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Grayscale Image Colorization: A Literature Survey

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Abstract : The procedure of converting grayscale images to colour images in a way that is acceptable to the eyes is known as colorization. It is a very famous image to image translation problem and has been a topic of research ever since the advent of Computer Vision and Neural Networks. Grayscale image colorization has a number of uses cases some of which are colouring CCTV snapshots, restoring of old photos, transformation of interstellar objects captured through satellites, colorization of manga panels. Till now, techniques have been invented- some having straightforward algorithms yet consume a lot of time because of inevitable human intervention to complex but more automated and efficient methods. Today research is mostly focused on automatic image colorization techniques which has become a node that links deep learning with art. This paper provides an overview and evaluates the existing methods available to convert grayscale images to colour images. We classify the algorithms, explain their core principles and state their disadvantages and advantages. Evaluating the quality of a coloured image is difficult due to the complexity of the human visual system. The metrics used to assess colorization methods evaluate the difference between the predicted colour and the ground truth, but this difference may not always align with the perceived realism of the image. These state GAN based methods are most successful in colorizing a grayscale image. We foresee that our paper will drive the consideration of scientists to dig into GAN's and develop efficient algorithms using them to colorize grayscale images. This review paper will highlight some of the various strategies that have been tested for the process of image colorization. Since ancient times, people have used many methods to colorize images. The current trend is toward totally automatic image colorization solutions. This paper provides an overview of various different approaches that have been attempted and implemented, as well as their benefits and drawbacks, as well as a comparison of them.

INTRODUCTION

Grayscale photographs are regarded as unique works of art with extraordinary artistic worth. It is also hard to properly comprehend the actual scene by merely glancing at them because colour is such a crucial component of visual representation. The perspective of viewers is significantly altered when black-and-white photos are coloured. The distance in time between the past and the present disappears, making the scene seem more plausible. The accurate reconstruction is complicated by the often absence of knowledge into the original hues of early pictures. However, the purpose of colorization is not to precisely rebuild the colour, but to fool the viewer into thinking that the colorized image is real. In essence, colorization is the act of assuming the presence of colour information. In a technical sense, it is a difficult procedure to visually realistic and assign three-dimensional RGB (Red, Green, Blue) colour information to every pixel with respect to intensity of a grayscale image. The principal uses of colorization include the restoration of vintage black-white photos, the colouring of astronomy photos, and movie restoration. Most of the time, no particular hue can be tied to a certain grey object (such as with balloons, clothing, plastic goods, etc.). Because there are so many things in the world that have a wide range of hues, colorization is an ill-posed problem for which there is no single answer. Due to its intricacy, colorization is an intriguing issue that keeps the academic community interested. The first hand colorization processes were developed in the nineteenth century [1]. Colorization was transferred to the computer sphere in the 1970s, as a result of the influence of the digital revolution. Two methods are used for colorizing grayscale images in computer graphics: user-assisted colour transfer, and data-driven automatic colorization. The first method involves the user manually applying colour to a grayscale image. However, this method requires a significant amount of user input. Researchers have developed data-driven colorization methods that colorize a grayscale image in two ways: matching it with a sample colour image from a database or learning the parametric mapping from grayscale to colour from a large-scale image dataset [4]. Image colorization approaches can be broadly categorized into four categories: manual, scribble-based, example-based, and learning based. Currently, deep learning technologies are being used to create a system that can colorize photos completely automatically. Automatic colorization is a field of study with numerous applications, ranging from black and white picture reconstruction to augmentation of greyscale drawings to image re-colorization. Automatic picture colorization involves adding colours without human input to a grayscale image. The issue is that it is not possible to add colours to a grayscale image without prior information. For instance, objects may have varying colours, such as tree leaves that can range from different shades of green to brown during fall, without changing their shape. For a long time, machine learning researchers have been working on automatic colorization of grayscale photos. This is owing to the wide range of applications, including Manga (Japanese comic) colorization, colour restoration, and animation colorization. While human grey movie colorization experiments were discovered in the 1980s, automatic colorization research has just recently begun. Gary picture colorization is a fresh image processing issue. There are numerous strategies emerging in the literature, and new studies and technology are being developed daily. Because a single grayscale value might correlate to a variety of different hues, there is no exact and objective solution to colour a black and white image. Because it is well known that finding a simple way to restore the original colour is challenging since the grey bandwidth consists of 256 colours whereas the true colour has variants 256*256*256. The goal of all colorization algorithms is to replace the scalar value, or brightness, of each pixel in a grayscale image with a vector in a three-dimensional colour space, such as a red, green, blue vector in the RGB colour space. The structure of the paper is as follows. Section 2 (Literature Survey) conducts a detailed examination of existing methodologies. We examined the various methodologies and their drawbacks in Section 3 (Overview of Literature Survey). We have completed our research, as discussed in Section 4 (Conclusion).

NEED OF THE STUDY

Grayscale image colorization using Generative Adversarial Networks (GANs) has become an increasingly popular research area in recent years. There is a growing need for this technology due to its potential applications in fields such as photography, art, and design. By using GANs to colorize grayscale images, we can enhance the visual quality of the images, providing a more engaging experience for viewers. Additionally, colorization can help us to better understand historical photos and artwork, as well as aid in medical imaging and scientific analysis. However, the challenge lies in producing high-quality and realistic colorizations that accurately represent the original image. Therefore, the need for further study in this area is crucial to improve the effectiveness and reliability of the colorization process.

RELATED WORK

A. Using a Semi-Automatic Approach to Colorize Grayscale Images and Videos:

A method for semi-automatic colorization is described in this study [7]. They segment the image, and distinct areas of the image should be coloured. The application helps add colour to each pixel by taking into account the placement of colour markers. After segmenting the image, it is coloured. Another method they use to colourize movies is to colourize some frames first, then transfer the colour to other frames. Key frames are arbitrarily selected local minima of block motion. Watershed segmentation is carried out utilizing the rain water simulation technique [8]. This segmentation method results in over-segmentation merging procedures. Following the process, each phase has a marker. For a substantial percentage of photographs, their results were visually appealing.

B. Deep Convolutional neural networks for infrared colorization:

The project [9] focuses on the post processing of near-infrared (NIR) images of traffic scenes taken by vehicle cameras. It makes use of a multi-scale deep convolutional neural system. Pre-processing, inference, and post-processing are the three phases of the methodology. During the pre-processing phase, they build an image pyramid using the input image at various resolutions. Each input is subsequently processed through a large number of convolutional layers and max pooling layers in order to infer the pyramid.

Next, using a fully linked layer, the outcomes of every component that has gone through the deep CNN are combined. The aforementioned result is post-processed with a bilateral filter to remove noise. The downside of the above-mentioned process is colorized images which resemble portraits rather than real photographs.

Fig. 1. (a) Source image (b) Colorized image (c) Target output

C. Convolutional Neural Network-Based Fully Automatic Image Colorization:

This study [10] utilizes a multi-stage, feed-forward architecture based on Convolutional Neural Networks to predict the U and colour channels of an input grayscale image. Anstey uses the pre-trained VGG-16 classifier, which has already been trained on a million images, to tackle the regression issue of image colorization. The framework generates the predicted U and V colour channels for the image using a two-stage Convolutional Neural Network and the VGG-16 model. The YUV colour model was chosen because there is the least correlation between its three Cartesian coordinates. For several shots, it delivered excellent results. They tested the system's performance using the Quaternion Structural Similarity Index Measure (QSSIM) [11], and their results had higher QSSIM values than many of the earlier approaches they compared with. A drawback of this approach is that it may cause the output to appear sepia or brownish in tone if the algorithm is unable to correctly identify the meaning of the image. In addition, the colour information from the image's larger semantic sections is occasionally transferred to the image's smaller semantic regions.

Fig. 2. First row shows colorized output images. Second row shows the Grayscale Input images, and third row shows the ground truth images

D. Patch based Image Colorization:

[12] This paper uses a patch-based image colorization method as an example. The approach, which utilizes patch descriptors of luminance information and a general distance selection strategy is built upon patch descriptors of luminance features and a model for predicting colour. The final colorized image is also processed with a Total Variation (TV) regularization to ensure that the colours are coherent across the image. Their proposed method for automatically colorizing Grayscale photos is shown to be effective through experimentation colour prediction is done using the brightness channel of both photos. One of the downsides of automated colorization is that it can cause a loss of spatial coherence during colour transfer, which can lead to inconsistent colorization in the final output. To capture image textures or complicated structures, the image colorization method is provided using patch characteristics as pixel descriptors.

Fig. 3. Comparisons with: (a) Source image (b) Target image (c) Results

E. Image Colorization using Generative Adversarial Networks:

Generative Adversarial Networks (GANs) are Artificial Neural Networks (ANNs) architectures developed by Ian GoodFellow in 2014 [13]. GANs are generative models based on game theory that use ANNs to simulate a data distribution.

GAN models can replicate a data distribution and generate synthesis data by applying a given standard deviation to generate fresh and never-before-seen data. Because of the unique properties of GANs, one of the domains where they have predicted a change in the quality of the synthesized data is computer vision. Despite the existence of earlier models [14, 15, 16], GANs have been found to produce sharper outcomes [17].

The main distinction of GANs is in their training, which is based on game theory and involves two neural networks competing in a min-max game. Both networks must optimize their own objective functions, resulting in a situation in which two players compete for opposing goals.

A GAN can be thought of as a new architecture for an unsupervised neural network that can outperform regular nets. GANs are made up of two independent nets that operate independently and behave as enemies (see the diagram below). The initial neural net is known as the Discriminator (D) which is trained, D is the classifier that will do the most of the heavy lifting once the training is over. The second network, known as the Generator (G), is charged with generating random samples that resemble actual samples but have a twist that makes them fake samples.

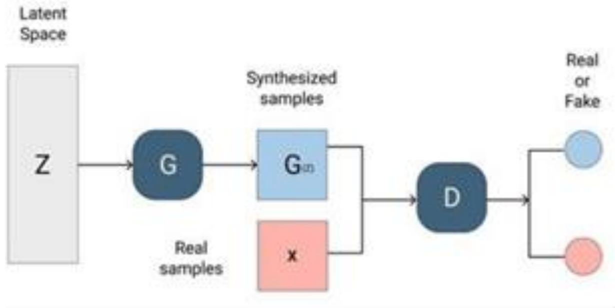

Fig. 4. Architecture of a GAN model

During training, D is shown authentic photos from training data and fake images generated by G. The Discriminator must separate these images. Accordingly, the machines fine-tune their parameters and improve their performance. If D correctly predicts, G changes its parameters to generate better false samples to trick D. If the forecast made by D is incorrect, it learns from its mistake to avoid similar errors in the future. D's accuracy is rewarded for each correct prediction, and the number of errors made by D serves as the reward for G. This process continues until a balance is achieved and D's training is improved.

CONCLUSION

Automating image colorization has been a challenging task and many efforts have been made in the past to achieve it. In this review work, we looked at many image colorization algorithms that have been developed, as well as their results and limitations. We've examined semi-automated ways as well as contemporary models of fully automatic image colorization employing convolutional neural networks and classifiers. We've also discovered that employing Generalized neural networks in conjunction with classifiers yields the greatest results for automatic image colorization so far. Convolutional Neural Networks (CNNs) create images with duller colours because of the averaging of colours in the vicinity during L2 loss optimization. On the other hand, Generative Adversarial Networks (GANs) generate images with much better colour brightness and clarity, even though they are harder to train. Additionally, GAN outperforms CNN quantitatively by producing images that are more accurate in terms of both L1 and L2 distance measures. Due to the additional information it carries, grayscale input produces superior colorization results than edge-only input. However, using GAN, the model is still capable of colorizing edge-only images satisfactorily.

The goal of future colorization system development will be to create even more creative architectures that are tailored to the colorization issue. A greater understanding of the features and context of images may result from further development of generalized adversarial networks. It has been established that higher image quality measures are required in order to evaluate colorization outcomes in accordance with the peculiarities of human perception.

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