RESTORATION OF SEA SURFACE TEMPERATURE IMAGES BY LEARNING-BASED AND OPTICAL-FLOW-BASED INPAINTING

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ABSTRACT

Sea surface temperature (SST) images taken from satellites are partially occluded by clouds. In this paper, we propose an inpainting approach for restoration of the partially occluded images. Assuming the sparseness of the SST images, we employ a learning based inpainting for filling the occluded parts. Images taken in the past several days is another clue for filling the occluded parts. These images are regarded as time series data and a video inpainting method is also available. We employ PCA-based inpainting as a learning-based approach and optical-flow-based inpainting as video inpainting, and combine the two restored images according to the expected their restoration error. Experimental results with real satellite images show the effectiveness of our method.

Index Terms— sea surface temperature, PCA-based inpainting, optical-flow-based inpainting, graph cut

1. INTRODUCTION

Sensing sea surface temperature (SST) is an essential method for measuring and forecasting weather. Many ocean-related industries such as fisheries and marine transportation require accurate and real-time SST data. The most effective sensor for measuring SST in real time is meteorological satellites that measures infrared radiation over in short time and wide area. The major drawback of it is that it can not measure the temperature in a region occluded by clouds.

Several approaches to overcome this drawback have been proposed. Data assimilation using oceanographic data [1] is the most widely used approach. It employs a physical model to interpolate the occluded region. However it incurs significant computational time, hence it is not suitable for real-time applications. Substituting the occluded region with recent past SST images is the second approach. It is applicable for real-time applications thanks to its low computational cost, but accuracy of these methods are not enough for practical applications. The third approach is to sense with Microwave sensors[2], which is robust against the occlusion compared to that with infrared radiation sensors. However they do not work in rainy conditions and only provide low spatial resolution data. Sensor fusion approaches that use infrared radiation sensors and microwave sensors [3] cannot provide enough spatial resolution.

In this paper, we propose a method to restore occluded SST images by using two different clues; sparseness of SST images and use of the previous days’ SST. Method overview is shown in Fig.1. Although SST is a physical phenomenon that is affected by many factors, when we treat SST as 2D images, they would have sparse characteristics. Thus SST images can be represented by a linear combination of a small number of components, and partially occluded SST images can be restored by estimating the linear combination, that is, learning-based image inpainting is feasible for this restoration.

Recent past SST images are the other clue for SST image restoration. SST changes constantly, however the position of clouds changes much more quickly; in many cases, a region of sea surfaces is eventually occluded by clouds in several days. SST change is mainly caused by sea surface currents(SSC). SST image of the target day, of which SST image we want to restore, can be synthesized by morphing a non-occluded SST image of the previous day with SSC. Even if the SSC is unavailable, assuming the change of SSC over recent several days is small, we can estimate the SSC of the target day by calculating the optical flow between SST of a day before and that of two days before. This is a type of video inpainting approaches[4]. This optical flow approach only works when non-occluded SST images in recent two days are available, however combining this approach with learning-based inpainting enables to use this clue effectively.

2. RELATED WORK

Restoration of SST images partially occluded by clouds can be considered as a non-blind image inpainting problem. Non-blind image inpainting attempts to restore occluded region in the image whose location is given in advance. In our case, existing cloud detecting techniques [5] [6] are available to detect such occluded regions.

In non-blind image inpainting, there are mainly two approaches, learning-based and non-learning-based approach. In non-learning-based approach, occluded regions are filled with similar neighborhoods of the occluded pixels [7][8] , with a pattern that is similar with occluded regions [9][10] , or with both similar neighborhoods and pattern [11]. Since
sacellite images are time series data, temporal clue can also be useful for the restoration [12][13]. Optical-flow-based approach [4] estimates the temporal change and uses it for inpainting. We thus employ optical-flow-based inpainting for SST image restoration.

Learning-based inpainting can be the other solution for SST image restoration. When we treat SST as 2D images, they exist in a sparse space. Some research papers related to analyzing SST in lower dimensions[14][15] also show the sparseness of SST images. Greeshma[16] attempted to restore cloudy satellite images using kernel principal component analysis(KPCA). We also employ PCA-based inpainting. Although learning-based inpainting with deep neural networks [17][18] can be a candidate as SST image inpainting, it requires huge number of non-occluded images, and thus impractical for us.

The main contribution of this paper is that a novel effective inpainting method combining learning-based inpainting and optical-flow-based inpainting is proposed.

3. PROPOSED METHOD

3.1. Method Overview

We use two types of clues for restoration of SST images; non-occluded regions of SST images and recent past SST images. For the first clue, assuming the sparseness of SST images, we estimate SST images with non-occluded region through learning-based inpainting. We use principal component analysis (PCA) as learning-based inpainting. For the second clue, we can estimate SST images using that of recent past. As we discussed in Section 1, SST image in the target day is determined by morphing the SST image in one day before, if the optical flow between the SST images taken one or two days prior to the target day is given. Two types of restored images, PCA-based inpainting and optical-flow-based inpainting, are combined by the pixel selection technique of graph cut. The basic model of our method is shown in Fig.2. We restore SST images recursively using the module shown in Fig.2. We pre-
that is restored with PCA-based inpainting, and the other one
In this way, we can get two types of restored images. One of

\[ \text{RM1} \]

where \( g_v(X_v) \) is the estimated error of restored pixel \( v \), which is data term. \( E \subset V \times V \) indicates a set of neighboring pixel pairs, and if \((u,v)\) is an adjacent term. The term \( h_{uv}(X_u, X_v) \) is smoothness term that attempts to take an

\[ \text{OF-based inpainting} \]

given by

\[ \text{PCA-based inpainting} \]

is restored with optical-flow-based inpainting. Then we inte-

\[ \text{RM2} \]

for pixels with short \( d_v \), restoration using PCA-based inpainting tends to be more accurate than that using OF-based inpainting; for pixels with long \( d_v \), PCA-based inpainting performs reduced accuracy. This fact is demonstrated in section 4.

We set \( g_v(X_v) \) according to the distance from the non-
occluded region, \( d_v \).

\[ g_v(X_v) = \begin{cases} I + (q - d_v) & \text{if } X_v = \text{PCA} \\ I - (q + d_v) & \text{if } X_v = \text{OF} \end{cases} \]

\[ (1) \]

3.3. Optical-Flow-based Inpainting

Since SST is time-series data, we can use a temporal clue to
restored SST images. As discussed in Section 1, the SST
image of the target day can be represented by morphing the
non-occluded SST image of the previous day with sea surface
currents(SSF). If we have two days sequential SST images,
the \((i+2)\)-th restored image and the \((i+1)\)-th restored image, we can calculate optical flow between them and use this flow
as an estimation of SSC between the day \(i+1\) and the day \(i\). Morphing the \((i+1)\)-th restored image with the estimated
SSC, the \(i\)-th image is restored.

Since optical flow does not always extract SSC precisely
due to restoration error, this inaccuracy might decrease the
precision of the whole system. So we also consider the
method without OF. This method is shown in Fig.3. In
Restoration Module2 in Fig.3, we restore the \(i\)-th image as
well as RM1 except the point that RM2 use the \((i+1)\)-th
restored image instead of the \(i\)-th OF restored image.

3.4. Pixel Selection by Graph-Cut

In this way, we can get two types of restored images. One of
that is restored with PCA-based inpainting, and the other one

is restored with optical-flow-based inpainting. Then we inte-
gra these images using pixel selection. By this integration,
expect the result images to be more reliable, keeping the
smoothness because SST images are smooth spatially. This is
formulated as follows.

\[ \min_X f(X) = \sum_{v \in V} g_v(X_v) + \sum_{(u,v) \in E} h_{uv}(X_u, X_v), \quad (2) \]

where \( V \) is a synthesized image, and \( v \) is a pixel of \( V \). \( X \)
is a binary label vector used to determine whether results,
PCA-based inpainting or OF-based inpainting, should be se-
lected pixel-wisely. Element of \( X \), \( X_v \), is a label assigned
to pixel \( v \), and it takes \( X_v = \text{PCA} \) or \( X_v = \text{OF} \). \( g_v(X_v) \)
is the estimated error of restored pixel \( v \), which is data term.

\[ (3) \]

is a constant value that makes \( g_v(X_v) \) non-negative,
and \( q \) is the distance where root mean squared error (RMSE)
of PCA-based inpainting is equal to that of OF-based inpainting and is determined in experiment. Note that these two RMSEs are measured in advance using ground truth (non-occluded SST images) and artificially occluded images.

Smoothness term, $h_{uv}(X_u, X_v)$, is given by the following equation,

$$h_{uv}(X_u, X_v) = |\tilde{p}_u^X - \tilde{p}_v^X|,$$

where $\tilde{p}_u^X$ be the restored pixel $u$ with the method $X_u = \{PCA, OF\}$.

4. EXPERIMENTS

We evaluated the accuracy of our method with satellite images. 418 satellite SST images observed by Himawari-8[20] from July, 2015 to August, 2016 are used for the experiment. Latitudes of these images are between 60S to 60N, and longitudes are between 80E to 180E, and the size of these images is 5001 x 6001 pixels (each pixel corresponds to 2km square region).

In this experiment, we used SST data which is 100km or more away from the continent to exclude the influence of continental structure. We extracted 256 x 256 pixel non-occluded 2000 images, half was used for PCA, and the other half was used as ground truth SST images. The experimental dataset was synthesized from the ground truth by masking the non-occluded images with cloud masks. The cloud masks were taken from real satellite images of other day and regions. The experimental dataset contained various occlusion rates (number of occluded pixels / total number of pixels), ranging from 5% to 80%.

We restored the experimental dataset using six methods; fast image inpainting method(TELEA[8]) and fluid dynamics based inpainting method(NS[10]) as non-learning-based method, PCA-based inpainting (PCAI), interpolation with mean value of images in recent past days (IMVIRP) which is commonly used in the fishery industry, our method with optical flow, and our method without optical flow. The 5th method and 6th method are shown in Fig.2 and Fig.3 respectively. 200 principal components are used for our methods and PCAI. To restore a 256 x 256 pixel region of a SST image with our method, we used $n = 15$ days sequential images of the same region. The increase of precision was converged around $n = 15$, so we fixed $n = 15$ throughout this experiment.

Fig 4 shows the relation between the distance from the non-occluded region of each pixel and RMSE. Since occluded region of SST images prevents from calculating optical flow, we used IMVIRP instead of OF-based inpainting to evaluate temporal clue. RMSE of PCAI and IMVIRP is equal where the distance was about 22. According to this result, in our method we used PCAI until the distance reached approximately 22, and OF-based inpainting when the distance is over 22 as discussed in 3.4. Since TELEA[8], non-learning based inpainting, restores less effectively than PCAI in pixels near a non-occluded region, and than IMVIRP in pixels far from a non-occluded region, our method can improve precision by taking advantages of clue in both non-occluded region and recent past SST images.

Table 1 shows the quantitative results of RMSE(°C). Our method restore more precisely than the other methods at all mean occlusion rate(MOR) and occlusion rate(OR). Our method without OF is slightly better than our method with OF. So our method without OF is appropriate for practical use. However, if we extract optical flow adequately, our method with OF may restore better than our method without OF. Fig.5 shows the results obtained with several inputs. Our method demonstrates the best accuracy in all images.

We also restored an overall image from a satellite, Himawari-8 taken at 6:00(GMT), September 18, 2015, as shown in Fig.6(a). The result is Fig.6(b). In this experiment, we applied our method to each 256 x 256 region on Fig.6(a) except regions which have over 30% occlusion rate, and repeatedly applied our method until overall image (5001 x 6001 pixel) is restored. Fig.6(a) has very large occluded region, so the predicted SST may not precise in deeply occluded pixels. However, our method may restore well in pixels near non-occluded region. Additionally, our method took 62 minutes to restore in each 1000km squared region with a consumer computer, Core i7-5820K 3.30GHz with 16GB memory, and this local restoration time is sufficiently fast for industrial real-time applications.

5. CONCLUSION

In this paper we have proposed a method to restore SST images. We combine learning-based inpainting with PCA and optical-flow-based inpainting to use clue in non-occluded re-
Table 1: RMSE(°C) of restoration with each methods. Red color refers the best precision for each mean occlusion rate(MOR) in 15 days sequential SST images or occlusion rate(OR) of target SST images, and blue color indicates the second best. For all MOR or OR, our method is the best.

<table>
<thead>
<tr>
<th>MOR/OR(%)</th>
<th>TELEA[8]</th>
<th>NS[10]</th>
<th>PCAI</th>
<th>IMVIRP</th>
<th>Our Method w/o OF</th>
<th>Our Method w/ OF</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 ~ 20</td>
<td>0.480/0.541</td>
<td>0.468/0.524</td>
<td>0.450/0.447</td>
<td>0.582/0.644</td>
<td>0.403/0.434</td>
<td>0.411/0.438</td>
</tr>
<tr>
<td>21 ~ 40</td>
<td>0.522/0.441</td>
<td>0.512/0.436</td>
<td>0.617/0.397</td>
<td>0.599/0.572</td>
<td>0.439/0.379</td>
<td>0.448/0.382</td>
</tr>
<tr>
<td>41 ~ 60</td>
<td>0.534/0.514</td>
<td>0.524/0.508</td>
<td>0.603/0.542</td>
<td>0.649/0.604</td>
<td>0.461/0.450</td>
<td>0.470/0.457</td>
</tr>
<tr>
<td>61 ~ 80</td>
<td>0.489/0.568</td>
<td>0.478/0.551</td>
<td>0.576/0.740</td>
<td>0.600/0.629</td>
<td>0.473/0.470</td>
<td>0.453/0.483</td>
</tr>
<tr>
<td>5 ~ 80</td>
<td>0.513/0.513</td>
<td>0.503/0.503</td>
<td>0.577/0.577</td>
<td>0.605/0.605</td>
<td>0.436/0.436</td>
<td>0.444/0.444</td>
</tr>
</tbody>
</table>

Fig. 5: Experimental results. (a) Ground Truth. (b) Input image. White pixels indicate an occluded region, and OR (occlusion rate) and MOR (mean occlusion rate of recent past 15 days) are shown below the image. (c)-(h) RMSE are shown below the restored image.

Fig. 6: Restoration result of overall satellite image with our method. (a) Input data. White pixels indicate occluded region by clouds, and black pixels indicate land. (b) Result of our method.
gion and recent past SST images. Our method can restore SST images more precisely than other methods, taking advantages of these clues. In future work, we will improve the accuracy of our method using the latest learning-based inpainting, such as auto encoder and Generative Adversarial Nets. Additionally, Improvement on extraction of optical flow may also make our method more effective.

6. ACKNOWLEDGEMENT
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7. REFERENCES