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An efficient image inpainting using patch sparsity with geodesic distance

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Abstract Image inpainting could be a technique that is employed to patch up the missing portion in an image. In this paper, we have introduced an efficient approach for patch-based image inpainting by exploitation geodesic distance metric. Textural descriptors are accustomed guide and identify the layout for well-matching (candidate) patches. A strong top-down rending procedure splits the image into variable size blocks consistent with their texture, restricting there by the layout for candidate patches to nonlocal image regions with matching texture. This technique is used to improve the speed and performance of any patch primarily based inpainting methodology. Geodesic propagation algorithm continuously updates the weights of geodesic distances values till the patches are propagated to any or all the pixels. With the help of geodesic distance value of the patch, we can easily identify the most suitable patch for filling up the missing or affecting area of the image. The experiment is evaluated with various data sets and existing techniques to show the effectiveness and efficiency of the proposed method.

Keywords: Belief propagation, Contextual descriptions, Diffusion, Geodesic distance, Texture synthesis**.**

1. Introduction

Image inpainting concept is useful for fill up the corrupted /missing data within the image. Image reinstallation consists of restoration of old images/photographs associated damaged image by elimination of an unwanted thing like a person, animal, tree etc. is understood as object removal [1]. The goal of image inpainting is not solely to recover the photographs, however to come up with few images that have closely similar with the original image. In literature survey, two classes of image inpainting methodologies are often described. They are diffusion based method and patch-based method. Diffusion primarily based methods fill the inside the lacking region (“the hole”) through easily propagating image content from the boundary to the internal of the missing region. The diffusion- based inpainting algorithm produces nice results or filling the non-textured or comparatively smaller missing area [3].The disadvantage of the diffusion method is it introduces some blur, which becomes noticeable when filling larger regions. Patch primarily based technique fill inside the missing or corrupted part patch-by-patch by checking out properly matching alternative patches (candidate patches) inside the unbroken area of the image and repetition them to respective places [4], whereas these processes contribute few thoughts with patch primarily oriented texture synthesis. In addition to that they concentrate on structure propagation either via shaping and the filling order exploitation involvement or by dividing the image into texture and structure elements.

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Patch-based strategies could also be classified into greedy, multiple candidate and global. In the greedy method, the grasping ones pick just one well matching healthy patch for each and every patch to be crammed decision the objective patch, depends on its recognized pixels. It can be often obtained in associate repetitive methodology which gently fills the missing area. Multiple candidate methods infer the lacking location exploitation weighted average or a allotted aggregate of more than one candidate patches at every region [5]. At last, global ways outline the inpainting as a worldwide improvement performs. Many global ways define inpainting as a global improvement drawback [13]. Many methods are available in which global image context with a geodesic distance. A main issue of patch primarily based approaches is that the look for candidate patches. Solutions to keep away from the time overwhelming complete tracing embrace lock up the search to a region window, directional search, search on user-designed curves and using already present segmentation of the image [2].

Patch Match, a quick patch seeking technique is applied in conjunction with the world technique. For discourse description, we have a tendency to utilized normalized texon histograms calculated from Gabor filter output as discourse descriptions. Some texon histograms are calculated from the output of assorted filters that area unit already utilized for image segmentation, classification of texture and image retrieval [6]. We have a tendency to take under consideration two fully completely different ways for splitting the image into various regions supported the texture: An easy division into rigid size square non-overlapping blocks and plenty of subtle division into blocks of reconciling sizes [15]. Compared to the similar technique, this method is quicker and occupies less memory, permitting method of larger size images.

2. Proposed Methodology for Image Inpainting using Geodesic Distance ::

2.1 Division into Blocks of Fixed Sizes

Let the input image I be outlined on a lattice S. Pixel positions on this lattice are indicated by single index p ε S, assumptive formation. Let Ω C S denote the region to be filled (target region) and ϕ C S denote the best-known part of the image (source region), wherever Ω U ϕ =S.

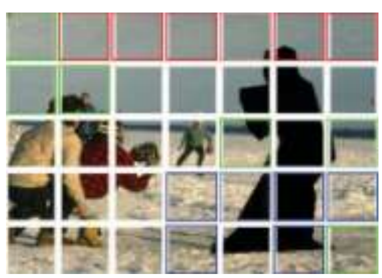

Fig 1 Image division into 5x7 fixed block size

The test image is split into 5x7-block size it is shown in above fig 1. Moreover, the optimum size of blocks will take issue from one image to a different. For the missing region at intervals a given block, well-matching candidate patches are going to be found within the contextually similar blocks [14]. Suppose we have a tendency to divide the image into M x N square non-overlapping blocks. We have a tendency to denote by B_l an

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image block targeted at the position l. The central positions of all the blocks make a set λ that is set, along with the block sizes, by the actual block division scheme [9].

Algorithm 1 Patch Selection

1: **for all** Bl such that $l \in \lambda$ and $Bl \cap \phi \neq$ null do
2: set $\phi^{(l)}$ =null
3: **if** B_l is reliable **then**
4: Compute $H^{(l,m)}$, Θ $\forall$ $m \in \lambda$ (Eq. (1))
5: define new source region $\phi^{(l)}$ (Eq. (2) and (3))
6: **else**
7: **for all** neighbouring blocks B_n **do**
8: repeat steps 2-5
9: add $\phi^{(n)}$ to $\phi^{(l)}$
10: **end for**
11: **end if**
12: **end for**

The idea is constrain the supply region for target patches from a block B_l to a neighborhood $\phi^{(l)} C \phi$ with the context well matching that of B_l. We have a tendency to assign to every block B_l a discourse descriptor $c^{(1)}$, that generally, is a few feature vector that characterizes spatial content and textures among the block. Let us outline a measure of discourse difference $H^{(l,m)}$

$$H^{(l,m)} = d(c^{(l)},c^{(m)}) \tag{1}$$

Where $d(c^{(l)},c^{(m)})$ is some distance measure between contextual descriptors $c^{(l)}$ and $c^{(m)}$.

The additional similar denote the set of positions of the blocks that similar context of the blocks B_l and B_m, the lower $H^{(l,m)}$ [17]. Let $\Sigma^{(l)}$ denote the set of positions of the blocks which are contextually the same as B_l. In general, we will write

$$\Sigma^{(l)} = \{m \mid H^{(l,m)} \leq £ \wedge m \in \lambda \} \tag{2}$$

Where £ is some block similarity threshold.

The affected source $\phi^{(l)}$ is then a union of region proverbial elements of block indexed in $\Sigma^{(l)}$.

$$\phi^{(l)} = U_{m \in \Sigma(l)} (B_m \cap \phi) \tag{3}$$

The planned approach is summarized as pseudo code. It additionally applies to the adaptive blocks simply that the set λ is set by the adaptive block division scheme.

2.2 Division into Blocks of Adaptive sizes

In most natural images, some image areas imply finer division than the others. Moreover, the optimum size of blocks will disagree from one image to a different [11]. A top-down splitting procedure that divides the image into several blocks with adjustable sizes based on the homogeneity of their texture.

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Top-down splitting Pseudo code:

```
if δ^(l) = h then
  t1:
     if H_h > £ then
          d=h;
     else
          if δ^(l) = h then
               goto t2;
          else
               B_l is not divided further
               stop
          end
     end
  else
   t2:
       if H_v > £ then
          d=v;
       else
          if δ^(l) = v then
               goto t1;
          else
               B_l is not divided further
               Stop
          end
       end
   end
   divide B_l into B_l1d and B_l2d along the direction d
   assign zero to j.
    t3:
         Increment the j value by 1
         if j>2 then
             stop
         else
              if check the minimum size reached or
              unreliable block?
                   B_l is not divided further
                   goto t3;
              else
                   B_ljd is amenable to further splitting
                   δ^(ljd) = d ;
                   goto t3;
```

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end
end

There is a desire to favour that the splits in horizontal and vertical directions alternate through levels so as splitting τνεϖερπto on one direction solely. Therefore, we have a tendency to assign every $\phi^{(l)}$ ε {h,v}, block at directional flag.

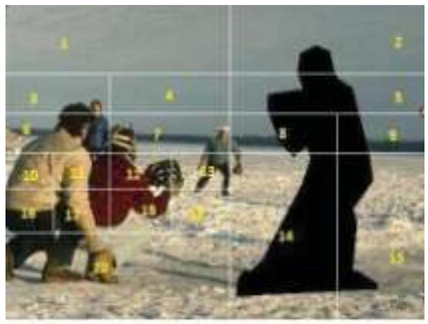

Fig 2 Image with Adaptive block size

The test image divided into adaptive block size and it is shown in the above fig 2. In this every block is more separated into varied sizes [19]. This flag determines the direction horizontal (h) or vertical (v) on that the analysis of the block's homogeneity can have the priority Let B_{l1d} and B_{l2d} denote two sub-blocks of B_l along direction d. we have a tendency to measure the non-uniformity of the block B_l on direction d because the contextual dissimilarity from Eq. (1):

$$H_d^{(l)} = H^{(l1d,l2d)},\ d=h,v \tag{4}$$

Splitting along the direction d is allowed as long as $H_d^{(l)}$ exceeds a given block similarity threshold £. $H_d^{(l)}$and $H_v^{(l)}$ are evaluated consecutive, within the order that depends on the directional flag $\phi^{(l)}$.

2.3 Geodesic Propagation

Given an input image I, the patch is to assign every pixel x ε I with a exact label l ε L, wherever L = {1, 2, …N}. We have a tendency to build up a 4- neighbor-connected graph G = (V, E) on the image lattice. We then choose strong seeds to propagate labels throughout the entire image [3].

2.3.1 Edge Weight

In order to propagate assured labels to applicable pixels, numerous image features have to be in an elaborate way designed. These features can indicate real objects distribution on the input image and guide geodesic propagation approaching to the inherent labeling [4]. Based on the popularity proposal, we tend to include global color distribution is varied across all objects of a class [16]. However, within the input image, the determinable color distribution across a number of instances is compact. Such determinable color distribution captures a plenty of precise image-specific look feature than former class-specific recognition system. Moreover, it will capture several clusters in feature space, demonstrating a capability to handle inner-class selection [20]. Here we have a tendency to calculate the expected color histogram H (x | l_i) of the recognition proposal p (l | I) for each class. Under the idea of Gaussian Model in HSV color space, we estimate the color probability p (xx|l) through EM algorithm [18]. By Bayesian theorem, we further calculate the posterior probability p (l|x) = p(x|l) p(l) /Σ_i p(x|l_i)which indicates however probably the pixel x belongs to the label l. The edge weight is defined as

$$w^c(x,x`|l) = \frac{\| p(l|x) - p(l|x`)\|}{(p(l|x) + p(l|x`))} \quad (5)$$

2.3.2 Geodesic Propagation Algorithm

The solution to image inpainting is developed as a way to calculate the shortest geodesic path from every pixel to the hole. We have a tendency to propose a geodesic propagation algorithmic rule generalized from Fast Marching Algorithm at the same time propagate the geodesic distance of all categories with efficiently. For a pixel x, if one patch l_i is propagated to x prior to alternative patches, then the corresponding geodesic distance D_l (x) to l_i is shorter than others, We have a tendency to propagate all patches at the same time to the whole image and once the geodesic path of patch l_i reaches pixel x, its shortest geodesic distance min $_{l\varepsilon L}$ D_l (x) is decided[8]. The time complexity of the algorithm is more economical than alternative algorithms.

During geodesic propagation, every vertex has three statuses: labeled, reachable and unlabeled. The labeled vertex is allotted label determinately also as its marginal geodesic distance. The set of approachable vertices includes the neighbors around the labeled vertices. The approachable vertices are sorted in step with their geodesic distance and place into the ordered queue Q_R. Different vertices are marked as unlabelled to point that the geodesic propagation has not reached them nevertheless. Our rule iteratively selects the vertex vi of the minimum distance within the reachable queue Q_R, sets v_i as labeled and propagates labels to its neighboring vertices till the reachable queue is empty. Almost like the Dijkstra algorithm, our algorithm will with efficiency calculate the most effective labeling with marginal distance from every pixel to the initial seeds [7]. The time complexness of the proposed algorithm solely depends on the image resolution. The computational time will increase linearly with the image size.

The GP algorithm encodes less contextual relationship between objects. Therefore, we have a tendency to propose a geodesic algorithm encoding context constraints. Given an input image, we have a tendency to first get the similar image set from the annotated dataset exploitation Gist matching. We have a tendency to infer the proposal map of the input image for texture and boundary features of the input image and also the contextual similarity of the similar images are integrated into geodesic propagation to fill the hole. Every super pixel sp_i may be a vertex v in graph G, and is allotted a selected label l contained within the dataset through geodesic propagation procedure. The edge set E consists of the edges between neighboring vertices. We have a tendency to outline the weight of edge W ($sp_{i,}$ sp_j) on a hybrid manifold, incorporating texture and boundary features. The edge weight indicates the smoothness between neighboring vertices sp_i and sp_j. Every super pixel sp_i ε I is matched to proper super pixel r (sp_i) ε R that has the smallest matching distance. The subsequent distance metric is employed to calculate the matching distance within the re-ranking procedure. Given two image I and R, the matching distance D_r (I, R) is scored a

$$D_r(I,R) = \Sigma \ \| (fv_{spi} - fv_{r(spj)}\|^2 \quad (6)$$

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s_{pi} ε I, r(spi) ε R

Where fv_{spi} could be a 22-dimension descriptor of sp_i, includes average HSV colors, coordinates and 17 dimension**.** The Euclidean distance metric is employed in implementation. Once re-ranking the gist similar image consistent with their matching scores, we have a tendency to get the highest K similar images that are denoted as $\{R_K\}$. In our experiment, use $\{R_K\}$ because the similar image set rather than{R}.

2.4 Propagation Indicator

Each image R $\{R_K\}$ is similar to the input image in some aspects, like the appearance and also the contextual data. Therefore we tend to assume that the contextual similarity between the similar image set and also the input image will offer helpful information for parsing the input image. Based on this assumption, we tend to take indicator for propagation. A group of classifiers is learned on the similar image set to guide the propagation and every semantic class has its corresponding classifier [12]. we tend to denote these classifiers because the propagation indicators. We tend to introduce the way to get the indicator of every class.

Our indicator is employed to classify whether or not to propagate path from super pixel sp_i to its neighbor spj within the input image. To measure the weight of edge $W_{spi,spj}$ on graph G, here we tend to integrate two elements: the texture component and the boundary component[5]. The weight function W between neighboring vertices is demonstrated in Equation 7. Regions of different categories will usually present apparent texture disparities [11]. Thus, we tend to use a texture descriptor to live the $W_{texture}$ (sp_i, sp_j) with Euclidean distance metric. This texture descriptor consists of average HSV colours and 17 filter responses features. The boundary, as vital local changes, carries robust information for object distinction [10]. We tend to apply reliable Berkely edge detector combining color, brightness and texture cues to capture the boundary confidence. The weight function for boundary component W_{bdry} is outlined in equation 8, within which is θ the threshold for boundary confidence P_b. We tend to discover the boundaries at pixel level then convert these boundary confidences into super pixel level.

$$W(sp_i, sp_j) = \lambda 1 \ W_{texture}(sp_i, sp_j) + \lambda 2 \ W_{bdry}(sp_i, sp_j) \qquad (7)$$

Where $W_{texture}$,W_{bdry} are texture component and boundary component respectively.

λ1 , λ2 are tuning parameters.

$$W_{bdry}(sp_i, sp_j) = P_b(sp_i, sp_j\ \theta) \qquad (8)$$

Algorithm 2: Geodesic Propagation Algorithm

Require: Candidate seed set S = $\{v_i : (x_i,y_i,p_i,l_i,),i \in [1,S], l_i \in [1,N]\}$

Ensure: label set L=$\{l_i\}$ where $l_i \in \{1,...N\}$

1: Put all nodes v_i into unlabeled set Q;

2: Push S into reachable queue Q_R;

$v_i \leftarrow$ head of Q_R and put v_i into labeled set L;

3: Choose any neighbor node $\{v_j)$ of v_i;

4: Push v_j in Q into Q_R;

5: Update v_j in Q_R

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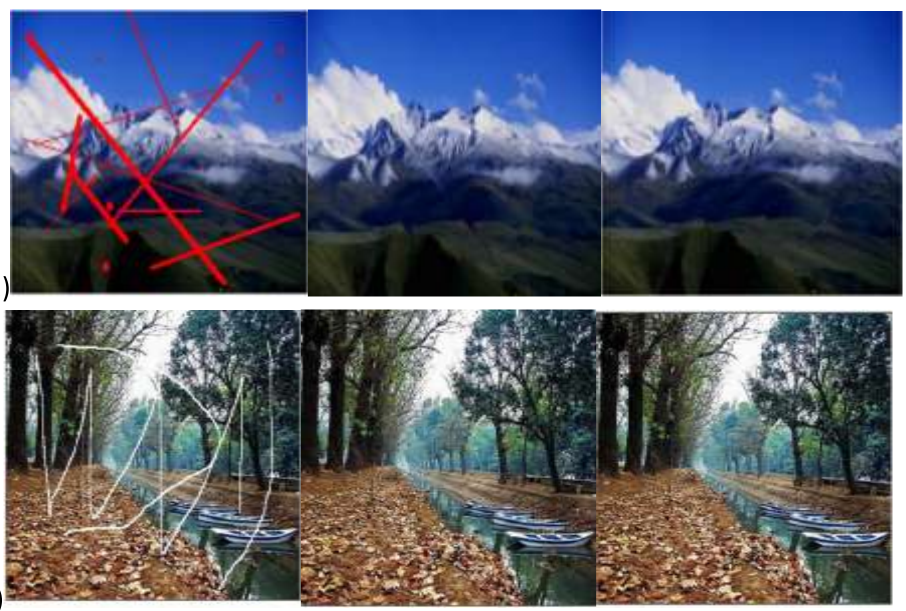
if $D_i + W_{ij} < D_j$ then
update D_j with $D_i + W_{ij}$;
assign l_i to l_j;
else
D_j an l_j remain;
end if
6. Repeat steps (3) to (5) until Q_R is empty.
----

3. Complexity analysis

Experimental results show that the computation time of the p-BP (Belief Propagation) and also the planned technique, exploitation our own MatLab implementation of every strategy. On several take a look at images, for the sake of honest comparison, we have a tendency to check the algorithms for a similar patch size as represented inside the primary column of the table. The planned technique is applied clearly a lot of quicker (for some pictures up to six times). Most of the computation time for every strategy is spent on label pruning. Therefore, acceleration of our methodology is because of the use of contextual data, that yields a smaller label set and thus there is less work for pruning. Low-level formatting is additionally a lot of accelerated due to same reason.



(1)

(2)

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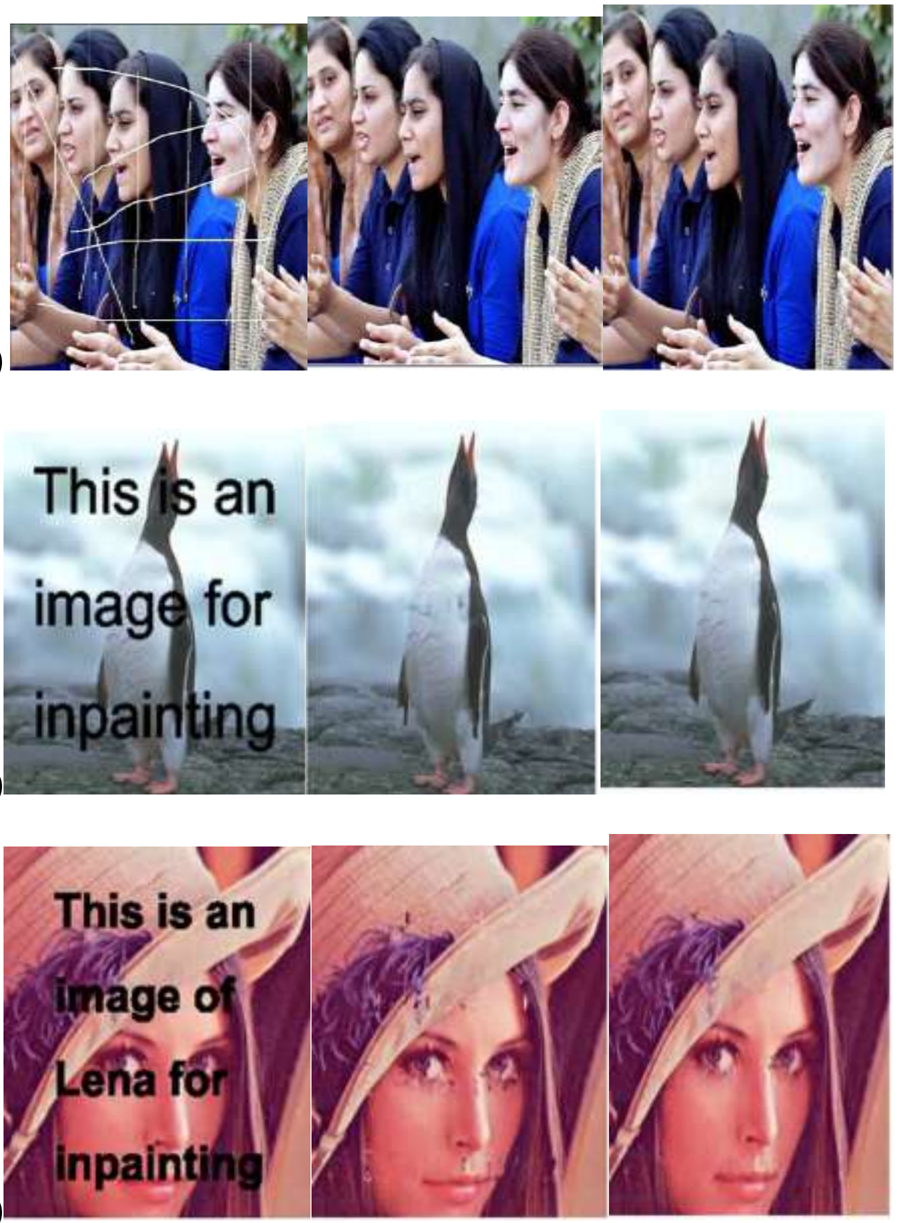

(3)

(4)

(5)

(a) (b) (c)

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Fig 3. Comparison of Scratch and text removal. Image 1, 2,3,4,5 a) Original Image. Results of simultaneous texture and structure inpainting approach b) Inpainted by Belief propagation c) Inpainted by Geodesic propagation. **Comparison of Object removal**. a) Original Image b) Masked Image c) Inpainted image by Belief propagation d) Inpainted image by Geodesic propagation.

Table I: Comparison of the inpainting results in PSNR for the seven images of the fig 3.

Image	Total Variation	Belief propagation	Geodesic propagation (Proposed Method)
1)	19.3 dB	20.8 dB	21.4 dB
2)	23.6 dB	23.9 dB	24.9 dB
3)	25.5 dB	25.8 dB	26.2 dB
4)	28.6 dB	28.9 dB	29.9 dB
5)	30.6 dB	31.1 dB	31.9 dB
6)	38.7 dB	40.1 dB	41.8 dB
7)	39.2 dB	40.8 dB	42.1 dB

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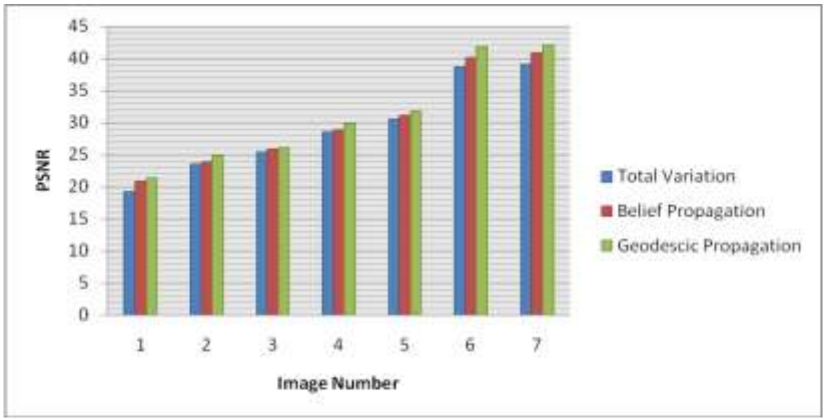

Fig 4. PSNR Values of Belief propagation and Geodesic propagation

Table II: Average Computation times per each phase of the algorithms for the above Data set for w=7

Phase	p-BP	p-GP (Proposed Method)
Threshold computation	144.44s	73.35s
Initialization	20.29s	7.88s
Label pruning	1126.45s	400.76s
Inference	2.67s	0.82s
Overhead computations	2.1s	16.69s

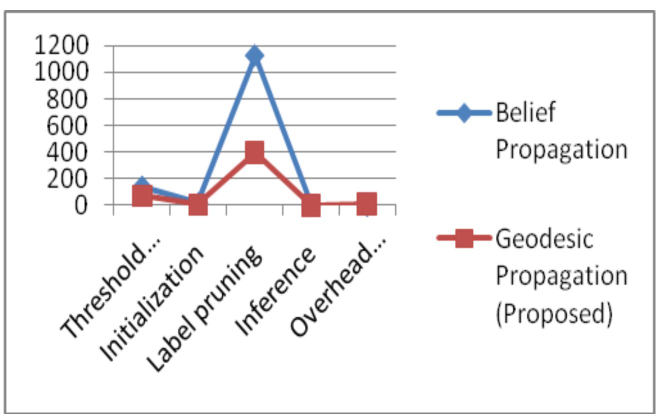

Fig 5 Computation times of BP and GP

The above fig 3 compares the results of our proposed technique with existing p-BP technique is tested using numerous pictures. For the given input set of images initially acquire the similar image set from the annotated dataset exploitation Gist matching input image with missing region is pictured in black then we have a tendency to apply masking to the input image. This method is employed to selectively obscure or hold back elements of an image. So as to quantitatively compare the results, the peak signal-to-noise ratio (PSNR) between the original and also the inpainted pictures are evaluated.

Patch based image inpainting technique is applied to disguised image Geodesic propagation algorithmic program helps to calculate the shortest geodesic path from every component to the hole. Our methodology looks to be a lot of prosperous in conserving image structure and produces the foremost visually pleasing result. The computation time of the existing p-BP and proposed methodology as illustrated in above Table II. Threshold computation of the given test images exploitation existing methodology is 144.44s whereas the proposed methodology has 73.35s. Initialization of the given test images exploitation existing methodology is 20.29s the proposed methodology has 7.88s only. Label pruning of the given test images exploitation existing methodology is 1126.45s however the proposed methodology has 400.76s. Inference of the given test images using existing methodology is 2.67s whereas the proposed methodology has 0.82s only. Overhead computations of the given test images exploitation existing methodology is 2.1s however the proposed methodology has 16.69s.

Computation time comparison for the present belief propagation and the proposed Geodesic propagation is shown in fig 5. It represents that our proposed methodology performance is better than existing methodology. Time and area complexness of existing belief propagation and the proposed Geodesic propagation is compared. Time complexness refers to the quantity of computations performed by the algorithmic program. The proposed methodology label value computation in initialization (per node), set of potential computation in label pruning (per edge), and pre-computation of pair wise potential in logical thinking (per edge) is nice compared to existing methodology. Area complexness refers to memory need: the foremost memory is required to store label costs, beliefs and/or messages, and every vector of spatiality adequate to the amount of labels per node. Proposed methodology needs less memory than existing methodology.

4. Conclusion

This robust patch sparsity with geodesic distance oriented inpainting method that make use of texture-aware approach to minimize the number of viable labels according to node and select them in such a manner that they higher suit the adjacent context. Context is represented within blocks of constant or adaptive sizes using contextual descriptors inside the shape of normalized texon histograms. Additionally, to divide the image into blocks of adaptive size, a unique top-down splitting approach was used. In this paper, Patch primarily based image inpainting approach is implemented to disguised image Geodesic propagation algorithmic rule helps to calculate the shortest geodesic distance from each component to the missing area. The weighted geodesic distance on the basis of spatial and temporal gradients, therefore can calculate the distance in linear complexity. By using the geodesic distance value of the patch, we can easily identify the suitable patch for filling up the missing or affecting portion of the image. Our methodology looks to be a lot of prosperous in conserving image structure and produces the foremost visually fascinating end result. Results demonstrated the benefits of such associate degree approach compared with the state-of-the art techniques. Higher degree of time and space efficiency is achieved in this proposed geodesic propagation method when compared with the existing belief propagation method. This proposed method permits larger size images also.

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