Image Enhancement using Contrast Enhancement and Synthetic Multi Exposure Fusion

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***Abstract*—Recently many hardware and software advancements have been made to improve image quality in smartphones but unsuitable lightening conditions are still a big impediment to image quality. To counter this problem we present an image enhancement pipeline based upon synthetic multi image exposure fusion and contrast enhancement that is robust to different lightening conditions. In this paper we propose a novel way of generating synthetic multi exposure images by applying gamma correction to input image using different values based upon its luminosity to generate multiple intermediate images and then applying contrast enhancement to these intermediate images. As a result contrast enhancement for each image focuses on specific region of image resulting in varying exposure, colors and details in resulting synthetic images. Visual and statistical analysis shows that our method performs better in various lightening scenarios and achieve better statistical naturalness measure and discrete entropy score compared to existing methods.**

***Index Terms*—Image Enhancement, Synthetic Multi Exposure Images Generation, Contrast Enhancement, Exposure Fusion, Gamma Correction**

I. Introduction

Presently, combination of hardware and software advancements are improving image quality in smartphone cameras. Poor lightning scenarios are still a big impediment to image quality. These scenarios include low light conditions and high dynamic range scenes.

Various software techniques have been proposed to improve visual quality in these conditions. The goal of these techniques is to improve visibility in low light areas while avoiding to degrade quality in other regions. Different variants of Histogram equalization techniques [1]–[4] try to improve contrast and visibility of photos. Adaptive gamma correction techniques [5], [6] have also been proposed to improve contrast in images. However, these techniques can over enhance images in bright regions and under enhance in dark regions. Neural network based techniques [7], [8] have also been proposed which perform specific image enhancement tasks. However, these techniques are either very slow, consume large amounts of memory, require large amount of training data which is not easily available or do not generalize well to different scenarios making them unsuitable for many tasks such as use in smartphones. Exposure Fusion [9], [10] improves quality of an image by combining multiple low dynamic range images of varying exposures and fusing best parts of each image. However, this technique introduce artifacts in presence of motion blur in the image stack. It is nearly impossible to capture a static burst of images from smartphone cameras. Burst image alignment techniques have been proposed to mitigate this problem. Other than that, different methods [11]–[13] have been proposed to generate pseudo multi exposure images from a single image to utilize the benefits of exposure fusion.

In this paper we propose a novel method of generating synthetic multi exposure images by applying gamma corrections to input image with different gamma parameters and processing these images with existing image enhancement techniques. Input image is segmented into different regions based upon its luminosity. This results in more variation of exposure in generated images as each generated image has focus on a specific region during enhancement process. We extend this method to create a four step image enhancement pipeline which utilizes contrast enhancement and exposure fusion to generate output image. Our methodology is more robust to different imaging scenarios and produce better visual quality than existing methods.

II. Related Work

There are several techniques for image enhancement that improve visual quality in images. Some most common techniques work on low light and high dynamic range scenarios. In darker regions, visual quality can be improved by increasing luminosity. But this has to be done in such a way as to keep noise minimal and avoid over blowing details in brighter regions. There exist various approaches to solve this problem including neural network approaches [7], [8], gamma correction [5], [6], burst image alignment [14]–[16] and retinex based methods [17], [18]. Most of them are some form of contrast enhancement techniques. Our goal for this work was that our method should work on smartphones. Therefore it has to perform in less amount of time and must not be computationally expensive and take much memory. This resulted in discarding use of such techniques that violates these conditions. Our work utilize these contrast enhancement techniques that are based upon histogram based methods and synthetic exposure fusion based approaches which we discuss in detail in this section.

A. Histogram Based Methods

Most common contrast enhancement technique is Histogram Equalization [1]. The goal of this technique is to make the histogram of image uniformly distributed to increase contrast. Various extensions of this method have been proposed. These extensions usually perform global or local histogram equalization.

Contrast Limited Adaptive Histogram Equalization (CLAHE) [2] is a commonly used local contrast enhancement technique which divides image into several tiles. Contrast transformation for each tile is performed. Afterwards, these tiles are combined using bi-linear interpolation to avoid unnatural boundaries between tiles. Joint histogram equalization approaches have also been proposed which combine both global and local approaches.

Joint Histogram Equalization (JHE) [4] uses average image along with the original image to create a two-dimensional joint histogram. A two-dimensional cumulative distribution function is then calculated which is used to generate the contrast enhanced output pixel value.

Global and Local Contrast Adaptive Enhancement for Non-uniform Illumination Color Images (GLF) [3] also utilizes both local and global contrast enhancement. Input image is linearly stretched, globally and locally enhanced, globally and locally enhanced images are merged and then hue preservation is performed. Global contrast enhancement is performed by obtaining a modified histogram which is closest to a uniform histogram. For local contrast enhancement CLAHE is used. Hue preservation equation from Nikolova et al. [19] is used. These enhanced images are merged by using weighted sums. Weight maps are generated by applying Laplacian filter and fitting pixel intensity to Gaussian curve.

B. Synthetic Exposure Fusion

Exposure fusion [9] is a technique used to combine multiple low dynamic range images of the same scene to get a single high quality image. Best parts from the input sequence are taken and fused together seamlessly. However, there are strict requirements for this technique to work properly. Input image sequence must have varying exposures and the scene must be static. Usually with digital cameras capturing multiple images while keeping the scene static is not possible. To counter this problem, multiple techniques have been proposed recently which generate multiple synthetic images with varying exposures which are then fused together using exposure fusion.

Bio-inspired Multi-exposure Fusion Framework (BioMEF) [13] propose a four step procedure for this task. In first step, required number of synthetic images is determined. In second step, camera response model is used to generate the synthetic images. These images are then assigned weight maps and combined in third and fourth step respectively.

Scene Segmentation-Based Luminance Adjustment (SSLA) [12] also provides an approach to generate multiple synthetic exposure images from a single image. Gamma correction with a fixed value of 2.2 is applied on the input image. In the next step, local contrast enhancement is done on the input image. Then the luminosity values of this image are sorted and divided into M equal regions. Enhancement factor is calculated from each region which are then used to scale existing image to generate the synthetic images. Inverse gamma correction is performed and then these images are fused using exposure fusion.

In this paper, we propose a novel way of generating multiple synthetic exposure fusion by applying gamma corrections to the input image based upon its luminosity values before using already existing image enhancement techniques. In this way we force image enhancement techniques to specifically target a specific under or over exposed region of image which results in higher variation in synthetically generated images. We propose an image enhancement pipeline that is more robust to different lightening scenarios and works well to improve image quality.

III. Proposed Methodology

The proposed image enhancement pipeline consists of four parts: image analysis, gamma parameter calculation, synthetic images generation, exposure fusion. An overview of the proposed method is given in figure(1) and then the complete pipeline is explained step by step below.

A. Overview

To increase robustness of our method to different imaging scenarios, input images are divided into three categories: normal, dark and extreme. Dark images are those which are taken in very low light conditions. Extreme images have regions which are extremely underexposed and other region which are overexposed or have correct exposure. These two types of images are usually over or under enhanced by exiting methods hence the need for categorization. All other images are part of normal category. This categorization is done in the first step i.e. image analysis. In the next step, parameters for gamma correction are determined. The image is divided into three regions based upon its luminosity. These regions determine the four gamma parameters used in the next step. In the next step multiple synthetic images are generated. Input image is subjected to gamma corrections using generated gamma parameters. First three of these images are subjected to contrast enhancement based upon GLF. This results in aggressive enhancement. The fourth image is subjected to modified version of SSLA. This algorithms improves image

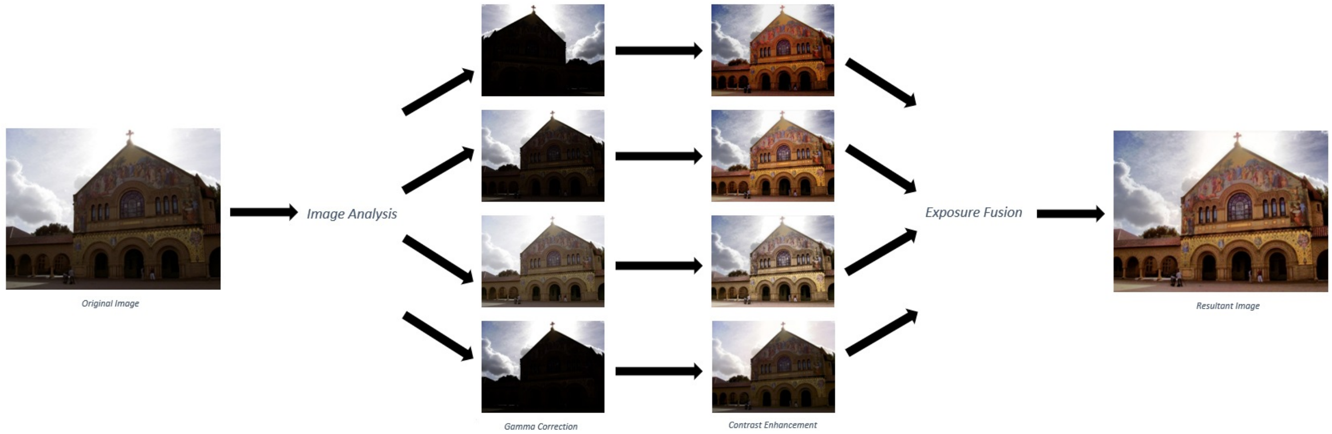


Fig. 1: Image Enhancement Pipeline

quality but retain much information from the original image. This is especially necessary for dark and extreme images. In the final step, synthetic images are merged together using exposure fusion.

B. Image Analysis

Images having very low light conditions or having large exposure difference among regions are susceptible to over or under enhancements. To avoid this, input images are divided into three categories: normal, dark and extreme. Luminance channel L of n image is extracted. If the mean value of intensities of L is less than 85, image is classified as dark. Next we check whether the image lies in extreme category. For this the intensities are divided in two regions: bright and dark. If intensity at a pixel is greater than 127, it is considered bright else it is considered dark. If the mean of dark pixels is less than 28 and the ratio between dark and bright pixels is between 20 and 80, image lies in category of extreme images. If an image lies in both dark and extreme categories, it is treated as extreme image. All other images are classified as normal. To speedup this process, we reduce the size of image by 95 percent as the overall composition of image remains same even when down sampled and resizing does not effect the result.

C. Gamma Parameter Calculation

In this step, we again work with Luminance channel L. L is divided into three equal regions based upon pixel intensity values. Let L_s be array of sorted luminosity values of size n. We get the length k of each region by

$$k = \frac{max(L_s) - min(L_s)}{3} \tag{1}$$

First k entries of L_s are assigned to the first region, next k entries to the second region and the remaining to the third region. Afterwards gamma parameter for all three regions are calculated using equations (2) and (3).

$$v_i = \frac{1}{|R_i|} \sum_{p \in R_i} log(max(p, \epsilon)) \tag{2}$$

$$\alpha_i = \frac{v_i}{2.2} \tag{3}$$

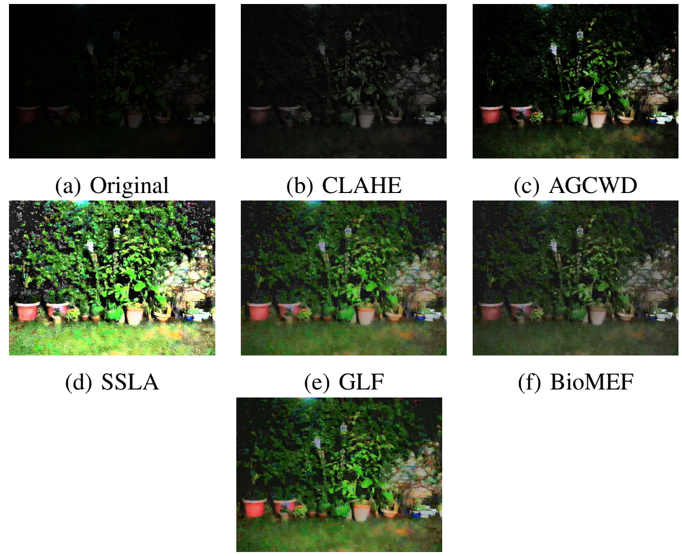
where R_i is the i-th region, ϵ is assigned to a small value to avoid singularities where $p = 0$ and α_i is the calculated i-th parameter. This gives us the first three parameters. In the next step, the generated parameters are further adjusted to give best visual and statistical results and the value of fourth parameter is also assigned. These adjustments are defined in table (I). These parameters are used in the next part to generate synthetic images. Again we reduce image size at this step to improve speed.

TABLE I: Parameter adjustment

Parameter	Normal	Dark	Extreme
α_0	α_0	1	α_1
α_1	$\frac{1}{\alpha_1}$	α_1	α_2
α_2	$\frac{1}{\alpha_2}$	$\frac{1}{\alpha_2}$	$\frac{1}{\alpha_2}$
α_4	α_0	$\frac{1}{\alpha_1}$	α_2

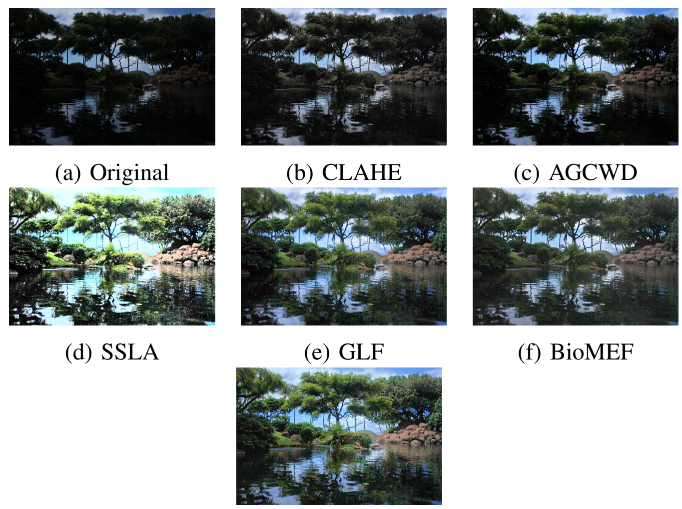
D. Synthetic Image Generation

In this step multiple synthetic images are generated from the single source image. The previously calculated parameters are used to perform gamma corrections on input image to generate four different images. Each gamma corrected image corresponds to a different level of exposure. Two images are overexposed whereas other two are underexposed to varying degrees as shown in figure (1). First three gamma corrected images are passed to modified GLF module. This module consists of two parts; local contrast enhancement and global contrast enhancement. We utilize JHE for global contrast enhancement while other implementation details remain the same as original paper. This module aggressively enhances the contrast of image. However this could result in unwanted artifacts and too much deviation from original colors especially in dark and extreme images. To maintain closeness to original image, we also use a modified version of SSLA. We use approach 2 defined in the paper to segment the image into seven parts. We also resize the image to a very small size while calculating the luminance scaling factor to speed up the process. Moreover, the original implementation performs gamma correction of 2.2 which is not suitable in all scenarios. Instead we pass already gamma corrected image with gamma parameter α_4. Like in the original implementation, we perform inverse gamma correction with value α_4 before fusing the generated images. We also skip the local contrast enhancement step. This module results in enhanced image which is much closer to original image and avoids over enhancements. At the end of this step, we have obtained four synthetically generated multi exposure images.



(a) Original (b) CLAHE (c) AGCWD (d) SSLA (e) GLF (f) BioMEF (g) Proposed

Fig. 2: Low Light Scenario



(a) Original (b) CLAHE (c) AGCWD (d) SSLA (e) GLF (f) BioMEF (g) Proposed

Fig. 3: High Dynamic Range Scene

E. Exposure Fusion

In the last part of our image enhancement pipeline, we use exposure fusion to combine the synthetic images to generate final output image. All four synthetic images and the input image are merge together using exposure fusion to generate high quality image.

IV. Results and Comparison

We tested our method on images with different lightening scenarios. We used VV dataset [20] to test our method. This dataset contains 24 images under extreme lightning conditions. Each image in this dataset has a part which is correctly exposed while other parts are extremely under or over exposed. Moreover, we generated our own dataset consisting of 44 images having variety of different lightening conditions including low light images, high dynamic range scenes, properly exposed scenes and extreme lightening conditions similar to VV dataset [20]. We compared our methodology to CLAHE, AGCWD, SSLA, GLF and BioMef.

A. Visual Analysis

In this subsection we provide a visual comparison of our methodology to other methodologies and compare results. We perform this visual analysis on different lightening scenarios.

Figure (2) show that our methodology works quite well under extreme low light conditions. Colors and details are better than other methodologies. Only GLF come close to match the visual quality of our method.

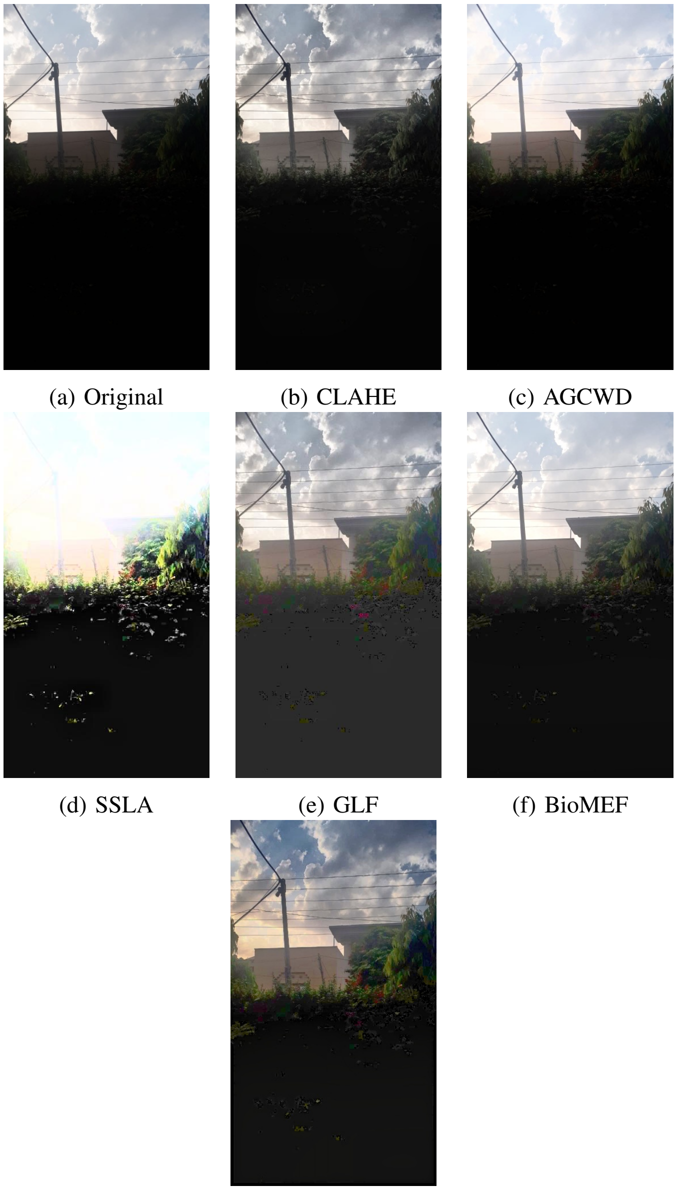
In figure(3) which depicts a high dynamic range scene, our methodology retains a good balance between exposing under exposed regions and retaining color and details in the remaining regions of original image. Again GLF is the method that is closest to our method in this visual comparison.

The extreme scene in figure(4) shows that our method has more vivid colors in foreground and the sky. Again GLF seem to come close but it does produce some unwanted artifacts such as pink box of pixel in the middle of image.

Under normal lightening scenario depicted by figure(5), our method improve visual quality the most while retaining details. Colors have started to fade in GLF which has been performing quite well so far. SSLA and BioMEF performs well but their is a bit hazing effect. AGCWD also performs well but overexposes some part of image.

In overexposed scenario shown in figure (6), AGCWD shows good colors but does not deals with overexposed parts. GLF shortcoming are also exposed as it is not well suited for properly or highly exposed scenes. Hazing effect in BioMEF is also highlighted in this scenario. Our methodology again shows a good balance between colors and details.

Visual comparison in different scenarios proves robustness of our method as compared to other methods. Also the visual quality steadily remains the best in all scenarios.



(a) Original (b) CLAHE (c) AGCWD

(d) SSLA (e) GLF (f) BioMEF

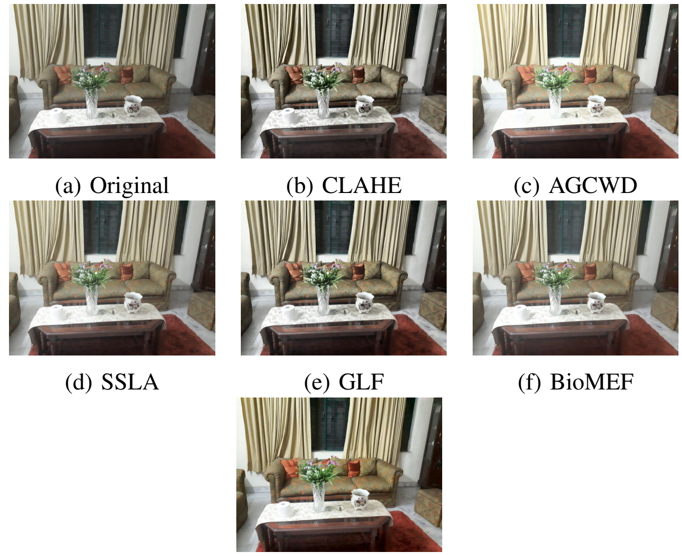
(g) Proposed

Fig. 4: Extreme Lightening Scene

B. Statistical Analysis

For statistical analysis we use discrete entropy(DE) and statistical naturalness measure(SNM) to compare our method with above mentioned techniques. Discrete entropy shows the richness of details in image. But this measure can be effected by overenhanced images which score higher in this category. So we also introduced statistical naturalness measure to keep check of over enhancements. Sum of discrete entropy and statistical naturalness measure scores of all images in respective dataset is shown in table(II) and table(III). Higher score means better result.

Our method achieves highest discrete entropy scores on both datsets but achieves a close second in statistical naturalness measure. This confirm our observations made during the visual



(a) Original (b) CLAHE (c) AGCWD

(d) SSLA (e) GLF (f) BioMEF

(g) Proposed

Fig. 5: Normal Scenario

(a) Original (b) CLAHE (c) AGCWD

(d) SSLA (e) GLF (f) BioMEF

(g) Proposed

Fig. 6: Overexposed Scene

TABLE II: Comparison on our Dataset

	DE	SNM
CLAHE	289.86	14.15
AGCWD	282.16	13.23
SSLA	209.82	24.84
GLF	325.18	25.64
BioMEF	289.74	20.64
Proposed	332.76	24.93

TABLE III: Comparison on VV Dataset

	DE	SNM
CLAHE	164.78	7.31
AGCWD	163.19	10.28
SSLA	171.77	14.85
GLF	176.25	13.92
BioMEF	169.22	12.93
Proposed	177.86	14.75

TABLE IV: Time Comparison

	CLAHE	AGCWD	SSLA	GLF	BioMEF	Proposed
Time(s)	1.01	9.29	32.38	50.10	276.59	36.21

comparison that our method improves quality and retain details better than other methods in all tested scenarios while avoiding over or under enhancements. Table (IV) shows time taken by each method to generate results for our dataset. SSLA and GLF have code available in matlab. AGCWD, BioMef and CLAHE have implementations available in python. Our method runs on C++. Although programming languages effect this time comparison but the comparison gives a general idea about speed of algorithms. We see that all methods other than BioMef generate result in respectable amount of time.

V. Conclusion

(a) Original

(b) Proposed

Fig. 7: Failure Case

In this paper we have proposed a novel way of generating synthetic multi exposure fusion images having much more variation in exposure than existing methods. This is achieved by generating gamma correction parameters based upon luminsoity of image, applying gamma correction using these parameters and enhancing these intermediate images using existing contrast enhancement techniques. Use of differently gamma corrected images before enhancement ensure that each synthetic image generated has a focus on specific exposure region. This results in higher variation of exposure, color and details in generated images. We extended this work to create an image enhancement pipeline that is robust to different lightening scenarios. Visual and statistical comparison shows that our methodology improve the quality of image while retaining details in all multiple imaging scenarios.

Like all other methodologies, this one also has some limitations that need to be addressed int the future. Our method does not performs any sort of noise reduction resulting in noisy images especially in low light scenarios. Contrast enhancement techniques used in this paper although work well in most cases, but can produce some unwanted artifacts such as shown in figure (7). Currently we currently use two different methods for enhancement purposes. In future a single more robust contrast enhancement technique could be used for this purpose. Finally, the number of generated gamma parameters and their defined adjustments should be looked upon in the future for better results.

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