REMOTE SENSING IMAGE SYNTHESIS

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1. INTRODUCTION

The systematic evaluation of data analysis tools, such as segmentation and classification algorithms for geographic information systems, is difficult given the unavailability of ground-truth data in most cases. Testing is therefore typically limited to small sets of pseudo-ground truth data collected manually by trained experts, or primitive synthetic sets composed of simple geometries [1]. The reliability of performance assessment using pseudo-ground truth data is limited not only by the small set of test data available, but also by the limited time and accuracy of trained experts who are able to produce manual segmentations and classifications on a pixel level. The primitive synthetic tests are a poor representation of real remote sensing imagery and, as such, do not provide a realistic testing scenario.

To address this issue, we propose a more substantial approach to the synthesis of remote sensing data for use as a reliable evaluation,test-bed. However, the scale-dependent, non-stationary nature of remotely sensed data (e.g. Fig. 1(a),(c)) is not easily captured. Although general nonparametric texture synthesis methods (e.g. [18]) are able to better capture both textural and structural characteristics, they cannot provide a corresponding label field required as ground truth (e.g. Fig. 1(b),(d)).

In this paper, we will explicitly synthesize the *label field*, which contains the complex structural characteristics, and separately synthesize the texture using a modification of the nonparametric texture synthesis strategy proposed by Efros and Leung [2]. Explicitly synthesizing the label field gives the combined benefit of providing the ground truth for algorithm testing, and the scale separation between coarse-scale labels and fine-scale textures, which allows for more accurate modeling. We propose to combine resolution-oriented and region-oriented hierarchies, a novel combination for image synthesis.

2. HIERARCHICAL FIELDS

In this paper, we are proposing synthesize images on the basis of first synthesizing a label field, using methods taken from Hierarchical Markov Random Fields (HMRFs), such that U is defined via a sequence of fields $\{U^k, k \in K = (0, 1, \cdots, M)\}$, where $k = 0$ denotes the finest scale and $k = M$ the coarsest. At each scale k, U^k is defined on site space S^k and results from the downsampling of $U \equiv U^0$. A HMRF model can be written as

$$p(u^0, \cdots, u^M) \quad = \quad \Big[\prod_{k=0}^{M-1} p(u^k|u^{k+1}) \Big] \cdot p(u^M) \qquad (1)$$

The advantage of hierarchical modeling is that nonlocal large-scale features become local at a sufficiently coarse scale, therefore at each scale a single Markov Random Field (MRF) can be used to capture the features local to that scale, inherently allowing for scale-dependent structures. We will define u_s^k to be the label state at site s on scale k, with an associated local neighbourhood $\mathcal{N}_s^k$ and parent $u_{\wp(s)}^{k+1}$ on the next coarser scale.

To improve computational efficiency, we adopt a Frozen State Hierarchical Field (FSHF) [3], in which a given binary field $(u = u^0)$ can be represented by a hierarchical field $\{u^k\}$, where u^k is ternary $u^k(s) \in \{0, 1, \frac{1}{2}\}$, where $0, 1$ (black, white) are
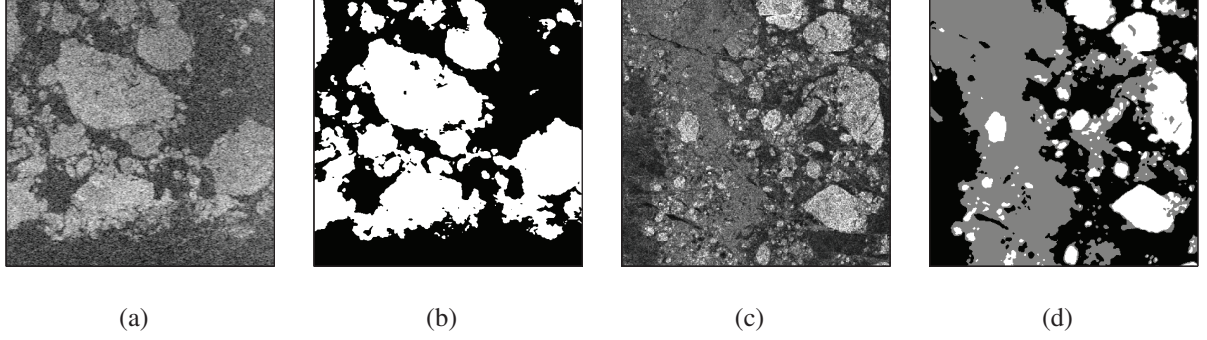
| (a) | (b) | (c) | (d) |

Fig. 1. Sea-ice texture samples (a,c) and their underlying label maps (b,d). Many remote sensing textures have underlying label maps with multi-scale structures which can be binary (b) or multi-labeled (d). The scale-dependent behavior in (b, d) will usually not be well captured by a single random field.

determined states, and $\frac{1}{2}$ (gray) is undetermined. In terms of *modeling*, a fine to coarse representation can be derived as

$$
u_s^k = \begin{cases} 1 & \text{if } u_q^{k-1} = 1, \quad \forall q \in \Re^{k-1}(s) \\ 0 & \text{if } u_q^{k-1} = 0, \quad \forall q \in \Re^{k-1}(s) \\ \frac{1}{2} & \text{otherwise} \end{cases}
\tag{2}
$$

where $\Re^{k-1}(s)$ is the set of sites in scale $k-1$ corresponding to the location s in scale k. For *synthesis*, the key idea of the FSHF model is that, at each scale, only the sites which are undetermined need to be sampled:

$$
p(u_s^k | u_{S \setminus s}^k) = \begin{cases} \delta_{u_s^k, u_{\wp(s)}^{k+1}} & \text{if } u_{\wp(s)}^{k+1} \in \{0,1\} \quad \longleftarrow \text{ Frozen} \\ p(u_s^k | u_{\mathcal{N}_s^k}^k) & \text{if } u_{\wp(s)}^{k+1} = \frac{1}{2} \quad \longleftarrow \text{ Sampled} \end{cases}
\tag{3}
$$

With the frozen state, large scale features captured at the coarse scales are frozen and maintained to the fine scale, regardless of annealing schedule or sampling method. Since the interface between determined regions represents only a small fraction of pixels, this approach offers a huge reduction in computational complexity relative to full-sampling hierarchical techniques.

3. TREE-STRUCTURED HIERARCHICAL FIELDS (TSHF)

Although the FSHF method in Section 2 offers a compelling approach to modeling, there are two issues that need to be addressed for synthesis of complex label fields: first, we generally have to solve a multi-label problem; second the label maps may be nonstationary, which can not be well modeled by a single (stationary) hierarchy.

There is an existing literature on partition trees [4, 5] which allows a given image or label map to be partitioned, whereby behaviours are split and successively subdivided until homogeneous portions are found. The key idea is to use the partition trees to combine multiple hierarchical models, as in Fig. 2(a), to allow nonstationary and nonbinary representations, at the same time preserving the scale-dependent computational efficiency of the hierarchical approach. We propose to specify the structural components of U by a sequence of nodes in a binary tree $T = \{U^i | \mathcal{Q}^i, 0 \le i < N\}$ from mixed to pure labeled states. Each node is a conditional hierarchical field $U^i | \mathcal{Q}^i = \{U^{i,k} | \mathcal{Q}^i$, where $\mathcal{Q}^i$ denotes the set of conditioned fields.

The influence of U^i on the partition tree is mediated through the up to two children of U^i, conditional on U^i or $\bar{U}^i$, such that binary field U^i controls the spatial extent of its children. The conditioning is encoded in $\mathcal{Q}^i$:

$$
\begin{aligned}
\mathcal{Q}^i &= U^a & \to U_s^i = 0 & \quad \text{if } U_s^a = 0 \\
\mathcal{Q}^i &= \bar{U}^a, U^b & \to U_s^i = 0 & \quad \text{if } U_s^a = 1 \text{ or } U_s^b = 0
\end{aligned}
\tag{4}
$$

Since each node under T only models simple binary/ternary structures, each field $U^i | \mathcal{Q}^i$ can be well modeled by the FSHF, as discussed in Section 2. The process by which we infer a partition tree structure T from a given ground truth label field sample is a creative one, requiring human input, and is highly problem dependent. Each scale of each field $U^{i,k} | \mathcal{Q}^i$ can be sampled recursively, first over all scales in U^0, then over fields further down the partition tree, as

$$
\hat{U}^{i,k} | \mathcal{Q}^i \leftarrow p\left(U^{i,k} | \mathcal{Q}^i \big| \hat{U}^{i,k+1}\right).
\tag{5}
$$

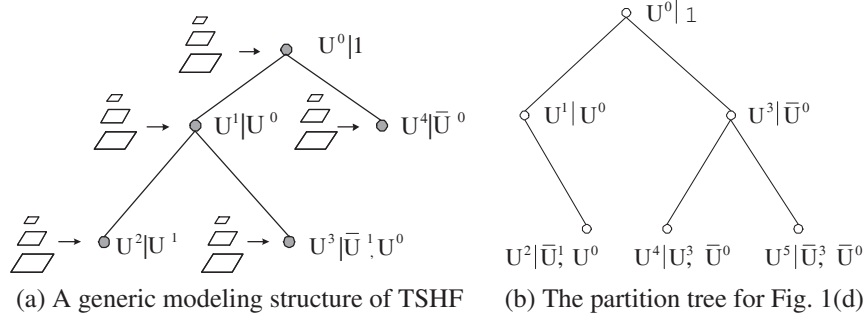(a) A generic modeling structure of TSHF (b) The partition tree for Fig. 1(d)

Fig. 2. In a modeling structure of TSHF (a), the partition tree has a hierarchical field at each node, where the field U^i is conditioned on the behaviour of its parent, or both parent and grandparent. As an example, (b) shows the partition tree structure corresponding to a selected label field (Fig. 1(d)).

Having specified a partition tree, the inverse step, the process of recombining the synthesized conditional fields $\{U^i | \mathcal{Q}^i\}$ to get $\hat{u} = J(\hat{u}^0, \cdots, \hat{u}^M)$, is straightforward. A hierarchical model on its own, such as the FSHF, can be considered as a special case of the TSHF with only one region-oriented component.

4. IMAGE SYNTHESIS

The textured images in Fig. 1(a,b) are complex, non-local, non-stationary. Therefore the direct synthesis

$$\hat{x} \leftarrow p(x) \tag{6}$$

is a complicated undertaking. On the other hand, because U represents the salient features of interest in X, what remains in X, given U, are the fine-scale details not of interest: noise, speckle, quantization, blurring etc., all of which are comparatively simple and *local* textural phenomena. That is, the synthesis

$$\hat{x} \leftarrow p(x|u) \tag{7}$$

is comparatively straightforward, therefore we are deliberately picking an existing, standard texture synthesize method [2] to generate the fine-scale texture on top of $\hat{u}$. We slightly modify [2] to allow a synthesized texture $\hat{x}$ to be sampled from the conditional MRF $X|U$, rather than directly from the texture field X. There is nothing inherent necessitating the use of [2]; indeed, any other texture synthesis may be used as well.

5. EXPERIMENTAL RESULTS AND CONCLUSIONS

A test for the proposed TSHF is the image shown in Fig. 1(c), with a corresponding label field in Fig. 1(d). Based on the tree-structured modeling representation of Section 3, a partition tree of binary or ternary component fields is constructed, as shown in Fig. 2(b), such that the hidden field is produced from the components as

$$\begin{aligned} \hat{u} &= J(\hat{u}^0, \cdots, \hat{u}^M) \\ &= \hat{u}^0|1 + \hat{u}^1|\hat{u}^0 - \hat{u}^2|\hat{u}^0, \bar{\hat{u}}^1 + \hat{u}^3|\bar{\hat{u}}^0 - \hat{u}^4|\hat{u}^3, \bar{\hat{u}}^0 + \hat{u}^5|\bar{\hat{u}}^3, \bar{\hat{u}}^0 \end{aligned} \tag{8}$$

Given the synthesized label field (Fig. 3(d)), the sea-ice texture may be generated (Fig. 4(d)), comparing well with Fig. 1(c).
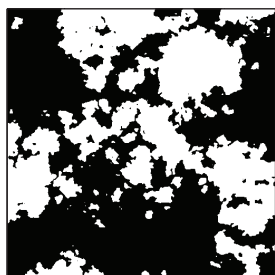
We compare our proposed method with others in label field modeling and texture synthesis. First, a single MRF is used to synthesize both binary and ternary fields, in Fig. 3(a,c), with synthesized structures both local and stationary, rather than the multi-scale structures in the true label maps. In contrast, the FSHF and TSHF models exhibit their scale-dependent modeling capabilities in Fig. 3(b,d).

A second comparison compares our proposed method with non-parametric texture synthesis methods [2], for which the basic idea is to directly sample a given image using self-similarity. The nonparametric results in Fig. 4(a,c) are aesthetically attractive and possess good structure. However, the nonparametric method is sensitive to the synthesis starting seed, such that for certain seeds the synthesis may fail to sense certain significant structures present in the training data. Similarly a small window may fail to sense large-scale structures, whereas a large window can lead to copying the training image rather than
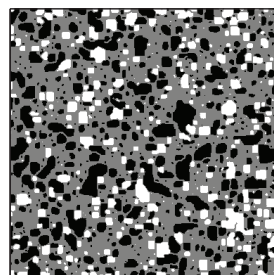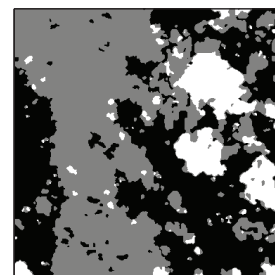
Fig. 1(b) synthesis:
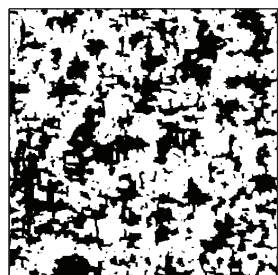
Fig. 1(d) synthesis:

(a) Chordlength Model   (b) FSHF Model   (c) Local Histogram Model   (d) Proposed TSHF

Fig. 3. Sea-ice label map synthesis comparison. Panels (a,c) show label fields resulting from single Markov fields, whereas panels (b,d) show the label fields from the proposed scale-dependent FSHF and TSHF. The single Markov models provide only stationary fields, with structure on one scale, as opposed to the more complex and scale-dependent structures possessed by the real label maps Fig 1(b,d) and FSHF, TSHF syntheses.
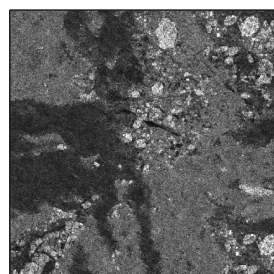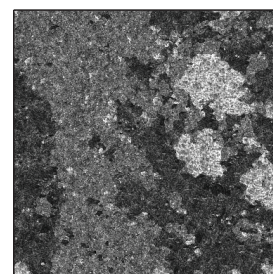
Fig. 1(a) synthesis:
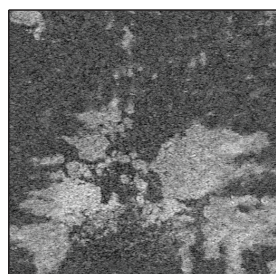
Fig. 1(c) synthesis:
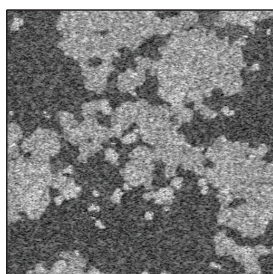
(a) Method of [2]   (b) Proposed TSHF   (c) Method of [2]   (d) Proposed TSHF

Fig. 4. Sea-ice texture synthesis comparison, based on the pixel-based non-parametric sampling method [2] (a,c), and our proposed texture synthesis (b,d).

random sampling, as may be seen in comparing Fig. 4(a,c) with Fig. 1(a,c). Finally, and most significantly, the texture synthesis methods synthesize *only* the texture, and have no notion of the underlying label field, which is essential for the testing of classification and segmentation algorithms.

Although here the proposed TSHF was demonstrated in the synthesis of SAR sea-ice and land-mass imagery, it is non-specific and can be applied to a wide variety of different remote sensing problems.

6. REFERENCES

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