33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

A Photogrammetry-based System for 3D Surface Reconstruction of Prosthetics and Orthotics

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Abstract—**The objective of this study is to develop an innovative close range digital photogrammetry (CRDP) system using the commercial digital SLR cameras to measure and reconstruct the 3D surface of prosthetics and orthotics. This paper describes the instrumentation, techniques and preliminary results of the proposed system. The technique works by taking pictures of the object from multiple view angles. The series of pictures were post-processed via feature point extraction, point match and 3D surface reconstruction. In comparison with the traditional method such as laser scanning, the major advantages of our instrument include the lower cost, compact and easy-to-use hardware, satisfactory measurement accuracy, and significantly less measurement time. Besides its potential applications in prosthetics and orthotics surface measurement, the simple setup and its ease of use will make it suitable for various 3D surface reconstructions.**

I. Introduction

Orthoses are commonly used to stabilize joints, reduce pain and improve function. The National Health Interview Survey indicated that those using orthoses are over 3.5 million in the U.S.A. and the total number of persons who will use orthoses is expected to double and reach 7.3 million by the year 2020. Prostheses are needed for those with limb loss. Currently, there are about 1.9 million people living with limb loss. A prosthetic device can cost between $2,500 and $50,000 and an adult usually needs to replace it every one to three years. As a child grows, he/she needs a new one every three to six months. In clinical practice, an impression is taken via wrapping the body part using plaster bandage. The whole procedure is labor-intensive, time-consuming and uncomfortable to patient. The accuracy of the casted mold is subject to the clinician's experience and technical skill as well as body shape changes caused by the pressure during the casting procedure. Both prostheses and orthoses are closely contoured to the patient's skin, thus a comfortable and perfect fit is the top priority for both patients and practitioners. Recently, more advanced technologies have been used to measure and reconstruct the 3D shape of the body part via a reverse engineering approach. Among these, laser scanning technique has been commercialized and used in the clinical sites. The benefits of laser scanning include ease of use and high accuracy and precision. However, the long acquisition time (usually around minutes) inevitably introduces movement-related distortion. Also the high cost of laser scanning equipment (usually $30,000-50,000) hinders its wide adoption. This method of measuring shape is called time/light in flight which uses the direct measurement of the time of flight of a laser or other light source pulse [1]. In general, picosecond pulse width diode laser are essential to achieve 1mm resolution, which require expensive component to achieve reasonable accuracy. In this study, we proposed an innovative close range digital photogrammetry (CRDP) approach using the commercial low cost digital SLR cameras to measure and reconstruct the surface of prosthetics and orthotics. There is great potential of performing precise 3D measurements using CRDP at a fraction of the time and cost of laser scanning with same level of accuracy.

Manuscript received March 26, 2011. This work was supported in part by the NIH under Grant 1R41HD066803-01.

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II. Methodology

A. Data acquisition and calibration

The fundamental principle used by CRDP is triangulation. As shown in Figure 1, by taking 2D digital images (photos) from multiple locations, the so called "line of sight" can be constructed from each camera to points on the object. These lines of sight are mathematically intercepted to produce the 3-dimensional coordinates of the points of interest. In our preliminary study, the 3D measurements were performed on a Prosthetic plaster mold covered with a nylon sock. To provide seamless 360-degree 3D surface model, we move the cameras' position around the object to take multiple photos to achieve a 360 degree view configuration (Figure 1), and an algorithm was developed to join the neighboring sets of point cloud and to generate the merged 360 degrees 3D surface.

The system hardware components are all commercial off-the shelf hardware: a digital single-lens reflex (SLR) camera (Canon EOS Rebel 500D 15.1 MP) with Canon EF 50mm f/1.8 II camera lens was used to generate the source 2D digital images. The measurement can be taken under conditions of regular ambient lighting. To achieve a 360 degree view configuration, fifteen pictures from different view angles were taken. The whole measurement procedure takes less than one minute. Please note that the measurement procedure is quite flexible and doesn't require the knowledge of camera locations beforehand. Whether these pictures were taken at different horizontal planes (due to inevitable movement) or at irregular angle distance, the calculation results remains unchanged. The detailed technical specifications of the camera are listed in Table 1. The choice of this camera assures stable interior geometry, (need to be calibrated), high resolution, ability of manual focus, high shutter speed, and low cost.

Table 1. Specifications of the digital SLR camera.

Parameters	Values
Max resolution	4752x3168
Sensor size	22.3x14.9 mm
Total pixels	15.1 million
Lens focal length (f)	50 mm
Distance from object (D)	2 m
Average image scale (m)	1:40
Pixel size (p)	4.7 µm

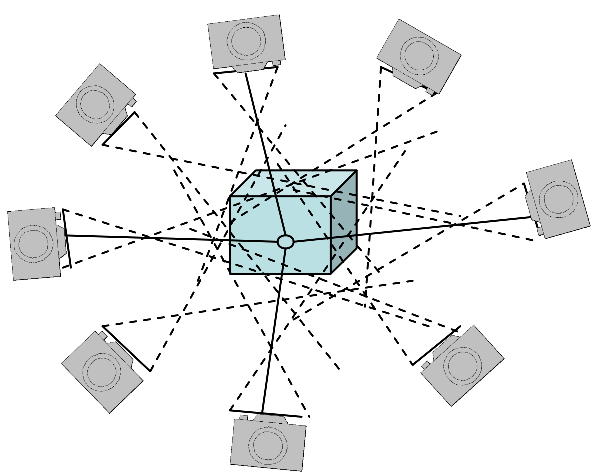

Fig. 1. Photogrammetry picture sequence

Accurate camera calibration is essential in digital photogrammetry. Primarily, camera calibration is to identify the characteristics internal to the camera that affect the imaging process. Careful camera calibration will provide accurate information of the camera parameters such as position of the image center, focal length, scaling factors for row and column pixels, skew factor and lens distortion. Camera calibration has been extensively studied and a camera system is often modeled by a pinhole system with intrinsic parameters including focal length, the principle point, the pixel skew effect and the pixel size as well as extrinsic parameters including the rotation and translation from the world coordinate system to the local camera coordinate system.

For camera calibration, a flat checkerboard is used to calculate the intrinsic parameters of the camera. In this study, we used a checkerboard with 10 × 10 mm squares. Images are taken with checkerboard posed at different angles. A series of images illustrated in Fig. 2 are used to obtain the intrinsic parameters of the camera using MATLAB (Mathworks Inc. MA, USA)[2].

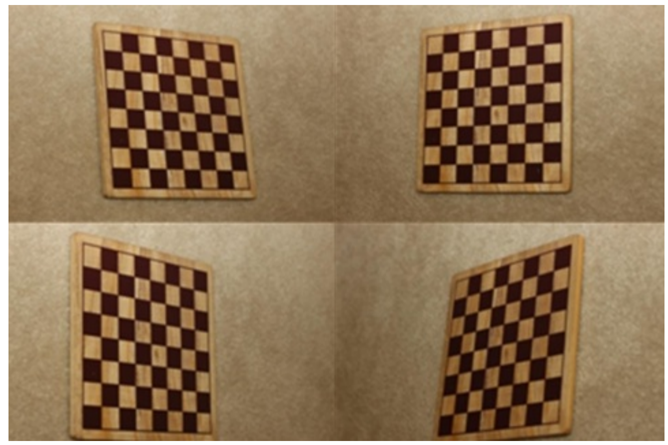

Fig. 2. Images of checkerboard for camera calibration.

B. Feature Point Extraction and Match process

In CRDP, the correspondence problem only becomes feasible when the surfaces are textured and/or there are feature points easily distinguishable (e.g. image corners). Combining the requirement of a simple, portable, affordable and cost effective sensor that can perform real-time measurement on human body, we applied random color fabric paint to the outside surface of a stretchable nylon prosthetics sock. In our preliminary study, the 3D measurements were performed on a Prosthetic plaster mold covered with the painted nylon sock, as shown in Fig. 3.

Fig. 3. Plaster mold covered with painted sock.

The point correspondence was established before construction of the 3D surface in space. Scale Invariant Feature Transform (SIFT)[3] , which transforms image data into scale-invariant coordinates relative to local features, was implemented. The SIFT algorithm uses difference of Gaussian kernels of varying widths to generate features along edges and at corners in the image. A gradient of the region around each feature is calculated. Matching features using SIFT is done by finding the closest matching descriptor between two images using a minimum Euclidean distance between the descriptor vectors. In addition, we examined the correlation within windows surrounding the pairs of the feature point to further improve the accuracy of the initial correspondence found by SIFT method. Fig. 4 shows the feature points (>10000 points) extracted from a pair of images. Fig. 5 shows the points correspondence after applying SIFT match method. It is shown that around 2000 correspondences were found that meet the threshold. Once the correspondences are found the next step is to remove the bad correspondences and estimate the epipolar geometry of the system (i.e. Random Sample Consensus (RANSAC) model fitting approach[4]).

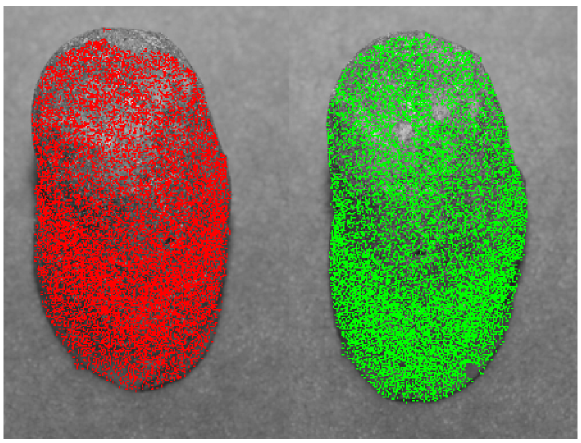

Fig. 4. Illustration of feature points extraction.

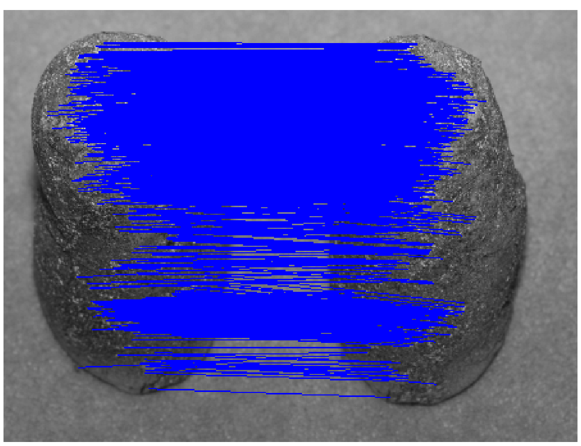

Fig. 5. Illustration of point correspondence of 2 views.

C. 3D Scene Reconstruction

We implement epipolar geometry[5] to establish the feature point correspondence, and carry out 3D reconstruction of the scene up to an overall 3D projective deformation. The basic reconstruction scheme with feature point correspondence from 2D views is listed as follows:

1) Compute fundamental matrix F, representing the intrinsic projective geometry between two views and satisfying the relation $x'^T F x=0$ for any pair of corresponding points x and x' in two images.
2) Calculate camera projective matrix using epipolar constraints.
3) For each of interest point in each image its position in 3D scene is calculated using triangulation.

Because the corresponding points are measured inexactly ("noise"), with hundreds of thousands of corresponding points extracted from pattern match, an optimal solution with minimized cost function needs to be determined. Minimizing such cost function requires nonlinear iterative techniques using Maximum Likelihood Estimation (MLE). The transformation (or other entity) to be computed is expressed in terms of a finite number of parameters. Gold Standard algorithm[6] with Sampson distance was implemented for estimating the fundamental matrix. Given the intrinsic parameters of the camera, the camera's projection matrix is determined, up to a similarity ambiguity, from the computed fundamental matrix. The computation of scene structure is achieved by triangulation – the point X in 3-space is computed as the intersection of rays back projected from the corresponding points via their associated cameras projection matrix. Fig. 6 shows the point clouds of the recovered 3D surface from the two images in Fig. 4.

The next step is to reconstruct the 360 degrees of 3D surface from the series of measured images. Based upon our process of measurement, there is no prior knowledge about the internal orientation of the camera at different view angles. This reconstruction problem is solved by initially computing a 3D point cloud from first pair of images and defining it as the world coordinate. The subsequent $image_{i+1}$, are incorporated into the reconstruction by calculating the projection matrix based upon the feature point correspondence between image{i} and image{i+1}, the pre-calculated projection matrix of the previous image P{i} and the 3D point cloud is calculated based on image{i-1} and image{i}.

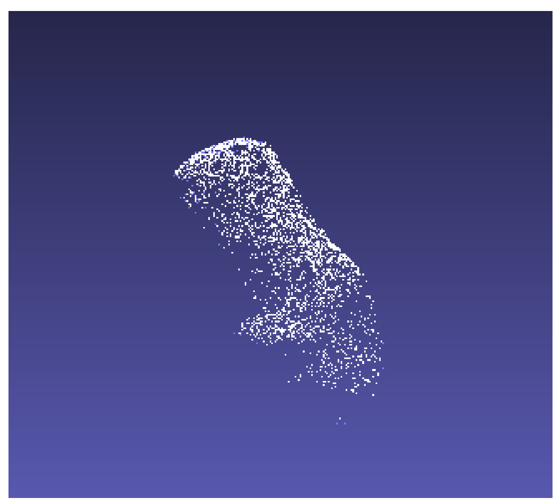

Fig. 6. 3D point cloud.

After the point clouds are merged to cover the 360 degree view, the Ball Pivoting algorithm (BPA)[7] is used to reconstruct the 3D surface from the merged point cloud, the resultant 3D surface triangle mesh can be exported to various types of data format for CAD system. Currently, the STL format and AutoCAD DXF format are supported. After necessary adjustment for critical portion of the 3D limb model and smoothing, the 3D model can be fed into CNC machine or digital carver to manufacture the positive mold for prosthesis or orthotics.

III. RESULTS

In our measurement, a Canon speedlite 480EXII with shutter speed of 1/400, aperture of f/6.3 was used to take 15 pictures from different view angles around the target object (a plaster positive mould) and reconstruct the 3D surface (Fig. 7).

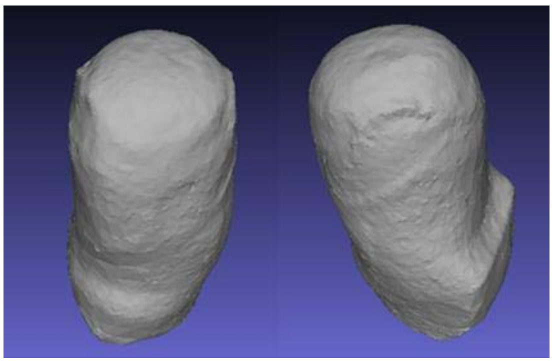

Fig. 7. Reconstructed 3D surfaces.

Typically, when the point correspondences are defined in a pair of images, there is always some error in defining the match which might be related to, blurred images, local instead of global correspondence maximum, etc. The residual error function can be defined as:

$$\varepsilon_{res} = \frac{1}{\sqrt{4n}}\left(\sum_{i=1}^{n} d(X_i, \hat{X}_i)^2 + \sum_{i=1}^{n} d(X'_i, \hat{X}'_i)^2\right)$$

$\hat{X}$ and $\hat{X}'$ represent the perfectly matched points, and d represents the distance between the measured point and the ideal perfectly matched point. The image scale number is defined by the ratio of object distance h to the principal distance c (lens focal length with additional of an extension to achieve sharp focus) of the camera system used. For our experimental set-up, we assume the object is 2 meters away from the camera, (h=2m), and the lens focal length is 50mm, (c=0.05m). Thus we can calculate the image scale as $\boldsymbol{m=h/c = 1/M = 40}$.

The uncertainty of an image measurement dx' can be transferred into object space by image scale number m: $\boldsymbol{dX = mdx'}$. The quality of 3D surface reconstruction depends on the quality of images. Fig. 8 shows the calculated residual error, which is the distance of the feature points to the perfectly matching points, for all the 3D points. There are total of around 15k points generated. It is shown that the mean error is around 0.3 of a pixel. With each pixel of size about 4.7 µm, which is shown in table 1, the estimated 1δ accuracy of the 3D measurement will be about 0.05 mm.

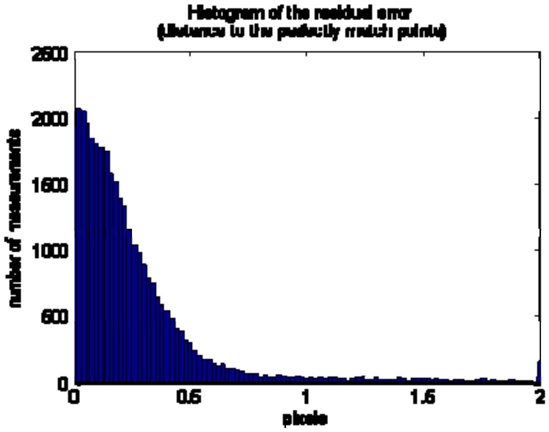

Fig. 8. Histogram of the residual errors.

IV. DISCUSSION AND CONCLUSION

In the current study, a CRDP system with high accuracy and low cost has been successfully developed. In the pilot test, the system was used to reconstruct the 3D surface of a positive plaster mould and has shown that the instrument performs measurements quickly with satisfactory accuracy. Unlike the commercial laser scanner, the key component of the developed system is a portable off-the-shelf, consumer grade digital camera which eliminates the need of data communication between scanner and computer. In addition, the system can be carried out at normal ambient light conditions using a flash light which makes it very suitable to be used in the clinic. In comparison with laser scanning, the major advantage of the system includes significantly lower cost (~$700 USD), compact and easy–to-use hardware, satisfactory measurement accuracy (0.05mm), and significantly less measurement time (less than 1 min). Besides its potential applications in prosthetics and orthotics surface measurement the simple setup and its ease of use will make it suitable for various 3D surface reconstructions via a reverse engineering approach (e.g., clothes design and tool development etc.). The performance of the system will be compared to commercial scanners and further investigation is underway.

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