Abstract: Recently, portable LCD projectors have become increasingly popular for various usages. However, a careful aligning to the projection surface or a flat screen are necessary for getting a good projection effect. If a projector can display an undistorted image on an unknown geometry surface, more and more applications can be expected. In this paper, we present a new approach allowing a projector to display an undistorted image on an unknown geometry surface. To realize it, a single camera is used to capture the viewer’s perspective of the projection surface. There is no explicit camera and projector calibration needed in the approach. The procedure establishes the mapping from camera image to projector image by a well trained neural network (NN). After the mapping has been established, a transform converter table is constructed from the output of NN. With the transform converter table (TCT), one can display an image corrected in real-time for the point of view of an observer, which takes into account his position, the surface distortion, and the projector position and orientation. With using of NN, we do not need to carry out all image pixels for establishing the mapping. The mapping can be obtained correctly, if enough teaching points can be provided. The simulation results show that our approach is effective for correcting distortion caused by continuous projective surface and practical enough for most projector presentation.

Key-Words: Projector-camera system, Projective mapping, Distortion correction, Neural network, Computer Graphics, Keystone

1. Introduction

With rapid advances in electrics and manufacture, low price and high performance portable LCD projectors have become increasingly popular for various usages. However, a careful aligning to the projection surface or a flat screen or wall are necessary for getting a good projection effect. However, without a careful aligning to the projection surface (wall or screen), the resulting image on the projection surface may appear distorted, or keystoned. If the surface used for projection is not flat completely, a nonlinear distortion will occur caused by nonlinear surface (not in a flat plane). Such distortion is undesirable, for such warping may bring distraction to audiences, and detriments to the interpretation of visual information such as graphs, table and charts and technical drawings. Keystoning can be avoided or reduced by aligning the projection system’s optical axis, so that it is perpendicular to the screen, and ensuring that the image is not rotated with respect to the screen. For fixed projectors that can be mounted from the ceiling and carefully aligned once by some experts with experiences, these constraints are surmountable; however, an alignment at the start of each presentation session must be required for portable projectors. This manual adjusting process is tedious; it can also be impractical to align a portable projector in a manner that eliminates all keystoning effects, since optimal alignment may place the projector in an awkward position (such as in the middle of the audience). If the projection surface is not flat as expected, or we want to project a image on a curved surface, it is impossible to get a non-distorted projecting image by normal alignment. The above reasons motivate the need for a better presentation interface: one that allows arbitrary placement of the projector.

Several works for camera-based automation calibration or correction of projector have recently been proposed. Sukthankar[1] present an automatic keystone correction for camera-assisted presentation interface, which use a digital camera to observe the pro-
jected image, some linear projective transforms are constructed by identification process, finally they are used to prewarp the image that will be projected to a flat screen. H.Chen[2] also gave some ideas for calibrating camera-projector system, which use a camera homograph tree to construct the linear projective transform that will be used for image prewarp. But most of their works concern a flat surface ( a flat screen ), their methods may not be effective for a curved surface or unknown geometry surface, which may be met in many cases for a portable projector usage or some special usage.

This paper presents a automatic approach for correcting distortion caused by both keystone and curved projection surface. For such distortion is not linear, the projective transform must be a nonlinear mapping. Neural Network have been used in various application for its excellent learning ability and nonlinear mapping approximation ability. Also there are many researches on neural network, some learning algorithms give good performance in both quick convergence and global stability[4,5,6]. To get the nonlinear projective transform in a high accuracy, we adopt a neural network with three layered structure to obtain an approximation of the projective transform that will be used for prewarping the image projected. A digital camera is used for capturing the viewer’s perspective of the projection surface, and the distortion information will be extracted from the camera image. The extracted information will be used for training NN before presentation. The simulation results show that the approach is much effective and practical enough for a continuous curved projective surface.

2. System Calibration

As shown in Fig.1, the system discussed here are: a standard computer, a digital camera, and a portable LCD projector.

There is no specific constraint on the position or the orientation of the projector and the camera with respect to the projection surface, except that area visible to the camera must be covered by the projector. In detail, the projector can be mounted anywhere, as long as the image falls entirely within the projection surface area. The camera must be mounted such that the projection screen is within its field of view. Therefore, there are three spaces: source image space (that will be projected to the projection surface), physical projection surface space and camera image space.

To implement an effective distortion correction, the projective transform mapping between the source image space and the camera image space must be determined. If the projection surface space is flat completely, the projective transform from source image space to the projective surface space and the projective transform from the projective surface space to the camera image space are linear mapping both. Such transform mapping can be shown in the following.

\[
\begin{bmatrix}
wx \\
wz \\
w
\end{bmatrix}
= \begin{bmatrix}
p_1 & p_2 & p_3 \\
p_4 & p_5 & p_6 \\
p_7 & p_8 & p_9
\end{bmatrix}
\begin{bmatrix}
X \\
Y \\
1
\end{bmatrix}
\]

where \((x, y)\) and \((X, Y)\) are corresponding points in two 2-D spaces of reference, and \(p = (p_1 \ldots p_9)^T\) are parameters specifying the homographies. Because the projective transform from the source image space to the camera image space can be derived by simple matrix calculation, the projective transform is a linear mapping. In this case, the parameters contained in the mapping can be identified by using some point correspondences in the spaces. Here, we assume that the projection surface is a smooth curved surface with unknown geometry, it is easy to know that the projective transform from the source image space to the camera image space must be a nonlinear mapping, and the linear approach can not be used for solving the problem. In general, the nonlinear mapping between pixels in the source image space \((x, y)\) and the camera image space \((u, v)\) can be shown as

\[
x = P_x(u, v) \quad (1)
\]
\[
y = P_y(u, v) \quad (2)
\]

where \(P_x\) and \(P_y\) are nonlinear functions which can
not be determined by only parameters.

It is well known that Neural Network has been used in various applications for its excellent learning ability and nonlinear mapping approximation ability. To get the nonlinear projective transform in a high accuracy, we adopt a neural network with three layered structure as shown in Fig.2 to obtain an approximation of the projective transform that will be used for prewarping the image projected. To training the NN, we select the algorithm by [4] that provides a both fast convergence and good global stability. After training with some teaching data, the NN may give a correct approximation of the projective transform.

![Figure 2: a 3-layer Neural Network for Nonlinear Mapping Approximation](image)

The source image may be projected to an arbitrary quadrilateral with curved sides in the projection image space as shown in Fig.3. Since the prewarped image can only be displayed within the area of the bounded source image space, the corrected image must lie within the bounds of the quadrilateral. Also the projected image should be as large as possible for a better efficiency. This is equivalent to finding the largest rectangle with appropriate aspect ratio within the projection image space, this process is easy to implement.

With the desired size and location of the corrected image, we will construct a transform converter table with well trained NN. The size of TCT will be affected by the resolution of the projector and the available rectangle area in the camera space. In our approach, the trained NN will not be used in presentation to pursue a quick image transformation calculation. The nonlinear distortion correction will be implemented by only TCT. The TCT can be generated as follows:

**step 1** calculate a possible rectangular area in projection surface, if necessary, the ratio of length and height should be considered for showing graphics or photos.

**step 2** based on the available resolution provided by the projector, determine the pixels numbers in horizontal and vertical direction for the rectangular area obtained in previous step. Assume that the rectangular area is filled a by \(M \times N\) pixels matrix., and the rectangular area is shown by \((u_{left}, v_{top})\) and \((u_{right}, v_{bottom})\).

**step 3** for \(1 \leq i \leq M\) and \(1 \leq j \leq N\), calculate \(T_x(i, j) = P_x(u_i, v_j)\) and \(T_y(i, j) = P_y(u_i, v_j)\) iteratively, where

\[
\begin{align*}
u_i &= u_{left} + \frac{u_{right} - u_{left}}{M - 1} (i - 1) \\
v_j &= v_{top} + \frac{v_{top} - v_{bottom}}{N - 1} (j - 1)
\end{align*}
\]

\(T_x(i, j)\) and \(T_y(i, j)\) are the elements of TCT, \(P_x\) and \(P_y\) are the approximation of the nonlinear projective transform \(P_x\) and \(P_y\) by well trained NN.

3. **Distortion Correction**

Based on the nonlinear TCT that represent the projective transform between projector and camera, we can
correct the distortion by how to prewarp the source image so that it can projected as a rectangular image on the projection surface. The prewarped source image is generated as followings.

**step 1** has a pre-processing of the source image, adjust the resolution of the source image to $M \times N$, in general this operation may bring some loss of image quality, if the available rectangular area hold a smaller ratio for all projection area. Then processed the source image can be shown as $I_s(i,j)$, where $1 \leq i \leq M$ and $1 \leq j \leq N$

**step 2** for $1 \leq i \leq M$ and $1 \leq j \leq N$, let $I_w(i,j) = 0$

**step 3** warp the source image $I_s$ to prewarped source image $I_w$ as follows if $I_w(T_x(i,j), T_y(i,j)) = 0$, then

$$I_w(T_x(i,j), T_y(i,j)) = I_s(i,j) \quad (3)$$

else

$$I_w(T_x(i,j), T_y(i,j)) = (1-\alpha)I_s(i,j) + \alpha I_w(T_x(i,j), T_y(i,j)) \quad (4)$$

where $\alpha < 1$.

the above operation will be iterated for $1 \leq i \leq M$ and $1 \leq j \leq N$

Since the computed point is real-valued, it may not exactly correspond to a dispersed pixel in the source image space. Here a technique that use bilinear interpolation[7]. The application image is embedded in a temporary image of black pixels to ensure that only pixels within the corrected image are illuminated. By the above operations, the final image shown in camera view will appears undistorted, even with a misalignment of projector or curved projection surface as shown in Fig.4 conceptually. To measure the distortion correction errors, Assuming $(u_i, v_j)$ is the projected pixel with our distortion correction for the pixel $I_{ij}$ in the source image, and $(\hat{u}_i, \hat{v}_j)$ is the position that $I_{ij}$ is correctly projected to the camera image space, with $(u_i, v_j)$ and $(\hat{u}_i, \hat{v}_j)$, we can construct an Euclidean distance error $E(i,j)$ on the camera image space as

$$E(i,j) = (u_i - \hat{u}_i)^2 + (v_j - \hat{v}_j)^2 \quad (5)$$

To confirm the performance of the nonlinear correction, We defined a quadratic cost function as follows with the error $E(i,j)$,

$$J = \sum_{i=1}^{M} \sum_{j=1}^{N} E(i,j) \quad (6)$$

By checking the value of the error cost function, we can evaluate how the distortion correction accomplished by the NN and TCT. The calibration and correction operations can be done iteratively until obtaining a satisfactory correction level.

4. **Simulation and Discussion**

In order to evaluate the nonlinear distortion correction ability, we made a simple simulator on the platform of Matlab, which generates some type of misalignment of projector and a curved projective surface. We considered a simulation system shown in Fig.5. Here about 20x16 calibration points were used to calibrate the system, these position information is also used for training the NN that will give an approximation for the projective transform between the projector space and camera space. The NN used here has three layers, which middle layer has 40 to 50 neurons. To training the NN, we adopt Bayesian regularization approach, which updates the weight and bias values according to Levenberg-Marquardt optimization. It minimizes a combination of squared errors and weights, and then determines the correct combination so as to produce a network which generalizes well.

Here we chose some typical curved surfaces such as plane and quadratic surface for simulation tests. The
some simulation results for several typical surface are shown in Fig. 6 to Fig. 11.

Figure 6: Simulation result for a plane surface

Figure 7: Simulation result for a curved surface: case 1

Figure 8: Simulation result for a curved surface: case 2

not be a drawback of our approach. If a neural network hardware can be used, the computation time is be reduced greatly.

5. Conclusions
In this paper, we described a new nonlinear distortion correction approach for projector-camera system. In our approach, a neural network is used to approximate the nonlinear projective transform mapping. Because a transform converter table is introduced and constructed by a well trained NN to implement a real-time prewarping operation, we obtain a both high distortion correction accuracy and a fast computation speed which is important for real-time processing without special hardware support in our approach. Therefore,
our system is a low cost system and is easy to implement for a wide application. Simulation results show that the approach is effective and practical enough for a continuous curved projective surface. We will implement the approach presented in this paper to a real system to confirm its results and consider some improvements.

As our future research, some improved pattern images for capturing the distortion information will be developed for an accurate mapping approximation and decreasing the acquisition time.

At current research phase, we assume that the observe camera is placed in a proper position in audience area to get a better view for image distortion correction. In fact, this assumption may be removed, if we introduce another perspective transform from projection image space to camera image space, there will be our next research subject. Also, our approach may be used to develop a new type portable projector that can be used in most condition.

References:

Figure 12: Simulation result with a Grid Pattern