Subjective and Objective Quality Evaluation of Sonar Images for Underwater Acoustic Transmission

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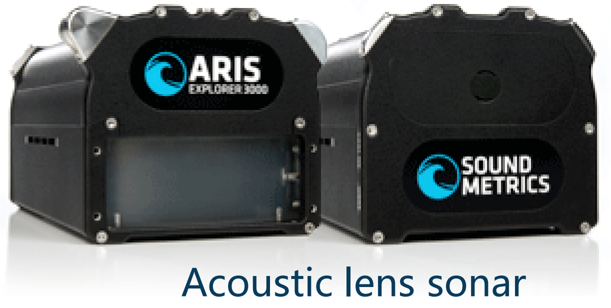
PART ONE

Introduction

01 Introduction

▷ Sonar Images

- Submarine geomorphology
- Marine organism
- Wreck remains

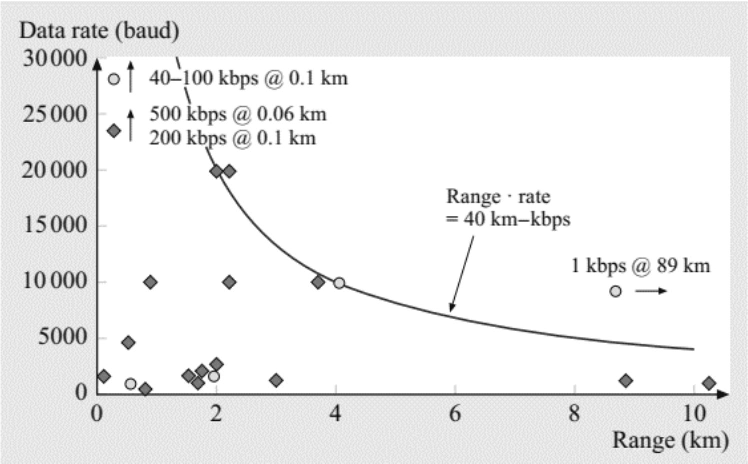


Acoustic lens sonar

Side-scan sonar

▷ Underwater Acoustic Transmission

- Limited bandwidth
- Transmission loss
- Multipath fading
- Time variation



Plot of rate [kbps] versus range [km]

▷ A Pivotal Role of Sonar IQA

- Estimating the quality degradation
- Optimization of compressions
- Basis of retransmission
- Benchmark in the process of image post-processing

Subjective quality assessment

- A sonar image quality database (SIQD) which consists of 40 reference images, 800 test images distorted via compression or transmission and their subjective qualities.

- Mean opinion score (MOS) to represent the image quality and existence of target (EOT) which describes whether the image is useful.

Objective quality assessment

- A novel full-reference (FR) local entropy backed sonar image quality predictor (LESQP) is developed.

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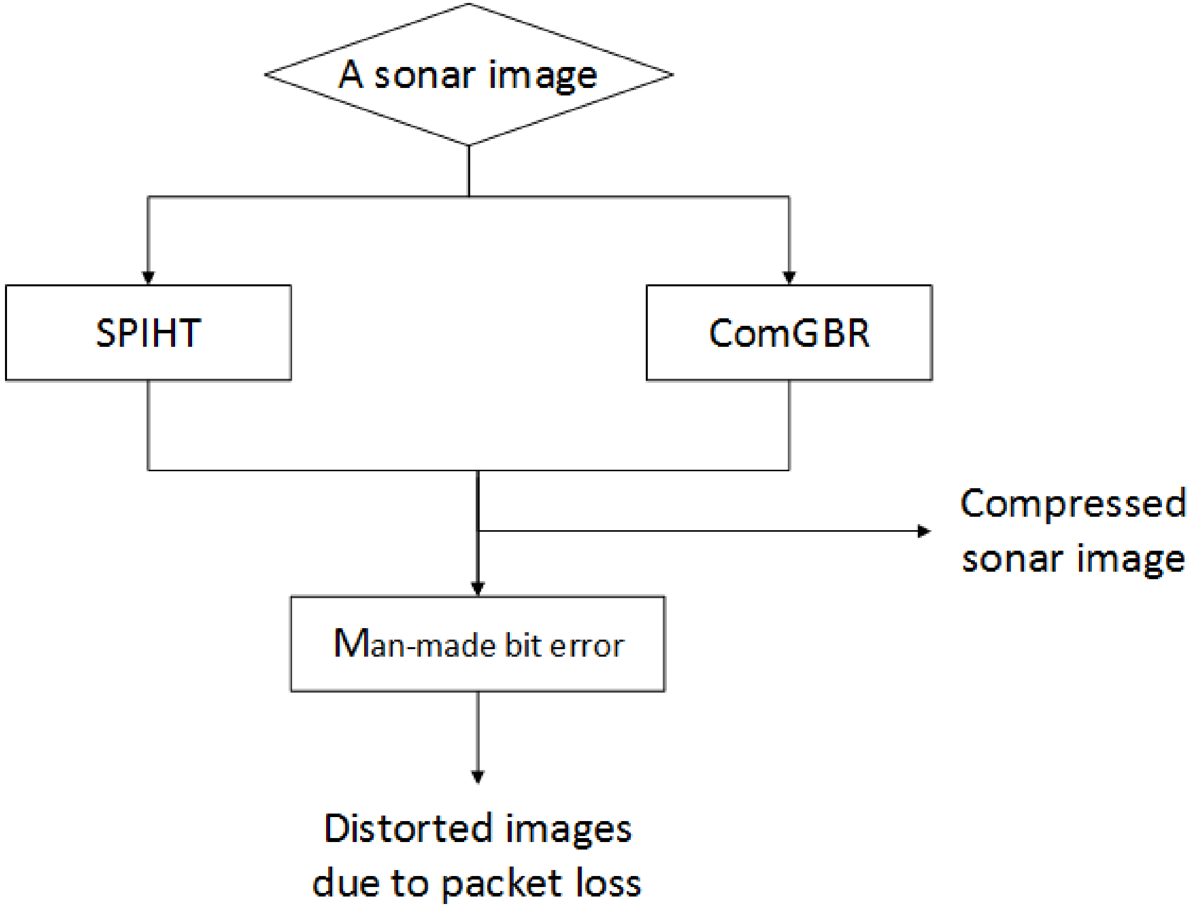
PART TWO

Subjective Quality Assessment

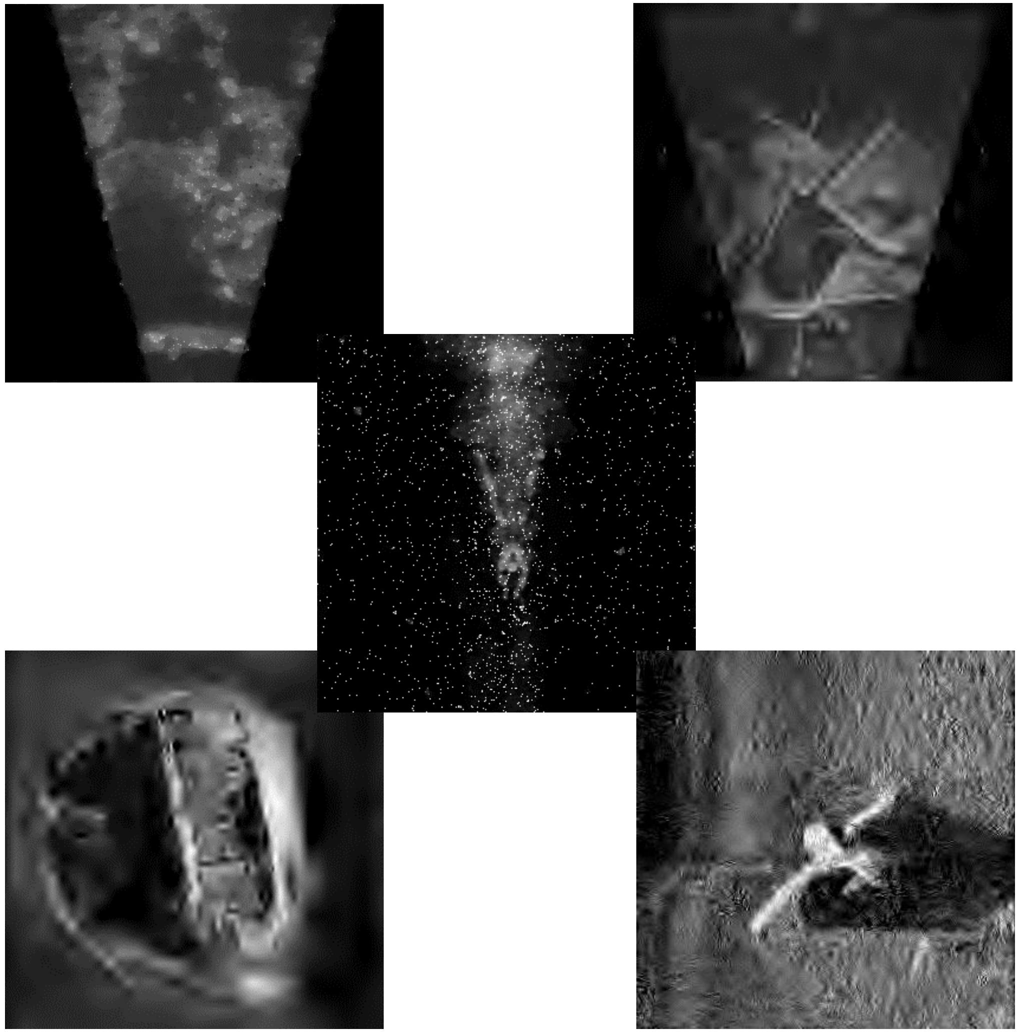
02 Subjective Quality Assessment

02 Subjective Quality Assessment

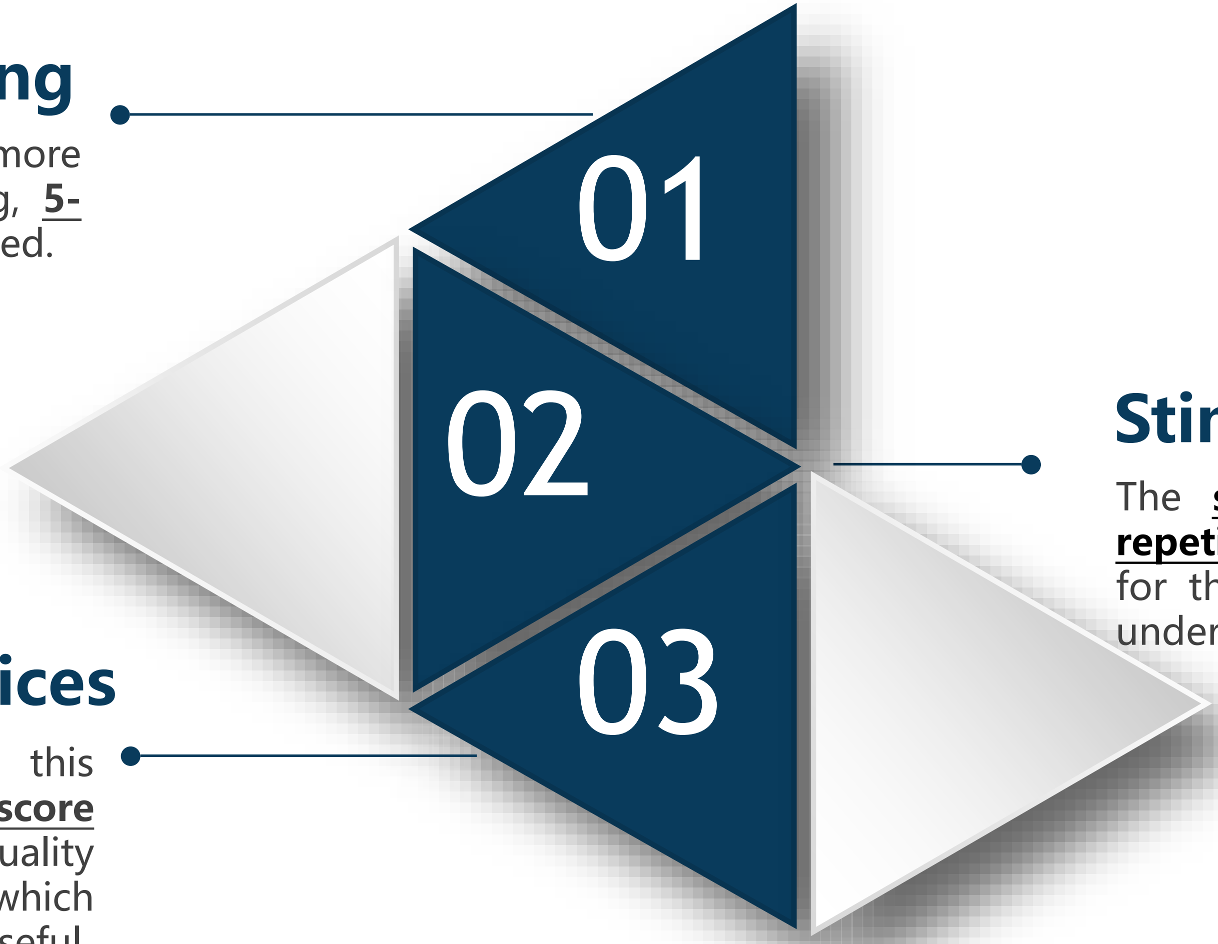
Distortion Types



Overview of the distortion procedure



Subjective Score Obtaining



Quality Rating

In order to make viewers be more certain about the quality rating, **5-category discrete scale** is obtained.

Stimulus Approach

The **single stimulus with multiple repetition (SSMR)** are more suitable for the quality assessment based on underwater acoustic transmission.

Quality Indices

Two indices are gathered in this paper, they are: **mean opinion score (MOS)** to represent the image quality and **existence of target (EOT)** which describes whether the image is useful.

02 Subjective Quality Assessment

Data Processing and Indices Obtaining

$$EOT = \arg\max_{Q} P_Q(i)$$

$$Q \in \{\text{with target}, \text{without target}\}$$

where i denotes test image. $P_Q(\cdot)$ is the fraction of viewers who label the image i with label Q, it approximates to the probability when image i is labeled Q.

EUD

0.12 ~ 0.18

NCC

0.93 ~ 0.95

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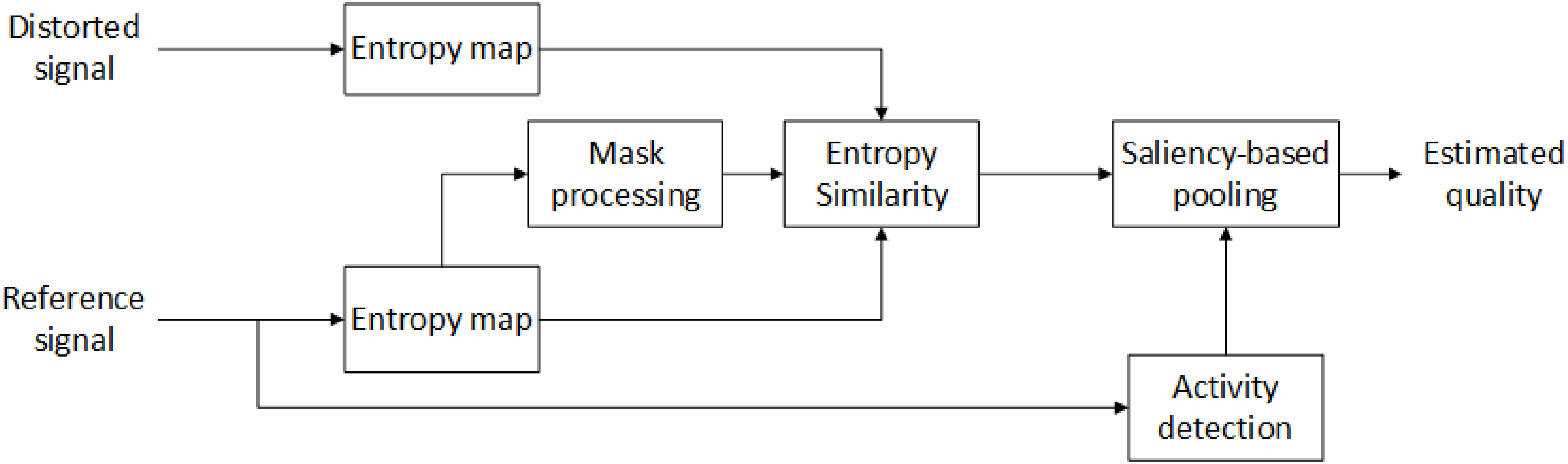
PART THREE

Objective Quality Assessment

03 Objective Quality Assessment

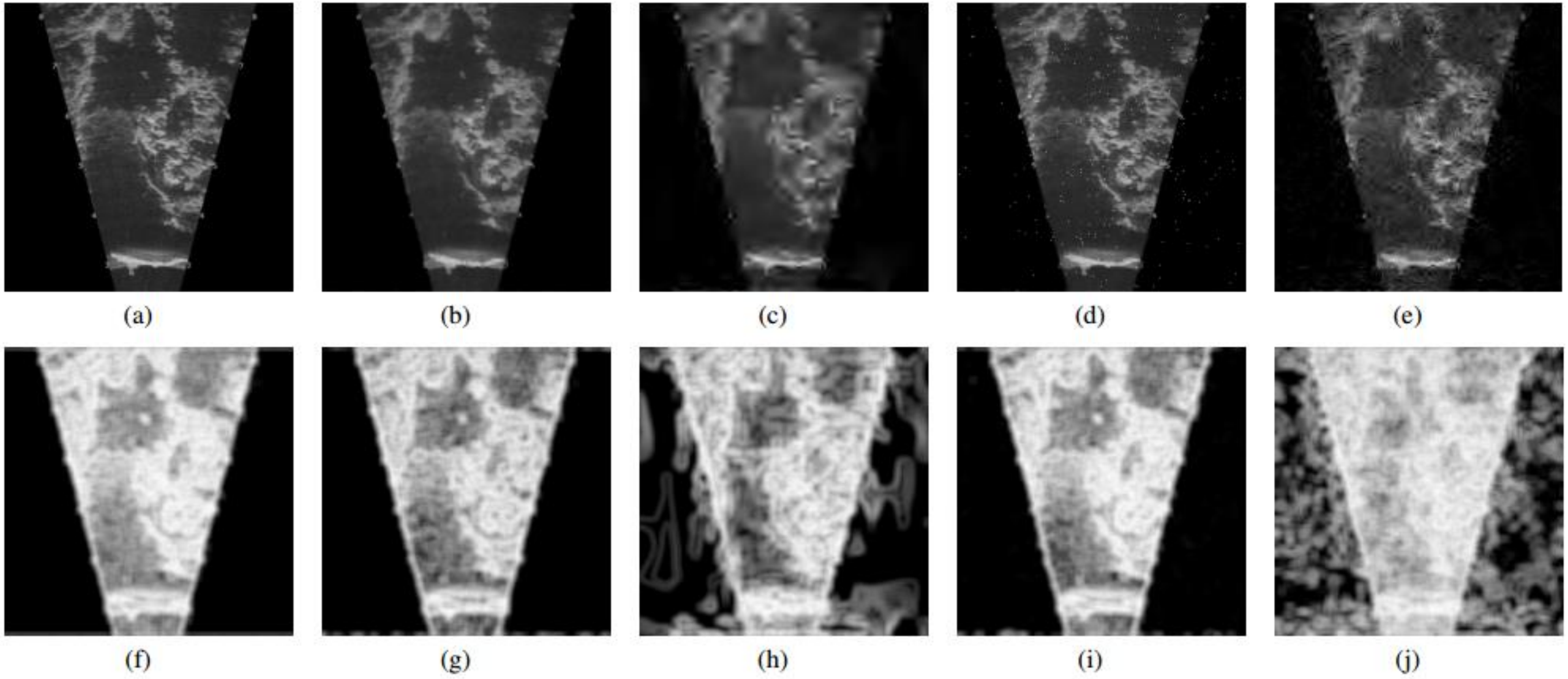


Block diagram of the proposed LESQP metric

01 Local entropy map

$$H_f(x,y) = -\sum_{i=0}^{255} P_i \log P_i$$

$$\hat{H}_{f_r}(x,y) = H_{f_r}(x,y) \cdot M_r(x,y)$$
$$\hat{H}_{f_d}(x,y) = H_{f_d}(x,y) \cdot M_d(x,y)$$



(f)-(j) are local entropy maps extracted from sonar images (a)-(e). (a) reference sonar image; (b) sonar image distorted by ComGBR coding, MOS=61.31; (c) sonar image distorted by SPIHT coding, MOS=30.4; (d) ComGBR-coded sonar image distorted by bit error, MOS=57.15; (e) SPIHT-coded sonar image distorted by bit error, MOS=29.39.

03 Objective Quality Assessment

02 Entropy similarity & Mask processing

$$s(x,y) = \frac{2\hat{H}_{f_r}(x,y)\cdot\hat{H}_{f_d}(x,y)+c}{\hat{H}^2_{f_r}(x,y)+\hat{H}^2_{f_d}(x,y)+c} \qquad c = K*\min(H_{f_r}(x,y), H_{f_r}(x,y))$$

03 Activity detection & Saliency-based pooling

$$I(x,y) = IAM(f_r) \qquad LESQP = \sum\sum s(x,y)\cdot I(x,y)$$

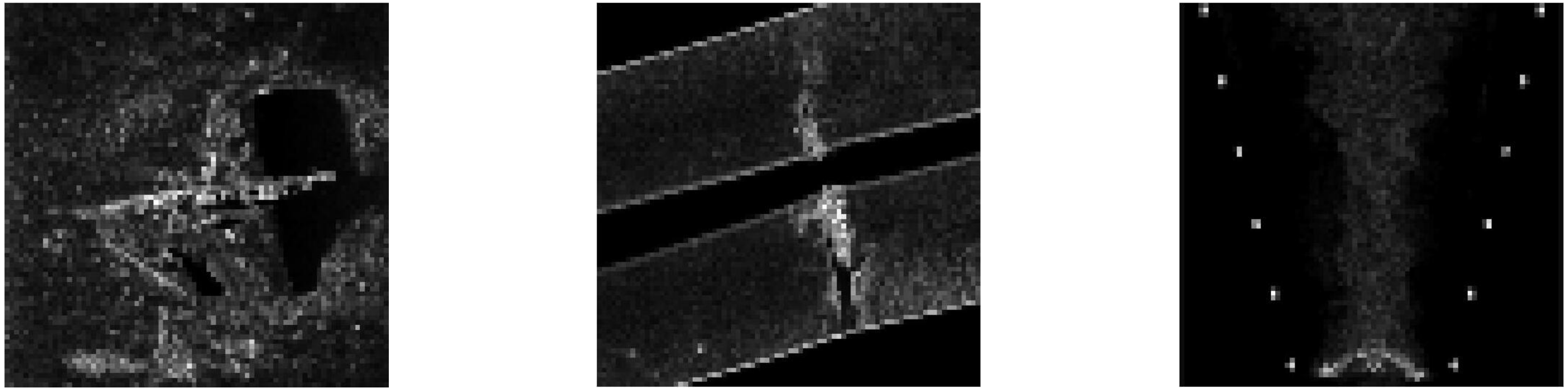


Illustration of activity maps for different sonar images.

Liu, A., Lin, W., Narwaria, M., "Image quality assessment based on gradient similarity," IEEE Transactions on Image Processing, vol. 21, no. 4, pp. 1500-1512, Apr. 2012

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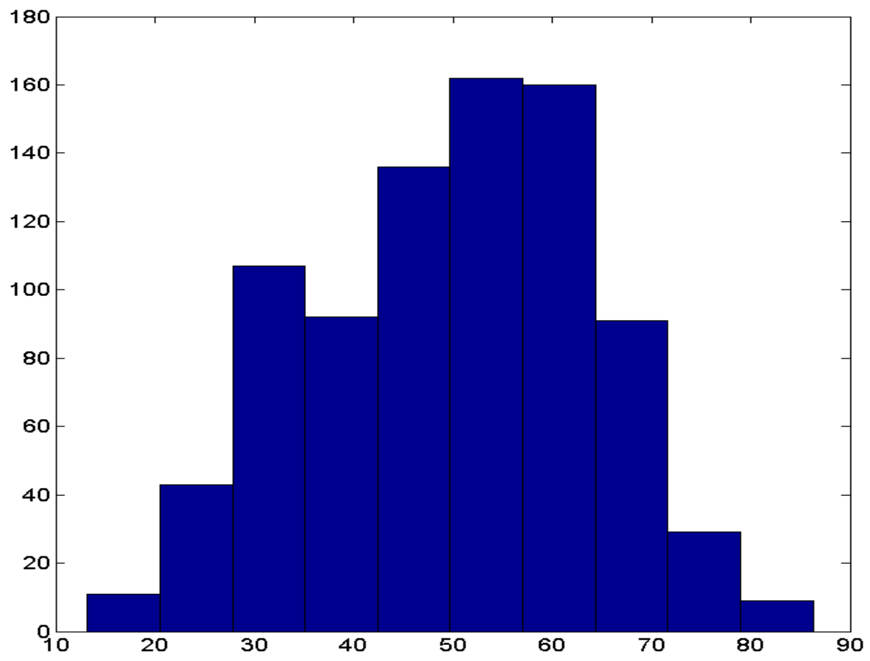
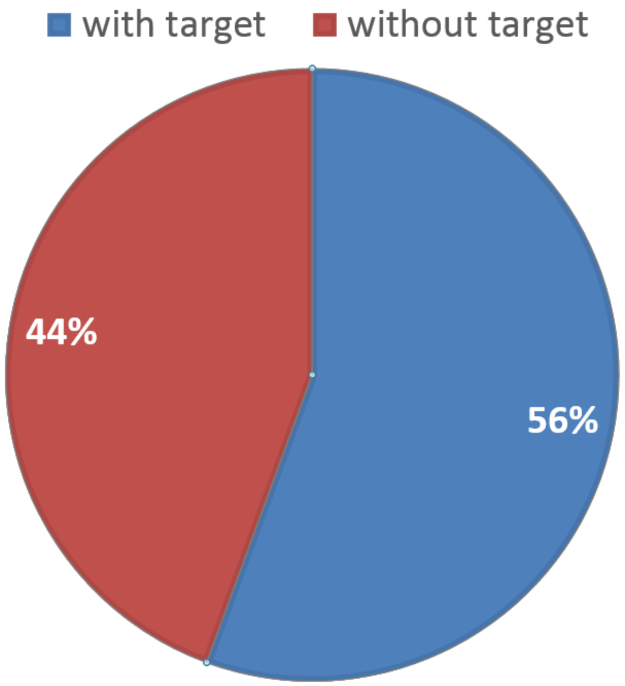
PART FOUR

Experimental Results

The Results of Indices Obtaining



Histogram of MOSs for images in the SIQD database



Pie chart of EOTs for images in the SIQD database

Comparative Analysis for Quality Metrics

A five parameter logistic mapping: $$f(x)=\beta_1\left(\frac{1}{2}-\frac{1}{1+\exp(\beta_2(x-\beta_3))}\right)+\beta_4 x+\beta_5$$

Performance comparison for IQA algorithms on the SIQD database

Criteria	FSIM	VSNR	MAD	ADD-SSIM	GSM	SSIM	GMSD	VSI	PSIM	CPCQI	LESQP
SROCC	0.686	0.433	0.701	0.709	0.615	0.627	0.707	0.720	0.727	0.549	**0.785**
CC	0.707	0.476	0.726	0.731	0.633	0.650	0.714	0.736	0.738	0.567	**0.796**
RMSE	9.631	11.980	9.369	9.298	10.541	10.356	9.532	9.219	9.433	11.517	**8.474**
KROCC	0.490	0.299	0.509	0.509	0.429	0.417	0.503	0.523	0.528	0.377	**0.593**
MAE	7.539	9.772	7.307	7.331	8.316	8.554	7.621	7.148	7.492	9.241	**6.427**

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PART FIVE

Conclusion

Distortions in the SIQD database

All the distortions contained in the SIQD database are collected within the actual progress of compression coding and transmission.

MOS & EOT

There are two quality indices in the SIQD database. The MOS shows the visual feel of subjective viewers for each test image, while the EOT reflects whether the target is able to be recognized in the sonar-captured image.

LESQP

The performance of 10 state-of-the-art FR IQA algorithms are compared with the proposed LESQP metric in SIQD database. Among the 11 algorithms, the proposed LESQP metric shows the better performance than the other 10 FR IQA algorithms.

THANKS!

Q & A

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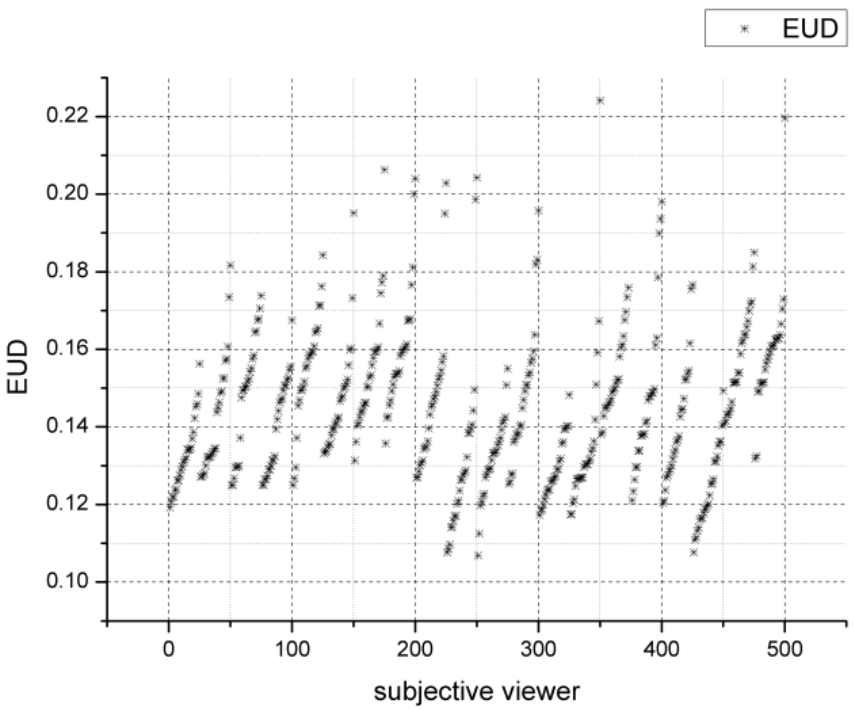
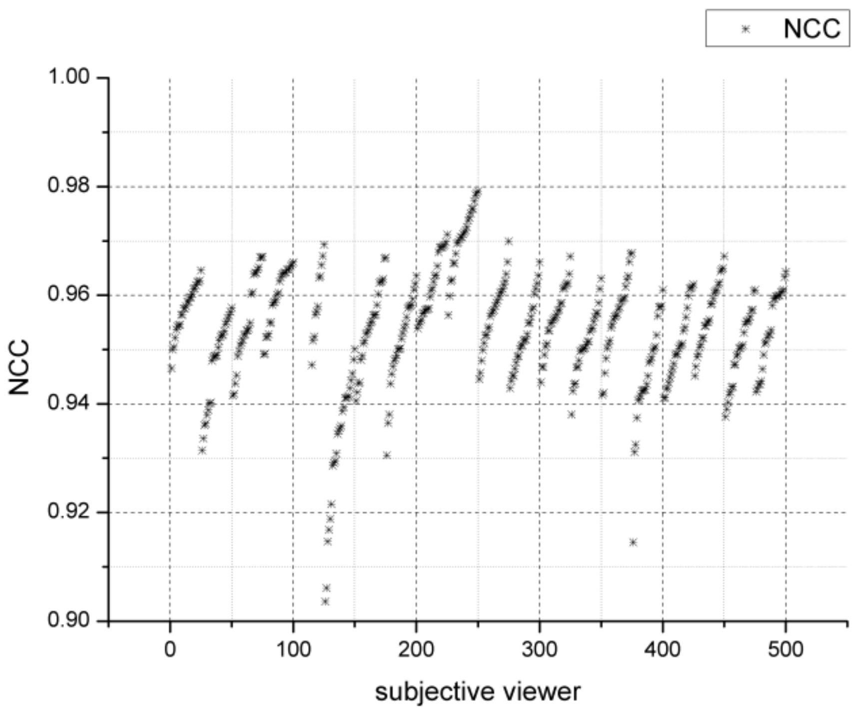
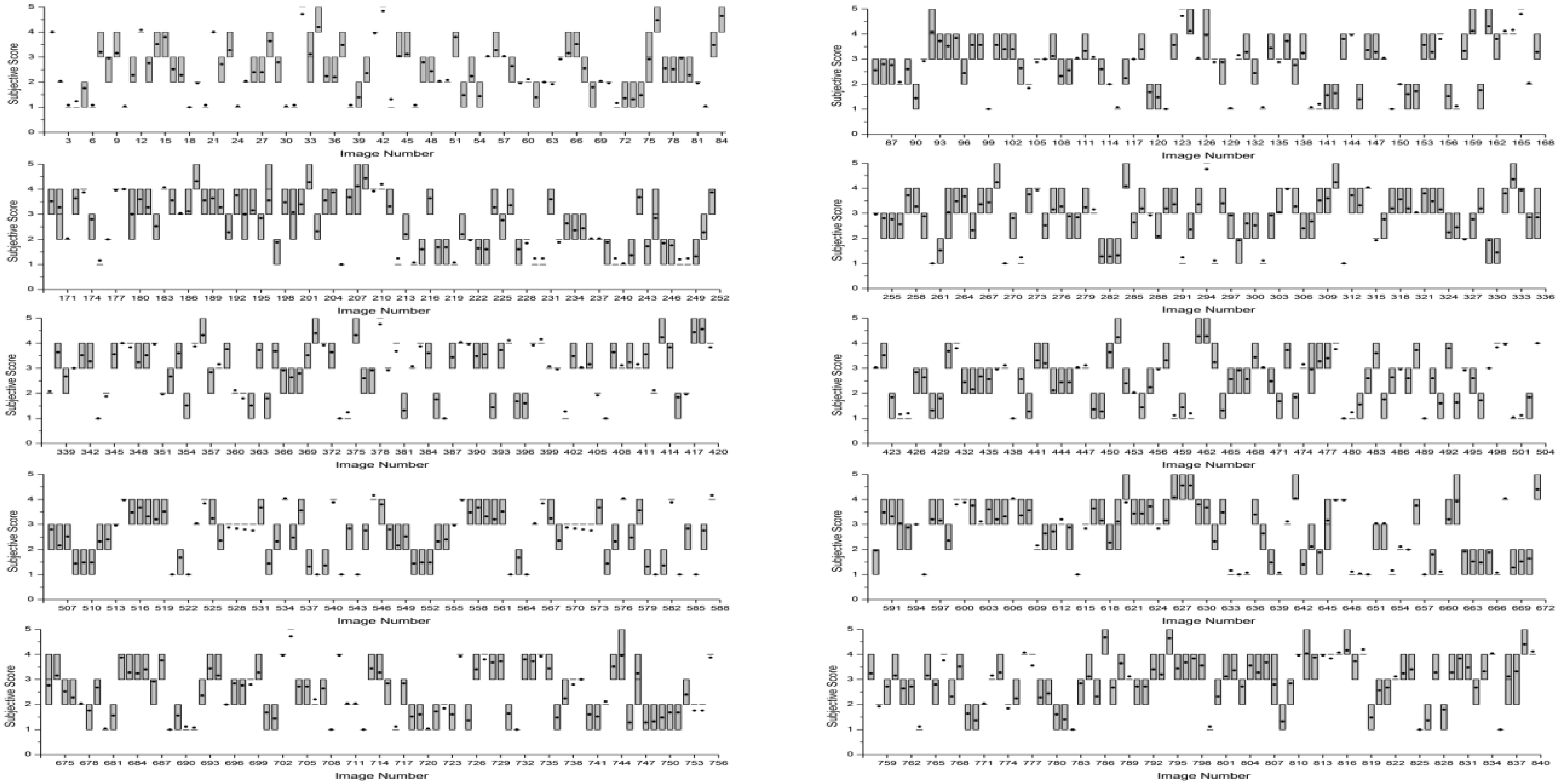

EUD
0.22
0.20
0.18
0.16
0.14
0.12
0.10
0
100
200
300
400
500
subjective viewer


NCC
1.00
0.98
0.96
0.94
0.92
0.90
0
100
200
300
400
500
subjective viewer


Subjective Score
Image Number

$$OC = \frac{N_{outlier}}{N_{total}}$$

For the test images, 21 out of 840 are recognized as outlier images, which implies that OC=2.5%. This demonstrates that most test images had agreement among viewers.

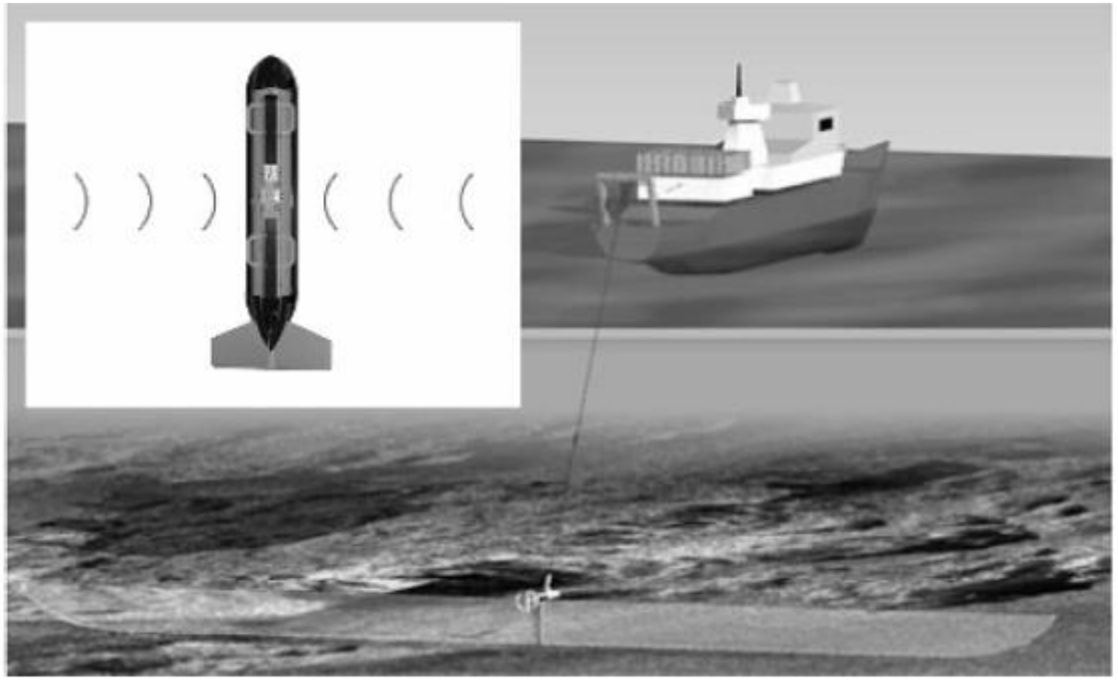
$$IAM_0 = \frac{1}{m \times n}[A + B]$$

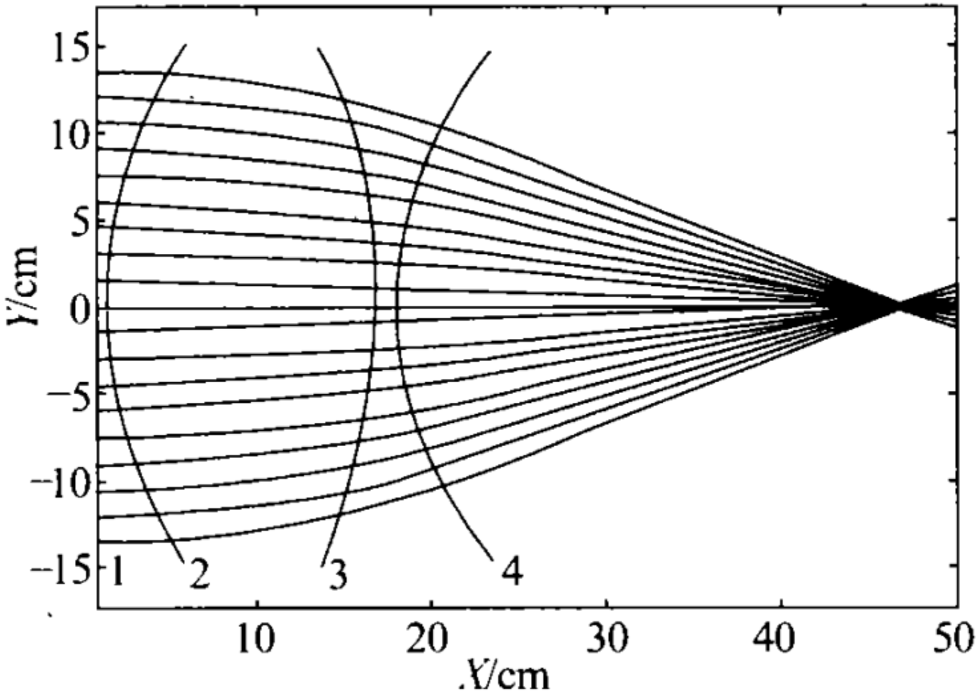
where A and B are defined as:

$$A = \sum_{i=1}^{m-1} \sum_{j=1}^{n} |I(i,j) - I(i+1,j)|$$

$$B = \sum_{i=1}^{m} \sum_{j=1}^{n-1} |I(i,j) - I(i,j+1)|.$$

$$\overline{IAM}_{map}(x,y) = \frac{IAM_{map}(x,y)}{\sum_{x} \sum_{y} IAM_{map}(x,y)}.$$




15
10
5
0
−5
−10
−15
Y/cm
1
2
3
4
10
20
30
40
50
X/cm