Spatial Display Model of Oil Painting Art Based on Digital Vision Design

QiongYang*, Zixuan Yue
School of Architecture Engineering, Xuzhou College of Industrial Technology, Xuzhou, 221000, China

***Abstract*—Oil painting, owing to its unique expressive approach, holds infinite charm in classical artistic creation, yet introduces complexities in terms of manual maintenance. In pursuit of digital spatial visualization of oil painting art, this study employs a stereo matching algorithm and Efficient large-scale stereo matching, focusing on aspects like disparity maps and pixel contrasts. Furthermore, enhancements in the algorithm involve the incorporation of the cross-arms strategy for image registration and the selection of auxiliary point sets to optimize the handling of image features. Results indicate that the proposed model, evaluated on the Middlebury dataset, achieves high accuracy, recall rates, and F1 scores, measuring 97.2%, 95.0%, and 97.5% respectively, surpassing the DecStereo algorithm by 3.4%, 8.2%, and 5.7%. When tested on the Photo2monet oil painting dataset, the proposed model achieves peak signal-to-noise ratio and average structural similarity index values of 16.781 and 0.833 respectively. This suggests that the proposed model excels in digital visual representation of oil paintings, exhibiting higher image precision, stronger stereo matching capabilities, and superior spatial display performance.**

Keywords—Oil painting; spatial visualization; Stereo matching; Spatial display; ELAS

I. Introduction

Oil painting is an art form that combines lines and colors, showcasing significant changes in color during creation, primarily reliant on the movement and intensity control of painting tools, employing layered pigment transitions to portray various color combinations [1]. Although colors may change during the creation of an oil painting, it essentially relies on precise control of the painting tools and changes in the layers of pigment to show different color effects. In recent years, with the development of technology, especially advances in digital visual design, the way oil painting art is displayed and created is undergoing a revolutionary change. Three-dimensional visualization methods demonstrate image content from multiple angles through 3D scanning and associated nodal information. Techniques and artistic styles hold pivotal positions in contemporary oil painting creation [2]. However, limitations in traditional oil painting methods and tools lead to susceptibility to damage or color fading, even with strict protective measures. Stereo matching technology, a critical component of stereo vision systems, has garnered increased attention and research among scholars [3]. This method rectifies positional differences between left and right images after epipolar line correction, determining matching cost values based on disparities among image points. As it utilizes partial window regions for computation, it boasts higher computational efficiency and suitability for parallel processing, especially in scenarios demanding high real-time performance [4]. Yet, due to its reliance on partial image windows, it yields numerous false matches, diminishing accuracy in disparity determination. Three-dimensional solid matching methods eschew cost aggregation, exclusively computing matching costs, disparities, and undergoing post-processing. Overall, employing holistic visual perception methods that consider individual pixel points across the entire image constructs an energy function to optimize disparity estimation for the whole image, thereby enhancing matching accuracy and overall visual effect [5]. Presently, scholars worldwide focus on enhancing image processing accuracy and real-time performance. However, no method adequately balances disparity and matching speed, where high-precision algorithms often sacrifice computational speed. This research focuses on developing a new type of spatial matching model for oil painting art images by applying stereo matching technology and three-dimensional visualization construction methods to enhance the presentation skills and styles of modern oil paintings. Traditional oil painting creation and display are limited by physical media and tools, and are prone to problems such as damage or color loss. In addition traditional methods often fail to provide an interactive and immersive art experience. Therefore, the research is dedicated to overcoming these limitations by utilizing digital technology to accurately capture and analyze the oil brush paths as well as the key frames of the paintings through 3D visualization techniques, so as to preserve and enhance the style and realism in the creation of contemporary oil paintings. In view of this, the stereo matching technique and 3D entity matching method used in this study can efficiently deal with the parallax problem in images and improve the matching accuracy. The use of this technique not only improves the accuracy and real-time of image processing, but also makes the digital presentation of art works more realistic and dynamic. A spatial matching model for oil painting art images based on a fast and effective stereo matching algorithm is developed. The model not only preserves the style and realism of contemporary oil painting, but also enhances the audience's participation and the expressiveness of the artwork. In addition, the research has innovatively transformed the way of displaying and appreciating oil painting art by integrating advanced technologies such as image processing, virtual reality and interaction design, which has brought a long-term impact on the art field. A spatial matching model for oil painting art images based on a fast and effective stereo matching algorithm is studied and developed. The model not only preserves the style and realism in the creation of contemporary oil paintings, but also enhances the audience's participation and the expressiveness of the artwork. In addition, by integrating advanced technologies such as image processing, virtual reality and interaction design, the research has innovatively transformed the way of displaying and appreciating oil paintings, which has brought a long-term impact on the art field.

The research is mainly divided into four sections: Section II involves a literature review related to digital visual design and art design; Section III focuses on the construction of an oil painting spatial display model based on image stereo matching algorithms; Section III analyzes the performance results and application outcomes of the image stereo matching algorithm; discussion and conclusion is given in Section V and VI respectively.

II. Related Works

Numerous scholars have conducted diverse research in the field of digital visual design. Logeshwaran et al. proposed a segmentation-based visual processing algorithm aimed at enhancing resolution and clarity to some extent through multi-visual enhanced pixels [6]. Parker and others studied the impact of digital technology on artwork design, illustrating how new technologies positively and negatively affect work resources based on various factors [7]. Peng and colleagues considered visibility analysis as an important research area in visual landscape research and developed a new computational algorithm for complex environments that can analyze views from multiple angles [8]. Johnson et al. constructed a pseudo-image-based color mapping table, optimized 3D scanning meshes for data visualization, and synthesized textures from pseudo-images. Additionally, there is an interactive rendering engine with custom algorithms and interfaces that can showcase various new visual styles to depict points, lines, surfaces, and volumetric data [9]. Ye et al. proposed a feasible method to quantitatively measure perception-based street visual quality and developed a Java-based program to automatically collect experienced urban designers' preferences for representative sample images. The results indicated that the evaluation model has satisfactory accuracy and provides insights into the perception-based visual quality and detailed mapping of various key elements in streets, offering accurate design guidance to aid more effective street renovations [10]. Chen et al. achieved a paradigm shift in perceptive environments by capturing local pixel-level intensity changes and generating asynchronous event streams. From standard computer vision to event-based neural morphological vision, advanced technologies in autonomous vehicle visual sensing systems have been developed [11]. Ren et al. systematically discussed the history and current status of optical lighting, image acquisition, image processing, and image analysis in the field of visual detection. The latest advances in machine vision-based industrial defect detection were introduced, emphasizing the increasing importance of deep learning in the further development of visual detection [12].

In the realm of digital research in art, particularly in the digitization of oil paintings, Castellano G and others have outlined some of the most relevant deep learning methods for pattern extraction and recognition in visual arts, especially in painting and sketching. The ongoing advancements in deep learning and computer vision, coupled with the ever-expanding collections of digitally visualized artworks, present new opportunities for computer science researchers [13]. Sandoval and colleagues introduced a novel two-stage image classification method aimed at enhancing the accuracy of style classification. Experiments conducted on three standard art classification datasets indicated a significant improvement over existing baseline techniques [14]. Scholar Mao W conducted research and analysis on oil painting art education videos using machine learning combined with virtual reality computing. Through the application of virtual reality technology in teaching practices, the study analyzed the effectiveness of teaching methods, allowing students to immerse themselves in art appreciation activities, embrace multiculturalism, experience learning, and enhance aesthetic qualities [15]. Mills and others investigated users' creative digital designs, including a popular 3D virtual painting program. The analysis focused on how students convey the same story in written, oral, and virtual painting modes, tracking key themes in students' virtual experiences [16]. Scholar Kent examined the works of McNeill and Hamill, emphasizing the importance of conducting abstract experiments in virtual reality as a creative medium [17]. Scholar van der Veen M approached the intersection of two visual modes from an augmented reality perspective. In this approach, the real environment is sensed by machines, magnified, scanned, located, and linked to a 3D model [18]. Scholar Doyle provided a historical overview of virtual reality, analyzed major works in the first wave, and discussed the application of virtual reality in contemporary practices through the concept of emotional engagement [19]. Ren Shihong et al. proposed a web-based VPL, JSPatcher, in order to address the problem of multimedia presentation or content generation.The tool allows users to build audio graphs using the Web Audio API and to graphically design and run digital signal processor algorithms using domain-specific audio processing languages. Experimental results show that the tool can be used with other JavaScript language built-ins, Web APIs, etc. to create interactive programs and artworks that can be shared online [20]. Nicole Johnson-Glauch et al. in order to explore how students can utilize representational features, proposed a synthesis of the results of two previous studies Method. The results suggest that visual representations have an impact on students' ability to access and use domain knowledge. Students may confuse concepts represented by similar features and not use concepts without salient features, and statics students are more coordinated in switching representations. These findings provide a generic domain pathway for redesigning the notation and representation of engineering concepts and suggest future research directions [21].

In summary, scholars have primarily focused their attention on environmental perception or programming methods in the digital visualization of images. There is a limited application of these approaches in the direction of oil painting. The integration of artworks and computer vision is often approached through theoretical analysis with a lesser emphasis on incorporating machine vision algorithms. In light of this, the current study aims to design a spatial display model for oil painting art based on an improved image stereo matching algorithm.

III. Oil Painting Art Spatial Display Model Based on Improved Stereo Matching Algorithm

To achieve the three-dimensional spatial display of oil painting art, this study, from the perspective of image stereo matching, constructs a method of digital visualization for oil paintings based on a fast and efficient stereo matching algorithm. The goal is to realize the modern intelligent preservation of traditional hand-painted oil paintings.

A. Stereo Matching Algorithm for Oil Painting Images Based on PatchMatchStereo-ELAS

PatchMatch Stereo This is an image matching algorithm used in stereo vision. The core idea of PatchMatch is to find the best match between images using random search. This method finds correspondences between images by quickly and randomly guessing the matching points and iteratively improving them. PatchMatch Stereo is used to compute parallax maps between images captured by two cameras, which is very important for reconstructing the three-dimensional structure of a scene. Efficient Large-Scale Stereo Matching (ELAS) algorithm is an efficient stereo matching method mainly used to compute the depth information of large-scale scenes. It employs a dense method that utilizes geometric constraints between pixels to improve the matching process, thus improving the computational efficiency and matching accuracy. Drawing inspiration from the PatchMatch approach, it employs various propagation techniques such as random initialization, spatial propagation, viewpoint propagation, temporal propagation, and surface optimization to obtain sub-pixel disparity values [22]. However, this method requires the initialization of unit normal vectors and disparity values for each pixel in an oil painting image. A challenge arises as the chosen initial values often deviate significantly from the actual data, making it difficult to find a surface that best fits the real data during the iterative algorithm, resulting in prolonged computation times. In this study, an efficient large-scale stereo matching algorithm (ELAS) is proposed to acquire initial information for oil painting images and 3D labels, thus circumventing the issue of arbitrary initial values in traditional three-dimensional image processing. Fig. 1 illustrates the process of the Patch Match Stereo-ELAS algorithm.

The PatchMatchStereo algorithm initially initializes the disparity map and surface normals for each pixel in oil painting images and then iteratively propagates the disparity map and surface normals. This process incurs a substantial computational cost. On the other hand, ELAS divides the problem into multiple disparity surfaces to obtain robust matching support points. While it enables rapid computation of the disparity map, its performance on low-dimensional measurement images is often inferior to high-resolution images. To address this, the proposed approach first utilizes the ELAS method to obtain robust support points and disparity values. Subsequently, the original disparity values and the constructed parameters of the disparity surface are input into the PatchMatchStereo algorithm. This joint algorithm utilizes support points as vertices within the smaller texture range of oil painting images, enhancing the disparity effect. Eq. (1) represents the calculation of pixel disparity values.

$$d_p = a_{f_p} p_u + b_{f_p} p_v + c_{f_p} \tag{1}$$

In Eq. (1), d_p represents the disparity value, a_{f_p}, b_{f_p}, c_{f_p} represent disparity parameters, and p represents a pixel. With the aid of equation 1, the problem of estimating disparity can be transformed into the estimation of the disparity plane, i.e., determining how to satisfy the optimization conditions of the disparity surface for each pixel. Eq. (2) illustrates the relationship between the three parameters of the disparity plane and the plane's normal vector.

$$\begin{cases} a_{f_p} = -n_x / n_z \\ b_{f_p} = -n_y / n_z \\ c_{f_p} = -\left(n_x * p_u + n_y * p_v + n_z * d_p\right) / n_z \end{cases} \tag{2}$$

In Eq. (2), n_x, n_y, and n_z represent the coordinate values in the xyz directions. Equation 3 is the expression for computing the matching cost.

$$m(p,f) = \sum_{q \in W_p} w(p,q)\beta\left(q, q - \left(a_f q_u + b_f q_v + c_f\right)\right) \tag{3}$$

In Eq. (3), $m(p,f)$ represents the cost value, f represents the disparity plane, W_p represents the specified square matching window, and $w(p,q)$ represents the adaptive weight. Eq. (4) is the expression for calculating the adaptive weight.

$$w(p,q) = e^{-\left\|I_p - I_q\right\|/\gamma} \tag{4}$$

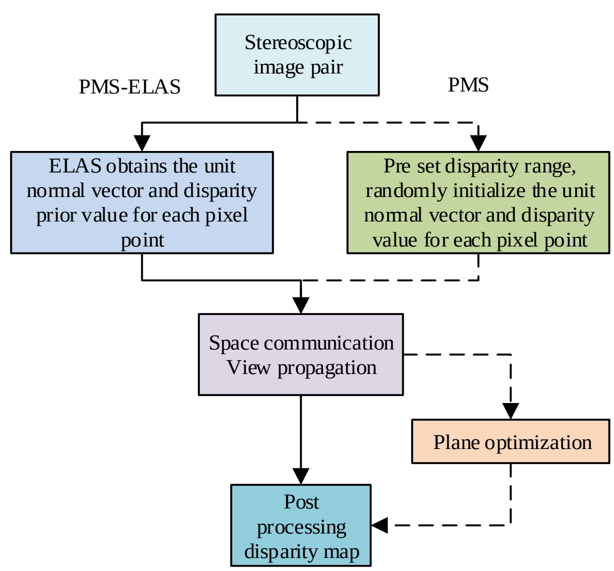


Fig. 1. Process diagram of patchmatchstereo ELAS algorithm.

In Eq. (4), γ represents a custom parameter, and $\|I_p - I_q\|$ represents the L1 distance of the RGB colors of pixels p and q. If the color difference between two adjacent pixels is large, then these two points are less likely to lie on the same plane, hence $w(p,q)$ is smaller. The Census transformation compares the grayscale values of the central pixel in a given window with the grayscale values of adjacent pixels. The size relationship is set to 0 and 1, expressing the grayscale information of the central pixel as a binary bit sequence of 0s and 1s. By comparing the bits, the Hamming distance is calculated. Fig. 2 illustrates the Census transformation.

123	125	129
128	127	128
126	121	131

→

0	0	1
1	*	1
0	0	1

121	113	106
115	110	101
106	142	138

→

1	1	0
1	*	0
0	1	1

Fig. 2. Schematic diagram of census transformation.

Census transformation effectively considers the differences between points in the window and the central point, reducing the adverse effects of changes in lighting conditions. It is robust in regions of oil painting images with low noise and weak texture. In this process, the study will use both color and grayscale information in the image, combining them with Census transformation for image matching. Eq. (5) represents the improved matching cost expression.

$$\beta(q,q') = \frac{(1-\alpha)}{1+\varepsilon}\left(\|G_q - G_{q'}\| + \varepsilon * \|Cen_q - Cen_{q'}\|\right) + \alpha \min\left(\|\nabla I_q - \nabla I_{q'}\|, \tau_{grad}\right) \quad (5)$$

In Eq. (5), $\|G_q - G_{q'}\|$ represents the absolute difference in grayscale values between pixels q and q', $\|Cen_q - Cen_{q'}\|$ is the Hamming distance of their Census values, ε is a custom scalar parameter for adjusting the ratio of feature grayscale size to Census transformation, and $\|\nabla I_q - \nabla I_{q'}\|$ represents the absolute difference in gradients between q and q'. α is a custom scalar parameter for balancing the color and gradient proportions of each pixel. Fig. 3 shows the spatial propagation schematic of the PMS-ELAS algorithm.

The PMS-ELAS algorithm utilizes the prior disparity information obtained from ELAS to enhance the positioning accuracy in weak texture areas and the local optimization ability in weak or non-textured regions. It iteratively goes through two phases: spatial expansion and view propagation, involving odd and even iterations in both upward and downward directions. This approach can be applied to multiple images and reduces the disparity regions in PMS, thereby improving computational speed and potentially eliminating the need for plane optimization.

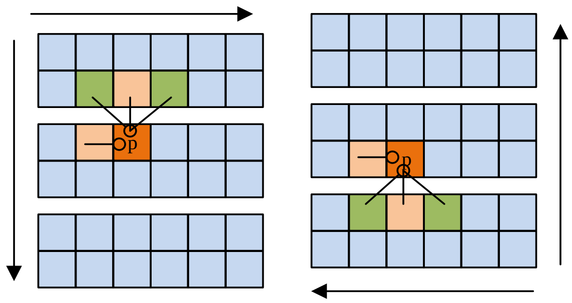


Fig. 3. Schematic diagram of spatial propagation of PMS-ELAS algorithm.

B. ELAS Algorithm Improved by Cross-Arm

The ELAS algorithm utilizes pixel counts with high confidence levels to form a triangular disparity plane, followed by rapid interpolation on the triangular surface. This method not only reduces computational speed but also swiftly calculates disparities in high-resolution images. However, mismatches in support points can introduce errors in constructing the disparity search distance, increasing the disparity values between points on the disparity surface. Consequently, this diminishes the disparity after interpolation and maximum a posteriori probability estimation on the same plane. Moreover, since the feature points extracted from oil paintings are often distributed in texture-rich and rapidly changing areas, ELAS-derived support points are mostly located at borders and areas with drastic changes. Robust support points are scarce for weakly textured or non-textured regions. To address these issues, research is proposed to enhance the accuracy and efficiency of support point localization and improve the accuracy of disparity estimation using an ELAS algorithm based on cross-arm enhancement. Fig. 4 illustrates the schematic diagram of the improved ELAS framework.

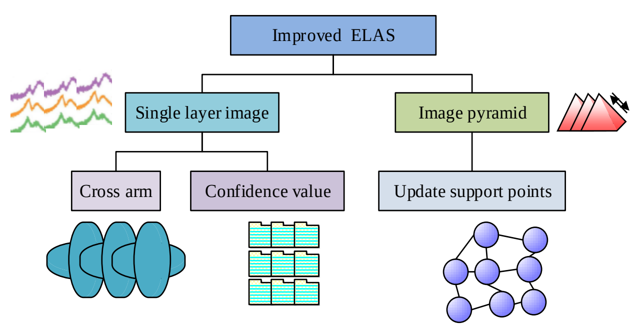


Fig. 4. Schematic diagram of improving the ELAS framework.

Considering the relationship between a single oil painting image and hierarchical images, the disparity calculation for each hierarchical image is based on support point selection and matching costs. Cross-arm structures are employed for image registration and auxiliary point set selection. By matching hierarchical images, confidence values for each level are obtained, enabling layered processing of images. Sampling is primarily conducted in a pyramid-like fashion, and based on confidence values, support point sets for high-resolution images are updated, simultaneously reducing the search range for each hierarchical image. Using a 3D Sobel operator on both left and right images, the grayscale gradients in the X and Y directions are employed for grayscale estimation in the left and right images. Feature descriptors for the images are constructed by selecting appropriate gradient values in the vicinity of each pixel among 32 points and computing corresponding matching costs. Let (u_n, v_n) be the pixel coordinates, $d(u_n, v_n)$D be the disparity of the pixel, and $f(u_n, v_n)$ be the 32-dimensional feature vector in the region, including gradients in the horizontal and vertical directions for each pixel. Fig. 5 illustrates the selection method for auxiliary points.

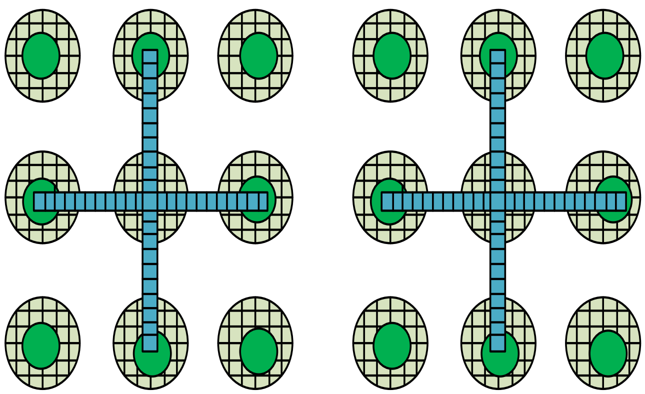


Fig. 5. Selection method of auxiliary points.

The local matching algorithm utilizes a larger window width, resulting in higher image quality and reduced noise. However, it tends to lose texture details and boundary features in the image while also leading to increased time complexity and decreased efficiency. On the other hand, a smaller window can capture more texture details and edge information, providing faster operation and effectively extracting image features to enhance algorithm execution efficiency. By jointly processing multiple feature vectors of multiple points, referred to as auxiliary points, and selecting these auxiliary points strategically, multiple small windows in different regions can be merged into larger windows, leveraging their respective advantages. This improves the overall accuracy of image registration while minimizing the image size for efficient computation, emphasizing local features to enhance computational efficiency. The proposed cross-shaped structure extends the arms to increase the selection window for auxiliary points, reducing dual inconsistencies. Establishing a window involves determining the arm lengths in the upward, downward, leftward, and rightward directions from the central pixel, with the stretch length determined based on the pixel differences. Stretching occurs in a specific direction until a significant color difference is encountered, and there is a maximum arm length limit. The cross arms maximize the perception range of the recognition window and efficiently detect boundaries. Eq. (6) represents the mathematical expression for confidence calculation.

$$cf_{(u,v)}^{s} = 1 - \frac{\min_d E(u,v,d)}{\min_{d \neq D(u,z)} E(u,v,d)} \tag{6}$$

In Eq. (6), $E(u,v,d)$ represents the matching cost value of pixel (u,v) at disparity d. $D(u,v)$ represents the disparity when the minimum cost value is found in the disparity search area. Confidence is constrained to the range [0,1]. The ratio between the minimum and second-minimum cost values reflects confidence. Fig. 6 illustrates the schematic diagram of image pyramid upsampling.

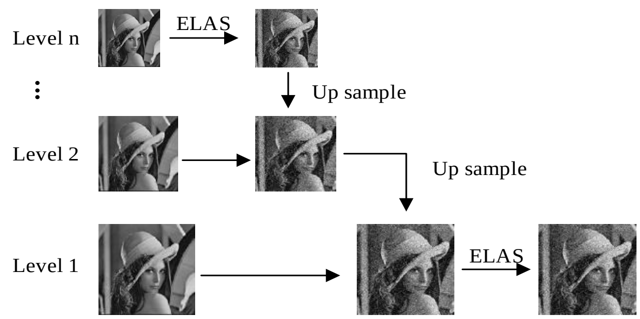


Fig. 6. Schematic diagram of image pyramid upsampling.

In local stereo matching, effective local information around the central pixel improves matching accuracy. For smaller texture areas, increasing the cross configuration expands alignment coverage, captures more image features, and enhances feature characterization accuracy. However, using a larger window width increases computational complexity and noise. Therefore, a method combining image pyramids and confidence is proposed for multi-scale fusion of support point sets. Downsampling two stereo image pairs yields a higher spatial resolution image pair, from which support points and corresponding disparity and confidence at different levels are obtained. If the disparity values of pixels satisfy left-right consistency conditions, their confidence values increase by a constant $\triangle$cf. In high-resolution images, a deep downsample of the disparity and confidence maps is performed to obtain the disparity map and confidence of the high-resolution image. Upsampling is then used to obtain a higher confidence support point set when searching for support points.

IV. Analysis of the Utility of the Oil Painting Artistic Space Display Model Based on Improved Stereo Vision Matching Algorithm

To validate the performance of the stereo matching based on the improved ELAS algorithm on image datasets and evaluate its capability in stereo matching spatial imaging applications, this study selected the Middlebury dataset, KITTI dataset, and Photo2monet oil painting style dataset as experimental samples. Diverse image quality evaluation metrics were employed for data analysis, resulting in comparative results for different image recognition algorithms.

A. Performance Analysis of the Improved Stereo Vision Matching Algorithm

The study utilized the Middlebury dataset and KITTI dataset as experimental samples for the visual matching algorithm. The Middlebury dataset comprises 33 pairs of static stereo images in indoor settings, with a maximum resolution of up to 6 million pixels and a maximum disparity range from 200 to 800. The KITTI dataset is used for stereo matching and includes 389 pairs of grayscale stereo images, consisting of 194 training data pairs and 195 testing data pairs. The compared algorithms include the ELAS algorithm, DecStereo algorithm, and Semi-global Matching (SGM). Evaluation metrics include accuracy, recall, and F1 score. Fig. 7 shows the accuracy results.

From Fig. 7(a), it is evident that the proposed model achieved the highest accuracy on the Middlebury dataset, reaching 97.2%. In comparison, the accuracy values of the ELAS algorithm, DecStereo algorithm, and SGM algorithm are all below 96%, with values of 90.0%, 93.8%, and 90.2%, respectively. Therefore, the proposed model improved accuracy on this dataset by 7.2%, 3.4%, and 7.0%. From Fig. 7(a), On the KITTI dataset, the proposed model achieved the highest accuracy of 95.3%. In contrast, the accuracy values of the ELAS algorithm, DecStereo algorithm, and SGM algorithm are all below 92%, with values of 87.8%, 88.5%, and 91.6%, respectively. Consequently, the proposed model improved accuracy on this dataset by 7.5%, 6.9%, and 3.7%. Fig. 8 presents the recall results.

From Fig. 8, it can be observed that on the Middlebury dataset, the recall curve of the proposed model shows a progressively increasing trend, reaching a convergence value of 95.0% at 50 iterations. In contrast, the recall curves of the ELAS algorithm, DecStereo algorithm, and SGM algorithm exhibit significant fluctuations with a decreasing trend during iterations, and their final convergence values are 85.2%, 86.8%, and 88.6%, respectively. Therefore, the proposed model outperforms them by 9.8%, 8.2%, and 6.4%, respectively. On the KITTI dataset, the recall curve of the proposed model exhibits a stepwise linear increasing trend, reaching a convergence value of 96.8% at 50 iterations. Comparatively, the final convergence values of the ELAS algorithm and SGM algorithm are 87.5% and 90.3%, respectively. The DecStereo algorithm did not achieve a convergence value. Consequently, the proposed model surpasses them by 9.3% and 6.5%. Fig. 9 illustrates the F1 score results.

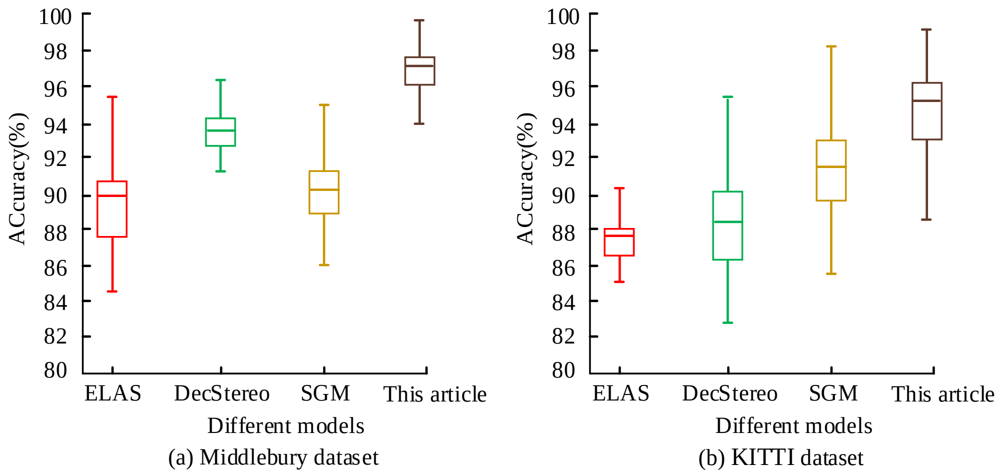


Fig. 7. Accuracy result chart.

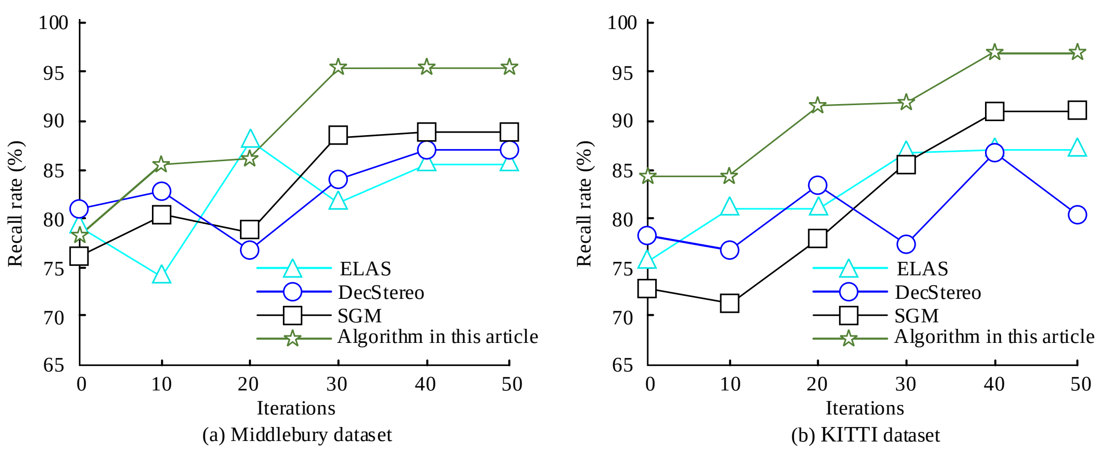
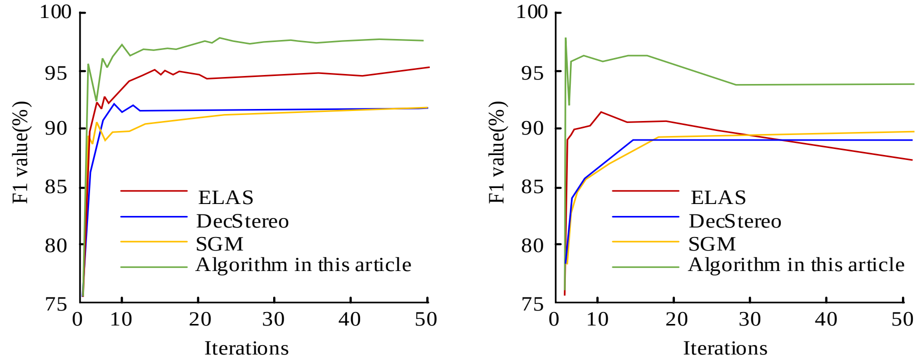


Fig. 8. Recall rate result chart.



(a) Middlebury dataset (b) KITTI dataset

Fig. 9. F1 value result graph.

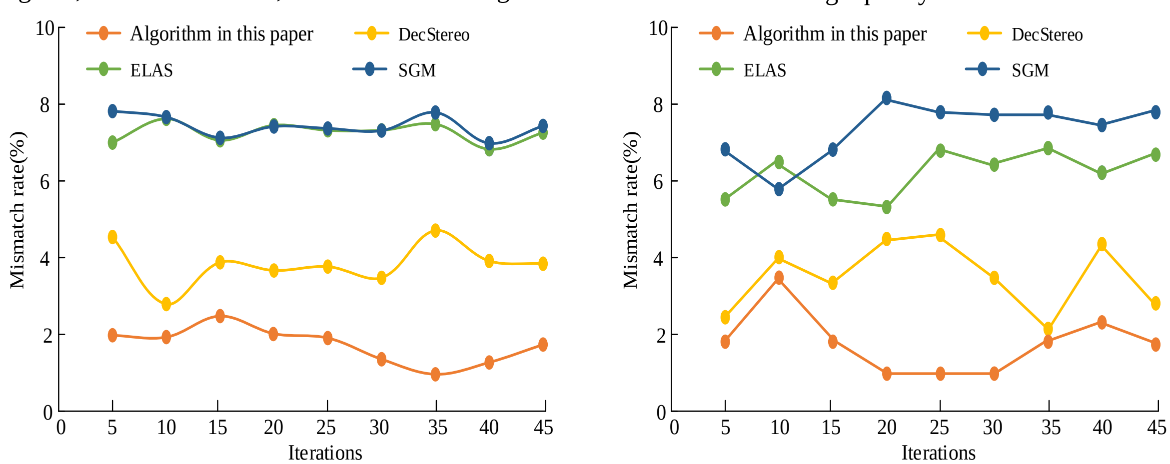
For the Middlebury dataset, the F1 score curves of the proposed model and the comparative models show fluctuating yet gradually increasing trends. At 50 iterations, the convergence values of the proposed model, ELAS algorithm, DecStereo algorithm, and SGM algorithm are 97.5%, 95.0%, 91.8%, and 91.8%, respectively. Hence, the proposed model outperforms them by 2.5%, 5.7%, and 5.7%. Concerning the KITTI dataset, only the proposed model, DecStereo algorithm, and SGM algorithm achieved convergence values, which are 94.2%, 89.8%, and 89.6%, respectively. Therefore, the proposed algorithm surpasses them by 4.4% and 4.6%, while the ELAS algorithm did not achieve a convergence value.

B. Analysis of the Application Effect of a Spatial Matching Display Model for Oil Painting Art

The study employed the Photo2monet oil painting style dataset for experimentation, with a training-to-testing set ratio of 3:1. All dataset images were RGB color images of size 256×256. The evaluation metrics chosen for the study included the mismatch rate, average absolute error, Peak Signal to Noise Ratio (PSNR), and Structural Similarity (SSIM). ELAS algorithm, DecStereo algorithm, and SGM algorithm were selected as comparative algorithms. Fig. 10 illustrates the mismatch rate results.

From Fig. 10, it is evident that, in both the training and testing sets, the proposed model consistently achieved the lowest mismatch rates, with curves showing variations around a horizontal value of 2. The lowest and highest mismatch rates for the training set were 1.0% and 2.5%, respectively. For the testing set, the corresponding values were 0.9% and 3.6%. In contrast, the ELAS and SGM algorithms exhibited mismatch rates above 5% in both training and testing phases, while the DecStereo algorithm fluctuated around 3.5%. The proposed algorithm reduced the fluctuation level by 1.4%. Fig. 11 presents the average absolute error results.

From Fig. 11(a) shows that during the training phase, the proposed model exhibited a smooth descent followed by horizontal convergence, starting to converge at 20 iterations, with a final average absolute error convergence value of 1.78%. In contrast, the average absolute error curves for ELAS, DecStereo, and SGM algorithms in the training dataset displayed significant fluctuations before 25 iterations, with final convergence values of 2.40%, 4.35%, and 2.80%, respectively. Hence, the proposed model reduced the error by 0.62%, 2.57%, and 1.02%. In the testing phase, From Fig. 11(a), the proposed model achieved a convergence value of 1.68%, while the DecStereo and SGM algorithms had corresponding values of 3.96% and 4.62%, indicating reductions of 2.28% and 2.94%, respectively. Table I summarizes the image quality assessment results.



(a) Training set (b) Testing set

Fig. 10. Mismatch rate.

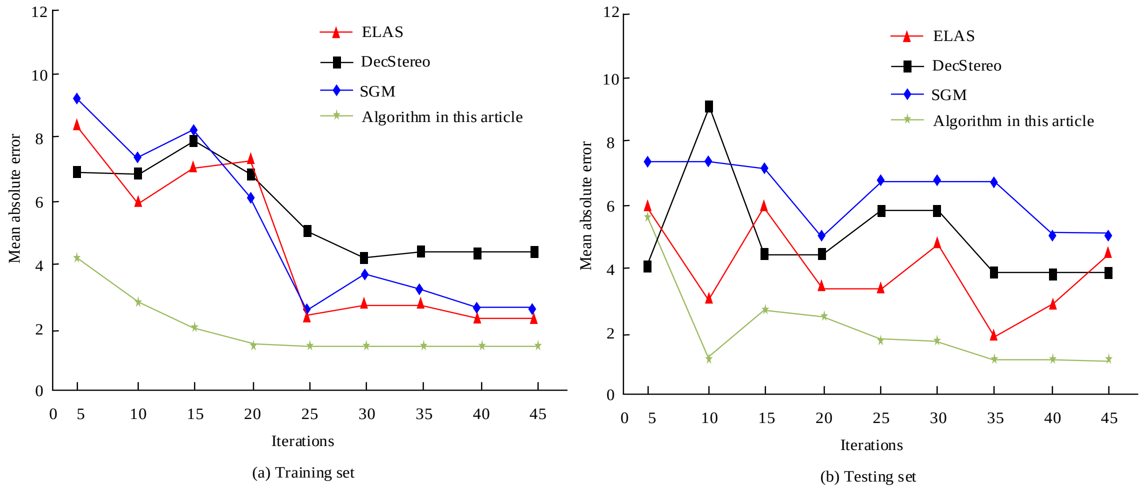


Fig. 11. Mean absolute error.

TABLE I. IMAGE QUALITY EVALUATION RESULTS

Oil Painting Dataset	Evaluating indicator	ELAS	DecStereo	SGM	Model in this article
Training set	PSNR	11.214	14.65	16.781	18.429
	SSIM	0.346	0.801	0.726	0.888
Testing set	PSNR	9.464	15.564	12.927	16.525
	SSIM	0.301	0.833	0.622	0.846

From Table I, it can be observed that the model proposed by the research institute achieved the highest values in image quality evaluation metrics, both in the training and testing sets. Specifically, the PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) metrics for the training set were 18.429 and 0.888, respectively, while for the testing set, these metrics were 16.525 and 0.846. In comparison, the highest values for the PSNR and SSIM metrics of the contrast models ELAS, DecStereo, and the SGM algorithm were 16.781 and 0.833, indicating an improvement of 1.648 and 0.042 by the proposed model.

V. DISCUSSION

In the field of contemporary art, oil painting, as an ancient and classic art form, has been widely appreciated and studied. However, with the rapid development of digital technology, traditional oil painting art is facing new challenges and opportunities. When comparing the accuracy of the system model, it is found that the accuracy of the algorithmic model used in the research can reach the highest value in the dataset Middlebury, in which for the accuracy of other algorithmic models the accuracy of the research using the algorithmic model is higher, and it can get a better ability to test the data, which indicates that the research using the model of the current construction can achieve better data processing ability on the dataset. At the same time on the KITTI dataset, the accuracy rate of the research use method is also the highest value, which at the same time shows that the research use method in the two datasets to get the best accuracy rate, the research use method for the different datasets have less impact on the accuracy rate of all can get a relatively good accuracy rate. In comparing the recall of different algorithmic models, the recall curve of the research proposed model shows an increasing trend, while the recall of the research used model is higher. This indicates that the current research use algorithmic model is able to maintain a relatively smooth curve change in the recall test, and has a better data test correctness rate compared to other algorithmic models. When comparing the F1 values of different algorithmic models, the F1 values of the research use model can reach 97.5% and 94.2%, comparing with the other algorithmic models higher F1 values, which indicates that the research use model performs better indicators in different data sets, and it can achieve a better processing effect for the processing of oil painting image art. When comparing the change of the false matching rate of the test set and training set of different algorithm models, the research and use method is at the lowest value of the false matching rate index, and the curves show a straight line around the level value of 2. Meanwhile, the change of the false matching rate of the research and use model is higher than that of the other algorithm models, which is due to the fact that the research and use method can achieve better stability in the training and testing. When comparing the convergence of the algorithmic models, the convergence curve of the research use model shows a smooth decline and then a horizontal convergence trend, and starts to converge when the number of iterations is 20, and the final average absolute error convergence value is 1.78%, then it will show that the research use method has better convergence, and it is easier for convergence to take place, which has a better performance for the testing and analyzing of the data. In comparing the quality assessment of the research use method, the research use method is able to achieve better indicator values, which indicates that the research use method is able to get better data testing results either in the training or testing set.

In summary, the research using method can perform well in the comparison of different data indexes, which indicates that the data model constructed by the current research can complete and achieve better data analysis and testing in the optimization of image data processing, and the method has better performance, which has a good guiding value for the subsequent research in this direction.

VI. CONCLUSION

The enduring artistic value of oil paintings has attracted attention in the context of integrating it with the trends of digital modernization. To achieve virtual creation of oil paintings in a three-dimensional visual presentation, this study, The research successfully integrates the artistic value of oil painting with digital modernization technology, and realizes the virtual presentation of oil painting art in three-dimensional visual space through the improved stereo matching model of ELAS algorithm. Meanwhile, the algorithm model algorithm is improved from the level of parallax map and pixel contrast in order to optimize the processing of image features, especially in the cross-crossing arm strategy image alignment and the selection of auxiliary point sets are improved and innovated. This research adopts the stereo matching technology and three-dimensional entity matching method, which not only improves the accuracy and real-time of image processing, but also makes the digital presentation of artworks more realistic and dynamic. Meanwhile, the research also developed a fast and effective stereo matching algorithm for the spatial matching model of oil painting art images, which retains the style and realism in the creation of oil paintings, and enhances the audience's participation and the expressive power of the artwork. The results indicate that, for the KITTI dataset, the proposed model achieved accuracy, recall, and F1 values of 95.3%, 96.8%, and 94.2%, respectively, surpassing the SGM algorithm by 3.7%, 6.5%, and 4.6%. For the Photo2monet oil painting style dataset, the proposed model exhibited the lowest error matching rate, with fluctuations around 2% during both training and testing phases, while the error matching rate for the DecStereo algorithm fluctuated around 3.5%. In terms of the mean absolute error metric, the proposed model achieved a convergence value of 1.68% in the final testing phase, representing a reduction of 2.28% and 2.94% compared to the DecStereo and SGM algorithms, respectively. Therefore, these findings suggest that the proposed spatial stereo matching model has a distinct advantage in the digital presentation of oil painting art, preserving the realism and artistic style of oil paintings. This study has achieved a lot of results, but there are some problems with the use of data in the study, such as the use of a small dataset, for this reason more and larger datasets will be included in subsequent studies to be analyzed.

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