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A REVIEW ON IMAGE COLORIZATION ALGORITHM

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ABSTRACT

we propose a fully automatic image colorization method for grayscale images. Image colorization algorithms aim to add realistic colorized to grayscale images. They typically leverage deep learning models, such as convolutional neural networks (CNNs), trained on large datasets. These models learn mappings between grayscale and colorized images, capturing complex relationships. Utilizing techniques like auto encoders or GANs, they generate colorization predictions based on input grayscale features. The process involves extracting features, mapping them to colorization and refining predictions iteratively. Dataset diversity, model architecture, and training strategies play crucial roles in achieving accurate and visually appealing colorizations. This research paper includes various research on image colorization.

Keyword: Colorization, Convolutional neural networks, Generative Adversarial Network, Grayscale images.

1. INTRODUCTION

Although black and white photos are precious to the preservation, they are very dim and lifeless. Compared with black and white pictures, colorization, which gives people an immersive feeling, can make the pictures look more vivid and real, and show significant of its shooting more vividly. It is a not difficult to convert a colorization image directly to block and white, but the reverse, the process is more difficult.

Without any references the colorization is dependent upon imagination, and sometimes the colorization result is very unrealistic. Colorization technology is under a very long history.in the early days. people painted their favourite colorization on block and white films evolved into colorization images, and the image colorization technology became more and more mature. interactive colorization methods and automatic colorization method [1] .

Automatic colorization methods such as that by have removed the burden of annotating the image with colorization scribbles by using a colorization reference image to transfer colorization. They are able to produce realistic results if a suitable reference colorization image is provided by the user. Such work focuses on performing colorization transfer automatically from reference images and propagating the colorization from a small number of transferred colorization scribbles, In contrast with the task of traditional colorization transfer. the destination image does not have colorization information, so colorization mainly relies on matching of luminance and texture information. In many cases, the objects have different scales in the reference and destination images. Therefore, feature matching in different scales is essential. Although some advanced feature detectors, such as SIFT and SURF, can provide scale-invariant features, they are sparse and not suitable for dense matching required. for colorization. In this paper, we propose a cross-scale matching method that considers different potential scales locally when matching the reference and destination images, which are then fused globally with graph-cut to find spatially coherent scales with good matching quality. [2] Colorization transfer via texture matching may result in some semantic errors, e.g. when similar textures cause confusion, some of the sky may be colorized in the colorization of grass. Such unreasonable colorization results cannot be detected by low-level texture features, although appear obviously wrong to a human observer. Instead of using machine learning which requires a large number of training images and loses the flexibility of easily specifying the desired colorization style, we focus on a class of simple semantic violations where the up-down spatial relationship is violated. [3] This is a reasonable assumption as images are normally taken with an (near) upright camera.

We perform statistics of up-down relationships of colorization distribution in the reference image, which is then used to help detect and correct unreasonable matching results in the destination image, as we assume the content of the reference and destination images are semantically related.

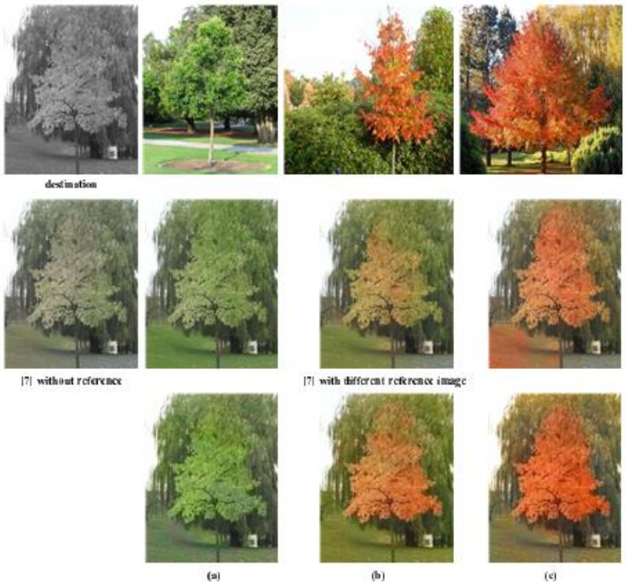

Fig 1: Colourisation result with different references images.**[2]**

2. LITERATURE SURVEY

A. Colorization of Grayscale Images: represents a semi-automatic approach for Colorization. They make use of segmentation, and colorization different areas of images should be colorized. The algorithm adds colorization to each pixel by considering the position of colorization markers. It first segments the image and then colorizes it. They also attempt to colorize videos, by some frames, colorizing them, then transferring the colorization to other frames. Key frames are selected local minima of block motion. Segmentation done using rain water simulation technique of watershed segmentation.[3]

This method of segmentation leads to over-segmentation merging operations. of a unique segment, each with a marker after the process. Their results looked visually good for a large number of images.

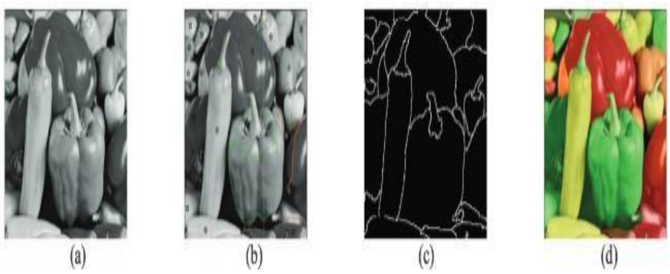

Fig 2 Comparisons with **(a):** Grayscale image **(b):** Grayscale image with colorization markers **(c):** Segmented image **(d):** Colorised output image.

B. Infrared Colorization Using Deep Convolutional Neural Networks: deals with Colorization of Near infrared (NIR) images of road scenes captured from cameras of cars. They make use of a multi-scale deep convolutional neural network. The approach consists of 3 parts, namely pre-processing, inference, and post processing. In pre-processing stage, they make up an image pyramid of the input image in multiple resolutions. Then for inference, each element of the pyramid passes through several convolutional layers and max pooling layers. After this, the result of each element passing through the deep CNN is merged using a fully connected layer. A bilateral filter is applied onto the result of above, as post-processing, to reduce noise produced in the result. The disadvantage of this method is that the resulting colorized images looks more like paintings that real world pictures.[4]

Fig.3 (a): Source image (b): Colorised image (c): Target output.

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C. Fully automatic image Colorization: based on Convolutional Neural Network [5], a feed-forward, 2 stage architecture based on Convolutional Neural Network is used, to predict U and Colorization channels of an input Grayscale image. Colorization is looked at as a regression problem and is resolved using Anstey make use of the pre-trained VGG-16 classifier, which is already trained on a million images. The architecture consists of the VGG-16 model along with a 2 stage CNN that outputs the predicted U and V colorization channels of the image. They have used the YUV colorization model because it has the minimum correlation between the 3 coordinate axes. It produced very good results for some images. They evaluated the performance of the system using Quaternion Structural Similarity Index Measure (QSSIM)[8] , and obtained better values of QSSIM for their results than many of the previous methods which they compared with. Drawbacks of this method are that, if the system cannot clearly identify semantic information in the image, it tends to blur the output with a sepia or brownish tone. Also, sometimes the colorization information of the bigger semantic regions of the image get transferred to the smaller semantic regions Figure 3. First row shows colorize.[5]

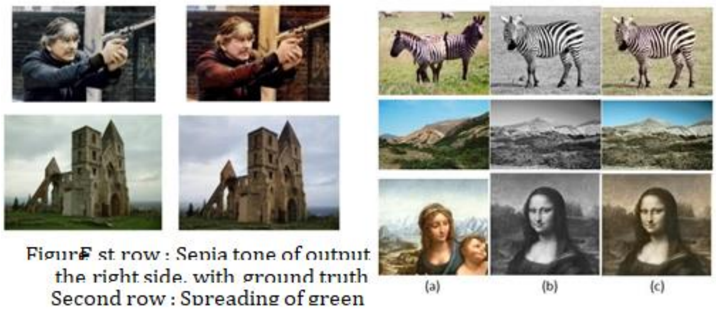

Figure 4

3. METHODOLOGY

COLORIZATION: Our goal is to automatically propagate the indicated colorization of interest points obtained from the trained colorization model to achieve a fully colorized image. A collection of interest points is determined using the SLIC image segmentation method. Given a collection of interest points from all training images, the colorization method proposed in this paper uses a feature extraction method to describe the characteristics of the input target grayscale image at the first step. Secondly, the trained model is used to colorize the interest points of the target grayscale image. We present a cost function that is used to propagate the pixel values from colorized interest points to the whole image region. At extraction method to describe the characteristics of the input target grayscale image at the first step. Secondly, the trained model is used to colorize the interest points of the target grayscale image. We present a cost function that is used to propagate the pixel values from colorized interest points to the whole image region.

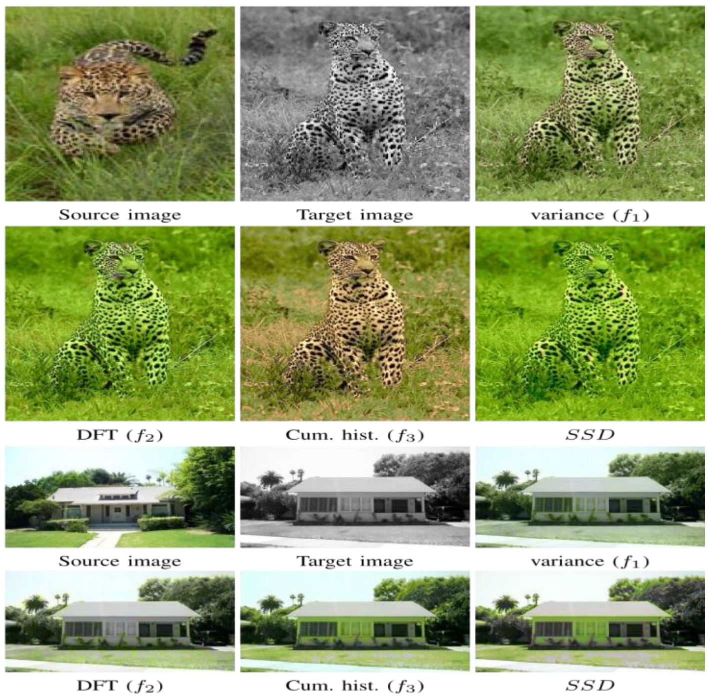

Figure 5: source image, target image, variance

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A. Scribble-Based Colorization

Levin et al. [6] propose an effective approach that requires the user to provide colorization scribbles on the grayscale target image. The colorization information on the scribbles is then propagated to the rest of the target image using least-square optimization. Huang et al. develop an adaptive edge detection algorithm to reduce the colorization bleeding artifact around the region boundaries. Yatzival. [7] colorize the pixels using a weighted combination of user¡¯ scribbles. and utilize the texture feature to reduce the amount of required scribbles.

B. Example-Based Colorization

Unlike scribble-based colorization methods, the example-based methods transfer the colorization information from a reference image to the target grayscale image. The example-based colorization methods can be further divided into two categories according to the source of reference images:

1) Colorization Using User-Supplied Example(s): This type of methods requires the user to provide a suitable reference image. Inspired by image analogies [7] and the colorization transfer technique [8], employ the pixel intensity and neighbourhood statistics to find a similar pixel in the reference image and then transfer the colorization of the matched pixel to the target pixel. It is later improved in by taking into account the texture feature. propose a global optimization algorithm to colorize a pixel. develop a colorization method based on super pixel to improve the spatial coherency. These methods share the limitation that the colorization quality relies heavily on example image(s) provided by the user. However, there is not a standard criterion on the example image(s), thus finding a suitable reference image is a difficult task.
2) Colorization Using Web-Supplied Example(s): To release the users' burden of finding a suitable image, and Chia et al. [7] utilize the massive image data on the Internet. Liu et al. [9] compute an intrinsic image using a set of similar reference images collected from the Internet. This method is robust to illumination difference between the target and reference images, but it requires the images to contain identical object(s)/scene(s) for precise per-pixel registration between the reference images and the target grayscale image. It is unable to colorize the dynamic factors (e.g. person, car) among the reference and target images, since these factors are excluded during the computation of the intrinsic image. As a result, it is limited to static scenes and the objects/scenes with a rigid shape (e.g. famous landmarks). Chia et al. propose an image filter framework to still suitable reference images from the collected Internet images. It requires the user to provide semantic text label to search for suitable reference image on the Internet and human-segmentation cues for the foreground objects.

C. Learning-Based Colorization

Our previous work proposes a fully-automatic colorization method based on a single neural network. Deshpande et al. develop a learning-based framework that formulates this problem as a quadratic objective function. Histogram correction is applied to improve the initial colorization results. However, a suitable scene histogram is required in their refinement step. The other limitation is their low speed of colorization.

Recently, fully-automatic colorization methods based on Convolutional Neural Network (CNN) technology have been released. Dahl et al. [10] integrate the features extracted from multiple layers of VGG-16 [25] by residual connections and train a regressor that maps the raw grayscale to the chrominance values. Iizuka et al. [11] propose an end-to-end network consisting of multi-level sub-networks to jointly learn the global image priors and local patch features. Within the training phase, the semantic class label is used to assist in the learning of the global image.

Algorithm 1 Image Colorization – Training Step

Input: Pairs of reference images: $\Lambda = \{\vec{G}, \vec{C}\}$.
Output: A trained neural network ensemble.

1: Extract global descriptors of the reference images, group these images into different clusters adaptively and compute the semantic histogram of each cluster;
2: Compute feature descriptors $\vec{x}$ at sampled pixels in $\vec{G}$ and the corresponding chrominance values $\vec{y}$ in $\vec{C}$;
3: Construct a fully-connected neural network for each cluster;
4: Train the neural networks using the training set $\Psi = \{\vec{x}, \vec{y}\}$.

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A. Interest point section:

[15] The super pixels algorithm performs the pixel clustering operation to make them in an atomic level region. This procedure not only has perceptual meaning but can also be used to replace the rigid structure of the pixel grid. By eliminating image redundancy, it is possible to filter out better original images for feature acquisition and reduce the difficulty of subsequent work. SLIC super pixels are fast to compute, produce high-quality segmentation, and simple to use. It can adhere well to image boundaries with low computational complexity. In we select the convergence cluster center each SLIC super pixel as the interest point location. SLIC converts images from RGB colorized space to Lab colorized space, the colorized values and (x, y) coordinates corresponding to each pixel form a 5-dimensional vector V = [L, a, b, x, y].

The algorithm initializes T super pixel cluster centres $C_t = [l_t, a_t, b_t, x_t, y_t]$ with $t \in \{1,...,T\}$at regular grid steps each of size S. For an image with N pixels, the number of super pixels is $T = N/S^2$, the approximate area of each super pixel is S × S. Then, the nearest pixels from a 2S × 2S square neigh bur hood around each super pixel cluster center are determined based on the distance measure Ds:

$$Ds = d_{lab} + \frac{m}{S} d_{xy}$$

$$d_{lab} = \sqrt{(L_t - L_i)^2 + (a_t - a_i)^2 + (b_t - b_i)^2}$$

$$d_{xy} = \sqrt{(X_t - X_i)^2 + (Y_t - Y_i)^2}$$

Where,

m is used to adjust the weight of d_{xy}. Then the average vector values of all the pixels are calculated for each super pixel, T cluster centers are updated, and the 22222iteration is repeated until convergence. In the particular SLIC super pixel segmentation scheme of grayscale images, the attribute of each super pixel is defined by two parameters, region size, and regular [33]. The region size determines the size of each atomic region, and the regular determines the spatial proximity and the pixel similarity. In our case, the region size of super pixel S^2 is set to 6 × 6 and the regular m is set to 10.[12].

B. Descriptor Computation: It is a morbid problem to rely solely on the Gray value of one pixel to infer its initial RGB value. Currently, without prior knowledge of the scenario, there is no general solver for such problems. Therefore, more details of the pixel's characteristics are necessary to enhance its information richness and describe its local neigh borhoods in a more robust way. In our algorithm, local structures, textures, and context information are involved. The first step in the processing of RGB colorized images is the conversion to obtain a grayscale image. The formula for converting colorized images into grayscale images is Y = 0.299R + 0.587G + 0.114B. This operation ensures that the input and output images for training and testing steps are at the same luminance. Multiple options for feature descriptors are available, including SIFT, Gabor, etc. A study showed that patch feature and DAISY descriptors make sense on the colorized images by Chengetal. Therefore, in our method, the length and width of the patch feature for each pixel combination are 7, the DAISY feature [13]and the Gab or feature, are combined for each pixel. All the descriptors turn into a 121 × 1 dimensional feature for every interest point of the original and the reference image.

a) Patch features: The algorithm in this paper only needs to obtainthegrayvalueofonepixelinthe7 × 7neighborhood, and the 49-dimensional feature vector $D_P(\mathbf{r})$ of the pixel r is determined. This is the most intuitive representation of the structure around the pixel.

b) DAISY features: We characterize the dense features by the DAISY feature vector $D_D(\mathbf{r})$ of the pixel r. The $D_D(\mathbf{r})$ in this paper is 32-dimensional, that is eight orientations in four positions. Considering the dense matching process, the DAISY features can significantly improve the colorization effect complex scenes dense matching. But as in, DAISY is ineffective for sparse-text on images. Texture features: The Gabor feature $D_T(\mathbf{r})$ becomes the ultimate feature involved in this algorithm. The Gabor feature works through a Gabor filter to obtain local features come by any pixel. Gabor filters have important properties that are constant for image deformation. In this study, the Gabor feature vectorisation 40-dimensional vector, which is constructed based on 40 Gabor filters [14], in five scales and eight orientations. The last descriptor $D(\mathbf{r})$ of pixel **r** is the integration of the patch, DAISY and Gabor descriptors for the original and the corresponding grayscale image. $D(\mathbf{r})$ is defined by:

$D(\mathbf{r}) = D_P(\mathbf{r}) \cup D_D(\mathbf{r}) \cup D_T(\mathbf{r})$

where ∪ denotes the concatenation operator.

The experimental results in Fig. 2 are used to illustrate the sensitivity of the selected descriptors to the color diversity and texture complexity of the images. We draw a conclusion that the more colours and the more complexity of texture, the longer convergence time and the lower final convergence accuracy.

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C. Network Design

Now a days, deep learning has achieved great success in the field of computer vision. It can be expressed as a corresponding colorized image from a monochrome one when a deep learning method issued to solve the colorization problem.

The goal of the colorization approach is to estimate RGB values for all the pixels in the monochrome image. The colorization model in this paper is used to learn a continuous function of Gray -to-colorized mapping, which is represented as a correspondence between features obtained in every pixel from the initial monochrome image and colorized values in the relevant output image.

D. Network Structure: We built a concise but efficient network, which is 1 input layer and 2 hidden layers and 1 output layer, to serve in the proposed colorization approach.

To find the properly hidden layers, Fig. 3 indicates the MSE curve of the interest points when training for the proposed network in a To combination of different colorization spaces and hidden layers. Obviously, it can be concluded that a network built by two hidden layers in RGB space is optimal. Meanwhile, it consists of 121 input layer neurons, 60 neurons in each hidden layer and 3 output layer neurons.

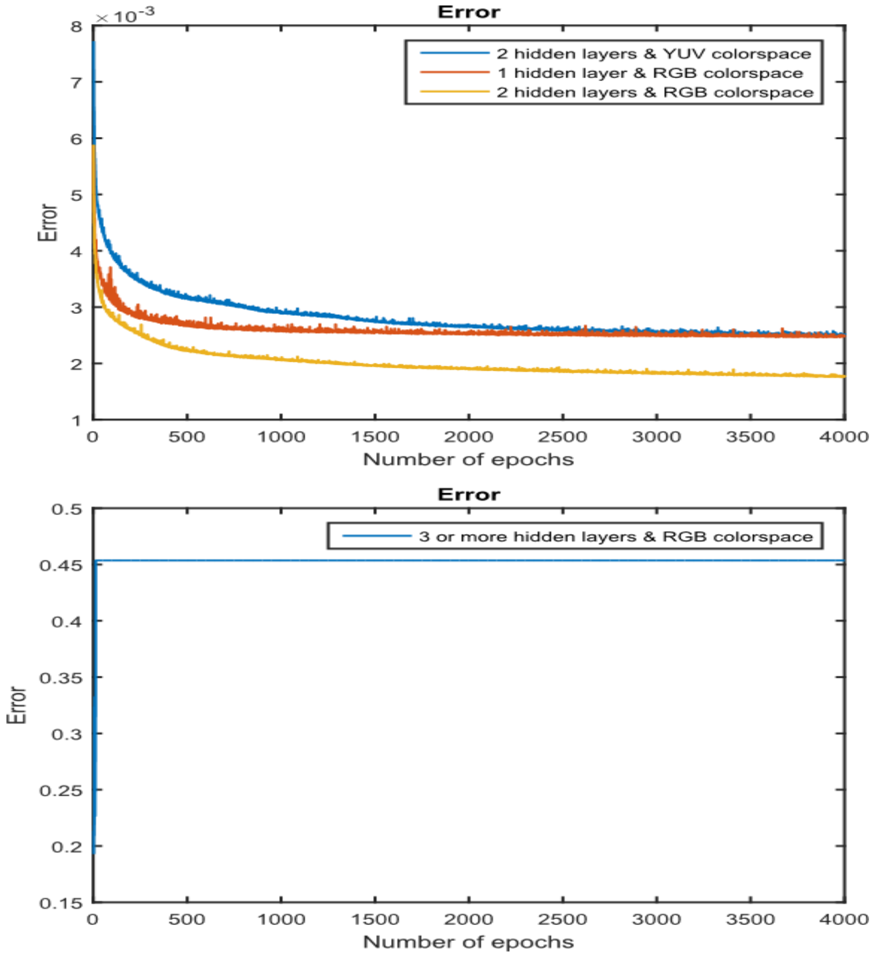

Figure 6:number of epochs

E. Internal Settings: In order for all neurons to be inter connected between layers, meanwhile each connection is weighted, our colorization network uses a fully connected network. For the calculation of the optimal weight values, the classical error back-propagation algorithm is used to enable errors propagating to the hidden layer. We choose RLU (Rectified Linear Units) as the activation function to maintain relative intensity information through the layers. Due to the huge training dataset,[13] it becomes infeasible to load all the data at once.

Therefore, mini-batches learning is used in this paper to train the colorization model. Mini-batches learning is a variant of the stochastic gradient descent method, which uses a small number of training samples to calculate the gradient and update the model parameters. Batch size refers to the number of training samples in each mini-batch. For the same neural network structure, adjusting the batch size to an appropriate value can achieve the best optimization in time and the final convergence precision. In our case, the batch size is set to 400. Meanwhile, the sigmoid activation function is used in the output layer. Fig:4 below shows the architecture of the proposed network.

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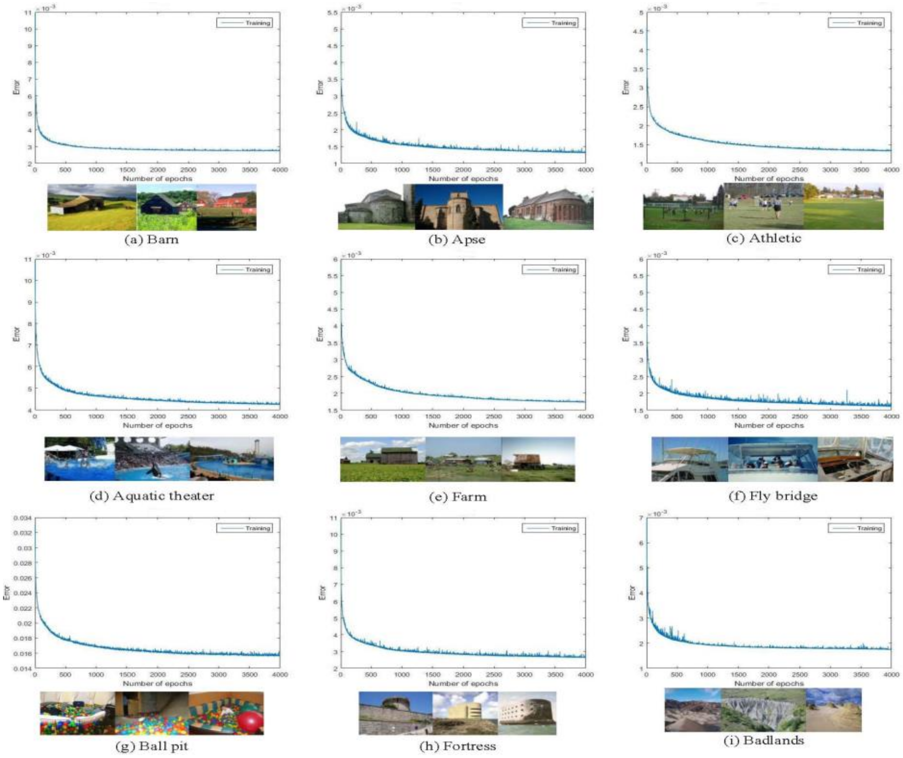

Figure .7

where the feature vector is represented by $D = [D_P \cup D_D \cup D_T] \in R^{N\times 121}$ of each interest point location in target image, and N the number of super pixels. For our colorization method, the Quarter Video Graphics Array (QVGA) resolution is used to resize all images. F denotes the trained colorization function. $G = [g_1, g_2, ..., g_N] \in R^{N\times 3}$ denotes the corresponding RGB values of all interest points. An overview of the proposed colorization method is presented in Figure 1. Similar to the other learning-based approaches, the proposed method has two major steps: training a neural network ensemble using a set of example reference images; using the learned neural network ensemble to colorize a target grayscale image. These two steps are summarized in Algorithm 1 and 2, respectively.

4. NEURAL NETWORK FOR IMAGE COLORIZATION

This section formulates image colorization as a regression problem and solves it using a regular fully-connected neural network.

The fully-connected network can be implemented as a convolution neural network with a series of 1×1 convolution kernels that are performed pixel-wise.

1)Formulation: A fully-connected neural network is a universal approximator that can represent arbitrarily complex continuous functions. Given a set of exemplars = {G,C}, where G are grayscale images and C are corresponding images respectively, our method is based on a premise: there exists a complex Gray-to-colorization mapping function F that can map the features extracted at each pixel in G to the corresponding chrominance values in C.[16]

Algorithm 2 Image Colorization – Testing Step

Input: A target grayscale image I and the trained neural network ensemble.

Output: A corresponding color image: $\hat{I}$.

1: Compute global descriptor and semantic histogram of I, then find its nearest cluster center and corresponding trained neural network;
2: Extract a feature descriptor at each pixel location in I;
3: Send feature descriptors extracted from I to the trained neural network to obtain the corresponding chrominance values;
4: Refine the chrominance values to remove potential artifacts;
5: Combine the refined chrominance values and I to obtain the color image $\hat{I}$.

[15] We aim at learning such a mapping function from so that the conversion from a new Gray image to colour image can be achieved by using F. In our model, the YUV colorization space is employed, since this colour space minimizes the correlation between the three coordinate axes of the colour space. For a pixel p in G, the output of F is simply the U and V channels of the corresponding pixel in C and the input of F is the feature descriptors we compute at pixel p. The feature descriptors are introduced in detail in Sec. III-B. We reformulate the Gray-to-colour mapping function as $c_p = F(, x_p)$, where x_p is the feature descriptor extracted at pixel p and c_p are the corresponding chrominance values. are the parameters of the mapping function F to be learned.

We solve the following least squares minimization problem to learn the parameters :

n argmin $\subseteq\Upsilon$ $_p$=1F(, x_p) − c_p^2 (1)

where n is the total number of training pixels sampled from and Υ is the function space of F(, x_p).

A fully-connected neural network typically consists of one input layer, multiple hidden layers and one output layer. Generally, each layer can comprise various numbers of neurons. In our model, the number of neurons in the input layer is equal to the dimension of the feature descriptor extracted from each pixel location in a grayscale image and the output layer has two neurons which output the U and V channels of the corresponding color value, respectively. We perceptually set the number of neurons in the hidden layer to half of that in the input layer. Each neuron in the hidden or output layer is connected to all the neurons in the proceeding layer and each connection is associated with a weight. Let o^l_j denote the output of the j neuron in the l layer. o^l_j can be expressed as follows:

$$olj = f(wlj0b + wljioli{-}1)i{>}0 \quad \textbf{(2)}$$

where $w^l{}_{ji}$ is the weight of the connection between the j^{th} neuron in the l^{th} layer and the i^{th} neuron in the $(l-1)^{th}$ layer,

Fig.7: Evaluation of patch feature. (a) is the target grayscale image, (b) removes the low-level patch feature, and (c) includes all the proposed features.

The b is the bias neuron which outputs value one constantly and f (z) is an activation function which is typically nonlinear (e.g., tanh, sigmoid, RLU). The output of the neurons in the output layer is just the weighted combination of the outputs of the neurons in the proceeding layer. In our method, we utilize RLU as the activation function as it can speed up the convergence of the training process. The architecture of our neural network is presented in Figure [21] We apply the classical error back-propagation algorithm to train the connected power of the neural network, and the weights of the connections between pairs of neurons in the trained neural network are the parameters to be learned.

5. REVERSIBILITY COLORIZATION

The general purpose of the proposed algorithm is to hide the color information of image I in its luminance channel. The output is a Gray-scale image Yc whose contrast is increased with respect to the original luminance. Subsequently, in the colorization process, the color information can be extracted from the modified luminance, and the original information can be recovered. Finally, the luminance is colorized using the extracted information to obtain a colorized image I′ that is visually similar to the original image. Fig. shows an example of this proposal. If we repeat the hiding process with I′ as the input and apply the colorizing process to the contrasted luminance Yc, we can recover the same colorized image I′. Therefore, we can switch between the colorized image I′ and the contrasted luminance Yc in a completely reversible manner.[23]

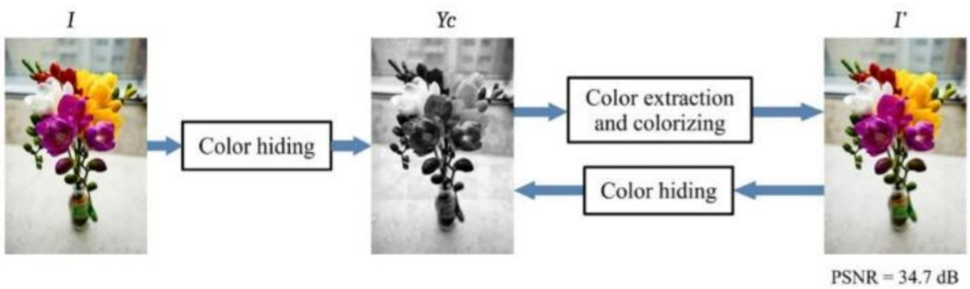

Figure:8 Reversibility process between **Yc** and **I**. The colorization image is taken from COCO dataset.[17]

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In other words, a Gray - scale version of the colorization image can contain all the information required for colorizing itself. This luminance is one channel in size and can be stored in a local device or cloud service for subsequent sharing. If the security of the storage medium is compromised and the image is illegally extracted, it cannot be used normally because it does not contain colorization.

To increase the level of protection, we propose two additional methods that mainly affect the contrasted luminance. These additional approaches give four security options, as shown in Fig. The first approach decreases the structural quality of the contrasted luminance when hiding the colorization information, making unauthorized reconstruction more difficult. This technique can be achieved by defining the objective function of an optimization method, such that the luminance quality decreases.

This function defines the trade-off between the quality of the colorized image and contrasted luminance. In the distorted mode, we define the function such that the colorized image has the best possible quality, whereas the contrasted luminance is distorted. In the balanced mode, the qualities of the colorized and contrasted images increase simultaneously. In the second approach, visible imperceptible watermarks with the owner logo are embedded into the colorized image. The watermark in the colorized image is not visible at first sight and is visually revealed in the contrasted luminance, when the colorization information is hidden. Thus, the owner logo toggles between hidden and revealed when the image toggles between colorized and Gray-scale, respectively. Thus, the copyright of the colorized image can be detected outside the storage device in case of unauthorized usage. Fig.. shows examples of the contrasted luminance for each possible solution of the proposed method. We can see in the second column the distortion effect, and a magnification is achieved in the second row to see that the watermark is reveled. On the other hand, Fig. shows the colorized images corresponding to the four security options of Fig. 2. The objective is that four colorized images are qualitative and visually similar, with high quality. Therefore, it is important to notice that the visual and peak signal-to noise-ratio(PSNR) qualities of the colorized images are not.

Figure 9: with and without imperceptible

Co and Cg using the luminance Y. The sets of coefficients are defined as Ao = $\{Ao_1, Ao_2, ..., Ao_N\}$,Bo = $\{Bo_1, Bo_2, ..., Bo_N$ for the Co channel and Ag = $Ag_1, Ag_2, ..., Ag_N$,Bg = $\{Bg_1, Bg_2, ..., Bg_N$ for the Cg channel, where each element in the set corresponds to each segment in Segs. shows the colorizing process, where the luminance Y and the coefficients in Ao, Bo, Ag and Bg are used to obtain the approximated chrominances Co' and Cg', and obtain the colorized image I'. The basic processes shown in Fig. 9 are used for the complete colorization as shown the color.

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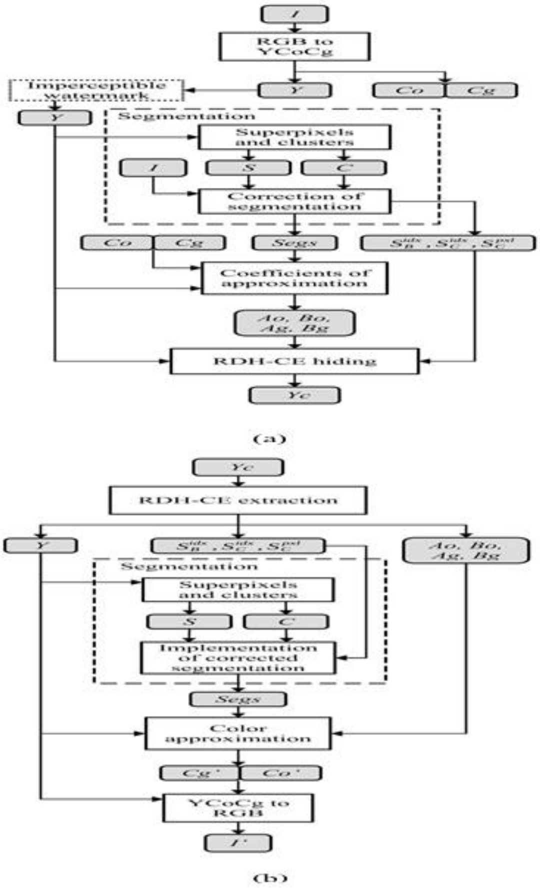

Figure.10

super pixels $S = \{S_1, S_2, ..., S_N\}$, and the number of segments is then reduced in cluster regions $C = \{C_1, C_2, ..., C_M\}$, where $M < N$, using the approach described in Section [18]. In our proposed colorizing method, we assume a high correlation between luminance and colorization . Nevertheless, this may not always occur; therefore, if we colorize each segment of luminance Y, the colorization of some areas will not be recovered properly. To address this problem, an evaluation process is performed to find and correct faulty segmentation using colorization image I and the segments in S and C. The correction method decolorizes and colorizes the image according to the procedure shown the figure First, colorization is achieved using cluster C segmentation, the colorized image is evaluated, and a new segmentation is proposed. The second evaluated segmentation includes the clusters together with the faulty super pixel areas, and the result returns super pixels that improved and super pixels that did not. [19]. The latter super pixels are then divided into two segments to create the final segmentation Segs.

based on the weight (5) and the IGFT matrix G.
Calculate the eigenvectors of the N local graph Laplacians based on the weights (9).
$^{\{i\}}$ $(i = 1, \ldots, N)$ of the local graphs.
Calculate $C \leftarrow HG$
Generate $C^{(1)}$ from C, and calculate s^* by solving the problem (14), and calculate $f_c^{(2)^*} \leftarrow C^{(2)} s^*$.
Ensure: $f_c^{(2)^*}$.

construct the following equation,

$$f_c = H g_c, \tag{12}$$

where the ith row vector of H corresponds to $H_2^{\{i\}^T} H_1^{\{i\}^\dagger}$. Then the chrominance image f_c is represented by using the colorization matrix $C = HG \in R^{N \times N'}$ as follows,

$$f_c = H g_c = HGs = Cs. \tag{13}$$

B. Estimation of the Graph Spectrum Based on the Sparse Optimization

In order to calculate the values of $f_c^{(2)}$, this letter applies sparse optimization approach. Let $C^{(1)} \in R^{P \times N'}$ and $C^{(2)} \in R^{(N-P) \times N'}$ be the submatrix corresponding to the first P row

SELECTED COLOR PIXELS

Image	Pixels	Values	[6]	[7]	[8]	[15]	Ours
a	2	PSNR[dB]	25.97	18.51	27.50	26.34	**28.52**
		SSIM	0.957	0.817	0.973	0.959	**0.974**
b	4	PSNR[dB]	22.77	22.55	24.20	23.95	**24.92**
		SSIM	0.872	0.865	0.890	0.903	**0.922**
c	3	PSNR[dB]	20.27	19.57	25.77	26.00	**26.08**
		SSIM	0.492	0.446	0.895	**0.910**	0.904
d	3	PSNR[dB]	21.75	21.16	17.20	32.21	**33.23**
		SSIM	0.811	0.802	0.617	**0.978**	0.973
e	3	PSNR[dB]	21.87	14.61	23.95	24.13	**24.86**
		SSIM	0.693	0.321	0.817	0.829	**0.859**
f	3	PSNR[dB]	26.13	26.13	29.48	29.86	**32.39**
		SSIM	0.898	0.897	0.951	0.956	**0.964**
g	3	PSNR[dB]	21.17	11.05	20.49	24.60	**27.09**
		SSIM	0.853	0.175	0.886	0.931	**0.960**
h	3	PSNR[dB]	17.53	18.91	**24.99**	23.85	24.10
		SSIM	0.726	0.793	0.917	**0.927**	0.917
i	4	PSNR[dB]	15.63	17.07	20.16	19.15	**20.25**
		SSIM	0.685	0.717	0.824	0.810	**0.845**
j	4	PSNR[dB]	20.98	19.81	**26.98**	25.37	26.48
		SSIM	0.551	0.557	**0.924**	0.902	0.909
k	3	PSNR[dB]	13.05	14.27	11.11	23.22	**24.87**
		SSIM	0.632	0.729	0.431	**0.961**	0.942
l	3	PSNR[dB]	5.67	5.63	7.91	9.27	∞
		SSIM	-0.044	-0.052	0.467	0.563	**1**

Figure 11.

In addition, the correction algorithm returns three data points to recover the final segmentation without any evaluation. [20] That is, the super pixel indexes $S_B{}^{idx}$ that are faulty and improved in colorization, the indexes $S_C{}^{idx}$ of the super pixels that are segmented into two parts, and the segmented pixels S_C of the segmentation applied to the set of super pixels indicated in $S_C{}^{idx}$.

A detailed description of segmentation correction is provided in Section Once we obtain the final segmentation Segs, we calculate the coefficients Ao, Bo, Ag and Bg according to the colorizing method described. The coefficients are hidden in luminance Y together with $S_C{}^{idx}$, $S_C{}^{idx}$ and $S_C{}^{idx}$ using the RDHCE embedding method described . obtaining the contrasted luminance Yc.

6. CONCLUSION

Image Colorization had always been a tedious task, and much attempts have been done to automate this task. In this review paper, we have seen different methods of image Colorization that have been modelled and their results and drawbacks. We have seen approaches that are semi-automatics well as the current models of fully automatic image colour using convolutional neural networks and classifiers. We have also seen that the best.

7. REFERENCES

[1] Gupta, R.K; Chia, Y.S.; Rajan, D.; Ng, E. S.; Huang, z. y. image colorization using similar images in Proceedings of the 20th ACM international Conference on multimedia, Nara, Japan,29 october-2 november2012; pp.369-378.
[2] Victor Osma-Ruiz Juan I. Godino-Llorente Nicolas Saenz Lechon, and Pedro Gomez-Vilda an improved watershed algorithm based on efficient computation of shortest path, pattern Recogn.,40(3),10781090(2007).
[3] Matthias Limmer, Hendrik P. A. Lensch, "Infrared Colorization Using Deep Convolutional Neural Networks", 2016 15th IEEE International Conference on Machine Learning and Applications (ICMLA).
[4] Domonkos Varga, Tams S zirnyi , "Fully automatic image Colorization based on Convolutional Neural Network", 2016 23rd International Conference on Pattern Recognition (ICPR).
[5] in Proc. SIGGRAPH, 2004, pp. 689-694. [3] Q. Luan, F. Wen, D. Cohen-Or, L. Liang, Y.-Q. Xu, and H.-Y. Shum, "Natural image colorization," in Proc. 18th Euro graph. Conf. Rendering Techn. (EGSR), 2007, pp. 309-320.
[6] Y. Qu. T.-T. Wong, and P-A. Heng, "Manga colorization," in Proc. SIGGRAPH, 2006, pp. 1214-1220.
[7] L. Yatziv and G. Sapiro, "Fast image and video colorization using chrominance blending." IEEE Trans. Image Process., vol. 15, no. 5, 2005
[8] X. Liu et al., "Intrinsic colorization," ACM Trans. Graph, vol. 27, no. 5,.152.2008.
[9] R. Dahl. (2016). Automatic Colorization. [Online]. Available: http://tinyclouds.org/colorize.
[10] S. Iizuka, E. Simo-Serra, and H. Ishikawa, "Let there be colorization Joint end-to-end learning of global and local image priors for automatic image colorization with simultaneous classification." ACM Trans. Graph. vol. 35, no. 4, p. 110, 2016.
[11] E. Tola, V. Lepetit, and P. Fua, "A fast local descriptor for dense matching."
[12] K. Jack, Video Demystified, Oxford, U.K.: Newness, 2005.
[13] Yang. D. D. Zhang, A. F. Fringe, and J.-Y. Yang, "Two-dimensional PCA: A new approach to appearance-based face representation and recognition, IEEE Trans. Pattern Anal, Mach. In tell., vol. 26, no. 1, pp. 131-137, Jan, 2004.
[14] S. Iizuka, E. Simo-Serra, and H. Ishikawa, "Let there be colour! Joint end-to-end learning of global and local image priors for automatic image colorization with simultaneous classification," ACM Trans. Graph.
[15] with deep convolutional neural networks," in Proc. Adv. Neural Inf. Process. Syst. (NIPS), 2012, pp. 1097-1105.
[16] J. Ches. Z. Li and B. Hazeg. "Linear spectral chastering super pisel."
[17] T. Fusuwa and M. Behara "Colour image caling hased on in eat contumation of adaptive colompuces in Proc. IEEE Int Acoast, Speech Signal Process (ICASSP), Mar. 2017, pp. 1522-1326 dok 18.110SICASSP2017.7953411colompucesProc.
[18] IEEE Int Acoast, Speech Signal Proces (ICASSP), Mar. 2017, pp. 1522-1326, dok 10.110SICASSP2017.7953411
[19] M. H Noumen, H. Khaled, and H. M. Fabcom. "Image colorization A
[20] A. Levin, D. Lischinski, and Y. Weiss, "Colorization using optimize ACM Tram Graph, v 23, no. 1, pp. 659-494, Aug, 2004, d
[21] J. Ches. Z. Li and B. Hazel. "Linear spectral chestering superpisel." IEEE Trans Image Process, wol 26, no. 7. pp. 3317-3131. Aul. 2017.