Complex Valued Independent Component Analysis for Image Enhancement

DR Sumanapala, DR Sumanapala, S Thushan#, MPB Ekanayake, GMRI Godaliyadda, SAHA Suraweera and JV Wijayakulasooriya

Department of Electrical and Electronic Engineering, University of Peradeniya, Peradeniya, Sri Lanka

#thushan.e10@gmail.com

Abstract— *Independent Component Analysis (ICA), a category of blind source separation, can be effectively used for extraction of unknown independent source signals from signal mixtures in a wide range of signal processing applications. For example, ICA based methods can be applied in the areas of biomedicine, surveillance, face recognition and financial analysis. In this study, a new ICA based image equalization method is proposed. Our equalization method can be used to enhance the image quality by reducing shadowy and dark areas. The proposed method employs complex valued ICA for extracting equalized intensity component from the RGB components of an image. The extracted intensity component is then used to replace the value component of the hue-saturation-value (HSV) representation of the original image. Further, in order to identify the correct independent components that are used to generate the final equalized image, a new technique is proposed. The new image equalization method presented in this work could produce superior results and therefore, it is useful for implementing low cost vision based image enhancement applications.*

Keywords— **:** *Image Processing, Independent Component Analysis (ICA), Image Restoration*

I. INTRODUCTION

Image equalization and shadow removal are key pre-activities performed in many image processing applications such as video and image editing applications. Shadows in an image will cause loss of information, adversely affect the results of target tracking, object recognition, image segmentation, image matching and related problems in computer vision.

In the available literature, shadow removal methods based on shadow models and shadow properties have been presented. Shadow removal methods based on shadow models can be established with the help of prior information. However, these methods can produce accurate results only when the target's parameters such as the shape, angle and light direction are known. In many cases of practical importance, accurate estimation of these parameters is cumbersome. Therefore, such model based shadow removal methods have significant limitations and limited practical value. Methods based on shadow properties have wide applicability, however, also has its drawbacks such as high computational complexity. The proposed method has a lower complexity with the ability of producing high quality results.

In this paper, we present details of image enhancement by removing shadowy and dark areas and obtain intensity equalized images which have a high quality appearance compared to the original image. A new process based on complex valued ICA is proposed. Using this complex valued ICA algorithm, a novel process is used to generate properly equalized images from any kind of a photograph. The proposed method has a lower computational complexity with the ability of producing high quality results.

The remainder of this paper is organized as follows. Section II and Section III respectively describes the real valued ICA and complex valued ICA concepts. The process used for applying ICA to image mixtures for restoration is explained in Section IV. Section V explains the process for source extraction from RGB components of the image. Section VI describes the method used to select the best equalized image from the three results obtained from ICA. Section VII presents some results obtained for different types of example images. Finally, conclusions are given in Section VIII.

II. THE ICA CONCEPT

In this work, complex valued ICA is used as the tool for extracting the equalized intensity component from the RGB components to generate equalized images. Complex valued ICA is the generalization of the time domain real valued algorithm for complex valued signal mixtures. Therefore, in this section, we will describe the basic theory behind the conventional real valued ICA. The mixing process of signals can be modelled as

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

where $\boldsymbol{S}$ represents the source signals. The mixing matrix $\boldsymbol{A}$ results in the generation of source mixture matrix $\boldsymbol{X}$. First, a Principal Component Analysis based dimension reduction process is used to remove unwanted redundant dimensions from the signal mixture. After this dimension reduction process, the dimension of the mixture matrix $\boldsymbol{X}$ reduces such that the remaining number of mixtures is equal to the number of source signals. The ICA algorithm utilizes a tunable weight vector $\boldsymbol{w}$, that can generate the output vector which contains the separated source signals through,

$$\boldsymbol{y} = \boldsymbol{wx}. \tag{2}$$

The weight vector is tuned such that the non-Gaussianity of the extracted signal is maximized. As explained by central limit theorem, a source should be more non-Gaussian than a mixture. Therefore, by increasing non-Gaussianity of the separated signal $\boldsymbol{y}$, it is possible to obtain a source signal. In this study, kurtosis is used as a measure of non-Gaussianity. Kurtosis is zero for Gaussian signal, positive for super-Gaussian signals and negative for sub-Gaussian signals. At a local maximum of the kurtosis surface, the corresponding output vector $\boldsymbol{y}$ will give a super Gaussian source signal. At a local minimum of the kurtosis surface, the corresponding output signal will give a sub Gaussian source.

The given process is repeated after removing the separated source from the mixture matrix by using Gram Schmidt Orthogonalization.

III. COMPLEX VALUED ICA

The above discussed real valued ICA algorithm reliably works for real signals mixed through real valued mixing matrix. But if the mixing process is complex valued, so that the mixtures are complex valued, it is required to extend the real valued algorithm to a complex valued algorithm. For this purpose, kurtosis of a complex valued signal is employed. The kurtosis K of a complex valued signal and can be expressed as follows:

$$K = E[|\mathbf{y}|^4] - 2(E[|\mathbf{y}|^2])^2 - |E[\mathbf{y}^2]|^2 \tag{3}$$

In complex valued ICA, the unmixing process is complex valued. The resulting extracted source signals are also complex valued. The real part or the imaginary part of the extracted sources will give real signals corresponding to the real valued source signals. The most important features of the complex valued algorithm are the higher speed and the better accuracy of the extraction process.

IV. APPLICATION OF ICA TECHNIQUES FOR IMAGE MIXTURES

For application of the ICA techniques to images, first the images should be converted to one-dimensional signals. Therefore, before applying ICA, the images are converted into 1-dimensional signals by breaking up the rows of the image and stacking or concatenating them together as shown by the Figure 1.

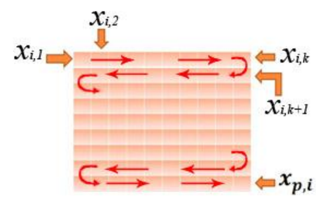


Figure 1: Converting image to a signal.

After this unwrapping process, the resulting vectors can be arranged as rows of the matrix $\boldsymbol{X}$ where each row representing one unwrapped image and each column represents a particular pixel's value for all the images. For RGB images, the unwrapping process can be done sequentially for all R, G and B matrices one after other such that each row of the matrix contains signals of all three R, G and B values one after other. This can improve the accuracy of the results compared to applying ICA to R, G, and B components separately and then combining to get the final image as it enables ICA to construct independent components based on the combined statistics of the entire RGB space.

After the unwrapping process, ICA is applied to the resulting mixture matrix $\boldsymbol{X}$. Both real and imaginary parts of the extracted sources may represent the real valued sources at two different amplification levels. Therefore, real or imaginary part of the extracted source signals can be converted back to images.

In the extracted sources, it can be observed that about half of the images are inverted due to the fact that the kurtosis surface has local maxima or minima when the weight vector is at a location of a source signal as well as when it is at the location of its negative value. In other words ICA recovers sources up to a scaling of the original source signal. The scaling can be negative or positive valued. As a result of this property, some of the extracted images become inverted. Therefore, a method for detecting and recorrecting the inverted images is required. In this paper, a simple method is explained. For this, the image waveforms are scaled in-between 0 and 255 for an 8 – bit image. Then the number of pixels is counted for two cases where the pixel value is larger than 255/2 and smaller than 255/2 for all three R, G and B matrices of the image. If the number of pixels which have higher value than 255/2 is greater than the number of pixels which have lower value than 255/2, then the image is considered to be inverted. Also this method can be adapted depending on different applications by using general unwrapped image statistics such as RGB mean, root mean square value etc. instead of the value 255/2 to detect inverted images.

After finding the inverted images using this method, those images can be easily inverted back to get proper un-inverted images.

V. EXTRACTION OF SOURCES FROM RGB COMPONENTS

The image equalization method utilizes the unwrapped signals of RGB components of the original image as 3 mixtures. The complex valued ICA algorithm is used to successfully generate the equalized intensity component of the image. Since, three images are used as input to the algorithm, in most cases, there will be three significant independent components in the outputs. Out of those, only one image represents a proper equalized image. For understanding this phenomenon, let's take an example image and see the results obtained by applying the complex valued ICA algorithm to its RGB components. Figures 2-4 show the original image, RGB components of the original image, extracted independent components of the RGB components respectively. Figure 5 shows the image obtained by replacing value component of the HSV representation of the original image in Figure 2 for all three obtained independent components.

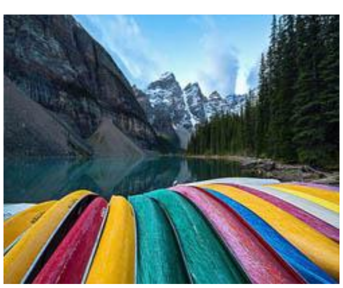


Figure 2: Original image used for equalization.

(a) (b) (c)

Figure 3: (a) Red component of the image. (b) Green component of the image. (c) Blue component of the image.

(a) (b) (c)

Figure 4: Extracted images from RGB components using complex ICA algorithm.

(a) (b) (c)

Figure 5: RGB images obtained by replacing value component of HSV image with the extracted independent components (a), (b) and (c) respectively.

We observe that the image shown in Figure 5 (b) is a properly equalized image of the original image. The dark regions of the image have become lighter so that the resulting image looks more flattened with less intensity variation. It is also possible to conclude that the other two images have too much flattened intensity variation and they are too much deviated from the natural appearance of the original image.

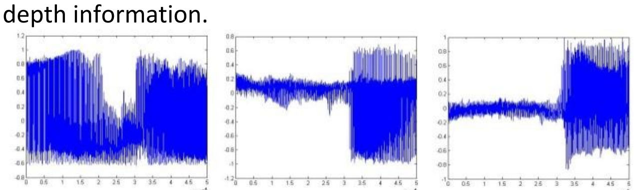
In order to compare the performance of the equalized image, we took another simple method to see whether we can obtain a properly equalized image. The mean image of the three RGB components was obtained and it was used to replace the value component of the HSV representation of the original image. The mean image and the RGB image obtained by replacing intensity component are shown in Figures 6 and 7 respectively. The obtained result in Figure 7 clearly indicates that the image is not equalized as in Figure 5 (b). Therefore, it is clear that, by using this kind of simple averaging method, it is difficult to get properly equalized images.

Figure 6: Image obtained by averaging RGB components of the original image.

Figure 7: RGB image obtained by replacing value component of the HSV representation of original image with RGB average.

VI. BEST EQUALIZED IMAGE SELECTION

As mentioned in Section V, there are three significant independent components at the output of the ICA algorithm which represent three equalized images. But in most cases, only one image has the properly equalized image appearance while the other two images looks too much flattened in intensity (lack depth information). Therefore, it is important to identify which image represents the properly equalized image. In order to achieve this, images are ordered according to their variance. The waveforms and the corresponding images are shown in Figures 8 and 9 respectively. These results show that the largest variance waveform represents the properly equalized image whereas the other two waveforms with low variances produce images that lack depth information.



(a) (b) (c)

Figure 8: Waveforms of the images when they are ordered according to their variance in descending order with (a) largest, (b) second largest and (c) smallest variance waveform.

(a) (b) (c)

Figure 9: Images corresponding to (a), (b) and (c) of Figure 7.

This result was tested for many different image samples and found that most of the natural photographs can be identified using this method.

VII. RESULTS FOR DIFFERENT EXAMPLES

In reality, there is no general theory for determining what the best image enhancement is when it comes to human perception. The perception about an image may vary from person to person. Therefore, it is almost impossible to show the performance of the image enhancement using a measure. Hence, the proposed image equalization procedure was followed for several natural photographs which have different characteristics in terms of colour, intensity level and the overall appearance. Almost all the images were successfully equalized and have highly improved quality and appearance compared to the original images. The original images and the obtained results using the equalization method are shown in Figure 10 (a) and (b) respectively.

The demand of an image appearance varies from person to person or depends on the situation. Therefore, it is important to vary the level of equalization of the image. But the discussed process can only generate one image and the level of equalization cannot be adjusted by using any kind of method using ICA since the ICA algorithm will always look for the local maxima or minima so that the result will always give only one equalized image which cannot be adjusted manually within the process. Therefore, the equalization level should be adjusted in some external step before or after applying ICA.

Therefore, the quality and the appearance of the obtained results can be further enhanced or adjusted by linearly superimposing the original image on top of the equalized image sample in different proportions. This can be used to tune the level of equalization obtained from the image. Such an example is shown in Figure 11 (a), (b) and (c) which represent the equalized image when it is super imposed by different levels of the original image.

(a) (b)

Figure 10: (a) Original images, (b) equalized images.

(a) (b) (c)

Figure 11: The equalized image component replaced by (a) 20% of original image, (b) 50% of original image and (c) 100% of original image.

VIII. CONCLUSIONS

In this paper, we considered the problem of blind source separation of equalized intensity component from RGB components of the image. In particular the complex valued ICA used is capable of generating equalized intensity component from an image when photographed or natural images are used. Furthermore, the proposed variance based method can be successfully used to identify the correct independent component required to generate the equalized RGB image which has high quality appearance. The images can be further enhanced by linearly super-imposing the original image on top of the obtained equalized image in different proportions to get different levels of equalization. Therefore, the presented method is a useful technique for implementing low cost vision based image enhancement applications.

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BIOGRAPHY OF AUTHORS

Ms Dilika Sumanapala. is an Electrical and Electronic Engineering student at University of Peradeniya. She is interested in signal processing and telecommunication. She is involved in two final year projects which are independent component analysis techniques for source separation and 3D rendering of objects through multi vision sensor array system.

Sivalingam Thushan.completed his undergraduate studies (Bsc.Eng) in last october in Electrical and Electronic Engineering and Currently working in Dialog Axiata Plc in the section of Access Network Planning in Eastern Region. He did two major projects in my undergraduate period and published 3 technical papers.