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Methods of Image Re-targeting Algorithm Using Markov Random Field

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Abstract

This article offers a new image re-targeting algorithm, focusing on Markov Random Field (MRF) to refine energy in image by means of Bayesian formulation. The key idea to this approach is that an energy-map is embedded into a MRF model under a Bayesian framework. The likelihood function, characterizing the saliency map likelihood at a site, is obtained based on gradient energy. These saliency maps are obtained using this likelihood function solely to model the MRF. To refine the importance maps, a priori knowledge is introduced. It will be shown that it is possible to build each of the potentials from specific PDFs. A simulated annealing algorithm is implemented to find the MAP solution. Eventually the experiments' results, gained from the model in question, was compared to three previous methods, namely Seam Carving, , Crop, and Scaling with the performance of the image re-targeting, and the advantages of the model as well as the proposed methodology outlined at the end.

Keywords: *Image Retargeting, Markov Random Field, Clique, Saliency, SIFT*

1. Introduction

With the development of display devices with different aspect ratios and resolutions, effective image or video retargeting techniques are becoming an active research topic and many methods have been proposed, such as simple scaling, cropping. Simple scaling samples the whole image uniformly and is oblivious to the content of image, hence significant features may be distorted during the sampling process. Cropping operator searches for the most important regions according to saliency map and can achieve satisfactory results. However, most of these approaches are not appropriate for low-end devices because of their high computation. The aim in this paper is to refine image energy using MRF that be salience and they don't appear during select a sequence of pixels in seam carving algorithm; this cause image structures does not distort during eliminate seams. Markov Random Fields (MRFs) constitute a powerful tool to incorporate spatial local interactions within a global context [2], [3]. As such the article proposes a simple methodology to design a Markovian model based on a Bayesian formulation that includes a prior model

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and a measurement model derived from gradient energy. The methodology proposed has a great flexibility and it can be used to account for specific design requirements in MRF applications.

Fig. 1: From left to right: main image, cropping, scaling, seam carving, and the present method

The rest of the article is organized as follows: In Section 2 some related work will be described. The proposed method will be introduced in Section 3 with Section 4 and 5 showing the analysis as well as experimental results respectively, the latter part comparing these results with other existing re-targeting operators. Finally, Section 6 will give the article's conclusion.

2. Related Work

Scaling and cropping have been long used in image editing and re-targeting for which automatic methods have been used for conducting [4], [5]. However, these operations face fundamental limitations. Scaling keeps uninteresting parts of the image, while distorting structured objects such as faces and man-made objects when the scaling is non-uniform. A good crop maintains only the interesting parts of the image, but not all may fit within the desired output image size. Cropping has been generalized to more flexible pixel removal methods. These methods may remove areas of uninteresting content while being able to rearrange the image to better show all of the interesting parts. Seam carving [1] fits into this category. Using simple low level energy terms, this algorithm iteratively removes pixels. Re-targeted images at a range of sizes can be quickly generated.

Its simplicity, speed and effectiveness have led it to be used as a component of many re-targeting methods including [6], [7], [8], [9]. Although most people use seam carving as a complete algorithm, the previous work by Hashemi and Boroumandnia extended seam carving to protect objects during re-targeting better, redefining seams for video re-targeting to achieve improved results [10]. These methods also operate by pixel removal, including shift map image editing [11] that optimizes a mapping from pixels in the output image to pixels in the input image. For re-targeting they add a label ordering constraint which maintains the ordering of pixels in the input image in the output image. In this case, the result can equivalently be generated by removing pixels. Shift map image editing without this constraint, and other

algorithms which generate outputs in terms of input pixels, e.g. [12], [7], also owe much of their effectiveness to pixel removal.

However, allowing pixel re-arrangement and duplication gives greater flexibility, which must be appropriately constrained. These methods have a number of drawbacks. When approximating scaling through down-sampling, these methods suffer the same problem of causing nonuniform scaling of structured objects. Also, they may lead to discontinuities in lines and curves in the image, which can be very visually disturbing. These issues have motivated other paradigms for re-targeting.

Non-linear warping/interpolation is used in [19] among others to determine the output image. Pixel estimation is used in [14] to minimize a patch-based bidirectional image similarity. The patch match algorithm [14] achieves interactive speeds, and allows very effective user interaction to be used to preserve lines and structured regions. However, these methods can be complex to implement, and usually require the optimization to be re-run from the beginning for each target size. However, despite the drawbacks of seam carving, it is still popular in practice due to its simplicity, speed and effectiveness in a wide range of images. This makes the article's aim to better understand and improve seam carving, which is done through the framework of the visibility map, introduced in the next section.

3. Proposed Method

Given an input image, the method, proposed in this article, is to use Bayesian framework to estimate some feature in the image that are in special shape (eg vertical, horizontal, etc.) and preserve energy of that feature and decrease else energy. First the prior distribution is calculated, using potential function with different clique. With this distribution the likelihood function can be obtained, as well as a simulated annealing algorithm is implemented to find the MAP solution; then by means of seam carving algorithm the optimal seam is firstly found and then removed to decrease the image size.

3.1. Markov Random Fields

This section presents the basic definitions of Markov random fields, which is a probabilistic model defined by local conditional probabilities. Consider a set of sites S = {s1, s2,… sN} in a bi-dimensional space. Let X = {Xs, s ∈ S} denote any family of random variables, each with a different state space s. Let V = {V(s), s ∈ S} be a neighborhood system for S. In image modeling, a hierarchically ordered sequence of neighborhood systems are most commonly used. In the first-order neighborhood system, every pixel has four neighbors, as shown in Fig. 2, where x denotes the considered pixel and 1's denote its neighbors. In the second order neighborhood system, there are eight neighbors for each pixel, as shown in Fig. 2, where the 1's and 2's are its neighbors. The cliques associated with the first- and second-order neighborhood systems are shown in Fig. 3. A subset C ⊂ S is a clique if every pair of distinct sites in C are neighbors [1]. Let C denote the set of cliques. X is a MRF with respect to V if

$$p(X = x) > 0 \tag{1}$$

$$p\left(X_{S_i} = x_{s_i} | X_{S_j} = X_{s_j}\,,\ s_j = s_i\right) = p(X_{S_i} = x_{s_i} | X_{S_j} = x_{S_j}, S_j \in V(S_i) \tag{2}$$

For every x ∈ X and si, sj ∈ S. The collection of functions on the right-hand side of (3) is called the local characteristic of the MRF and they uniquely determine the field [21] and they are Gibbs functions [1] so

$$p(X = x) = \frac{1}{Z}\exp(-\mathrm{U(x)}) \tag{3}$$

Where U is called the energy function:

$$U(x) = \sum V_c(x) \tag{4}$$

And

$$Z = \sum exp_c(-U(x)) \tag{5}$$

Where C = C1 ∪ C2 ∪ C3 ∪ … is the set of cliques and is Vc the clique potential associated with the clique c. Thus, the joint probability P(X = x) can be determined by specifying the clique potential functions Vc (x). How to choose the forms and parameters of the potential functions for a specific problem is a major topic in MRF modeling. In the next section, we will discuss the use of MRF models in energy refinement and give some specific forms of potential functions.

3.2. Bayesian framework for refine energy using MRFs

The Bayesian method is one of the most powerful approaches to the extract feature from image. In this paper, the focus is on the extract special image feature issue. Let Y denote the observed image with special feature N

$$Y = X + N \tag{6}$$

Where X represents the true image. Then, Bayes theorem allows us to obtain the conditional probability of the field x given y:

$$p(x|y) = \frac{p(y|x)p(x)}{p(y)} \tag{7}$$

Where p(x) is the prior probability defined by an MRF, p(y=x) is the likelihood function of x for fixed y, and p(y) is a constant when y is a given observation.

3.3. The Likelihood PDF

The process deals with the influence of the measurement on the energy function [18]. Transition probabilities give a measure of the probability of a certain observation y, given an outcome of the MRF, X = x. The PDF defined has the desired behavior, now, the potentials for the MRF can be extracted, taking into account that

$$p(y|x) = \frac{1}{Z_{y/x}} \exp(-U(y/x)) \tag{8}$$

The energy of the MRF due to importance map measures will be:

$$U(y/x) = \sum_{s_i \epsilon S} V_l\left(c_{s_i} - x_i\right) \tag{9}$$

5	4	3	4	5
4	2	1	2	4
3	1	x	1	3
4	2	1	2	4
5	4	3	4	5

Fig. 2: Neighborhood systems on a lattice of regular sites.

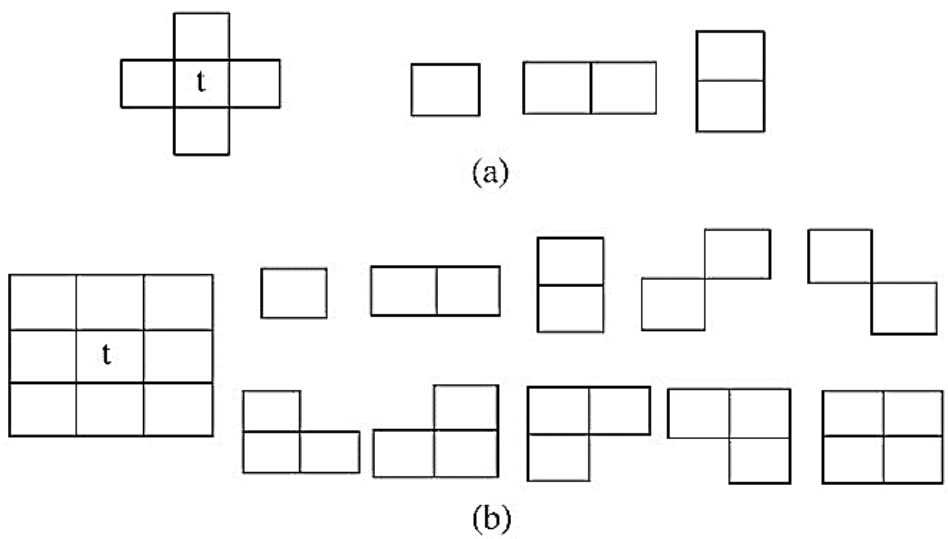

Fig. 3: The first (a) and second (b) neighborhood systems and their associated cliques.

3.4. A Priori Knowledge

From the discussion of MRF in the previous section, we can write the above joint prior distribution of X in the form of a Gibbs random field. We only consider the cliques of size two. In this case, Eq. 4 can be rewritten as

$$U_p(\mathrm{y}) = \sum_{c\epsilon C} V_c(Y_{ij}, \mathrm{i}, \mathrm{j}\epsilon c) = \sum ij\epsilon S\left[V_u(y_{ij}, y_{i,,j-1}) + V_u(y_{ij}, y_{i,j+1}) + V_h(y_{ij}, y_{i+1,j}) + V_h(y_{ij}, y_{i-1,j}) + V_d(y_{ij}, y_{i-1,j-1}) + V_d(y_{ij}, y_{i-1,j+1}) + V_d(y_{ij}, y_{i+1,j+1}) + V_d(y_{ij}, y_{i+1,j-1)}\right] \quad (10)$$

Where Vv,Vh and Vd correspond to vertical, horizontal and diagonal cliques, respectively.

3.5. The Posterior PDF

Using the Bayes rule, the posterior distribution will be found:

$$p({}^{x}/_{y}) \propto p(x)p({}^{y}/_{x}) \quad (11)$$

The MAP estimate is equivalent to the following optimization problem:

$$y^* = argmin\, U(^{x}/_{y}) \tag{12}$$

We can use the PDF function [22]

$$\emptyset(u) = \frac{-1}{1 + \left(^{u}/_{\Delta}\right)^2} \tag{13}$$

For prior and likelihood function, where _ is a positive scaling parameter, which affects the performance of our approach to control degree of smoothness. From the above discussion, the prior and likelihood probability can be written. Simulated annealing is adopted to find the global minimum of the posterior energy U (xjy). The convergence of this approach has been proved in Ref. [2].

$$T(t) = \frac{C}{log(t+1)}, \text{ C is a constant, and } t \geq 1 \tag{14}$$

Where T(t) is temperature during the kth iteration. Numerous applications have demonstrated that using this logarithmic scheme can reach a suboptimal result within limited iterations [23]. The MAP algorithm depends on an annealing schedule, which refer to the slow decrease of a parameter T that corresponds to temperature in the physical system. As T decrease, samples from the posterior distribution are forced forward the minimal energy configuration; these correspond to model of distribution. This paper employs this logarithmic scheme to optimize the simple MRF model and generate extraction results.

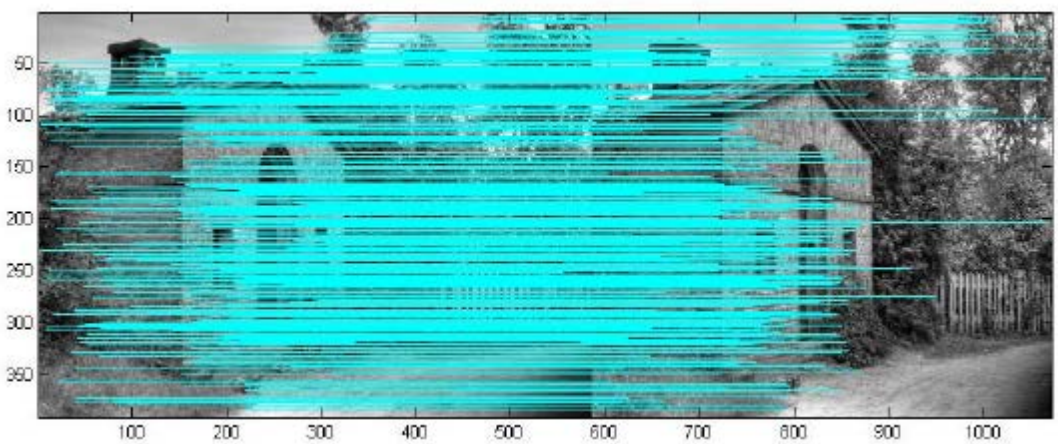

Fig. 4: Match key between main image and re-targeted image using SIFT method

3.6. Seam Carving Review

Avidan and Shamir [1] define a vertical (horizontal) seem to be an 8-connected path of low energy pixels in the image from top to bottom (left to right) containing one, and only one, pixel in each row (column) of the image. Thus, removing a vertical (horizontal) seam reduces the width (height) by one pixel. Finding the globally minimum energy seam, which removes the least salient content, is posed as a dynamic programming optimization problem. The energy maps are computed using the L1-norm of the intensity gradient as:

$$E_g(x,y) = \left|\frac{\partial}{\partial^x} I(x,y)\right| + \left|\frac{\partial}{\partial_y} \mathrm{I}(x,y)\right| \tag{15}$$

Where Eg(x; y) is the resulting importance value of a pixel at column x and row y, and I is the grayscale intensity image. For a vertical seam removal, the dynamic programming memorization table entry M(x; y) is given as:

$$M(x,y) = E_g(x,y) + min\begin{cases} M(x-1,y-1) \\ M(x,y-1) \\ M(x+1,y) \end{cases} \tag{16}$$

The globally minimum energy seam is found by backtracking from the minimum value of the last row in M to the first row.

4. Image Re-targeting Quality Assessment

To compare image quality by different re-targeting methods, a method is needed to extract key point in two image and match together to identify different between two image. A scale-space matching method base in SIFT matching method [17] is designed to facilitate extraction of global geometric structures from re-targeted images. Main step of the SIFT method as following:

- Finding the Key Point
- Finding extreme points in scale space
- Locating Key Points
- Orientation Assignment
- Display the Key Point Description
- Feature Vector Matching

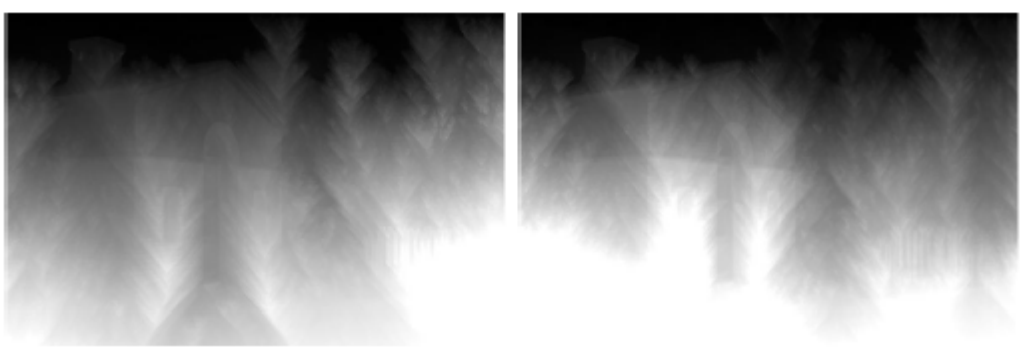

Fig. 5: Left picture is gradient energy and another is MRF energy in seam carving algorithm after calculate energy. It can be seen that energy accumulate in side of house and its structure is preserved

	Crop	Scaling	Seam Carving	
Found Key Point	2792	3093	3108	2999
Match Key Point	583	612	679	786

Fig. 6: Compare image re-targeting method base SIFT matching

5. Experiments

The proposed method is implemented with Matlab, testing its performance under Linux 64bit OS equipped with Intel Core2 Quad CPU 2.40GHz. In Fig. 5, the results of energy calculation are calculated with seam carving method as well as the present method. It can be seen that the latter method calculates energy and salience region better. In Fig. 4 key point, extracted from different methods, are compared and it is seen that SIFT matching find more match point with respect to method, given in this article. Also Fig. 6 shows a number of key point that matched with other methods.

Conclusion

This paper designed an image re-targeting algorithm based on MRF in order to preserve main structure of image in seam carving algorithm. To do so it used some type of clique in image and calculate them energy with Gibbs functions. Fig. 1 shows the proposed method find better sequence of pixels (seam) in the image and after remove it in image, main structure in image will be preserve.

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