

**A Review on Approaches for Classification of Sonar Textures**Shaha Rasika S.¹, Prof. Rangole Jyoti S.²¹ Department of Electronics and Communication Engineering, Vidya Pratishthan's College of Engineering, Baramati,² Department of Electronics and Communication Engineering, Vidya Pratishthan's College of Engineering, Baramati,

Abstract — Texture analysis describes a wide variety of image-analysis techniques that quantify the variation in surface intensity or patterns, including some that are unnoticeable to the human visual system. Texture analysis describes a wide range of techniques that enable calculation of the gray-level patterns, pixel interrelationships, and the spectral properties of an image. The increasing scientific and economic interest in the visual exploration and monitoring of marine areas is creating huge amounts of new underwater image and video data and approach of computational assistance for texture analysis is desperately needed.

Side Scan Sonar texture pattern highly depends on incident angles, These types of variance need to be addressed for sonar texture characterization. Recently, more advances have been gained in computer vision for invariant texture recognition by considering invariances to contrast changes and affine transforms. This paper presents a review on different texture analysis approaches and classification of sediments using Side Scan Sonar useful for underwater image analysis.

Keywords- Acoustic remote sensing, sonar texture, Visual Key point, log-Gaussian Cox process.

I. INTRODUCTION

High rate of flow results in heavy sediments being carried by rivers down to reservoirs, lakes etc. Such depositions unfavorably impact long term utilization for irrigation, power generation, industry, and urban power supply and flood moderation. In view of the fact that acoustic techniques suffer from being sensitive to the medium fluctuations, sidescan sonar has been an important tool for seafloor survey over the past few decades. Analysis of the details and structure from the sonar echoes provides the means to classify sediments to determine the composition (sand, rock, mud etc.). Texture analysis techniques become natural choices for sidescan sonar image analysis due to the highly textured form of sonar images. Texture analysis of sidescan sonar imagery can be applied to various geological feature recognitions [1].

Texture analysis is an energetic area in the fields of computer vision and pattern recognition, and has many possible applications. Remotely sensed images in general, and sidescan sonar images in particular, are mainly described by their tonal and textural properties. In the case of sonar images, the tone corresponds to the amount of energy backscattered by each point in the image and is expressed as grey levels. Textural properties correspond to the spatial organisation of the grey levels within neighbourhood [2]. Texture is defined as a visual pattern characterized by the repetition of a few basic primitives. Textures can be described as smooth or rough, small-scale or large-scale, random or organized patterns. The patterns can be the result of physical surface properties such as roughness or oriented strands which often have a tactile quality, or they could be the result of reflectance differences such as the color on a surface. Thus, texture can be regarded as a similarity grouping in an image. The local subpattern properties give rise to the perceived lightness, uniformity, density, roughness, regularity, linearity, frequency, phase, directionality, coarseness, randomness, fineness, smoothness, granulation, etc., of the texture as a whole [3].

There are two major categories to characterize texture: Statistical and Syntactic. Statistical approaches compute different properties and are suitable if texture primitive sizes are comparable with the pixel sizes which include Fourier transforms, convolution filters, co-occurrence matrix, spatial autocorrelation, fractals, etc. Statistical methods analyze the spatial distribution of gray values, by computing local features at each point in the image, and deriving a set of statistics from the distributions of the local features. Depending on the number of pixels defining the local feature, statistical methods can be further classified into first order (one pixel), second-order (two pixels) and higher-order (three or more pixels) statistics. The basic difference is that first-order statistics estimate properties of individual pixel values and ignores the spatial interaction between image pixels, whereas second- and higher order statistics estimate properties of two or more pixel values occurring at specific locations relative to each other. Statistical approaches yield characterizations of textures as fine, coarse etc. Syntactic method is suitable for textures where primitives can be described using a larger variety of properties than just tonal properties [3].

II. LITERATURE SURVEY

Peter Brouwer [1] This paper presents several approaches exist to classify river and sea bottom sediments. Here a method where backscatter measurements are directly correlated to the output of a model in order to estimate the sediment type has been investigated. The method presented here strongly reduces the need of these bottom samples. The model simulates the return signals of a single beam echosounder.

Ph. Blondel, L.M. Parson et.al. [2] This paper presents that geophysical and environmental seafloor surveys make an extensive use of sidescan sonar imagery. Here a method of textural analysis called the TexAn technique has been extensively ground-truthed in complex midocean ridge terrains, using submersible and ROV observations, and in-situ sampling. TexAn enables quantitative assessments of sidescan sonar imagery, at all stages of processing and in all conditions.

G. N. Srinivasan, and Shobha G. [3] This paper presents an overview of the methodologies and algorithms for statistical texture analysis of 2D images. In this paper methods for digital-image texture analysis are reviewed. In this paper different approaches to texture analysis have been discussed.

Huu-Giao Nyugen et.al.[4] This paper addresses the seabed characterization and recognition using keypoint based approaches where spatial statistics are considered. For detecting the keypoints Difference of Gaussian is used and scale invariant feature transform descriptor is used for describing the detected keypoints. The SIFT descriptor is highly discriminant but, being a 128-vector, is relatively slow to compute and match. This is a drawback of SIFT for real time applications.

K. Mikolajczyk, T. Tuytelaars et.al.[5] The paper presents the state of the art in affine covariant region detectors, and compares their performance on a set of test images under varying imaging conditions. Six types of detectors are included in this paper. These detectors based on affine normalization around Harris and Hessian points. The performance is measured against changes in viewpoint, scale, illumination, defocus and image compression. In this paper Har-Lap approach to detect the image keypoints has been applied.

E.Tola, V.Lepetit, and P.Fua[6]. This paper presents the hes-Lap approach to detect the image keypoints has been applied. The Daisy descriptor relies on histograms of oriented Gaussian filters. Here 8 orientations i.e. $\Pi/4i, i=1,8$ at 3 levels of rings where each level has 8 rings with radius $R=15$. The resulting feature vector is made of $8+8*3*3=200$ -dimensional extracted from 25 locations and 8 orientations. Rather than considering gradient orientations, the SURF descriptor (Speeded Up Robust Features) relies on the distribution of Haar-wavelet responses whereas the Daisy descriptor exploits responses to oriented Gaussian filters.

H.Bay, T.Tuytelaars, and L.V.Gool[7]. In this paper, a novel scale and rotation-invariant interest point detector and descriptor has been presented based on coined SURF (Speeded Up Robust Features). A 64-dimensional orientation histogram of SURF descriptor is calculated from the distribution of 4 bins of Haar-wavelet responses in $4*4$ windows. Since the descriptor is a 64-vector of floating point values, representing it still requires 256 bytes. It approximates or even outperforms with respect to repeatability, distinctiveness, and robustness. This descriptor can be computed and compared much faster. SURF is fast descriptor for computation and matching as compared to SIFT. Like SIFT, it relies on local gradient histograms but uses integral images to speed up the computation.

Lindeberg. T.[8]. This paper is based on interest Point Detectors. The most widely used detector is the Harris corner detector which is based on the eigen values of the second-moment matrix. However, Harris corners are not scale invariant.

M.Calonder, V.Lepetit, C.Strecha et al.[9]. In this paper binary strings as an efficient feature point descriptor called BRIEF. For this descriptor similarity can be evaluated using the Hamming distance as a result BRIEF is very fast both to build and match. The work in this paper has suggested way to speed up matching and reduce memory consumption with use of short descriptors, such as PCA, SIFT, SURF.

G.Csurka, C.Bray, C.Dance, and L.Fan[10]. This paper presents Bag-of-keypoints were inspired by bag-of-words characteristics widely used for text characterization and retrieval. Given a set of keypoints, the BoK method relies on the construction of a codebook of the visual signatures of the keypoints using a k-mean-like method. A discrete value is then assigned for each keypoint group and the image is characterized by the occurrence statistics of each keypoint category which is referred to as visual words. BoK however also ignores the spatial organization of the visual keypoints.

Jesper Moller, Anne Randi Syversveen[11]. This paper has proposed second-order spatial statistics are the sufficient statistics describing log-Gaussian Cox model. The parametric forms of these point process models provide a more compact representation of the spatial keypoint patterns.

Ahmed Nait-Chabane et. al.[12] In this paper, Sidescan sonar records energy of acoustical wave backscattered by seafloor, orthogonally to track followed. Textural features and spectral features are extracted using Gray level co-occurrence matrix and Fourier transform respectively. Unsupervised classifiers, K-means clustering and Self Organizing feature map are used for classification purpose.

Timm Schoening et. al.[13].This paper presents an image patch feature representation concept,the Bag of Prototype (BoP),to cope with the individual problems in underwater image analysis.The approach is capable of describing the local feature setup of complex object entities(i.e.the nodules)while it is straightforward to implement.For computational simplicity,low-level colour feature are used,rather than common SIFT/SURF features.

Ajay Kumar Singh et al.[14].In this paper,comparision of different classifiers compared are Feed Forward Neural Network,Naives Bayes Classifier,K-nearest neighbor classifier and cascaded Neural Network.

III. CONCLUSION

It can be seen from the review that characterization and recognition of seabed images can be done by using different texture analysis methods. But extracting categories of visual keypoints and their positions in sonar images using scale invariant feature transform is popular amongst all. The analysis of keypoint detection statistics for various seabed types indicated that DoG keypoints may be more appropriate to deal with the structures observed in sonar images.

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