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Review

From Textural Inpainting to Deep Generative Models: An Extensive Survey of Image Inpainting Techniques

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Abstract: Image inpainting is an evolving discipline of image processing with the objective of reconstructing an image by removing unwanted information, adding missing information or presenting the information appealing to the human visual system. In the presented manuscript, we have exhibited an extensive survey of various image inpainting techniques. The effectiveness of the techniques is together summarized with significant comparisons and assessed by analyzing the merits and demerits. For applicability of image inpainting imparting optimum results in the field of loss concealment, object removal, image restoration or disocclusion, the information from nearby regions is seeked to acquire an image with restored absent information. The inpainted image result can be evaluated using subjective and objective analysis, with emphasis on subjective analysis as a dedicated tool for evaluation.

Keywords: Image Inpainting, Structural Inpainting, Textural Inpainting, Partial Differential Equation (PDE), Exemplar-Based Inpainting, Deep Generative Models

Introduction

Image inpainting is a branch of image processing which aims at reconstruction of a distorted image (Pushpalwar and Bhandari, 2016). The reconstructed image so formed should be conceivable and convincing to the human visual system. The efforts always sustain on primarily focusing on obtaining an inpainted image by resembling to the source image. The reconstructed image focuses on removal of unwanted information, incorporation of missing information or showcasing information in an imperceptible manner (Bertalmio *et al*., 2000). Considering practical implementation, image inpainting is widely used in remote sensing area to eliminate hindrances like clouds and shadows to receive a good quality image (Lakshmanan and Gomathi, 2017). Various other applications of image inpainting lie in the removal of scratches, unnecessary objects, unwanted texts and generating pleasing visual effects to images. Image inpainting has no precise and comprehensive solution since it is an ill-assorted problem. Several solutions have been posed to image inpainting by selecting a particular method and optimizing the parameters. The parameters are optimized and iterated in order to get the desired results. The iterations performed should not produce any unappealing and undesirable effects over smoothing effects. The resultant image inpainted obtained should preserve the edge information along with texture uniformity. Meanwhile, various techniques have been discovered with the presumption that the pixels of known and unknown sections of the image share identical statistical attributes and geometric structures. This presumption leads to the formation of an image with better visual traits by interpreting into local or global priors (Zeng *et al*., 2019; Guillemot and Meur, 2013). Summing up, image inpainting methodology is gathering spatial information from the nearby pixels in order to fill the absent information. The two primary methods of image inpainting include structural inpainting and texture inpainting. Many methods, such as hybrid inpainting includes the combined use of structure as well as texture inpainting have been proposed. Here, Fig. 1 classifies different methods of image inpainting.

It is true to say that structural and texture inpainting have their practical implementations and uses in the field of image processing. Structural inpainting focuses on using geometric techniques for filling the absent information. This technique targets on the uniformity of the geometrical structure. Texture inpainting focuses on texture synthesis by gathering pixel values from the nearby pixels to complete the absent information (Arias *et al*., 2011). Further proceeding, variational image inpainting methods are based on the uniformity of the geometrical construction of the image. There are certain cases where information is not reflected truly due to some obstructions. Thus, Bertalmio *et al*. (2000) presented an information recovering technique established on the use of Partial Differential Equations (PDE) which generates information towards isophotes. Since, this includes the use of anisotropic diffusion, therefore leading to blurring effects in the image. Differential based inpainting uses the concept of variational methods and PDEs. Exemplar based inpainting focuses on filling absent information from nearby surrounding pixels at patch level (Ogawa and Haseyama, 2013; Amasidha *et al*., 2016; Vreja and Brad, 2014). The performance assessment of image inpainting can be judged on the basis of the produced subspaces and linear coefficients for estimating linear combination (Ogawa and Haseyama, 2013).

Image inpainting is a class of interpolation. It can also be applied to the restoration of antique historical images and video compression. Furthermore, algorithms based on sparse representation are popularizing nowadays. The motive of research in the field of image inpainting lies in implementing these algorithms for super-resolution images. Image inpainting not only focuses on rebuilding of an image but also on maintaining similarity of the inpainted image with the reference image. Moreover, in the context of obtaining the best matching patch in reach of a particular range established on color details is difficult. The detection of the location of the best patch in minimal time is appreciated. The evaluation of the inpainted image could be assessed by subjective and objective analysis. In the proposed paper, an effort to explore and scrutinize techniques with merits and demerits as conferred in Table 1.

Table 1: Evaluation of various image inpainting techniques

Year	Author	Basis of image inpainting	Merits	Demerits
1995	Heeger and Bergen	-Texture synthesis via pyramid approach	-Simple -Can be used in computer graphics	-Fails on non-uniform textures, quasi-periodic textures
1997	De Bonet	-Sampling approach for texture synthesis	-Performs well in generating textures	-Fails at the total visual structure of texture images
1997	Igehy and Pereira	-Texture composition for image restoration	-Performs well on stochastic textures	-Fails at recovering structured textures
1999	Efros and Leung	-Algorithm operates on all-inclusiveness of textures	-Rebuilds texture pixel by pixel	-Fails at distinct and multiple texels in texture sample
2000	Bertalmio	-Image inpainting with the use of PDE	-Automatic image inpainting by just specifying the area to be inpainted	-Fails at the rebuilding of large textured areas
2002	Masnou	-Disocclusion via level lines	-Aims at recovery of geometrical information	-Fails at recovering texture
2000	Wei and Levoy	-Faster production of texture using tree structured vector quantization	-Quality and speed of the algorithm is better than the other techniques	-Fails at 3D shapes-Poor and depth
2000	Ballester *et al*.	-Image inpainting algorithm based on Gestaltist's principle	-Works equally good for totally different structures	-Not applicable to the filling in textured regions.
2003	Bertalmio *et al*.	-Texture and structure inpainting performed together	-A successful technique by the union of image decomposition along with structure and texture synthesis	-Unable to perform well on 3D data
2003	Drori *et al*.	-Iterative construction of the image with the help of image fragments	-Image inpainting with the union of transformations	-Fails particularly when absent info involves perpendicular ines crossing
2003	Levin *et al*.	- Global image statistics	-Adjusts well to a particular image even if nearby local regions are same	-Performs poorly in textured regions. -Unable to produce a sharper image.
2004	Criminisi *et al*.	-Removal of object. -Filling of the area produced by exemplar	-Edge preservation -Fast -Efficient	-Fails at curved structures -Depth ambiguities
2004	Telea	-Fast marching method	-Simple -Easy -Fast to implement	-Generates blurs when inpainting regions are thick
2004	Pei *et al*.	-Reclamation of Chinese paintings	-Simple -Efficient -Remove unwanted patterns	-High computational time
2005	Ogawa *et al*.	-GMRF model especially for still images	-Precisely recover the missing areas and edges	-High Computational complexity
2005	Rares *et al*.	-Edge information	-Performs well on piecewise-smooth images -Use local as well as global features of edges	-Fails at textured images
2005	Elad *et al*.	-Concurrent cartoon as well as texture	-Missing pixels accepted. -Automatic filling of absent pixels.	-Fails at the complete sparse representation of the object
2005	Cheng *et al*.	-Concluding a priority function for better performance	-Applied to images with different properties -Uniting structure and texture details	-High computational complexity

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Table 1: Continue

2006	Calvetti *et al*.	-Bootstrap priors	-Fast -Efficient -Flexible	-Computationally inefficient on using hyper models
2006	Shao *et al*.	-Poisson equation	-Works well on complicated structures, elimination of large objects	Increase in computational time
2006	Chen *et al*.	-Sketch model and guided	-Recovering of curve structures	-Lags behind few techniques in case of removal of large objects
2007	Mairal *et al*.	-Sparse representation on colored images.	-Good for image denoising, image inpainting and demosaicing	-Need to work in multichannel images, MRI images, astronomical data
2010	Aujol *et al*.	-Local geometric knowledge	-Global rebuilding of geometry -No deprivation of quality for texture rebuilding	-Need to work on the proposed algorithms for better inpainting results
2010	Kwok *et al*.	-Fast query exemplar based algorithm	-Efficient -Better visual results	-Slower in some cases
2010	Xu and Sun	-Exemplar based	-Best PSNR values achieved -Sharpness preserved	-Unable to recover structures in the absence of structure cue
2012	Zhang and Lin	-Color distribution analysis	-Maintains texture uniformity and edge continuity	-Unable to rebuild geometry in the absence of an example
2012	Le Meur and Guillemot	-Resolution based	-Computationally efficient -Less noise	-Need to work on low resolution images
2012	Dong *et al*.	-Blind image inpainting technique	-Eliminates random impulse noise, image deblurring, -No user interaction while recovering images	-Needs work on blind deconvolution
2012	Martínez-Noriega *et al*.	-Exemplar based technique concerning priority and candidate patches	-Decrement in error generation. -Linear edge preservation	-Needs improvement in classification of patches
2013	Wang *et al*.	-Image inpainting designed for geometric methods	-Efficient -Performs better. -Restores Textures	-Computationally complex in some cases
2013	Ogawa and Haseyama	-Sparse representations with use of SSIM index	-Rebuilding of large areas with no blurring artifacts	-Computational complexity -Added artifacts.
2013	Guillemot *et al*.	-K-NN and LLE-LDNR	-Works better in loss concealment and object removal	-Works poorly for large missing areas.
2014	Ružić and Pižurica	-Textural descriptors	-Efficient -Reduction in space complexity	Incorrect adjustment of τ can lead to undesirable results
2014	Huang *et al*.	-Planer structures	-Excellent for large regions and multiple planes	-Artifacts added. -Reverts to fron to parallel completion in case of failure in detection of plane regularities
2015	Jin and Ye	-Image inpainting via matrix	-Fast -Better visual results	-High computational complexity
2017	Yang *et al*.	-Multiscale neural patch combination	-Works well on inconsistent holes	-Added discontinuities and artifacts
2017	Ying *et al*.	-Segmentation	-Efficient -Better image inpainting quality	-Not applicable to images with different colors and textures
2017	Yeh *et al*.	-Deep generative models	-Works well for simple structures and large absent areas	-Unable to handle complex structures
2018	Yu *et al*.	-Deep learning with contextual attention	Reduced artifacts -Works on holes with different resolutions.	Doesn't work on higher resolutions.
2019	Nazeri *et al*.	-Edge connect	-Works well on non-uniform missing regions,	-Fails in interpreting edges of highly textured images

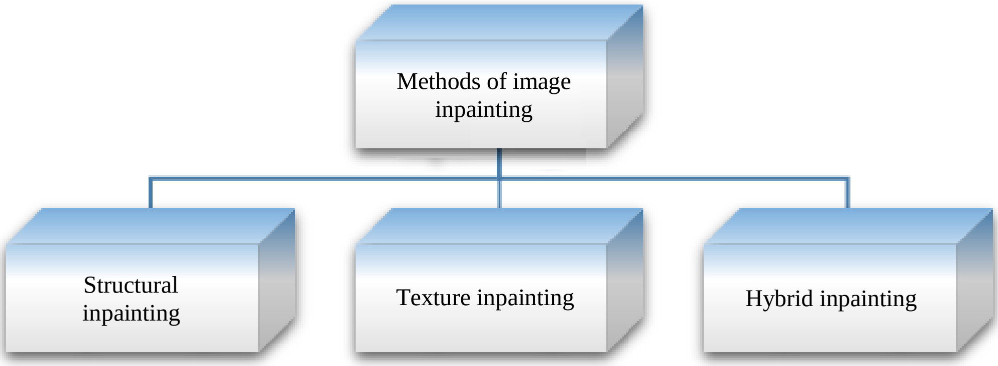


Fig. 1: Methods of image inpainting

The paramount objective of the paper lies in reviewing the different image inpainting techniques with section II targeting various image inpainting techniques, section III covering the essential applications of image inpainting, section IV describing the objective metrics, section V delivering the discussions and finally concluding in section VI.

Background

There has been a requirement of developing a framework to recover the harmed and distorted images with the aim of rebuilding of damaged or absent regions. It has been observed that with the passage of time, an image gets distorted due to various reasons. Therefore, there was a need to invent a technique to rebuild the absent regions, which led to the invention of image inpainting. This technique must be applied in a way that it is undetectable to the human eye, maintaining the integrity of human visual system. With various applications of image inpainting, this is one of the most prevailing research field in the broad area of image processing to rebuild the missing or absent regions.

Heeger and Bergen (1995) presented a texture reconstruction technique. This technique is suitable for stochastic textures, forming an image pyramid comprising of transitional images. This automatic technique helps in producing texture to recover the object required.

De Bonet (1997) put forward a technique in which the texture images taken as input are considered as probability density estimators. This technique undergoes two stages from figuring out joint occurrences beyond multiple resolutions of various features to consecutively sampling spatial frequency bands forming texture. This technique provides better results than the existing ones. In the same year, Igehy and Pereira (1997) introduced an algorithm based on Heeger and Bergen (1995). This algorithm carries forward the concept of earlier proposed algorithm by adding a step which determines the extent of information needed to synthesize the texture from the input image taken.

Masnou (2002) proposed an algorithm in which by the help of level lines complete and detailed information can be depicted from the images. The proposed algorithm can be deduced as a reflection of Nitzberg-Mumford-Shiota's algorithm, shown in Fig. 2.

The major drawback of this algorithm lies in recognizing the preceding edges. The proposed algorithm by Simon Masnou deals with rebuilding the object by incorporating the absent parts under specific geometric constraints. The foremost steps involved in the algorithm includes estimation of the polygonal line with respect to occlusion borderline, followed by determining and estimating the T-junction, then triangulation of the occlusion, further proceeding to join the combination of T-junctions by computing with dynamic programming, then illustrating with respective geodesic paths and finally geodesic transmission for reconstructing the image.

Heading further, the main contribution on texture synthesis was given by Efros and Leung (1999). The suggested algorithm was based on Markov Random Field (MRF), where the probability distribution of brightness values for a pixel is presumed, concerning brightness values of pixels in the spatial region is supposed to be individualistic of the remaining image. A square window of any size is selected and set as a framework for nearby pixels. The suggested algorithm works on various distinct orientations of the window. Therefore, this works on the given value to the pixel by its nearby surrounding pixels. Few prominent and vital applications of texture synthesis are presented in Fig. 3.

Bertalmio *et al*. (2000) presented a structural inpainting technique which involves the use of Partial Differential Equations (PDEs) with the aim of generating information towards isophotes. It aims for automatic digital inpainting within few minutes with the algorithm proposed, by just pointing towards the area to be inpainted. The first step involves anisotropic diffusion smoothing to reduce the effect of noise. The values are manipulated once the image gets into the inpainting loop. After a few successive transmissions, anisotropic diffusion is applied until a steady-state is achieved. The main advantage of this technique is, it requires no user interference once the area to be inpainted is selected by the user. Subsequently proceeding further, Wei and Levoy (2000) presented an algorithm for texture inpainting. The technique put forward by them is acquired from Markov Random Field (MRF). The process is catalyzed by using tree-structured vector quantization with utilization of multi-resolution pyramid and a simple searching algorithm. The significant advantage of using this technique lies in generating high quality and faster results compared with other existing techniques.

The analysis and performance of the technique proposed by Masnou (2002), is established on the Gestaltist principle. This approach tends to extend isophotes lines automatically into the area of absent information. This is based on a joint combination of gray levels with isophotes directions.

Bertalmio *et al*. (2003) proposed a hybrid image inpainting algorithm which aims at decomposing the original image into two layers, one layer with structural attributes and other layer with textural attributes. Structural inpainting algorithm by Bertalmio is applied to the first layer (Bertalmio *et al*., 2000) and texture inpainting algorithm by Efros and Leung (1999) is applied to the other layer. Finally, the resultant from the two layers confer to the final image. The flow chart for hybrid inpainting by Bertalmio is given in Fig. 4.

Simultaneously in the year 2003, a fragment-based image inpainting was proposed by Drori *et al*. (2003). This focuses on recreating an image with the help of given image and inverse matte. The objective lies in rebuilding an image by smooth reconstruction with the help of combination of fragments through an iterative process. With the help of this proposed technique, the lost or absent parts can be recovered from the visible and known regions. The limitations of this technique include no knowledge about the 3D structures in the image and when the absent area reflects the crossing of the two perpendicular lines. Levin *et al*. (2003) proposed a technique where global image statistics were used to inpaint the image. In this technique, local features of histograms are used to make an exponential family distribution. The inpainting is done by finding a suitable image to fit and inpaint the hole with the help of this distribution. The augmentation is practiced by loopy belief propagation.

Criminisi *et al*. (2004) invented an exemplar-based technique, targeting removal of the objects while simultaneously filling the empty spaces so produced. The resultant image so produced with this technique is appealing and fascinating to the human visual system. This technique does not undergo from blur artefact, in addition, is a simpler and faster technique compared to the other techniques. The order of priority of each patch enables the algorithm to perform faster. In the same year, an inpainting techanique was put forward by Telea (2004) based on image smoothness. The missing regions are treated as level sets and then using the fast marching method (Sethian, 1996). This method is relatively simple and easy to implement. Proceeding further, Pei *et al*. (2004) conferred a technique for reclamation of Chinese paintings. The technique follows color contrast enhancement as well as lacuna texture synthesis. This was a simple and efficient technique to maintain and restore the Chinese paintings.

Ogawa *et al*. (2005) presented an image restoration technique particularly based on Gaussian Markov Random Field (GMRF) model. The earlier techniques which used GMRF considered the fact that the image is constant and stationary, whereas the image inclusive of edges is not stationary. Therefore, the performance of the restored image decreases in the latter case. In the new technique, they considered the fact that an image comprises of areas where each area comprises of sub image which is weakly stationary. With the new consideration taken into account, it is observed that performance assessment of the image restored in the edges increases. Further Rares *et al*. (2005) introduced an algorithm mainly based on edge information. The steps involved in the technique are shown in Fig. 5. The image and artefact are processed for detection of edges and extraction of features of edges. Some of the features are supposed to be selected from the edges and important edges are therefore used for further completion of the process. The next step includes the recreation of the structure from the image utilizing different characteristics of edges like spatial order and continuity of edges, object color. Proceeding towards the last step, the recreated image structure is considered for edge based inpainting to evaluate the absent artefact part.

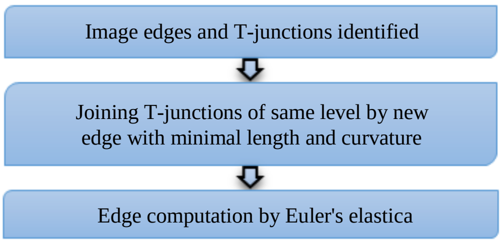


Fig. 2: Flowchart of Nitzberg-Mumford-Shiota (Masnou, 2002)

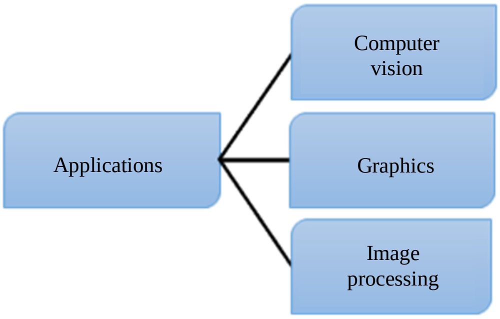


Fig. 3: Applications of texture synthesis

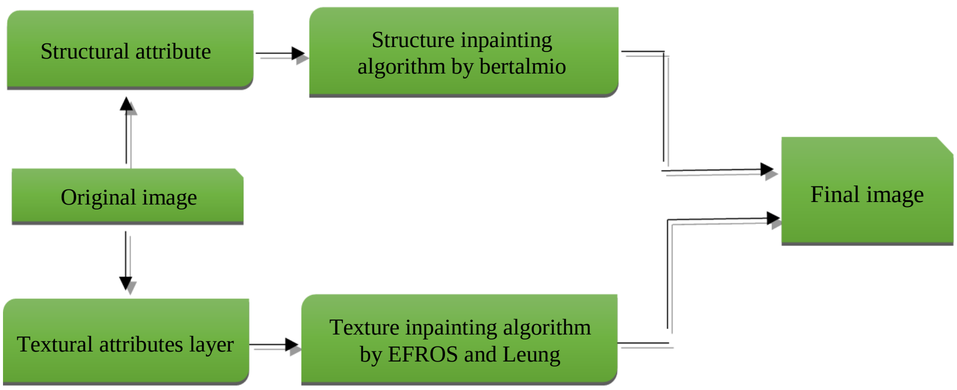


Fig. 4: Flow chart for hybrid inpainting by Bertalmio *et al*. (2003)

Elad *et al*. (2005) presented an image inpainting technique which aims at concurrently performing together cartoon as well as texture image inpainting. This is done via Morphological Component Analysis (MCA). The technique also included sparse representations, moreover image with additive white noise and missing pixels are accepted. Cheng *et al*. (2005) concludes the priority function to increase the performance of the exemplar image inpainting techniques. With user concern, this technique is applied to various images having different properties as well.

An algorithm was put forward by Calvetti *et al*. (2006) based on bootstrapping mechanism. In this algorithm, first the incomplete input image is smoothed, followed by estimating the gradient field outside the obstructed area. The pilot image is fabricated, once the gradient field is being inpainted. The pilot image that is smoothed determines the bootstrap prior. In the algorithm, the computations are established on Bayesian explanation. Shao *et al*. (2006) presented technique based on Poisson equation. This technique decomposes the input image into images with structural properties and textural properties respectively, followed by applying Laplacian operator, structure based inpainting and at last rebuilding with Poisson equation successively. On the other hand, texture based inpainting is applied to the image with textural properties. At last the resultant from these two images are combined to form the final inpainted image. The algorithm is presented in Fig. 6.

Following up with newer techniques in the same year, Chen *et al*. (2006) invented a technique where each image taken into account is considered to be formed of different textures formulated by elemental structure. The resultant inpainted image is formed by passing from two stages. First, the input image taken is passed through the sketch model to rebuild the image structure, followed by guided by the structure. Both the structure and texture are recovered simultaneously.

Mairal *et al*. (2007) proposed an algorithm based on sparse representations. The main aim lies in enhancing the K-SVD (Aharon *et al*., 2006) algorithm by expanding the contribution made in (Elad and Aharon, 2006) for color images. The algorithm presented focuses on accurately and appropriately managing of homogeneous noise which is helpful in case of missing information such as in image inpainting. This algorithm is beneficial in the case of small size of holes that are to be filled.

Aujol *et al*. (2010) contributed towards this field of image processing. His contribution aims at imparting experimental justification that exemplar-based algorithms can reconstruct local geometric information. It also stated that, the minimization of variational models permits a global reconstruction of geometry, especially of smooth edges. Using the concept of exemplar matching, Kwok *et al*. (2010) proposed an algorithm. The algorithm aims at using the concept of fast query. The data structure used for the fast query is search array which in return is responsible for fast and productive conduct of the algorithm. This is primarily useful in estimating the patch similarities. The prime feature of this algorithm lies in reducing computational time. Xu and Sun (2010) proposed an image inpainting technique in the year 2010. This exemplar based image inpainting technique uses the theory of sparsity at the patch level. To proceed with the main aim, that is inpainting, a patch from the absent region is chosen on the basis of priority. Next, the patch chosen is inpainted with the help of exemplars. In order to inpaint the chosen patch, the techniques proposed in (Criminisi *et al*., 2004; 2003) are considered among the prime techniques. For robust patch inpainting, the technique proposed in (Wong and Orchard, 2008) is considered.

Fig. 5: Flow chart of algorithm proposed by (Rares *et al*., 2005)

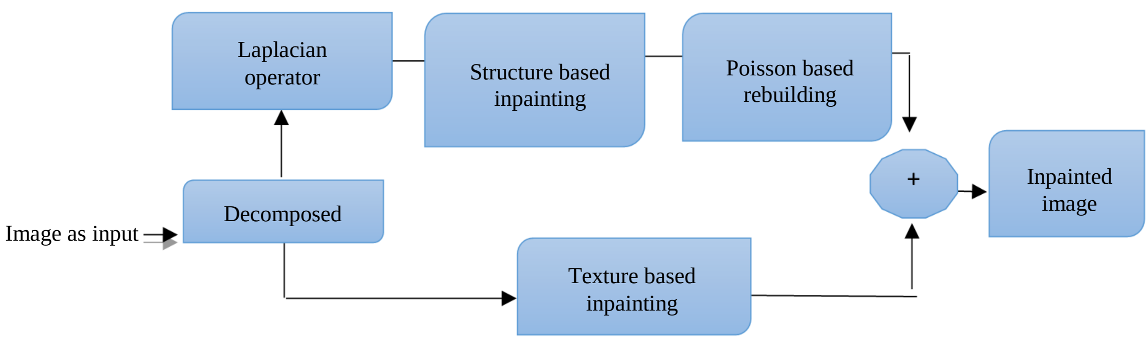


Fig. 6: Image inpainting based on Poisson equation (Shao *et al*., 2006)

The criteria of presenting an algorithm on color distribution analysis was presented by Zhang and Lin (2012). In this algorithm, a higher priority is given to structures, when it comes to distinguishing between structures and textures. It is noted that this algorithm performs better in retaining texture consistency as well as edge continuity. Moreover, visually pleasing results are obtained by using this algorithm. Le Meur and Guillemot (2012) presented an exemplar based image inpainting algorithm. Inpainting of the coarse version of the input image taken was done, resulting in minimization the computational complexity, furthermore reducing the noise sensitivity as well. In the same year, (Dong *et al*., 2012) introduced an image inpainting technique, particularly a blind image inpainting technique with the aim of recovering images where details are not present as well as cannot be perceived (Dong *et al*., 2012). The presented technique was able to eliminate random valued impulse noise, improving blurred and scratched images. Following up, in 2012, a technique was proposed by Martínez-Noriega *et al*. (2012) in which there was an improvement in filling with respect to priority, earlier presented by Criminisi *et al*. (2004). Moreover, from the candidate patches, we can conclude a better and efficient identification of the outliers. With this approach, there had been linear edge preservation and decrement in error generation.

With the advent of traditional geometric methods, it was observed that those methods bear low efficiency. Therefore, Wang *et al*. (2013) proposed a technique where an image as input is given, then decomposing the image, followed by applying the restoration process and later with Laplacian diffusion. This technique helps in progressing with PSNR as well. This technique not only works on geometric methods but also on hybrid and texture methods. A simple flow chart of the technique is given in Fig. 7.

Ogawa and Haseyama (2013) presented a technique based upon sparse representations improved concerning with perpetual metric. The technique presented uses Structural Similarity (SSIM) index for the better conduct of the image data. It includes two main steps, assessment of the sparse representation coefficients and revising of the dictionary, which is put forward in Fig. 8. The results of the proposed technique perform exceptionally well.

Guillemot *et al*. (2013) proposed an exemplar-based image inpainting technique utilizing locally linear neighbor embedding technique with low-dimensional neighborhood representation LLE-LDNR. The technique first aims at searching K nearest neighbors followed by linearly integrating with LLE-LDNR to incorporate the absent areas. K-NN search is enhanced with linear regression.

Moving towards newer techniques, Ružić and Pižurica (2014) proposed a technique based on textural descriptors. The idea behind using textual descriptors was to stimulate the speed for inspection of candidate patches. In this approach, text on histograms determined from Gabon filter is used for image inpainting as textual descriptors. A novel and improved optimization technique, established in (Ružić *et al*., 2012) is applied to MRF based inpainting. This is particularly applied to huge labels making it superior to (Komodakis and Tziritas, 2007) in terms of speed and memory consumption. In the same year, an automatic image completion technique was presented by Huang *et al*. (2014). Two algorithms have been used to implement this technique (Wexler *et al*., 2007; Barnes *et al*., 2009). This technique aims at recognizing multiple planes, followed by calculating perspective parameters, estimating their spatial support, then exploring their translational regularity and finally discovering prior probabilities.

Jin and Ye (2015) presented a technique based on Hankel structured matrix. A low rank matrix completion technique is used in order to fill the absent blocks from the patches (Signoretto *et al*., 2013; Wen *et al*., 2012). It is observed that the proposed technique by Kyong Hwan Jin performs better than the existing techniques.

With the advancement in technology and deep learning as an emerging field, Yang *et al*. (2017) presented a technique based on multi scale neural network synthesis in the year. The technique has been applied to ImageNet and Paris Streetview. The technique is basically applied to high resolution images particularly aiming at joint optimization of image content as well as texture constraints. It has been observed that the features obtained from middle layers are utilized for the incorporation of contents and textures in the images. In the same year, Ying *et al*. (2017) presented a revised and upgraded image inpainting algorithm especially on the images with large texture information. The technique used watershed image segmentation together with curvature features of isophotes which shows the specifics of texture information. The proposed algorithm has higher PSNR value reflecting the improved image inpainting. In the same year as well, a semantic image inpainting technique was proposed by Yeh *et al*. (2017), which basically deals with the available information present. In this technique, a deep generative model is in such a way trained that it finds the encoding of the distorted image nearest to the latent space of the image. It is observed that this technique performs at par with the other techniques.

The intrusion of unwanted structures in the inpainted images due to inconsistency with surroundings led to the invention of technique by Yu *et al*. (2018). The technique has been applied to various datasets like Places2 (Zhou *et al*., 2017), CelebA faces (Liu *et al*., 2015), CelebA-HQ faces (Karras *et al*., 2017), DTD textures (Cimpoi *et al*., 2014), ImageNet (Russakovsky *et al*., 2015). This fully convolutional neural network with contextual attention layer uses the surrounding image features helped to train a model better resulting in improved predictions.

Fig. 7: Flow chart for proposed methodology by (Wang *et al*., 2013)

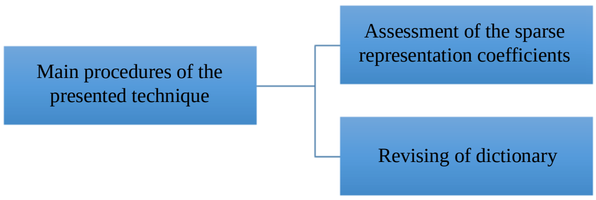


Fig. 8: Main procedures of the presented technique (Ogawa and Haseyama, 2013)

Since this is the era of deep learning, a better and efficient image inpainting technique is introduced by Nazeri *et al*. (2019). Edgeconnect is presented in this technique for edge generator for completion of missing regions pursued by image integration network for image completion from absent regions. These steps includes the involvement of adversarial framework (Goodfellow *et al*., 2014). It has been applied to various datasets like CelebA (Liu *et al*., 2015), Places2 (Zhou *et al*., 2017) and Paris StreetView (Doersch *et al*., 2012).

In this manuscript various state-of-the-art techniques have been presented. The above mentioned techniques demonstrate in producing good quality results. Various techniques are taken into account for interpretation. The techniques selected for assessment are representative for the division they refer to. Further developments in the sector of image inpainting lies in abolishing of a few constraints like computational cost, computational time and aiming to generate better results of the inpainted image. From 1995 to 2019, there has been drastic change in the field of image inpainting with advancement of technology from using textural inpainting to deep generative models. Here, Table. 1 shows the comparison and evaluation of various image inpainting techniques on the basis of the algorithm used along with highlighting the merits as well as demerits.

Objective Metrics

The assessment of image quality can be evaluated by subjective and objective measures. The subjective measures include a human judgment for the analysis of image quality, whereas objective measures include various statistical methods. The objective measures for image quality assessment are described below (Hore and Ziou, 2010; Tiefenbacher *et al*., 2015). It is often noticed that visual analysis is considered for the evaluation of inpainting results since there is no committed image evaluation tool (Trung *et al*., 2013). Since visual analysis holds a decent and stable approach but the below listed objective metrics can be used as well.

Mean Square Error (MSE)

It is computed by mean of the squared intensity differences of the pixels of the reference image with respect to the test image:

$$MSE(s,t) = \frac{1}{AB}\sum_{p=1}^{A}\sum_{q=1}^{B}\left(s_{pq} - t_{pq}\right)^2 \qquad (1)$$

where, $A \times B$ the size of the reference and test images is, s is the reference image and t is the test image.

Peak Signal to Noise Ratio (PSNR)

It evaluates the variation among the individual pixel values. If the reference image and inpainted image are alike, PSNR is high, whereas if the reference image and inpainted differs, then the PSNR value is low. Therefore, it is recommended to have positive correlation with the quality scores. It is responsible for measuring the differences among individual pixel values. It is observed that if MSE approaches zero, then the value of PSNR approaches infinity, showing that higher PSNR value depicts better quality of the image:

$$\text{PSNR} = 10\left(\frac{\log_{10}(255)^2}{MSE(s,t)}\right) \qquad (2)$$

Structural Similarity Index Measure (SSIM)

It is an approach to measure the similarity among the two images:

$$SSIM = d(s,t) \times e(s,t) \times f(s,t) \qquad (3)$$

Where:

$$d(s,t) = \left(2\mu_s\mu_t + C_1\right) / \left(\mu_s^2 + \mu_t^2 + C_1\right) \qquad (4)$$

$$e(s,t) = 2\sigma_s\sigma_t + C_2 / \sigma_s^2 + \sigma_t^2 + C_2 \qquad (5)$$

$$f(s,t) = \left(\mu_{st}^2 + C_3\right) / \left(\sigma_s\sigma_t + C_3\right) \qquad (6)$$

And C_1, C_2, C_3 are positive constants

Here, Equation (4) reflects luminance comparison which computes the adjacency of mean luminance (μ_s and μ_t) of two images, Equation (5) reflects contrast comparison which estimates the adjacency of contrast of two respective images which is calculated by standard deviation σ_s, σ_t, Equation (6) reflects structure comparison which evaluates the correlation coefficient between the two images *s* and *t* and $\sigma_s\sigma_t$ is the covariance between *s* and *t*.

There are no specific rules laid on choosing the PSNR or SSIM values when there is need of image evaluation. It is observed that PSNR is affected by Gaussian noise while the converse is for jpeg compression while both of them have moderately similar sensitivity to Gaussian blur as well as jpeg2000 compression (Hore and Ziou, 2010).

Applications

The basic idea of image inpainting lies in the restoration of the absent or missing parts of an image. The capability of image inpainting is confronted with various applications. The main objective of image inpainting is to develop visually pleasing results. Some of the important applications are mentioned below.

Loss Concealment

Image as well as video transmission undergo packet losses resulting in loss of information. This loss of information is depicted in the form of absent parts in the decoded image. Therefore, there is a need to recover the information that is lost via transmission. Subsequently, after decoding the image, the absent regions are recovered with the help of loss concealment. In view of practical implementations, loss concealment is conducted by means of accurately received earlier frames or adopting simple spatiotemporal interpolation. Taking into account the complexity issue, if image inpainting is done in real-time, then it will be very useful in yielding better results with hybrid methods integrating diffusion and exemplar-based techniques or patch-based methods utilizing exemplars or sparse priors. Figure 9 illustrates the application of image inpainting in case of loss concealment.

Object Removal

Proceeding further, application of image inpainting includes object removal. This refers to the removal of the object in order to clearly picture the information. Here, the object is removed, resulting in the formation of a hole. The hole is to be filled with the correct depiction of the information. Various methods have been discovered to recover the hole produced. It is noticed that exemplar-based techniques perform outstandingly well with impressive results compared to other techniques. Figure 10 illustrates the application of image inpainting for object removal with different methods.

Image Restoration

Progressing ahead towards other applications, image restoration stands among one of the most foremost application. Image restoration deals with recovering the real image from the degradations that the image went through. To deal with image degradation, the initial step lies in perceptive knowledge of the applications. It can be the restoration of ancient paintings (Pei *et al*., 2004), endoscopic images (Arnold *et al*., 2010) or fingerprint restoration (Bornemann and März, 2007). Since, in the case of restoration, the absent region is not too large. Therefore, local diffusion and patch-based or global methods provide a competent outcome. Figure 11 illustrates the application of image inpainting for image restoration.

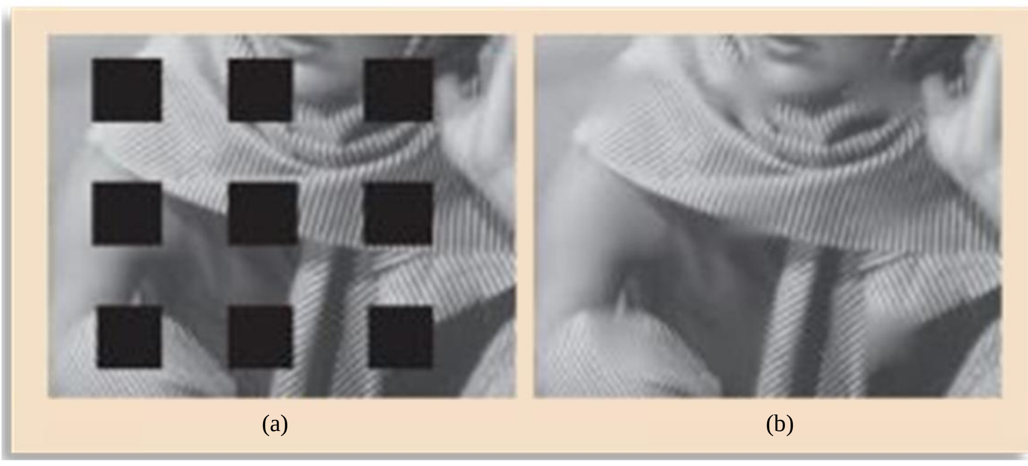


Fig. 9: Depiction of loss concealment. The lost regions in (a) are recovered in (b) (Guillemot and Meur, 2013)

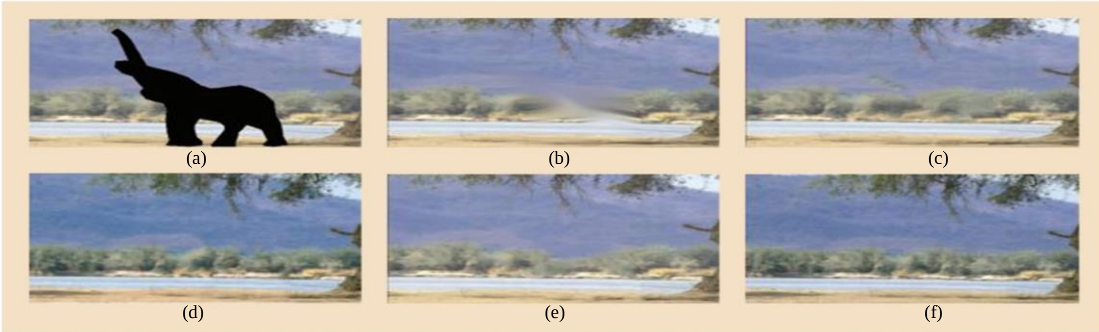
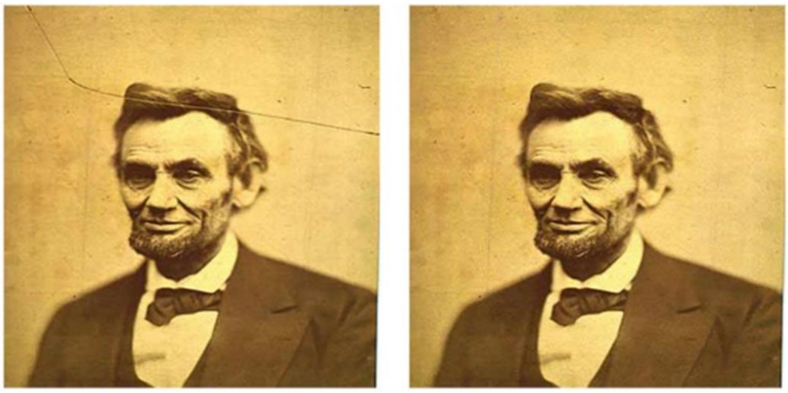


Fig. 10: Implementation of object removal with; (a) Mask and inpainting outcomes with techniques from different categories; (b) Anisotropic diffusion; (c) Exemplar based with LLE (locally linear embedding); (d) Patch sparse representation; (e) Hybrid with one global energy minimization; (f) Patch offsets (Guillemot and Meur, 2013)



(a) (b)

Fig. 11: Degraded image; (a) restored in; (b) (Le, 2016)

Fig. 12: (a) The familiar reference view estimated into virtual view points; (b) Projection and estimation of the reference view on a virtual viewpoint; (c) Inpainting result (Guillemot and Meur, 2013)

Disocclusion

There is a necessity of inpainting algorithms in 3DTV rendering on stereoscopic or autostereoscopic displays, moreover in the framework for free-viewpoint interpretation of a 3-D scene. To help the user operate in the 3D scene, virtual views are fabricated with IBR algorithms that use the actual images, various camera parameters and depth maps. It may be noted that at the time of the projection process, some sections of the 3D scene are not visible in the actual image due to obstruction by foreground objects whereas they are visible in virtual view. While synthesis of a virtual view, these sections become disoccluded. This results in pixels with unknown color. These pixels are thus required to be evaluated using inpainting techniques. Figure 12 illustrates the application of image inpainting for disocclusion.

Discussion

With the advancement in research and technology, image inpainting maintained the position of one of the prevailing topics in the past few decades. The applicability of image inpainting can be viewed from the aspect of image restoration, loss concealment, object removal and disocclusion. The algorithm to choose for image inpainting depends on the context of application. However, the techniques failed at producing desirable results in case of video inpainting. Tracking objects that are in motion in video remains a challenging task. The above-mentioned table presents the various image inpainting techniques along with their merits and demerits. It is noticed from most of the above-mentioned techniques that quality and time are proportionate to each other. From the research and investigation, it is observed that with the increase in quality there is a maximization of the computational time and with the reduction in computational time, there is a decrement in quality of the image (Mahajan and Bhanodia, 2014). Moreover, the computational cost is another major problem in developing an efficient algorithm for image inpainting.

The techniques mainly used for real time environment have also been discussed. Among the above mentioned algorithms, some of them are particularly designed for small regions whereas if applied to large absent regions they can introduce blurring effects, thus reducing the quality of the image. There are techniques that can reconstruct large absent areas without the addition of blurring artifacts, but computational complexity is increased manifold. There are also techniques which are scrutinized on the basis of PSNR values. It is expected from an algorithm that it should reproduce texture while maintaining the structure of the nearby areas of the inpainted area. Consequently, an algorithm maintaining textural and structural information in the inpainted image is considered to produce desirable and visually pleasing results. Furthermore, computational cost and computational time should be minimal in the development of an efficient image inpainting technique.

There have been many techniques that became prominent with regards to their advantages and usage. Even though many techniques and algorithms have been presented, but each technique has its own drawbacks. Therefore, specifying and selecting a single technique for image inpainting yielding better results is nearly impossible until now. Here, we have concluded and discussed various image inpainting techniques. Inspecting the techniques with respect to performance, it is perceived that, algorithms based on Partial Differential Equation (PDE) function well on preserving structural details whereas lacking behind on inpainting of large absent regions by introducing blurring artifacts. The inpainting algorithms based on texture synthesis has the edge over other techniques since it does not produce artifacts or blurs but fall short on applying to curved structures as well as on thick scratched areas. The hybrid image inpainting techniques retain the structural as well as textural details and restoring smoothness but unable to operate well by introducing blocky effect if the patch size is incorrect and the absent area is too large. The exemplar-based texture synthesis gives remarkable results by preserving the structural in addition to textural information as well whereas gives undesirable results if the distorted regions are expanded towards most of the image. The convolution-based image inpainting algorithms produce magnificent results without introducing blurring effects, but in some cases if the distorted area is greater than ten pixels, blurring is introduced in the image (Patel *et al*., 2015). It is noticed that the calculative complexity increases for the algorithms with a large number of matrix inversions.

The capability of choosing the correct parameters that yield the optimum PSNR values and therefore, presenting the inpainted image with relevant and significant details should be considered. Thus, relevant parameters should be chosen for producing convincing results. The quality analysis and evaluation of the inpainted image is a pivotal and crucial problem. The inpainted image visual quality should be superior when the subjective analysis is taken into account for image quality assessment. Since there are no reliable quantitative metrics, therefore, subjective analysis is considered while evaluating the performance of inpainted image. Thus, subjective analysis is taken into account for estimating that the inpainted image is visually pleasing. Further development in image inpainting techniques in future will primarily focus on optimizing and reducing the above mentioned problems, thus innovating a technique with visually pleasing results and betterment of a technique regarding the computational time taken by the image inpainting algorithm.

Conclusion

In this paper, we conferred a comprehensive review of various image inpainting techniques with an extensive survey on accentuating advantages and disadvantages for each of the technique presented. In order to evaluate various techniques from the perspective of structural and textural characteristics, it should be noted out that the inpainted image retaining both structural and textural characteristics is considered to be visually pleasing. The hidden regions in the image can be recovered, demonstrating the effectiveness of image inpainting techniques. It is expedient to note that the context of an application is put into consideration for determining the use of a particular technique. With the advancement in technology in the field of image inpainting has made it very useful in various aspects. With the development and evolution of plethora of techniques in the domain of image inpainting, the concern lies in specifying a particular technique as the relevant one. It is worth noticing that the combination of structural and textural image inpainting techniques perform better, but at the cost of increased complexity. The primary focus of all the techniques lies in developing a better image inpainting technique with improved efficiency with respect to the time taken and computational cost. The technique should perfectly retain the edge structure and texture uniformity, besides visually pleasing to human perception. The inclination lies in developing an image inpainting technique in which the human brain recognizes no artificially generated variation. Few techniques tend to work slower due to involvement of calculations. There is a dire need of developing an image inpainting technique which deals with high resolution images with significantly low computational time. Furthermore, image inpainting techniques for remote sensing images should be emerged, thus producing desirable results. Various experiments have been carried out to extend image inpainting techniques from 2D to 3D with visually pleasing results. The concern also lies in inpainting of high resolution images with the aim of producing better results in less time. Moreover, there should be an extension of image inpainting techniques to the field of video inpainting as well. Another exploration of this technique lies in researching from still images to sequence of images which comes under the category of video processing. Therefore, video inpainting can also be one of the prevailing topics in future. Video processing may initiate new aspects into the problem but it also initiates new details with meaningful consequences. Equalizing and maintaining the equilibrium of quality and time is another major crucial problem, also to consider accuracy one of the central aspects of image inpainting. Researchers are thriving in originating advance techniques. The future research will pay attention to developing techniques with the objective of less addition of artifacts, thus emerging a perceptually optimized technique by handling both simple and complex structures simultaneously.

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Author’s Contributions

All the authors have equally contributed for development and proof reading this manuscript.

Ethics

Keeping in view of the standard ethical practices, the authors read, agreed and approved to publish the presented manuscript addressing it as original with unpublished material.

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