

# CONTEXT ENHANCEMENT THROUGH IMAGE FUSION: A MULTIREOLUTION APPROACH BASED ON CONVOLUTION OF CAUCHY DISTRIBUTIONS

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## ABSTRACT

A novel context enhancement technique is presented to automatically combine images of the same scene captured at different times or seasons. A unique characteristic of the algorithm is its ability to extract and maintain the meaningful information in the enhanced image while recovering the surrounding scene information by fusing the background image. The input images are first decomposed into multiresolution representations using the Dual-Tree Complex Wavelet Transform (DT-CWT) with the subband coefficients modelled as Cauchy random variables. Then, the convolution of Cauchy distributions is applied as a probabilistic prior to model the fused coefficients, and the weights used to combine the source images are optimised via Maximum Likelihood (ML) estimation. Finally, the importance map is produced to construct the composite approximation image. Experiments show that this new model significantly improves the reliability of the feature selection and enhances fusion process.

**Index Terms**— context enhancement, image fusion, surveillance, Cauchy distribution, wavelet decomposition.

## 1. INTRODUCTION

Context enhancement (CE) is used in numerous applications such as surveillance and civilian or military image processing. Context enhancement aims to detect, recognize and track objects such as people and cars from the image while being aware of the existing surroundings. Moreover, CE helps analyse background information that is essential to understand object behaviour without requiring expensive human visual inspection. One way of achieving context enhancement is fusing a low quality image (i.e., foreground image) and a high quality image (i.e., background image) at the same viewpoint. However, extracting the important features from the foreground image and combining them efficiently with the environmental context from the background image still remains a challenging problem.

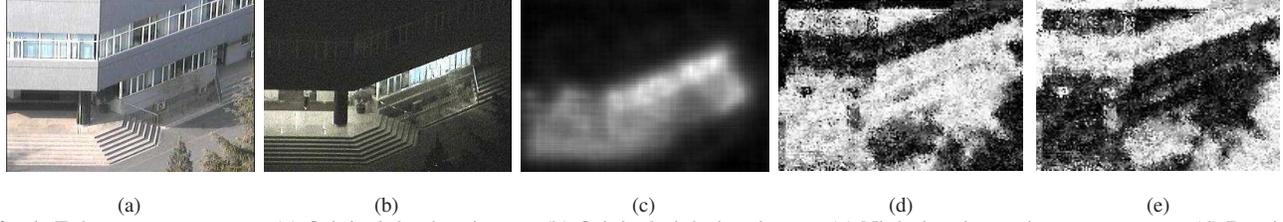
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In past decades, there has been considerable interest in combining source images through weighted averaging in the wavelet domain [1, 2, 3]. For example, Burt and Kolczinski [1] presented an image fusion algorithm which calculates a normalised correlation between the two images' subbands over a small local area. The fused coefficients arise from the local variance via a weighted combination of the two images' coefficients. Achim *et al.* [2] derived a fusion approach using fractional lower order moments as a weight estimator to fuse the input images. In previous work [3], we developed a fusion algorithm based on generalized Gaussian distributions (GGD), in which the Shannon entropy is used to produce the weights to synthesize the fused detail and approximation images. Recently, a statistical fusion method employing Independent Component Analysis (ICA) was introduced in [4]. The method involves computing the combination weights via Laplacian and Verhulstian priors.

In this paper, we propose a new image fusion technique based on Cauchy convolution where the combination weights are optimised through ML estimation. We demonstrate that, compared with previous methods, our algorithm has a number of advantages. First, by using convolution of Cauchy models, we are able to develop a generative model where the distribution of the fused subband is determined by the distributions of the input subbands. Thus, the new model leads to a more accurate and reliable optimisation process in comparison with Laplacian and Verhulstian models in [4] that do not take into account any assumption about the input images. Moreover, the applied dual-tree complex wavelet transform [5] provides near shift invariance and good directional selectivity while preserving the usual properties of perfect reconstruction and computational efficiency. As a result, the overall algorithm performs in a near-optimal way to enhance the perceptive quality of the fused images.

The rest of the paper is organized as follows. In Section 2, a framework for weighted average fusion is described. Section 3 provides a brief introduction on the convolution of Cauchy distributions. A novel optimisation approach using the Cauchy convolution and experimental results are presented in Section 4 and Section 5, respectively. Finally, conclusions are made in Section 6.



**Fig. 1.** Enhancement process. (a) Original daytime image. (b) Original nighttime image. (c) Nighttime image importance map. (d) Daytime image weight map. (e) Nighttime image weight map. Bright colour indicates the high values, and dark colour indicates the low values.

## 2. WEIGHTED AVERAGE FUSION

The weighted average image fusion algorithm consists of two main components. First, the detailed wavelet coefficients are composed using weighted combination:

$$D_F = w_1 D_1 + w_2 D_2, \quad (1)$$

where  $D_1$  and  $D_2$  are the wavelet coefficients of two source images, and  $D_F$  are the composite coefficients.  $w_1$  and  $w_2$  are the weights for these two input images, respectively.

Because of their different physical meaning, the approximation and detail images are usually treated by the combination algorithm in different ways. As we deal with the asymmetrical fusion in which the salient objects are from the foreground image and the surrounding context is from the reference background image, a better option is to give more importance to the regions of interest in the foreground image. This is to make sure that no information in the foreground image is lost in the enhanced image. The importance map, which is used to detect salient objects, is calculated based on the Cauchy parameter  $\gamma$  estimated on the foreground image, as shown in Fig.1(c). A preliminary version of this method has been already reported in [6]. Hence, the composite approximation image  $A_F$  can be computed by:

$$A_F = I A_1 + (1 - I) A_2, \quad (2)$$

where  $I$  is the importance map of which the values are constrained between 0 to 1. Finally, the fused image is obtained by taking an inverse wavelet transform.

## 3. CONVOLUTION OF CAUCHY DISTRIBUTIONS

The Cauchy distribution is a member of the alpha-stable family for modelling heavy-tailed non-Gaussian behaviour. Unlike alpha-stable distributions which lack a compact analytical expression for their probability density function (PDF), the Cauchy model has the PDF:

$$P(x; \mu, \gamma) = \frac{1}{\pi} \left[ \frac{\gamma}{(x - \mu)^2 + \gamma^2} \right], \quad (3)$$

where  $\mu$  ( $-\infty < \mu < \infty$ ) is the location parameter, specifying the location of the peak of the distribution, and  $\gamma$  ( $\gamma > 0$ ) is the dispersion of the distribution that determines the spread of the distribution centered on  $\mu$ . According to the stability property of alpha-stable distributions for the particular case of the Cauchy density [7], the class of Cauchy distributions is closed under convolution. For example, if two independent random variables  $X_1$  and  $X_2$  follow Cauchy distributions with parameters  $(\mu_1, \gamma_1)$  and  $(\mu_2, \gamma_2)$ , respectively, then the random variable  $Y = X_1 + X_2$  follows the convolution of the distributions of  $X_1$  and  $X_2$ , which is also a Cauchy

distribution:

$$\begin{aligned} P(y; \mu, \gamma) &= P(x; \mu_1, \gamma_1) * P(x; \mu_2, \gamma_2) \\ &= P(x; \mu_1 + \mu_2, \gamma_1 + \gamma_2). \end{aligned} \quad (4)$$

More generally, it can be shown [8] that the distribution of a weighted sum of two independent Cauchy random variables,  $Z = w_1 X_1 + w_2 X_2$ , also follows the Cauchy distribution with parameters  $\mu$  and  $\gamma$  defined as:

$$\mu = w_1 \mu_1 + w_2 \mu_2, \quad \gamma = w_1 \gamma_1 + w_2 \gamma_2. \quad (5)$$

In this paper, we assume that there are two input images, which are decomposed in the wavelet domain.  $Z$  represents the weighted combination of the two source images, where  $X_1$  and  $X_2$  are their corresponding wavelet coefficients. By using convolution of the two distributions, the proposed model is able to take into account the local characteristics contained in both images.

## 4. OPTIMISING WEIGHTS VIA CAUCHY CONVOLUTION

In this section, we introduce a new statistical optimisation approach combining the wavelet transform with the convolution of Cauchy distributions, in which the distributions of input images are considered. Wavelets have emerged as an effective tool to analyse texture feature due to its energy compaction property. It has been pointed out that the wavelet transforms of real-world images tend to be sparse, resulting in a large number of small coefficients and a small number of large coefficients [9]. The problem of fusion can be posed as an optimisation problem of estimating appropriate combination weights, so that the enhanced image highlights salient information from the low quality image, while fusing the background scene smoothly. It makes sense to assume that the fusion process maximizes the sparsity of the resulting image in the wavelet domain, which emphasizes the existence of strong coefficients in the transform, whilst suppressing small values. This should enhance the visual quality of the fused images [4].

### 4.1. Optimisation Scheme

The proposed method aims to investigate an optimisation algorithm and develop a new methodology for image enhancement applications. The approach intends to maximize the cost function derived from the convolution of Cauchy distributions. The optimal weights determine how much each individual source image contributes into the fused image.

We assume that the distributions of wavelet coefficients corresponding to the input images are modelled by Cauchy distributions.

Thus, the distribution of weighted sum of wavelet coefficients can be derived from the Cauchy convolution. The PDF is given below:

$$P(x; \mu, \gamma) = \frac{1}{\pi} \left[ \frac{w_1 \gamma_1 + w_2 \gamma_2}{(x - w_1 \mu_1 - w_2 \mu_2)^2 + (w_1 \gamma_1 + w_2 \gamma_2)^2} \right], \quad (6)$$

where  $(\mu_1, \gamma_1)$  and  $(\mu_2, \gamma_2)$  are the model parameters from the distributions of input subbands, while  $w_1$  and  $w_2$  are the weights of the two source images, respectively.

The likelihood expression for Maximum Likelihood estimation is  $L = -\log(P(x; \mu, \gamma))$ . ML estimation can be performed by maximizing the cost function [4]:

$$C(w_1, w_2) = E[L], \quad (7)$$

where the weights  $w_1$  and  $w_2$  remain always positive and they sum up to one, and  $E[\cdot]$  is the expectation function. The optimal weights are obtained when they give the maximum value to (7). After a few straightforward transforms, the partial derivatives on (7) with respect to  $w_1$  and  $w_2$  are:

$$\begin{cases} \frac{\partial C(w_1, w_2)}{\partial w_1} = E \left\{ -\frac{\gamma_1}{\gamma} + \frac{2Q(x_1 - \mu_1) + 2\gamma_1 \gamma_2 w_2 + 2\gamma_1^2 w_1}{(x - \mu)^2 + \gamma^2} \right\} \\ \frac{\partial C(w_1, w_2)}{\partial w_2} = E \left\{ -\frac{\gamma_2}{\gamma} + \frac{2Q(x_2 - \mu_2) + 2\gamma_1 \gamma_2 w_1 + 2\gamma_2^2 w_2}{(x - \mu)^2 + \gamma^2} \right\} \end{cases} \quad (8)$$

with

$$Q = (x_1 - \mu_1)w_1 + (x_2 - \mu_2)w_2, \quad (9)$$

where  $x_1$  and  $x_2$  are the wavelet coefficients of the input images, while  $\gamma$  and  $\mu$  are the model parameters defined in (5). The ML estimation can be implemented through the steepest ascent method. By using the instantaneous estimation of the expectation, the updating procedures are simplified as:

$$\begin{cases} w_{1,k+1} = w_{1,k} + \eta \frac{\partial C(w_{1,k}, w_{2,k})}{\partial w_{1,k}} \\ w_{2,k+1} = w_{2,k} + \eta \frac{\partial C(w_{1,k}, w_{2,k})}{\partial w_{2,k}}, \end{cases} \quad (10)$$

where  $k$  refers to the iterating index and  $\eta$  is the learning rate. In this paper,  $\eta$  is assigned with 0.05. The above update rule is applied until the stopping criterion reaches:

$$\max\{\|w_{i,k+1} - w_{i,k}\|\} \leq \varepsilon \quad i = 1, 2 \quad (11)$$

where  $\varepsilon$  is the value of the error threshold. It must be very small (e.g., 0.001). Fig.1(d) and 1(e) show an example of the weight maps of the daytime and nighttime images. As it can be seen, the desirable features within both images are well extracted by the proposed statistical model.

## 4.2. Parameter Estimation

In order to estimate the parameters from wavelet coefficients, a method based on log absolute moment has been proposed in [10]. In our work, the method is used in a square-shaped neighborhood of size  $7 \times 7$  for each reference coefficient:

$$X = \log[|D_j(x, y)|] \quad (x, y) \in W, \quad (12)$$

where  $W$  refers to the  $7 \times 7$  window, and  $D_j(x, y)$  is the detail coefficient in the  $j^{th}$  subband at location  $(x, y)$ . It can be shown [10] that the derived equation is given by:

$$\hat{\gamma} = \exp(E[X]). \quad (13)$$

Since our developments are in the framework of wavelet analysis, we assume that the location parameter  $\mu = 0$  for the simplified case.

In contrast with the method reported in [4], which updated the model parameters in each iteration of optimising the weights, the proposed method only updates the parameters once. The updated parameters then will be used through all the iterations. This leads to a computationally more efficient optimisation process.

## 5. EXPERIMENTAL RESULTS AND DISCUSSIONS

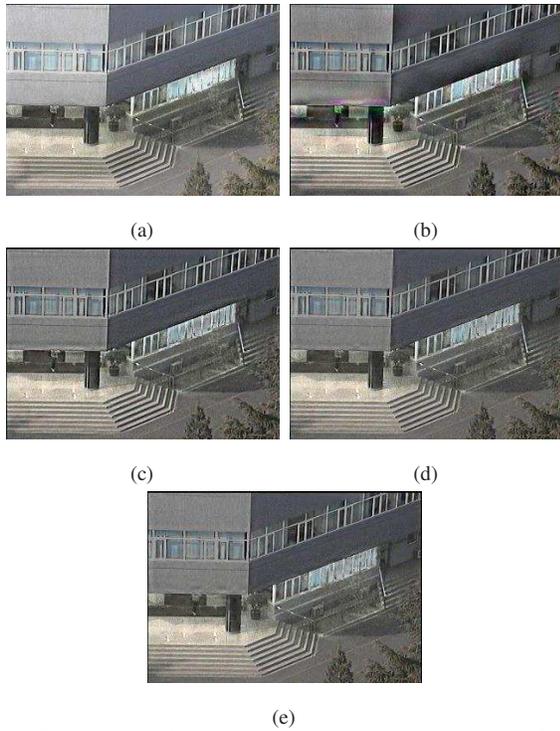
Subjective tests and objective measurements are used for qualitatively and quantitatively assessing the performance of the proposed methodology. In many applications, the human perception of the fused image is of paramount importance. Therefore, we choose multi-time and multi-season images, apply the algorithm, and visually evaluate the enhanced image in comparison with the previously proposed fusion methods, including the weighted average (WA) method [1], and the fusion approach by making use of fractional lower order moments (FLOM) [2]. We also implemented Mitianoudis and Stathaki's method [4] for Cauchy and GGD models but applied in the wavelet domain instead of ICA bases for the sake of fair comparison.

The first example (see Fig.2) shows an outdoor scene combined from a daytime image (Fig.1(a)) and a nighttime image (Fig.1(b)). The proposed method achieves improved performance by successfully providing context to dark images while reducing blocking artefacts which obviously appear around the edge of the building in Fig.2(b) and 2(c). As a second example, we choose to illustrate the fusion of two natural images captured under different seasons from the same view. Fig.3(c) shows that the resulting image using Cauchy convolution not only preserves useful features, but also maintains smooth transition from background to foreground compared with other fusion schemes. The proposed method seems to balance between the details and the different contrast information that exists in the input images.

An objective evaluation criterion should also be applied to compare results obtained using different algorithms. A quality metric which does not require a ground-truth was proposed by Piella and Heijmans [11] in which the important edge information is taken into account to evaluate the relative amount of salient information conveyed into the fused image. We use their defined criterion to evaluate the fusion performance. The results are shown in Table 1, which indicate that the proposed algorithm obtains the higher evaluation values compared with the Cauchy and GGD priors except for the multi-season images when the WA scheme is rated highest. It indicates that the WA method intends to preserve most of the edge information. However, it may cause distortions that make the final image look inferior perceptually.

## 6. CONCLUSIONS AND FUTURE WORK

We have proposed a novel context enhancement method using convolution of Cauchy distributions in the wavelet domain. The salient features contained in the input images are captured and modelled by Cauchy distributions, and the fused coefficients are obtained by maximizing the cost function derived from the Cauchy convolution that takes into account this important information. Maximum likelihood estimation is used to calculate the weights thus leading to an optimised fusion process. The main contribution of this work that it provides a precise and robust statistical model to perform an automatic context enhancement task. Future work will concentrate on combining our optimisation method with higher-complexity fusion



**Fig. 2.** Fusion for multi-time images. (a) Image fused using Cauchy convolution. (b) Image fused using WA scheme. (c) Image fused using FLOM rule. (d) Image fused using Cauchy prior. (e) Image fused using GGD prior.

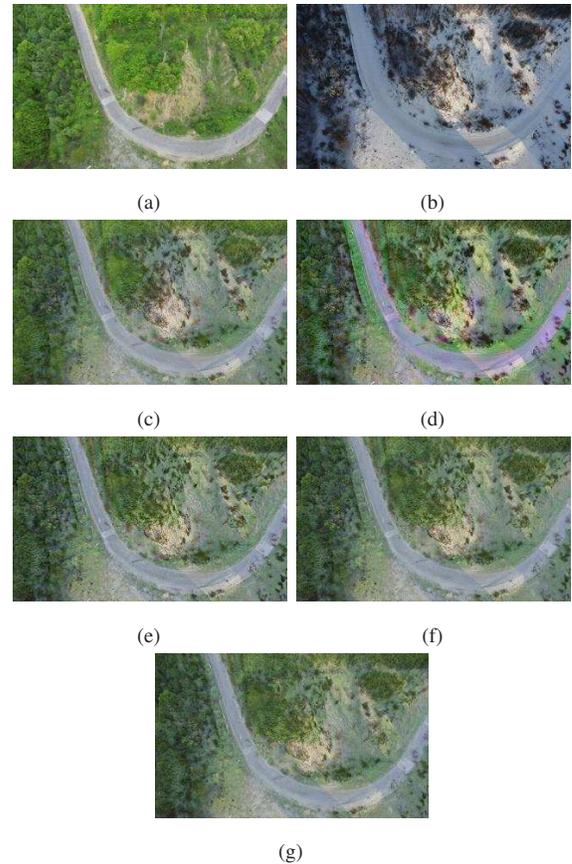
rules and extending the proposed algorithm to the general case of symmetric alpha-stable ( $S\alpha S$ ) distributions.

**Table 1.** Performance comparisons using Piella's metric [11]

Example	Methods				
	WA	FLOM	GGD	Cauchy	Convolution
multi-time	0.8211	0.8166	0.7695	0.7779	0.8293
multi-season	0.7659	0.7514	0.6956	0.7147	0.7588

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**Fig. 3.** Fusion for multi-season images. (a) Original spring image. (b) Original winter image. (c) Image fused using Cauchy convolution. (d) Image fused using WA scheme. (e) Image fused using FLOM rule. (f) Image fused using Cauchy prior. (g) Image fused using GGD prior.

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