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A Review: New Histogram for Bilateral Filtering and Nearest Neighbor Searching

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Abstract: Noise not only degrades quality of image but also results in loss of important information in images. There are different types of noise are available such as Gaussian, impulse, mixed noise etc. Filtering plays vital role in image processing and computer vision to remove noise. In this work, we have reviewed and analyzed different nearest neighbor field (NNF) methods using bilateral filtering to preserve edges. Computing NNF is nothing but, for each patch in one image, find out the most similar patch in other image. Bilateral filtering overcomes limitation of using box spatial filter kernel by using locality sensitive histogram (LSH). The computational complexity of bilateral filter is linear in number of pixels. Also new bilateral weighted histogram (BWH) is proposed for edge preserving patch-match. In this paper, we have studied and reviewed different patch-matching methods.

Keywords: locality sensitive histogram, bilateral weighted histogram, bilateral filter, nearest neighbor field.

I. INTRODUCTION

Bilateral filter is non-linear, noise reducing filter used for gray and color images. It is used in various applications such as stereo matching, image denoising, tone mapping, contrast management, 3D fairing [8]. Bilateral filter is technique to smooth images while preserving edges. Different techniques have been proposed to improve efficiency and accuracy of bilateral filters. The histogram-based bilateral filtering methods [10] make use of box spatial filter kernel which has finite impulse response and it causes ambiguities around edges in image. In this, bilateral filter is derived from locality sensitive histogram (LSH) which computes histogram at each pixel location and floating point value is added to the corresponding bins. Gaussian filter takes into account only spatial information and bilateral filter not only consider spatial distance but also the intensity value of image in order to preserve edges. It depends on two parameters: spatial parameter and rangeparameter, to measure radiometric distances between center pixel and its neighbors.The computational complexity of bilateral filter is not dependent of kernel size. Bilateral filtering can be improved to get linear time joint bilateral filtering and multi-dimensional filtering to reduce complexity.

(a)Input image (b) Box filter (c) LSH

Fig.1: Colorization using bilateral filter with different spatial kernels

Further bilateral weighted histogram (BWH) is developed from LSH, which require both spatial and color information to reconstruct original image while maintaining the efficiency of LSH. The implementation of BWH is simple and can be done by applying recursive approximation of range kernel. Like patch-match method [7], it is very effective for nearest neighbor searching. Patch-based methods have certain limitations since they are unable to preserve boundaries of reconstructed image well. BWH overcomes the limitation as the introduced range kernel provides a geodesic based similarity to recover structure of image in proper way. It is used in various applications such as image reconstruction, optical flow, example based colorization. This method has less reconstruction errors and about 2 to 3 times faster than original patch-match maintaining similar accuracy. The proposed method achieves better performance than the original PatchMatch algorithm in terms of speed, accuracy and visual quality.

II.LITERATURE SURVEY

A. Large displacement optical flow from nearest neighbor fields

Zhuoyan Chen et al. [3], proposed optical flow algorithm for large displacement motions to improve standard coarse-to-fine framework. Motion estimation is formulated as motion segmentation. It uses approximate nearest neighbor field algorithm to compute initial dense correspondence field. Coherency Sensitive Hashing (CSH) scheme is used to compute nearest neighbor field. CSH is based on image coherence and Walsh-Hadamard kernels to propagate good matches. Local deformation is included in motion segmentation as it reduces the number of motion patterns required to describe motion and thus it improves efficiency of algorithm. Histogram statistics is applied to extract most frequent motion modes by using similarity

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and affine transformations. These modes are nothing but dominant motion patterns. It is found that affine transformation models have poor performance than similaritytransformation.Finally continuous flow refinement is applied to estimate sub-pixel motion field. Experimental result shows that proposed method successfully handles large displacement motions and preserves motion details.

B. Patch match for large displacement optical flow

LinchaoBao et al. [2], proposed fast local optical flow algorithm to handle large displacement motions and boundary preservation. Optical flow estimation is one of the important task in computer vision. In many video editing tasks, severe problem occurs in coarse-to-fine approaches due to large motions in real-world videos. Stereo matching aims to find correspondence between two images captured in different views. Local and global methods are two types of stereo matching algorithm. The traditional coarse-to-fine framework performs well for large objects but gives poor result on fine scale image structures. Matching cost computation, cost aggregation, correspondence selection and refinement are 4 steps involved in method. Speed of algorithm is increased by utilizing self-similarity propagation scheme and hierarchical matching scheme. According to original patch-match method, random correspondence field is initialized and then good guesses are propagated among neighboring pixels. Bilateral weights are added into matching cost calculation to preserve details of input image. Self-similarity propagation algorithm is based on assumption that adjacent pixels are likely to be similar to each other. For each pixel, randomly select n pixels from its surrounding region and store them into self-similarity vector, then scan image from top-left to bottom-right. For each pixel, merge its adjacent pixels vector. The computation needed for algorithm is not dependent on patch size. If input image is large, applying patch-match on all pixels is time consuming. Thus hierarchical matching scheme is employed to further increase speed of algorithm. For this, images are downsampled to certain lower resolution and then apply algorithm to find nearest neighbor field (NNF) on these downsampled images. Thisprocess is repeated until finally get NNF on original resolution.

C. Nearest neighbor fields via Propagation-assisted KD-trees

Kaiming He and Jian Sun [5], proposed Propagation-Assisted KD-Trees to quickly compute an approximate solution to patch-match. Computing nearest-neighbor fields is a computationally challenging search task, because both the query set and the candidate set are of image size. In this proposed method, Propagation-Assisted KD-Trees is applied to quickly compute an approximate solution. The tree nodes checked by each query are propagated from the nearby queries. A p by p patch in a color image can be represented by $3p^2$dimensional space and similarity between two patches is described by L_2 distance in this space using Walsh-Hadamard Transform (WHT). After computing WHT, build traditional kd-tree in the 24-d representation space. The algorithm used is non-iterative and finishes in one scan. First it descend the tree to leaf and propagate a leaf from left and similarly from top, then find the nearest neighbor in all leaves. The speed and accuracy can be improved by three more operations, namely, enrichment, pruning and re-ranking. A kd-tree with WHT representations is good way to organize the candidates. This method not only avoids the time-consuming backtracking in traditional tree methods, but is more accurate.

D. Visual tracking using locality sensitive histogram

Shengfeng He et al. [4], proposed tracking framework based on locality sensitive histogram which provide new framework that is robust to illumination changes and multi-region tracking. In object tracking, pixels further away from target center more likely contain background information or occluding objects, so if these pixels are weighted less, their contribution to histogram can be diminished. Locality sensitive histogram (LSH) can handle this issue well as it is computed at each pixel location and floating point value is added to the corresponding bin for each occurrence of an intensity value. The floating-point value declines exponentially with respect to the distance to the pixel location where the histogram is computed; thus every pixel is considered but those that are far away can be neglected due to the very small weights assigned. The appearance of object can affected by different illumination conditions. A new method is developed which is nothing but image transform to extract dense illumination invariant features. LSH is used instead of histogram computed from a window for extracting illumination features as takes into account the contribution from all image pixels. Given an image I, the LSH, HE_p^E, at pixel p is computed by:

$$H_p^E(b) = \sum_{q=1}^{W} a\,|p-q| . Q(I_{q,} b) \qquad b = 1,2\ldots B \tag{1}$$

where W is the number of pixels, B is the number of bins, Q(Iq; b) is zero except when intensity value Iq (at pixel location q) belongs to bin b, and 2 (0; 1) is a parameter controlling the decreasing weight as a pixel moves away from the target center.

Also multi-region tracking algorithm is proposed using LSH, since illumination invariant features and region matching scores can be computed efficiently. A single region tracking has limitation that spatial information is missing, to account for appearance change caused by factors such as illumination and occlusion and applicable for limited number of non-overlapping regions. The multi-region tracking capture spatial information of target object and represents a target object with multiple overlapping regions. The regions are weighted based on their locations from each region center. This facilitates more robust matching results when the regions are partially occluded. An exhaustive search within the search region is performed, where every pixel is considered as a candidate target center. The experimental results shows that the proposed method performs well where target objects undergo large pose variation, illumination changes and abrupt motion. It is able to relocate the target after heavy occlusion.

E. Coherency sensitive hashing

Simon Korman and ShaiAvidan [6], proposed Coherency Sensitive Hashing (CSH) technique to find matching patches between two images. Traditional patch-match method is based on assumption that images are coherent. That is, if we find pair of similar patches, then their neighbors are likely to be similar. But it is slow and less accurate. The reconstruction errors of CSH are lower than patch-match method. Incoherency term is used to measure reconstruction errors by calculating the number of neighboring patches in one image that are mapped to neighboring patches in other image. The proposed CSH is mainly divided into two stages: Indexing stage and Search stage. In indexing stage, new set of functions is determined, which make use of Walsh-Hadamard kernels. At search stage, set of candidate nearest patches is generated and find out most similar patch. In this method, error-to-time trade off of CSH is compared with patch-match and it is found that CSH is faster, avoid many artifacts along edges, more accurate, especially in textured regions.

F. Bilateral filtering for gray and color images

C, Tomasi and R. Manduchi [], proposed bilateral filtering that smooths images while preserving edges, by means of nonlinear combination of nearby image values. The idea behind bilateral filtering is to do in range of image what traditional filters do in its domain.Two pixels can be closeto one another, that is, occupy nearby spatial location, or they can be similarto one another, that is, have nearby values, possibly in a perceptually meaningful fashion. Closeness refers to vicinity in the domain, similarity to vicinity in the range. Traditional filtering is domain filtering, and enforces closeness by weighing pixel values with coefficients that fall off with distance. Similarly, range filtering is defined, which averages image values with weights that decay with dissimilarity. Range filters are nonlinear because their weights depend on image intensity or color. The combination of range and domain filtering is known as bilateral filtering given as:

$$h(x) = k^{-1}(x)\iint_{-\infty}^{\infty} f(\xi)c(\xi, x)s(f(\xi), f(x))d\xi$$

with the normalization

$$k(x) = \iint_{-\infty}^{\infty} c(\xi, x)s(f(\xi), f(x))d\xi$$

It replaces the pixel value at x with an average of similar and nearby pixel values. In smooth regions, pixel values in a small neighborhood are similar to each other, and the normalized similarity function $k^{-1}$is close to one. As a consequence, the bilateral filter acts essentially as a standard domain filter, and averages away the small, weakly correlated differences between pixel values caused by noise. Bilateral filtering produces no phantom colors along edges in color images, and reduces phantom colors where they appear in color image.

III.CONCLUSION

In this paper, an efficient bilateral filtering algorithm based on LSHs and an edge-preserving PatchMatch based on BWHs is proposed. Different techniques of patch-match and nearest neighbor field have been studied along with their advantages and limitations.The proposed bilateral filtering algorithm overcomes the box spatial kernel restrictionof existing histogram-based methods, makes use of an exponential kernel, and the new BWH leads to an accurate and efficient way for image matching.

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