MULTI-ERROR CORRECTION OF IMAGE FORMING SYSTEMS BY TRAINING SAMPLES MAINTAINING COLORS

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Abstract: Optical and electronic components of image forming devices degrade objective and subjective quality of the acquired or reproduced images. Classical restoration techniques usually require an explicit estimation or measurement of parameters for each error source. We propose to derive restoration parameters in a training phase with suitable test patterns for a particular system to be corrected. Space varying properties of different classes of image degradations are considered simultaneously. It is shown how training is performed in such a way that colors are reproduced correctly independently of the used test patterns.

1 INTRODUCTION

Whereas enhancement algorithms mostly seek to improve subjective image quality (e.g.(Kober et al., 2003)), image restoration algorithms aim to determine an image which is as similar to the original as possible (e.g.(Berriel et al., 1983)). Many approaches to image restoration and enhancement often consider a certain image with its degradations and then try to find correction parameters for this particular image. We use a training procedure instead with suitable test patterns in order to compensate defect mechanisms of the image forming system. This enables us to design a powerful correction system for the simultaneous compensation of several image defects. Training data are selected and modified carefully and the training is applied in such a way that the behavior of the applied color model can be controlled in a deterministic way.

Typical image defects are shown in Fig. 1. For simplicity the image of a black and white line camera is shown.

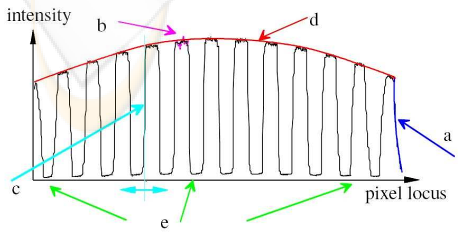

Figure 1: Typical types of image degradation demonstrated with an image of a regular grating captured by a line camera.

Typical image defects to be considered by the proposed correction technique include (see Fig. 1 for referring letters)

- a blur: caused by defraction limitations or misfocussing of lens
- b noise: caused by optical sensor electronics and image digitization
- c geometric distortion: deformation by lens system
- d vignetation: shading of lens or display
- e space variance: errors usually increase with distance from optical axis

These effects usually occur simultaneously and space-varying. In multichannel systems as used in color imaging, additional errors occur. We distinguish between static and dynamic color errors in this paper. Different blur and distortion properties of the image channels lead to color divergence in the images resulting in smeared color transition at edges. Fig. 2 shows such errors by a 2-dimensional color image of a black object on white background: the edges have a smeared color transition. We call such effects *dynamic color errors*, here.

Errors and limitations of the color model inducing a wrong reproduction of colors even in flat image regions are *static color errors*. To maintain colors means in the optimal case that a certain color is reproduced with the same value by the image forming system. Many investigations have been undertaken in the field of color constancy, where the main focus is

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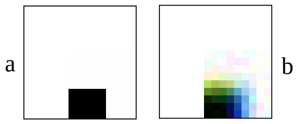

Figure 2: Color divergence as a typical defect in multichannel image systems: a) ideal convergence; b) edge smearing caused by color divergence.

the estimation of the color of object in images with an illumination by light of unknown color characteristics ((Barnard et al., 1997; Kobus, 2002; Verges-Llahi and Sanfeliu, 2003; Ebner, 2003)). In this paper we consider how the restoration system is trained by suitable test patterns. Normally, additional constraints must be introduced to avoid a too strong dependence of the correction result on the selected test patterns. Otherwise a correct color reproduction for random input images is not given. It is clear that the restorations system must not induce additional color errors, but if required it should compensate color errors of the image forming system instead.

In many investigations of image restoration (Gonzalez and Woods, 1993; Andrews, 1977; Zheng and Hellwich, 2007) the process of image formation and restoration is treated by a system as shown in Fig. 3. We generalize the considerations for a multidimensional system with continuous coordinates $\vec{x} = \begin{bmatrix} x_1 & \dots & x_K \end{bmatrix}^T$ and C channels (e.g. colors). This scheme is very similar to approaches in system theory (Unbehauen, 1970; Küpfmüller, 1949). (Jahn and Reulke, 1995) applies system theory directly to optical sensors. As an initial assumption, the characteris-

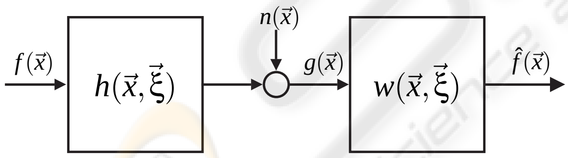

Figure 3: Basic model of image forming and restoration.

tics of the correction system are opposite or "inverse" to those of the degrading system - provided the corrected image approximates the input image as far as possible. Such inverse problems are in general "ill-posed". In traditional designs, additional constraints for a reasonable and stable solution are introduced (Gonzalez and Woods, 1993). Well- known image restoration techniques such as the Wiener or Inverse Filtering methods are available (Stearns and Hush, 1999). Such techniques estimating optimal correction systems are also called deconvolution (Gull and Daniell, 1978; Andrews, 1977; Zheng and Hellwich, 2007). However, deconvolution requires knowledge of system parameters such as noise impact or point spread function that have to be measured or estimated in advance. Furthermore, other image degradations, namely, geometrical distortions, space-variance of parameters and unknown errors require additional correction methods.

In a K-dimensional[1] image forming system with C channels (colors for instance), channel c has the illumination distribution $g_c(\vec{x})$ resulting by summing up the K-ply integrals of the object illumination distribution channels $f_c(\vec{x})$ above the pulse response of the the image formation system between channels c and q, $h_{c,q}(\vec{x},\vec{\xi})$, also called cross point spread function (PSF), and superposition with channel specific noise function $n_c(\vec{x})$:

$$g_c(\vec{x}) = \sum_{q=1}^{C} \int_{-\infty}^{\infty} \dots \int_{-\infty}^{\infty} h_{c,q}\left(\vec{x},\vec{\xi}\right) f_q\left(\vec{\xi}\right) d\xi_0 \dots d\xi_{K-1} + n_c(\vec{x}) \quad (1)$$

with

$\vec{x} = \begin{bmatrix} x_1 & \dots & x_K \end{bmatrix}^T$ the vector of continuous coordinates. The continuous vector of local coordinates $\vec{\xi} = \begin{bmatrix} \xi_1 & \dots & \xi_K \end{bmatrix}^T$ enables us to model space variance of the PSF. Geometric distortions are usually modeled by coordinate transforms and also covered by Eq. 1.

This equation changes to a simple convolution if the pulse response of the system to be corrected can be considered stationary (space invariant, see (Andrews, 1977)). (Andrews, 1977) defines *image restoration* as to determine the original object distribution f given the recorded image g and knowledge about the point-spread-function h. Approaches that compensate for a convolution of the original by the PSF are often called image deconvolution (Gonzalez and Woods, 1993; Andrews, 1977). The task of image restoration requires therefore the determination of a system with the pulse response $w(\vec{x},\vec{\xi})$ which produces an output $\hat{f}(\vec{x})$ approximating the input $f(\vec{x})$.

Considering pixel-based image forming devices with images of limited extent leads to a discrete, algebraic representation of the system which is shown in Fig. 4a). Multi-dimensional image data is vectorized to form image vectors . The length of these vectors is the product of numbers of pixels in each dimension by the number of channels. As an example, let us consider the pixel values of an original image $f_{l_1,\cdots,l_K,c}$ where $l_1 \cdots l_K$ are the pixel indexes in the K dimensions and c is the index of the image channel. This image is described by object vector $\vec{f}$ which is obtained by vectorization of the input image pixels in

[1] We generalize our approach for multidimensional image systems with any number of channels

each dimension and each channel as:
$\vec{f} = \begin{bmatrix} f_{1,\cdots,1} & \cdots & f_{D_1,\cdots,D_K,1} & \cdots & f_{D_1,\cdots,D_K,C} \end{bmatrix}^T$.
$D_1 \cdots D_K$ are the image extents in the K dimensions and C the channel number. Noise superposition vector $\vec{n}$ and restoration vector $\hat{\vec{f}}$ yield by vectorization in the same way.

This kind of image restoration model is often subject of so called optimal restoration approaches (e.g. (Jain, 1998; Katsaggelos, 1999)). Such techniques usually seek a trade-off between noise suppression and sharpening in the restored image vector $\hat{\vec{f}}$. $\vec{H}$ and $\vec{W}$ describe the point spread function matrices of the image forming and the restoration systems, respectively. With the assumption of perfect compensation,

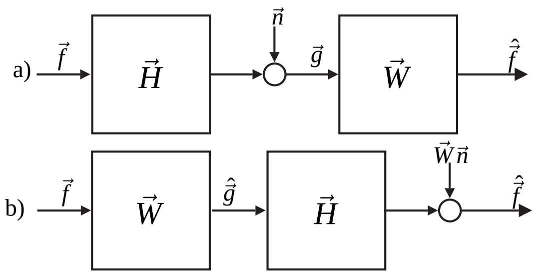

Figure 4: Restoration of image acquisition (a) and reproduction (b).

the systems $\vec{H}$ and $\vec{W}$ can change their position in the processing chain (Fig. 4b) which corresponds to the situation of an image reproduction system like a display or printer In this case, not the restored image appears at the output of the restoration system $\vec{W}$ but an image $\hat{\vec{g}}$ with degradations tending to compensate those induced by the image forming system $\vec{H}$.

Linearity is an important prerequisite if linear filtering should be applied correctly. Especially the Gamma distortion integrated in most systems for acquisition and display must be considered. Often, also the sensors of CMOS cameras possess a nonlinear response in order to allow a high dynamic range of light intensity. In such cases, often a linear approximation at the point of operation is possible or a non-linear correction of the overall system is required.

In both cases of Fig. 4, the remaining deviation $\vec{\varepsilon} = \vec{f} - \hat{\vec{f}}$ is the restoration error. With the euclidean norm $\|\vec{\varepsilon}\| = \sqrt{\vec{\varepsilon}^T \cdot \vec{\varepsilon}}$ as the dot product of the transposed and non-transposed deviation vector the mean-square error is defined $MSE = \frac{1}{N} \|\vec{\varepsilon}\|^2$, i.e. the quadratic euclidean norm normalized by the number N of elements in $\vec{f}$ or $\hat{\vec{f}}$. Generally, other quality criteria are also acceptable, but MSE is easy and reliable to calculate and in most cases the quadratical criterion has been proved to correlate very well with subjective image quality rating .

2 SYSTEM TRAINING

In common restoration approaches, system parameters such as PSF and noise impact are a-priori known or explicitly measured. This is sometimes cumbersome and not practical, especially if we consider space-variant systems. We apply a training method instead similar to supervised learning of artificial neural networks (ANN). Here, suitable training and target patterns are presented to the network. In an learning phase, the weights of the ANN are optimized in such a way that a training criterion is matched. ANNs are widely known in nonlinear image processing applications, for instance in image segmentation and object recognition. Other applications use the adaptive behavior of ANNs to combine properties of biological nerve cells with well known ideas of systems theory (Marko, 1969) or with digital Filters (Flach et al., 1992). We have a very simple neural model in mind for modeling the image forming process (see Fig. 5) which can be applied to technical systems for the image acquisition and reproduction. A similar model may be also used for the early processing stages in the retina.

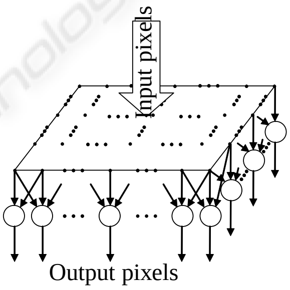

Figure 5: Image forming as a simple neural layer with lateral coupling.

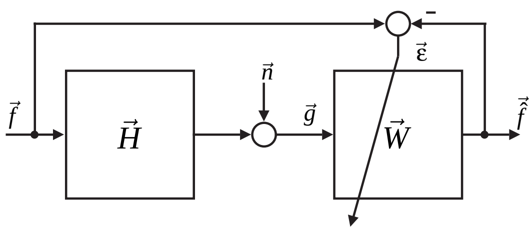

Figure 6: Estimation of restoration parameters by adaption.

Applying the aforementioned ideas to the image forming system Fig. 6 yields. In this example an image acquisition system was considered according to Fig. 4a. The deviation between the original image vector $\vec{f}$ and the restored image vector $\hat{\vec{f}}$ is assessed for the adaption of the correction matrix $\vec{W}$. As stated above we assume an image forming system with linear behavior in the operating range. This is also motivated by the demand that the system should work at different brightness levels in the same manner (superposition principle). In this case the least mean square problem is directly treated by solving a linear equation system for $\vec{W}$.

We use L training sample image pairs $\vec{f}_\nu$ and $\vec{\tilde{f}}_\nu$ each producing a restoration error $\vec{\varepsilon}_\nu = \vec{f}_\nu - \vec{\tilde{f}}_\nu$. The number of training samples should assure that enough linear independent equations are established to estimate the correction weight matrix $\vec{W}$. Test images can be random patterns to be input to the system, but for a greater number of parameters in $\vec{W}$ correspondingly more test patterns are required what is often too much effort. Alternatively training data can be thus gained by taking the pixel data of a neighborhood as sample data assuming that the system properties in the local neighborhood is approximately constant. With this simplification we can train the correction system with a single test image pair.

The learning objective in the two cases of image acquisition and reproduction can be formulated for the whole image and all training samples as:

$$Q = \sum_{\nu=1}^{L} \|\vec{\varepsilon}_\nu\| \Rightarrow Min. \tag{2}$$

that is, the norm of the image error accumulated for the training data set of size L should be minimized. If we put all training vectors of the training data set in matrices: $\vec{F} = \left[\begin{array}{ccc} \vec{f}_1 & \cdots & \vec{f}_L \end{array} \right]$, $\vec{\tilde{F}} = \left[\begin{array}{ccc} \vec{\tilde{f}}_1 & \cdots & \vec{\tilde{f}}_L \end{array} \right]$ we obtain target and recall matrices, respectively.

The quality criterion Eq. 2 can be separated for each independent pixel to be corrected or for regions if constant correction parameters are accepted for that region. The quality criterion can be stated for each row number i of the target and recall matrices:

$$Q_i = \left\| \vec{\tilde{F}}_i - \vec{F}_i \right\| \Rightarrow Min. \tag{3}$$

Because of the vectorized form of the data in the columns of $\vec{F}$ and $\vec{\tilde{F}}$ the index i corresponds to a certain location in the image.

The influence of pixels surrounding a pixel to be corrected is per se decreasing with increasing distance (see Fig. 7). Hence the training input data are cut around a considered pixel forming the learning matrix at a certain location in the image

$$\vec{G} = \left[\begin{array}{ccccc} \vec{g}_1 & \cdots & \vec{g}_j & \cdots & \vec{g}_L \end{array} \right]$$

consisting of the training vectors $\vec{g}_j$ resulting by vectorization of the couple regions according to Fig. 7

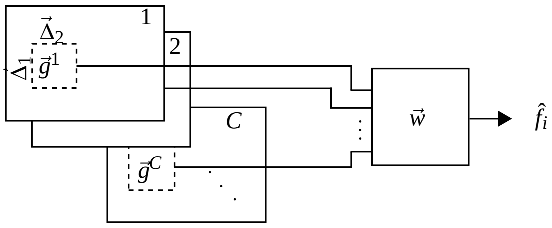

Figure 7: Restoration of one channel component $\hat{f}_i$ of one pixel by correction vector $\vec{w}$ coupling restricted regions $\vec{g}^1 \ldots \vec{g}^C$ of the training image channels $1 \ldots C$, in the example for a 2-dimensional system (K=2).

i.e. the training vectors are obtained by vectorization of the surrounding pixels of all C channels in the local neighborhood of size $\Delta_1 \Delta_2 \cdots \Delta_K$ in the K dimensions. Hence, the length of each training vector $\vec{g}_j$ and weight vector $\vec{w}$ is $N = \Delta_1 \Delta_2 \cdots \Delta_K C$. The calculation effort for the determination of the weight vector $\vec{w}$ and for the the calculation of the correction result (recall) can be considerably reduced if the multi-dimensional problem is separated for each dimension. In this case C weight vectors of lengths $\Delta_1 \cdots \Delta_C$ are to estimate which is a considerably reduced number of parameters $N_{sep} = \sum_{k=1}^{K} \Delta_k C$. With the correction weight vector at a certain location i of one channel $\vec{w} = \left[\begin{array}{ccc} w_{1,\cdots,1} & \cdots & w_{\Delta_1,\cdots,\Delta_K,C} \end{array} \right]^T$ and $\vec{\tilde{F}}_i = \vec{w}^T \vec{G}$ the vector of corrected training pixels (row i of $\vec{\tilde{F}}$), Eq. 3 becomes

$$Q_i = \left\| \vec{w}^T \vec{G} - \vec{F}_i \right\| \Rightarrow Min. \tag{4}$$

The correction weight vector $\vec{w}$ satisfying Eq. 4 is the least-mean square solution of the equation system which is overdetermined if $L > N$ (linear independent training patterns assumed). It can be calculated by typical least mean square methods, for instance

$$\vec{w}^T = \vec{F}_i \vec{G}^T inv\left(\vec{G}\vec{G}^T\right)$$

with $inv()$ the inverse matrix operator or more general

$$\vec{w}^T = \vec{F}_i / \vec{G} \tag{5}$$

with / the matrix division operator. This holds in the following considerations analogously.

This looks like a simple solution, but operating with real images requires some additional considerations. Due to a nonzero black level of real image forming systems offset parameters $o_1 \cdots o_C$ should be included in the compensation system (see Fig. 8). Otherwise the quality criterion Eq. 4 leads to distortions regarding compensation of the dynamic color errors: the compensating filters tend to compensate

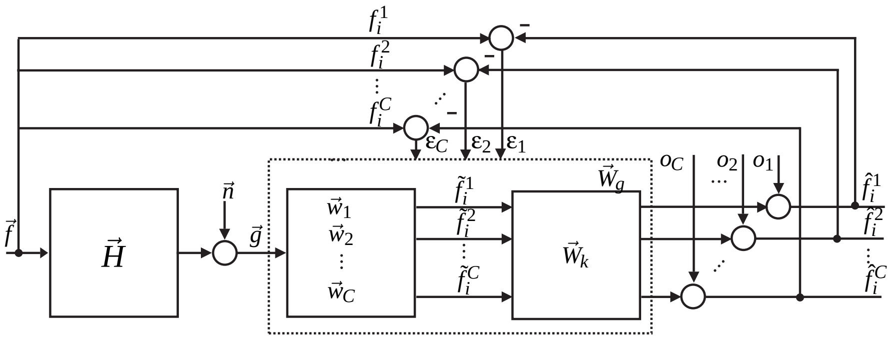

Figure 8: Estimation of parameters for color transform.

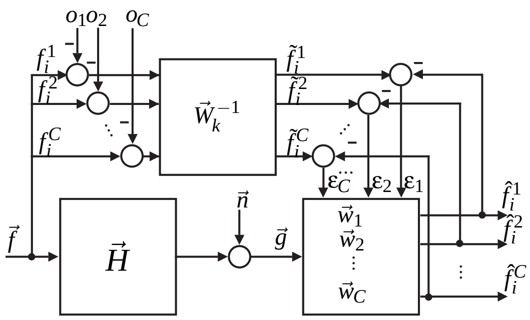

Figure 9: Estimation of restoration parameters with color-adapted training data.

the offset in the image data which leads to overshooting and oscillation at edges and other artifacts. Additionally, real color systems reproduce colors only with a limited accuracy. The main reason for that are the absorption curves of the sensor elements in image acquisition devices or the spectral response of the pixels of image reproducing devices. These phenomenons lead to a cross coupling between the channels and can be usually seen as a transformation of color space. If we want to train the system while considering color model and offset correctly, we therefore have to estimate C additional cross coupling parameters and one offset parameter for each color channel of a C-channel system.

Because human eye is very sensitive to color changes it is essential to preserve color constancy in the over-all system. As an example, if the input of the restoration system is considered correct regarding the color space the restoration system should not alter the static colors. That is colors in flat regions should maintain their values at the output of the correction system. With this demand, the direct coupling weight vectors have a sum of 1.0 and the cross coupling vectors a sum value of 0.0. Also the offset value should be zero to keep the black value as it was. But how to fulfill this demand? Fig. 8 demonstrates the problem. It specifies the general system adaption of Fig. 6 for C image channels and introduces offset elements $o_1 \cdots o_C$ forming offset vector $\vec{o}$. The weight vectors $\vec{w}_1 \cdots \vec{w}_C$ together with a coordinate transform matrix $\vec{W}_k$ of size C by C establish the general correction matrix $\vec{W}_g$. $\vec{W}_g$ and $\vec{o}$ can be directly calculated by the solution of the equation

$$\begin{bmatrix} \vec{W}_g & \vec{o} \end{bmatrix} \begin{bmatrix} \vec{G} \\ \vec{1}^T \end{bmatrix} = \begin{bmatrix} \vec{F}_i^1 \\ \vdots \\ \vec{F}_i^C \end{bmatrix} \qquad (6)$$

when $\vec{F}_i^1 \cdots \vec{F}_i^C$ are the selected row vectors of $\vec{F}$ for the image channels $1 \cdots C$ at a certain location i similar to Eq. 3 and $\vec{1}^T = \begin{bmatrix} 1 & \cdots & 1 \end{bmatrix}$ is a row vector of L ones.

In Fig. 8 the matrix $\vec{W}_g$ is partitioned in two parts: the weight vectors $\vec{w}_1 \cdots \vec{w}_C$ and the coordinate transform matrix $\vec{W}_k$. The weight vectors $\vec{w}_1 \cdots \vec{w}_C$ should only be responsible for the correction of local effects like blur, color divergence and geometric distortions (dynamic color errors, see above). $\vec{W}_k$ instead should compensate for intensity related and cross coupling effects of the image channels (static color errors).

An alternative for the estimation of a correction system that does not effect static colors is to introduce constraints in the estimation of $\vec{W}_g$ to maintain color constancy in flat image regions. Such a constraint could be to claim sums of 1.0 for the main coupling weight vectors and zero sums for the cross coupling weight vectors. But investigations have shown that such a constraint affects the correction of dynamic color errors and the correction result is unsatisfying.

Therefore another approach is chosen: we adapt training input and target data so to reflect the same color coordinate system. Eq. 6 is firstly solved just to estimate the color rotation between $\vec{F}_i$ and $\vec{G}$. The parameters to transform $\vec{G}$ into the color space of $\vec{F}_i$ are the sums of elements of the direct and cross coupling weight vectors in $\vec{W}_g$. These sums form $\vec{W}_k$ specifying the color transform which is applied to $\vec{F}$ as follows:

$$\begin{bmatrix} \vec{\tilde{F}}_i^1 \\ \vdots \\ \vec{\tilde{F}}_i^C \end{bmatrix} = \vec{W}_k^{-1} \left[\begin{bmatrix} \vec{F}_i^1 \\ \vdots \\ \vec{F}_i^C \end{bmatrix} - \vec{o}\vec{1}^T \right]. \quad (7)$$

This can be proved assuming that constant colors in the coupling regions of Fig. 7 are producing the same value in the restoration pixel (see explanations above concerning constraints for color constancy). To adapt the target data $\vec{F}$ to $\vec{G}$ we have to subtract the offset vector (coordinate translation) and to apply the inverse of this transformation matrix $\vec{W}_k$(see Fig. 9). Weight vectors for the correction of dynamic color errors but neutral regarding static color errors can then be estimated by solving the equation:

$$\begin{bmatrix} \vec{w}_1 \\ \vdots \\ \vec{w}_C \end{bmatrix} \vec{G} = \begin{bmatrix} \vec{\tilde{F}}_i^1 \\ \vdots \\ \vec{\tilde{F}}_i^C \end{bmatrix}. \quad (8)$$

3 RESULTS

In principle, random test patterns for training of the systems are possible. But the training data set should reflect all properties of the image errors as much as possible. We therefore prefer test patterns with maximal levels of each color and well defined positions of the edges. As an example a 2-dimensional RGB color image ($C = 3$, $K = 2$) of checker board type has been used as input training pattern (Fig. 10b). Such type of test image assures a sufficient number of linear independent input-output relations in the training data.

The image has been displayed by a digital projection system and captured by a usual digital camera. The acquired image is shown in Fig. 10a. The result of training is given in Fig. 10c. Separable weight vectors have been estimated of lengths 30 ($\Delta_1 \cdots \Delta_3 = 10$). Fig. 10d and e show the error of the training image without and with correction, respectively. The good compensation of geometric distortions and blur is obvious. A certain deviation even in the corrected image remains because of the limited dynamics of real image forming systems.

As the restoration matrix $\vec{W}$ is estimated using the training patterns it can be applied to random data as long as the degrading system characterized by matrix $\vec{H}$ doesn't change very much. This has been done in Fig. 11. A real-world scene (Fig. 11a) has been displayed on the digital projection system and again captured by a digital camera (Fig. 11b). The correction result is given in Fig. 11c. This example shows the application of the correction method to a combined image acquisition and reproduction system, in this case consisting of a digital camera and a video projector. If we assume the camera having a much better image quality than the projections system we can use it as a restoration system for the latter. We should then apply the restoration system $\vec{W}$ to the images to be displayed.

4 CONCLUSIONS

A teaching approach for the restoration of multichannel image forming systems has been proposed. Several kinds of space-variant errors are treated simultaneously and cross-channel effects and offsets are considered.

The training is based on deterministic test patterns, but the trained system can be applied to random images. The selection of test patterns is not critical due to the adaption of the color spaces of input and target patterns. The required transform matrix is determined in an intermediate step. This avoids the introduction of explicit constraints. The required channel transform matrix is determined in an intermediate step. This avoids the introduction of explicit constraints. The color transform is estimated correctly even if training and target regions are not aligned correctly due to geometric distortions. This way the correction of the static color model is separated from the correction of the dynamic errors. This can be important for the technical realization of the correction. A serial connection of a color transform unit and of a filter processor for each channel can thus be driven by the estimated parameters. One main benefit of the proposed approach is the reduction of additional errors, such as geometric distortions and cross channel errors, that cannot directly be reduced by conventional deconvolution algorithms which are mostly based on the idea of the Wiener Filter. An explicit estimation of PSF and noise is not required. By taking into account the space variant system offset and cross coupling behavior of real color sensors typical distortions and color errors are minimized.

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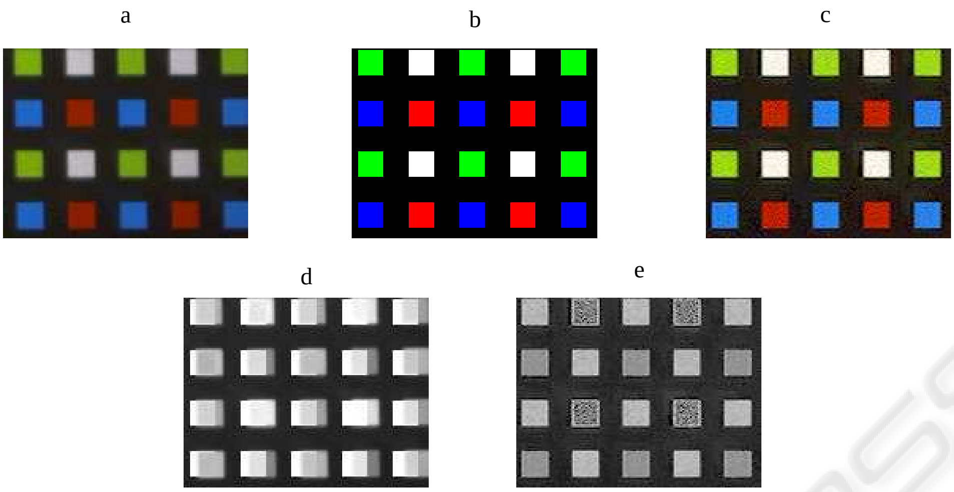

Figure 10: Training images: Reproduction (a) Test image (b) Training result (c),(d,e) error images.

Figure 11: Test images (recall): Original (a), reproduction (b), reproduction with correction (c).

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