The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLII-2/W7, 2017 ISPRS Geospatial Week 2017, 18–22 September 2017, Wuhan, China

A**Example 2013 A Extraction A** *Lease of a CORE Extraction CORE EXECUTE ALIFERS Geospatial Week 2017, 18–22 September 2017, Wuhan, China
 A New 2D Otsu for Water Extraction from SAR Image

Guo Yaru^{a,*} The Matter Sensing and Spaular Information Sciences, volume
Sek 2017, 18–22 September 2017, Wuhan, China
Super Water Extraction from SAR Image
Guo Yaru ^{a,b}, Zhang Jixian c
g Technical University, Fuxin, China-463715703@q **Example School of Geomatics, Liaoning Technical University, Fuxin, China**
 **A New 2D Otsu for Water Extraction from SAR Image

SPRS Geospatial Week 2017, 18–22 September 2017, Wuhan, China

4 New 2D Otsu for Water Extrac** ole Sensing and Spaliar information Sciences, v.
17, 18–22 September 2017, Wuhan, China
ater Extraction from SAR Image
faru^{a,b}, Zhang Jixian connection SAR Image
strated University, Fuxin, China-463715703@qc
Surveying

brought to you by ω CORE

The intermoderatives of the Photographineury, remode Sensing and Spatian mionifation Schences, volume ALIEZIWI, 2011

ISPRS Geospatial Week 2017, 18–22 September 2017, Wuhan, China

A New 2D Ot CONTRITURE CONSIDENT IS PRESS Geospatial Week 2017, 18-22 September 2017, Wuhan, China

ISPRS Geospatial Week 2017, 18-22 September 2017, Wuhan, China

A New 2D Otsu for Water Extraction from SAR Image

Guo Yaru^{a,b}, Zhan

KEY WORDS:2D OTSU method, gray level co-occurrence matrix(GLCM), synthetic aperture radar(SAR), water extraction, texture
ABSTRACT:
ABSTRACT: factors or Water Extraction from SAR Image

Guo Yaru^{a,b}, Zhang Jixian c

g Technical University, Fuxin, China-463715703@qq.com

eau of Surveying and Mapping, Chinese Academy of Surveyin

Beijing, China

sting Center for Surveyin

ABSTRACT:
SAR image segmentation is a crucial step that heavily influences the performance of image interpretation. The texture factor to ^b Key Laboratory of Geo-Informatics, Chaoming redunctant onwestay, Texture, China-4005 *117.19 Soggel*Com-

Feijing, China

Feijing, China

Commission III, WG III/6

KEY WORDS:2D OTSU method, gray level co-occurrence mat replace the neighborhood mean dimension in the neighborhood mean dimension in the substitution in the neighborhood mean dimension in the traditional Quality Inspection and Testing Center for Surveying and Mapping Products, SAR image segmentation is a crucial step that has unique characteristics and Mapping Products, Beijing, China

Commission III, WG III/6

KEY WORDS:2D OTSU method, gray level co-occurrence matrix(GLCM), synthetic aperture r Transity inspection and resultig center to surveying and wiapping Protacts, beijing, climat

Commission III, WG III/6

KEY WORDS:2D OTSU method, gray level co-occurrence matrix(GLCM), synthetic aperture radar(SAR), water e **EXELA WORDS:2D OTSU method, gray level co-occurrence matrix(GLCM), synthetic aperture radar(SAR), water extraction, texture factors**
factors
determined the structural characteristics and the original parameteristics of th KEY WORDS:2D OTSU method, gray level co-occurrence matrix(GLCM), synthetic aperture radar(SAR), water extraction, texture factors
factors
dSTRACT:
ABSTRACT:
ABSTRACT:
ABSTRACT:
ABSTRACT:
abSER image regnentation is a cruci KEY WORDS:2D OTSU method, gray level co-occurrence matrix(GLCM), synthetic aperture radar(SAR), water extraction, texture factors
factors
ABSTRACT:
SAR image segmentation is a crucial step that heavily influences the perfo KEY WORDS:2D OTSU method, gray level co-occurrence matrix(GLCM), synthetic aperture radar(SAR), water extraction, texture factors
dators
dators
ABSTRACT:
SAR image segmentation is a crucial step that heavily influences the has a high practical value for SAR Image water segmentation.

ABSTRACT:

SAR image segmentation is a crucial step that heavily influences the performance

scare replace the neighborhood mean dimension in the traditional Ot Interior is a crucial step that heavily influences the perform
 1. The transformal content of the complement of the single band and single polarization is us

1. In the single band and single polarization is us

1. Inter replace the neighborhood mean unmension in the traditional Osti method is proposed in this work.

SAR image has unique characteristics and the original 2D Ots unethod only considers the pixel neight

this paper, TerraSAR i SAK image has unique characteristics and the original 2D Otsu method only considers the price bused to value α this paper, TerraSAR image with the single band and single polarization is used to value extraction. Then, this paper, 1 errasAR image with the single band and single polarization is used to wate
used to analyze the structural characteristics of the sample image to determine the operate
extraction. Then, calculate the textural used to analyze the structural characteristics of the sample image to determine the extraction. Then, calculate the textural measures such as contrast, entropy, homogeneous also cocurrence matrix(GLCM) method. The results **2. TRADITIONAL 2D OTSU**
**2. The Set of the Set of the Set of the Set of the pixel neighborhood mean information. In water extraction. Firstly, the semantic function is
2. explored** parameters of the texture information
p Let the pixels of a pixel method is proposed in this work, alternal at the problem that the bido only considers the pixel neighborhood mean information. In tho is to determine the optimal parameters of the exture informat fillon is used to water extraction. Firstly, the semantic function is
to determine the optimal parameters of the texture information
intropy, homogeneity, mean and second moment based on gray
ared with the artificially ma tion is used to water extraction. Firstly, the semantic function is
to determine the optimal parameters of the texture information
entropy, homogeneity, mean and second moment based on gray
ared with the artificially mark n, thma-463/13) Miggaq com

E, Chinese Academy of Surveying and Mapping,

E, Chinese Academy of Surveying and Mapping,

Hotel aperture radar(SAR), water extraction, texture

there are of image interpretation. The texture

Evel co-occurrence matrix(GLCM) method. The results are compared with the artificially mate-
original 2D Otsu. The experimental results achieve higher objective values, which shows the prop
has a high practical value for original 2D Otsu. The experimental results achieve higher objective values, which shows
has a high practical value for SAR Image water segmentation.

1. INTRODUCTION 2.

With the rapid development of remote sensing techno **1. INTRODUCTION** 2. **TRADITION** 3. Let the pixels of a given image of great significance to recogniz **1. INTRODUCTION**
 2. TRADIT

With the rapid development of remote sensing technology, it is Let the pixels of a given ima

of great significance to recognize water rapidly and accurately the local average gray level

i **1. INTRODUCTION 2. TRAD**

With the rapid development of remote sensing technology, it is Let the pixels of a given in

of great significance to recognize water rapidly and accurately the local average gray leven

in th **1. INTRODUCTION** 2. **TRADIT**

With the rapid development of remote sensing technology, it is Let the pixels of a given im

of great significance to recognize water rapidly and accurately the local average gray level

in **EXECUTE 11. INTRODUCTION**
 EXECUTE 11. INTRODUCTION

IT is the pixels of a given image of great significance to recognize water rapidly and accurately the local average gray level

in the field of flood disaster manage With the rapid development of remote sensing technology, it is Let the pixels of a given image
of great significance to recognize water rapidly and accurately
in the local average gray level
in the field of flood disaster while the taplet difficult of the end of great in the field of flood disaster management, environmental when she field of flood disaster management, environmental wheres. Let f_{ij} be the total n
monitoring, transportati or great significance to recognize water input) and accuracity

in the field of flood disaster management, environmental values. Let fig be the total num

monitoring, transportation and urban planning .

At present, water in the held of hood usaster management, environmental values. Let t_{il} be the total im
monitoring, transportation and urban planning. which represents the gray v
been relatively abundant, including threshold segmentation monitoring, transportation and uban planning. Which represents the gray values of the present, water segmentation methods for SAR image have been relatively abundant, including threshold segmentation. ID Otsu threshold se At present, water segmentation methods for SAR image have
been relatively abundant, including threshold segmentation,
which is more general, fast and easy to implementation. ID
Otsu threshold segmentation algorithm only c At present, water segmentation methods to satisfactory been relatively abundant, including threshold segmentation,

which is more general, fast and easy to implementation. ID

Otsu threshold segmentation algorithm only co been relatively abundant, including threshood segmentation, 1D
which is more general, fast and easy to implementation. 1D
Otsu threshold segmentation algorithm only considers the gray
information of source image, but for Otsu. influenced by the noise image, but on the image winch is given the set in the electron endeptheneod by the noise, the gray information can not show
structure and detail information completely. Therefore, J.Z. Liu
took adv muence by un loos, the gay mindulation can into show
structure and detail information completely. Therefore, J.Z. Liu
took advantage of neighborhood spatial information and
extended one dimension algorithm to two-dimensio suctue and each information conpletely. Therefore, J.E. L. L.

took advantage of neighborhood spatial information and

extended one dimension algorithm to two-dimensional space.

The algorithm not only ensures accuracy an box avantage of neglatomod spatial into mathematical and the extended one dimensional agree.

extended one dimensional agricultor to two-dimensional space.

The algorithm not only ensures accuracy and speed of the

remote

Exercise on equivals on applied to the exercist of the exercist of the remote sensing image segmentation, but also resists some noise. Where ω_0 , ω_1 = the probabil However, if the 2D Otsu method is applied directly The algorium not only ensuse accuacy and speed on the
remote sensing image segmentation, but also resists some noise. Where ω_0 , ω_1 = the p
However, if the 2D Otsu method is applied directly to SAR μ_0 , μ_1 = Enote sensing mage segmentation, out also resists some noise. Where ω_0 , ω_1 = the However, if the 2D Otsu method is applied directly to SAR μ_0 , μ_1 = the satisfactory due to the multiplicative noise in SAR i However, it ince 2D bust method is applied uncertly to SAR image segmentation, the segmentation results will be not satisfactory due to the multiplicative noise in SAR image and The threshold vector (s,t) is sell the pixe mage segmentation, the segmentation ressurs with the original statistic deviation of the pixel neighborhood mean information in the original 2D Otsu.

Tr $(s, t) = Ma$.

Compared with the optical image, SAR image has rich text Sausiactory due to the multiplicative holse in SAR image and
the pixel neighborhood mean information in the original 2D
Otsu.
Compared with the optical image, SAR image has rich texture
information which can distinguish so

to determine the optimal parameters of the texture information
entropy, homogeneity, mean and second moment based on gray
ared with the artificially marked images and the results of the
values, which shows the proposed al entropy, nomogeneity, mean and second moment based on gray
ared with the artificially marked images and the results of the
values, which shows the proposed algorithm using texture factor
2. TRADITIONAL 2D OTSU
Let the **2. TRADITIONAL 2D OTSU**

Let the pixels of a given image be represented in L gray levels,

the local average gray level is also divided into the same L

values. Let f_{ij} be the total number of frequency of the pair $(i,$ 2. **TRADITIONAL 2D OTSU**

Let the pixels of a given image be represented in L gray levels,

the local average gray level is also divided into the same L

values. Let f_{ij} be the total number of frequency of the pair $(i,$ which represents the gray value and its average value, then the
joint probability mass function p_{ij} is given by
joint probability mass function p_{ij} is given by
 $p_{ij} = f_{ij} / N(i, j = 0, 1, \dots, L - 1)$ (1)
Where $N =$ the tota

$$
p_{ij} = f_{ij} / N(i, j = 0, 1, \cdots, L - 1)
$$
 (1)

probability mass function
$$
p_{ij}
$$
 is given by
\n
$$
p_{ij} = f_{ij} / N(i, j = 0, 1, \dots, L - 1)
$$
\n
$$
N= the total pixels of the image\nbetween-class variance matrix is defined as\n
$$
\sigma_B = \omega_0 [(\mu_0 - \mu_T)(\mu_0 - \mu_T)^T] + \omega_1 [(\mu_1 - \mu_T)(\mu_1 - \mu_T)^T]
$$
\n
$$
P = \omega_0, \quad \omega_1 = \text{the probabilities of class occurrence}
$$
\n
$$
\mu_0, \quad \mu_1 = \text{the corresponding class mean levels}
$$
\nthreshold vector (s,t) is selected by maximizing:
$$

 $p_{ij} = f_{ij} / N(i, j = 0, 1, \dots, L - 1)$ (1)

Where N= the total pixels of the image

The between-class variance matrix is defined as
 $\sigma_B = \omega_0 \left[(\mu_0 - \mu_T)(\mu_0 - \mu_T)^T \right] + \omega_i \left[(\mu_1 - \mu_T)(\mu_1 - \mu_T)^T \right]$ (2)

Where ω_0 , ω_1 = th

$$
Tr (s, t) = Max (Tr(\sigma_B))
$$
\n(3)

The between-class variance matrix is defined as
 $\sigma_B = \omega_0 \left[(\mu_0 - \mu_r)(\mu_0 - \mu_r)^r \right] + \omega_l \left[(\mu_1 - \mu_r)(\mu_1 - \mu_r)^r \right]$ (2)

Where ω_0 , ω_1 = the probabilities of class occurrence
 μ_0 , μ_1 = the corresponding class $\sigma_B = \omega_0 \left[(\mu_0 - \mu_r)(\mu_0 - \mu_r)^r \right] + \omega_1 \left[(\mu_1 - \mu_r)(\mu_1 - \mu_r)^r \right]$ (2)

Where ω_0 , ω_1 = the probabilities of class occurrence
 μ_0 , μ_1 = the corresponding class mean levels

The threshold vector (s,t) is sele $\sigma_B = \omega_0 \left[(\mu_0 - \mu_r)(\mu_0 - \mu_r)^r \right] + \omega_i \left[(\mu_1 - \mu_r)(\mu_1 - \mu_r)^r \right]$ (2)

Where ω_0 , ω_1 = the probabilities of class occurrence
 μ_0 , μ_1 = the corresponding class mean levels

The threshold vector (s,t) is selec Where ω_0 , ω_1 = the probabilities of class occurrence
 μ_0 , ω_1 = the probabilities of class occurrence
 μ_0 , μ_1 = the corresponding class mean levels

The threshold vector (s,t) is selected by maximiz Where ω_0 , ω_1 = the probabilities of class occurrence
 μ_0 , μ_1 = the corresponding class mean levels

The threshold vector (s,t) is selected by maximizing:
 $Tr (s, t) = Max (Tr(\sigma_B))$ (3)

Although the traditional 2D Where ω_0 , ω_1 = the probabilities of class occurrence
 μ_0 , μ_1 = the corresponding class mean levels

The threshold vector (s,t) is selected by maximizing:
 $Tr (s, t) = Max (Tr(\sigma_B))$ (3)

Although the traditional 2D

The International Archives of the Photogrammetry, Re

ISPRS Geospatial Week 2
 3.1 GLCM

The texture of the image shows the common intrinsic p

of the surface of objects, and includes important infor

about the organizat The International Archives of the Photogrammetry, Remote Sensing and Spatial Information

ISPRS Geospatial Week 2017, 18–22 September 2017, Wuhan,

3. **TEXTURE EXTRACTION BASED ON GLCM**

3. **IGLCM**

3. **IGLCM**

3. **IGLCM** The International Archives of the Photogrammetry, Remote Sensing and Spatial Informat

ISPRS Geospatial Week 2017, 18–22 September 2017, Wurk

3. **IEXTURE EXTRACTION BASED ON GLCM**

3. **IEXTURE EXTRACTION BASED ON GLCM**
 The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Science ISPRS Geospatial Week 2017, 18–22 September 2017, Wuhan, Chin

3. **TEXTURE EXTRACTION BASED ON GLCM**

3.1 **GLCM**

3.1 **GLCM** 3. TEXTURE EXTRACTION BASED ON GLC
3.1 GLCM
The texture of the image shows the common intrinsic p
of the surface of objects, and includes important info
about the organization of objects and its connection
 $P(i, j | d, \theta) = \{[($ **TEXTURE EXTRACTION BASED ON GLCM**

sure of the image shows the common intrinsic property

urface of objects, and includes important information

e organization of objects and its connection to the
 $P(i, j | d, \theta) = \{[(x, y), (x +$ EM

interpretent of the image shows the common intrinsic proface of objects, and includes important inform

interaction of objects and its connection
 $P(i, j | d, \theta) = \{[(x, y), (x + dr, y)]\}$
 $d = (dr, dc)$
 $dr, dc = the row and the column dir$

ent
 $dy = x$ is **EVA**

the spatial correlation of

unrative of the inage shows the common intrinsic property

unrative difference of objects, and includes important information

e organization of objects and its connection to the
 $P(i, j |$

$$
P(i, j | d, \theta) = \{ [(x, y), (x + dr, y + dc)] | f(x, y) = i; f(x + dr, y + dc) = j] \}
$$
 (4)

displacement

pixels.

of the surface of objects, and includes important about the organization of objects and its connec
 $P(i, j | d, \theta) = \{[(x, y), (x + \theta)]\}$

Where $d = (dr, dc)$
 $dr, dc = the row$ and the column

displacement
 $x, y = \text{coordinate of the pixel}$
 $i, j = \text{gray level}$
 $\theta =$ $P(i, j | d, \theta) = \{[(x, y), (x + dr, y + dc)] | f (x, y) = i; f (x + dr, z)\}$

Where $d = (dt, dc)$

dr, dc= the row and the column direction

and is of the texture values are

displacement
 $x, y =$ coordinate of the pixel
 $y, y = 0$ and the gray level
 θ Where $d = (dr, dc)$
 $dr, dc =$ the row and the column direction matrix. The matrix is a fu

displacement
 $x, y=$ coordinate of the pixel
 $\theta = 0^\circ, 45^\circ, 90^\circ, 135^\circ$, the direction of the statistical between the

pixels.
 3.2 Where $d = (dr, dc)$
 $dr, dc =$ the row and the column direction matrix. The matrix is a functi
 $x, y =$ coordinate of the pixel
 $i, j =$ gray level
 $\theta = 0^\circ, 45^\circ, 90^\circ, 135^\circ$, the direction of the statistical
 $\theta = 0^\circ, 45^\circ, 9$ Where $d = (dr, dc)$

dr, dc= the row and t

displacement

x, y= coordinate of the pixel

i, j= gray level
 $\theta = 0^\circ$, 45 °, 90 °, 135 °, the dire

pixels.
 3.2 Structre values

Haralick et al. defined 14 texture features

l dc= the row and the column direction matrix. The mat

and distance bet

or occurrences

specified neighbors
 $\frac{1}{2}$, $\frac{1}{2}$, $\frac{1}{2}$, $\frac{1}{2}$, the direction of the statistical
 $\frac{1}{2}$, $\frac{1}{2}$, $\frac{1}{2}$, 3.3 Semi-variogram

3.2 Structre values

Haralick et al. defined 14 texture features according to the gray

The GLCM is affected by the

level co-occurrence matrices. In this paper, Contrast, Entropy, Since the semi-vario 3.2 **Structre values**

The GLCM is affected by the

Haralick et al. defined 14 texture features according to the gray

The GLCM is affected by the

level co-occurrence matrices. In this paper, Contrast, Entropy, Since the Haralick et al. defined 14 texture features according to the gray
level co-occurrence matrices. In this paper, Contrast, Entropy,
Homogeneity, Mean and Second Moment are used. Here follow
the calculations:
1) Contrast
 $f_$

$$
f_1 = \sum_i \sum_j p(i, j)^2 \tag{5}
$$

$$
f_4 = -\sum_{i} \sum_{j} p(i, j) \log (p(i, j)) \tag{6}
$$

1) Contrast
 $f_1 = \sum_i \sum_j p(i, j)^2$

(5)

This feature reflects the clarity of the image and the degree of

the texture depth. The deeper the texture is, the bigger the

contrast is, with a clear visual effect.

2) Entropy
 $f_1 = \sum_i \sum_j p(i, j)^2$ (5)

This feature reflects the clarity of the image and the degree of

the texture depth. The deeper the texture is, the bigger the

contrast is, with a clear visual effect.

2) Entropy
 $f_4 = -\sum_i \sum_j p(i,$ This feature reflects the clarity of the image and the degree of

the texture depth. The deeper the texture is, the bigger the

contrast is, with a clear visual effect.

2) Entropy
 $f_4 = -\sum_i \sum_j p(i, j) \log (p(i, j))$

(6)

This f This feature reflects the clarity of the image and the degree of

the texture depth. The deeper the texture is, the bigger the

contrast is, with a clear visual effect.

2) Entropy
 $f_4 = -\sum_i \sum_j p(i, j) \log (p(i, j))$
 $f_5 = \frac{1}{2$ This feature reflects the clarity of the image and the degree of

the texture depth. The deeper the texture is, the bigger the

contrast is, with a clear visual effect.

2) Entropy
 $f_4 = -\sum_i \sum_j p(i, j) \log (p(i, j))$
 $f_5 = \frac{1}{2$ The texture depth. The deeper the texture is, the bigger the $\theta = 45$
contrast is, with a clear visual effect.
2) Entropy $f_4 = -\sum_i \sum_j p(i, j) \log (p(i, j))$ (6)
This feature reflects the complexity of the texture in the image.
1) 2) Entropy
 $f_4 = -\sum_i \sum_j p(i, j) \log (p(i, j))$

This feature reflects the complexity of the more uniform the image is, the small

the more complex the texture of the im-

entropy is. What's more, the entropy

randomness of the te $\sum_{j} p(i, j) \log (p(i, j))$
 $\sum_{j} p(i, j) \log (p(i, j))$
 $\cos(\theta) = 96$
 $\sum_{j} p(i, j) \log (p(i, j))$
 $\cos(\theta) = 12$
 $\cos(\theta) = 12$
 $\sum_{j} \sum_{j} \log p(i, j)$
 $\sum_{j} \sum_{j} \frac{p(i, j)}{1 + (i - j)^2}$
 $\sum_{j} \sum_{j} \frac{p(i, j)}{1 + (i - j)^2}$
 $\sum_{j} \log(\theta)$
 $\sum_{j} \log(\theta)$
 \sum This feature reflects the complexity of the texture in the image.

The more uniform the image is, the smaller the entropy is, while

the more complex the texture of the image is, the greater the

entropy is. What's more, This feature reflects the complexity of the texture in the image.

The more uniform the image is, the smaller the entropy is, while

the more complex the texture of the image is, the greater the

entropy is. What's more, The more uniform the image is, the smaller the entropy is, while
the more complex the texture of the image is, the greater the
entropy is. What's more, the entropy can also measure the
randomness of the texture of the ima entropy is. What's more, the entropy can a
randomness of the texture of the image, therefore and randomness of the texture of the image.
3) Homogeneity
3) Homogeneity
 $f_s = \sum_i \sum_j \frac{p(i, j)}{1 + (i - j)^2}$
This feature reflects th *i* manned in the texture of the image is, the greater the

more, the entropy can also measure the

texture of the image, there is, the greater the

more, the entropy can also measure the

texture of the image, there is,

$$
f_s = \sum_i \sum_j \frac{p(i,j)}{1 + (i-j)^2}
$$
 (7) M

3) Homogeneity
 $f_s = \sum_i \sum_j \frac{p(i, j)}{1 + (i - j)^2}$ (7) M= the

direction and s

This feature reflects the homogeneity of the image, measuring

the changes in the local image. Large value indicates that the

texture of the loca $\sum_{j} \frac{p(i, j)}{1 + (i - j)^2}$ (7) a

interaction

interaction

image. Large value indicates that the

is very uniform.
 $\sum_{i} \sum_{j} p(i, j)$ (8) The text
 $\sum_{i} \sum_{j} p(i, j)$ (8) The text

let g(x,

overall gray of the image.

Int

$$
f_6 = \frac{1}{N \times N} \sum_{i} \sum_{j} p(i, j)
$$
 the gra
(8) the tr

$$
f_8 = \sum_{i} \sum_{j} \{p(i, j)\}^2
$$
g

Extitute of the local image is very uniform.

4) Mean (Mean)
 $f_6 = \frac{1}{N \times N} \sum_i p(i, j)$
 $f_7 = \frac{1}{N \times N} \sum_i p(i, j)$
 $f_8 = \sum_{i} \sum_{j} p(i, j)^2$

5) Second Moment (Second Moment)
 $f_s = \sum_{i} \sum_{j} \{p(i, j)\}^2$

(9)

This feature show 4) Mean (Mean)
 $f_6 = \frac{1}{N \times N} \sum_i \sum_j p(i, j)$
 $\begin{aligned}\n&= \frac{1}{N \times N} \sum_i \sum_j p(i, j) \\
&= \frac{1}{N \times N} \sum_j p(i, j)\n\end{aligned}$ (8) the gray level of a pixel and

This feature measures the overall gray of the image.

5) Second Moment (Second Mom 4) Mean (Mean)
 $f_6 = \frac{1}{N \times N} \sum_i \sum_j p(i, j)$ (8)

This feature measures the overall gray of the image.

5) Second Moment (Second Moment)
 $f_8 = \sum_i \sum_j \{p(i, j)\}^2$ (9)

This feature shows the uniformity of the gray distributi

The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences,

ISPRS Geospatial Week 2017, 18–22 September 2017, Wuhan, China

3. **TEXTURE EXTRACTION BASED ON GLCM**

5. **ISPREMANTION BA** Summer Spatial Information Sciences, Volume XLII-2/W7, 2017
September 2017, Wuhan, China
surrounding environment. The gray level co-occurrence matrix
is a generally used method to describe the texture by studying
the spati or and Spatial Information Sciences, Volume XLII-2/W7, 2017

September 2017, Wuhan, China

surrounding environment. The gray level co-occurrence matrix

is a generally used method to describe the texture by studying

the In and Spatial Information Sciences, Volume XLII-2/W7, 2017

September 2017, Wuhan, China

surrounding environment. The gray level co-occurrence matrix

is a generally used method to describe the texture by studying

the s matrix that the pixel i corresponds to the occurrence matrix

factor and the pixel intervalsed in the pixel co-occurrence matrix

is a generally used method to describe the texture by studying

the spatial correlation of of the pixel information Sciences, Volume XLII-2/W7, 2017

September 2017, Wuhan, China

surrounding environment. The gray level co-occurrence matrix

is a generally used method to describe the texture by studying

the sp and Spatial Information Sciences, Volume XLII-2/W7, 2017

September 2017, Wuhan, China

surrounding environment. The gray level co-occurrence may

is a generally used method to describe the texture by study

the spatial c URE EXTRACTION BASED ON GLCM

is a generally used meth

the spatial correlation of

the image shows the common intrinsic property

of the pixel j in the proce

of objects, and includes important information

in the pixel surrounding environment. The gray level co-occurrence matrix
is a generally used method to describe the texture by studying
the spatial correlation of gray scale. It is a relative frequency
matrix that the pixel i corresp surrounding environment. The gray level co-occurrence matrix
is a generally used method to describe the texture by studying
the spatial correlation of gray scale. It is a relative frequency
matrix that the pixel i corresp

$$
= \{ [(x, y), (x + dr, y + dc)] | f (x, y) = i; f (x + dr, y + dc) = j] \}
$$
 (4)

INDEXEDENTION BASED ON GLCM
 EXENCEDENTION BASED ON GLCM
 ISPRS Geospatial Week 2017, 18–22 September 2017, Wuhan, China
 RE EXTRACTION BASED ON GLCM
 ISPREMELY SET ALCOND
 ISPREMELY AND A SURVERTION BASED ON G The international Archives of the Photogrammetry, Renote Setsing and Spatial information Sciences, Vourne XLI+2XV7, 2017

1) Contrast (SPRS Georgianis West 2017, 10-22 September 2017, Walter, Contra

1) The Lexistic of th The international Actives of the Photogrammely, Revious Stations of Spatial Information Scheme, Volume XII-2007, 2017

2) ENTR Consequence Station Consequence Stationary (1975) September 2017: Norma, Omen

2) I. CLCM

2) as and its connection to the

and the detector of and the detector of $x + dy$, $y + dz$ = $f[(x, y), (x + dt', y + dz)] f(x, y) = i; f(x + dr', y + dz) = j]$

we and the column direction and since between methods are calculated from the column direction an surrounding environment. The gray level co-occurrence matrix
is a generally used method to describe the texture by studying
the spatial correlation of gray scale. It is a relative frequency
matrix that the pixel i corresp surrounding environment. The gray level co-occurrence matrix
is a generally used method to describe the texture by studying
the spatial correlation of gray scale. It is a relative frequency
matrix that the pixel i corresp is a generally used method to describe the texture by studying
the spatial correlation of gray scale. It is a relative frequency
matrix that the pixel i corresponds to the occurrence frequency
of the pixel jin the process the spatial correlation of gray scale. It is a relative frequency
matrix that the pixel i corresponds to the occurrence frequency
of the pixel j in the processing window at a specific distance d
and the direction θ . It of the pixel j in the processing window at a specific distance
and the direction θ . It follows:
 $f(x, y) = i$; $f(x + dr, y + dc) = j$ } (4
All of the texture values are calculated from the co-occurre
matrix. The matrix is a function $f(x, y) = i$; $f(x + dr, y + dc) = j$ (4)

All of the texture values are calculated from the co-occurrence

matrix. The matrix is a function of both the angular relationship

and distance between neighboring pixels. It shows the numbe $f(x, y) = i$; $f(x + dr, y + dc) = j$ (4)

All of the texture values are calculated from the co-occurrence

matrix. The matrix is a function of both the angular relationship

and distance between neighboring pixels. It shows the numbe All of the texture values are calculated from the co-occurrence
matrix. The matrix is a function of both the angular relationship
and distance between neighboring pixels. It shows the number
of occurrences of the relation All of the texture values are calculated from the co-occurrence
matrix. The matrix is a function of both the angular relationship
and distance between neighboring pixels. It shows the number
of occurrences of the relation tion Sciences, Volume XLII-2/W7, 2017
han, China
hent. The gray level co-occurrence matrix
enth(of to describe the texture by studying
in of gray scale. It is a relative frequency
is corresponds to the occurrence frequenc tion Sciences, Volume XLII-2/W7, 2017

than, China

nent. The gray level co-occurrence matrix

enthot to describe the texture by studying

i of gray scale. It is a relative frequency

i corresponds to the occurrence frequ tion Sciences, Volume XLII-2/W7, 2017

than, China

nent. The gray level co-occurrence matrix

trethod to describe the texture by studying

no f gray scale. It is a relative frequency

i corresponds to the occurrence freq nent. The gray level co-occurrence matrix
terbiol to describe the texture by studying
o of gray scale. It is a relative frequency
i corresponds to the occurrence frequency
forcessing window at a specific distance d
follo

ii defined 14 texture features according to the gray
 ii Find CLCM is affected by the direction

urrence matrices. In this paper, Contrast, Entropy, Since the semi-variogram can reflect

by, Mean and Second Moment are All of the natrix is a function and disturned and distance between neighboring pixels. It shows the number and distance between neighboring pixels. It shows the number of occurrences of the relationship between a pixel an matrix. The matrix is a function of both the angular relationship
and distance between neighboring pixels. It shows the number
of occurrences of the relationship between a pixel and its
specified neighbor. The co-occurren or occurrences of the relationship between a pixel a
specified neighbor. The co-occurrence matrix statisti
better for SAR image than the occurrence matrix statisti
3.3 Semi-variogram
The GLCM is affected by the directi In a summan is a numerion of bound in angular ielations
of the relationship pixels. It shows the number
of the relationship between a pixel and its
bor. The co-occurrence matrix statistics are
mage than the occurrence mat *j* the relationship between a pixel and its
 j the relationship between a pixel and its
 j. The co-occurrence matrix statistics are

ge than the occurrence matrix.
 am

and the occurrence matrix.
 am

and the occ 3.3 Semi-variogram

The GLCM is affected by the direction θ , the step δ , and

window size w, indirectly affecting the texture factor v.

Since the semi-variogram can reflect the randomness

structure of the image, a mage than the occurrence matrix.
 ogram

inffected by the direction θ , the step δ , and the

infinition can reflect the randomness and

image, and the objects also exhibits good spatial

interacture features, the a **am**
 june 10
 june Since the semi-variogram can reflect the randomness
structure of the image, and the objects also exhibits good s
correlation and texture features, the above parameters c:
calculated by the semi-variogram γ .
 $\theta = 0^{\circ}$ atiected by the direction θ , the step δ , and the

invertibly affecting the texture factor values.

invariogram can reflect the randomness and

dimage, and the objects also exhibits good spatial

texture features, th functify and the object the randomness and
rigogram can reflect the randomness and
ge, and the objects also exhibits good spatial
ture features, the above parameters can be
mi-variogram γ .
 $\frac{1}{m} \sum_{i=1}^{n} \sum_{j=1}^{n} [$

$$
\theta = 0^{\circ} \; : \;
$$

(5)
\n
$$
\theta = 0^{\circ} :
$$
\n
$$
\gamma_{1} = \frac{1}{2m} \sum_{i=1}^{n} \sum_{j=1}^{n} [Z(i, j) - Z(i, j + \delta)]^{2}
$$
\n(10)
\ngree of
\n
$$
\theta = 45^{\circ} :
$$
\n
$$
\gamma_{2} = \frac{1}{2m} \sum_{i=1}^{n} \sum_{j=1}^{n} [Z(i, j + \delta) - Z(i + \delta, j)]^{2}
$$
\n(11)
\n
$$
\theta = 90^{\circ} :
$$
\n(6)
\n
$$
\gamma_{3} = \frac{1}{2m} \sum_{i=1}^{n} \sum_{j=1}^{n} [Z(i, j) - Z(i + \delta, j)]^{2}
$$
\n(12)
\n
$$
\beta = 135^{\circ} :
$$
\n(13)
\n
$$
\gamma_{4} = \frac{1}{2m} \sum_{i=1}^{n} \sum_{j=1}^{n} [Z(i, j) - Z(i + \delta, j + \delta)]^{2}
$$
\n(13)

correlation and texture features, the above parameters can be calculated by the semi-variogram
$$
\gamma
$$
.
\n
$$
\theta = 0^{\circ} : \qquad \gamma_1 = \frac{1}{2m} \sum_{i=1}^n \sum_{j=1}^n [Z(i, j) - Z(i, j + \delta)]^2
$$
\n
$$
\theta = 45^{\circ} : \qquad \gamma_2 = \frac{1}{2m} \sum_{i=1}^n \sum_{j=1}^n [Z(i, j + \delta) - Z(i + \delta, j)]^2
$$
\n
$$
\theta = 90^{\circ} : \qquad \gamma_3 = \frac{1}{2m} \sum_{i=1}^n \sum_{j=1}^n [Z(i, j) - Z(i + \delta, j)]^2
$$
\n
$$
\theta = 135^{\circ} : \qquad \gamma_4 = \frac{1}{2m} \sum_{i=1}^n \sum_{j=1}^n [Z(i, j) - Z(i + \delta, j + \delta)]^2
$$
\n(12)
\nWhere δ = the distance
\n n = the sample image size
\n $Z(i, j)$ = the gray value of the pixel (i, j)
\n M = the number of calculated data pairs, determined by direction and steps.

$$
\gamma_3 = \frac{1}{2m} \sum_{i=1}^n \sum_{j=1}^n [Z(i,j) - Z(i + \delta, j)]^2
$$
\n(12)

$$
\gamma_2 = \frac{1}{2m} \sum_{i=1}^{n} [Z(i, j + \delta) - Z(i + \delta, j)]^2
$$
\n(11)
\n $\theta = 90^\circ$:
\n
$$
\gamma_3 = \frac{1}{2m} \sum_{i=1}^{n} \sum_{j=1}^{n} [Z(i, j) - Z(i + \delta, j)]^2
$$
\n(12)
\n $\theta = 135^\circ$:
\n
$$
\gamma_4 = \frac{1}{2m} \sum_{i=1}^{n} \sum_{j=1}^{n} [Z(i, j) - Z(i + \delta, j + \delta)]^2
$$
\n(13)
\nWhere δ = the distance
\n n = the sample image size
\n $Z(i, j)$ = the gray value of the pixel (i, j)
\n M = the number of calculated data pairs, determined by
\ndirection and steps.
\n4. A NEW 2D OTSU
\nAn image with size M × N can be represented by a 2D level

 $p(i, j)$ (7) M= the number of calculated da direction and steps.

For expansion the squared probable in specify later and the proportion of the squared proportion between the squared by the
specifical proportion of the proportion of the proportion of the system interpersent
specifical p For row and the column direction multi-line that constrained interting the spin of the particular multi-line interting that the spin of the particular prior of the particular properties of the particular properties of t The textural gray level is also divided into the same L values,
let $g(x, y)$ be the function of the textural gray level. Level one contents on the second of the second in the proportion of the second of the second Moment (Second Moment ($\frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} [Z(i, j) - Z(i + \delta, j + \delta)]^2$ (12)
 $-\sum_{i=1}^{n} \sum_{j=1}^{n} [Z(i, j) - Z(i + \delta, j + \delta)]^2$ (13)

annee

le image size

gray value of the pixel (i, j)

ber of calculated data pairs, determined by

4. **A NEW 2D OTSU** $\theta = 135^\circ$:
 $\gamma_4 = \frac{1}{2m} \sum_{i=1}^n \sum_{j=1}^n [Z(i, j) - Z(i + \delta, j + \delta)]^2$ (13)

Where δ = the distance

n = the sample image size
 $Z(i, j)$ = the gray value of the pixel (i, j)

M= the number of calculated data pairs, determ and distance between neighboring pixels. It shows the number
of occurrences of the relationship between a pixel and its
precified neighbor. The co-occurrence matrix statistics are
better for SAR image than the occurrence horing pixels. It shows the number
altionship between a pixel and its
aco-occurrence matrix statistics are
the occurrence matrix.
The direction 0, the step δ, and the
affecting the texture factor values.
1. can reflect t (13)

ermined by

a 2D level

is the gray

ng method,

both used.

E L values, 2*m* $\frac{2}{t-1}$ (33) (13)

Where δ = the distance

n = the sample image size

Z(i, j) = the gray value of the pixel (i, j)

M= the number of calculated data pairs, determined by

direction and steps.

4. **A NEW 2D OTS** Where δ = the distance

n = the sample image size

Z(i, j) = the gray value of the pixel (i, j)

M= the number of calculated data pairs, determined by

direction and steps.
 4. A NEW 2D OTSU

An image with size M × Where δ = the distance

n = the sample image size

Z(i, j) = the gray value of the pixel (i, j)

M= the number of calculated data pairs, determined by

direction and steps.

4. **A NEW 2D OTSU**

An image with size M × N **3.3 Semi-variogram**

The GLCM is affected by the direction 0, the step δ , and the sime of the strain-variogram can reflect the transformation of the image, and the objects also exhibits good spatial sorrelation of the $Z(i, j)$ = the gray value of the pixel (i, j)

M= the number of calculated data pairs, determined by

direction and steps.

4. **A NEW 2D OTSU**

An image with size $M \times N$ can be represented by a 2D level

intensity function The GLCM is affected by the direction 9, the step δ , and the
vindow size w. indirectly affecting the texture factor values.
Since the semi-variogram can reflect the randomness and
since the semi-variogram of the since IFe GLCM is affected by the direction 0, the stp δ , and the
then the joint probability in the image, and the image, and the state state series is
since the semi-variogram can reflect the randomness and
interduce of the 4. A NEW 2D OTSU

An image with size $M \times N$ can be represe

intensity function $f(x, y)$. The value of

level, ranging from 0 to L-1. In a new 2D th

the gray level of a pixel and its textural fa

The textural gray level is ze w, indirectly affecting the texture factor values
semi-variogram can reflect the randomness and
semi-variogram can reflect the randomness and
and texture features, the above parameters can be
by the semi-variogram γ **4. A NEW 2D OTSU**
with size $M \times N$ can be represented by a 2D levention $f(x, y)$. The value of $f(x, y)$ is the gring from 0 to L-1. In a new 2D thresholding method of a pixel and its textural factor are both use all gray l

given by

(9)
$$
p_{ij} = f_{ij} / M \times N(i, j = 0, 1, \dots, L-1)
$$
 (14)

Where
$$
\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} p_{ij} = 1
$$

The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Science ISPRS Geospatial Week 2017, 18–22 September 2017, Wuhan, China

Now suppose that the pixels are partitioned into two classes The International Archives of the Photogrammetry, Remote Sensing and Spatial

ISPRS Geospatial Week 2017, 18–22 September 20

Now suppose that the pixels are partitioned into two classes C₀

and C₁(background and obje tional Archives of the Photogrammetry, Remote Sensing an

ISPRS Geospatial Week 2017, 18–22 Sep

that the pixels are partitioned into two classes C₀

uund and objects) by a threshold pair (s, t), then

of class occurren Now suppose that the pixels are partitioned into two classes C₀

and C₁(background and objects) by a threshold pair (s, t), then

the probability of class occurrence are given by
 $\omega = p_r(c_0) = \sum_{i=0}^{s} \sum_{j=0}^{r} p_{ij} = \$

$$
\omega = p_r(c_0) = \sum_{i=0}^{s} \sum_{j=0}^{t} p_{ij} = \omega_0(s, t)
$$
\n(15)

$$
v = p_r(c_1) = \sum_{i=s+1}^{L} \sum_{j=t+1}^{L} p_{ij} = \omega_i(s, t)
$$
\n(16)

The International Archives of the Photogrammetry, Renote Sensing and Spatial Information Sciences, Volume XLII-2W7, 2017
\nNow suppose that the pixels are partitioned into two classes C₆
\nand C₁(background and objects) by a threshold pair (s, 0, then
\nthe probability of class occurrence are given by
\n
$$
\omega = p_1(c_1) = \sum_{r=0}^{1} \sum_{j=0}^{r} p_j = a_0(s, t)
$$
\nand the corresponding class mean levels are
\n
$$
\mu_0 = (\mu_0, \mu_0, Y) = \left(\sum_{r=0}^{1} \frac{1}{r} p_j = \mu_0(s, t)\right)^2
$$
\nand the corresponding class mean levels are
\n
$$
\mu_0 = (\mu_0, \mu_0, Y) = \left(\sum_{r=0}^{1} \frac{1}{r} p_j = \mu_0(s, t)\right)^2
$$
\n
$$
= (\mu_0, \mu_0, Y) = \left(\sum_{r=0}^{1} \frac{1}{r} p_r = \mu_0(s, t)\right)^2
$$
\n
$$
= (\mu_0, \mu_0, Y) = \left(\sum_{r=0}^{1} \frac{1}{r} p_r = \mu_0(s, t)\right)^2
$$
\n
$$
= (\mu_0, \mu_0, Y) = \left(\sum_{r=0}^{1} \frac{1}{r} p_r = \mu_0(s, t)\right)^2
$$
\n
$$
= (\mu_0, \mu_0, Y) = \left(\sum_{r=0}^{1} \frac{1}{r} p_r = \mu_0(s, t)\right)^2
$$
\n
$$
= (\mu_0, \mu_0, Y) = \left(\sum_{r=0}^{1} \frac{1}{r} p_r = \mu_0(s, t)\right)^2
$$
\n
$$
= (\mu_0, \mu_0, Y) = \left(\sum_{r=1}^{1} \frac{1}{r} p_r = \mu_0(s, t)\right)^2
$$
\n
$$
= (\mu_0, \mu_0, Y) = \left(\sum_{r=1}^{1} \frac{1}{r} p_r = \mu_0(s, t)\right)^2
$$
\n
$$
= (\mu_0, \mu_0, Y) = \left(\sum_{r=1}^{1} \frac{1}{r} p_r = \mu_0(s, t)\right)^2
$$
\n
$$
= (\mu_0, \mu_0, Y) = \mu_0(s
$$

$$
\mu_{T} = (\mu_{T_1}, \quad \mu_{T_j})^T = \left(\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} i p_{ij}, \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} j p_{ij} \right)^T
$$
\nnew 2D Otsu method, the following three tests are designed:
\nA. Artificially marked image
\nB. Segmentation based on traditional 2D Otsu algorithm
\nC. The prepared method

In the total metal rever vector of the 2D instogram is
 $\mu_T = (\mu_{T_1}, \mu_{T_1})^T = \left(\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} i p_{ij}, \sum_{i=0}^{L-1} j p_{ij}\right)^T$

In most cases, the probability of diagonals away fristogram is negligible, so it can be r In most cases, the probability of diagonals a
histogram is negligible, so it can be reasonably as
two regions pij = 0, it is easy to prove that
relationship holds:
 $\omega_0 + \omega_1 \approx 1$, $\mu_T \approx \omega_0 \mu_0 + \omega_1 \mu_1$
Define a varian

$$
\omega_0 + \omega_1 \approx 1, \quad \mu_T \approx \omega_0 \mu_0 + \omega_1 \mu_1 \tag{20}
$$

$$
\sigma_B = a_0 \left[(\mu_0 - \mu_T)(\mu_0 - \mu_T)^T \right] + a_1 \left[(\mu_1 - \mu_T)(\mu_1 - \mu_T)^T \right]_{(21)}
$$

$$
Tr(s,t) = Max(Tr(\sigma_B))
$$
\n(22)

 ≈ 1 , $\mu_T \approx \omega_0 \mu_0 + \omega_1 \mu_1$ (20)

∴
 $\left[\gamma - \mu_T\right]^T + \omega_1 \left[(\mu_1 - \mu_T)(\mu_1 - \mu_T)^T \right]$ (21)

is selected when the matrix is the
 t) = *Max*(*T*r(σ_B)) (22)

5. **RESULTS**

d the TerraSAR image of a region of

26, 2016

directions

From the figure, we can see that not only the water body has $f(x) = \frac{f(x)}{g(x)} \left(\frac{f(x)}{g(x)} + \frac{f(y)}{g(x)} \right)^T$ $\qquad \qquad 9 \times 9, \quad \delta = 1, \quad \theta = 135$, and the five texture measures $i p_{ij} / \omega_1$, $\sum_{i} j p_{ij} / \omega_1$ significant space dependency within the window. The $c_j = (\mu_{1i}, \mu_{1j})^T = \left(\sum_i i p_r (i/c_1) \sum_j j p_r (j/c_1) \right)$ The sill value of γ 1 and γ 2 is higher than γ 3 and γ 4, and window size of the texture information extraction is selected as smooth at 9 pixels, indicating that the sample reach the most the range of γ 3 and γ 4 are basically consistent, relatively structure, but the structure in different directions is inconsistent. are extracted. $\frac{1}{20}$
 $\frac{$ the range of γ 3 and γ 4 are basically consistent, relatively
since the range of γ 3 and γ 4 are basically consistent, relatively
since are basically consistent, relatively
since are basically consistent, relatively
sin Figure 1. Semi-variogram of water sample in different

Figure 1. Semi-variogram of water sample in different

Figure 1. Semi-variogram of water sample in different

From the figure, we can see that not only the water body Figure 1. Semi-variogram of water sample in different
Figure 1. Semi-variogram of water sample in different
directions
From the figure, we can see that not only the water body has
structure, but the structure in different $56\frac{1}{\text{pi}}$ to $\frac{1}{20}$ $\frac{30}{\text{pi}}$ $\frac{40}{40}$ $\frac{60}{50}$ $\frac{60}{60}$ $\frac{1}{\text{pi}}$

Figure 1. Semi-variogram of water sample in different

directions

From the figure, we can see that not only the water body has
 Figure 1. Semi-variogram of water sample in different
directions
From the figure, we can see that not only the water body has
structure, but the structure in different directions is inconsistent.
The sill value of γ 1 Figure 1. Semi-variogram of water sa
directions
from the figure, we can see that not onl
structure, but the structure in different dir-
The sill value of γ 1 and γ 2 is higher th
the range of γ 3 and γ 4 are b directions

In the figure, we can see that not only the water body has

structure, but the structure in different directions is inconsistent.

The sill value of γ 1 and γ 2 is higher than γ 3 and γ 4, and

the From the figure, we can see that not only the water body has structure, but the structure in different directions is inconsistent. The sill value of γ 1 and γ 2 is higher than γ 3 and γ 4, and the range of γ From the figure, we can see that not only the water body
structure, but the structure in different directions is inconsiste
The sill value of γ 1 and γ 2 is higher than γ 3 and γ 4, it
the range of γ 3 and structure, but the structure in different directions is inconsistent.
The sill value of γ 1 and γ 2 is higher than γ 3 and γ 4, and
the range of γ 3 and γ 4 are basically consistent, relatively
smooth at The sill value of γ 1 and γ 2 is higher than γ 3 and
the range of γ 3 and γ 4 are basically consistent, 1
smooth at 9 pixels, indicating that the sample reach
significant space dependency within the window. smooth at 9 pixels, indicating that the sample reach the most
significant space dependency within the window. Thus, the
window size of the texture information extraction is selected as
 9×9 , $\delta = 1$, $\theta = 135$, and the

 $T = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}^T$ new 2D Otsu method, t

-
-

D₂.Entropy D₃.Homogeneity

The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLII-2/W7, 2017 ISPRS Geospatial Week 2017, 18–22 September 2017, Wuhan, China

In the Figure 2, the water targets are slightly affected by the
From the Figure 2, the water targets are slightly affected by the
obvious road in the left of the SAR image. Compared with the
traditional 2D Otsu method, the op and Spatial Information Sciences, Volume XLII-2/W7, 2017
September 2017, Wuhan, China
Trom the Figure 2, the water targets are slightly affected by the
obvious road in the left of the SAR image. Compared with the
tradit Implementation Sciences, Volume XLII-2/W7, 2017
September 2017, Wuhan, China
From the Figure 2, the water targets are slightly affected by the
obvious road in the left of the SAR image. Compared with the
traditional 2D Ots In and Spatial Information Sciences, Volume XLII-2/W7, 2017

September 2017, Wuhan, China

From the Figure 2, the water targets are slightly affected by the

obvious road in the left of the SAR image. Compared with the

tr my and Spatial Information Sciences, Volume XLII-2/W7, 2017
September 2017, Wuhan, China
Trom the Figure 2, the water targets are slightly affected by the
obvious road in the left of the SAR image. Compared with the
tradit commission. September 2017, Wuhan, China

From the Figure 2, the water targets are slightly affected by the

obvious road in the left of the SAR image. Compared with the

traditional 2D Otsu method, the proposed method well erases

th From the Figure 2, the water targets are slightly affected by the obvious road in the left of the SAR image. Compared with the traditional 2D Otsu method, the proposed method well erases the road using using entropy, homog From the Figure 2, the water targets are slightly affec
obvious road in the left of the SAR image. Compared
traditional 2D Otsu method, the proposed method w
the road using using entropy, homogeneity and mea
factors. That

 D_5 94.84 0.8969 8.36 1.57 98.43 91.64

 $\begin{array}{|l|l|} \hline \text{C} & 93.83 & 0.8768 & 9.85 & 1.89 & 9:1 \\ \hline \text{D}_1 & 94.53 & 0.8907 & 6.32 & 4.76 & 9:1 \\ \hline \text{D}_2 & 89.98 & 0.7992 & 7.34 & 13.65 & 8:1 \\ \hline \text{D}_3 & 96.88 & 0.9376 & 2.1 & 4.32 & 9:1 \\ \hline \text{D}_4 & 93.51 & 0.8704 & 9.68 & 2.86 & 9:1 \\$ $\frac{D_1}{D_2}$ 94.53 0.8907 6.32 4.76
 $\frac{D_2}{D_3}$ 89.98 0.7992 7.34 13.65
 $\frac{D_3}{D_4}$ 96.88 0.9376 2.1 4.32
 $\frac{D_4}{D_5}$ 94.84 0.8704 9.68 2.86
 $\frac{D_5}{D_5}$ 94.84 0.8969 8.36 1.57

As reflected in Table 1, the co features. **6.551 6.7576 6.7576 6.7576 6.7576 6.7576 6.876 6.876 6.886 6.886 1.84 6.8969 8.36 6.8969 8.36 6.9969 6.836 1. c d 6.8969 6.836 1. c d 6.8969 6.836 1. c d 6.9569** $\frac{125}{94.84}$ 0.8969 $\frac{125}{94.84}$ 0.8969 $\frac{125}{94.84}$
As reflected in Table 1, the commission of the water is declined,
but the magnitude for the different texture factors is different.
Compared with the tradition As reflected in Table 1, the commission of the water is declined,
but the magnitude for the different texture factors is different.
Compared with the traditional 2D Otsu method, after using the
homogeneity factor, the OA As reflected in 1able 1, the commission of the water is declined,

but the magnitude for the different texture factors is different.

Compared with the traditional 2D Otsu method, after using the

homogeneity factor, the O

based on gray luce to the direct tractive reactors is directed.
Compared with the traditional 2D Otsu method, after using the
homogeneity factor, the OA of data set D₃ is increased by 3.05%,
and the commission is decline Compared with the traditional 2D Otsu, method, after using the
homogeneity factor, the OA of data set D_3 is increased by 3.05%,
and the commission is declined by 7.75%. That is, the proposed
method shows the best impro nomogenety tactor, the OA of data set D₃, is increased by 3.05%,
and the commission is declined by 7.75%. That is, the proposed
method shows the best improvement. This shows that the
proposed method is more effective for and the commission is declined by /./5%. That is, the proposed
method shows the best improvement. This shows that the
proposed method is more effective for areas with texture
features.
6. CONCLUSION
This paper deduces a ne method shows the best improvement. This shows that the
proposed method is more effective for areas with texture
features.
This paper deduces a new 2D Otsu method for water extraction
from SAR image, which calculates the te proposed method is more effective for areas with texture
features.
6. CONCLUSION
This paper deduces a new 2D Otsu method for water extraction
from SAR image, which calculates the texture factors such as
contrast, entropy This paper deduces a new 2D Otsu method for water extraction
from SAR image, which calculates the texture factors such as
contrast, entropy, homogeneity, mean and second moment
based on gray level co-occurrence matrix(GLCM This paper deduces a new 2D Otsu method for water extraction
from SAR image, which calculates the texture factors such as
contrast, entropy, homogeneity, mean and second moment
based on gray level co-occurrence matrix(GLCM from SAR image, which calculates the texture factors such as
contrast, entropy, homogeneity, mean and second moment
based on gray level co-occurrence matrix(GLCM) method and
introduces them into the traditional 2D Otsu, op based on gray level co-occurrence matrix(GLCM) method and
introduces them into the traditional 2D Otsu, optimizing the de-
noising capability of the original 2D Otsu . The results show the
the better effect than the tradit introduces them into the traditional 2D Otsu, optimizing the denoising capability of the original 2D Otsu. The results show the better effect than the traditional 2D Otsu, which provides support for the further extraction

REFERENCES

the better effect than the traditional 2D Otsu, which provides
support for the further extraction of water bodies and show a
new basic step for disaster emergency monitoring.
REFERENCES
Zhang J., 2008. Image segmentation support for the further extraction of water bodies and show a
new basic step for disaster emergency monitoring.
REFERENCES
Zhang J., 2008. Image segmentation based on 2D Otsu method
with histogram analysis. International new basic step for disaster emergency monitoring.
 REFERENCES

Zhang J., 2008. Image segmentation based on 2D Otsu method

with histogram analysis. International Conference on Computer

Science and Software Engineering. 3041-3052. Zhang J., 2008. Image segmentation based on 2D Otsu method
with histogram analysis. International Conference on Computer
Science and Software Engineering. IEEE, pp. 105-108.
Haralichr, 1973. Texture features for image clas Zhang J., 2008. Image segmentation based on 2D Otsu method
with histogram analysis. International Conference on Computer
Science and Software Engineering. IEEE, pp. 105-108.
Haralichr, 1973. Texture features for image clas with histogram analysis. International Conference on Computer
Science and Software Engineering. IEEE, pp. 105-108.
Haralichr, 1973. Texture features for image classification. IEEE
Transactions on Systems Man Cybernet, pp.