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TEXTURE MISSING PARTS GENERATION BASED ON IMAGE STATISTICAL ANALYSIS

Introduction. *Restoration of damaged images is a long lasting problem that currently does not have a generalized solution. Many methods which are being used nowadays are damage type specific, which means that for each case of damaged image an algorithm must be picked by a human. A state of the art generative algorithms, which may handle many of the damage types, still lack the precision and require huge training datasets. Thus an algorithm that is able to handle most common damage types and does not demand lots of time and computational power is still in need.*

The purpose of the paper *is to research the current state of the art algorithms that solve texture missing part generation problem as well as to propose a new method, which might provide both precision and ease of use for solving said problem for most of the damage types using the same approach.*

Methods*. Research and analytics are used for processing found literature on the topic to substantiate the main approaches and best practices for the solution of the texture missing parts generation problem. As for purposed method, Gibbs sampling is used as a means of generating missing pixels of the image. Some additional algorithms, which might be used to generate probabilistic distribution for sampler and the means of getting the pixel value from the sampling process, are mentioned in the article itself.*

Results*. State of the art approaches for solving texture missing parts generation are analyzed and compared. Main groups of generative, texture reparation, gradient filling and combined methods are described and compared. New method for generating missing parts of the texture based on statistical analysis of the scene images is proposed. The generation of the pixel values in said method is based on Gibbs sampling. The first results of purposed method with patch based probabilistic distribution generation are shown.*

Conclusions*. The proposed Gibbs sampling based method is able to provide results, which are comparable with those generated by other modern methods. As a future work, it is planned to develop new more sophisticated and precise patches matching algorithms as well as to research other methods of both generating probability distribution and gathering pixel value from the sampling process.*

Keywords: *Gibbs sampling, texture restoration, image restoration, patches matching.*

INTRODUCTION

The problem of texture missing parts restoration is a sub-problem of the general damage restoration problem. Many types of image damage occur due to imperfections in the process of transferring or capturing the image in both camera, lenses, transmitters and receivers or their settings, damaged camera sensors, scene occlusion, optical effects such as sun glare, atmospheric refraction and others [1]. Restoring or filling lost, damaged or distorted parts of the image is the main task in such cases.

Restoration process of the damaged image consists of few main steps.

1. Damaged region detection. On this step all of the damaged pixels of the image should be found for further processing. Some approaches for specific damage types don't include this step as they don't distinguish between good and bad pixels. In those cases all of the image pixels are processed in the same manner. In other cases, where algorithms must know location of the damaged pixels, finding those pixels may be done by a special automatic detector, which looks for specific damage type and masks it, or by a human, who can manually mask the region that should be processed. Sometimes methods of restoration that can generate the texture might be used to enhance the look of the image in some specific regions, for example, by removing some unwanted objects in the image filling them with the continuous background.

2. Surrounding pixels analysis. On this step the information from the boundary pixels (in some cases it might be whole image or even other images of the same scene) is gathered, analyzed and processed. This is the main step as it creates some sort of model of the image, using which the actual restoration is accomplished. In some simple cases, when for example statistical model of the noise occurrent in the image is known, this step is skipped. In most of the modern generative approaches, which use neural networks, this step takes huge amounts of image data and processing time to gather the image model. But once this step is complete such model is applicable to most of the images without any other analysis.

3. Restoration. On this step all of the information from both previous steps is used to restore the damaged image. Depending on the damage types and models used the processes might be split into two groups: restoration and generation. Restoration processes most commonly work with smaller damage areas which occur all over the image and use the pixel data itself to remove distortions. Generation methods work with larger damage areas which might not contain any information or the information in the area might be unusable for the restoration, thus generating of the whole damaged area anew is needed.

4. Post processing. Sometimes after the restoration step some extra post processing is used to enhance the quality of the restored image. This might include some smoothing, sharpening or other quality increasing algorithms. In some cases such approaches are needed to blend in the restored or regenerated are into the existing undamaged image or to weaken the effect of the restoration process on the overall quality of the image.

Most of the approaches both old and modern are skipping the first step as it might vary depending on the goal of our restoration process, but the rest of the algorithms used will still be applicable. In such cases damaged pixels or regions must be externally specified by human or another program, which might be used in pair with the restoration algorithms.

There are many damage types of images in general, but most of them can be classified into few types.

1. Impulsive noise (salt and pepper). This damage type applied to an image changes some of the pixel drastically compared to its neighbors. Back in the days when most of the images were grayscale this noise type would change the pixel color to either black or white (which is why it has such a name). It naturally occurs in damaged camera sensor or in the process of transferring image in transmitter or receiver.

2. Statistical noise. This is damage type, which is applied to the whole image, uses some probability function (most commonly Gaussian) to determine the amount of noise applied to each pixel. While salt and pepper overwrites the information in the pixel completely this damage type preserves the information and distorts it with some random value. It naturally occurs in the condition of low light, when the overall brightness of the image must be increased by the softwear, not the actual increase in the captured light.

3. Mixed noise. This type of noise combines both impulsive and statistical noises. The main struggle in dealing with this type of noise occurs when trying to remove one damage type while preserving enough information to remove another one. Approaches in removing one of the noises mostly fail in removing both, thus more complicated methods are used in such cases.

4. Blur. This damage type occurs when the image was created by a camera which was not properly focused on the object in the image. The way to deal with this damage type is to sharpen the image, restoring distinct edges of the image. In the most extreme cases it is quite a challenge, because most of the information about fine features of the objects in the image is lost.

5. Rolling shutter distortions. This damage type includes many distortions which occurs when the object on the image or the camera itself are moving fast enough that the process of saving pixels of the image is not fast enough to track that motion, thus the object as a whole does not look consistent on the image (it might be only partially lighted by a flash, part of it might be shifted no the side etc.).

6. Missing areas of the image. This is a general type of damage, which actually includes not only real damages applied to the image but also some special masking which might be used to remove objects from the image itself. While this damage type is the hardest to restore, it is the most demanded one. The biggest difference between this type and other types is that we don’t have any usable information around pixels in the middle of the damaged area. While other types have either information from the original image available or the information about closest boundary to the damaged pixel, the missing area damage type does not provide any information, which means, that the area of the image must be restored either by other images of the same scene or by using more information than the nearest boundary from the whole image. This damage type might occur while streaming video and losing some of the packages, which contain rectangular part of the image, while taking images with damaged camera sensor, while taking images or video of the scene with some occlusions, such as, people, street lamps, drone propellers or anything else that might be in the way, while digitalizing burnt or chemically damaged film.

NOISE REMOVAL APPROACHES

Impulsive noise damage type was one of the first ones to occur due to imperfections in encoders, transmitters, receiver and decoders, which were used to transfer images. Statistical noise damage type was also very common due to imperfections of cameras and their limitations in light perception.

The first approaches of removing any noise were based on filtering process [2]. Filtering is based on the simple technique of using small fixed-size matrices (filters) to traverse the whole image and perform some operations over pixels.

Most commonly known filters are used to remove noise by some type of averaging. The idea behind said process is to eliminate the noise by using information from the surrounding pixels. The approach is based on the assumption that in most of the times we will have one of the following cases:

1) the noisy pixels are less common then the noise-less ones in the filter;

2) the amount of the noise present in the pixels is much less than the information left in those pixels;

3) the noise in the filter can cancel itself out if averaged over the filter area.

The most common filter types are mean, median and Gaussian filters. While both mean and Gaussian filters remove the statistical noise to some degree, they are not able to deal with salt and pepper noise. In contrary median filter is able to deal with the salt and pepper due to the fact, that it does not use information from all of the surrounding pixels but only from one of them, which has the median color. Such property implies that after median filtering the statistical noise will still remain [3].

The main problem with such filters is the blurring effect which occurs after usage. The amount of blur depends on the type and size of the filter, but so does the noise removal capabilities. With each filtering the edges of the image are becoming blurred and the fine details are becoming less and less distinct. The bigger the size of the filter the bigger the size of the features that are getting lost.

Unlike previous filtering methods modern ones are able to deal with both noise types at the same type while still preserving the sharpness of the image. Such capabilities of the modern filtering processes are achievable due to the notion of edge preservation filters [4].

Usage of filtering techniques that not only remove noise from the image but also don’t blur it provides us with the solution of the image restoration problem for the noise damage types. Even though there is no proper metric to evaluate the results of the algorithms other than visual comparison with other restoration methods or an overall visual evaluation made by human observer, the current state of the art noise removal filtering methods are at the peak of the both speed and quality. But such methods are not applicable to any other damage type, due to the fact that they are specifically developed for the noise type damage problems.

DEBLURRING

The next damage type is blur, which is one of the most common types of image damage, due to the nature of its occurrence. First methods of dealing with blur are sharpening filters that try to increase the distinction of edges on the image thus providing some level of sharpening. Even though such methods didn’t provide any distinguished results they were applicable to all of the blurred images with some level of success [5].

State of the art methods of dealing with the blur are specific to the nature of it. There are three types of blur that cover most of its occurrences [6].

1. Out of focus blur. This type of blur appears commonly when the camera is not properly focused on the object. Even though the name implies that this type of blur connected only to the unfocused camera there are some other types of blur that are related to it and have similar resulting effect on the image. Most common blur types are Gaussian and averaging blurs, which created similar “out of focus” image.

2. Motion blur. This type of blur occurs when the fast moving object becomes unfocused due to rapid change of the distance to the focus plane of the camera and due to the inability of camera to capture the image fast enough so the pixels start to shift with the object itself creating ghost effect of the object. This type of blur can be easily recreated using special motion blur filters.

3. Atmospheric turbulence blur. This type of blur occurs when the image of the far object is taken. Due to turbulent movement of the air and its ability to act as a type of lens over a far enough distance the image of the far object is distorted in two ways: by geometric shifting and by out of focus blur. Even though this dual effect is not the pure type of blur the name “Atmospheric turbulence blur” is commonly used to describe it as well as more precise name “Atmospheric turbulent degradation”.

Modern methods of dealing with blur are divided into two groups: those which know the blur matrix (non-blind), and those that don’t know it (blind) [7].

Also methods for solving blur problem are divided into two main groups: traditional methods and neural network approaches.

Traditional methods consist of methods that use some type of filtering and/or Bayesian algorithm. The most well-known and proven to work on practice are the following.

1. Weiner filter [8]. This method relies on prior knowledge of the blur parameters. Main goal is to minimize the mean square error between desired and estimated random processes. If used on the motion blurred image without additive noise applied Weiner filter is reduced to the ideal inverse filter, but when some noise is added to the mix the results are not as good.

2. Richardson-Lucy algorithm [9, 10]. It is an iterative procedure that aims to restore blurred image based on known motion blur filter or as it is commonly called point spread function. The main downside of this process is the amount of iteration it takes to deblur the image. If too many iterations are used the image might have the “ringing effect”, while not enough iterations means that the image won’t be deblurred. There are modifications of those algorithms that are trying to deal with said problem as well as decrease the time taken to process the image.

3. Blind deconvolution approach [11, 12]. This is a set of methods that aim to restore the image by estimating point spread function using blurred image or set of images. One of the most known algorithms that solve blind deconvolution problem is Expectation-Maximization algorithm [13, 14]. It is an iterative algorithm that maximizes likelihood of the blur and noise parameters by repeating two steps — Expectation and Maximization. On the first step of the iteration algorithm creates expectation function of log-likelihood using current

estimated blur and noise parameters. On the second step it uses that function to computer parameters which maximize it.

In recent years more advanced methods based on the traditional approaches were developed. Most of the newly developed methods are based on the unknown blur and noise parameters as these cases are the most common in real-life applications.

One of the best-performing method is ASDS-AR, which stand for adaptive sparse domain selection — autoregressive [15]. It is a complex algorithm that utilizes pre-collected image dataset to create sparse domain that is able to represent most of the occurring input images. Based on that image data a set of autoregressive models is created to then be used in finding the best model which represents given patch. Such model then used on image local structures to regularize them. This approach and its variations outperform most of the other traditional methods as shown in [16].

While non-blind methods are not as interesting on their own due to lack of real-life cases, where the parameters of the blur and noise are strictly defined, there are newly established techniques to estimate those parameters and then use non-blind methods as if blur or/and noise parameters were known before the process of image restoration. As shown in [17], parameter estimation techniques are possible to use together with non-blind methods for some degree of success.

Most of the methods mentioned above are related to first two types of blur, because not all traditional methods are capable of dealing with Atmospheric turbulence blur. Even though the algorithms for solving said problem with decent quality of the result were developed quite a long time ago for both ground [18] and space [19] applications, these methods keep on developing increasing both their speed and precision at the same time [20, 21].

Other type of methods, which are based on neural networks, are starting to dominate the field in recent years. Due to excess amount of image data and abundance of computational capabilities of modern clusters it became possible to use such methods quite successfully.

Neural network approach is based on the notion of a perceptron, a simple cell that receives many input signals and gives off a weighted sum of those signals as an output. When stacked together those cells create layers of the neural network. Nowadays there are much more complicated concepts and representation of said structures such as convolutional neural networks, recurrent neural networks, generative adversarial networks, long short-term memory and many more [22] but the bottom line of all of them is the idea of a simple classifier such as perceptron being stacked in a specific manner and some weight training algorithms applied to the whole structure to train the network.

Using the modern neural networks deblurring of both atmospheric [23, 24] and motion [25] blurs became much less complicated of a task even though the state of the art approaches are a mix of both traditional methods and neural networks [26, 27].

ROLLING SHUTTER EFFECT REMOVAL

Rolling shutter effect is most commonly referred to in the context of video, as the still image does not fully uncover the effect itself. Only by watching the movement of the objects on the video one can see the rolling shutter effects.

These effects are generally splitted into three groups.

1. Skew. It occurs when the camera moves in some direction with almost constant speed, which is high enough that the time it takes camera sensor to capture a row of pixels is enough for the camera to move some distance which will make the next row of pixels appear to be shifted in the opposite direction to the movement.

2. Wobble. It occurs when there is acceleration of the camera high enough to interfere in the process of image capturing. Such distortions are commonly present on the cameras, which are mounted on fast-moving vehicles such as helicopters, planes or drones.

3. Partial exposure. It occurs when a fast changing light is present on the scene. Such light source might be a lightning or a strobe. This effect causes some parts of the image to be lighter than the others.

Last type of rolling shutter effect is least explored as most of the times it is either fixable eternally by setting proper strobe speed or does not provide enough information to light up unlit areas of the image due to huge differences in the light levels.

Skew can be corrected knowing the global motion of the camera itself [28], or, in the case of object movement rather than camera movement, an optical flow is used to correct the effect [29].

The main rolling shutter challenge is the wobble. There are two methods for solving that problem: ones that require external calibration and calibration-free ones.

The first type of methods demands some external camera parameters, which can not be simply gathered from the video. Sometimes those parameters can be estimated using the video, but the errors of such estimations may add more wobble to the result, as shown in [30].

Second type does not rely on such parameters and fixes the rolling shutter effects just using the video information. Most of those method rely on some kind of motion estimation using which an approximate model of rolling shutter can be obtained and used to correct the effect [31].

Also there are methods which work with images and do not need any external parameters, but they mostly rely on the straight lines in the man-made environment [32]. These methods are able to correct even the strongest of the rolling shutter effects, but only in very few specific scenes, which are full of man-made lines. Due to the limited applications these methods are not as popular as others.

Neural networks are also used to solve the rolling shutter correction problem and nowadays they outperform traditional methods used in this field. This is very fast-growing research field, thus each year the new generation of neural networks beats previous state of the art networks and methods in precision, speed and compactness [33, 34]. Unlike some of the traditional methods though, most, if not all, of the neural networks are not accepting any external camera parameters, thus being unable to compete with state of the art methods that are using those parameters.

DAMAGED IMAGE AREAS RESTORATION

As with both previous damage types, methods that are used to remove the damaged areas from the images can be split into traditional and neural network approaches.

Traditional methods are mostly represented by two types of methods.

1. Diffusion. These methods use partial differentials to propagate edges and then use them coupled with diffusion mechanisms to restore the damaged areas. Such methods are usable only on small regions without big texture variations. When used on big areas of the image results seem fuzzy and the textures are not restored at all, because such methods can not gather any information about the texture itself [35].

2. Texture-based. These methods are estimating information about the textures present on the image and then trying to generate those textures using pixels that surround the damaged area. Such approach makes it possible to fill in larger areas restoring the fine texture details [36].

As it might seem from the description of two traditional methods the second one is much better, as it allows filling bigger areas, but the main problem with it is the fact, that the texture generated is not always going to blend well with undamaged image. This is due to the fact that those approaches are trying to generate infinite texture, which is not what most real-life application need.

There are also methods, which embody both of those approaches using not only background texture information, but also the edge information to properly blend the textures [37].

Neural network approaches include many different paradigms of the network construction and mechanisms used. But one of the most prominent of them all, as shown in [38], is CVAE-GAN [39], which is able to generate different images of the same object classes, which allows it to vary the output result. This network is based on two ideas.

1. GAN (generative neural networks) models, which takes a noise vector as an input and uses special trained generator together with the noise vector to generate the resulting image or its part. Even though the resulting image is clear in some sense it is not real, which means that it can't be used in some precision-requiring tasks.

2. VAE (variational auto-encoder) [40], which is able to provide real, but quite fuzzy images.

Main idea of CVAE-GAN is that combining those two methods will create the model, which is able to generate both clear and real images.

LITERATURE ANALYSIS SUMMURY

Based on the experience of the previous researchers, generative algorithms are the most common way of restoration of the most damage types. No matter is it traditional texture restoration or a neural network approach, generative algorithms, which take into account the surrounding fine features of the image, are the way to go.

Also, as practice of the recent years shows that neural networks, which are able to synthesize important connections in data, which are too complex and complicated for humans to see and understand, are superior in both precision and visual appeal for a human eye than any other method available. The main downside of neural networks being the need of huge amounts of clean classified training data and a lot of computational power.

Thus, method, that does not require so many data and time to train, but is still based on the same principles of generativeness, feature aggregation and ability to use fine details is in need.

PROPOSED METHOD

Main algorithm used in the proposed method is the Gibbs sampling [41]. Its main idea is to sample using conditional distribution rather than joint distribution. It is achieved by traversing elements in some order, freezing other elements and using conditional distribution to sample new value for current element, which will be used in calculations of further distributions.

The usage of Gibbs sampling in texture generation is not a new groundbreaking achievement on its own. It has been done in [42] with some degree of success. But that approach has many drawbacks and limitations.

We propose usage of Gibbs sampling process together with patch based probability distribution function builder as a means of generating damaged pixels. The idea is that we can gather some statistical information about the scene from the training dataset and then use it to sample missing pixels. Using patch based approach we might be able to preserve fine details and at the same time gather statistical information about textures, which appear on the image.

The method can be used for regenerating single images, image collections or videos, as the only difference is the training data used for probability distribution function builder. Also proposed method might be able to deal not only with missing areas of the image but also with some types of noise and blur with some degree of success.

APPROBATION

We decided to use simple ways of using patches and generating probability distribution at first, to test the potential of real-life usage of the proposed method.

For the experiment five images of the same scene, but from different angles and positions, were taken. One of them will be damaged and used as a testing, others as training datasets.

From every image of the training dataset a square patches of a fixed size with fixed padding were cut and stored. These will be our patches, from which probability distribution will be built.

Testing image was damaged by erasing data from the central rectangle of the image, which contains intersection of three different texture: flowers, wooden wall and leafs.

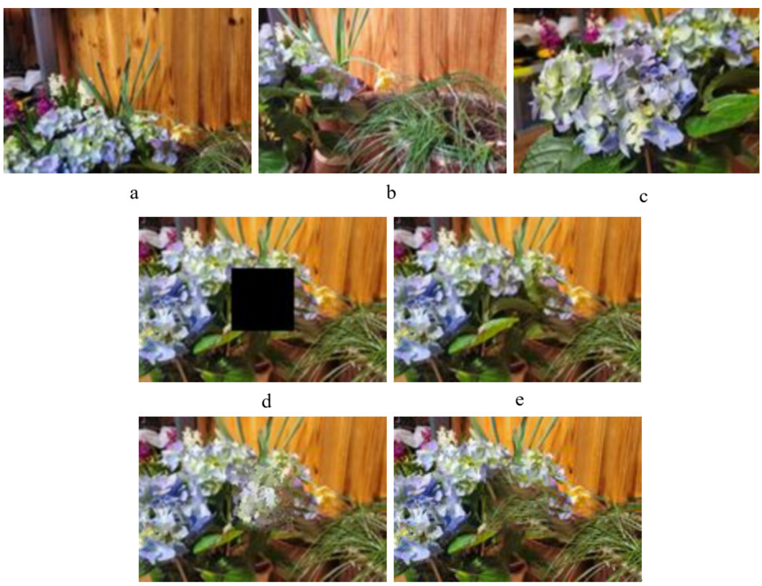
As a preprocessing step the damaged area might be filled with some type of simple inpainting algorithm, with a mean color of neighboring pixels or just left empty as it is. This step might increase the speed of convergence of the Gibbs sampling, but the effect of such preprocessing must be further investigated. In the test that is shown in the article the damaged area was left without any pre-filling.

The iterating process of Gibbs sampling begins. On each iteration we traverse damaged pixels in the left to right, top to bottom order and overlaying patches from training dataset we calculate the similarity of the patches as a negative weighted sum of euclidean distances between colors in corresponding pixels. Similarity between patches might vary depending on weights used. If we want patches to be similar at any distance from the center of the patches, then we might set the weights to 1. If we want only the few central pixels to be important, then we should use any bell-like function. In the experiment Gaussian function was used with such parameters, that the corner weights were close to 0.5, while the central one was 1.

To build probability distribution we use normalized exponents of similarities. Using that distribution we sample the closest patch. The idea here is to find such parameters, that the amount of patches that has reasonable chances to be picked is quite small, but not equal to 1. In case it is equal to one most of the times, we won't have any "generative" properties as there won't be any randomness involved into picking the patch. In case the number of decently probable patches being too big, the result will be too random, which means that any fine features of the textures and whole textures themselves are unlikely to be restored with any decent level of precision. The parameters that influence the amount of probable patches are: similarity function, probability distribution builder, patch size relative to common texture size on the image, overall amount of patches and their uniqueness.

As a last step of the processing the pixel data from the sampled patch is gathered. The simplest way is to take just the central pixel and overwrite the previous value with the new one. But also approaches like mixing new and old colors or spreading the color to neighboring pixels might be used.

After traversing over all damaged pixels and assigning them new values one iteration of the sampling process is complete. Depending on the image size and damaged area the amount of steps required to achieve any decent-looking results will vary. Every iteration propagates "reliable" information to the center of the damaged area, starting from the surrounding pixels, filling the first layers of the damaged pixels, which are adjacent to undamaged ones, and continuing doing the same for further pixels on the next iterations.



a b c

d e

f g

Fig. 1. Training dataset (a, b, c), damaged image (d), original image without damage (e), restored image using proposed approach (f), restored image using content aware generative fill based on GAN approach realized in Adobe Photoshop version 24.7.0 Release (g).

Visually analyzing resulting images we are able to conclude that the proposed method is able to produce comparable results with the state of the art commercial models.

We can see that the neural network left some kind of border while reusing big parts of the image and blending them in with the surrounding pixels. While it did a good job of gradually changing the colors of the reused part to match the color of flowers the overall connectivity of texture doesn't make much sense.

The proposed method on the other hand, not only generated its own petals to mimic the flowers texture but also merged the textures around it quite well. While being bound to the colors of the central pixels of the patches from train dataset it does not provide us with much variety of color. Also the damaged part generated by proposed method has some kind of salt and pepper noise (which might not be visible well enough due to small picture resolution). This might be an artifact created by the lack of color and patches to match with the surrounding generated petals. Also it might occur due to the fact of absence of any external smoothing mechanism, which might be needed in this method. But the main downside of current version of the method is its speed. The algorithm for the patch matching iterates over too many patches and processes too many pixels on each iteration. Decreasing the amount of patches will decrease variety in available colors, which will drastically decrease the quality of the resulting image.

CONCLUSION

State of the art methods of common damage types restoration are described and analyzed. Main advantages of the best currently available methods are determined. New method of texture missing parts generation based on image statistical analysis is proposed. Basic algorithms, which might be used in proposed method are described. Approbation of the proposed method using said algorithms is made. Results are analyzed and compared to state of the art neural network model.

Analysis confirms that the proposed method is worth developing further as it is able to provide decent results even using basic algorithms for calculating probability distributions and getting pixel value out of the sampling results.

It is planned in future researches to develop better and faster pattern matching algorithms, to research other possibilities of using patch based approach for generating probability distributions and to test the new iterations of the developed method on other damage types and with dataset of different kinds and origins.

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ГЕНЕРУВАННЯ ВІДСУТНІХ ЧАСТИН ТЕКСТУРИ
НА ОСНОВІ СТАТИСТИЧНОГО АНАЛІЗУ ЗОБРАЖЕНЬ

Вступ. *Відновлення пошкоджених зображень є довгостроковою проблемою, яка наразі не має узагальненого рішення. Багато методів, використовуваних сьогодні, залежать від типу пошкодження, а це означає, що для кожного випадку пошкодженого зображення алгоритм повинен підбиратися людиною. Сучасним генеративним алгоритмам, які можуть впоратися з багатьма типами пошкоджень, все ще бракує точності, і вони потребують великих наборів даних для навчання. Отже, все ще потрібно розробити алгоритм оброблення більшості поширених типів пошкоджень, який би не потребував багато часу та обчислювальних потужностей.*

Мета статті *полягає в дослідженні поточного стану алгоритмів, які вирішують проблему генерування фрагментів текстури, а також в пропонуванні нового методу, який міг би забезпечити як точність, так і простоту використання для вирішення цієї проблеми для більшості типів пошкоджень, використовуючи той самий підхід.*

Методи. *Дослідження та аналітика використовуються для оброблення літературних джерел за темою і для обґрунтування основних підходів і кращих практик для вирішення проблеми генерування відсутніх частин текстури. Щодо спеціального методу, семплювання за Гіббсом використовується як засіб генерування відсутніх пікселів зображення. У самій статті згадуються деякі додаткові алгоритми, які можуть бути використані для генерування ймовірнісного розподілу для семплера та засоби отримання значення пікселя з процесу семплювання.*

Результати. *Проаналізовано та порівняно сучасні підходи до вирішення проблеми генерування відсутніх текстур. Описано та порівняно основні групи методів генерування, текстурної репарації, градієнтного заповнення та комбінованих методів. Запропоновано новий метод генерування відсутніх частин текстури на основі статистичного аналізу зображень сцени. Генерування піксельних значень у зазначеному методі базується на семплюванні за Гіббсом. Показано перші результати використання методу з генеруванням ймовірнісного розподілу на основі латок.*

Висновки. *Запропонований метод на основі семплювання за Гіббсом здатен забезпечити результати, які можна порівняти з результатами, отриманими іншими сучасними методами. В якості майбутньої роботи планується розробити нові складніші та точніші алгоритми зіставлення патчів, а також дослідити генерування розподілу ймовірностей для інших типів пошкоджень.*

Ключові слова: *семплювання за Гіббсом, відновлення текстури, відновлення зображення, відповідність патчів.*