INTEGRATING AI AND FUSION METHODS FOR HIGH-QUALITY MULTI-FOCUS IMAGING

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ABSTRACT

Multi-focus image fusion methods can be mainly divided into two categories: transform domain methods and spatial domain methods. Recent emerged deep learning (DL)-based methods actually satisfy this taxonomy as well. Visual quality evaluation with many numbers of statistical quality metrics were used to evaluate the fusion results with different algorithms. This image fusion approach was also extended to study the texture analysis of final fused image and proposed to incorporate the laws of texture-based energy operator for the image fusion process. Multi-focus image fusion synthesizes a sharp image from multiple partially focused images. However, traditional fused images usually suffer from blurring effects and pixel distortions. EWCM calculates the weights at each position in a content-adaptive manner, suppressing the effects of vignetting artifacts near the edges to preserve more edge details. Specifically, a residual architecture that includes a multi-scale feature extraction module and a dual-attention module is designed as the basic unit of a deep convolutional network, which is firstly used to obtain an initial fused image from the source images. As an important branch in the field of image fusion, the multi-focus image fusion technique can effectively solve the problem of optical lens depth of field, making two or more partially focused images fuse into a fully focused image.

Keywords: *Multi-focus image fusion, image structure-driven, Visual quality, EWCM, dual-attention module, blurred images.*

INTRODUCTION

Image fusion is a process of generating an image superior to the original image and using a special application based on the study of multiple image features in the same scene by using redundant and complementary information among image data. According to the types of input source images, the image fusion can be divided into remote sensing image fusion, medical image fusion, multi-focus image fusion, multi-exposure image fusion, infrared and visible image fusion, etc. Image fusion technology has been developed for more than 40 years, with more and more research methods and applications rising. Among them, multi-focus image fusion technology has a very broad application prospect in digital photography, computer vision, target tracking, and monitoring, microscopic imaging, and other fields. The so-called multi-focus problem can be explained as follows: due to the limited focus range of visible-light imaging systems, it is difficult to clearly capture all objects in the same scene. The application of these operations extends to various types of visual data, including photographs, illustrations, medical images, satellite images, and more. These techniques aim to enhance the interpretability of images for both human and machine analysis, facilitating more effective decision-making in various applications. Multiview fusion improves the image with higher resolution and also recovers the 3D representation of a scene. Multimodal fusion combines images from different sensors and is referred to as multi-sensor fusion. Its main applications include medical imagery, surveillance, and security. The reduction in costs is achieved through image fusion, eliminating the need to transmit multiple images of the same scene with different focal points. Instead, a single, all-in-focus image is transmitted.

LITERATURE VIEW

Ha Cong Nguyen (2024) claims that by combining data from several sensors into one image, image fusion technology may streamline equipment and increase observational efficiency. In tasks including scene recognition, memorization, and identification, colour image fusion outperforms greyscale image fusion by decomposing sensor images into their separate colour channels. This study suggests using statistical colour transform technology in YUV colour space to fix the problem of night vision colour image fusion. By incorporating real-world colour statistical data into the fused image and selecting optimal fusion parameters, this method enhances the visibility and realism of infrared objects. The findings of the study, which included both statistical analysis of colour and human eye observation, demonstrated the effectiveness of the recommended colour image fusion technique.

Guoqing Wu, (2023) To solve the problem of low-light object identification performance while using just visible photographs, researchers are investigating the decision-level fusion detection method that combines visible and infrared images. At its core, our light-sensing-based solution is YOLOX, a deep learning object identification network. On a decision-level, it can tell the difference between infrared and visible images. For such studies, scientists consult the low light vision visible-infrared paired data-set, or LLVIP. Light sensing and decision-level fusion utilizing Soft-NMS achieved a target AP value of 69.0%, surpassing object recognition using infrared photos (1.1% performance) and visible photo object identification (11.4%). According to the results, the decision-level fusion approach based on Soft-NMS may improve object detection in low-light conditions by combining complementary infrared and visible image data.

Reza Pourgholi (2023) The addition of direction and magnitude to vectors makes them more informative than scalars, as stated by. As a result, converting the scalar images to the vector field may reveal a lot of hidden information about the photos. This study lays forth a method that, prior to fusing, converts images from scalar to vector fields. It alters the pitch by means of the Nab-la operator. Applying the inverse transform is the next step in restoring the combined medical image. We statistically compared the results of a battery of experiments to show that the proposed method was effective. The results of the experiments prove that the proposed approach is superior than previous attempts.

Hamid Bahai (2022) After that, we will go over the pros and cons of the present approaches, highlighting the good and bad points of each. Using the guided filter to enhance the local standard deviations of the linked Laplacian images of the source pictures (2022), we create an effective and user-friendly multi-focus picture fusion method in this work. This pixel-based approach is based on the idea that sharper pixels should have bigger standard deviations and local variations. Applying the Laplacian operation to each partially focused source image of the same scene allows us to estimate the local standard deviation for each pixel. The next step is to enhance the local standard deviations using the guided filter. Following this, we construct a pixel selection decision map with the small area elimination method in conjunction with the filtered local standard deviation of the Laplacian image. First, this will be the main attraction.

Tang Hao, (2021) Methods for assessing the artificial intelligence capabilities of commercial smart terminals. Characteristics and temperature variations of common smart terminal hardware with varying specifications are informed by data from numerous AI industrial applications. A correlation model taking into account the features of a typical smart terminal device in relation to the temperature change is an essential initial step. Using this model, we can predict the range of possible temperature changes for the smart terminal device under test. One way to determine if an AI industrial application is working as intended is to compare the predicted and actual temperature changes of the intelligent terminal device.

Multi-Focus image fusion using Deep Learning

Image fusion applications like multi-focus photo fusion now employ deep learning. Liu et al. were the first to use CNN to merge images taken from different angles. They were successful in differentiating between focused and unfocused areas by using the Siamese design. First, the picture is divided into focused and unfocused regions using a multi-scale constitutional neural network (MSCNN). This allows us to generate the segmented decision map. Separating broad from narrow patches was achieved by means of the pixel-wise convolution neural network, or p-CNN.

Problems and mistakes abound in their first segmented decision maps. The fusion decision map makes use of a number of post-processing methods. Some of these methods include morphological operations, watershed analysis, guiding filters, CV, and small area reduction. Many multi-focus picture fusion methods employ CNNs, however fully constitutional networks are sometimes used.

ECNN: Ensemble of CNN for Multi-Focus Image Fusion

A lot of people are very into the multi-focus picture fusion techniques that use Constitutional Neural Networks (CNNs) these days. Still, these approaches need extensive post-processing algorithms to get to a good decision map, and they haven't gotten there yet. One new approach that makes use of ensemble learning is the ECNN technique, which is based on constitutional neural networks (CNNs). It makes perfect sense to employ many models and datasets instead of simply one. Over-fitting on the training data-set is an issue that ensemble learning based approaches aim to reduce by pursuing increased diversity across the models and datasets. Results from an ensemble of constitutional neural networks (CNNs) clearly outperform those from a single CNN. In addition, a novel, straightforward class of multi-focus pictures data-set is presented by the suggested technique. Getting improved accuracy is as easy as changing the arrangement of the patches in the multi-focus datasets. Consequently, the suggested approach brings a novel network that builds the first segmented decision map using three constitutional neural network (CNN) models trained on three separate datasets. Compared to previous final decision maps of CNNs based techniques that have been created after using several post-processing algorithms, the suggested method's initial segmented decision map is much improved by these concepts.

Artificial intelligence art

It is possible for artists to create visual art with AI algorithms. Once the discipline of artificial intelligence took root in the mid to late 20th century, artists began to experiment with AI in their work. The evolution of AI art has raised several philosophical concerns about the human mind, artificial beings, and the role of art in human-AI collaboration. Since the beginning of the century, artists have been integrating AI into their work. Some of these paintings have even gone on to get acclaim and museum exhibits. Because AI art tools became more widely available in the 2020s, more individuals outside of academia and the art world were able to have a go at creating AI-generated artwork. Concerns concerning copyright, dishonesty, and defamation have dominated conversations about AI art in the 2020s, along with the implications of AI on traditional artists, such technical unemployment.

Analysis of existing art using AI

Not only that, but research methodologies for statistically analyzing digital art collections have been developed that make use of AI. Since artwork has been extensively digitized in the last few decades, this has become a reality. The use of AI to examine preexisting art collections, argue CETINIC and SHE (2022), may provide light on the evolution of creative styles and the determination of their respective influences in new ways. Common computational ways to analyzing digital art include close reading and distant watching. The practice of close reading entails analyzing a single work of art in detail.

Machines can analyse brushstrokes or textural features, as well as computationally authenticate artists, as part of close reading procedures. However, statistical visualization of the similarity across a whole collection for a particular characteristic is possible using remote viewing approaches. Automatic categorization, object identification, multi-modal tasks, computational aesthetics, and information finding in art history are common tasks related to this technology. Art authentication and forgery detection AI systems may also be trained using synthetic pictures.

Image restoration by artificial intelligence

The restoration procedure may bring a damaged or fuzzy picture back to its original, untouched state. Among the many forms of corruption are noise, fuzzy focus, and motion blur. In order to restore a blurred picture, it is necessary to get a point spread function (PSF) image of the source, as this will retain all the information that was obscured by the blurring process. In contrast to image enhancement, which aims to improve the appearance of the picture without necessarily generating scientifically correct data, image restoration focuses on restoring a photograph to its original condition. Standard picture enhancing tools in imaging software, such as contrast stretching and closest neighbour technique DE-blurring, do not rely on any kind of a priori description of the image-creation process. Even when picture improvement may eradicate noise, the loss of information is sometimes too significant to warrant the loss of quality.

Quality Measurements for Image Fusion Applications

No widely agreed-upon metric for evaluating the efficacy of image fusion algorithms exists at the present moment. By comparing the inherent information of the original and fused photos, you may have a fair sense of the processes. When using the human visual system, subjective assessments are also necessary. There are a number of factors taken into account while evaluating images.

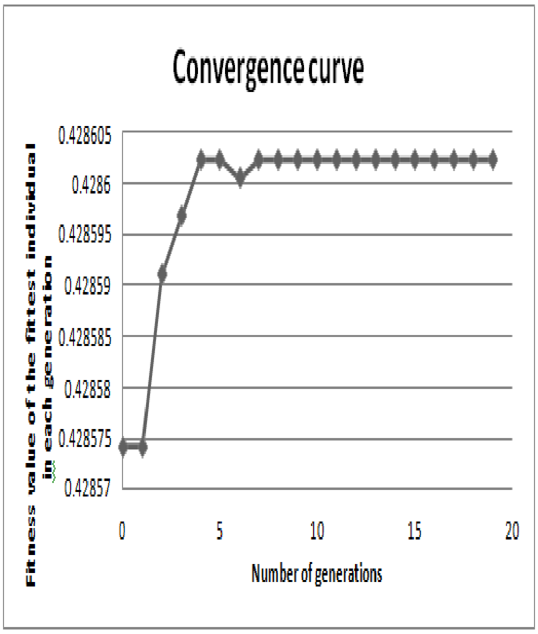
Components include lighting, contrast, details, scene realism, aberrations, and object completeness. The comparisons are used to evaluate the techniques' efficacy, and they include both quantitative and qualitative data. The problem is that there are pros and cons to any policy. In order to provide a thorough analysis, it is crucial to include as many facts as possible in the comparisons. This study will examine many popular assessment tools and discuss their advantages and disadvantages.

RESEARCH METHODOLOGY

The intention of fusion is to collect more information from diverse focus values of same scene by applying different rules. These images used as inputs for several common fusion techniques, various visual and quantitative indicators were used to evaluate how well these algorithms performed. Images are playing dominant role in various applications, basically for analysis of images visual quality is very important. Due to the combination of different focus values the integrated output image provides reliable information with acceptable visual perception for secondary process. The integrated image provides consistent results by increasing the interpretation abilities. Various standard multi-focus images are analyzed using the proposed algorithm to understand the quality, important characteristics of the fused image. Comparison of performance evaluation is based on visual quality and quantitative performance measures. To attain acceptable visual quality for analysis and diagnosis wide range of methods are available. Among them one of the important techniques is image fusion. In the process of secondary image processing feature extraction, segmentation and object recognition can be easier. The proposed scheme is a combination of frequency partition based discrete cosine transformation which is used for fusion process. For further enhancement modified PCA is applied. From several decades many numbers of researchers proposed wide range of algorithms based on image fusion. Low resolution images are considered in this work to generate high resolution image with desired size using convolutional neural networks.

RESULTS AND DISCUSSIONS

The optimized 3 value is acquired by applying the same method to the second input image. Graph 1 shows the fitness value curve that the fittest obtain in each generation. Using 100 code strings as a population, delves into the 25-generation GA execution. Graph 1 shows the documented and visually shown value that was decided to be the fittest after evaluating the fitness of each code string in each generation. The value has either steadied or been optimized by the eleventh generation.



Graph 1: Convergence curve of GA

You may see the outcomes of an impartial assessment of the Edge-Super and Edge-GA-Super algorithms' output fused images in Table 1. This area makes extensive use of spatial domain approaches, of which both methods are prime examples. Thanks to the parameter settings, we can see that the fused picture has the same quality as DWT-based image fusion. Due to the short fusion period, the edge super imposition approach is clearly a quick fusion technique, as seen in the last column of the chart.

Table 1: Quantitative evaluation of the output fused images of Vase

Algorithm	Entropy (EN)	Mutual Information (MI)	Structural Similarity (SSIM)	Image Quality Index (IQI)	Time (sec)
Edge-Superimposition	7.5506	5.1778	0.7714	0.5666	0.0308
Edge-GA-Superimposition	7.5908	5.2289	0.7738	0.5777	0.7149

This method accomplishes the fusion efficiently and rapidly. The method is computationally simple as it avoids multi-scale decomposition. This reduces the memory demand, which in turn reduces the hardware need. The edge-based technique is also optimized using the genetic algorithm, with the fitness function being the modified MSE.

Table 2 displays the outcomes of the objective assessment of the output fused picture that was created utilizing the DBN-based fusion approach. This approach, which is based on abstract fusion, outperforms all others. However, merging two multi-focus photos using DBN is still a work in progress.

Table 2: Objective results for sample images fused using DBN

Input image pair	Entropy (EN)	Mutual Information (MI)	Structural Similarity (SSIM)	Image Quality Index (IQI)	Time(sec)
Vase	7.6470	5.2477	0.7749	0.5705	1.1670

Another advantage of this technique is how easy it is to utilize DBN, which automatically computes fusion weights and extracts image features when given raw pixel values. This improves the computing load required for input image preparation as well as the algorithm's abstraction level.

The artificial intelligence image fusion method based on DBN will be discussed in this part. One first: fusing multi-focus images using DBN. To evaluate the input image's pixels, DBN employs a probabilistic processing technique. Generative networks like DBN make data categorisation a real possibility. This is how DBN determines the likelihood of pixels being clear or fuzzy. As a measure, the weighted image fusion rule takes these probability averages and uses them. An algorithm such as this one does not exist.

CONCLUSIONS

Many fusion solutions based on artificial intelligence are therefore put into action. These methods get their computational power from AI, ANN, and DBN. The primary focus of these solutions is simplifying the fusion process with the aim of reducing computer complexity and hardware need. Smart systems that take in photographs and produce a fused image might be built using these methods. There will be many futures uses for these systems establishing a new model that uses image information to estimate fusion weights and depends on edge-based superimposition is the first step in establishing an efficient fusion model. Fusion methods based on artificial neural networks provide DWT-GA-like outcomes; nevertheless, the resulting fused pictures have low numbers for the picture quality index. These methods additionally need more time for fusion due to the training of network models and the preparation of input image pairings. The loneliness of wavelet decomposition may be understood in this light; in contrast, the feature-free edge-super imposition method makes use of image statistics. For the first time, a deep belief network is utilized to fuse multi-focus photographs using a weighted fusion rule. Third, optimization techniques like DBN and GA are used to optimize the superimposition rapid fusion model's weights. A small data-set consisting of real-time multi-focus image pairings is used in the research attempt.

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