Separation of Reflection Components by Kernel Independent Component Analysis

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Summary
When we view a scene through transparent glass, the image is a linear superposition of two images, a real image observed through a glass and a virtual image reflected on it. We can separate the reflections by a polarization and Independent Component Analysis (ICA). Since the image observed through digital camera is non-linearly transformed by gamma correction etc, it may cause error in image processing for image analysis and measurement. The kernel-based methods are effective for such non-linearity. In this paper, we remove the reflections by using Kernel Independent Component Analysis (KICA) and show that KICA is more effective than ICA even if the observed image is non-linearly transformed by camera.

Key words:
Separating Reflections, Independent Component Analysis, Camera's Non-linearity, Kernel Independent Component Analysis.

1. Introduction

When we take a picture through a window, the observed image is often a linear superposition of two images, the image of the scene beyond the window and the image of the scene reflected by window. In such cases we cannot view clearly a scene due to the reflections from dielectric surfaces (e.g. glass). The dichromatic reflection model [1 ~ 3] describes the surface reflection as the sum of two components, diffuse and specular reflections. The specular reflection components are considered as obstacles for digital archive, image recognition, etc. In computer vision research, several techniques for removing these reflections have been developed [4 ~ 8]. Since reflections off a semireflecting medium such as a glass window at an oblique angle or the specular reflection components of images are partially polarized, the strength of the reflection can be manipulated with a polarizer. However the reflection can only be completely eliminated when the viewing angle and the incident light direction are in particular configuration called the Brewster angle. By using a polarization and Independent Component Analysis (ICA) [9], this problem can be solved [5,6]. In order to separate reflections, we use the images obtained through a polarizer at two or more orientations and apply ICA to them.

Though CCD is inherently a linear device, the phosphors that are used to make monitors are non-linear. Therefore a normal camera needs the gamma correction in order to display properly the intensity of an observed object. But this non-linear transformation may cause failures in image processing for image analysis and measurement. In this case, we need do transformation of inverse property of gamma correction [10] or use the camera that has linear transform property. The kernel-based methods are effective for such non-linearity [13,14]. The kernel methods allow for the development of a non-linear extension of some linear algorithms, such as ICA, principal component analysis, and canonical correlation analysis (CCA) etc. Recently, Bach presented a new learning method of ICA, which use contrast functions based on canonical correlations in a Reproducing Kernel Hilbert Space (RKHS), named Kernel Independent Component Analysis (Kernel ICA or KICA) [12].
In this paper, we will separate the reflections by using KICA and show that KICA is more effective than ICA even if the observed image is non-linearly transformed. We give a separation result for simulated artificial data and a separation result for real scenes.
Section 2 describes a non-linear model of camera. Section 3 presents KICA. Section 4 describes experimental results. Section 5 summaries our conclusion.

2. Non-linear model of camera

When we take a picture through a window, the observed image is a linear combination of the light reflected by the scene beyond window and the light directly reflected by the window. These images observed through a polarizer of different orientations $\mathbf{X} = (\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_M)^T$ are as follows:

$$\mathbf{X} = \mathbf{AS} \tag{1}$$

The matrix **A** and matrix **S** are written as follows:

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$$\mathbf{A} = \begin{bmatrix} a_1 & b_1 \\ a_2 & b_2 \\ \cdots & \\ a_M & b_M \end{bmatrix}, \quad \mathbf{S} = \begin{bmatrix} \mathbf{P} \\ \mathbf{R} \end{bmatrix} \qquad (2)$$

where $\mathbf{P} = (\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_M)^T$ and $\mathbf{R} = (\mathbf{r}_1, \mathbf{r}_2, \cdots, \mathbf{r}_M)^T$ are the amount of light contributed by the scene and reflection. The observed imaged $\mathbf{X}$ is a linear sum of these images, and the coefficients $(a_1, a_2, \cdots, a_M)$ and $(b_1, b_2, \cdots, b_M)$ are changed by the orientation of the polarizer. In the dichromatic reflection model [1 ~ 3], we can regard $\mathbf{P}$ and $\mathbf{R}$ as the diffuse and specular reflection images.

Eq.(1) is a linear model neglecting non-linearity due to camera. However Electric-light transform property of *CRT* display actually has gamma distortion of non-linear:

$$I_{out} = cI_{in}^{\ r} \qquad (3)$$

where I_{in} is an input signal, I_{out} is an output signal and c is constant. Therefore normal cameras need gamma correction in order to display properly the intensity of an observed object. The gamma correction is effective when human look images of *CRT* display, but it may cause failures of image processing for image analysis and measurement because the intensity of light energy is non-linearly transformed. In this case, we need do transformation of inverse property of gamma correction [10]. The value r of Eq.(3) is typically determined experimentally by passing a calibration target with a full range of known luminance values through the imaging system [11]. But often such calibration is not available or direct access to the imaging device is not possible, for example when downloading an image from the web. In addition, there are other non-linear factors due to camera's Lens Shutter and CCD. Fig.1 shows an example of non-linear camera model.

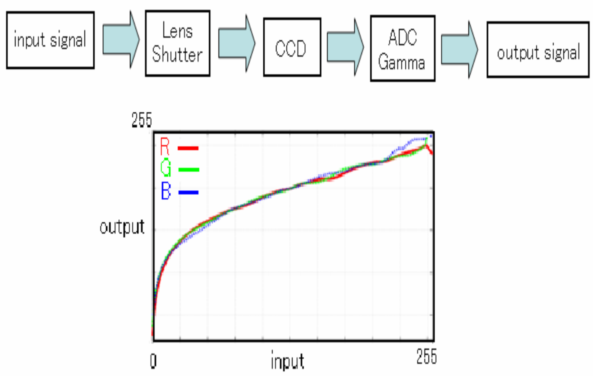

Fig 1:non-linear camera model.

Including these non-linearities, we can rewrite Eq.(1) to:

$$\mathbf{X} = f(\mathbf{AS}) \qquad (4)$$

where f is a non-linear function. Firstly the source signals $\mathbf{S}$ are mixed by the linear model of Eq.(1), then a non-linear function f applies and it is finally observed as $\mathbf{X}$.

3. Kernel ICA

Assuming $\mathbf{X} = (\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_M)^T$ is the matrix of samples, the idea of ICA seeks to find a transformation matrix $\mathbf{W}$, $\mathbf{U} = \mathbf{WX}$, to make the projection $\mathbf{U}$ high-order statistically independent besides the second order independent. Since ICA is based on a linear model, ICA can be failure in the case of non-linearity. Recently, Bach presented a new method of ICA, named Kernel ICA [12]. His idea regards maximizing independence as minimizing correlation with kernel.

Kernel based learning algorithms use the following idea [14]: via a non-linear mapping

$$\Phi : \Re^t \to F \quad \mathbf{x} \to \Phi(\mathbf{x}) \qquad (5)$$

the data in the input space $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_M \in \Re^t$ is mapped to a potentially much higher dimensional feature space F and the data is converted easy data to analysis. Instead of considering the given learning problem in input space $\Re^t$, one can deal with $\Phi(\mathbf{x}_1), \Phi(\mathbf{x}_2), \ldots, \Phi(\mathbf{x}_M)$ in feature space F and then we find a linear discriminant function in feature space F. This linear discriminant function in feature space F is a non-linear discriminant function in input space $\Re^t$. The idea of the kernel trick is to project the input data into a high dimensional implicit feature space through a non-linear mapping, and the non-linear relation in the input data can be analyzed in this feature space F. In implementation, the kernel trick does not need to compute implicit feature vector in F explicitly. It just needs to calculate the inner product of two vectors in F with a kernel function $k(\cdot,\cdot)$:

$$\langle \Phi(\mathbf{x}_i), \Phi(\mathbf{x}_j) \rangle = k(\mathbf{x}_i, \mathbf{x}_j) \qquad (6)$$

where $\langle \cdot,\cdot \rangle$ denotes an inner product. There are several kernel functions such as Gaussian kernel:

$$k(\mathbf{x}, \mathbf{y}) = \exp\left(-\frac{1}{\delta^2} \|\mathbf{y} - \mathbf{x}\|^2 \right) \qquad (7)$$

The Kernel ICA presented by Bach is a new method based on a kernel measure of independence. Kernel ICA assumes RKHS F with $k(\mathbf{x}, \mathbf{y})$ and feature map $\Phi(\mathbf{x}) = k(\cdot, \mathbf{x})$. Then the F-correlation is defined as the maximal correlation between the two random variables $f(\mathbf{x})$ and $g(\mathbf{y})$, where f and g range over F [15]:

$$\begin{aligned}\rho_F &= \max_{f,g\in F} corr(f(\mathbf{x}), g(\mathbf{y})) \\ &= \max_{f,g\in F} \frac{\mathrm{cov}(f(\mathbf{x}), g(\mathbf{y}))}{\sqrt{\{\mathrm{var}\, f(\mathbf{x})\}\{\mathrm{var}\, g(\mathbf{y})\}}}\end{aligned} \quad (8)$$

Clearly, if the random variables $\mathbf{x}$ and $\mathbf{y}$ are independent, then the *F*-correlation is zero. Moreover, the converse is also true provided that the set *F* is large enough. This means that ρ_F = 0 implies $\mathbf{x}$ and $\mathbf{y}$ are independent. Bach [12] shows that the converse is also true for the RKHS based on Gaussian kernels and define contrast function as:

$$I_{\rho_F} = -\frac{1}{2}\log(1-\rho_F) \quad (9)$$

This function is always non-negative and equal to zero if and only if the variables $\mathbf{x}$ and $\mathbf{y}$ are independent.

In order to obtain a computationally tractable implementation of *F*-correlation, the reproducing property of RKHS is used to estimate the *F*-correlation,

$$f(\mathbf{x}) = \langle f, \Phi(\mathbf{x})\rangle = \langle f, k(\cdot,\mathbf{x})\rangle \quad (10)$$

Let S_1 and S_2 be the linear spaces spanned by the Φ images of the data samples, then f and g can be decomposed into two parts, i.e.

$$f = \sum_{k=1}^{M}\alpha_k \Phi(\mathbf{x}_k) + f^{\perp}, g = \sum_{k=1}^{M}\beta_k \Phi(\mathbf{y}_k) + g^{\perp} \quad (11)$$

where $f^{\perp}$ and $g^{\perp}$ are orthogonal to S_1 and S_2 respectively. Using the empirical data to approximate the population value, the *F*-correlation can be estimated as

$$\hat{\rho}_F = \max_{\boldsymbol{\alpha},\boldsymbol{\beta}\in R^M} \frac{\boldsymbol{\alpha}^T \mathbf{K_x}\mathbf{K_y}\boldsymbol{\beta}}{\sqrt{\boldsymbol{\alpha}^T {\mathbf{K_x}}^2\boldsymbol{\alpha}}\sqrt{\boldsymbol{\beta}^T {\mathbf{K_y}}^2\boldsymbol{\beta}}} \quad (12)$$

where $\mathbf{K_x}$ and $\mathbf{K_y}$ are the Gram matrices associated with the data sets $\{\mathbf{x}_k\}$ and $\{\mathbf{y}_k\}$ defined as $(\mathbf{K_x})_{ij} = k(\mathbf{x}_i, \mathbf{x}_j)$, $(\mathbf{K_y})_{ij} = k(\mathbf{y}_i, \mathbf{y}_j)$.

The algorithm of Kernel ICA is firstly to set **U** = **WX**, **W** is random parameters, and we set of the *M* centered Gram matrices $(\mathbf{K}_1, \mathbf{K}_2, \ldots, \mathbf{K}_M)$. These Gram matrices (which depend on **W**) define the contrast function, $C(\mathbf{W}) = \hat{I}_{\rho_F}(\mathbf{K}_1, \mathbf{K}_2, \ldots, \mathbf{K}_M)$ from Eq.(9),(12). The Kernel ICA algorithm involves minimizing this function *C*(**W**) with respect to **W**.

4. Experimental results

4.1 Simulated data

Our first experiment is intended to show the general efficiency of the image separation. Fig.2 shows a comparison result between ICA and KICA in the case of non-linear model (Eq.(3) *r* = 0.45). The input images (X_1, X_2) are

$$\begin{aligned} X_1 &= 0.7 I_1 + 0.3 I_2 \\ X_2 &= 0.4 I_1 + 0.6 I_2 \end{aligned} \quad (13)$$

Thus, the mixing matrix **A** is as follows:

$$\mathbf{A} = \begin{bmatrix} 0.7 & 0.3 \\ 0.4 & 0.6 \end{bmatrix} \quad (14)$$

In the case of linear model (Eq.(3) *r* = 1), the estimated mixing matrix $(\mathbf{A}_{ICA}, \mathbf{A}_{KICA})$ by ICA and KICA are as follows:

$$\mathbf{A}_{ICA} = \begin{bmatrix} 0.71 & 0.29 \\ 0.38 & 0.60 \end{bmatrix}, \mathbf{A}_{KICA} = \begin{bmatrix} 0.70 & 0.29 \\ 0.39 & 0.61 \end{bmatrix} \quad (15)$$

In the case of non-linear model (Eq.(3) *r* = 0.45), the estimated mixing matrix $(\mathbf{A}'_{ICA}, \mathbf{A}'_{KICA})$ by ICA and KICA are as follows:

$$\mathbf{A}'_{ICA} = \begin{bmatrix} 0.80 & 0.21 \\ 0.31 & 0.71 \end{bmatrix}, \mathbf{A}'_{KICA} = \begin{bmatrix} 0.72 & 0.28 \\ 0.37 & 0.62 \end{bmatrix} \quad (16)$$

From (14),(15),(16) KICA is gives more correct result than ICA in the case of non-linear model, though KICA is the same performance with ICA in the case of linear model.

Fig 2:Image Separation of non-linear model. (a),(b):input images. (c),(d):ICA. (e),(f):KICA.

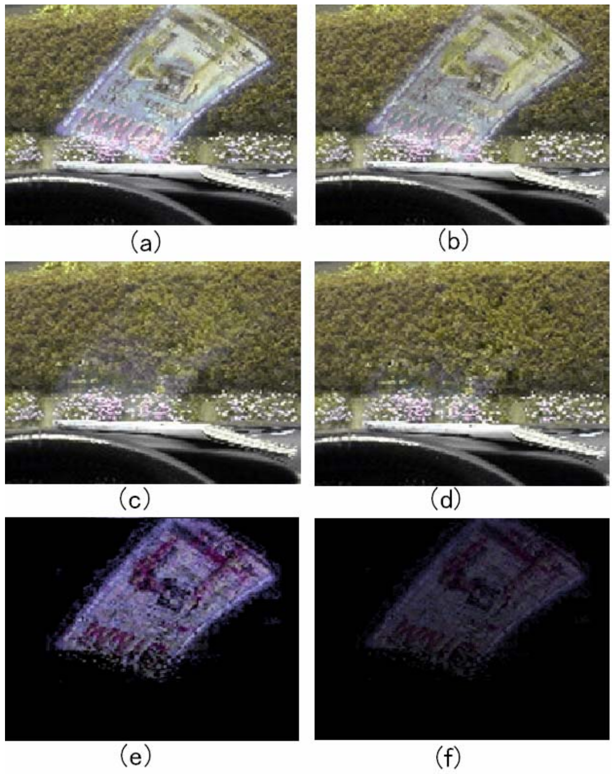

Fig 3: Separation of reflection by window. (a),(b):input images. (c):separated image (ICA). (d):separated image (KICA). (e):error residual(ICA). (f):error residual(KICA).

4.2 Real Scene Data

In this subsection, we give results of several experiments using real images that are taken by a digital camera. Fig.3 shows a comparison result between ICA and KICA, Figs3.(a),(b) images were taken in the car where the reflections from a front window, in the angle between the image of the scene reflected by window and camera view direction was about 90 degrees. Figs3.(e),(f) are the difference between the separated images by ICA(Fig3.(c)) and KICA(Fig3.(d)) and the completely separated image by polarizing filters. The RMS(root of mean square) of ICA (Fig3.(e)) is 0.0921 and KICA (Fig3.(f)) is 0.0092. Fig.4 shows a comparison result of diffuse and specular separation between ICA and KICA, Figs4.(a),(b) images were taken in the angle between light source direction and camera view direction was about 90 degrees. Figs4.(e),(f) are the difference between the separated diffuse image by ICA (Fig4.(c)) and KICA (Fig4.(d)) and the completely separated diffuse image by polarizing filters. The RMS of ICA (Fig4.(e)) is 0.0137 and KICA (Fig4.(f)) is 0.0028. These error pixels in the Figs.3(e)(f) and Figs.4(e)(f) represent about 10 ~ 20 pixel intensity difference. As can be seen from these results, KICA is more efficient than ICA.

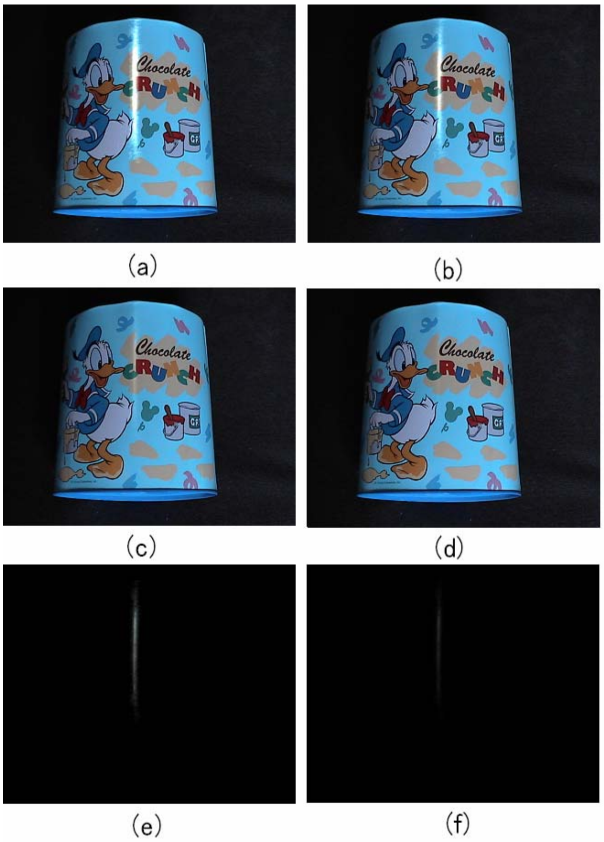

Fig 4: Separation of diffuse reflection. (a),(b):input images. (c):diffuse (ICA). (d):diffuse(KICA). (e):error residual (ICA). (f):error residual(KICA).

5. Conclusion

We have shown that kernel ICA-based method is more effective than ICA-based method even if there is a non-linearity due to camera. Surely we can remove the non-linearity by the reverse transformation of the non-linearity. However kernel ICA based method does not need these adjustments. That is to say it is a more simple method. Further investigations will be made to select kernel functions.

References

[1] G.J. Klinker, S.A. Shafer and T. Kanade, "The measurement of highlight in color images," *Int'l Journal of Computer Vision*, vol. 2, No.1, pp. 7-32, 1988.

[2] R.L. Cook and K.E. Torrance, "A Reflectance Model for Computer Graphics," *ACM Trans. Graphics*, vol. 1, No.1, pp. 7-24, 1982.

[3] S.Shafer, "Using Color to Separate Reflection Components," *Color Research Applications*, vol. 10, pp. 210-218, 1985.

[4] L.B. Wolff, "Using Polarization to Separate Reflectance Components," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, pp. 363-369, 1989.

[5] H. Farid and E. Adelson, "Separating Reflection and Lighting Using Independent Component Analysis," *Proc. IEEE Conf. Computer Vision and Pattern Recognition*, pp. 262-267, 1999.

[6] S. Umeyama, "Separation of Diffuse and Specular Components of Surface Reflection by Use of Polarization and Statistical Analysis of Images," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 26, no. 5, pp. 639-647, 2004.

[7] K. Schluns and A. Koschan, "Global and Local Highlight Analysis in Color Images," *Proc. Int'l Conf. Color In Graphics and Image Processing*, pp. 300-304, 2000.

[8] G.J. Klinker, S.A. Shafer and T. Kanade, "Using a Color Reflection Model to Separate Highlights from Objects Color," *Proc. IEEE Int'l Conf. Computer Vision*, pp. 145-150, 1987.

[9] A. Hyvarinen, J. Karhunen and E. Oja, *Independent Component Analysis.* Wiley-Interscience, 2001.

[10] H. Farid, "Blind inverse gamma correction," *IEEE Trans. Image Processing*, pp. 1428-1433, 2001.

[11] Y.C. Chang and J.F. Reid, "RGB calibration for analysis in machine vision," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 5, no. 10, pp. 1414-1422, 1996.

[12] F. R. Bach, M. I. Jordan, "Kernel Independent Component Analysis", *Journal of Machine Learning Research*, vol.3, pp. 1-48, 2002.

[13] S. Harmeling, A. Ziehe, M. Kawanabe, and K. R. Muller, "Kernel-based non-linear blind source separation," *Neural Computation*, vol. 15, pp. 1089-1124, 2003.

[14] B. Scholkopf and A. Smola, *Learning with Kernels*, Cambridge, Mass,: MIT Press, 2002

[15] S. Akaho, *A kernel method for canonical correlation analysis*, Int'l Meeting on Psychometric Society, 2001.

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