 5.1


Figure 5.1 System components of a CMM

A CMM consists of the following essential system components:

1. mechanical set-up with the three axes, and the displacement transducers,
2. probe head,
3. optional remote control unit, and
4. digital computer with peripheral equipment (printer, plotter), and software to calculate and represent results.

A measurement with a CMM follows these steps:

1. Calibration of the stylus or probe tip with respect to the probe head reference point,
2. Metrological determination of the workpiece position (workpiece related coordinate system $\left.X_{W}, Y_{W}, Z_{W}\right)$ in the measuring machine related coordinate system $X_{M}, \mathbf{Y}_{\mathbf{M}}$. $\mathbf{Z}_{\mathrm{M}}$,
3. Measurement of the surface points on the workpiece in the measuring machine related coordinate system,
4. Evaluation of the geometric parameters of the workpiece, and
5. Representation of the measurement results after coordinate transformation into the workpiece related coordinate system.

The target used by the vision system is a flat surface and has two rectangular stripes.
As CMMs cannot be used to do measurements of points on a surface, the setup shown in Figure 5.2 was used when actually taking the measurements. This setup consists of two parts: i) the upper block, which has an opening with the shape, and size of the target, and ii) the lower block, to which the target printed on a paper is attached. To assure that the upper block fits all the time in the same way over flat target attached to the lower block dowel holes and dowel pines were used to create the connection.


Figure 5.2 Target used for measurements done with the CMM

Steps in collecting the measurement data using the CMM include:

1. Positioning the block with the target attached to it in the field of view of both cameras.
2. Fixing this block to the CMM-s work piece table.
3. Taking the stereo image using the IWF image processing software and CCD cameras.
4. Recognizing the target in both images.
5. Slowly positioning the upper block over the target.
6. Collecting the measurements.

Each comer point of the target is considered as an intersection among three planes, one of them being the plan of the target and the other two being two of the four inside planes of the upper blocks. Each of these surfaces was probed eight times and the best-fit planes were considered to get the intersection point, which was actually the target point.

To find the expected precision of measurements the upper and lower blocks were measured before starting any data recording. The measurements were done to test the surfaces and to see what kind of machining errors are present. The results of these measurements showed that, due to machining, an error of $3 \div 7 \mu$ is present. For this set of measurements the target was redesigned to have the dimensions of the upper blocks opening. The new target was printed intending to eliminate the errors due machining. The new target was glued to the lower block's surface using. The positioning of target was done manually, and this procedure cannot be considered error free, so some errors
would still appear. An error of $3 \div 7 \mu$ has to be considered as measurement error. The probe tip that has 1 mm radius was used along with two 10 mm extensions. The extensions were needed due to the limited accessibility of target when in the field of view of both cameras. The probe tip is designed so that when measurements are done along the major axes the error is minimized. In this case, due to limited space it was assumed that error up to $5 \mu$ may occur because of the deflections of probe tip at the time of measurements. The setup for data collection is presented in Figure 5.3.


Figure 5.3 Data collection using the CMM.

In the setup from Figure 5.3 height measurement, which is the distance from the targets surface to the cameras, was conducted by taking sets of points at the level of the CMM's table, on the targets surface, and on the structure that had the cameras attached.

To find the actual distance between the target and cameras, the file containing the measurements from above was passed to the program called "Surfacer". With the help of one of the basic features offered by this software, the height measurement was calculated for different camera positions.

The data collected with the above three methods (uler, vemier, CMM) was used to calculate the calibration coefficients that were saved in separate files so that the coefficients resulting from each calibration method could be accessed later.

### 5.3 Stereo Matching and Triangulation

Stereo vision is one of the most prominent ranging methods, it is promising and practical due to its potentially high-speed and high accuracy levels. The main purpose of stereo vision analysis is to recover range (depth) information of objects in a threedimensional (3-D) scene based on an image pair taken from two distinct views. In stereo vision, depth information is obtained from triangulation of corresponding points in the stereo image pair. A stereo image pair refers to two perspective projection images taken of the same scene from slightly different positions. The common area appearing in both images of the stereo pair is usually $40 \%$ to $80 \%$ of the total image area. A point $p$ on one image and a point $q$ on a second image are said to form a corresponding point pair $(p, q)$ if
$p$ and $q$ are each a different sensor projection of the same three-dimensional point. Triangulation refers to the process of determining the $(x, y, z)$ coordinates of a threedimensional point from the observed position of two perspective projections of the point. The centers of perspectivity and the perspective projection planes are assumed known. [Haralick, 1993].

The triangulation procedure is the determination of a 3 D point from the intersection of more than two rays. Consider the case when the lens geometric distortions are totally compensated and assuming that ( $f_{L}, g_{L}$ ) and ( $f_{R}, g_{R}$ ) is the perspective projection of a 3D point ( $x, y, z$ ). The triangulation procedure makes use of the parallax, which is the displacement in the perspective projection of a point caused by a translational change in the position of observation. The basic stereo triangulation procedure (Haralik, 1993) when we consider the position of the left camera lens is at:

$$
\left(\begin{array}{c}
-b_{x} / 2  \tag{5.5}\\
0 \\
0
\end{array}\right)
$$

Considering the position of the right camera lens it is at:

$$
\left(\begin{array}{c}
b_{x} / 2  \tag{5.6}\\
0 \\
0
\end{array}\right)
$$

Assuming that the image plan is at a distance $f$ in front of each camera lens, and that both cameras are oriented identically, with the x -axis of the camera reference frame oriented along the line defined by the position of the camera lenses. Let $(x, y, z)$ be an 3D point
and ( $f_{L}, g_{L}$ ) and ( $f_{R}, g_{R}$ ) be its perspective projection on the left and right images, respectively. Then:

$$
\begin{align*}
& \binom{f_{L}}{g_{L}}=\frac{f}{x}\binom{x+b_{x} / 2}{y}  \tag{5.7}\\
& \binom{f_{R}}{g_{R}}=\frac{f}{x}\binom{x-b_{x} / 2}{y} \tag{5.8}
\end{align*}
$$

In this situation $g_{L}=g_{R}$ so that the $y$-parallax is zero. The solution for $(z, y, z)$, given ( $f_{L}$, $g_{L}$ ) and ( $f_{R}, g_{R}$ ), can be obtained from the difference $f_{L}-f_{R}$, which is called $x$-parallax.

$$
\begin{equation*}
f_{L}-f_{R}=\frac{f}{z}\left[x+\frac{b_{x}}{L}-\left(x-\frac{b_{x}}{L}\right)\right]=\frac{f}{z}\left(b_{x}\right) \tag{5.9}
\end{equation*}
$$

Hence:

$$
\begin{equation*}
z=\frac{f \cdot b_{x}}{f_{L}-f_{R}} \tag{5.10}
\end{equation*}
$$

Once the depth $z$ is determined, the $(x, y)$ coordinates are easily determined from the perspective projection equations:

$$
\begin{equation*}
\binom{x}{y}=\frac{z}{f}\binom{f_{L}}{f_{L}}-\binom{b_{x} / 2}{0}=\frac{z}{f}\binom{f_{R}}{f_{R}}+\binom{b_{x} / 2}{0} \tag{5.11}
\end{equation*}
$$

The equation (5.1) to determine the depth from the x-parallax is a classic relation that in a real-world situation is actually close to being useless, for three simple reasons [Haralik, 1993]:

1. The observed perspective projections are subject to measurement errors, so that $g_{L} \neq g_{R}$ for corresponding points.
2. The camera reference frames for the left and right images may often have slightly different orientations.
3. When there are two different cameras that take the left and right images, it is almost always the case that the camera constant $f_{R} \neq f_{L}$.

Considering the triangulation model represented through Equations 5.1 to 5.4 (5.1 Stereo Vision Geometric Calibration) which is taking in consideration the camera parameters and the lens distortion model in f respectively g , the world coordinates of a 3D point can be determined. First, the camera parameters and distortion parameters are calculated when geometrically calibrating the cameras. Then using these coefficients, the $x, y$, and $z$ are calculated.

The program written in Borland $\mathrm{C}++$ is presented in Appendix $\mathrm{C}_{\text {; }}$ it uses the output file from the calibration program, which contains all the camera and calibration coefficients. The triangulation algorithm uses two input files. One of them is a file that contains the pixel locations of corresponding points, and the other file has all the calibration coefficients. In the first stage, there is a memory allocation part that locates in the memory positions where matrixes $\mathrm{C}[4 \times 3], \mathrm{V}[3 \times 3]$ and vectors $w[3], \mathrm{b}[4]$ used in the mathematical part are going to be stored. The next part is solving a set of mathematical equations that lead to a matrix representation $C[4 \times 3]$ that is decomposed using the singular value decomposition (SVD) function [Press, 1990] and results in the output ( $\mathrm{x}, \mathrm{y}$, z) written in an ASCII file. For the orientation of target, the position of two comers A, B
of target are calculated using the above method the gradient of straight line going through these two points was: $m=\left(y_{2}-y_{l}\right) /\left(x_{2}-x_{l}\right)=\tan \alpha$

Where $m$ is the gradient of line, $\left(x_{1}, y_{1}\right)$ and $\left(x_{2}, y_{2}\right)$ the coordinates of two points and $\alpha$ is the angle which is the orientation of target. These functions are implemented in Image Workframe (IWF) (Image processing software) and can be accessed through the buttons under the 'Stereo'. There are two options: the first of them is "X,Y,Z" that calculates the ( $\mathbf{x}, \mathbf{y}, \mathbf{z}$ ) coordinates of corresponding targets and writes them in a file called "coord.dat" and also gives an output on the screen with the calculated data. The other option would be "Orientation" that calculates the orientation of target. Figure 5.4 shows where the position and orientation finding algorithms can be accessed.


Figure 5.4 The software development that calculates the position of the target.

### 5.4 Experimentation of Finding the Targets Position

Once the stereo triangulation is completed, the accuracy of the position and orientation has to be tested. For this experiment the setup in Figure 5.5 was used. This is the same setup that was used for collecting the calibration data using a ruler or vemier (5.2.2). In this setup the cameras are positioned on a fixture at a certain height above the targets. The targets are placed on a surface covered by graph paper. The graph paper was used to help position the target at a well defined ( $\mathbf{x}, \mathbf{y}, \mathbf{z}$ ). First, the target was positioned on a well-defined location and under a well-defined orientation.


Figure 5.5 Testing the accuracy of position and orientation finding.

Then, stereo image was taken of the scene and, after recognizing the targets in both images and finding the corresponding points for the target, the position and orientation was found with the help of the algorithms.

The position and orientation of the two PULNIX CCD cameras were kept the same, as they were when the calibration data was collected. In this fixed position the two cameras were moved up and down on the fixture this way the height was adjusted.

Table 5.1 shows the true position values against the computed values for six different target positions and the three sets of calibration data.

|  | Position | Coeffs $\%$ (ruler) | Coeffs $\% 2$ (vernier) | Coeffs $\% 3$ (CMM) |
| :---: | :---: | :---: | :---: | :---: |
| 1 | $(20,140,600)$ | $(21.64,140.7,603.12)$ | $(22.56,143.09,604.19)$ | $(21.09,139.71,601.02)$ |
| 2 | $(40,140,600)$ | $(42.13,141.42,603.64)$ | $(41.97,143.23,602.71)$ | $(40.59,140.09,599.06)$ |
| 3 | $(10,150,600)$ | $(10.89,149.27,602.87)$ | $(8.98,152.07,602.84)$ | $(10.19,150.43,600.95)$ |
| 4 | $(20,140,650)$ | $(22.45,143.11,652.17)$ | $(23.81,142.7,649.93)$ | $(20.71,139.29,651.05)$ |
| 5 | $(40,140,650)$ | $(38.05,141.24,652.88)$ | $(41.98,140.06,651.67)$ | $(41.01,141.1,651.18)$ |
| 6 | $(10,150,650)$ | $(9.08,152.45,653.09)$ | $(11.28,152.79,651.28)$ | $(10.94,151.02,651.73)$ |

## Table 5.1 Comparison of calculated position against true position.

In Table 5.1 all data are presented in mm. The average of the absolute deviations in the $x, y$, and $z$ directions between the true value and the calculated value under different setups show that this procedure of locating and positioning the artificial target is a good method.

The results show that the compounded position values are close to the true values, indicating that the method used to calculate positions is valid.

## 6. Discussion

This thesis presented a new method for camera-based pose computation using simple artificial targets, off shelf cameras and an image-processing software.

The artificial targets were designed for easy detection and simplicity of the pose computation. The targets detected here are simple and unique. The simplicity of these targets stems from their simple rectangular shapes. A large number of targets were tested to determine their brightness information in terms of brightness ratios at the boundaries of the target regions and also to find out the maximum number of targets that can be used in the same time by the system. The results of the measurements were stored in a database to be used later for matching.

The robustness of the target detection algorithm was investigated against illumination variation, shadows, and target changes in orientation. Real situations were chosen to create an image of the capabilities offered by the target recognition algorithm. Finally this algorithm proved to be suitable for the purposes of this research.

The geometric calibration of the camera system is a procedure that computes the cameras parameters based on a number of points whose object coordinates in the ( $\mathbf{x}, \mathrm{y}, \mathrm{z}$ ) coordinate system were measured and whose image coordinates (pixel locations) were known. Three possibilities are presented for collecting the calibration data. The calibration data consist of a large number of 3D positions ( $x, y, z$ ), and the corresponding pixel locations in both images. The calibration coefficients resulted from each of the approaches were saved in data files to be used later for the position finding of targets.

Stereo vision is one of the most promising and practical ranging methods due to its potentially high-speed and high accuracy levels. Triangulation refers to the process of determining the $x, y$, and $z$ coordinates of a three-dimensional point from the observed position of two perspective projections of the point. Using the stereo triangulation model presented in chapter 5 equations 5.1 to 5.4 a $\mathrm{C}++$ algorithm was developed to find the position and orientation of the artificial targets placed in various positions in the cameras field of view. This algorithm is implemented in Image Workframe (IWF) image processing software as a development and can be accessed by clicking on one of the buttons offered under the "Stereo" tools. The position finding algorithm is optionally taking into consideration one of the files containing the calibration coefficients. Results of position detection are also presented. This addition to the software offers to the user an extra feature that opens the door for more complicated applications of the software for such as calibration of a robotic workcell.

In this work stereo vision was used to find $x, y$, and $z$ coordinates of a three dimensional point from the observed position of two perspective projections of the point. The position-finding technique presented here is based on relatively chip components as an image processing software, computer, and simple surveillance cameras. This technique can be used to find robot and workpiece information, that can be used further for robot calibration and accurate positioning of the robot, end effector and parts within its workspace, to allow successful execution of high accuracy robotic tasks. This is suggested as a topic for future research.

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## APPENDIX A

## TARGET BRIGHTNESS CALIBRATION (MEASUREMENTS)

Using the designed artificial targets (Chapter 4) brightness measurements were done and the results stored in a database to be used later on for matching. This information consists mainly of brightness information in terms of brightness ratios at the boundaries of the target regions. This brightness ratio information is obtained interactively by selecting points at the boundaries of the targets.

The table from figure A. 1 was used to record the target calibration measurements.
These measurements were done for two purposes:

1. Since the target recognition algorithm is relying on the brightness ratio and gradient magnitude information's these were collected for every target and saved in a spreadsheet. This information is needed by the recognition algorithm in order to recognize the artificial targets. Whenever a target is used in the vision system the corresponding data (in terms of brightness ratio and gradient magnitude) is taken from the spreadsheet and used.
2. To decide how many and which artificial targets can be used by the vision system in the same time without the possibility of targets being confused.


Figure A.I The format of table and data recorded.

In the figure A. 1 is also shown what kind of information were recorded for every set of measurement. These informations's are:

- Which camera was used to record the image (camera A or camera B).
- The camera settings:

Apperture (allows the control of the amount of light that passes through the lens),

Camera modes (capture or transfer mode). The cameras are equipped with back panel switches to adjust the gamma mode (1.0/0.45). The gamma $=1$ (linear) mode gives a linear relationship between the scene brightness and the video signal
(converted to image intensities). The gamma $=0.45$ results in a video signal that is approximately proportional to the scene brightness to the power 0.45 .

- Brightness measurements: minimum, maximum, and the ratio of brightness measurements for the functional and nonfunctional areas of the artificial targets. Brightness is defined as the amount of radiant energy (light) which an imaging system receives per unit apparent area.
- Gradient magnitude: The idea underlining most edge detection techniques is the computation of a local derivative operator. The magnitude of the first derivative can be used to detect the presence of an edge. The first derivative at any point in an image can be obtained by using the magnitude of the gradient at that point. The gradient of an image $f(x, y)$ at location $(x, y)$ is defined as the two dimensional vector (Haralick, 1993):

$$
G[f(x, y)]=\left[\begin{array}{l}
G_{x}  \tag{A.1}\\
G_{y}
\end{array}\right]=\left[\begin{array}{l}
\frac{\partial f}{\partial x} \\
\frac{\partial f}{\partial y}
\end{array}\right]
$$

For edge detection we are interested in the magnitude of this vector, generally referred as the gradient and denoted by:

$$
\begin{equation*}
G[f(x, y)]=\left[G_{x}^{2}+G_{y}^{2}\right]^{1 / 2}=\left[\left(\frac{\partial f}{\partial x}\right)^{2}\left(\frac{\partial f}{\partial y}\right)^{2}\right]^{1 / 2} \tag{A.2}
\end{equation*}
$$

The table 4.1 and 4.2 and figures 4.6, 4.7, and 4.8 (Chapter 4) resulted from the data presented on the following pages.



| enmen $A$ <br> cace 1 <br> Ter | gammal |  |  |
| :---: | :---: | :---: | :---: |
|  | (App 8) |  |  |
|  |  |  |  |
| Niner [what | Mandr [Tincl | Retio | Grad.m |
| 14.5 | 82.8 | 0.175 | 201.642 |
| 13.8 | 82.4 | 0.168 | 201.012 |
| 13.4 | 848 | 0.150 | 261.476 |
| 13,6 | 84 | 0.162 | 223.172 |
| 12.8 | 84.3 | 0.153 | 258,033 |
| 12.8 | 81.8 | 0.157 | 244.512 |
| 13 | 78.3 | 0.163 | 227,549 |
| 12.6 | 0.5 | 0.157 | 289.531 |
| 14.5 | 83 | 0.175 | 260.190 |
| 12.8 | 82.6 | 0.157 | 225.338 |
| 12 | 82.3 | 0.146 | 275.732 |
| 14.3 | 2.8 | 0.172 | 217.033 |
| 14.1 | 82 | 0.172 | 215.203 |
| 13.2 | 83.2 | 0.150 | 250.825 |
| 18.2 | 03.8 | 0.150 | 258.768 |
| 13.2 | 83.3 | 0.150 | 283.141 |
|  | mm | 0.146 | 201.012 |
|  | 四的 | 0.175 | 275.732 |
|  | er. | 0.1623 | 209.135 |



| cemmera 4 |  | gamma 0.45 |  |
| :---: | :---: | :---: | :---: |
| Min ${ }^{\text {ar man }}$ | Maxbr [w/n) | Retio | Gred.m |
| 15.3 | 81.5 | 0.188 | 255.558 |
| 14.8 | 81.2 | 0.183 | 260.902 |
| 15.1 | 80.8 | 0.187 | 254.734 |
| 15.3 | 82.3 | 0.188 | 268.548 |
| 14.8 | 78.5 | 0.187 | 224.162 |
| 14.3 | 75.8 | 0.188 | 215.658 |
| 14 | 76 | 0.189 | 214.037 |
| 15.2 | 80.7 | 0.188 | 259,361 |
| 14.8 | 82 | 0.181 | 258.771 |
| 14.8 | 82.3 | 0.18 | 268.677 |
| 17.5 | 80.9 | 0.216 | 208.876 |
| 16.8 | 81 | 0.208 | 216.879 |
| 15.3 | 80.3 | 0.191 | 250.927 |
| 15.2 | 81 | 0.187 | 218.38 |
| 15.2 | 60.6 | 0.189 | 234.297 |
| 14.3 | 78.6 | 0.182 | 227.206 |
|  | $\min$ | 0.18 | 208.876 |
|  | max | 0.216 | 288.677 |
|  | Emr. | 0.1891 | 239.685 |


| cemera 4 |  | gamma 0,45 |  |
| :---: | :---: | :---: | :---: |
| case 1 | (App 8) |  |  |
| Tar 4 |  |  |  |
| WinBr [Wman |  | Maxer (winm | Retio | Grad.m |
| 20.8 | 80.6 | 0.24 | 203.091 |
| 21.2 | 88.7 | 0.24 | 223.477 |
| 18.8 | 87.1 | 0.228 | 281.22 |
| 19.3 | 85 | 0.228 | 254.755 |
| 18 | 83.2 | 0.228 | 249.878 |
| 18.5 | 81 | 0.228 | 215.331 |
| 18.6 | 792 | 0.285 | 212.723 |
| 18.5 | 81.2 | 0.228 | 213.26 |
| 20.1 | 83.8 | 0.24 | 220.59 |
| 198 | 83.4 | 0.237 | 230.867 |
| 20 | 84.3 | 0.237 | 236.805 |
| 20.5 | 04.5 | 0.242 | 198.838 |
| 19.8 | 85.3 | 0.234 | 208388 |
| 19.7 | 85.1 | 0.231 | 198.705 |
| 18.8 | 84 | 0.225 | 218.803 |
| 18.7 | 81 | 0.231 | 217.578 |
|  | min | 0.225 | 188.705 |
|  | max | 0.244 | 281.22 |
|  | avr. | 0.2336 | 224.451 |


| canmera Acase 2Tarre 3 | (App 4) | gamma 1 |  |
| :---: | :---: | :---: | :---: |
|  |  |  |  |
| MinBr [w/m) | MaxBr [whan | Retio | Grad.m |
| 20.7 | 102.1 | 0.202 | 297.516 |
| 20.2 | 102 | 0.180 | 295.587 |
| 18.8 | 1018 | 0.184 | 297.407 |
| 18 | 101.5 | 0.187 | 301.994 |
| 18.2 | 101.7 | 0.188 | 328.712 |
| 18.7 | 101.8 | 0.180 | 288.14 |
| 18.4 | 102 | 0.181 | 303.224 |
| 18.3 | 101.2 | 0.181 | 307.408 |
| 18.2 | 102.2 | 0.178 | 311.925 |
| 19.3 | 1022 | 0.18 | 293.2 |
| 22.5 | 102.1 | 0.221 | 278.880 |
| 20 | 1024 | 0.185 | 301.728 |
| 19.9 | 102.4 | 0.194 | 307.701 |
| 19.1 | 101.6 | 0.188 | 290.421 |
| 18.7 | 101.7 | 0.184 | 295.748 |
| 12.8 | 101.4 | 0.180 | 322.58 |
|  | min | 0.178 | 276.885 |
|  | max | 0.221 | 328.712 |
|  | mr. | 0.1506 | 301.262 |



| $\begin{aligned} & \text { camere A } \\ & \text { case } 2 \\ & \text { rurnt } 3 \end{aligned}$ | $(\operatorname{App} 4)$ | gamma |  |
| :---: | :---: | :---: | :---: |
| NinBr [whal |  | Retio | Grad.m |
| 22.1 | 114.7 | 0.183 | 298.377 |
| 22 | 114.7 | 0.182 | 291.967 |
| 22 | 115.1 | 0.182 | 303.002 |
| 21 | 113.6 | 0.180 | 359.283 |
| 20.5 | 112.6 | 0.182 | 316.766 |
| 20.2 | 104.1 | 0.190 | 218.178 |
| 20.4 | 110.4 | 0.185 | 313.804 |
| 19.8 | 112.8 | 0.175 | 322.891 |
| 21.4 | 113 | 0.180 | 309.946 |
| 21 | 115.1 | 0.182 | 337.205 |
| 22.2 | 115.7 | 0.188 | 292562 |
| 21.4 | 114.7 | 0.188 | 299.006 |
| 21.4 | 113.8 | 0.180 | 316.200 |
| 21.8 | 113.6 | 0.183 | 312150 |
| 21.5 | 113.6 | 0.189 | 344508 |
| 20.7 | 111.3 | 0.188 | 303.241 |
|  | min | 0.175 | 218.178 |
|  | $\max ^{\text {a }}$ | 0.194 | 350,203 |
|  | av. | 0.1877 | 300.585 |


|  |  | gemma 0.45 |  |
| :---: | :---: | :---: | :---: |
| Ninor [wint | MaxBr [w/n) | Ramio | Grad.m |
| 29.4 | 115.5 | 0.255 | 209.108 |
| 25.3 | 115.7 | 0.219 | 20.204 |
| 24.4 | 116.1 | 0.21 | 331.655 |
| 24.4 | 1122 | 0.210 | 330363 |
| 24.3 | 113.2 | 0.215 | 334.672 |
| 24.1 | 112.6 | 0.214 | 310.765 |
| 24.2 | 111.3 | 0.217 | 302802 |
| 24.5 | 115.3 | 0.212 | 300.00 |
| 25 | 115.1 | 0.217 | 330.38 |
| 28.7 | 118 | 0.249 | 208.107 |
| 27.8 | 119.4 | 0.283 | 302.633 |
| 25.8 | 118.8 | 0.217 | 322.527 |
| 24.7 | 116.3 | 0.212 | 300.429 |
| 24.6 | 113.8 | 0.216 | 318.633 |
| 24.6 | 111.5 | 0.221 | 277.409 |
| 24.6 | 110 | 0.224 | 291.383 |
|  | min | 0.21 | 269.108 |
|  | max | 0.255 | 338.388 |
|  | av. | 0.2218 | 307.303 |



| cemera 1 | gemma 1 |  |  |
| :---: | :---: | :---: | :---: |
|  | (App 8) |  |  |
| Tent |  |  |  |
| Wintr (whry | Mander [w/at | Ratio | Gradm |
| 22.7 | 70.1 | 0.324 | 174.823 |
| 20.8 | 71.1 | 0.204 | 214.046 |
| 22 | 70.4 | 0.312 | 151.677 |
| 27.1 | 71.6 | 0.379 | 146.712 |
| 24.8 | 71.4 | 0.348 | 152.178 |
| 22.3 | 72.2 | 0.31 | 180.158 |
| 21.4 | 70.E | 0.301 | 193.231 |
| 20.4 | 68.8 | 0.304 | 148.078 |
| 20.7 | 68.8 | 0.3 | 150.600 |
| 20. | 67 | 0.311 | 158.718 |
| 20.7 | 70.7 | 0.303 | 146.028 |
| 22.8 | 68.4 | 0.344 | 141.844 |
| 21.8 | 60.7 | 0,318 | 165.936 |
| 22 | 63.8 | 0.321 | 144.878 |
| 21.4 | 67.4 | 0.317 | 148.257 |
| 21.2 | 67.4 | 0.314 | 160.614 |
|  | min | 0.294 | 141,844 |
|  | max | 0.378 | 214.048 |
|  | Er. | 0.3228 | 160.874 |


| camera Acase 1Teryen 7 | (App 8) | gamma 0.45 |  |
| :---: | :---: | :---: | :---: |
|  |  |  |  |
|  |  |  |  |
| WinBr cwan | Maxder [why | Ratio | Gradm |
| 27.8 | 73.4 | 0.379 | 157.34 |
| 28.5 | 72.8 | 0.364 | 154.949 |
| 25.4 | 73.1 | 0.348 | 138.83 |
| 24 | 70.3 | 0,342 | 160.819 |
| 25.1 | 72.1 | 0.348 | 143.72 |
| 24.1 | 71.2 | 0.338 | 168.82 |
| 23.8 | 69.8 | 0.341 | 113.172 |
| 23.1 | 70.4 | 0,329 | 168.991 |
| 23.1 | 71 | 0.325 | 157.248 |
| 24.8 | 72.8 | 0,342 | 187,078 |
| 23.8 | 74 | 0,322 | 171.057 |
| 27.8 | 73.5 | 0.379 | 151.826 |
| 26 | 73.8 | 0,352 | 149.079 |
| 24.5 | 73.6 | 0.333 | 202.001 |
| 23.6 | 71.4 | 0.331 | 184.975 |
| 23.2 | 73 | 0,318 | 189.876 |
|  | min | 0.318 | 113.172 |
|  | max | 0.379 | 202.001 |
|  | Ev. | 0.3432 | $\underline{161.736}$ |


| $\begin{aligned} & \text { camera A } \\ & \text { cesee } 2 \\ & \text { Turen } 7 \end{aligned}$ | garnma 1 |  |  |
| :---: | :---: | :---: | :---: |
|  | (App 5.6) |  |  |
|  |  |  |  |
| Win ${ }^{\text {ar }}$ [W/m] | MaxBr [whal | Retio | Grad.m |
| 32.5 | 101.9 | 0.319 | 305.939 |
| 34.8 | 102.2 | 0.311 | 231.003 |
| 34.7 | 101.6 | 0.361 | 300.627 |
| 39.1 | 1013 | 0.383 | 219.795 |
| 37.2 | 1013 | 0.387 | 205.239 |
| 35.5 | 101 | 0.352 | 248.851 |
| 33.5 | 100.7 | 0.333 | 250.688 |
| 32.1 | 101.7 | 0.316 | 268.091 |
| 33.2 | 1003 | 0.331 | 251.843 |
| 33.1 | 101.4 | 0.328 | 214.881 |
| 37.4 | 101 | 0.371 | 198.46 |
| 38.8 | 100.8 | 0.508 | 228.351 |
| 38.1 | 100.6 | 0.350 | 238.134 |
| 35,5 | 101.6 | 0.35 | 231.003 |
| 33.3 | 99.7 | 0.334 | 239,412 |
| 33.7 | 101.3 | 0.333 | 203.662 |
|  | min | 0.316 | 198.48 |
|  | $\max$ | 0.303 | 305.939 |
|  | avr. | 0.3453 | 240.137 |


|  | (App 5.6) | gamma 0.45 |  |
| :---: | :---: | :---: | :---: |
|  | MaxBr [whal | Retio | Gradm |
| 44.7 | 121 | 0.37 | 228.273 |
| 40.2 | 119.6 | 0.336 | 292,568 |
| 38.1 | 120.6 | 0.316 | 297,406 |
| 36.5 | 118 | 0.31 | 283.764 |
| 35.3 | 110.6 | 0.318 | 241.873 |
| 38.4 | 117.6 | 0.31 | 200.408 |
| 40.9 | 120.4 | 0.34 | 281.775 |
| 38.2 | 120.8 | 0.316 | 335,000 |
| 46.5 | 120 | 0.387 | 228.581 |
| 42.1 | 118.2 | 0.353 | 227.878 |
| 39.4 | 117 | 0.337 | 265.16 |
| 39.3 | 114.6 | 0.343 | 250.518 |
| 36.2 | 100.9 | 0.383 | 228,456 |
| 37.8 | 115.9 | 0.328 | 240.05 |
| 38.7 | 115.3 | 0.353 | 271.600 |
| 38.4 | 117.4 | 0.327 | 275.601 |
|  | min | 0.31 | 228.501 |
|  | max | 0.387 | 335.009 |
|  | av. | 0.3349 | 204811 |



| camera $A$ <br> case 2 <br> Tuene | gamma 1 |  |  |
| :---: | :---: | :---: | :---: |
|  | (App 5.6) |  |  |
| Winibr [whly |  | Ratio | Gradm |
| 39.7 | 01.5 | 0.433 | 171.202 |
| 42.2 | 82.3 | 0.457 | 165.577 |
| 35.7 | 80.7 | 0.394 | 199.86 |
| 35.4 | 92.8 | 0.381 | 228.164 |
| 35.8 | 94.3 | 0.38 | 238.787 |
| 35.5 | 83 | 0.381 | 205,08 |
| 35.2 | 93.4 | 0.377 | 184.852 |
| 37.3 | 93.3 | 0.4 | 214.468 |
| 38.4 | 93.8 | 0.409 | 200.823 |
| 35.2 | 82.2 | 0,382 | 208.005 |
| 39.2 | 93 | 0.422 | 158.468 |
| 40.3 | 92.4 | 0.438 | 170.768 |
| 38.4 | 91 | 0.4 | 185.111 |
| 38.8 | 95.6 | 0.385 | 203.005 |
| 36.7 | 94.2 | D.389 | 208.742 |
| 36.7 | 94 | 0.39 | 202.858 |
|  | min | 0.377 | 158,468 |
|  | max | 0.457 | 236.787 |
|  | mr. | 0.401 | 198.918 |


| cemera Acese 2Torela | (App 5.6) | germma 0.45 |  |
| :---: | :---: | :---: | :---: |
|  |  |  |  |
| MinBr [w/al] | Maxar [Whay | ReNo | Gradm |
| 40.4 | 117.6 | 0.411 | 255.506 |
| 48.7 | 117.6 | 0.3897 | 2583.38 |
| 48.7 | 114 | 0.41 | 21,293 |
| 43.8 | 113.1 | 0.308 | 227,597 |
| 45.2 | 114.7 | 0.394 | $2 \times 2.234$ |
| 48.3 | 118.3 | 0.389 | 263603 |
| 49.1 | 118.5 | 0.422 | 252034 |
| 46.8 | 117.4 | 0.308 | 254.808 |
| 57.6 | 120.8 | 0.478 | 181,628 |
| 58.9 | 118.6 | 0.46 | 210.412 |
| 58 | 118.8 | 0.405 | 203.157 |
| 60 | 118.4 | 0.418 | 254.947 |
| 50.6 | 120 | 0.422 | 237,837 |
| 48.3 | 114.2 | 0.428 | 200.879 |
| 47.8 | 115 | 0.416 | 224005 |
| 49.2 | 118.4 | 0.418 | 281.508 |
|  | mm | 0.388 | 181.028 |
|  | max | 0.485 | 268.803 |
|  | man. | 0.4224 | 232.897 |






| camera A <br> case 1 <br> Itinn 13 |  | gamma 0.45 |  |
| :---: | :---: | :---: | :---: |
|  | (App 8) |  |  |
|  |  |  |  |
| WinEr [whal | MaxBr $\left[\right.$ Whas ${ }^{\text {a }}$ | Retio | Grad.m |
| 32.8 | 48.8 | 0.671 | 50.315 |
| 32.8 | 48.1 | 0.600 | 56.236 |
| 33.1 | 47.2 | 0.701 | 52.889 |
| 32.8 | 48.5 | 0,678 | 55.316 |
| 32.3 | 48.8 | 0.689 | 59.443 |
| 32.4 | 46.8 | 0.606 | 46.457 |
| 32.2 | 48.6 | 0.682 | 40.838 |
| 31.5 | 46.3 | 0.681 | 53.454 |
| 32.1 | 47.2 | 0.678 | 58.685 |
| 31.9 | 48.8 | 0.68 | 59.372 |
| 324 | 47.9 | 0.677 | 57.81 |
| 32.8 | 48.7 | 0.674 | 55.245 |
| 31.4 | 47.5 | 0,062 | 48.608 |
| 30,8 | 46.3 | 0.667 | 52.72 |
| 31 | 45.7 | 0.678 | 48.459 |
| 31.4 | 46 | 0.683 | 47.187 |
|  | min | 0.682 | 40,838 |
|  | max | 0.701 | 59.443 |
|  | av. | 0.6799 | 52.6808 |


| cemerea |  | gemma 0.45 |  |
| :---: | :---: | :---: | :---: |
| Tinimr [Whan | Wexicr [whmi] | Ratio | Grad.m |
| 37.3 | 47.7 | 0.782 | 35.154 |
| 35 | 45.2 | 0.714 | 37.808 |
| 35.2 | 45.3 | 0.778 | 31.298 |
| 35 | 45.2 | 0.774 | 37.808 |
| 35.2 | 45.3 | 0.772 | 31.298 |
| 37.1 | 48.5 | 0.768 | 35.562 |
| 38.6 | 48.6 | 0.783 | 35.58 |
| 35.1 | 48.1 | 0.782 | 39.25 |
| 35.8 | 46.3 | 0.774 | 31.781 |
| 35.1 | 40.3 | 0.758 | 4.500 |
| 37.1 | 485 | 0.768 | 35.562 |
| 37.7 | 48.6 | 0.775 | 39.803 |
| 36.5 | 47.7 | 0.768 | 33.900 |
| 35.4 | 46.2 | 0.768 | 34.894 |
| 38.3 | 48.2 | 0.787 | 36.817 |
| 34.8 | 45.1 | 0.774 | 31.187 |
|  | min | 0.758 | 31.197 |
|  | mex | 0.787 | 44.508 |
|  | me. | 0.773 | 35.7742 |



| $\begin{aligned} & \text { cmara A } \\ & \text { case } 2 \\ & \text { Tene is } \end{aligned}$ | (App 5.6) | gemma 0 |  |
| :---: | :---: | :---: | :---: |
| MinBr [whal | Maxicr | Retio | Grad,m |
| 79.3 | 106.2 | 0.747 | 83.592 |
| 82.1 | 107 | 0.768 | 81.801 |
| 79.5 | 104.2 | 0.763 | 84.759 |
| 78.1 | 102.4 | 0.763 | 83.242 |
| 77.1 | 83.5 | 0.788 | 60.035 |
| 76.8 | 97.1 | 0.792 | 65.542 |
| 74.4 | 88.4 | 0.772 | 68.202 |
| 78.6 | 93.5 | 0.77 C | 82.148 |
| 78.8 | 108 | 0.78 | 00.012 |
| 78.6 | 104.4 | 0.753 | 96.77 |
| 78.7 | 105.8 | 0.744 | 87.820 |
| 783 | 108.6 | 0.734 | 95,803 |
| 77.8 | 103.1 | 0.755 | 91.577 |
| 75.7 | 99.7 | 0.758 | 91,337 |
| 75.3 | 97.5 | 0.772 | 83.071 |
| 73.5 | 85.4 | 0.771 | 70.508 |
|  | min | 0.734 | 60.055 |
|  | max | 0.790 | 89.598 |
|  | -0r. | 0.7844 | 83.0412 |


| $\begin{aligned} & \text { centera A } \\ & \text { case } 2 \\ & \text { Tar. } 14 \\ & \hline \end{aligned}$ | (App 5.6) | gomina |  |
| :---: | :---: | :---: | :---: |
| NinBr [w/n) | Maxder (wmm) | Retio | Grad.m |
| 88.8 | 1042 | 0.831 | 53.327 |
| 87.2 | 105.1 | 0.83 | 63.788 |
| 83.5 | 103.5 | 0.007 | 60.208 |
| 83.5 | 99.6 | 0.838 | 57.003 |
| 80.3 | 97.3 | 0,825 | 62.05 |
| 79.3 | 88.5 | 0.803 | 62.700 |
| 79,3 | 95,6 | 0.83 | 57.805 |
| 78 | 95.6 | 0.827 | 64.282 |
| 79.5 | 98.1 | 0.827 | 61.447 |
| 79.2 | 88.8 | 0.818 | 68.204 |
| 82.6 | 88.2 | 0.842 | 51.522 |
| 83.7 | 100.8 | 0.83 | 54.128 |
| 87.5 | 104.0 | 0.634 | 56,357 |
| 87.5 | 106.6 | 0.821 | 55.163 |
| 85.4 | 102.4 | 0.834 | 60.378 |
| 89 | 99.2 | 0.847 | 50.274 |
|  | min | 0.805 | 51,522 |
|  | max | 0.847 | 68.378 |
|  | avt. | 0.8278 | 59.9188 |









## APPENDIX B

## TARGET PLASTIFYING OR LAMINATING (EFFECTS)

Other set of measurements in terms of brightness measurements was done to find the effects of laminating/plastifying of targets. Targets were covered with reflecting or nonreflecting (mate) tape. A comparation was made among the brightness measurements resulted in testing a plain target, target covered with reflecting tape and target covered with mate or nonreflecting tape. Conclusion of these measurements is that covering the surface of targets using either shiny or mate tape has an effect of slighly reducing the brightness of the images with an approx. 2-3\%. The results of tests are annexed. One inconvenient of covering targets with reflectance tape is that incident lighting is uncontrollably reflected and this has a negative effect on recognition.

Data is presented on the following pages along with charts that graphically present the changes caused by the laminating done to the target's surface.

|  | $\begin{aligned} & \text { comere a } \\ & \text { case } 1 \end{aligned}$ | (App 8) | garnma 1 |  |
| :---: | :---: | :---: | :---: | :---: |
| Taret 1 |  |  |  |  |
|  | Maner Cumy | marer ciman | Reto | Cradm |
|  | 5.2 | 74.6 | 0.000 | 210.206 |
|  | 7.2 | 76. | 0.000 | 227208 |
|  | 7.7 | 76.3 | 0.101 | 287.520 |
|  | 6.6 | 75.5 | 0.097 | 280.84 |
|  | 7 | 78.0 | 0.008 | 200.024 |
|  | 7 | 76.2 | 0.002 | 266.612 |
|  | 6.0 | 75.8 | 0.002 | 242.474 |
|  | 7 | 74.8 | 0.004 | 224.42 |
|  | 6.3 | 72.5 | 0.008 | 238.400 |
|  | 7.8 | 74.1 | 0.107 | 102.734 |
|  | 7.6 | 73.1 | 0.102 | 200.600 |
|  | 7.7 | 74.0 | 0.103 | 204,800 |
|  | 6 | 75.6 | $0.10 t$ | 280.608 |
|  | 6 | 76.7 | 0.001 | 280,40 |
|  | 6.8 | 74.6 | 0.002 | 267.4 |
|  | 8.8 | 74.7 | 0.000 | 271.284 |
|  | 6.2 | 77A | 0.101 | 201.472 |
|  | 6.4 | 76.2 | 0.080 | 278.821 |
| Mm |  |  | 0.000 | 162.734 |
| Max |  |  | 0.107 | 201.472 |
| Avr. |  |  | 0.006 | 241.407 |


|  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Ten in 10 | 1) |  |  | Ter ${ }^{\text {che }} 1$ |  |  |  |
|  |  |  | ANO | Oradm | Miner aimin | vertiva | Rewo | Cratm |
|  | 7.8 | 60, | 0.113 | 217.446 | 9.3 | 70 | 0.133 | 184.825 |
|  | 6.8 | 64.1 | 0.107 | $182.411^{1}$ | 0 | 70.1 | 0.120 | 103.051 |
|  | 7.1 | 008 | 0.102 | 101.306 | 8.4 | 70.8 | 0.138 | 178.230 |
|  | 7.1 | 008 | 0.102 | 217.406 | 4.4 | 70.2 | 0.132 | 200.871 |
|  | 8.6 | 68. | 0.124 | 213,403 | 0.3 | 84.7 | 0.149 | 202.300 |
|  | 7.6 | 60.6 | 0.115 | 213,409 | 0.5 | 6 | 0.128 | 203.180 |
|  | 7.4 | 60 | 0.100 | 217.440 | 10.9 | 00.3 | 0.131 | 200.280 |
|  | 8.5 | 600 | 0.124 | 102.431 | 10 | 097 | 0.128 | 201.150 |
|  | 7.1 | 69. | 0.102 | 191.308 | 0.9 | 008 | 0.120 | 109.521 |
|  |  | 029 | 0.124 | 224.010 | 0.3 | 64.7 | 0.143 | 171.602 |
|  | 0.0 | 64.6 | 0.136 | 197.400 | 0.8 | 66 | 0.120 | 182.208 |
|  | 0.0 | 64.1 | 0.107 | 198461 | 10.9 | 003 | 0.131 | 127.4.4 |
|  | 7.5 | 88 | 0.113 | 221.180 | 10 | 0.7 | 0.122 | 212.006 |
|  | 7.4 | 69 | 0.100 | 204947 | 0.8 | 00.5 | 0.126 | 218.272 |
|  | 8.5 | 68.2 | 0.124 | 224.810 | 0.3 | 70 | 0.139 | 214.603 |
|  | 82 | 0.1 | 0.119 | 228.122 | 9 | 70.1 | 0.120 | 220.767 |
|  | 8.3 | 71.6 | 0.116 | 220,32 | 0.4 | 70.8 | 0.132 | 221.004 |
|  | 7.6 | 68. | 0.113 | 200.288 | 0.4 | 70.0 | 0.132 | 221.604 |
| Mn |  |  | 0.102 | 101.306 |  |  | 0.122 | 127.44 |
| $\underline{\text { max }}$ |  |  | 0.139 | 261280 |  |  | 0.143 | 221.604 |
| Avr. |  |  | 0.114 | 211.404 |  |  | 0.131 | 197.256 |



|  | $\begin{aligned} & \text { cannere A } \\ & \text { caneo } 1 \end{aligned}$ | (App 日) | gamma |  |
| :---: | :---: | :---: | :---: | :---: |
| Terat ${ }^{\text {c }}$ |  |  |  |  |
|  | Minter simic | Maver ${ }^{\text {ander }}$ | Ravo | Gradm |
|  | 0.8 | 03.8 | 0.134 | 198.870 |
|  | 8.1 | Q3,6 | 0.127 | 178.490 |
|  | 8.8 | 63.2 | 0.134 | 166.e01 |
|  | 9.7 | 85.6 | 0.148 | 194.131 |
|  | 9.4 | 68.7 | 0.143 | 103.716 |
|  | 9.7 | 63.6 | 0.147 | 198.576 |
|  | 9.6 | 65.5 | 0.146 | 194.617 |
|  | 0.6 | 64.8 | 0.147 | 105.006 |
|  | 9.8 | 64.6 | 0.147 | 186.420 |
|  | 8.5 | 63. | 0.134 | 117.426 |
|  | 8.8 | 63.6 | 0.131 | 150808 |
|  | 8.5 | 03.2 | 0.134 | 147.532 |
|  | 0.2 | 0.1 | 0.128 | 197.042 |
|  | 0.5 | 0.0 | 0.131 | 203.119 |
|  | 8.5 | 62.8 | 0.134 | 100.545 |
|  | 8.8 | 63.2 | 0.134 | 180.227 |
|  | 8.5 | 63.2 | 0.134 | 194.523 |
|  | 8.8 | 63.6 | 0.131 | 180202 |
| Mn |  |  | 0.127 | 117.426 |
| Max |  |  | 0.140 | 209.118 |
| Avr. |  |  | 0.137 | 182.034 |




|  | cemere 8 <br> case 1 | (App 8) garmil 1 |  |  | (App $)^{\text {a }}$ (ammil |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Teret 1 |  |  |  |  | Teurn 1(moo 1) |  |  |  |  |  |  |  |  |
|  | Mrner (wimy | Mater (thery | Amo | Gredm |  | Mmer Living | meder ${ }^{\text {aning }}$ | Acto | Caxdm | Maner bumy | Mexter briny | Funo | Gradm |
|  | 5.7 | 81.6 | 0.111 | 168.971 |  | 8.6 | 45 | 0.13 | 157.456 | 6.5 | 40.6 | 0.110 | 122.600 |
|  | 4.8 | 52.6 | 0.001 | 14.81 |  | 6.3 | 478 | 0.11 | 167.460 | 5.6 | 48.6 | 0.12 | 119.80 |
|  | 4.9 | 52.8 | 0.098 | 152.021 |  | 6.6 | 43 | 0.83 | 141.447 | 5.8 | 48.1 | 0.121 | 118208 |
|  | 4.8 | 53.6 | 0.00 | 18.806 |  | 5.3 | 47.8 | 0.11 | 141.447 | 5.6 | 46.6 | 0.12 | 119.830 |
|  | 4.8 | 53.6 | 0.091 | 150.60 |  | 5.3 | 47.0 | 0.11 | 14.4001 | 6.2 | 406 | 0.120 | 163.221 |
|  | 4.0 | 53.5 | 0.001 | 150.68 |  | 8.8 | 48 | 0.121 | 167.456 | 5.8 | 48.6 | 0.118 | 156.518 |
|  | 4.4 | 40.3 | 0.06 | 140.408 |  | 5.3 | 47.0 | 0.11 | 157.466 | 5.8 | 40 | 0.110 | 154,384 |
|  | 4.6 | 40.5 | 0.001 | 148.408 |  | 5.6 | 47.4 | 0.118 | 154.736 | 5.9 | 40.7 | 0.118 | 156.04 |
|  | 4.5 | 50.5 | 0.000 | 158.778 |  | 5.8 | 40 | 0.121 | 151.240 | 5.8 | 40 | 0.118 | 140.434 |
|  | 4.7 | 60.1 | 0.009 | 160.500 |  | 5.6 | 43 | 0.13 | 120.080 | 5.9 | 45.7 | 0.13 | 128.724 |
|  | 4.6 | 50.2 | 0.002 | 159.167 |  | 5.3 | 47.8 | 0.11 | 157,466 | 5.6 | 48.6 | 0.110 | 122.60 |
|  | 4.8 | 60.2 | 0.009 | 161.413 |  | 4.8 | 42.0 | 0.106 | 120.619 | 5.6 | 46.6 | 0.12 | 119.956 |
|  | 8.6 | 52.2 | 0.106 | 175.604 |  | 8.3 | 47.8 | 0.11 | 161.02 | 6.8 | 40.4 | 0.130 | 146.679 |
|  | 5.3 | 61.8 | 0.103 | 173.420 |  | 5.0 | 40 | 0.121 | 165.476 | 7 | 50 | 0.14 | 148.002 |
|  | 6.7 | 61.8 | 0.111 | 18.8971 |  | 5.2 | 40.8 | 0.107 | 165.506 | 7.1 | 50.4 | 0.141 | 160.202 |
|  | 4.9 | 62.2 | 0.002 | 106.308 |  | 8.3 | 47.8 | 0.11 | 157.468 | 6.6 | 40.6 | 0.12 | 119.536 |
|  | 4.6 | 60.2 | 0.084 | 100.608 |  | 8.8 | 48 | 0.121 | 181,240 | 6.2 | 486 | $0.12{ }^{\text {a }}$ | 163.221 |
|  | 4.0 | 52.8 | 0.002 | 152.821 |  | 4.6 | 42.0 | 0.108 | 168.107 | 6.0 | 48.6 | 0.115 | 166.618 |
| Man |  |  | 0.006 | 148.406 | Mn |  |  | 0.108 | 120.980 |  |  | 0.116 | 118.298 |
| Mex |  |  | 0.111 | 176.090 | Max |  |  | 0.13 | 168.107 |  |  | 0.141 | 156.618 |
| Avr. |  |  | 0.006 | 180.520 | Avr. |  |  | 0.116 | 162.000 |  |  | 0.124 | 138.000 |



| camere ${ }^{\text {case } 1}$ (App 8 ) gamma 1 |  |  |  |  | gemme 1 |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  |  |  | case 1 | (App 8) |  |  |  |  |  |  |
| Terets |  |  |  |  | Terot Clepe 1) |  |  |  |  | Tered etmont |  |  |  |
|  | Manbe (wimy | Marer ${ }^{\text {aninay }}$ | Remo | Gredm |  | Minser (ting | Maver (many | Amo | Gred.m | Mantor (wnmy | Manar (wing | Reto | Crad.m |
|  | 0.2 | 4.0 | 0.142 | 193.800 |  | 84 | 51.7 | 0.182 | 131.746 | 8.1 | 60 | 0.163 | 144.449 |
|  | 8.2 | 64.6 | 0.137 | 102.682 |  | 7.2 | 49.8 | 0.146 | 135.123 | 8.6 | 49.8 | 0.172 | 131.840 |
|  | 9.2 | 4.2 | 0.142 | 103.800 |  | 7.7 | 61.7 | 0.16 | 136.064 | 7.8 | 48.4 | 0.16 | 133.762 |
|  | 9.1 | 66.2 | 0.130 | 100.046 |  | 7.6 | 50.0 | 0.16 | 143.116 | 8.4 | 40.2 | 0.17 | 133.304 |
|  | 0.2 | 48 | 0.142 | 183.809 |  | 7.6 | 48.1 | 0.156 | 160.520 | 0.1 | 48.5 | 0.178 | 129.294 |
|  | 9.2 | 64.8 | 0.142 | 193,500 |  | 8.4 | 61.7 | 0.102 | 131.746 | 7.7 | 48.9 | 0.184 | 133.752 |
|  | 9.1 | 45.2 | 0.130 | 103.046 |  | 8.2 | 40.2 | 0.167 | 154.280 | 7.7 | 46.3 | 0.167 | 133.304 |
|  | 0.2 | 64.8 | 0.142 | 193.900 |  | 7.2 | 42.7 | 0.148 | 160.756 | 7.0 | 46.4 | 0.160 | 133.752 |
|  | 8.8 | 64.5 | 0.137 | 192.032 |  | 7 | 48.4 | 0.146 | 163.03 | 7.8 | 47.3 | 0.186 | 134.747 |
|  | 10.6 | 50.6 | 0.176 | 164.006 |  | 7.3 | 48.2 | 0.162 | 161.640 | 9.1 | 402 | 0.188 | 138.600 |
|  | 0.2 | 40 | 0.142 | 193.500 |  | 8.3 | 49.5 | 0.160 | 124.16 | 8.7 | 40.2 | 0.181 | 138.171 |
|  | 8. | 64.5 | 0.137 | 192.632 |  | 8.4 | 51.7 | 0.182 | 131.746 | 8.4 | 40.2 | 0.17 | 133.304 |
|  | 8.7 | 6 | 0.138 | 200.571 |  | 0.6 | 51.2 | 0.16 | 127.52 | 8.2 | 40.1 | 0.160 | 121.710 |
|  | 8.7 | 0.1 | 0.138 | 210.5 |  | 7.6 | 50.6 | 0.16 | 143.118 | 0.1 | 48.2 | 0.188 | 134.600 |
|  | 2.4 | 60.6 | 0.131 | 216.26 |  | 7.6 | 49.1 | 0.156 | 180.522 | 04 | 40.2 | 0.17 | 124.830 |
|  | 8.4 | 64.3 | 0.131 | 212.283 |  | 7.0 | 52.4 | 0.16 | 157.521 | 0.1 | 40.2 | 0.180 | 130.60 |
|  | 0.2 | 64.2 | 0.142 | 103.000 |  | 8.6 | 61.2 | 0.165 | 168.730 | 0.6 | 40.9 | 0.172 | 131.840 |
|  | 8.0 | 64.5 | 0.137 | 192.632 |  | 8.6 | 51.8 | 0.168 | 160.207 | 8.6 | 40.9 | 0.172 | 131.840 |
| Mn |  |  | 0.131 | 104.080 | Min |  |  | 0.146 | 123.16 |  |  | 0.168 | 121.710 |
| max |  |  | 0.178 | 216.246 | max |  |  | 0.180 | 180.520 |  |  | 0.180 | 144.440 |
| Avr. |  |  | 0.141 | 195.961 | Avr. |  |  | 0.167 | 145,416 |  |  | 0.173 | 133.72 |



|  | cemere $A$ case 1 | (App 8) gemma 1 |  |  | (App 8) gamma 1 |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Tereote |  |  |  |  | Tereental) |  |  |  |  | Terst ${ }^{\text {chenet }}$ |  |  |  |
|  | Mance tival | Maxer (ming | Reto | Gratim |  | Monter (wing | atim | Revo | Cram | Maner ming | dor | Armo | Gradm |
|  | 14 | 0 | 0.208 | 194.11 |  | 16. | 74.0 | 0.228 | 226.06 | 16.0 | 70.8 | 0.298 | 178.006 |
|  | 14.4 | 63.3 | 0.211 | 180.364 |  | 16.5 | 73.7 | 0.224 | 181.046 | 16.1 | 062 | 0.237 | 172.827 |
|  | 14.6 | 88.7 | 0.212 | 174.077 |  | 16.4 | 72.4 | 0.212 | 188.740 | 15.6 | 72.3 | 0.216 | 208.447 |
|  | 14.4 | 73.1 | 0.180 | 180.1 |  | 15.0 | 76.3 | 0.207 | 205.200 | 14.7 | 72.7 | 0.202 | 212.006 |
|  | 14.6 | 63.7 | 0.212 | 174.077 |  | 16.8 | 74.2 | 0.223 | 223.231 | 15.3 | 72.6 | 0.211 | 216.00t |
|  | 14.2 | 72.9 | 0.106 | 189.161 |  | 16.9 | 75.6 | 0.228 | 236.270 | 15.6 | 70.7 | 0.22 | 200.704 |
|  | 14.4 | 73.1 | 0.180 | 189.1 |  | 16. | 75.6 | 0.223 | 225.278 | 14.0 | 70.5 | 0.211 | 203.560 |
|  | 14.6 | 73.1 | 0.2 | 207.796 |  | 18.2 | 74.2 | 0.286 | 225.645 | 14.8 | 0.2 | 0.214 | 207.267 |
|  | 14.6 | 73.1 | 0.2 | 207.780 |  | 16.2 | 74.9 | 0.228 | 225.606 | 15.1 | 60.7 | 0.217 | 201.501 |
|  | 14.6 | 73.1 | 0.2 | 210.686 |  | 16.8 | 74.8 | 0.220 | 226.086 | 15.0 | 67.8 | 0.296 | 184.721 |
|  | 14.6 | 72.2 | 0.206 | 207.606 |  | 16.5 | 67 | 0.240 | 163.116 | 16 | 47.8 | 0.236 | 181,42 |
|  | 14.6 | 73.1 | 0.2 | 207.708 |  | 16.9 | 74.0 | 0.228 | 226.046 | 17.7 | 6 | 0.20 | 169.500 |
|  | 14.6 | 73.1 | 0.2 | 207.780 |  | 17.9 | 74.1 | 0.241 | 211.78 | 17.4 | 72 | 0.242 | 182. 13 |
|  | 14.6 | 60.71 | 0.212 | 174.077 |  | 17.7 | 74.3 | 0.238 | 107.394 | 16.0 | 71.6 | 0.236 | 180.82 |
|  | 13.6 | 64.6 | 0.213 | 176.116 |  | 16.3 | 72.7 | 0.224 | 108.307 | 16 | 72.2 | 0.228 | 184,302 |
|  | 16 | 65.6 | 0.220 | 102.987 |  | 17 | 72.7 | 0.234 | 103.735 | 16 | 70.7 | 0.220 | 186.130 |
|  | 14.3 | 67.3 | 0.213 | 206.108 |  | 16.5 | 73 | 0.228 | 107.002 | 16.0 | 71 | 0.229 | 174.030 |
|  | 13.6 | 67 | 0.206 | 216.267 |  | 15.4 | 73.4 | 0.21 | 212.092 | 18 | 72.3 | 0.240 | 180.00 |
| Min |  |  | 0.186 | 174,077 | Min |  |  | 0.207 | 16.115 |  |  | 0.202 | 169.500 |
| Max |  |  | 0.226 | 210.207 | Max |  |  | 0.248 | 225.606 |  |  | 0,200 | 216.001 |
| Av. |  |  | 0.206 | 106.500 | Avr. |  |  | 0.228 | 200.607 |  |  | 0.220 | 101.000 |



|  | $\begin{aligned} & \text { cernera A } \\ & \text { cange } 1 \end{aligned}$ | (App 8) | garnme 1 |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Tewn 13-tar 1 |  |  |  |  | Tome 13-ber 1 (ceil) |  |  |  |  | Tane 12-6ar 2 (tase 8 ) |  |  |  |
|  | Munber (winy | Cuarer (wimy | R**O | Gradm |  | Wers Bual | mever ${ }^{\text {and }}$ | Ramo | Cradm | Miner minct | Mastor (min) | Rumo | Oradm |
|  | 20.6 | 71.1 | 0.403 | 136.016 |  | 25.7 | 74.3 | 0.346 | 164.043 | 27.5 | 03.0 | 0.411 | 142.68 |
|  | 25.8 | 00.8 | 0.371 | 171.100 |  | 334, | 75.1 | 0.44 | 130.730 | 30.0 | 00.3 | 0.46 | 124,400 |
|  | 25.5 | 70.4 | 0.302 | 171.006 |  | 32.5 | 75.6 | 0.429 | 138.112 | 30.6 | 00.3 | 0.44 | 120.020 |
|  | 25.5 | 70.4 | 0.362 | 171.006 |  | 31.8 | 74.5 | 0.423 | 142.108 | 27.0 | 00.5 | 0.407 | 147.42 |
|  | 26.1 | 72.1 | 0.340 | 174.171 |  | 35.2 | 75.1 | 0.46 | 129.778 | 27.3 | cas | 0.307 | 164.027 |
|  | 26.3 | 70.0 | 0.368 | 166.008 |  | 33.8 | 75.6 | 0.46 | 160.060 | 27 | 67.6 | 0.401 | 149.473 |
|  | 25.3 | 60.6 | 0.360 | 165.471 |  | 25.8 | 75.0 | 0.342 | 103.200 | 27.3 | 67.0 | 0.408 | 147.067 |
|  | 23.3 | 70.1 | 0.352 | 109841 |  | 20.7 | 72.0 | 0.506 | 179.73 | 27.5 | 63.9 | 0,411 | 142.586 |
|  | 25.2 | 00.6 | 0.362 | 169.306 |  | 20.7 | 72. | 0.306 | 178.73 | 20.4 | 63.3 | 0.308 | 141.726 |
|  | 25.9 | 0 | 0.375 | 150.000 |  | 25.2 | 74.8 | 0.397 | 180.000 | 27.1 | 00.7 | 0.447 | 111.367 |
|  | 24.8 | 68.8 | 0.382 | 163.293 |  | 25.2 | 74.8 | 0.337 | 180.000 | 27.6 | 60.3 | 0.467 | 108.061 |
|  | 27 | 72.1 | 0.375 | 122.678 |  | 28.7 | 71 | 0.376 | 188.413 | 26.0 | 63.8 | 0.421 | 111.450 |
|  | 27.1 | 70 | 0.380 | 147.000 |  | 28.7 | 71 | 0.376 | 162.413 | 24.7 | 66.1 | 0.30 | 174.06 |
|  | 28.3 | 68 | 0.380 | 161.825 |  | 28.6 | 70.5 | 0.377 | 168.024 | 28 | 68.9 | 0.38 | 178.550 |
|  | 24.6 | 70.9 | 0.346 | 144.220 |  | 28.1 | 70.7 | 0.411 | 136.402 | 26 | 66. | 0.378 | 174.08 |
|  | 24.6 | 70.6 | 0.346 | 135.175 |  | 27.5 | 67.3 | 0.400 | 120.10 | 25.5 | 63.2 | 0.384 | 174.000 |
|  | 28.3 | 71.2 | 0.308 | 133.506 |  | 26.3 | 70.7 | 0.360 | 140.842 | 25.8 | 67.6 | 0.302 | 173.432 |
|  | 20.2 | 70.3 | 0.401 | 136.776 |  | 22.1 | 72.4 | 0.300 | 100.003 | 25.6 | 67.8 | 0.308 | 173432 |
| Min |  |  | 0.342 | 122.570 | Mn |  |  | 0.300 | 128.10 |  |  | 0.578 | 108.061 |
| $\max$ |  |  | 0.402 | 171.006 | $\underline{m a x}$ |  |  | 0.46 | 100.000 |  |  | 0.457 | 178.650 |
| Avr. |  |  | 0.300 | 163.562 | Avr. |  |  | 0.367 | 156,384 |  |  | 0.407 | 147.031 |



|  | $\begin{aligned} & \text { cemera } \\ & \text { case } 1 \end{aligned}$ | (App 8) gemme 1 |  |  | (App 8) gamma 1 |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Tcmpe - bar 1 |  |  |  |  | Toune - bep 1 (tepel) |  |  |  |  | Tumen-ber 2 (caea) |  |  |  |
|  | MnBr (way | Marder Mriay | Raso | Cradm |  | Menter Sting | Maver ${ }^{\text {andy }}$ | Raso | Gradm | Mater $\min$ ch | maxter (way | Redo | Cradm |
|  | 10.7 | 47.7 | 0.226 | 130.208 |  | 11.4 | 53.2 | 0.214 | 119.009 | 12.3 | 52.4 | 0.248 | 122.702 |
|  | 10.9 | 40.8 | 0.218 | 130.21 |  | 15.4 | 634 | 0.200 | 100.802 | 10.8 | 61.4 | 0.21 | 124.801 |
|  | 11.1 | 40.8 | 0.222 | 127.500 |  | 13.5 | 62 | 0.20 | 117.266 | 11.1 | 40.7 | 0.228 | 117.703 |
|  | 10.6 | 40.3 | 0.213 | 148.400 |  | 14.2 | 56.2 | 0.27 | 140.43 | 10.7 | 81.7 | 0.200 | 123.053 |
|  | 10.6 | 42.6 | 0.218 | 142.844 |  | 112 | 64 | 0.207 | 151.026 | 10.5 | 49.0 | 0.211 | 138.211 |
|  | 10.6 | 40.6 | 0.210 | 142.844 |  | 11.2 | 34 | 0.207 | 151.026 | 10.4 | 49.4 | 0.21 | 135.090 |
|  | 11.2 | 47.1 | 0.230 | 131.530 |  | 9.4 | 61.7 | 0.102 | 153.24 | 10.7 | 82 | 0.207 | 132.880 |
|  | 10.8 | 46.8 | 0.247 | 119.762 |  | 11.4 | 53.5 | 0.214 | 165.628 | 10.6 | 40 | 0.216 | 13.200 |
|  | 10.7 | 47.7 | 0.226 | 130.208 |  | 10 | 63 | 0.19 | 160.066 | 10.6 | 62.11 | 0.202 | 120.201 |
|  | 11.5 | 46.4 | 0.254 | 110.513 |  | 10.1 | 50.5 | 0.2 | 160.733 | 10.4 | 47.2 | 0.218 | 128.230 |
|  | 10.7 | 47.7 | 0.226 | 130.283 |  | 10.2 | 40.7 | 0.206 | 135.606 | 10.3 | 47.3 | 0.218 | 125.776 |
|  | 10.9 | 43.6 | 0.26 | 107.002 |  | 10 | 50.6 | 0.197 | 137.034 | 10.6 | 47.7 | 0.221 | 127.62 |
|  | 9.7 | 47.8 | 0.202 | 149.468 |  | 10.3 | 51.3 | 0.2 | 136.106 | 10.0 | 46.6 | 0.233 | 122.181 |
|  | 9.7 | 47.0 | 0.202 | 144.548 |  | 14 | 80.5 | 0.277 | 125.046 | 13,4 | 47 | 0.206 | 112.36 |
|  | 10.7 | 47.7 | 0.226 | 130.200 |  | 15.7 | 64.2 | 0.20 | 131.19 | 11.1 | 46.9 | 0.238 | 110.92 |
|  | 10 | 48.4 | 0.200 | 123.620 |  | 15.6 | 84.7 | 0.294 | 126.606 | 12 | 52.6 | 0.220 | 131.567 |
|  | 11.1 | 40.3 | 0.228 | 130.128 |  | 13.8 | 84 | 0.258 | 131.703 | 11.6 | 52.8 | 0.218 | 131.80 |
|  | 10.3 | 40.1 | 0.21 | 140.050 |  | 12.2 | 63.2 | 0.223 | 138.212 | 11.3 | 32.5 | 0.216 | 133.024 |
| Min |  |  | 0.208 | 107.002 | Mat |  |  | 0.182 | 109.080 |  |  | 0.202 | 112.36 |
| Max |  |  | 0.254 | 149.460 | Max |  |  | 0.200 | 185.629 |  |  | 0.208 | 138.211 |
| Avr. |  |  | 0.223 | 133.006 | Avr. |  |  | 0.231 | 137.200 |  |  | 0.228 | 127.167 |




## APPENDIX C

## POSITION COMPUTATION ALGORITHM

Triangulation refers to the process of determining the ( $\mathrm{x}, \mathrm{y}, \mathrm{z}$ ) coordinates of a three-dimensional point from the observed position of two perspective projections of the point. The routine uses an algorithm [56] developed by Sensor Adaptive incorporation. The routine is based on the following camera model mapping $(\mathbf{x}, \mathbf{y}, \mathbf{z}$ ) to undistorted pixel (f,g):

$$
\begin{align*}
& f(u)=\frac{a(0) \cdot x+a(1) \cdot y+a(2) \cdot z+a(3)}{a(8) \cdot x+a(9) \cdot y+a(10) \cdot z+1}  \tag{A.3}\\
& f(u)=f+D(f)(d f, \text { order } f, g)  \tag{A.4}\\
& g(u)=\frac{a(4) \cdot x+a(5) \cdot y+a(6) \cdot z+a(7)}{a(8) \cdot x+a(9) \cdot y+a(10) \cdot z+1}  \tag{A.5}\\
& g(u)=g+D(g)(d g, \text { order } f, g) \tag{A.6}
\end{align*}
$$

Where:

- ( $\mathrm{f}, \mathrm{g}$ ) is frame buffer pixel coordinate(column,row) with arbitrary origin.
- ( $\mathbf{x}, \mathrm{y}, \mathrm{z}$ ) is world coordinate ie $(\mathrm{mm})$.
- $a(k) k=0 \ldots 10$ are unknown camera parameters.
- $D(f)(d f, o r d e r, f, g)$ is a polynomial lens distortion model in $f$.
- $\quad \mathrm{D}(\mathrm{g})(\mathrm{dg}$, order, $\mathrm{f}, \mathrm{g})$ is a polynomial lens distortion model in, g .

Using the previously calculated a(k) parameters and assuming that $\left(F_{1}, G_{1}\right)$ and $\left(F_{2}, G_{2}\right)$ is the perspective projection of a 3D point ( $x, y, z$ ) the position of target is calculated by solving the set of equations (A.3, ...A.6)

The C++ (Borland) algorithm
/transforms pixel locations into world coordinates//
\#include <ailoc.h>
\#include <windows.h>
\#include \lltring.h>
\#include <stdilib.h>
\#include <stdio.h>
\#include <process.h>
\#include <math.h>
\#include <dos.h> // used for computing the time ...
\#include <time.h>

```
double "'M;
double B[8][2];
```

int dvector(int, int, double "");
int dmatrix(int, int, int, int, double *"");
void nrerror(char);
void free_dvector(double *, int, int);
void free_dmatrix(double $*$. , int, int, int, int);
//void svdcmp(float a, int, int, float w,float v);
void dsvacmp(double ""a, int $m$, int $n$, double wD, double "*v);
int dsvbksb(double "*,double ",double "",int,int,double ",double ");
void get_coeficients();
void get_pixels();
int convert():
int main()
\{
\#define SINGULARITY_THRESHOLD (float)1e-8;
// \#define ERROR_CODE error = 0 ;
int error;

double " $\mathrm{V}_{\text {; }} / /$ output from svdcmp
double " $w$, "v;
dcuble *x; // world points
double " b ;

```
double " testVect;
double temp1,temp2;
double F1,F2,G1,G2;
double scaled_cam1_x, scaled_cam2_x,
    scaled_cam1_y, scaled_cam2_y;
double rSensorCoordinate_x, rSensorCoordinate_y, rSensorCoordinate_z;
    Int thaa;
FILE *ttr;
```

get_coeficients();
get_pixels();
/" if ( m _CalCoeffs.camera[0].fg_factors.f.offset $=$ = DBL_MAX )
// error $=$ SENSOR_IS_NOT_CALIBRATED;
// else
ftr=fopen("coord.dat","w");
if( $($ (error $=$ dmatrix $(1,4,1,3,8 C))$ )
$\{$
if( I(error $=$ dmatrix $(1,3,1,3, \& V)$ )
\{
if( !(error = dvector(1, 3, \&w)) )
\{
if( $($ (error $=$ dvector $(1,3,8 x))$ )
\{
if( $($ (error $=\operatorname{dvector}(1,4,8 \mathrm{~b}))$ )
\{
scaled_cam1_ $x=(B[0][0]-M[4][0]) / M[4][1] ;$
scaled_cam1_y = (B[0][1] - M[5][0])/M[5][1];
scaled_cam2_x $=(B[3][0]-M[9][0]) / M[9][1] ;$
scaled_cam2_y $=(\operatorname{B}[3][1]-M[10][0]) / M[10][1] ;$
temp1 $=$ scaled_cam1_x * scaled_cam1_xi
temp2 $=$ scaled_cam1_y ${ }^{\bullet}$ scaled_cam1_y;
F1 = scaled_cam1_x +
(M[2][0]+ scaled_cam1_x•M[2][1]+ scaled_cam1_y•M[2][2]+
temp1 - M[2][3] + scaled_cam1_x ${ }^{\bullet}$ scaled_cam1_ ${ }^{\bullet}$ M[2][4] +
temp2 * M[2][5] + scaled_cam1_x ${ }^{\bullet}$ temp1 ${ }^{\text {- }}$ M[2] $[6]+$
scaled_cam1_ $y^{*}$ temp1 ${ }^{-} M[2][7]+$
scaled_cam1_x * temp2 * M[2][8] +
scaled_cam1_y * temp2 * M[2][9]);
G1 = scaled_cam1_y +
(M[3][0]+ scaled_cam1_x ${ }^{-} M[3][1]+$ scaled_cam1_y ${ }^{\bullet} M[3][2]+$
temp1 ${ }^{-} \mathrm{M}[3][3]+$ scaled_cam1_ $x^{*}$ scaled_cam1_y ${ }^{\text {* }} \mathrm{M}[3][4]+$
temp2 ${ }^{\bullet} M[3][5]+$ scaled_cam1_X $^{\bullet}$ temp1 ${ }^{-} M[3][6]+$
scaled_cam1_y * temp1 ${ }^{-} \mathrm{M}[3][\bar{n}]+$

```
scaled_cam1_x * temp2 * M[3][8] +
scaled_cam1_y * temp2 " M[3][9]);
temp1 = scaled_cam2_x * scaled_cam2_x;
temp2 = scaled_cam2_y* scaled_cam2_y;
F2 = scaled_cam2_x +
    (M[7][0]+ scaled_cam2_x* M[7][1]+ scaled_cam2_y*M[7][2]+
    temp1 * M[7][3] + scaled_cam2_x* scaled_cam2_y* M[7][4] +
    temp2 * M[7][5] + scaled_cam2_x* temp1 M[7][6] +
    scaled_cam2_y* temp1* M[7][7] +
    scaled_cam2_x 'temp2 ' M[7][8] +
    scaled_cam2_y* temp2 * M(7][9]);
G2 = scaled_cam2_y +
    ( M[8][0]+ scaled_cam2_x M M[8][1]+ scaled_cam2_y`M[8][2]+
    temp1 'M[8][3] + scaled_cam2_x* scaled_cam2_y M M[8][4] +
    temp2 * M[8][5] + scaled_cam2_x* temp1 M[8][6] +
    scaled_cam2_y * temp1 *M[8][7] +
    scaled_cam2_x * temp2 * M[8][8] +
    scaled_cam2_y* temp2 * M[8][9]);
    b[1] = F1-M[1][3];
    b[2] = G1 - M[1][7];
    b[3] = F2-M[6][3];
    b[4] = G2 - M[6][7];
    C[1][1] = M[1][0] - (M[1][8] * F1);
    C[1][2] = M[1][1] - (M[1][9] * F1);
    C[1][3] = M[1][2] - (M[1][10]*F1);
    C[2][1] = M[1][4] - (M[1][8] 'G1);
    C[2][2] = M[1][5] - (M[1][9] * G1);
    C[2][3] = M[1][6] - (M[1][10] 'G1);
    C[3][1] = M[6][0] - (M[1][8] * F2);
    C[3][2] = M[6][1] - (M[1][9] * F2);
    C[3][3] = M[6][2] - (M[1][10] * F2);
    C[4][1] = M[6][4] - (M[1][8] * G2);
C[4][2] = M[6][5] - (M[1][9]*G2);
C[4][3] = M[6][6] - (M[1][10] * G2);
// find (x,y,z) coord.
dsvdcmp(C,4,3,w,V);
| puts("check");
//scanf("\%d", sthaa);
/I \{
\[
\underset{\{ }{\text { if }(!(e r r o r ~=~ d s v b k s b(C, w, V, 4,3, b, x))) ~}
\]
```

```
                                    printf("x[1] = %lf,x[2] = %/f,x[3] = %/f", x[1],x[2],x[3]);
                                    scanf("%/f", &x[1]);
                                    rSensorCoordinate_x = (double)(x[1] * M[11][1] + M[11][0]);
                                    rSensorCoordinate_y = (doubie)(x[2] *M[12][1] + M[12][0]);
                                    rSensorCoordinate_z = (double)(x[3] * M[13][1] + M[13][O]);
                                    fprintf(ftr,"%lf %lf %lf ",rSensorCoordinate_x,rSensorCoordinate_y,
                                    rSensorCoordinate_z);
                11}
                free_dvector(b, 1, 4);
                        }
                        free_dvector(x, 1, 3);
                    }
                        free_dvector( w, 1, 3);
            }
                free_dmatrix( V, 1, 3, 1, 3);
            }
            free_dmatrix( C, 1, 4, 1, 3);
        }
    fclose(ftr);
    // return error;
    return 0;
}
void nrerror(char error_text[)
//numerical recipes standard error handler
{
    // void exit();
    fprint((stderr,"Numerical Recipes run-time error...In");
    fprintf(stderr,"%sin",error_text);
    fprintf(stderr,"...now exiting to system...ln");
    exit(1);
}
int dvector(int nl, int nh, double "*v)
//allocates a double vector with range [nl..nh]
{
        *v = (double *)malloc((unsigned) (nh-nl+1+1)*sizeof(double));
        if (!(*V))
        {
            nrerror("allocation failure in vector()");
        return 1;
```

```
    }
    (*v) = nl;
    return 0;
}
/*
double *dvector(int nl, int nh)
//allocates a double vector with range [nl...nh.
{
    double "v;
    v = (double ")malloc((unsigned) (nh-ni+1)'sizeof(double));
    if ( !v ) nrerror("allocation failure in vector()");
    return v-nl;
}
int dmatrix(int nrl, int nrh, int ncl, int nch, double *""m)
//allocates a double matrix with range [nrl..nrh][ncl..nch]
{
    int i;
    /lallocate pointers to rows
    "m = (double "")malloc((unsigned)(nrh-nrl+1+1)*sizeof(double*));
    if(!(*m))
        {
            nrerror("allocation failure 2 in matrix()");
        return 1;
        }
            ("m)-=nrl;
            //allocate rows and set pointers to them
    for(i=nrl;i<=nrh;i++){
            ("m)[0]=(double ")malloc((unsigned)(nch-ncl+1+1)*sizeof(double));
        if(!(%m)[i])
            {
                nrerror("allocation failure 2 in matrix()");
            return 1;
            }
                (*m)[0-=ncl;
        }
        I/return pointer to array of pointers to rows
    return 0;
}
void free_dvector(double "v, int nl, int nh)
Ifrees a double vector allocated by vector()
{
    free(((v+nl)));
}
```

void free_dmatrix(double " $m$, int nrl, int nrh, int ncl, int nch)
I/frees a matrix allocated with dmatrix
\{
int i;
for (i=nrh;i>=nrl; ;-)free((m[i]+ncl));
free(( $m+n r l)$ );
\}
static double at,bt,ct;
\#define PYTHAG(a,b)
((at=fabs(a))>(bt=fabs(b))?(ct=bt/at,at*sqrt(1.0+ct*ct)):(bt?(ct=atht,bt’sqrt(1.0+ct*ct)):0.0))
static double maxarg1,maxarg2;
\#define $\operatorname{MAX}(\mathrm{a}, \mathrm{b})$ (maxarg1=(a), maxarg2=(b),(maxarg1)>(maxarg2)?(maxarg1):(maxarg2)) static double minarg1, minarg2;
\#define MIN(a,b)(minarg1=(a), minarg2=(b),(minarg1)<(minarg2)?(minarg1):(minarg2))
\#define SIGN( $\mathrm{a}, \mathrm{b}$ ) ( $(\mathrm{b})>=0.0$ ? fabs(a):-fabs(a))

void dsvdcmp(double "*a, int $m$, int $n$, double wa, double "*v)
\{
// float PYTHAG(fioat a, float b);
int flag, i, its, $, j, j, k, k, 1, n m ;$ double anorm,c,f,g,h,s,scale, x,y,z,"rv1;
dvector( $1, n, \& r v 1$ );
gescale=anorm=0.0;
for (i= $1 ; i<=n ; i++$ ) \{
$1=1+1$;
N1[0-scale"g;
$\mathrm{g}=\mathrm{s}=$ scale $=0.0$;
if $(i<m)\{$ for ( $k=i ; k<=m ; k++$ ) scale $+=$ fabs(alk][0]); if (scale) \{
for ( $k=1 ; k<=m ; k++$ ) $\{$
$a[k][0 /=$ scale;
$s+=a[k][]^{\prime} a[k][] ;$
\}
f=a(][1];
$g=-\operatorname{SIGN}(\mathrm{sqrt}(\mathrm{s}), \eta) ;$
hafig-s;
a[][0] $=9$ -

for $(s=0.0, k=i ; k<=m ; k++) s+=a[k][0] a[k][0] ;$
f=s/h;
for ( $k=i ; k<m ; k++$ ) $a[k][i]+=f^{*} a[k][i] ;$
\}
for ( $k$ mi; $k<=m ; k++$ ) a[k][0] $=$ scale;

```
        }
    }
    w(i)=scale "g;
    g=S=scale=0.0;
    if(i<mm&&i!= n){
        for (k=1;k<=n;k++) scale += fabs(a[][k]);
        if (scale) {
                for (k=1;k<=n;k++) {
                        a[][k] = scale;
                        s += a[i][k]"a[][k];
        }
        {=a[][\];
        g = -SIGN(sqrt(s),\);
        h=f'g-s;
        a([][\]=f-g;
        for (k=1;k<=n;k++) N1[k]=a[][k]/h;
        for (j=|;j<=m;j++) {
                        for (s=0.0,k=l;k<=n;k++) s += a[j[k]"a[][k];
                                for (k=l;k<=n;k++)a[j][k] += S"N1[k];
                }
                for (k=l;k<=n;k++) a[\[k] *= scale;
            }
    }
    anorm=MAX(anorm,(fabs(w(I])+fabs(rv1(I])));
}
for (l=n;i>=1;i-) {
    if (i<n)
        if (g) {
                        for (j=1;j<=n;j++)
                v([][]=(a[i[j]/a[i][])/g;
            for (j=1; j<=n;j++) {
                                    for (s=0.0,k=l;k<=n;k++) s += a[0][k]"v[k][];
                                    for (k=|;k<=n;k++)v[k][j] += s'v[k][D];
                    }
            }
                for (j=1;j<=n;j++) v(j][]=v[][0]=0.0;
    }
    v(0[0=1.0;
    g=N1[D];
    I=i;
}
for (i=MIN(m,n);i>=1;i-) {
    lmi+1;
    g=w(1);
    for (j=1;j<=n;j++)a[0][]=0.0;
    if (g) {
        g=1.0/g;
        for (j=l;j<=n;j++) {
                        for (s=0.0,k=l;k<mm;k++) s += a(k][0]a[k][j];
                f=(s/a[0])"g;
                for (k-i;k<=m;k++)a[k][] += f"a(k][D];
            }
            for (j=i;j<=m;j++) a[][[] "= g;
    } else for (j=i;j<=m;;++) a[][0]=0.0;
    ++a[][][]
}
```

```
for (k=n;k>=1;k-) {
    for (its=1;its<=30;its++) {
        flag=1;
        for (l=k;D=1;|) {
            nm=1-1;
            if ((float)(fabs(N1[J])+anorm) == anorm) {
                flag=0;
                break;
            }
    if (flag) {
                c=0.0;
                s=1.0;
                for (i=l;i<=k;i++) {
                f=s*N1[];
                N1(0]=c'v1[i];
                if ((float)(fabs(f)+anorm) == anorm) break;
                g=w(i);
                    h=PYTHAG(f,g);
                    w[j=h;
                    h=1.0/h;
                C=g"h;
                S = -f"h;
                for (j=1; ;<=m;j++) {
                    y=a[][nm];
                    z=a0%;
                        a[1][nm]=y*C+z*s;
                        a[][0]=\mp@subsup{z}{}{*}c-y*s;
                }
            }
    }
    z=w(k];
    if (l == k) {
                if (z<0.0){
                    w(k)=-z;
            for (j=1;j<=n;j++) v[][k] = -v[][k];
        }
        break;
    }
    if (its == 30) nrerror("no convergence in 30 svdcmp iterations");
    x=w[[];
    nm=k-1;
    y=w[nm];
    g=N1[nm];
    h=N1[k];
    f=((y-z)*}(y+z)+(g-h\mp@subsup{)}{}{*}(g+h))/(2.0"h"y)
    gmPYTHAG(f,1.0);
    f=((x-2)*(x+z)+h"((y/(f+SIGN(g,f))-h))/x;
    c=s=1.0;
    for (j=1;j<=nm;j++) {
                                i=j+1;
        g=v1[i];
        y=w[D;
        h=s"g;
        g=c*g;
```

```
    z=PYTHAG(f,h);
    n1[j=2;
    C=f/z;
    s=h/z;
    f=\mp@subsup{x}{}{*}c+\mp@subsup{g}{}{*}\mp@code{S}
    g= g*C-x*S;
    h=y*s;
    y*= c;
    for (j=1;j<<=n;ji++) {
        x=v[i])];
        z=v[价们;
        v[ij][i] =x* C+z*s;
        v[j][in=z* c-x*s;
    }
    z=PYTHAG(f,h);
    w[]=2;
    if (z) {
        2=1.0/2;
        C={"2;
        S=h'z;
    }
    f=c*g+s*y;
    x=c*y-s"g;
    for (j=1;ij<=m;ij++) {
        y=a[j][];
        z=a[j][]:
        a[ij] [j= =**+2*s;
        a[ij][0]=2* c-y*s;
    }
        }
        N1[]=0.0;
        N1[k]={;
        w(k)=x;
        }
    }
    free_dvector(nv1,1,n);
}
```

int dsvbksb(double "*u, double "w, double "*v,int m,int n, double "b,double "x)
/"solves $A^{*} X=B$ for a vector $X$, where $A$ is specified by the arrays $u[1 . . \mathrm{m}], \mathrm{w}[1 . . n], v[1 . . n][1 . . n]$ as returned by svdcmp. $m$ and $n$ are the dimensions of $A$, and will be equal for square matrices. $b[1 . . \mathrm{m}]$ is the input right-hand side. $x[1 . . n]$ is the output solution vector."/

```
{
            int jij,j;
    double s,"dtmp;
    dvector(1,n, &dtmp);
    for (j=1;j<=n;j++){ //calculate transpuse of U-B
            s=0.0;
        If (w[j]) {
            for (i=1; i<=m; i++)
```

```
                s+=u[i][[]"b[i];
            S/a W[l];
    }
    dtmp[]]=S;
    }
    for (j=1; ; <<=n; j++\){ //matrix multiply by V to get ansver.
        s=0.0;
        for (jj=1; ji<=n; jj++)s s+=v[j][j]"dtmp[ij];
        x[]=S;
    }
    free_dvector(dtmp,1,n);
    return 0;
}
void get_coeficients()
{
    FILE "Input_file ;
            int i,j, jj ;
            int mm[15] = {6,11,10,10,2,2,11,10,10,2,2,2,2,2,1} ;
            //Input_file = fopen("coeffs.txt", "r")
    //Input_file = fopen("verniercoefs.txt", "r")
    Input_file = fopen("cmmcoefs.txt", "r") ;
    //Input_file = fopen("rulercoefs.txt", "r") ;
            M = (double **)calloc(15, sizeof(double *));
            j=0 ;
            for(i=0;i<15;i++)
{
                                    M[i] = (double ")calloc( mm[i] , sizeof(double));
            j++ ;
}
            jj=0 ;
            for( i = 0; i< 15;i++)
            { for ( j=0;j<mm[ij]; j++)
            {or (j = 0; j<mm[ij] ; j++) (Input_file, "%/f", &M[i][i]); }
            }
    fclose(Input_file);
}
void get_pixels()
    FILE *fp;
    char buffer[80];
    int i=0;
    fp = fopen("Pixel_lo.dat", "r");
```


## while( fgets(buffer, 80, fp) != NULL )

sscanf(buffer, "\%if\%if", \&(B[0][0]), \&(B(0][1]) );
$\}^{\text {i++; }}$
fclose(p);
\}

## VITA AUCTORIS

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