Biofouling Detection Based on Image Processing Technique

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ABSTRACT

Traditional methods for performing biofouling detection are based upon probing object surfaces for subsequent laboratory research. Such methods result in large effort, they are expensive, and require expert consultations. Knowledge of the type of biological contaminants is necessary to protect objects from their harmful impact. In this paper we propose a method for determination of types of biological contaminants existing on the objects surface. The proposed method uses a collection of object's images as input. The collection contains images obtained in the visible and near infrared spectral bands. During pre-processing the series, all images are converted to a selected shooting point, and the background is removed. Feature vector is built from combinations of formal vegetation indices. To recognize the type of biological contaminants, we used a pre-trained classifier based on SVM method with RBF kernel.

Keywords

Image processing, pattern recognition, biological fouling identification.

1. INTRODUCTION

Biofouling is the result of unwanted accumulation of biological substances on objects surfaces which are constantly exposed to aggressive environments. These include surfaces of buildings, historical monuments, marine equipments, and even human body. Examples of these biological destructors are colonies of moss, lichens, algae, fungi, various types of mold, and inorganic matters. A traditional approach to detecting biological destructors is based upon probing surfaces for subsequent laboratory research [1]. It is worth noting that this approach results in large effort, is expensive, and requires expert consultations. Another technical approach is based on the measurement of biofouling by sensors. These sensors uses various physical principles, based on the use of luminescence effects and the light intensity measurement on the effects of internal reflection of light [2, 3]. However most of these sensors are only operational under laboratory conditions.

The proposed method is based on the property of biological materials to differently absorb and reflect light in different spectral bands. Different kinds of biological objects have different spectral characteristics. This makes it possible to identify the kind of a biological object basing upon its spectral characteristics. Digital photos of an object made in various bands of the spectrum allow for implicit assessment of spectral characteristics of biological destructors on its surface. This approach is used for processing space images of the Earth's surface. It is known that the most significant characteristics of biological objects, allowing to detect their difference, can be obtained by analyzing images obtained in the visible and near infra red (NIR) spectral bands. These characteristics are based on the well-known groups of vegetation indexes, such as NDVI, ENDVI, and similar [4].They are indirectly characterize the spectral properties of biological and nonbilogicals materials. Therefore, we propose to use a set of these indexes as a feature vector for the detection of biological contaminants. Identification of biological contamination types is carried out with the aid of a recognition system. Thus the proposed method is based on processing a series of images of the object obtained in the visible and NIR spectral bands, and building an appropriate recognition system.

2. THE BIOFOULING DETECTION ALGORITHM

2.1 The input data

The input data is a collection of images obtained during the peridical photography of an object. In each photo session, two photos are taken: one in the visible part of the spectrum, and one in near NIR spectral band. For selection of spectral band we use a system of filters in front of the camera, which allows to define the necessary range. Photography of the object should be done from about the same point and with the same angle. It is desirable that all images in the collection be shot by the same camera. As result of periodic photographing of object, collection of its images accumulates.

2.2 Preprocessing

All images of the same object will inevitably differ from each other due to the shift of the point and shooting angle. All images have a natural background. In order to correctly estimate the feature vectors referring only to the object, it is necessary to convert all used images of objects to a common point of shooting and to delete the background from each image. Thats why we do some preprocessing of objects images in a collection before applying the procedures of classifier training and recognition. The preprocessing of the image collection consists of two stages.

On the first stage, we pick a base image from the collection. Each image in a collection gets converted to a view from shooting point of the base image. To achieve that, for each image in the collection we evaluate a homographic matrix which is then used for conversion. To evaluate the homographic matrix, we look for key points

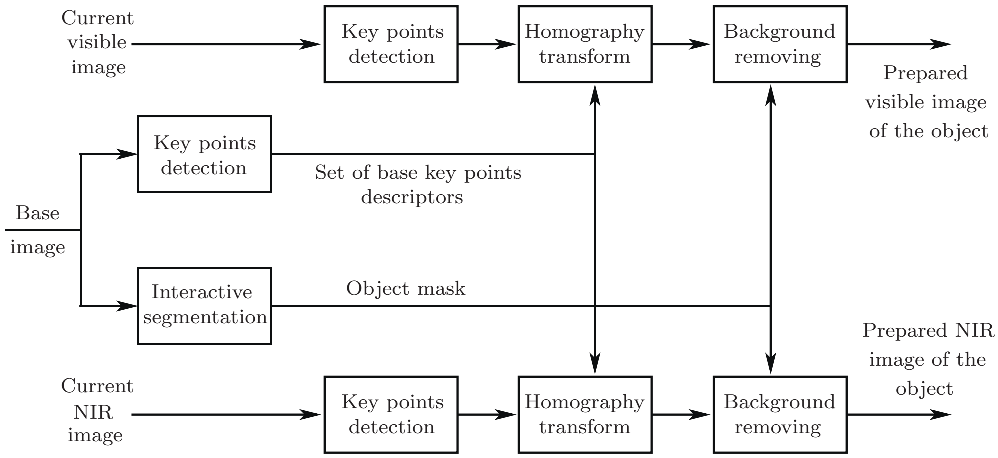

Figure 1. Preprocessing data flow

in basis and current images of a collection. Key points on the images are determined using known and well-proven methods, such as SURF, SIFT and ORB [5]. When finding singular points, their descriptors are also calculated. These descriptors are used to locate key points corresponding to each other on the base image and the current image. During the search for the correspondence of key points on the base image and the current images, the sets of their descriptors are compared with each other by the method of K nearest neighbors. The result of this procedure is a set of coordinates of only those points for which there is a match. Then, using the RANSAC [6] method, the homographic transformation parameters are searched. The homographic transformation with the found parameters is applied to the current image. In this way, the current image is converted to the view taken with the same shooting point from which the base image was obtained.

The second stage of processing is the segmentation of the object of interest on all the transformed images of the collection, and removing the surrounding background on them. The algorithm for performing these actions is as follows. The object of interest is segmented only on the base image using the GrabCut [7] interactive segmentation method. The user sets a rectangular area on the base image, inside which there is an object of interest. This rectangular area is the initial approximation for the location of the object. Further, this method finds an area on the base image that belongs only to the object of interest, and generates a binary mask of this region. The segmentation and background removal on all images of the collection is performed by using logical operation AND engaged in "pruning" the images by the object mask. As a result of the preprocessing procedure, a new collection of images containing only the object of interest is formed [9]. Data flow through the preprocessing stsges is shown in Fig. 1.

2.3 Features extraction

The types of biological destructors are determined using a previously trained classifier. As a vector V of informative features in the classifier, a set of vegetation indexes is used, both known and developed for this method. Calculations of each component V_i of the feature vector are performed by combining the values in certain color channels of the images. The classifier uses a feature vector containing 12 components. For the first and second components of the feature vector, we use NDVI (Normalized Difference Vegetation Index) and ENDVI (Extended Normalized Difference Vegetation Index). These indices characterize photosynthetic activity of biological objects [8]. Calculation of these indices for each pixel of the image is based on determining differences between the corresponding color channels of the ordinary image and of the near infrared image.

$$V_1 = ndvi = \frac{nR - R}{nR + R},$$

$$V_2 = endvi = \frac{nR + G - 2B}{nR + G + 2B}.$$

Here, nR is a value of *Red*-channel for the near infrared image; R, G and B are values of *Red*-, *Green*- and *Blue*-channel correspondingly for the ordinary image. Next 7 components of a feature vector, are formally calculated using the same formulas for the source images converted into LAB and HSV color spaces.

$$V_3 = \frac{nA - A}{nA + A},$$

$$V_4 = \frac{nB - B}{nB + B}.$$

Here, nA, nB, A, and B are values of channels A and B for the near infrared and ordinary images converted into LAB color space. For evaluation of these components, only color channels A and B are used. Lightness channel L not used.

$$V_5 = \frac{nH - H}{nH + H},$$

$$V_6 = \frac{nS - S}{nS + S},$$

$$V_7 = \frac{nV - V}{nV + V},$$

$$V_8 = \frac{nH + S - 2V}{nH + S + 2V},$$

$$V_9 = \frac{nH + V - 2S}{nH + V + 2S}.$$

Here, nH, nS, nV, H, S, and V are values of channels H, S, and V for the near infrared and ordinary images converted to HSV color space.

The last 3 components of the feature vector are computed as change in the angle between the color components in the LAB and HSV spaces for visible and infrared ranges. Adding these components to the feature vector used earlier [10] can improve recognition accuracy.

$$V_{10} = \arctan \frac{A}{B} - \arctan \frac{nA}{nB},$$

$$V_{11} = \arctan \frac{H}{S} - \arctan \frac{nH}{nS},$$

$$V_{12} = \arctan \frac{H}{V} - \arctan \frac{nH}{nV}.$$

2.4 Classifier

For recognition of the types of biofouling, a classifier based on a support vector machine (SVM) [11] is used. The classifier is trained by a set consisting of labeled feature vectors. This training sample is created from images of objects with biological contaminants, and from images of various biological objects. The images involved in the training set are preliminarily processed and brought to a single shooting point, in accordance with the algorithm described above.

The expert makes the labeling of images of training set. Expert analyzes the image and marks it in the areas relevant to the specific type of fouling, as well as areas pertaining to the material of the object. Small rectangular areas are used for marking, which are guaranteed to include only one type of contamination or material of the object. In this case, it is possible to quickly change the size of the marked areas. This method corresponds to the traditional procedure for taking biological samples on a real object. For each marked area, the average value of the feature vector of a given type of biological fouling or objects material is calculated. As a result of image processing training set of feature vectors is formed which is used for training the classifier.

Classifier training was carried out on several training series of images of real objects, on the surface of which there were different types of bio-contamination. Each series included images of the same object, received in the summer and autumn in the morning, afternoon and evening at different levels of natural illumination. The formation of such a training sample allowed to take into account the influence of changes in photosynthetic activity of biological objects depending on the seasons and illumination conditions.

Training of the classifier is carried out using the cross-validation technique. The following SVM kernels were in use during training: linear kernel, polynomial kernel, sigmoid kernel and an RBF-based kernel (RBF stands for radial basis functions). Of these kernels, RBF kernel and sigmoid kernel demonstrated the best results. However, the performance of the classifier with RBF cernel is more than 3 times higher than the classifier with a sigmoid kernel. Therefore, it was chosen for further recognition.

2.5 Biological contamination detection

When detecting types of biological contamination, the collection of infrared and conventional images of the object is processed. Preprocessing involves the conversion of all images in the series to the form that is observed from the base point of the survey and also getting segmented object's images without background. Next, for each pixel of the segmented image, the feature vector is calculated. This map of vectors is processed by a classifier that recognizes and assigns the corresponding pixel of the object's image to one of the types of contamination or one of material's types. As a result, for the object's images under processing, we get maps of distribution of different kinds of biofouling on the object's surface.

3. SOFTWARE IMPLEMENTATION

The proposed method is implemented in C# using image processing library EmguCV. This method has a pronounced parallelism in data. Each image in the collection, except the base image may be processed independently. Parallel branches of the method are implemented on the cluster using the MPI library [13]. The central host of the cluster solves the problems of data distribution among cluster nodes, synchronization of nodes, and is also used to store results. This host also implements a non-parallel branch of the method, which includes a single processing of the base image. This branch includes the search for base key points and the implementation of the interactive segmentation's algorithm. Other cluster nodes process the current images in the collection. They searches for key points, convert image to a common point of shooting, deletes the background and determines the types of biological fouling. After processing, the map of pollution is formed for each image. This map is sent to the storage located at the central node of the cluster. The resulted maps of the object's biological contamination are recording to the database The record in the database contains an image of a pollution map, pollution data, and related attributes.

4. EXPERIMENTAL RESULTS

For training the classifier, we used a series of 118 images of biological contaminants taken by photographing cultural heritage monuments made of stone. Prior to our experimenting, an expert classified this series into 11 classes of most dangerous biological contaminans found at monuments, and 6 kinds of materials the monuments have been made of. In addition, the training set included images of biological objects. Each of the 11 types of biological objects was represented by 30 photos taken under different lighting conditions.

After the training was done, at the control set of 352 images, our system was able to properly classify 94% of biological contaminants and building materials. The judgment on properness of the classification results was made by an expert who assessed the resulting visualized maps of distribution of recognized kinds of biofouling and building materials. An example of the objects source image and its corresponding map of distribution of biological destructors are shown in Fig. 2.

5. CONCLUSION

In this paper we propose the the method for detection biological contaminants. The method is based on the processing collections of object's images, obtained in the natural environment. Each element of the collection represents two images. The first image is taken in the visible spectral range, and the second is shot in the near infrared range. During preprocessing all the images in a collection are converted into a form which corresponds

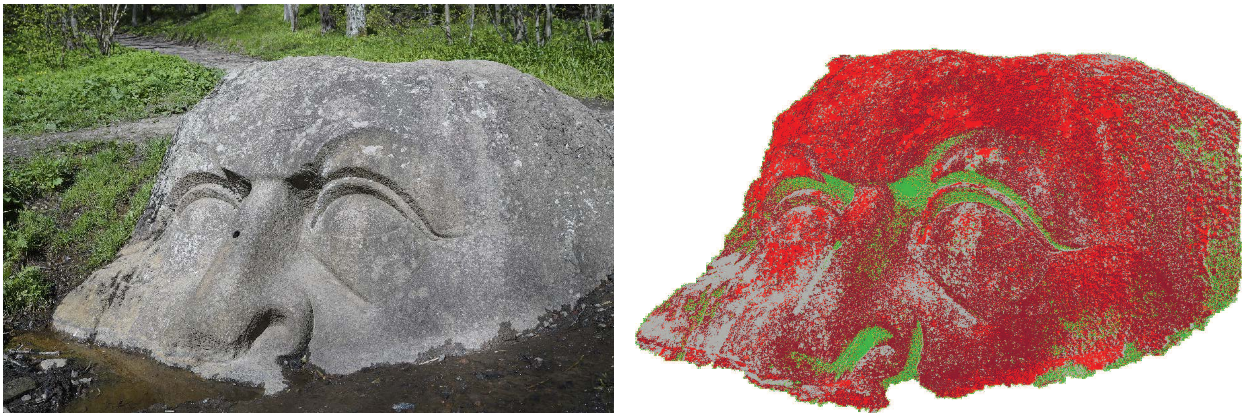

Figure 2: Source image of monument with natural background and map of biofouling: grey — monument material 25%, red — fungi 46%, brown — colonies of moss 11%, green — lichens 18%

to one base point shooting. At this stage of processing on all the images in the collection the background is removed. Pre-trained classificator recognizes the types of biological pollutants existing in the surface of the object and builds pollution distribution maps for all images in the collection. The feature vector is a combination of vegetation indices describing the spectral properties of biological objects.

The proposed method for detecting biological contamination was used to assess the current state of monuments in the museum Necropolis of St. Petersburg. It was also used to assess the effectiveness of conservation work on monuments. The results of the application of the proposed method show its effectiveness for solving problems of objective assessment of the state of monuments of cultural heritage.

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