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ORIGINAL RESEARCH PAPER

Engineering

CONTRAST ENHANCEMENT BY CUCKOO SEARCH ALGORITHM BASED ON RETRIEVED IMAGES IN CLOUD

KEY WORDS: Contrast enhancement, image quality assessment (IQA), retrieved images, unsharp masking, sigmoid transfer mapping, free-energy, surface quality, cuckoo search algorithm.

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ABSTRACT

This paper proposed an efficient algorithm for contrast enhancement of input image based on retrieved images in cloud. The contrast of images is very important characteristics by which the quality of images can be judged as good or poor. The proposed algorithm consists of two stages: In the first stage the poor quality of an image is processed by cuckoo search algorithm. In the second stage the retrieval of image from cloud based on input image. In the case of contrast enhancement algorithm, there is unsharp masking and histogram equalization techniques are added to improve the efficiency. Here cuckoo search algorithm is added to increase the speed of operation than existing method. In the case of image retrieval from cloud images is achieved by content based retrieval method and free energy calculation. Simulation and experimental results on benchmark test images demonstrates that proposed algorithm provides better results as compared to other state-of-art contrast enhancement techniques. Proposed algorithm performs efficiently in different dark and bright images by adjusting their contrast very frequently. Proposed algorithm is very simple, efficient and speedy approach for contrast enhancement of image.

I. INTRODUCTION

The contrast enhancement techniques are commonly used in various applications where quality of image is very important. The objective of image enhancement is to improve visual quality of image depending on the application. Contrast is an important factor for any individual estimation of image quality. It can be used as controlling tool for documenting and presenting information collection during examination.

The contrast enhancement of image infers the amount of color or gray differentiation that exists between various features in digital images. It is the range of the brightness present in an image. The images having a higher contrast level usually display a larger degree of color or gray scale difference as compared to lower contrast level. The contrast enhancement is a process that allows image features to show up more visibly by making best use of the color presented on the display devices.

To recover proper details for the captured scene, a common applied procedure in low-level computer vision is enhancing the image contrast. Generally, it is done by the context-free and context-sensitive approaches. The context-sensitive approach aims to enhance the local contrast that is dependent on the rate of change in local intensity.The context-free approach boosts the global contrast by adopting a statistical method such as manipulating the pixel histogram. The limitation of methods in this category falls into the lack of adaptation on various image content, such that the modified histograms of two different images with the same probability distribution may become identical.

The most frequently applied context-sensitive enhancement method is unsharp masking, which enhances the details of an image by combining the unsharp mask with the original images. In addition to the HE based methods, the tone-curve adjustment such as sigmoid transfer based brightness preserving (STBP) algorithm was proposed to produce visually pleasing enhanced image according to the close relationship between the skewness and the surface quality.In this paper, attempt to address two issues in contrast enhancement: Unifying context-sensitive associated with context-free methods and automatically deriving the proper enhancement level.

Optimization problem is solved by cuckoo search algorithm. The fundamental characteristic of this CS algorithm is that the amplitudes of its components can objectively reflect the contribution of the gray levels to the representation of image information for the best contrast value of an image. After selecting the best contrast value of an image in CS algorithm, morphological operations have to be done. In morphological operations, the intensity parameters of the image are adjusted to improve its quality.

Image retrieval in achieved by the content based retrieval method. Furthermore, following this framework, the best contrast level is inferred by taking advantages of the retrieved images that are selected with the help of a no-reference (NR) IQA method, which predicts the perceived quality of each retrieved image without referencing to its corresponding pristine quality original image. The basic principle behind it is from the reduced reference IQA approach , which is based upon the assumption that if the features extracted from the enhanced and guidance images can be better matched, the enhancement quality will be closer to that of the guidance image.

I. PROPOSED METHOD

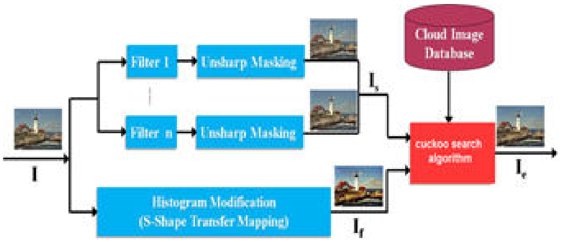

Fig.1.Illustration of the generalized contrast enhancement framework that unifies the context-free and context-sensitive approaches.

According to this block diagram Is and If are the images that are extracted from context sensitive and context free method.

A.Context-Sensitive Approach: The context-sensitive approach aims to enhance the local contrast that is dependent on the rate of change in local intensity.The most frequently applied context-sensitive enhancement method is unsharp masking, which enhances the details of an image by combining the unsharp mask with the original images. The unsharp mask is generally created by a linear or nonlinear filter that amplifies the high-frequency components of the image signal. Ideally, the filter should preserve sharp edges and be robust to noise, as the enhancement of noise may introduce undesirable details.Given the input image, the unsharp masking can be described as follows:

$I_S=I+w_1.I_{d1}+w_2.I_{d2}$

Where I_{d1} and I_{d2} are the high frequency signal generated following the image pre-processing with impulse function and bilateral filter, respectively. More specifically, the Gaussian smoothing is further applied on the pre-processed images and the residuals between the input and smoothened images are treated as the high frequency signal Id1and I_{d2} .$w_1$and w_2 are the control factors and

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here the equal weighting strategy is applied (w_1=w_2=0.5)

B. Context-Free Approach: The context-free approach boosts the global contrast by adopting a statistical method such as manipulating the pixel histogram.The context-free enhancement is achieved by the sigmoid transfer mapping. It is found that human eyes use skewness or a similar measure of histogram asymmetry in judging the surface quality (e.g., glossiness), and an image with a long positive tail in histogram (namely a positively skewed statistics) tends to appear darker and glossier. The context-free enhanced image *If* is obtained by a four-parameter logistic mapping M_s

$$I_f = f_{clip}\big(M_s(I,\phi)\big) = f_{clip}\left(\frac{\phi_1-\phi_2}{1+\exp\left(-\frac{I-\phi_3}{\phi_4}\right)}+\phi_2\right)$$

Where f_clip operation is used to clip the pixel values into the range of [0, 255] and ϕ={ϕ1, ϕ2, ϕ3, ϕ4} are parameters to be determined. This function characterizes the mapping curve, and to derive these parameters, four points on the curve, denoted as (xi,yi),i={1,2,3,4} should be firstly fixed prior to the transfer process. Here x and y indicates input intensity and transfer output respectively. As the sigmoid mapping is rolling- symmetry with respect to the straight line =x , three pairs are fixed as follows, $(x_1,y_1) = (0,0),(x_2,y_2) = (I_{max},I_{max})$,(x1,y1) = ($I_{max}$/2, I_{max}/2) where I_max is the maximum intensity value of the input image I_{max}=255). Another pair (x4,y4) can be set up to control the shape. For example, x_4 can be fixed as a certain number except x(1,) x(2,)and x_3 . Once x_4 is fixed, given a y_4 value, the optimal control parameters ϕ can be obtained by searching for the minimization of the following objective function:

$$\phi = \arg\min_{\phi}\sum_{i=1}^{4}|y_i - M_s(x_i,\phi)\,|$$

Consequently, y_4 is the only control parameter that alters the curvature of the transfer function. In this work, we fix x_4 as25 and set y_4 to be 3.

C. Unified Contrast Enhancement Framework: Both the context-sensitive and context-free approaches have their own advantages in calculating the contrast quality, and therefore in this paper we formulate the contrast enhancement as a multi-criteria optimization problem. Basically, the intentionl is to find an image that is close to the enhanced images as desired, but also preserve the structure from the input image I. Therefore, given the parameters B and B that control the contrast enhancement level, the generalized framework is defined as follows:

$$\min\{D(I_e,I)+\alpha.D(I_e,I_f)+\beta.D(I_e,I_s)\}$$

Where $I_e$denotes the enhanced image in the generalized contrast enhancement framework. The enhanced images I_f and I_s are generated by the context-free and context-sensitive approaches, respectively. To obtain an analytical solution, D is defined as the squared Euclidean distance. In general, given any two equal length vectors x and y, it is formulated as follows:

$$D(x,y)=\sum_i (x_i-y_i)^2$$

Resulting in the following image fusion process to get the final enhanced image

$$Ie = \frac{I+\alpha.I_f+\beta.I_s}{1+\alpha+\beta}$$

a and B will create different enhancement results. when goes to infinity converges to a global enhanced image, and when and becomes zero, *Ie* preserves the original input image. the enhancement parameters in deriving *Ie* and Is can be set as constant values that reach the maximum enhancement levels. Here set *a* =*B* =0.1.

According to fig 2 unified contrast enhancement explained in above section. In the case of guidance image selection there is two sections are present: first one is image retrieval from cloud using content based retrieval method next one is getting best quality image using free energy calculation of retrieved images.

ii. Guidance Image Selection:

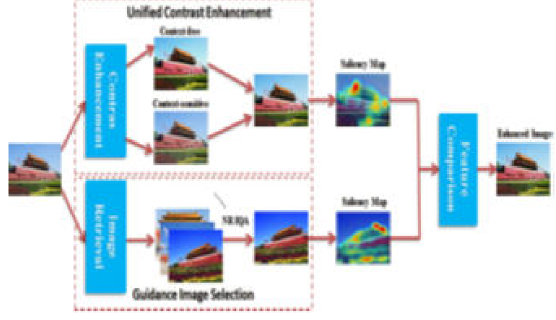

Fig 2, Flowchart of the automatic contrast enhancement scheme.

A Image Retrieval Using Content Based Image Retri eval(CBIR): A typical CBIR system automatically extract visual attributes (color, shape and texture) of each image in the database based on its pixel values and stores them in to a different database within the system called feature database. The feature data for each of the visual attributes of each image is very much smaller in size compared to the image data. The feature database contains an abstraction of the images in the image database; each image is represented by a compact representation of its contents like color, texture, shape and spatial information in the form of a fixed length real-valued multi-component feature vectors or signature. Here the input image present to the system. The system usually extract the visual attributes of the input image in the same mode as it does for each database image and then identifies images in the database whose feature vectors match those of the input image, and sorts the finest analogous objects according to their similarity value. During operation the system processes less compact feature vectors rather than the large size image data thus giving CBIR is contemptible, speedy and proficient advantageous over text-based retrieval. CBIR system can be used in one of two ways. First, precise image matching, that is matching two images, one an input image and another image in image database. Second is estimated image matching which is finding very intimately match images to a query image.

B. Guidance Image Selection with NR-IQA: In guidance image selection process the input image is used to retrieve highly correlated images from cloud. Since images in the cloud can be either perfect quality or corrupted by various types of distortions, it is desirable to apply anNo Reference (NR) IQA algorithm to rank these images and select the best one.

In the NR-IQA method, features that are based on the free-energy theory are used to establish the constructive IQA model. Based on the observation that there exists an approximate linear relationship between the structural degradation information and the free-energy of original images, the structural degradation *SDMμ* (I)*and SDM*⊠ (I) are compared with the free-energy feature F(I), and the divergence between them NRD1 (I)= F(I)-(⊠1.SDMμ (I)+⊠1) and NRD_2 (I)= F(I)-(E2.SDM⊠(I)+ϕ$_2$) are employed for quality evaluation. The structural degradation is evaluated by:

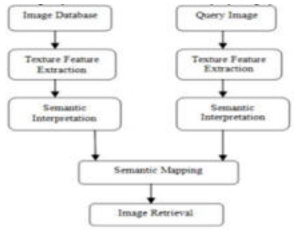

Fig 3,Block Diagram of Semantic Image Retrieval

$$SDM_{\mu}(\mathbf{I}) = E\left(\frac{\sigma_{\mu_1\bar{\mu}_1} + C_1}{\sigma_{\mu_1}\sigma_{\bar{\mu}_1} + C_1}\right)$$
$$SDM_{\sigma}(\mathbf{I}) = E\left(\frac{\sigma_{\sigma_1\bar{\sigma}_1} + C_1}{\sigma_{\sigma_1}\sigma_{\bar{\sigma}_1} + C_1}\right)$$

Where E (.) denotes the mathematical expectation operator and C1is a small positive stability constant that accounts for the saturation effects. Here μ1andσ1 are defined to be local mean and standard deviation of with a 2D circularly-symmetric Gaussian weighting function. By contrast,μ1 and σ1 are the local mean and standard deviation using theimpulse function instead of the Gaussian weighting function.σ(μ(1μ1))denotes the local covariance between two vectors μ1 and μ1 , such that the structural degradation information corresponds to the cosine of the angle between the two mean vectors. Analogies to that, σ(σ(1σ1))denotes the local covariance between two vectors 1and σ1.

a) Free-Energy-Based Brain Theory:The free-energy theory attempts to explain and unify several brain theories in biological and physical sciences about human action, perception and learning. The basic premise of the free-energy based brain theory is that the cognitive process is manipulated by an internal generative model (IGM). The human brain can actively infer predictions of the meaningful information of input visual signals and avoid the residual uncertainty in a constructive manner. In this work, the free-energy is applied both in NR-IQA as well as the feature matching for contrast enhancement level derivation.

Assuming that the IGM for visual perception is parametric, this explains the scene by adjusting the parameter. Given the input image I, its "surprise" (determined by entropy) is evaluated by integrating the joint distribution ***p*(Iv)** over the space of model parameters **V**

$$-\log P(I) = -log\int P(\mathrm{I},\mathrm{v})d\,\mathrm{v}$$

Since the precise expression of joint distribution *P*(I,v) is still well beyond our current level of knowledge about the details of how the brains are working, a dummy term *Q*(v|I) is integrated into both the denominator and numerator in (9), which can be rewritten as follows:

$$-\log P(I) = -log\int Q(\mathrm{v}|\mathrm{I}).\frac{P(\mathrm{I},\mathrm{v})}{Q(\mathrm{v}|\mathrm{I})}\mathrm{dv}$$

Where *Q*(v|I) is a posterior distribution of the model parameters given the input image signal I. This can be regarded as the posterior approximation to the true posterior of the model parameters *P*(v|I) in the cognitive process. Another interpretation is that when we perceive the image I, the parameter vector v of *Q*(v|I) is adjusted to obtain the optimal explanation of I, such that the discrepancy between the approximate posterior *Q*(v|I) and the true posterior *P*(v|I) is minimized. The same technique has been used in ensemble learning or in a variation Bayesian estimation framework. The negative "surprise" can also be interpreted as the log evidence of the image data given the model. In this manner, the minimization of surprise is equivalent with the maximization of the model evidence.

By applying Jensen's inequality,

$$-\log P(I) \le -log\int Q(\mathrm{v}|\mathrm{I}).\frac{P(\mathrm{I},\mathrm{v})}{Q(\mathrm{v}|\mathrm{I})}\mathrm{dv}$$

and the free-energy is defined as follows:

$$\mathrm{F}(I) = -\int Q(\mathrm{v}|\mathrm{I}).\frac{P(\mathrm{I},\mathrm{v})}{Q(\mathrm{v}|\mathrm{I})}dv$$

he free-energy F(*I*)defines the upper bound of the input image information as -log *P*(*I*)≤ F(I) . It is shown that the free-energy can be characterized by the total description length for the k th order autoregressive (AR) model

$$\mathrm{F}(I) = -\log P(\mathrm{I}|\mathrm{v}) + \frac{k}{2}.\log N \text{With} \qquad N \to \alpha$$

Where N denotes the total number of pixels in the images. Thus, the entropy of the prediction residuals between the input and predicted images plus the model cost can be used to estimate F(*I*) . The residuals are also known as the disorderly information that cannot be well explained by the HVS. The derivation process of the AR coefficients can be found in. In this stage, a fixed-model order is chosen, resulting in the ignorance of the second term k/2.log N in comparison.

The free-energy based brain theory also reveals that the HVS cannot fully process all of the sensation information and tries to avoid some surprises with uncertainties, which can be regarded as free-energy. In practice, positive contrast change renders high quality images by highlighting the visibility details, which produces more informative content. When perceiving the positive contrast image, the additional informative content will make the image more difficult to describe, as in general the HVS has stronger description ability for low-complexity images than high-complexity versions. This leads to higher free energy and vice versa. The prior information from the guidance is able to predict the appropriate free-energy of a visually-pleasing image with a good contrast, which is very efficient in deriving the contrast enhancement levels.

Visual Saliency Detection:The sign of each DCT component to generate the saliency map. As such, this model just requires a single bit per component, making it efficient with very low cost of computational complexity. Specifically, the image signature is defined as:

ImgSignature(I)=sign(DCT2(I))

Where sign(.) is the entry wise sign operator and for each entry with the input value ε**.**

$$\mathbf{sign}(\xi) = \begin{cases} 1, & \xi > 0 \\ 0, & \xi = 0 \\ -1, & \xi < 0. \end{cases}$$

Subsequently, the reconstructed image is derived by

I-=IDCT2(ImgSignature(I))

Where DCT2 and IDCT2 respectively stand for discrete cosine and inverse discrete cosine transforms for the two dimensional image signals. The saliency map is finally obtained by smoothing the squared reconstructed image

Where g is a Gaussian kernel and 'o' and '*' are the entry-wise and convolution product operators respectively. In practical implementations, the saliency map can be converted into an intensity image in the range from 0.0 to 1.0, and with the empirically determined threshold the saliency regions can be classified.

iii.Automatic Contrast Enhancement By Cuckoo Search Algorithm: This evolutionary algorithm is a search strategy model on brood parasitism of some cuckoo species by laying their eggs in the nests of other host birds. If a host bird discovers the eggs are not its own, it will either fling these alien eggs or simply desert its nest and put up a new nest elsewhere. In a CS system, each cuckoo species alter their position as time goes, and every egg in the nest stands for only one new solution. The better new solution will take place of the solution which is relatively worse in the nest. For simplicity, only three idealized rules are utilized to describe the CS algorithm as follows:

1) Each cuckoo lays one egg at a time and dumps it in a randomly selected nest.
2) The best nests with high quality of eggs (solutions) will be kept up to the next generation.
3) The number of available host nests is fixed, and a host can discover an alien egg with a probability (0.1)In this case, the host bird can either throw the egg away or abandon the nest so as to build a completely new nest in a new location.

Moreover, a mass of studies have indicated that flight behaviors of many animals and insects have the typical characteristics of the

Levy flights.

For an optimization problem, the quality of a solution could simply be corresponding to the fitness value of the objective function. Other forms of fitness can be defined in a parallel way to the objective function in other evolutionary algorithms. Three rules are defined in the algorithm; first, each egg in a nest stands for a solution; second, a cuckoo egg denotes a new solution; third all of the cuckoos are evaluated by the fitness value of the objective function to be optimized and have velocities which directly decide the cuckoos' flying; the intent is to use the new better solutions to replace the not so good solution in the nests.

In order to generate the new solutions x^{t+1} call the cuckoo i, a Levy flight can be defined as in the following:

$$x_i^{(t+1)} = x_i^{(t)} + \alpha \oplus \text{Levy}(\lambda),$$

Where, α>0 is the step size, which should be related to the scale of the problem of interest. The productmeans entry-wise multiplications. Here we consider a Lévy flight in which theability distribution Levy(λ)=t^(-λ),(1<λ≤3)

Which has an infinite variance here; the consecutive jumps/steps of a cuckoo essentially form a random walk process which obeys a power-law step length distribution with a heavy tail. It is worth pointing out that, in the real world, if a cuckoo's egg is very similar to a host's eggs, then this cuckoo's egg is less likely to be discovered, thus the fitness should be related to the difference in solutions. Therefore, it is a good idea to do a random walk in a biased way with some random step sizes.

I. EXPERIMENTAL CRITERIA

Sparse feature fidelity: The proposed method is divided into two stages: training and fidelity computation.

1. Training of Simple Cell Matrix

In the training stage, 9000 image patches of size 8 × 8 are randomly taken from nine natural color images with no distortion. Each patch forms a column vector by scanning the numerical values in the patch row-by row and channel-by-channel. Since a color image has three color channels, the length of the vector is 8×8×3 = 192.

2. Fidelity Computation

Step 1: Selection of reference-distorted patch pairs: The HVS is more sensitive to poor quality regions in images than the good ones [10], so we try to choose the reference-distorted patch pairs with large errors for the fidelity computation.

Step 2: Feature Extraction: After the selection step, let y_{dis} denote the retained reference and distorted image vectors, respectively. a W y , b W y (1) Since the size of W is 9 × 192, the length of a and b is M = 9. For simplicity, we use a vector pair, (a, b), to represent the sparse features of a reference image patch together with its distorted counterpart.

Step 3: Thresholding: As the simple cell matrix serves as a model of neurons in visual cortex, the feature vectors can be seemed as visual responses to image patches.

$$VT = \frac{T}{N}\sum_{i=1}^{N} VR(a_i)$$

Where T is a constant for adjustment of the threshold and its value is T = 0.35. In addition, VR represents the intensity of the visual response to an image patch, which is obtained by

$$VR(a) = \sum_{j=1}^{M} a_j^2$$

Wherea j is the j-th value of a.

After this thresholding step, all the retained feature (or response) vectors (ak and bk) for each reference and distorted image form two matrices, A^{th} and B^{th}

$$(A^{th}, B^{th}) = \{(a_k, b_k) | VR(a_k) > VT\}, k \in \{1, 2, \ldots, N\}$$

Step 4: Fidelity Measurement. Finally, the sparse feature fidelity index is given by:

$$SFF \quad \frac{1}{K.M}\sum_{i=1}^{K}\sum_{j=1}^{M}(2.A_{ij}^{th}.B_{ij}^{th} + C)/((A_{ij}^{th})^2 + (B_{ij}^{th})^2 + C)$$

Where K denotes the number of the retained feature vectors in an image A_{ij}^{th} and B_{ij}^{th} denote the values of the i-th column and j-th row in respectively. C is a small positive constant to stabilize the result, and its suitable value is 0.02.

I. RESULTS AND DISCUSSIONS

Experiments are conducted in MATLAB 2014 as simulation software. In this paper considering database 'Wang' is consi dering. To evaluate select some images from 'wang' and form new database. Here evaluation is done using free energy, Sparse feature fidelity and time.free energy calculation is specified in above section.

First consider a database having 10 images and select image of a tribe.

parameters	Proposed method	Existing method
Input image free energy	33.5050	33.5050
Enhanced image free energy	42.6787	35.5544
Sparse feature fidelity	0.9706	0.9603
Time (in seconds)	358.230017	1356.057631

Consider a database having 250 images and select image of nature.

parameters	Proposed method	Existing method
Input image free energy	17.5869	17.5869
Enhanced image free energy	31.6715	18.6732
Sparse feature fidelity	0.9655	0.9031
Time (in seconds)	3835.355142	4727.991829

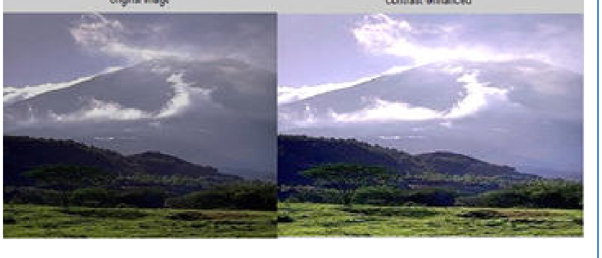

Fig 5, Example input and output image of nature which is in the database 'Wang'

I. CONCLUSION

Here proposed a guided image contrast enhancement framework based on the retrieved images in cloud, targeting at automatically generating a visually-pleasing enhanced image. And the proposed technique is speedy process than existing technique. The novelty of this paper lies in the unifying of context-sensitive and context-free contrast enhancement methods, and automatically estimating the enhancement level by matching the extracted features in visual salient region. In particular, the cuckoo search algorithm for automatic contrast enhancement of input image. With the utility of the retrieved image, the blind estimation of the contrast enhancement level is performed based on free-energy and surface quality. Experimental results demonstrate the effectiveness of the scheme in image enhancement applications.

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